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Competition & R&D Subsidies:
New Perspectives on the Public-Private Nexus*

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Abstract

Using a dynamic panel model, this paper empirically examines the effect of public R&D subsides on privately funded R&D in a new light. By synthesizing the theories on public R&D support with those on the relationship between R&D and market structure, we explore to what extent R&D expenditures may depend on public funding in a non-linear, concave fashion with respect to product market competition. In other words, we investigate whether the underlying mechanisms behind the invertedly U-shaped relationship between innovation activity and competition found by Aghion *et al.* (2005), also apply in the context of the leverage effect. Estimates using a difference GMM and X-differencing approach indicate strong support for the notion that public R&D subsidies complement private R&D funding. We are, however, not able to find any statistically significant results with regards to the inverted U and the relationship between the effectiveness of R&D subsidies and product market competition.

Keywords: Research and Development; Subsidies; Policy Evaluation; Competition; Generalized Methods of Moments Estimator

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1 Introduction

In the light of the secular stagnation, economic growth has become the word on everyone's lips. How to sustain economic growth and to what extent growth is compatible with the pursuit of sustainability, are two critical issues that need to be addressed.

One commonly proposed solution for sustaining economic growth is spelled innovation. There is a rather strong consensus among economists that innovation and firms' engagement in research and development constitutes the main contributor to sustained economic growth (Romer 1987, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). Due to this particular strand of research – called endogenous growth theory – a pronounced causal link between R&D, innovation and economic growth has been established.

Nevertheless, despite the relatively strong research consensus, inducing economic prosperity is far from a triviality. Although a clear causal link between R&D and economic output can be established, the basic postulate for such a causality to arise relies on the prerequisite that firms engage in innovative activities in the first place. However, a distinguishing characteristic of the innovational process, called incomplete appropriability, makes this postulate far from self-evident (Arrow, 1962). When firms engage in innovative activities, spillovers are created. Competing firms may indirectly benefit from the knowledge created, which implies that the value of innovation for society exceeds the value reaped by the individual firm making the initial R&D investment. In other words, the party incurring the cost of R&D is not able to appropriate the full benefits derived from it.

Hence, the incomplete appropriability ultimately leads to underinvestment in innovation – from a social perspective (Griliches, 1992). A market failure arises, which constitutes a justification for government intervention in the research sector. Therefore, it is of significant research interest to examine how the government ought to stimulate innovation in the best possible manner. Subsequently, it is also of utter relevance to quantify the actual effects of such stimuli. We are going to address both questions.

When addressing government innovation subsidies, the effect of the stimulus is commonly referred to as the leverage effect. The leverage effect measures how privately funded R&D changes with respect to changes in government subsidies. This has been widely researched, but with mixed evidence – some studies suggesting that the effect is negative due to the substitution of public funding for private funds, while others suggest a positive, stimulating effect (David et al., 2000). This ambiguity calls for further investigation.

At the same time, we have a whole different strand of economic research that, instead of focusing on governmental innovation support, is investigating the economic conditions conducive for innovation. Here, material attention has been paid to product market competition (PMC), and how competition may promote or preclude innovative activities. Some researchers claim that competition increases the incentives to innovate, by making innovation a main tool for surviving in competitive markets (Porter, 1990). Contrariwise, standard industrial organization models indicate an inverse relationship, claiming that competition is harmful for innovation by decreasing the economic return to R&D and thereby reducing investments in R&D (Schumpeter, 1934). Hence, the current state of knowledge is indubitably ambiguous.

To sum up, we have two strands of research with ambiguous findings, which in itself is interesting from a research perspective. Furthermore, to the best of our knowledge, no research has been conducted in the intersection between these fields. The effect of subsidies on private R&D has been widely researched, and so has the impact of competition on R&D. However, not a single paper has sought to merge these distinct branches of research. That will be the aim of this paper – to examine to what extent the leverage effect of R&D depends on product market competition. Our hypothesis is that the leverage effect is a nonlinear, concave function of competition – an inverted U, in more colloquial terms. When competition is low, we expect government subsidies to be ineffective since firms have low incentives to innovate. Indeed, why would a firm innovate if there is no competitor that could steal its customers? Contrariwise, when competition is very high, innovation should also be rather useless since hungry competitors would just leapfrog you with even newer, better inventions, that would make your own inventions obsolete.

Answering this question using the difference GMM estimator and a novel X-differencing approach enables us to evaluate public innovation policy and identify the economic conditions most conducive to public R&D subsidies. This yields a more policy-oriented knowledge, helping policymakers to tackle one of the great economic issues of our time.

1.1 Structure of the paper

In the next section of this thesis, we will provide a more extensive background to the topic. Starting with a general background of growth theory and the economics of innovation, the topic will be placed in a historical as well as a scientific context.

Following the general background is a more thorough review of the empirical as well as theoretical literature on the two disparate topics we are addressing. The section is concluded with a more precise articulation of our research focus, i.e., how we intend to synthesize these research fields and study how the effectiveness of public R&D subsidies may depend on product market competition in a nonlinear fashion.

The literature review will be of a more extensive nature than usual, primarily because of our intention to synthesize two different strands of research. To be able to do so, we need to cover both strands rather thoroughly for the synthesis to become conceptually clear.

Following the literature review is a description of how we intend to answer our research questions – including an exposition of the econometric model and the data. The empirical results are then presented and discussed, after which we conclude with our main findings and propose suggestions for future research.

2 Theoretical Background

To enhance the comprehensibility of the main line of reasoning in this thesis, we believe it to be fruitful to provide the reader with a context in which the arguments can be placed. Following is therefore a schematic overview of some important milestones in the history of economic growth, hopefully helping to contextualize occasionally rather abstract reasoning that is about to follow.

The foundation for how we today think of economic growth can to a large extent be dated back to the 1950s and attributed to the seminal paper of Robert Solow (1956). As a pioneer in the field of growth theory, Solow (1956) sought to explain economic growth with respect to the accumulation of physical capital – based on the notion that investments in machines and buildings were the main fuel of the economic engine. However, due to the diminishing marginal returns to capital and a constant depreciation rate of the capital stock, Solow rejected his hypothesis and concluded that capital accumulation could not be the dynamo of sustained economic growth. The only way of explaining continuous economic growth within Solow's framework was by assuming continuous growth in total factor productivity – a phenomenon Solow assumed to be exogenous in relation to the economic reality. Hence, Solow was among the first to infer the importance of technological change and productivity growth for explaining long term improvements in living standards.

The importance of productivity growth and innovation was further emphasized through the empirical work of Zvi Griliches (1979). However, as opposed to Solow, Griliches gave firms a much more central role in this process. By means of knowledge production functions, Griliches established a causal link between inputs and outputs in the innovation process – relating R&D efforts to its associated innovational output.

In the decade that followed, substantial academic attention was devoted to endogenizing this R&D process. Why do firms engage in innovative activities in the first place? everyone asked. One of the leading voices in this discourse was that of Paul Romer. As one of the pioneers in the field of endogenous growth theory, Romer (1990) described how spending on R&D originated from the ambitions of firms to maximize profits. This line of argument was further strengthened by Aghion & Howitt (1992), arguing from a Schumpeterian perspective that firms engage in innovation to obtain temporary monopoly profits. These temporary monopolies evaporate as competing firms make previous innovations obsolete, by producing even better innovation. This process is referred to as creative destruction and was originally coined by Joseph Schumpeter. From such a perspective, we can clearly see how product market competition plays an integral role when determining how to subsidize innovation. A Schumpeterian would be careful with granting support to firms facing harsh competition.

2.1 The determinants of R&D

This historic background conclusively illustrates the intimate relationship between innovation, economic growth, and competition. However, the theories described tell us little about what actually determines the amount of resources devoted to innovation.

To explore the determinants of R&D, an intellectually fruitful way of concretizing the innovational process is by treating it as a series of investment decisions, as proposed by McFetridge & Howe (1976). From such a perspective, resources will be allocated to R&D until the marginal rate of return to R&D (MRR) equals the marginal cost of capital (MCC) – a standard result in economic models. If the marginal return exceeds the marginal cost, incremental R&D will be profitable. But as a response to an increase in the level of R&D, the marginal cost will rise whereas the marginal gross return will fall – eventually yielding an equilibrium level of R&D. This can be depicted in the following way (R^* denotes the equilibrium) (Fig.1).

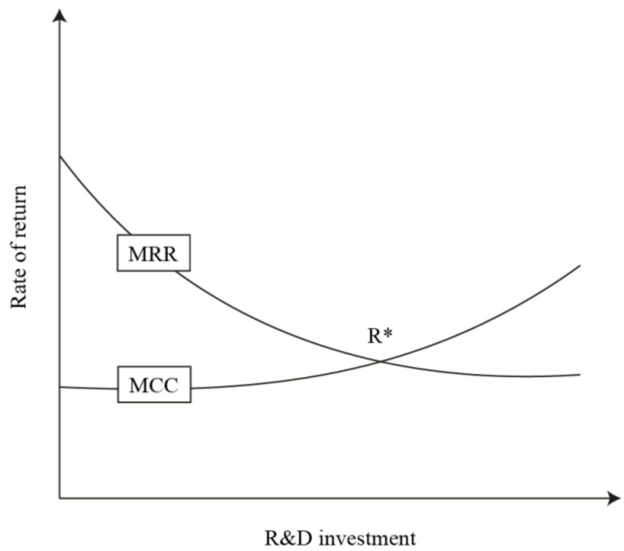

FIG 1. *Source:* Compiled by the authors

In the model, the marginal cost of capital is expressed as an increasing function of the level of R&D investments – meaning that R&D investments become increasingly expensive as the level of R&D increases. This relationship is primarily justified with regards to scarcity in resources. As the demand for the labor and capital used in the R&D process increases, labor and capital simply become more expensive.

Contrariwise, the marginal return is modelled as a decreasing function of the R&D stock. This assumption can be rationalized in several ways, for instance through the standard diminishing marginal return argument. More intuitively, we can conceptually think of the marginal return curve as a graphical representation of different R&D projects, with the left-most section of the graph representing the most profitable projects. Based on such reasoning, the intersection of the curves represents the point when all profitable innovational opportunities have been exhausted.

From this modeling exercise, we can infer that the level of R&D in the economy is determined by the relative position of the abovementioned curves. In turn, the relative position of the two curves is determined by an array of different factors. David et al. (2000) discuss some of the factors considered relevant. For the marginal return, technological opportunities, demand for potential products and institutions (including competition) affecting the appropriability of innovation benefits are likely to constitute important determinants.

Regarding the marginal cost of capital, David et al. mention policy measures (tax treatment and R&D subsidies), macroeconomic conditions, capital market conditions and the availability of venture funding, as integral factors determining how costly it is to invest in R&D.

Yet again, R&D subsidies and product market competition proves to be relevant factors for further analysis. Competition affects the return to R&D, whereas subsidies affect the cost of R&D.

2.2 The rationale for government intervention

From this simple investment perspective, innovation appears relatively hassle-free. However, there are several distinguishing characteristics of innovation that makes the analysis considerably more complicated. A key feature of the innovational process is that it generates positive externalities (spillovers). An idea generated from an innovational process might be of value for many actors in the economy besides the producing firm, giving rise to an unintentional, valuable byproduct that cannot be perfectly appropriated by the performing firm (Nelson, 1959; Arrow, 1962). Put differently, competitors cannot be fully precluded from being inspired by, or freeriding on, a firm's innovative output, which implies that the value of innovation from a social perspective exceeds the value of innovation incurred by the individual firm. In terms of McFetridge & Howe's framework,

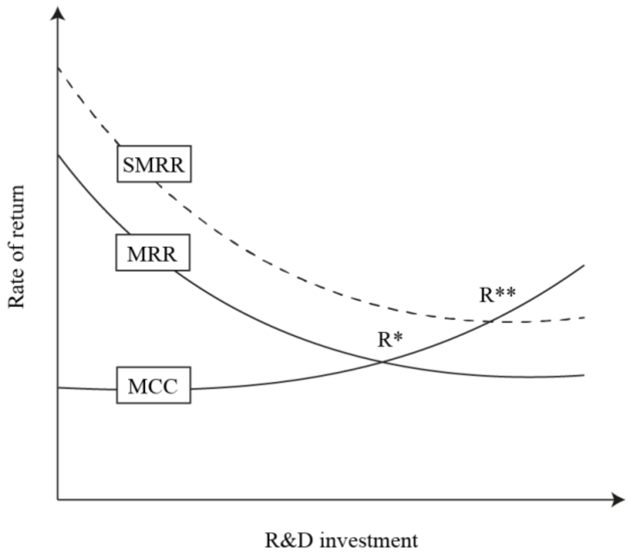

FIG 2. *Source:* Compiled by the authors

this can be illustrated through the existence of two different marginal return curves – one for society as a whole and another for the individual firm. We obtain Figure 2.

Since many firms may benefit from the innovations of a single firm, the social marginal return curve is located above the private marginal return curve – for any level of R&D investments. Hence, when the market is left to its own device, firms will underinvest in R&D which in Figure 2 is reflected by an equilibrium with a lower level of R&D investments than would be the case if the firms internalized the positive externalities.

This underinvestment constitutes a market failure, which is a textbook example of a situation when government intervention is justified. In this case, government intervention is needed to raise the level of R&D to its socially optimal level. Determining how this can be achieved in the most efficient way is therefore of utter importance, which is what this paper is all about.

In his 1962 paper, Arrow also mentions two other problematic aspects of innovation – apart from the incomplete appropriability. The first one touches upon capital market imperfections and uncertainty. Some R&D projects may simply pose such high risks that individual firms are unable to bear it. Moreover, the lack of opportunities for diversifying these risks, especially when the projects require substantial financing, leaves some projects unfunded despite being profitable.

The second problem that Arrow mentions originates from the increasing returns that innovation is associated with. Before a single unit of an invention can be manufactured, large fixed upfront research costs need to be incurred. The marginal cost of the first unit (which includes the R&D expenditures) is therefore substantial, whereas the marginal cost thereafter immediately decreases to only reflect the physical resources needed for additional output. If we permit perfect competition to prevail under these circumstances, allowing goods and services to be paid their marginal costs, the fixed upfront expenditures of R&D will never be recovered. Hence, no firm would voluntarily want to spend money on R&D. Once again, government intervention in one form or another is needed. And once again, the question of how government intervention appropriately should be designed needs to be answered.

To conclude, Arrow's market failure argument can be decomposed into three parts,

(a) Incomplete appropriability (spillovers).
(b) Increasing returns in use.
(c) Uncertainty and risk, leading to a shortfall in financing.

Theories aside, a substantial amount of empirical work has also been done in this field. One example is the work of Griliches (1992), demonstrating how the social return to R&D exceeds the private return. More recent meta evidence by Hall et al. (2010) confirms this conclusion – stating that the social return widely exceeds the firm-level internal rate of return (IRR).

2.3 Public policies to support R&D

Government intervention is therefore a necessity for correcting the aforementioned market failures.

Broadly speaking, there are two ways for the government to correct for this market failure, as described by Guellec & Van Pottelsberghe (2003). The government can either give direct support, which is either manifested through fiscal incentives (altering tax rates or imposing tax credits) or through subsidies and grants (giving money directly to firms). The government can also indirectly support business R&D, through research conducted at universities as well as in public research labs. The different forms of government support are illustrated in Figure 3.

Much research has been done on the effectiveness of these different ways of stimulating R&D, including Hall & Van Reenen's (1999) study on tax credits, Jaffe's (1993) study on the impact of university research and Blank & Stigler's (1957) seminal paper – examining the relationship between private and public R&D investments.

In this study, we are exclusively focusing on subsidies. Hence, our general question addresses how public research subsidies may affect private R&D and how this effect depends on the degree of product market competition.

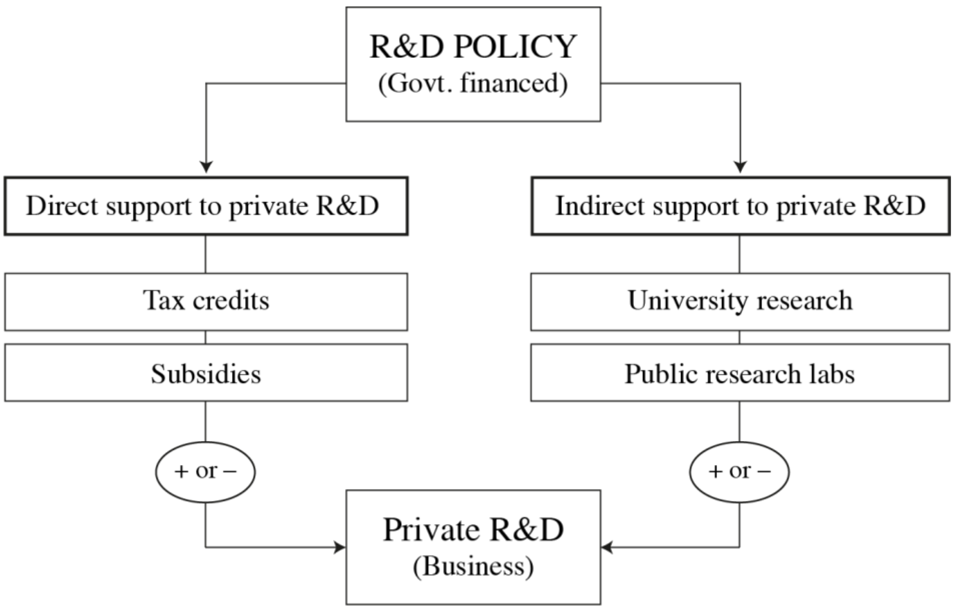

FIG 3. *Source:* Compiled by the authors

2.4 Subsidies: crowding in, or crowding out?

Notwithstanding the importance of public support, subsidies are not unequivocally positive for private R&D investments. Before delving into the previous empirical evidence on R&D subsidies, we therefore need to clarify the theoretical framework on how subsidies might affect privately funded R&D.

The general question is whether public funding is a complement or a substitute to private R&D funding. When discussing this, there are some key terms that need to be defined. In this text, we are going to use the term 'leverage effect' as the neutral word for the effect of public R&D subsidies on privately funded R&D. When this leverage effect is positive, we refer to it as additionality, crowding in or complementarity, whereas when the leverage effect is negative, we refer to it as crowding out or substitution.

Starting with additionality, Görg & Storbl (2007) discuss two main transmission channels. Firstly, since public funding reduces private costs, subsidies make it more profitable to invest in R&D. Marginal costs decrease while marginal returns remain unaltered. Secondly, the publicly funded projects may generate knowledge spillovers upon which further research may be built.

Concerning crowding out, there are a multitude of transmission channels. Firstly, since public funding from a firm perspective is cheaper than capital market funding, there are incentives for firms to substitute public funding for private funds. Thus, the publicly funded projects may have been pursued anyways – with or without public funding. According to Bergman (2012), this is particularly problematic when dealing with an ambitious government pursuing a 'picking the winner' strategy. The government intends to spend tax-payers' money in an as efficient way as possible. In the quest of doing so, government officials are likely to select the most profitable projects with the best prospects. These projects would probably have been financed anyways, thereby leading to substitution and crowding out. Nevertheless, if risk and uncertainty is what is discouraging firms from investing in R&D, it may be a good idea to also finance these high return projects.

Secondly, according to Guellec & Van Pottelsberghe (2003), government funding may be allocated in less efficient ways, thereby creating distortions. Such distortions could also arise with regards to competition, with public funding benefiting some firms at the expense of others.

Lastly, we may experience general equilibrium effects as government funding generates a higher demand for R&D. Goolsbee (1998) and David & Hall (2000) argue that one adverse effect of government funding is that it raises the wages of researchers. Facing higher research costs, firms will allocate funds to other activities than R&D. Thus, even if the nominal amount of R&D increases thanks to government funding, the real amount (measured by the number of researchers) may fall.

In this thesis, we are looking at the overall relationship between R&D subsidies and privately funded R&D. Thus, we are capturing the net effect of all these counteracting effects.

2.5 The theoretical narrative

Before we explore the recent empirical evidence, let us provide a short recap of the narrative we are intending to convey.

In its essence, the study is addressing the topic of economic growth, for which innovation plays an integral role. Because of the nature of innovation, including increasing returns, high uncertainty and incomplete appropriability, firms will underinvest in R&D. This justifies public support, which may vary in terms of efficiency. On the one hand, government funds might lower the cost of capital, but it might just as well become a substitute for private funding. We are going to examine the net effect of these forces, and whether this net effect (leverage effect) depends on product market competition in a nonlinear fashion.

2.6 Recent evidence on the leverage effect

The essential policy-implications of the public-private nexus has ever since Blank and Stigler's (1957) empirical paper investigating the effect of the sudden US R&D budget raise in the 1950's, spurred a rich and heterogenous literature exploring the additionality and crowding out of R&D input. After almost six decades of ongoing research, the empirical evidence is still inconclusive, providing little consensus on whether public support actually provides additional private R&D expenditures.

An initial note of caution must however be addressed: as there are numerous ways a government can stimulate private R&D expenditures, the semantical limitation – or say lack of terminology – has made the additionality concept imprecise. Studies address the additionality hypothesis through various units of analysis (country, industry, firm), different geographical scopes and with either total government spending, R&D tax credits, subsidies, or indirect support through university basic research and formation of high-skilled human capital as explanatory variables (Becker, 2015)[1]. All these methodological variations require different empirical approaches which besides generating heterogeneity in estimations, also make any comparisons between these studies hazardous (Zuniga-Vicente et al., 2014).

To structure the existing body of literature, studies typically adopt either a microeconomic or macroeconomic approach. The microeconomic studies use firm-level data and hence investigate the *direct effects* of businesses R&D decisions after receiving public subsidies. As these public subsidies are granted at the firm level and R&D is ultimately a decision undertaken by the individual firm, scholars have argued that it makes much sense to approach the question of additionality on a firm level basis (Mansfield and Switzer, 1984; Levy and Terleckyj, 1983; Ali-Yrkkö, 2005; Vicente, 2012). This commonly held notion is illustrated by the rich and growing number of studies using firm-level data (Zuniga-Vicente et al., 2014).

Macroeconomic studies on the contrary, assess how R&D investments change with respect to public R&D support at the industry or country level. Although studies at a high level of aggregation cannot account for the heterogeneity of firms (Vicente, 2012), studies at the aggregate-level can detect so called *indirect effects* of public R&D support. A firm receiving public support and therefore increasing their level of R&D expenditures will generate positive spillovers that other firms, through absorption capacity, can benefit from. Contrariwise, the same R&D expenditures might also entail negative spillovers and decrease the incentives for competitors to invest in R&D through creative destruction

[1] For studies on total expenditures, see for example Rehman (2020), Guellec & De La Potterie (2003). For studies on tax credit see for example Dechez-leprêtre et al. (2016), Castellacci and Lie (2015).

(Schumpeter, 1942). Hence, the indirect effects of public R&D support play a central role in detecting the true leverage effect of the public-private nexus.

David et al. (2000), surveying 33 of the existing studies up until 2000 on three different levels of aggregation (firm, industry, country), further emphasize that the additionality coefficient largely depends on the level of aggregation, where it seems more common to find evidence of complementarity the higher the aggregation level (David et al., 2000; García-Quevedo, 2004).

2.6.1 Microeconomic evidence

Although this study adopts a macroeconomic approach, leaving the microeconomic studies of secondary interest, there are relatively few macroeconomic studies undertaken on the leverage effect (Oxford Economics, 2020). We will thus briefly examine the recent firm-level results.

Historically, the firm-level evidence on the leverage effect has been encountered with vast fluctuations, ranging from full crowding-out effects (Wallsten, 2000) to additionality (Klette, Moen and Griliches, 1999).

When surveying the existing literature, David et al. (2000) concludes that until the late 1990s, firm-level evidence was ambiguous with both positive and negative elasticities ranging from -0.13 to 0.48. Nine out of nineteen studies found substitutional (or partial crowding-out) effects. Similarly, García-Quevedo (2004) using a meta-analysis, and more recently, Zùniga-Vicente et al. (2014), both found that barely half of the firm-level studies support the additionality hypothesis.

The studies prior to the turn of the millennium, examined by David et al. (2000), used simple regression models and have therefore been critiqued for the lack of addressing selection biases spurring an endogeneity problem. In order for a firm to receive public funding they must first apply for it and governments must thereafter decide who will receive support, potentially through a 'pick the winner' strategy where the most innovative firms will be supported (Hussinger and Czarnitzki, 2017). As these processes cannot be seen as random, the public support variable will be endogenous and cause inconsistent estimates (Busom, 2000). Kauko (1996) goes as far as claiming that the assumption of exogeneity of R&D subsidies is almost certainly unacceptable, leaving the evidence prior to 2000 obsolete.

As a consequence of the recent advancements in econometrics, controlling for selection effects, Becker (2015) concludes that the evidence of the modern literature is more in favor of the additionality hypothesis.

Busom (2000) was the first to apply a parametric estimation approach using Heckman's (1979) selection model. Busom found that public R&D subsidies on average stimulate R&D, but for 30% of the firms in the sample, full crowding out effects could not be rejected. Other studies adopting Heckman corrections have generally found similar results of additionality (see Hussinger (2008) and Cerulli and Potì (2012) for German and Italian firms respectively). The exception is Aristei et al. (2016) who did not find evidence of additionality for firms across five EU-countries, but likewise rejected a full crowding out.

Even more prevalent are studies adopting a non-parametric approach, including the propensity score matching (PSM). Using a combination of PSM (accounting for observable characteristics) and a difference in differences design (accounting for unobservable but fixed characteristics), Hassine et al. (2020) found an additionality of €1.875 for every €1 granted to French firms. Several other studies adopting the PSM methods find similar results (Hussinger, 2008; Engel et al., 2017; Hottenrott and Lopes-Bento, 2014; Yang et al., 2012; Czarnitzki and Delanote, 2015).

Although the PSM has gained considerable popularity controlling for the selection bias in the explanatory subsidy variable, King et al. (2011) points out severe drawbacks in the likelihood of finding an actual twin. Furthermore, firms receiving R&D support are typically more inclined to spend additional money on R&D. The PSM and DiD techniques do not account for such bias and one must therefore evaluate these results with caution.

Dimos and Pugh (2016) provides the most comprehensive survey on the microeconomic evidence since 2000, using a meta regressions analysis (MRA) of fifty-two published firm-level studies. After controlling for publication biases and a variety of article specific characteristics such as modelling techniques, they reject full crowding out and conclude a very small additionality effect at a MRA elasticity of less than 0.01 (Dimos and Pugh, 2016).

2.6.2 Macroeconomic evidence

As previously mentioned, the macroeconomic evidence on additionality in the public-private nexus has historically been more conclusive than its microeconomic counterpart (David et al., 2000).

The aggregate-level studies approach additionality typically at the national level using cross-country panel data, investigating whether variation in country-level private R&D expenditures can be explained by the public support for R&D (Economic Insight, 2015). Relatively few studies have been conducted at the industry level (see Zùniga-Vicente et al., 2014 for a survey).

As this paper focuses on the 'input additionality' – the impact that public funding has on the amount that the private sector spends on R&D – input additionality will be our focus when investigating the macroeconomic evidence. However, there are other branches of macroeconomic studies focusing on the 'output additionality' – investigating how the public support for R&D influences private sector innovation output measures like patents or productivity. Using a production function approach (see Jaffe, 1989 or Acs & Audretsch, 1988 for an illustration), these studies normally find a positive relationship.[2]

The historical macroeconomic evidence before year 2000 is surveyed by David et al. (2000), who – from the five papers examined – find a predominantly positive relationship between public and private investments, with two papers reporting elasticities ranging from 0.045 to 1.45.

[2] For studies on patenting see Azoulay (2015), Czarnitzki & Lopes-Bento (2011). For studies on sales of innovative products see Czarnitzki, Hanel & Rosa (2011), Hottenrott and Lopes-Bento (2014).

Despite the relatively meager existing body of macroeconomic papers, a wave of new studies has been undertaken. With private R&D expenditures as a percentage of GDP as the dependent variable and by using a first difference GMM estimation on a panel data set between 1970 and 2002 on 17 OECD countries, Falk (2006) finds a positive impact of tax incentives and direct support for R&D as well as positive indirect effects from university R&D expenditures.

Silaghi et al. (2014) uses a similar system GMM approach with a data set on Central and Eastern European countries (CEE) between 1998 and 2008 but find no statistically significant results. They argue however that public R&D neither has a crowding out effect on private R&D.

TABLE 1. Summarized Macroeconomic Evidence on the Leverage Effect

Author(s)	Estimated effect	Data	Estimation method	Leverage effect
Country-level				
Falk (2006)	Determinants of Business R&D intensity	Panel data on 21 OECD countries (1975–2002) with five-year average.	System GMM (1) Difference GMM (2)	0.03 (s) (1) 0.13 (l) (1) 0.10 (s) (2) 0.14 (l) (2)
Montmartin et al. (2013)	Public R&D direct support on private R&D	Panel data on 25 OECD countries (1990–2007)	CLSDV	-0.07 (s) (i) -0.0805 (l) (i)
Silaghi et al. (2014)	Public R&D and private R&D on GDP growth	Panel data on CEE countries (1998–2008)	System GMM	Insignificant but no crowding out
Economic Insight (2015)	Total public R&D expenditure on private R&D expenditure in UK and across countries	Panel data on 16 countries (1999–2012)	FE VECM ADL	0.49–0.58.
Oxford Economics (2020)	Public R&D on private R&D expenditure in UK and across countries	Panel data on 31 OECD countries (1995–2016)	System GMM	0.09–0.12 (s) 0.25–0.41 (l)
Rehman (2020)	Public R&D support on private R&D	Panel data on 10 OECD countries (2000-2014)	System GMM	–0.066 (i) 0.3133 (m) 0.726 (se)
Industry-level				
Lichtenberg (1984)	Public R&D expenditure on private R&D expenditure	Panel data on 12 US manufacturing industries (1963–1979)	FE OLS	0.01 (i)
Levin and Reiss (1984)	Public R&D expenditure on private R&D expenditure	Panel data on 20 US manufacturing industries (1963, 67, 72)	2SLS	0.12
Mamuneas and Nadiri (1996)	Total public R&D on business R&D expenditure	Panel data on 15 US Industries (1956–1988)	OLS	0.54
Becker and Pain (2008)	Public R&D support on total industry R&D expenditure.	Panel data on 11 UK industries (1993–2000)	IV	0.11 (s) 0.18 (l)

Notes: (s): Short-run, (l): Long-run, (i): insignificant, (m): manufacturing sector, (se): service sector.

Economic insight (2015) further investigates the impact of total public sector expenditures on total private sector expenditures using multiple data sets and estimation approaches (simple linear regressions with fixed effects, Vector Error Correction models, linear regressions with auto-distributive lags). They conclude that £1 of public funding increases the private expenditures by between £1.13 and £1.60 over 10 years, with £1.28 occurring within the first five years. Montmartin et al. (2015) nuance these results using panel data from 25 OECD countries between 1990 and 2009. They find substitution effects between different forms of public support; one form of support (i.e., tax incentives) will consequently reduce the leverage effect for other forms of support (i.e., subsidies).

One of the few and most recent macroeconomic studies specifically addressing the impact of government direct support for R&D on private R&D is provided by Oxford Economics (2020). Using a system GMM estimation approach with data from 31 OECD countries between 1995 and 2016, they find that the short-run leverage effect is 0.09 to 0.12 and the long-run leverage effect is 0.25 to 0.41. This corresponds to £0.79 to £1 in the short run, and £2.16 to £3.63 in the long run for every £1 of public support.

Surprisingly few industry-level studies have been conducted on the public-private nexus. Previous studies tend to find moderate, positive effects (Lichtenberg, 1984; Levin and Reiss, 1984; Mamuneas and Nadiri, 1996). One of the few more recent evidence is provided by Becker and Pain (2008) who use a panel of UK manufacturing industries between 1993 and 2000 in search for the determinants of industry R&D. They find that a one percentage point increase in the *share* of publicly funded R&D, increases the *level* of private R&D with 1.1% in the short-run and 1.8% in the long run (Becker and Pain, 2008). These approximately correspond to leverage effects of 0.11 and 0.18 respectively (Economic Insight, 2015).

2.7 Competition explaining R&D

The role of market structure explaining innovation activity and economic growth was first emphasized by Joseph Schumpeter (1934), stating that highly concentrated markets would enhance the appropriability of returns to R&D.[3] Succeeding Schumpeter's work, the "Schumpeterian paradigm" and the following Schumpeterian growth models argue that firms engage in innovation through the desire of earning monopoly rents, and theorizes a negative relationship between competition and innovation as competition reduces the expected payoff from R&D investments through the process of creative destruction (Aghion and Howitt, 1992). That is, one firm's innovations are assumed to be leapfrogged by more advanced firms closer to the technological frontier – making the innovation obsolete. Consequently, a firm will be reluctant to engaging in innovation the greater the risk of imitation (i.e., higher competition).

[3] The role of competition and innovation was first formally and extensively analyzed by the standard IO theories (see Tirole, 1988), stating that competition decreases innovation activity due to the reduction of the monopoly rents rewarding innovation (Dasgupta and Stiglitz, 1980).

Schumpeter argued that monopoly deadweight loss therefore is the price society must pay for firms to be incentivized to engage in R&D activities – hence the importance of preserving property rights through systems such as patent protection, mitigating the creative destruction effects.

These harsh predictions spurred an array of contrasting theoretical papers, arguing that competition in fact stimulates innovation and R&D. One of the more profound contributions is provided by Michael Porter (1990) who argues that competition is good for growth as it forces firms to innovate to stay afloat. On the same token, Scherer (1980) claims that lack of competition discourages innovation activity due to bureaucratic inertia.

The empirical findings of these two theoretically contradicting stands on the relationship between competition and innovation has historically been ambiguous. Inspired by the Schumpeterian paradigm, the early literature found a negative relationship between competition and innovation through linear specification (Horowitz, 1962; Mansfield, 1968; Kraft, 1989; Crépon et al., 1998). Contrariwise, more recent studies point at a positive relationship, confirming Porter's theories (Geroski, 1990; Blundell et al., 1995; Nickell, 1996; Blundell, Griffith and Van Reenen, 1999).

The prevalence of such contradictions suggests a potential non-linear relationship – which lies the foundation for our hypothesis. Indeed, a non-linear relationship between competition and innovation was originally hinted by Scherer (1967) who showed in a cross-sectional analysis of Fortune 500 firms a significant inverted U-shape between innovation and competition, albeit these findings were not explained or tested for robustness. The first theoretical explanation for the inverted U-shape was provided by Aghion, Dewatripont, and Rey (1999) and were later empirically validated by Aghion et al. (2005) using a UK firm-level panel data set.

2.7.1 Explaining the inverted U-shape

To account for a positive relationship between competition and innovation, Aghion et al. (1997) introduce a gradual, step-by-step technological progress approach to the Schumpeterian framework. That is, they replace the initial Schumpeterian assumption that incumbent innovators will automatically be leapfrogged by their more advanced competitors, with the assumption that firms engaging in R&D acquire tacit knowledge that is not appropriable by rivals without engaging in R&D themselves. (Aghion et al, 2009). A firm that is currently m steps behind the leading firm in the industry, must consequently be catching-up m steps before becoming the leader itself. Put differently, a non-leading innovator may under the new assumption become technologically at par with the leading but non-innovating firm.

These dynamics allow for two types of intermediate sectors in the economy: (1) a level (or neck-and-neck) sector where all firms are at, or near, the technological frontier and (2) an unlevel sector with a technologically leading firm and non-leading laggard firms.

None of the aforementioned and contradicting theories can solely explain the inverted U-shape first detected by Scherer. But by allowing industries to be leveled or unleveled, Aghion et al. (1997) effectively combines the Porterian and Schumpeterian theories into a single framework, where two opposite effects are simultaneously at play accounting for the positive and negative slopes of the curve.

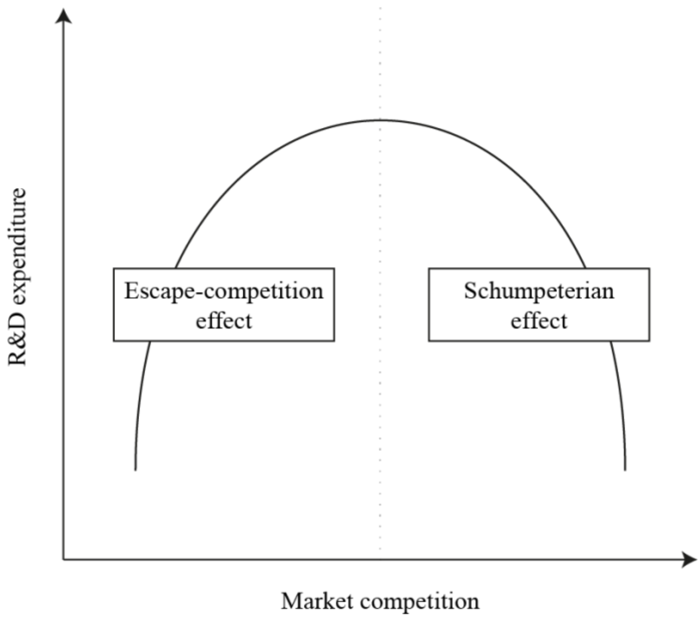

FIG 4. *Source:* Compiled by the authors

Observing Figure 4, the positive slope accounts for Porter's theory that competition induces more innovation. Since the decision to innovate depends on the difference between post- and pre-innovation rents (incremental profits) – an increase in competition will induce incremental innovation if and only if a firm's pre-innovation rents are reduced more than its post innovations rents. That is, competition constrains profits, and firms engage in innovation in an ambition to escape this situation (Aghion & Howitt 2009). Furthermore, this "*escape-competition effect"* should be most prevalent in the neck-and-neck sectors because pre-innovation rents are heavily reduced for incumbents when a single firm innovates in such sector. Put in other words, the pay-off of an edge over competitors is greater the more neck-and-neckness there is. This escape-competition effect can thus explain why competition induces innovative activity.

Contrariwise, the negative slope accounts for a "*Schumpeterian effect"* that results from the reduction of post-innovation rents as rivals are catching up with the innovator – making previous innovation obsolete. This effect should be most prevalent in unlevel sectors where leading firms more easily leapfrog laggard firms. Hence, from this perspective, an increase in competition will discourage innovation activity of laggard firms.

When combining these effects, an increase in market competition will have ambiguous effects on innovation activity; so why is the escape-effect dominating at lower degrees of product market competition, whereas the Schumpeterian effect is dominating at higher degrees of competition?

The inverted-U shape is a result of what Aghion and Howitt (2009) calls the "*composition effect"*, where a change in market competition will affect the steady-state fraction of the level versus unlevel sectors (dominated by the escape-competition and Schumpeterian effects, respectively).

With low market competition and a level sector containing few neck-and-neck competing firms at similar levels of technology, firms have no incentives to innovate as they already exploit monopoly or oligopoly rents. This in turn, means that unlevel sectors with laggard firms will innovate more intensively than level sectors, thus catching up with the technology frontier. Consequently, the unlevel sectors will transition to level sectors and the industry will spend more time as a level sector where the escape-competition effect is more prevalent. Hence, the escape-competition effect will dominate when competition is low and an increase in competition will spur a faster innovation rate.

With higher market competition and a level sector characterized by neck-and-neckness, firms are encouraged to innovate through the escape-competition effect. This in turn, will transition level sectors to unlevel sectors (some firms become leaders, others fall behind), where laggard firms are discouraged to innovate by the Schumpeterian effect. Thus, the Schumpeterian effect will dominate at high levels of competition and an increase in competition decreases the innovation rate further.

Consequently, the composition effect – rooted in the underlying escape-competition effect and Schumpeterian effect – gives rise to the inverted U-shape between innovation and competition. This nonlinear relationship has since Aghion et al. (2005), also been found by Poldahl and Tingvall (2006) and Azkenazy et al. (2008).

2.7.2 Competition and public support

We argue that Aghion and Howitt's (2009) explanation of the inverted U can be extended to the case of leverage effects. Despite measuring the relationship between competition and the leverage effect, we predict that the same underlying mechanism applies as for the relationship between competition and innovation activity.

Thus, in low market competition where level sectors are theoretically more prevalent, firms receiving grants in neck-and-neck competition have still small incentives to be innovative and hence we expect a low additionality or even a crowding-out effect from these firms. For laggard firms in low market competition, we expect leverage effects of additionality up to the point where firms have caught up with the technological frontier. On an industry average, if the degree of competition is initially low, we thus expect higher leverage effects as competition increases.

The question here is whether laggard firms are more prone to seek public support. If so, we might see on average higher leverage effects than expected as these firms might spend private R&D funds in order to catch up with leading firms.

For initially high levels of market competition, we expect low levels of additionality or even crowding out effects as the theoretically dominating unlevel sectors with laggard firms will, despite public support, have meager incentives to spend their own private funds on innovation due to the Schumpeterian effect. This may however seem rather contradictory to commonly held notions of public support policies, where firms are supported to stimulate competition. If we were to empirically validate these hypotheses, their profound policy implications are apparent.

3 Research Specification

3.1 Delimitations

Although we would like to draw as broadly applicable inference as possible, delimitations are needed. Partly for practical reasons, but also to make the research more relevant.

The most elemental of delimitations in this paper is that of aggregation level. The analysis is based on industry data, a choice which to some extent is due to the difficulty of gaining access to the oftentimes confidential microlevel data. As mentioned previously, this has major effects on how the results should be interpreted. One crucial benefit of quantifying the leverage effect on the industry-level is that it enables us to capture the indirect effects of R&D subsidies, i.e., the impact that the subsidies have on other firms (nonbeneficiaries) in the economy. These indirect effects are proven to be of large importance. In a study by Fölster and Trofimov (1996), R&D subsidies granted were shown to be associated with an increase in R&D for the beneficiary. However, total R&D by competitors were likely to decline. Many researchers also argue for substantial positive spillovers. For instance, Rehman (2020) mentions the significant knowledge spillovers that may arise from R&D, which supports the notion that a higher level of aggregation better captures the full range of effects from R&D subsidies.

Using industry-level data is also likely to be beneficial for the establishment of a causal relationship, as suggested by Guellec & Van Pottelsberghe (2003). With firm-level data, strict exogeneity is significantly more difficult to satisfy because of the intricate self-selection element of R&D subsidization. It may be the case that primarily certain kinds of firms, with certain characteristics, are applying for R&D subsidies. And that only certain kinds of firms, with certain characteristics, are granted R&D support. Hence, with firm-level data, an omitted variable bias might yield incorrect estimates. As Lichtenberg (1984. p.74) elegantly phrased it: “Federal contracts do not descend upon firms like manna from heaven”.

Of course, self-selection may also be prevalent on the industry level. It is reasonable to assume that government officials are more inclined to granting support to certain industries – such as hot, fast growing industries. Nevertheless, the self-selection dimension is thought to be smaller at the industry level and the possible confounders easier to identify – an aspect that is more thoroughly discussed in the following section.

Despite its identification benefits, using industry-level data also comes at a certain cost. First, when using industry-level data, we are not studying the effect on the level that the effect arises – which naturally is at the firm level. Indeed, firms are the units applying for the grants and deciding how much to spend on R&D. Moreover, industry-level data yields less data points which makes the inference less robust as opposed to an analysis utilizing micro-level data.

Industry-level data neither allows us to control for the market structures discussed by Aghion and Howitt (unlevel vs. level, see section 2.7.1). Hence, we are unable to test whether their specific explanation to the inverted U is consistent with our results. Instead, the theory of the inverted U only serves as our theoretical premise.

Another important delimitation, besides the level of aggregation, concerns the specific sample of industries used in the analysis. Our ambition was to include as many industries as possible, but due to the merging of two data sets (BERD and STAN, see section 4.1), only the industries common to both data sets are used in the regression. Still, the industries included are rather broadly defined, while those excluded are mostly subcategorization of broader industry classes. Thus, we still obtain a representative sample. However, it is worth reflecting on to what extent these industry exclusions reflect a selection bias – being correlated with our explanatory variable. We would argue that it is not, based on the aforementioned fact that the industries excluded were only more detailed industry classifications. The more general ones are kept, which makes the cross section comprehensive and representative of the economy as a whole – only not as granular as it could have been. Hence, robustness may be affected but the estimates will not suffer from any biases in this regard.

This very same selection bias is also prevalent on the country level. Not all countries included in the BERD data set are found in STAN, and vice versa. However, the overlap is significant, and a majority of all OECD member countries are common to both data sets. Hence, we find no reason for there to be any selection bias in our analysis when drawing inference at the OECD level. However, it is important to note that since we are only looking at the OECD, we can only draw conclusions based on the OECD and its average circumstances. This is important to remember when interpreting the data.

A third delimitation concerns the measurement of the explanatory variable. As mentioned previously, we are examining R&D support provided in the form of subsidies. In the BERD data set, subsidies are measured as private expenditures on R&D financed by the public sector. The reason why we are choosing to look at subsidies is twofold. One reason is that subsidies, together with fiscal incentives, are the most common form of technological policy for stimulating R&D (Afcha and Guillén, 2014). The other reason is simply that R&D subsidies have increased substantially in recent years, making knowledge about subsidies even more valuable (Haufler, 2020).

Naturally, many more delimitations will be discussed throughout the paper. These three are only the most central delimitations.

3.2 Academic contribution

We believe the contribution of this study to be threefold. First, the study will constitute a valuable guidance for policy making. Innovation is a top-priority issue in most of the world. Hence, knowledge on how to effectively subsidize innovation – in our case on the basis of product market competition – is a top priority as well.

From a more academic perspective, our study also helps bridging a gap in the current literature – the intersection between the research on the leverage effect and the research on product market competition and R&D. No research has been done in this intersection, which makes the insights from this paper unique from an empirical perspective.

Finally, the study also helps making the research on product market competition more policy oriented – which touches upon the other two contributions. The paper helps bridging the gap between theory and practice regarding the role of product market competition in the field of growth theory.

3.3 Research questions

Before we continue with the empirical investigations, let us reiterate the research focus but in somewhat more precise terms. The questions to be answered in the paper are,

1. What is the effect of R&D subsidies on private R&D expenditures? Is there an additionality effect, or is there a crowding out effect?

2. How does the leverage effect vary depending on product market competition? Is there evidence supporting a nonlinear, concave relationship between the leverage effect and product market competition? In other words, is there an inverted U?

4 Empirical Method

4.1 Data

To empirically gauge the research questions, we utilize two primary sources of OECD data. Our first data source is the data set 'Business enterprise Expenditure on R&D (BERD) by main activity and source of funds', which is a subset of the OECD Research and developments Statistics (RDS) database. The BERD database details the intramural gross expenditure on R&D for 38 OECD countries and 7 non-members from year 2000 to 2018. The data is broken down into 16 broad industry sectors in accordance with the ISIC rev.4[4] and further specified by source of funding (own funds, government, higher education, private non-profit, rest of the world), with varying levels of completeness.

The variable 'BERD by own funds' records R&D performed by all firms and institutions within the national geographical area, whose primary activity is the production of goods and services for sale to the public and the private non-profit institutions serving them. This data is normally collected through a census of all R&D-performing companies within a country, covering all large companies and a representative sample of smaller companies with no size threshold.

[4] The International Standard Industrial Classification of All Economic Activities revenue 4 (ISIC rev.4) is an internationally consistent classification system of economic activities that provides a framework for economic data collection and economic analysis (UN, 2008). The fourth revision of ISIC replaces ISIC rev. 3-3.1 (1990-2004) to better reflect the current structure of the world economy by harmonizing activities and product types, thereby adding complexity.

The variable 'BERD funded by government' refers to funds allocated by federal state or local governmental authorities and accounts for public direct support of private R&D. It covers grants and payments for procurements but not R&D tax incentives, repayable loans and equity investments (Szarowská, 2017).

This structure allows us to identify the variation in BERD funded by the government and BERD funded by enterprises themselves, and consequently estimate the effect of government support on private R&D expenditures at the industry level.

The BERD database is derived from R&D surveys and budgets conducted at the national level, submitted to the OECD via an OECD-Eurostat coordinated R&D data collection process and reviewed by the OECD to ensure consistency (OECD, 2015). Furthermore, the data collection by each country is executed in accordance with the standard OECD methodology for R&D statistics, recommended by the OECD Frascati Manual (2015). The Frascati Manual defines R&D as "creative and systematic work undertaken in order to increase the stock of knowledge – including knowledge of humankind, culture and society – and to devise new applications of available knowledge" (OECD, 2015. pp. 44-45). Consequently, the BERD data set does not distinguish between the type of R&D conducted (basic research or applied research) but rather reports the aggregated total business expenditures on R&D.

Our second data source is the Structural Analysis (STAN) database, detailing a large set of annual production measures for each industry and country. This allows us to compute a proxy for market competition as well as control for factors that are acclaimed to correlate with our dependent and explanatory variables, whose exclusion would potentially be spurring endogeneity.

The STAN database carries annual industry-level data across 37 OECD countries from 1970 to 2018. The data is primarily based on member country submissions of annual 'National Accounts by activity' tables, supplemented with additional sources such as national industrial surveys/censuses. These tables are often not directly measured but compiled from other national data sources with adjustments and estimations conducted by national experts (Horvát et al., 2020). Many of the data points in STAN are estimated and do not represent official member country submissions. STAN is, like the BERD database, broken down by industry sector with industrial classfication according to International Standard Industrial Classification, Revision 4 (ISIC rev.4) – making it compatible with related OECD databases.

By merging the BERD and STAN data sets by the common industry classification and countries, we obtain a cross-country industry-level unbalanced panel data set of 3818 observations covering 13 industries in 29 OECD countries over the period 2007 to 2017 i.e., 11 years. This consecutive time frame was chosen with respect to data availability in the BERD database – where data prior to 2007 is substantially limited (especially in terms of publicly funded R&D). The countries available are tabulated in table AI in Appendix I. As argued in section 3.1, we assume that the selected countries, as well as the remaining industries tabulated in Table 2, are representative of the OECD as a whole.

TABLE 2. List of industries

Industry	Freq.	Percent	Cum.
Accommodation and food service activities (i)	294	7.70	7.70
Administrative and support service activities (n)	282	7.39	15.09
Agriculture, forestry and fishing (a)	299	7.83	22.92
Construction (f)	299	7.83	30.75
Electricity, gas and water supply; sewerage, waste management and remediation activities (d-e)	295	7.73	38.48
Financial and insurance activities (k)	297	7.78	46.25
Information and communication (j)	297	7.78	54.03
Manufacturing (c)	295	7.73	61.76
Mining and quarrying (b)	293	7.67	69.43
Professional, scientific and technical activities (m)	283	7.41	76.85
Real estate activities (l)	296	7.75	84.60
Transportation and storage (h)	294	7.70	92.30
Wholesale and retail trade, repair of motor vehicles and motorcycles (g)	294	7.70	100.00
Total	3818	100.00	

Source: OECD

To allow comparability across time, it is fruitful to adjust the nominal figures in these data sets into real terms. This is particularly important considering that we are using the within-group variation to estimate the regression. Failing to account for inflation may lead to serious omitted variable biases. For instance, suppose that inflation has taken root in a country. Consequently, it is reasonable to assume that wages of researchers have increased as well, implying an increase in privately funded R&D from a nominal perspective. As inflation has risen, it is also likely that government subsidies have increased – to account for the new price level. Hence, because of inflation, both R&D expenditures and R&D subsidies have experienced a rise. Not adjusting for inflation would therefore falsely lead us to concluded that additional R&D subsidies have caused an increase in privately funded R&D.[5]

Hence, price level adjustments are needed. However, deflating nominal measures imposes a constraint on how inflation might affect the variables of our model. Instead of deflating the nominal variables, we will include inflation as a control variable in the regression. CPI[6] with 2015 as reference base will be used, which practically means that 2015 constant prices are applied, while at the same time allowing inflation to have a direct impact on our dependent variable. The adoption of CPI instead of the GDP deflator is

[5] Inflation also has an intertemporal impact on employment (Friedman, 1968). Assuming that wages are set ex ante by trade unions and workers, as inflation rises unexpectedly, real wages will decrease. This lower real wage makes firms want to employ more researchers (labor), which makes employment and thereby R&D expenditures go up. In the meantime, inflation might lead to seigniorage which enables the government to spend more money on R&D subsidies. A regression in which inflation is excluded might once again give rise to a spurious correlation.

[6] The consumer price index is calculated using the chained Laspeyres-method.

based on the greater accessibility of CPI data and can further be motivated with regards to the very high correlation between CPI and the GDP deflator (Economic Insight, 2015).

We make no adjustments with respect to exchange rates as the leverage effect of R&D may depend on the exchange rate itself.[7] Furthermore, as we are calculating elasticities, the monetary units of measurement are irrelevant for interpretation purposes.

4.1.1 Limitations with our panel data

In assembling the panel data set, several factors must be considered for the sake of robustness and efficiency in the estimates.

First, there remain a considerable number of missing values in our data set under the consecutive time frame. Although the unbalanced nature of our data set is not in itself an issue – as it is reasonable to assume that these values are missing by a factor uncorrelated with our idiosyncratic error term[8] – such gaps in our data will be magnified under the adoption of a difference GMM estimation approach, as variables are transformed into first differences. A missing value for one year will consequently lead to missing values of two years. For robustness to the occurrence of a situation where the missing values generated heavily influence our estimates, we also estimate our regression using Han-Phillips X-differencing, which undermines the aforementioned dilemma by using a different estimation technique. See section 4.4.3 for further elaboration.

A second issue stems from how the OECD BERD data have been compiled. The Frascati Manual recommends countries to report BERD data on an enterprise basis, meaning that a diversified firm will only be reported in the industrial class of its principal activity (OECD, 2021). Consequently, in cases where large firms are present in several industries, the reporting standard will lead to an underestimation of firms' secondary activities, thus potentially also underestimating the leverage effect. Furthermore, OECD states in their description of the BERD database that "not all countries follow a strict enterprise basis for allocating R&D expenditures to industrial classes". Hence, there might be inconsistencies in how the data have been compiled by the different national statistical offices, which ultimately may make it difficult for us to find valid estimates within a panel data framework.

On the same token, national statistics regulations prevent publication of data where very few firms make up the given category (OECD, 2021). This will naturally enforce an unbalanced panel due to gaps in our data. More importantly, however, exclusion of data where market concentrations are very high may prevent us from detecting the leverage effects of industries in the extreme lower end of product market competition.

[7] To see why, think of a situation where country A's exchange rate suddenly depreciates relative to country B. One might expect the leverage effect of public support to drop in currency B too, but it's not obvious that this is the case. If R&D becomes relatively less expensive in country A, multinational companies in country B might move their research to country A. If we were to adopt a fixed exchange rate, a depreciation in a currency might then be followed by an unexplainable increase in R&D activity in the affected country. A variable exchange rate will undermine such an issue.

[8] The missing values are mainly due to nonannual reporting frequencies, which does not bias our estimates (only leads to less data and lower power). However, some missing values are due to the confidentiality of highly concentrated industries. We address this issue in section 6.2.

4.2 Descriptive statistics

TABLE 3. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Source
Privately Funded R&D, MUSD	2,545	1,107	7,752	0	132,779	BERD
R&D Subsidies, MUSD	2,545	52	226	0	3,542	BERD
Price Cost Margin (%)	2,887	17	11	-20	68	STAN
Industry Value Added, MUSD	3,687	52,678	103,301	89	122,3988	STAN
GDP/capita, USD	3,818	34,897	20,302	9,013	102,906	OECD
Industry Growth Rate (%)	3,099	2	8	-52	90	OECD
Long-term interest rate (%)	3,558	4	3	0	22	OECD
Skills (Labor Cost per Empl, USD	3,109	42,821	26,707	4,081	200,699	STAN
Consumer Price Index	3,818	95	7	54	108	OECD

Note: Sample period 2007–2017 for 29 OECD countries and 13 industries. Source: OECD.

Aside from the general descriptive statistics tabulated in Table 3, we have included additional statistics on R&D subsidies and R&D expenditures in Appendix I. When graphing R&D subsidies and expenditures by industry (see Fig. AI-II, Appendix I), large heterogeneities become apparent. For instance, the manufacturing industry is by far the most R&D intensive industry – in terms of subsidies as well as expenditures. Hence, we should expect that our results to a large extent are to be driven by this particular industry.

Whether this large influence by a single industry is problematic is ambiguous. On the one hand, as the manufacturing industry is the most research-intensive industry, it is economically efficient if the results are tailored to that industry. On the other hand, we want our results to be broadly applicable. To examine the influence of single industries on the estimates, we will supplement our main analysis with a sensitivity analysis.

R&D expenditures and subsidies are also graphed with respect to time (see Fig. AIII-IV, Appendix I). Based on the time series, it looks like R&D subsidies and expenditures have declined in recent years – contrary to our previous assertions. The steep decline can be explained by lags in the national reporting.

4.3 Empirical framework

4.3.1 Estimation equation

The empirical framework we are applying to address our research question, is in essence based on a rather straight forward equation. On the one hand, we have privately funded R&D which is our dependent variable, and on the other hand we have R&D subsidies, which is our explanatory variable. In its most simplified form, the regression can mathematically be expressed in the following way,

$$RDbusiness_{i,t} = \alpha + \beta_2 RDsub_{i,t} + \mu_{i,t} \tag{1}$$

where $RDbusiness_{i,t}$ denotes privately funded R&D expenditures, α denotes the intercept (constant) of the model, $RDsub_{i,t}$ denotes the R&D subsidies granted by the government and $\mu_{i,t}$ represents the error term – capturing all the variables that affect business R&D that are not explicitly included in the model ($\mu_{i,t}$ accounts for all the unexplained variance in private R&D). Subscript i[9] denotes cross-sectional units, i.e., the specific country-industry combination, and subscript t denotes time – the year of measurement.

The aforementioned regression includes the most fundamental components for analyzing the leverage effect – the relationship between private R&D and public R&D subsidies. To this basic model, product market competition needs to be added in order to address our main research question: how the leverage effect depends on product market competition.

Before explaining how to model this unique amendment to the model, let us first discuss how to reliably measure product market competition.

Throughout the years, many measures have been suggested for quantifying product market competition. One of the most frequently used measures is the Herfindahl-Hirschman index (HHI), which measures the size of firms in relation to the size of the industry they are operating in. In other words, HHI measures how concentrated an industry is. However, there are several disadvantages of such a measure, not least that it relies on a very precise industry definition in both geographic as well as product market terms. And since many firms face international competition, such delimitations might yield a misleading measure of competition, as suggested by Aghion et al. (2005).

In lieu of HHI, we are using the price cost margin, as proposed by Nickell (1996), which provides a more holistic perspective on product market competition by capturing the effect that competition has on the margins that are charged by firms.

The price cost margin to be applied is computed as the ratio between the net operating surplus and the total production value of the industry.

$$PCM = \frac{NOPS}{PROD} \times 100 \tag{2}$$

A higher price cost margin means less competition, since firms can charge a higher price compared to their costs. After all, the main effect of competition lies in the limitation of profits in an industry.

Despite its benefits over HHI, one could argue that the price cost margin is capturing several other dimensions than merely competition, such as scale of production and fixed costs. We agree with such an argument but believe that the objection is primarily valid

[9] Note that subscript i represents the country-industry pairs. An alternative way of denoting this would be to use two separate subscripts – one for industry and one for country. We choose this more compact way of writing it, with only one subscript, which is more pedagogical considering that the clustering is done on a country-industry basis.

for a cross sectional analysis. As we are using panel data, estimating the relationship based on the within-group variation[10], we believe that the price cost margin in an adequate way reflects product market competition.

Empirically, the choice of competition measure has proven to be integral when estimating the inverted U. In their 2006 study, Tingvall and Poldahl demonstrate how the inverted U can be replicated when using Herfindahl, but not for the Lerner index – illustrating a delicate sensitivity. As previously argued, we believe price cost margin to be more relevant and to better capture what is intended to be captured, which is why we exclude Herfindahl from our analysis.

With a theoretically justified competition measure at our disposal, let us examine how competition comes into play in our analysis.

Considering that we intend to answer how the leverage effect depends on product market competition, an interaction term between R&D subsidies and competition needs to be included. The specification, including product market competition, turns out as follows[11]:

$$\begin{aligned} RDbusiness_{i,t} \;=\;& \alpha + \beta_2 RDsub_{i,t} + \beta_3 PCM_{i,t} + \beta_4 PCMsq_{i,t} + \beta_5 RDsubPCM_{i,t} \\ & + \beta_6 RDsubPCMsq_{i,t} + \mu_{i,t} \end{aligned} \tag{3}$$

Let us sort out the interpretation of these interactions. First, we control for $PCM_{i,t}$ and $PCMsq_{i,t}$[12], merely because competition itself is likely to have a direct effect on privately funded R&D (recall the standard theory of the inverted U). In addition, we include interactions between R&D subsidies and competition. By including $RDsubPCM_{i,t}$ we can measure how the effect of R&D subsidies varies as competition varies. Holding all other variables constant, the interaction term measures how the leverage effect changes if we increase the price cost margin with one percentage point. Hence, it measures how much the leverage effect changes as competition decreases – since a higher price cost margin corresponds to less competition.[13]

To capture the non-linearities that characterizes the inverted U, we also include the interaction term $RDsubPCMsq_{i,t}$. This interaction incorporates the possibility that the leverage effect might respond differently to changes in the price cost margin for different levels of the price cost margin. The heterogeneity in effects for high and low values of the price cost margin is obtained by squaring the price cost margin. Hence, by including a standard interaction term and a squared interaction, we are able to track how the leverage effect depends on competition – for different *levels* of competition. In other words, we capture convexity/concavity in the relationship.

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[10] Within-group variation refers to the variation within the cross-sectional units over time – as opposed to the variation between the cross-sectional units.

[11] All variables except the price cost margin are logarithmized, which simplifies the interpretation of results (elasticities). Changes in the price cost margin are already expressed in percentage points, which facilitates the interpretation.

[12] 'sq' denotes the mathematical operation of squaring.

[13] Recall that a high price cost margin corresponds to a low degree of competition. Hence, in terms of the inverted U, we start off from the right-hand side of the diagram.

To summarize in terms of the coefficients, β_5 measures how the leverage effect changes when the price cost margin changes at low price cost margin levels, while β_6 measures how the leverage effect changes when the price cost margin changes for high price cost margin levels. In terms of our hypotheses, we believe β_5 to be positive, i.e., as competition decreases, the leverage effect will increase (for high levels of competition). β_6 on the other hand, is hypothesized to be negative, i.e., for low levels of competition, as competition decreases even further, the leverage effect will decrease as well. Differently put, a positive β_5 reflects the Schumpeterian effect whereas a negative β_6 reflects the Porterian (escape-competition) effect.

In addition to these core components, also included in the model are country-industry fixed effects, year dummies, a lagged dependent variable, and a set of control variables. The final model specification can be expressed as,

$$\begin{aligned} RDbusiness_{i,t} \;=\;& \alpha + \beta_1 RDbusiness_{i,t-1} + \beta_2 RDsub_{i,t} + \beta_3 PCM_{i,t} + \beta_4 PCMsq_{i,t} \\ &+ \beta_5 RDsubPCM_{i,t} + \beta_6 RDsubPCMsq_{i,t} + \beta_7 year_t + \beta_8 X_{i,t} \\ &+ \eta_i + \mu_{i,t} \end{aligned} \tag{4}$$

where $RDbusiness$ denotes privately funded R&D expenditures, α denotes the intercept of the model, $RDsub$ denotes the R&D subsidies granted by the government, PCM is the price cost margin, $PCMsq$ is the price cost margin squared, $RDsubPCM$ is an interaction term between public R&D subsidies and the price cost margin, $RDsubPCMsq$ is an interaction term between public R&D subsidies and the price cost margin squared, $year$ is an indicator variable for the year of observation, X is a vector containing a set of relevant control variables, η represents country-industry fixed effects and μ is the idiosyncratic error capturing all other variables that affect business R&D that are not explicitly included in the model.

The time dummies are included to account for possible year fixed effects in the dependent variable, the industry-country fixed effects are included to account for effects that are constant over time but vary across the cross-sectional units (panel heterogeneity). The role of the control variables and the lagged dependent variable will be discussed in more depth in the upcoming sections.

4.3.2 Control variables

The vector of control variables serves two main purposes. Common to each control variable is that they are all believed to have an impact on the dependent variable. Hence, their inclusion helps increasing the precision of the estimates and contributes to the explanatory power of the model in its entirety. Moreover, some of these variables that helps explaining the variation in the dependent variable are also likely to be correlated with our explanatory variables of interest. Excluding such variables would lead to an omitted variable bias, implying that some of the correlation identified between the explanatory and dependent variables in fact is to be attributed to a third, omitted variable. Together with the fixed effects, including an appropriate set of control variables makes up our basic toolbox for establishing exogeneity and thus being able to produce credible inference regarding the causal relationship.

The control variables that we have chosen to include can broadly be placed into two main categories – aggregate economic variables and industry variables.

Aggregate economic variables

It is reasonable to assume that the R&D activity in an industry is influenced by overall economic activity in the country. The economic climate of a country may for example influence the availability of funding, the returns to R&D and the appetite for undertaking investments with uncertain returns (Oxford Economics, 2020).

First, we choose to control for GDP per capita. One motive for this, as suggested by Lederman and Maloney (2003), is the empirical finding that rich countries simply invest more intensively in R&D. Research may also be more profitable if incomes are high, as individuals can better afford the products that emanate from R&D.

Besides GDP, R&D activity is also likely to be influenced by interest rates. Interest rates determine the cost of capital for R&D activities, which is of importance not least when considering that R&D in fact is an investment decision. Thus, interest rates ought to be negatively correlated with R&D expenditures (a higher interest rate means more expensive funding).

Both variables likely contain a substantial time trend and might therefore to a large extent overlap with our time dummies. However, they are important to include in the specification because of their possible correlation with R&D subsidies. For instance, in good times (high per capita GDP), the government might be more inclined to grant R&D subsidies. The inclusion of the aforementioned controls therefore helps mitigating the omitted variable bias. Relying on them being captured by year fixed effects is an unnecessary risk to bear.

Industry specific variables

Regarding the industry specific variables, one central control variable is the industry value added (Falk, 2006). The industry value added effectively measures market size – with large industries assumed to invest more intensively in R&D. Large industries are also more likely to receive large amounts of grants, have greater access to financing and are exposed to larger markets – which increases the return to R&D (all else equal). Hence, industry value added ought to be positively correlated with private R&D expenditures.

We also include a lag of industry value added, partly to reflect the intertemporal spillovers of R&D and the fact that R&D is a process of long duration, and partly to reflect that governments to a large extent are backward looking when giving grants (history guides decision making).

A closely related variable is the industry growth rate. Hot, fast growing industries are likely to be provided a substantial amount of grants (because of ‘pick the winner’ strategies employed by governments), but are also likely to engage in a significant amount of privately financed R&D. Including the industry growth rates therefore increases precision and reduces biases.

The last industry specific variable to be included in the model is workers' skills and knowledge. Highly skilled workers may have greater capacity to identify and carry out R&D projects. As a proxy for skills, we are using labor costs per employee (highly skilled workers ought to be better paid on average).

The variables included in the regression are tabulated in Table AII, Appendix I.

4.3.3 Timing of variables

A complex aspect of the leverage effect is that of timing and time lags. We account for this by including a lagged dependent variable. The rationale for the inclusion of a lagged dependent variable is that R&D generally behaves as though it has high adjustment costs, which to a large extent emanates from the substantial costs of temporary hiring and firing highly skilled employees with firm-specific knowledge (Becker, 2008).

In addition, there is often a high degree of uncertainty associated with the R&D outcome, with sustained commitment being a key prerequisite for successful execution.

Mansfield summarizes these lines of argument in a crisp way:

> First it takes time to hire people and build laboratories. Second, there are often substantial costs in expanding too rapidly because it is difficult to assimilate large percentage increases in R&D staff. (…) Third, the firm may be uncertain as to how long expenditures of (desired) R&D levels can be maintained. It does not want to begin projects that will soon have to be interrupted. (Mansfield 1964, p. 320)

Additionally, there is also an important intertemporal dimension to R&D in the form of spillovers, which strengthens the case for including lags of the dependent variable.

The fact that it takes time for R&D subsidies to materialize makes it possible to distinguish between short and long-run effects of R&D support. The short-run effect is the immediate effect of the subsidy; the effect incurred on private R&D that arises at the time of subsidization. In the period that follows, this immediate effect will have aftereffects through the lagged dependent variable, which in turn will has aftereffects through the next period's lagged dependent variable, and so on.

In terms of the coefficients, β_2 reflects the immediate, short-run effect. In the subsequent period, the subsidy that now belongs to history will have spurred an increase in private R&D amounting to β_2 which consequently – because of the autoregressive path – will have a current impact on private R&D that amounts $\beta_2 \times \beta_1$, and the period after that amounts to $\beta_2 \times \beta_1^2$, etc. Hence, the long-run effect can be computed as the following geometric series,

$$\beta_2 \times \beta_1 + \beta_2 \times \beta_1^2 + \beta_2 \times \beta_1^3 + \cdots + \beta_2 \times \beta_1^\infty \tag{5}$$

which can be rewritten as:

$$\beta_2(1 + \beta_1 + \beta_1^2 + \cdots + \beta_1^\infty) = \beta_2\left(\frac{1}{1-\beta_1}\right) = \frac{\beta_2}{1-\beta_1} \tag{6}$$

With only a set of simple computations, we have obtained the full-scale effect of subsidies. This is indubitably important as we are living in a not static but dynamic world. We do not merely care about the immediate but also about the delayed effect of policy making.

However, this dynamic specification gives rise to serious estimation biases, which we are covering in the following sections. In the next section, we also introduce the estimation strategy to be applied to our empirical framework.

4.4 Estimation strategy

4.4.1 Dynamic panel bias

The inclusion of a temporally lagged dependent variable in our regression model (4), motivated by the frictions associated with adjusting R&D investments, creates complications in the modelling process. Nickell (1981) notes that the inclusion of a lagged dependent variable as a predictor, will spur an endogeneity problem in an OLS setting as the lagged dependent variable is correlated with the fixed effects in the error term. Hence, the correlation of the regressor and the error term violates the zero conditional mean assumption for consistent OLS estimates. This "dynamic panel bias" is known as the Nickell bias (Nickell, 1981).

$$E\left[lnRDbusiness_{i,t-1}, \varepsilon_i\right] \neq 0 \tag{7}$$

An intuitive solution to the Nickell bias is to remove the fixed effects by first differencing. However, this approach will not remove dynamic panel bias (Nickell, 1981; Bond, 2002). Under a within-group transformation, a correlation between the lagged variable and the unobserved error term arises. This can most easily be illustrated in a first-differencing equation:

$$\begin{aligned}(RDbusiness_{i,t} - RDbusiness_{i,t-1}) \;=\; & (RDbusiness_{i,t-1} - RDbusiness_{i,t-2}) \\ & + (\mu_{i,t} - \mu_{i,t-1})\end{aligned} \tag{8}$$

When writing the estimation in this form, we clearly see how the explanatory variable is correlated with the error term, since the lagged error $\mu_{i,t-1}$ is both included in the first-differenced error term and in the first difference of the lagged dependent variable. This issue is especially problematic for data sets with a small T and a large N (number of country-industry combinations in this case).

4.4.2 Consistent estimators

The economic literature has developed a diverse set of consistent estimators to account for the presence of the Nickell bias. Kiviet (1995) argues that the most prominent way of handling the dynamic panel bias is to use a least square dummy variable estimator (LSDV). However, this technique only works for balanced panel data sets and does not allow us to include other instruments to account for endogeneity in other regressors.

A more common and suitable estimation approach for the purpose of this paper is the Generalized Method of Moments estimator, for situations with "small T, large N" panels, proposed by Arellano and Bover (1995) and advanced by Blundell and Bond (1998).

There are two GMM approaches to dynamic panel models: a difference GMM and a system GMM. The difference GMM, also known as the Arellano–Bond estimation, begins by transforming all regressors in the estimation equation (4) using first differencing, removing country-industry time-invariant effects,

$$\Delta RDbusiness_{i,t} = \Delta\beta_1 RDbusiness_{i,t-1} + \Delta\delta X'_{i,t} + (\eta_i - \eta_i) + \Delta\mu_{i,t} \tag{9}$$

where Δ account for the difference operator. Although the fixed effects are now removed, as illustrated by the term $(\eta_i - \eta_i)$, the model will still endure an endogeneity problem since the differenced error,

$$\Delta\mu_{i,t} = \mu_{i,t} - \mu_{i,t-1} \tag{10}$$

and the differenced regressor,

$$\Delta RDbusiness_{i,t-1} = RDbusiness_{i,t-1} - RDbusiness_{i,t-2} \tag{11}$$

both contain the error $\mu_{i,t-1}$ and are therefore correlated.

To account for this endogeneity, the difference GMM uses an instrumental variable modelling approach where the endogenous variables are instrumented by external or internal relevant variables. As outside instruments are difficult to obtain, we must choose instruments drawn from within our data set. As suggested by Roodman (2009), GMM allows us to use internal lagged variables as instruments. In our case, this means that the endogenous lagged dependent variable $\Delta RDbusiness_{it-1}$ is instrumented by $RDbusiness_{i,t-s}$ – representing a lag of two periods or more.[14]

The lagged dependent variable qualifies as an instrument as it satisfies the relevance assumption as well as the exclusion criterion. It is *relevant* due to its autoregressive path, which we have extensively argued for previously (recall that the autoregressive path is

[14] Note that lagged instruments are not equivalent to using lags as explanatory variables. The latter is used to estimate causality in the relationship of interest, whereas the former mitigates endogeneity issues in this very same estimation of causality.

the reason why we are including the lagged dependent variable in the first place). The relevance can also partly be seen mathematically, as both the regressor,

$$\Delta RDbusiness_{i,t-1} = RDbusiness_{i,t-1} - RDbusiness_{i,t-2} \tag{12}$$

and the instrument,

$$RDbusiness_{i,t-2} \tag{13}$$

contain the term $RDbusiness_{i,t-2}$.

The instrument is *exogenous* by an assumption of sequential exogeneity, $E[RDBusiness_{it-s}, \Delta u_{it}] = 0$, meaning that past values of our lagged dependent variable are not correlated with future error terms.

We test this assumption using the Sargan test for overidentifying restrictions. The Sargan test checks for overidentification of the instruments, with the null hypothesis of a valid exogenous instrument.[15] If we reject the null, we choose a lag further back in time – although at the expense of weaker instruments. If we fail to reject the null, our instruments may still be jointly inconsistent. This is however unlikely as lagged values of the lagged dependent variable of private R&D expenditures has historically been proven as a useful instrument in dynamic panel models with lagged private R&D expenditures (see for example, Rehman 2020; Oxford economics 2020). We report the Sargan test in the regression output tables.

Furthermore, exogeneity in the difference GMM IV technique also rests upon the assumption that the error terms are not autocorrelated. If the idiosyncratic error $\mu_{i,t}$ is serially correlated, our level instrument $RDbusiness_{it-2}$ will be serially correlated with $\mu_{i,t-1}$ in the difference error term $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$, causing sequential endogeneity. This would make our instrument invalid. To test for autocorrelation in the idiosyncratic error, we apply the Arellano–Bond test for autocorrelation (AR) in the differenced residuals. Failing to reject the null hypothesis of serially uncorrelated error terms indicates that there is no evidence of model misspecification. We report the AR(2) tests in the regression output tables.[16]

[15] In the case of multiple instruments, the Sargan test for overidentifying restrictions allows us to test whether the instruments are exogenous. The test holds the null hypothesis of valid exogenous instruments. The procedure is to first obtain an estimate of the residual. This residual hat is then estimated with our instruments as regressors which gives a value of the R-squared, depicting how well the instruments describe the residual hat. As $nR^2 \sim \chi^2(n)$ with *n* degrees of freedom, where *n* is equal to the number of instruments subtracted by the number of endogenous variables, we can test if the probability of getting the value of nR^2 is statistically significant and hence reject the null of a valid exogenous instrument. The null of the Sargan test implies that all instruments are valid with a p-value > 5%. The Sargan test is not robust to heteroscedasticity but is not weakened by a large number of instruments.

[16] There are two Arellano-Bond tests for autocorrelation. The AR(1) has the null hypothesis of no autocorrelation in the error term with one lag. The AR(2) has the null hypothesis of no autocorrelation in the error term with two lags. While the first-order correlation is not an issue given that the equation is in first difference, second-order correlation might be. We fail to reject the null if the P-value > 5%.

By using instrumental variables in difference GMM, we also face the potential risk of "instrument proliferation" as the number of instruments grows quadratically in T and difference GMM becomes inconsistent as the number of instruments diverges (Roodman, 2009). We therefore follow the general rule of thumb, proposed by Roodman (2009), to keep the number of instruments lower than the number of groups.

Finally, Blundell and Bond (1998) notes that the difference GMM approach can perform poorly if the autoregressive lagged dependent variable is at or close to unity ($\beta_1 = 1$), spurring weak correlation between the current differences of the regressor and its lagged levels (which are used as instruments). To see why this is the case, suppose that our dependent variable follows a random walk. Then it follows that, $RDbusiness_t = RDbusiness_{t-1} + \varepsilon_t$. Taking the first difference, we obtain that $RDbusiness_t - RDbusiness_{t-1} = \varepsilon_t$. Since the error term is the only remainder, we clearly see why instrumentation becomes difficult (the levels of lags will not be able to predict the differences in lags).

In other words, the Arellano-Bond estimator is expected to suffer from weak instruments if past lagged levels of R&D expenditures provide little information about future changes in R&D expenditures. Considering such potential presence of weak instrumentation from our lagged dependent variable, we perform the Fisher-type unit root tests, based on the Phillips-Perron test. Ever since the seminal papers of Levin and Lin (1992, 1993), testing for unit roots has become common practice for panel data structures – not only for pure times series analysis.

The unit root test indicates no presence of non-stationarity. Thus, we reject the null that all panels contain unit roots.[17]

Besides the difference GMM, we also perform a series of other estimation methods for robustness checks. We initially estimate our specifications using a naïve OLS and fixed effects regression, since the estimate of the difference GMM should lie between the downwardly biased fixed effects and the upwardly biased OLS estimates (Roodman, 2009). If this is not the case, we can assume biased estimates.

Blundell and Bond (1998) suggest the inefficiency from weak instruments in the difference GMM could be mitigated by making additional assumptions, leading to what is referred to as the system GMM approach. The additional assumption in the system GMM is that transformed differenced instrumental variables are uncorrelated with the fixed effects: $E[\Delta lnRDBusiness_{it-1}, \eta_i] = 0$. Consequently, Blundell and Bond suggest a system of two equations: a first difference (transformed) equation, similar to the difference GMM with lagged level dependent variables as instruments, and an original level (endogenous) equation which is instrumented with exogenous differenced instruments taken from the transformed equation. This increases the relevance of the instruments as past changes may be more indicative of current levels of R&D

[17] There is a common objection that unit root tests should not be applied on short panels, as the confidence limits are not correct for such a small sample. As a complement to the unit roots test, we also base our conclusion of stationarity on previous research with long panels finding no evidence of non-stationarity (see Oxford Economics (2020), for instance). Moreover, as we are using a short panel, non-stationarity is a marginal issue. The main reason why we are interested in unit roots is simply because of the instrumentation in the Arellano-Bond framework.

expenditures than past levels are of current R&D expenditures. However, system GMM still performs poorly in cases where the relative variance ratio between the fixed effects and the idiosyncratic error is large (Han et al., 2014)

4.4.3 Han-Phillips X-differencing

Instead of a system GMM, we adopt an alternative, novel approach to eliminate the fixed effects in the presence of an autoregressive lagged variable and with weak instruments called X-differencing, developed by Han et al. (2014). X-differencing eliminates fixed effects while retaining information and signaling strength. The method is acclaimed to have superior statistical features to the system GMM counterpart, which would then better validate the results from our difference GMM estimation.

The procedure begins by transforming the original endogenous autoregressive equation (4), to a forward-looking equation. For pedagogical simplicity, we lump all explanatory variables and controls in a vector $x'_{i,s}$. We get,

$$Y_{i,s} = \beta_1 Y_{i,s+1} + \delta x'_{i,s} + \eta_i + \mu *_{i,s} \tag{12}$$

where $\mu *_{i,s} = \mu_{i,t} - \beta_1 (Y_{i,s+1} - Y_{i,t-1})$. Next, subtracting Equation (12) from Equation (4) we obtain the new regression equation,

$$Y_{i,t} - Y_{i,s} = \beta_1 (Y_{i,t-1} - Y_{i,s+1}) + \delta (x''_{i,t} - x'_{i,s}) + (\mu_{i,t} - \mu *_{i,s}) \tag{13}$$

If $\mu_{i,t}$ is serially uncorrelated, $s < t - 1$ and $|\beta_1| < 1$, the regressor $(Y_{i,t-1} - Y_{i,s+1})$ and error $(\mu_{i,t} - \mu *_{i,s})$ will be uncorrelated and the following orthogonality condition holds:

$$E(Y_{i,t-1} - Y_{i,s+1})(\mu_{i,t} - \mu *_{i,s}) = 0 \text{ for all } s < t - 1 \text{ and } |\beta_1| < 1 \tag{14}$$

Han et al. (2014) continues by suggesting stacking all regression equations for all possible values of s = 1, 2…, t–3 and apply a least square regression to obtain what is referred to as the PFAE estimator.

This PFAE estimator is acclaimed to have excellent statistical features for finite samples, dominating other methods such as system GMM (Han et al., 2014). Moreover, as opposed to the GMM estimators, a major benefit of the X-differencing method lies in the limitation of the researcher's degrees of freedom. Using an X-differencing approach, the researcher is not able to engage in data dredging by manipulating the instrument matrix, since these characteristics are already determined by the method when using X-differencing. A system or difference GMM on the other hand, could practically be manipulated to such an extent that any desirable results are produced. Hence, by using a Han-Phillips X-differencing approach, the credibility of our analysis is enhanced.

4.4.4 Further empirical considerations

Beyond the dynamic panel bias, it is possible that some of our explanatory variables (besides the autoregressive term) suffer from endogeneity. One of the key assumptions for a panel data regression with fixed effects is that of strict exogeneity – that the error term μ is uncorrelated with all explanatory variables for all time periods t. Mathematically, this can be expressed as,

$$E(\mu_{i,t}|X) = 0 \tag{15}$$

where X denotes a matrix of our explanatory variables at the different time periods t.

We have already been touching upon several aspects of this assumption. One key approach for satisfying this strict exogeneity assumption is by including control variables, especially controlling for the country-industry time invariant effects. This lies at the heart of our fixed effects model. What we are essentially doing is that we are time-demeaning all the variables (subtracting the mean within the cross-sectional unit for each variable). By decomposing the error term into two parts,

$$\varepsilon_{i,t} = \eta_i + \mu_{i,t} \tag{16}$$

one component that varies only across cross-sectional units, and another that varies across both time and cross-sectional unit, we can clearly see how we are able to discard η_i from the error term when time demeaning (since the mean of η_i over time is equal to η_i). This decreases the likelihood of a correlation between the explanatory variables and the error term, since the error term now consists of fewer variables.

But in order to at least with some certainty establish a causality, there are several other integral considerations that needs to be made, which are discussed in the following sections.

Two-way causality

Throughout this paper, we have been communicating a very clear causal narrative: that R&D subsidies cause private R&D expenditures, and not the other way around. There are, however, legitimate reasons to be cautious since the causal relationship may in fact also be reversed. It is reasonable to assume that as R&D increases in a particular industry, governments are more inclined to grant subsidies to that industry – and the individual firms may also be more tempted to seek subsidies in the first place when also doing a lot of privately financed R&D. Hence, there may exists a mutual influence – a two-way causality – between R&D subsidies and R&D expenditures. A failure to account for this may significantly bias our estimates.

One commonly proposed solution for this problem is to use instrumental variables by including a third variable that shares some variation with our explanatory variable but is not correlated with the error term. This enables us to identify the exogenous variation in the explanatory variable through the exogenous variation in our instrumental variable. However, finding external instruments is not an easy task. Thomson and Jensen (2013) therefore propose the use of lagged values of public R&D investments as instruments.

As we have described earlier, the difference GMM approach allows us to include instruments. But in order to be a valid instrument, two criteria need to be fulfilled: exogeneity and relevance. Exogeneity, oftentimes referred to as the exclusion restriction, requires that the instrument *is uncorrelated* with the error term of the model. Relevance, on the other hand, means that the instrument *is correlated* with the explanatory variable – simply that it is relevant to use as an instrument for another variable. If these conditions are fulfilled, we obtain consistent estimates of our coefficients.

We therefore need to ensure that lagged values of public R&D are correlated with future values of public R&D and that they are not correlated with future error terms.

Regarding the relevance, we believe the autoregressive path to be rather self-evident, considering the nature of R&D. R&D is a game played in the long run, a process that endures for several years. Hence, R&D subsidization entails a certain commitment that yields an intertemporal dependence – implying that lags of R&D subsidies are relevant instruments for current R&D subsidies.

Regarding exogeneity, the assumption is far from self-evident. Lags of R&D are likely to have a direct effect on our dependent variable of interest, which violates the exogeneity assumption. However, we believe that the long-run effect of R&D subsidies on privately funded R&D primarily is transmitted through the lagged dependent variable. Hence, by choosing a lag that is sufficiently distant and controlling for the autoregressive path in privately funded R&D, we believe exogeneity to be reasonably satisfied. Although, this comes at the expense of the strength of the instruments (more distant lags become less relevant predictors of current lags).

As we are instrumenting a regression with multiple regressors, we can also test for overidentifying restrictions. The test for overidentifying restrictions enables us to gain more confidence to our exogeneity assumption. For this purpose, the Sargan test is applied which is reported for each regression.

Selection bias

As touched upon earlier, cross-industry studies may also suffer from a selection bias – either because of industries doing more R&D might have better data availability or because industries that receive more support are those with the highest leverage effect or those doing a lot of privately funded R&D.

We have previously described how control variables may mitigate certain forms of selection bias. Now we can also see how our panel data structure, were we control for country-industry fixed effects, helps further mitigating this risk to a certain extent.

4.4.5 Limitations

We naturally want to be able to draw as solid conclusions as possible, but as we are working with observational data it is important to acknowledge the limitations of the study.

First, because of the aforementioned endogeneity issue, our estimates will be afflicted with uncertainty – notwithstanding that we are including controls, fixed effects and instruments to identify the exogenous variation. For instance, the instrumental variable approach substitutes the exclusion restriction for the strict exogeneity, which becomes our new cause for concern. And we cannot be perfectly sure that the exclusion restriction is not violated – the safety measures and reasoning can only take us that far in reducing the risk for endogeneity. Moreover, to ensure that the exclusion restriction is satisfied, we also need to choose distant lags as instruments. This comes at the expense of relevance. Thus, the internal instruments used are a compromise to make the best out of the data that is available. When interpreting the data, the reader should have the potential presence of endogeneity in mind.

Second, to test for potentially heteroskedastic errors, the modified Wald test is applied.[18] The test gives a clear indication of heteroskedasticity, which is problematic. In a twostep GMM framework, heteroskedasticity leads to significantly biased estimates. We correct for this by applying the Windmeijer correction, which makes the results robust to heteroskedasticity as well as serial correlation. The Windmeijer correction reduces most of the biasedness, but we should expect at least some bias to remain.

Third, the empirical method of choice is not optimized with regards to the multi-level structure of the data. Using a multi-level model, the intricate interdependence of the country-industry structure would have been accounted for. Naturally, a trade-off had to be made. But in the best of worlds, the hierarchical structure had been taken into consideration by the model. However, a multi-level model requires a much larger data set, and typically cannot account for the dynamic nature of the innovation process.

Fourth, the results from our regressions shall not be interpreted in terms of innovational output but in terms of innovational input. To what extent an increase in R&D spending leads to more innovation ultimately depends on the research productivity. Instead, what we are interested in is to what extent the subsidies affect incentives and research effort – which is a totally different story. This distinction is central when interpreting our result

Lastly, it is important to note that we are not fully controlling for endogeneity in the price cost margin. We include fixed effects and a variety of control variables, but are not using any instrumentation to strengthen the strict exogeneity assumption for the price cost margin. While this is a reasonable objection, it is important to appreciate the difference

[18] Regarding the assumption of no perfect collinearity, a correlation matrix is attached in table AIV, Appendix I. In addition, the techniques we are using are automatically correcting for multicollinearity (variables that violate the assumption are automatically excluded from the estimation). Regarding the assumption of normality, since our sample is relatively large, asymptotic normality can be assumed to hold. As the sample size increases, coefficient estimates will approach a normal distribution as they essentially constitute complicated weighted averages, making the central limit theory applicable.

between our inverted U and that of Aghion et al. (2005). Aghion et al. are looking at the effect of competition on innovation. Hence, competition is the relevant "treatment" variable – which makes the need for instrumentation inevitable. In our case however, competition is merely a heterogeneity. Competition is the heterogeneity to which we are examining the effect of subsidies. We can conceptually think of it as a moderator in the causal relationship. Hence, what is relevant in our case is not that the price cost margin itself is exogenous, but rather that subsidies are exogenous in relation to the price cost margin. Put differently, the estimates of the interaction will be consistent under the assumption that that the heterogeneity (PCM, in this case) and the omitted variables (variables making PCM endogenous) are jointly independent of the policy measure (Nizalova and Murtazashvili, 2016). As previously argued, we believe that the empirical measures taken (controls, fixed effects and instrumental variables) make it legitimate to assume that R&D subsidies are to be treated exogenously. Hence, we also believe our estimates of the interaction terms to be consistent.

5 Empirical Results

To empirically test our hypotheses, two separate regressions will be run. When testing for heterogeneities in the leverage effect with regards to product market competition, we need to include the interaction terms. However, the inclusion of interaction terms makes the leverage effect difficult to interpret. In an interaction term regression, the leverage effect reported will be the leverage effect that prevails when the price cost margin is zero and all other variables are held constant. Indeed, such interpretation is very narrow in its applicability. When estimating the leverage effect, we will therefore apply a regression that excludes the interaction effects.

Starting with the general leverage effect, we estimate the following regression,

$$\begin{aligned} RDbusiness_{i,t} \;=\;& \alpha + \beta_1 RDbusiness_{i,t-1} + \beta_2 RDsub_{i,t} + \beta_3 PCM_{i,t} \\ & + \beta_4 PCMsq_{i,t} + \beta_7 year_t + \beta_8 X_{i,t} + \eta_i + \mu_{i,t} \end{aligned} \tag{17}$$

after which we include interaction terms, thereby estimating the regression:

$$\begin{aligned} RDbusiness_{i,t} \;=\;& \alpha + \beta_1 RDbusiness_{i,t-1} + \beta_2 RDsub_{i,t} + \beta_3 PCM_{i,t} \\ & + \beta_4 PCMsq_{i,t} + \beta_5 RDsubPCM_{i,t} + \beta_6 RDsubPCMsq_{i,t} \\ & + \beta_7 year_t + \beta_8 X_{i,t} + \eta_i + \mu_{i,t} \end{aligned} \tag{18}$$

5.1 Estimates of the leverage effect

TABLE 4. Leverage Effect of Public R&D Support

	(1)	(2)	(3)	(4)	(5)
Ln($RDbusiness_{it-1}$)	0.888***	0.888***	0.836***	0.337***	0.199
	(0.0267)	(0.0263)	(0.0374)	(0.0535)	(0.126)
Ln($RDsub_{it}$)	0.0934***	0.0929***	0.0969***	0.134***	0.0929***
	(0.0220)	(0.0216)	(0.0209)	(0.0357)	(0.0323)
PCM_{it}	-0.00368	-0.00414	-0.00354	0.0117	0.00237
	(0.00387)	(0.00397)	(0.00372)	(0.0119)	(0.0133)
$PCMsq_{it}$	4.80e-05	5.42e-05	-1.59e-05	2.93e-05	3.74e-05
	(9.54e-05)	(9.62e-05)	(9.04e-05)	(0.000166)	(0.000319)
Ln($valueadded_{it}$)			0.318	-0.168	-0.0593
			(0.366)	(0.452)	(0.453)
Ln($valueadded_{it-1}$)			-0.234	0.00142	0.203
			(0.357)	(0.206)	(0.267)
Ln(GDP_{it})			-0.211***	0.448	0.576
			(0.0601)	(0.594)	(0.722)
Ln($indg_{it}$)			0.00320	0.00195	0.00353
			(0.00410)	(0.00288)	(0.00295)
$Interestrate_{it}$			-0.0191*	-0.0247	-0.0226**
			(0.0107)	(0.0167)	(0.0114)
Ln($skills_{it}$)			0.185***	-0.341	-0.441
			(0.0593)	(0.382)	(0.276)
$Inflation_{it}$			0.00186	0.0188**	0.0286**
			(0.00948)	(0.00906)	(0.0129)
Constant	0.480***	0.591***	1.387	0.0484	-4.482
	(0.116)	(0.129)	(0.995)	(6.842)	(8.592)
Observations	1,024	1,024	960	960	782
Year Dummies	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
Fixed Effect	No	No	No	Yes	Yes
GMM	No	No	No	No	Yes
R^2	0.980	0.981	0.983	0.409	
Adjusted. R^2	0.980	0.980	0.982	0.397	
AR(2)[a]					0.874
Sargan[c]					0.5083

Notes: Dependent variable Ln($RDbusiness_{it}$): sample period 2007–2017 for 29 OECD countries and 13 industries. Source: OECD. Robust standard errors in parentheses. * p<.10, ** p<.05, *** p<.01. Regression (1) to (3) estimates the basic dynamic panel model by OLS with and without controls and year dummies, respectively. Regression (4) is a fixed effects estimation. Regression (5) uses the difference two-step GMM.

[a] AR(2) reports the p-value of the Arellano-Bond test for second-order autocorrelation in first difference, with the null hypothesis of no autocorrelation.

[c] Sargan reports p-values for the Sargan test for overidentifying restrictions, with the null hypothesis of valid instruments.

The results from the leverage effect regression are presented in Table 4. Starting off with a naïve OLS (1), where all observations are pooled into a single sample and no consideration is taken to the heterogeneities between cross-sectional units, we initially obtain a highly significant coefficient for the leverage effect and the lagged dependent variable. Neither controls for year and country-industry fixed effects nor other economically important controls (beside competition) are included. Hence, the estimates ought to suffer from a substantial amount of omitted variable bias. For instance, our hypothesis is that per capita GDP and industry value-added are positively correlated with privately funded R&D as well as R&D subsidies. When these aforementioned variables are excluded, the R&D subsidies estimate is essentially capturing the impact they have on our dependent variable, thereby likely yielding biased coefficient.

In regression two (2), when merely adding the year fixed effects, the overall result does not change. However, as we add the set of control variables (3), the leverage effect increases. This likely reflects the previously negative biasedness in the coefficient from per capita GDP – which is rather surprising since we were expecting a positive bias from per capita GDP.[19] Moreover, the R-squared is very high in all these regressions, which is expected considering the nature of the variables we have chosen to include in the regression. The explanatory variables are all highly relevant in the light of economic theory, implying that they in an empirical setting should be able to explain a large share of the variation in private R&D expenditures.

Besides the leverage effect, also the lagged dependent variable is significant at $\alpha = 0.01$. As we have previously argued however, this lagged dependent variable is far from exogenous in an OLS – partly due to the heterogeneities in the panel data, partly because of the dynamic panel bias.

To capture the time-invariant heterogeneities between cross-sectional units, we include fixed effects. The result from this regression is shown in column (4). When controlling for the country-industry fixed effects, and only using the within-group variation to estimate the coefficients, our results are substantially altered. First, the R-squared falls, reflecting that the variables face more difficulty in explaining the variation within a specific industry and country over time. Second, the leverage effect increases substantially – indicating that the panel heterogeneities previously lead to a negative omitted variable bias.

The final estimates are reported in column (5), where we additionally control for the endogeneity in the lagged dependent variable and R&D subsidies, by instrumenting their variation using distant lags. The leverage effect is significant at $\alpha = 0.01$, while the lagged dependent variable is statistically insignificant.

In this Arellano-Bond estimation, we also test for autocorrelation in the error terms and for overidentifying restrictions. These tests are reported under "Sargan" and "AR(2)". Neither of the p-values are significant, indicating that the model does not suffer from autocorrelation and that the instrumentation does not suffer from overidentification.

[19] This theoretical contradiction stems from the fact that we have yet not included the fixed effects. The impact of GDP is capturing some of the panel heterogeneities, thereby yielding a very counterintuitive result.

As mentioned in section 4.4.2, the data indicate no presence of unit roots with regards to the lagged dependent variable – meaning that the instrumentation of the difference GMM ought to yield reasonable estimates. However, the estimate of the lagged dependent variable may still be biased.

For further investigation, we apply the rule of thumb by Roodman (2006), stating that reasonable estimates should lie between that of a naïve OLS and fixed effect. That is not the case with our estimates. Hence, in order to increase the reliability of the analysis, following is also an application of the Han-Phillips X-differencing technique – which aims at improving upon the results of the GMM. Results are presented in table 5.

TABLE 5. Leverage Effect of Public R&D Support

	(6)
Ln($RDbusiness_{it-1}$)	0.846***
	(0.0831)
Ln($RDsub_{it}$)	0.0707***
	(0.0180)
PCM_{it}	-0.00414
	(0.0174)
$PCMsq_{it}$	4.02e-05
	(0.000219)
Constant	0.710
	(1.830)
Observations	.

Notes: Dependent variable Ln($RDbusiness_{it}$): sample period 2007–2017 for 29 OECD countries and 13 industries. Source: OECD. Robust standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Regression (6) estimates the model by Han-Phillip's X-differencing, obtaining consistent PFAE estimates.

The X-differencing approach confirms the general picture conveyed by the difference GMM estimator. However, the leverage effect is now smaller while the lagged dependent variable is significantly larger. Our suspicions of biased estimates therefore turn out to be correct. Moreover, the efficiency of the X-differencing is significantly higher.

5.2 Estimates of the inverted U

Turning to our second regression, the results from including the interaction terms are presented in Table 6.

TABLE 6. Competition Effect on Leverage Effect

	(1)	(2)	(3)	(4)	(5)
Ln(*RDbusiness*$_{it-1}$)	0.888***	0.889***	0.836***	0.336***	0.194
	(0.0266)	(0.0261)	(0.0372)	(0.0538)	(0.204)
Ln(*RDsub*$_{it}$)	0.0908***	0.0897***	0.0916***	0.117***	0.0743**
	(0.0233)	(0.0231)	(0.0220)	(0.0316)	(0.0357)
Ln(*RDsub)*PCM*$_{it}$	-0.000153	-0.000151	0.000218	0.00214	0.000546
	(0.00127)	(0.00128)	(0.00121)	(0.00159)	(0.00233)
Ln(*RDsub)*PCMsq*$_{it}$	1.32e-05	1.47e-05	8.16e-06	-2.10e-05	2.24e-05
	(3.85e-05)	(3.83e-05)	(3.61e-05)	(6.40e-05)	(6.44e-05)
PCM$_{it}$	-0.00357	-0.00410	-0.00494	0.00248	-0.00194
	(0.00525)	(0.00529)	(0.00522)	(0.0134)	(0.0193)
PCMsq$_{it}$	2.13e-05	2.50e-05	-1.97e-05	0.000145	7.91e-05
	(0.000115)	(0.000113)	(0.000114)	(0.000192)	(0.000342)
Constant	0.486***	0.420***	1.452	0.256	-3.873
	(0.119)	(0.125)	(1.030)	(6.864)	(9.097)
Observations	1,024	1,024	960	960	782
Year Dummies	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
Fixed Effect	No	No	No	Yes	Yes
GMM	No	No	No	No	Yes
R^2	0.980	0.981	0.983	0.412	
Adjusted. R^2	0.980	0.980	0.982	0.399	
AR(2)[a]					0.875
Sargan[c]					0.5549

Notes: Dependent variable Ln(*RDbusiness*$_{it}$): sample period 2007–2017 for 29 OECD countries and 13 industries. Source: OECD. Robust standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Regression (1) to (3) estimates the basic dynamic panel model by OLS with and without controls and year dummies, respectively. Regression (4) is a fixed effects estimation. Regression (5) uses the difference two-step GMM.

[a] AR(2) reports the p-value of the Arellano-Bond test for second-order autocorrelation in first difference, with the null hypothesis of no autocorrelation.

[c] Sargan reports p-values for the Sargan test for overidentifying restrictions, with the null hypothesis of valid instruments.

For the corresponding difference GMM estimate in the regression with interaction terms (5), we end up with similar estimates in terms of the leverage effect and the lagged dependent variable. Moreover, both of the interaction terms are positive, but neither of them are statistically significant at any conventional level of significance. The Sargan test for overidentifying restrictions and the Arellano-Bond test for autocorrelation of the second order are once again satisfied.

The robustness of the results is generally confirmed by the Han-Phillips X-differencing. However, for the interaction terms, the coefficients are very imprecisely estimated with the Han-Phillips X-differencing. Hence, the estimates do not give us any clear indication of alternative hypotheses for future research.

TABLE 7. Competition Effect

	(6)
Ln($RDbusiness_{it-1}$)	0.845***
	(0.0828)
Ln($RDsub_{it}$)	0.0659***
	(0.0214)
Ln($RDsub)*PCM_{it}$	0.000452
	(0.00107)
Ln($RDsub)*PCMsq_{it}$	-0.00488
	(0.0175)
PCM_{it}	4.65e-05
	(0.000219)
$PCMsq_{it}$	0.766
	(1.853)
Constant	0.845***
	(0.0828)
Observations	.

Notes: Dependent variable Ln($RDbusiness_{it}$): sample period 2007–2017 for 29 OECD countries and 13 industries. Source: OECD. Robust standard errors in parentheses. * p<.10, ** p<.05, *** p<.01. Regression (6) estimates the model by Han-Phillip's X-differencing, obtaining consistent PFAE estimates.

5.3 Interpretation

As previously argued, the Arellano-Bond difference GMM method likely yielded biased estimates of the lagged dependent variables. For the analysis of the leverage effect, we will therefore be using the Han-Phillips estimates. Regarding the inverted U, neither of our results were significant. Hence, no inference can be drawn. However, it might be fruitful for future research to provide some sort of discussion regarding the results. And since Han-Phillips provided very imprecise estimates with high standard errors, we are going to use the difference GMM as our basis for discussion on the inverted U.[20]

[20] Note that the choice of regression output for the interpretation of the inverted U is not based on any pursuit of statistically significant results. Neither Arellano-Bond nor Han-Philips provides any significant results. The sole reason why we choose to analyze the Arellano-Bond results is that they are more precisely estimated. Hence, the Arellano-Bond estimates provide a more qualified conjecture as a point of departure for future research. We do not intend to produce inference on insignificant results.

TABLE 8. Leverage Effect and U–Curve

	(1) Leverage Effect	(2) U-curve
Ln(*RDbusiness*$_{it-1}$)	0.846***	0.194
	(0.0831)	(0.204)
Ln(*RDsub*$_{it}$)	0.0707***	0.0743**
	(0.0180)	(0.0357)
Ln(*RDsub)*PCM*$_{it}$		0.000546
		(0.00233)
Ln(*RDsub)*PCMsq*$_{it}$		2.24e-05
		(6.44e-05)
PCM$_{it}$	-0.00414	-0.00194
	(0.0174)	(0.0193)
PCMsq$_{it}$	4.02e-05	7.91e-05
	(0.000219)	(0.000342)
Constant	0.710	-3.873
	(1.830)	(9.097)
Observations	·	782
Year Dummies	Yes	Yes
Controls	Yes	Yes
Fixed Effect	Yes	Yes
GMM	No	Yes
X-diff	Yes	No
R^2		
Adjusted. R^2		
AR(2)[a]	·	0.875
Sargan[c]	·	0.5549

Notes: Dependent variable Ln(*RDbusiness*$_{it}$): sample period 2007–2017 for 29 OECD countries and 13 industries. Source: OECD. Robust standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Regression (1) is estimated by Han-Phillips X-differencing whereas regression (2) is estimated by the difference two-step GMM.

[a] AR(2) reports the p-value of the Arellano-Bond test for second-order autocorrelation in first difference, with the null hypothesis of no autocorrelation.

[c] Sargan reports p-values for the Sargan test for overidentifying restrictions, with the null hypothesis of valid instruments.

First, we can conclude that the leverage effect is statistically significant with a coefficient of 0.07. This number is expressed in terms of elasticities, meaning that a hundred percent increase in R&D subsidies approximately translates to a 7 percent increase in privately funded R&D (in addition to what is financed by the subsidy), holding other variables fixed. Hence, we reject the null hypothesis that R&D subsidies have no effect on privately funded R&D and conclude that the evidence indicates an additionality, meaning that the subsidies crowd in additional private investments in R&D.

The lagged dependent variable is significant as well, containing a positive sign. Based on this, evidence suggests that there are important intertemporal spillovers as well as adjustment costs – which is in line with the current literature on the R&D process. The coefficient amounts to 0.846, implying that a 100 percent increase in the R&D

expenditures at period $t-1$ translates to an 85 % increase in R&D expenditures the subsequent time period, period t.

Based on these results we can compute the long-run leverage effect, which is defined as the effect that R&D subsidies has on private R&D when we account for the fact that current R&D investments affect future R&D investments and that a policy thereby creates intertemporal ripples effects. The long-run propensity is computed in the following way:

$$long\ run\ leverage\ effect: \frac{\beta_2}{1-\beta_1} = \frac{0.0707}{1-0.846} \approx 0.459$$

where β_2 denotes the short-run leverage effect and β_1 denotes the coefficient of the lagged dependent variable, i.e., the “multiplier” that makes innovation policy have long-lasting effects. The long-run effect of R&D subsidies amounts to 0.459, which means that if the government increases R&D subsidies with 100%, privately funded R&D will rise with approximately 46% in total, in the long run.

Turning to our investigations of the inverted U, we find no significant results. The coefficients of both interaction terms are positive, indicating that as the price cost margin increases (competition decreases), the leverage effect will increase as well. The $RDsubPCM$-coefficient amounts to 0.000546, which means that as the price cost margin increases with one percentage point (recall that the price cost margin is multiplied by 100), the leverage effect approximately increases with 0.05%. The $RDsubPCMsq$-coefficient is also positive, thus indicating that the positive impact of a higher price cost margin becomes even greater at high levels of the price cost margins. However, these estimates are not significant which means that one should not put any confidence in the estimates. Nevertheless, it is important to know how they should be interpreted.

5.4 Sensitivity analysis

To further verify the robustness of our results, several additional sensitivity analyses have been conducted. To see whether our estimates are skewed by certain individual industries and countries that pose significant influence on the results, we run a sensitivity test by successively dropping one country at a time from our sample, while retaining the full sample of industries. Results are presented in Table AV in Appendix II. By running our model (5) 29 times, dropping each country at a time, our sensitivity analysis indicates that no single country drives our results. Estimates remain at similar levels and significance. Next, we pursued the same procedure with regards to industries. By running our regression 13 times, dropping one industry at a time, estimates remain the same with only small fluctuation of levels and significance. Results are presented in Table AVI in Appendix II and indicate that no single industry have such a large impact that it single-handedly drives the qualitative conclusions of our regressions.

6 Discussion

With the results at hand, let us revisit the research questions that this thesis set out to answer.

1. What is the effect of R&D subsidies on private R&D expenditures? Is there an additionality effect, or is there a crowding out effect?
2. How does the leverage effect vary depending on product market competition? Is there evidence supporting a nonlinear, concave relationship between the leverage effect and product market competition? In other words, is there an inverted U?

6.1 Leverage effect

Based on our computation of the leverage effect, the evidence clearly indicates that a substantial additionality effect exists. That is, public R&D subsidies stimulate additional private R&D activity, beyond what is initially funded. Our estimates for OECD countries between 2007–2017 yield a short-run leverage effect of 0.07 while the long-run leverage effect amounts to 0.459. Comparing these results to a sample of recent studies in Table 9, we find that our estimates are well in line with previous macroeconomic evidence on both the country and industry level.

The similarity to the estimates found by previous studies comes to some surprise. Historically, the diversity of data sets, time periods, estimation models and estimation techniques has spurred a rich and contradicting pile of evidence regarding the effects of public R&D subsidies on private R&D expenditure.

TABLE 9. Comparison of Macroeconomic Evidence on the Leverage Effect

Paper	*Short-run*	*Long-run*
Nordahl & Sjöberg (2021)	0.07	0.46
Becker & Pain (2008)	0.11	0.18
Falk (2006)	0.10	0.14
Oxford Economics (2020)	0.09–0.12	0.25–0.41

Our study used a novel estimation technique along with an OECD panel data set exploiting industry data across 29 countries which, to the best of our knowledge, has not been undertaken to study the leverage effect before. Consequently, we suspected some deviations to previous studies. Becker & Pain (2008), for example, studied 11 UK industries during 1993 to 2000 whereas Falk (2006) studied 21 OECD countries on an aggregated level using ANBERD (which do not specify industries) between 1975 to 2002. While our estimates for the short-run leverage effects is very similar to both these studies, the deviation in the long-run leverage effect is apparent. Our results are much more in line with the most recent piece of evidence, provided by Oxford Economics (2020). This perhaps indicates a final convergence of the leverage effect at a macroeconomic level as econometric techniques have progressed.

A note ought to be made about the comparison to the country level estimates of Oxford economics (2020). Their short-run as well as long-run estimates partially mimics our findings, where their highest long-run effect is in par with our long-run estimates. Oxford economics (2020) approach the leverage effect at the country level using OECD GERD[21] data and system GMM. This difference in data set might contribute to the divergence of our results albeit this difference ought to be marginal as GERD data shares similar qualities to the BERD data set we have been using. This indicates that any difference to our estimates could instead be attributed to cross-industry spillovers.

As our study exploit cross-country industry-level data, we obtain indirect effects of public R&D subsides on private R&D within, but not across industries. That is, R&D undertaken by one firm in an industry will create spillovers and other firms may absorb this knowledge through their absorption capacity. As we find very similar results to the country-level study by Oxford economics, this indicates that much of the spillovers seems to be appropriated within the industries, but not between them. This yields important implications for innovation and growth policy. Governments may interpret the increasing pile of country-level studies – finding evidence of a substantial long-run additionality effect at the country level – as indications that R&D subsidies may benefit the economy as a whole. Our findings indicate, however, that R&D subsidies benefit certain industries rather than the entire economy, as the long-run spillover effects seems to be contained within these industries. This unveils nuance to the country-level studies, as it indicates that their findings can easily be misinterpreted.

On the same token, our reported effect compared to the microeconomic evidence is substantially larger. For instance, Dimos and Pugh (2016) provides the most rigorous meta-analysis of the microeconomic evidence up to date, estimating an additionality of approximately 0.01. This divergence strengthens the argument for positive externalities attributed to public R&D subsidies. That is, R&D subsidies will not only affect the firms receiving direct support, but also stimulate the R&D activity of competitors.

A key takeaway from a policy perspective is consequently the importance of considering the full range of effects in a policy decision regarding R&D subsidization. Our results strongly indicates that a large share of the value that is created by subsidies is accrued over both time and space.

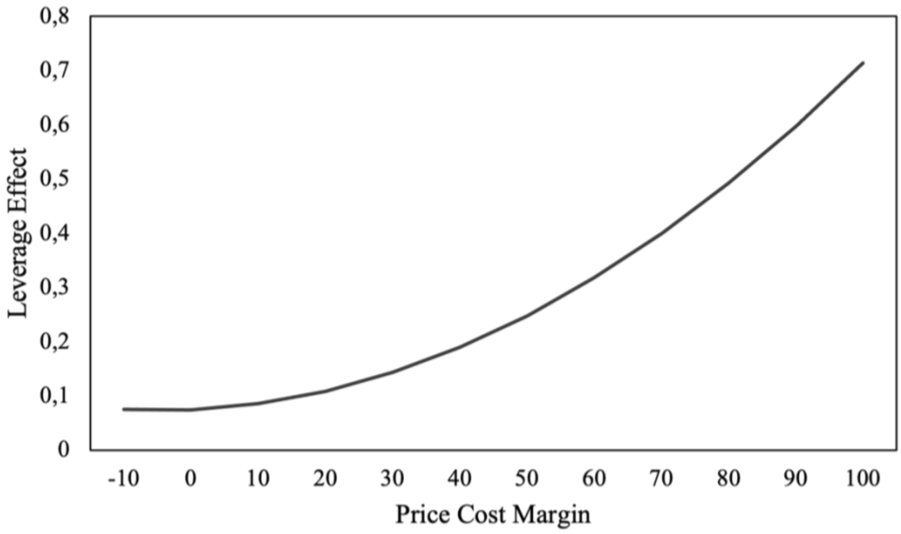
However, many innovation programs are designed in such a way that the subsidies granted are conditional on that additional, privately funded R&D is undertaken by the beneficiary (Czarnitzi and Hussinger, 2018). Thus, the high additionality is not a natural law but likely a product of well-designed subsidy programs.

[21] GERD is an acronym for Gross Domestic Expenditure on R&D.

6.2 Competition and leverage effect

Turning to our second research question, regarding how the leverage effect varies depending on product market competition, we are not able to draw any conclusions on this matter from our regression. For illustrative purposes however, Figure 5 contains the graph we obtain by depicting our results. Note that since we use price cost margin as our proxy for competition, the curve is horizontally inverted compared to the inverted U by Aghion et al. (2005) found in section 2.7.1 (a low price cost margin indicates fierce competition and vice versa).

FIG 5. Leverage Effect and Competition Curve



Note: Graph depicts statistically insignificant estimates
Source: Estimates from Table 8

Before analyzing the actual results, let us reiterate the theoretical reasoning for our hypothesis as described in section 2.7.

According to the theories of Aghion & Howitt (2009), R&D subsidies granted to firms in low competition (right side of our graph) would yield low leverage effects if firms are technologically at par (neck-and-neckness). Indeed, firms will have no incentives to spend their own money on new innovations if they already exploit monopoly rents. Furthermore, Aghion & Howitt argue that since laggard firms behind the technological frontier are more inclined to innovate in order to 'catch up', the sectors will spend relatively more time as level sectors – where incumbents are at the frontier and the escape-competition effect prevails. That is, firms are increasingly incentivized to innovate the fiercer competition there is in order to stay afloat. In such a context, R&D subsidies would accelerate R&D activity among competing firms along the technological frontier, and this effect would increase with competition. Consequently, at lower levels of competition (right side of our graph), we would witness a negative slope with smaller leverage effects the higher the PCM.

In section 2.7.2, we further hypothesized a situation where laggard firms' ambitions to 'catch up' with the technological frontier would – in the context of the leverage effect – yield the opposite effect to the predictions of Aghion & Howitt. That is – in the presence of low competition – laggard firms find incentives to innovate as the Schumpeterian effect is low and the risk of imitation is low, with few competitors.

If we instead look at the higher levels of competition (left side of our graph), Aghion & Howitt's theories – in the context of leverage effects – would correspond to predictions of a positive slope with increased leverage effects the higher the PCM. That is, the Schumpeterian effect would dominate as firms find no incentives to spend their own money when the risk of imitation and creative destruction is high. This seems especially intuitive in a situation where firms experience low margins.

In sum, according to our hypothesis, R&D subsidies are expected to induce more private R&D activity the less competition there is. This Schumpeterian relationship would prevail up to the point where, in theory, the sector spends relatively more time as a level sector (every firm is at the technological frontier), which in turn is dominated by the negatively sloped escape-competition effect.

Depending on the relative rate of laggard firms in the low competition sectors, however, we hypothesize a possibility that the Schumpeterian effect may overshadow the escape-competition effect normally prevalent in the low competition, level sectors. Hence, looking at the relationship between the leverage effect and competition, rather than R&D activity and competition directly, we may therefore see a positive, linear slope as opposed to the inverted U-shape.

Our results in Figure 5 are not statistically significant, which makes the illustration unreliable in its predictions. Hence, we cannot draw any conclusions regarding our hypothesis. That the results were insignificant could be due to two main reasons: a low-powered regression with too few observations to be able to reject the null, or that there exists no actual effect and interdependence between competition and the leverage effect.

Assuming that there is a positive relationship between the price cost margin and the leverage effect in accordance with our depiction; how could this be synthesized with the current theory on the inverted U developed by Aghion et al. (2005)? As we see it, there are multiple potential explanations to this upwards sloping curve.

First, as previously mentioned in our hypothesis, a positive linear curve represents the domination of the Schumpeterian effect. Less competition is good for innovation: as the price cost margin increases, the leverage effect increases. A dominating Schumpeterian effect means an industry characterized by an unleveled market structure. In such environment, we have one leader and a bunch of laggard firms. As competition increases, the laggard firms have less incentives to innovate as their innovations rapidly will be leapfrogged by the market leader. This is in line with our expectations and corresponds to the underling theory of the inverted U-curve. However, our linear curve indicates that the escape-competition effect in low levels of competitions is not dominating the Schumpeterian effect, as this would have yielded a negative slope in the upper right end on our graph. This discrepancy from the theory could have been caused by an overrepresentation of unlevel sectors or a selection bias in that laggard firms are more likely to apply for grants and that the leverage effect characteristics is thereby mainly driven by laggard firms.

An alternative explanation could be that the relationship in fact is shaped as an inverted U, but because of the exclusion of highly concentrated industries from the OECD data, our estimates does not capture the Porterian, escape competition effect. The absence of highly concentrated industries might have implied that the estimation was only based on the Schumpeterian part of the inverted U, which then is what our graph is representing – an incomplete inverted U. For such an explanation to be valid, the true inverted U would need to be shaped as a reversed checkmark rather than an inverted U.

A third possible explanation, that goes beyond the theories of Aghion et al., lies in the measurement of the price cost margin. Albeit our attempt to use the price cost margin as a proxy for competition, by including a set of relevant controls and by using the within-group variation which is more likely to reflect differences in product market competition, the price cost margin might partially reflect other important economic phenomena. This would distort our inference. For instance, a Marshallian argument could be made that variation in the price cost margin corresponds to variation in quasi-rents. From such perspective, fluctuations in innovation are merely delayed, optimal responses to quasi-rents. This may indicate that the choice of competition measure is even more delicate than illustrated in the literature.

On the same token, it is important to note that the evidence on the inverted U historically has been somewhat ambiguous. Tingvall and Poldahl found support when using Herfindahl, but not for the Lerner index. Aghion et al. found support for the inverted U when using quality adjusted patents but statistically insignificant results when using R&D expenditures. Hence, this study confirms the puzzling sensitivity of the inverted U.

However, without any controls for level and unlevel industries, the discussion is merely based on hypothetical reasoning. Hence, to draw any conclusions with certainty, an updated empirical method is needed.

6.3 Future Research

Based on our discussion, there are multiple interesting improvements that could be done to our framework, in order to answer the questions that has arisen from this thesis. First, a study using micro-level data would be valuable as it increases the power. Using a Heckman correction or a propensity score matching approach to adjust for selection bias, a similar study on firm data would enable the control for level and unlevel sectors (the characteristics of competition). However, such a study would be limited in the possibility of capturing indirect effects to a certain extent. Nevertheless, it would still yield interesting findings on how the leverage effect covaries with competition.

Access to confidential, micro-level data would also make it possible to include the entire spectrum of product market competition. The most concentrated industries could be included, which would make it possible to capture the full dynamics of the Schumpeterian vs the escape competition effects. Such a study would be able to build upon our findings and identify the true relationship between the leverage effect and product market competition.

Lastly, it would be valuable to validate our results using a broader range of measures for competition and R&D intensity. Aghion et al. (2005) found tendencies, but not statistically significant results for the inverted U with respect to R&D expenditures – an incertitude that is partially confirmed by our study. The difference between input and output lies in the research productivity. Hence, it would also be interesting to examine the inverted U with respect to research productivity.

7 Conclusion

The aim of this study has been to empirically determine the effect of public R&D support on private R&D expenditures – the so-called *leverage effect* – and investigate how this relationship might depend on the degree of product market competition. Using the OECD BERD and STAN data sets, we obtain a sample of cross-country industry panel data for 29 OECD countries over the period of 2007–2017.

Our main results could be summarized as follows. Estimating a dynamic panel model, we find that there is a significant and substantial additionality effect between R&D subsidies and private R&D expenditure, regardless of estimation technique. Using difference GMM and Han-Phillips X-differencing techniques, we obtain significant estimates of the leverage effect with elasticities ranging from 0.09 to 0.07 in the short run, indicating that a 100% increase in public subsidies increases private R&D expenditure by 9% or 7% on an industry average. In the long run, the corresponding estimate amount to 0.46, indicating a 46% increase in private R&D expenditures at the industry level as a response to a hundred percent increase in subsidies.

Furthermore, we find insufficient evidence for our hypothesis that the leverage effect depends on product market competition in a nonlinear, concave fashion. The underlying mechanisms of the inverted-U shaped relationship between R&D and competition found by Aghion et al. (2005) may still apply in the context of leverage effects. However, our estimates albeit insignificant, indicate a different story.

It is without doubt that R&D subsidization needs to be placed on centre stage in government innovational policy. How these subsidies should be designed with regards product market competition is not obvious as we cannot conclude what mechanism applies for R&D subsidization in context of competition. Further research is therefore needed in order to pin down the market structure conditions most conducive to effective R&D subsidization. We look forward toward progression on this largely neglected yet evidently relevant policy issue.

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Appendix

Appendix I: Descriptive statistics

TABLE AI. List of countries

Country Code	Country	Freq.	Percent	Cum.
AUS	Australia	130	3.40	3.40
AUT	Austria	130	3.40	6.81
BEL	Belgium	130	3.40	10.21
CAN	Canada	130	3.40	13.62
CHE	Chile	143	3.75	17.37
CHL	Switzerland	122	3.20	20.56
CZE	Czech Republic	130	3.40	23.97
DEU	Germany	130	3.40	27.37
ESP	Spain	135	3.54	30.91
EST	Estonia	130	3.40	34.31
FIN	Finland	130	3.40	37.72
FRA	France	130	3.40	41.12
GBR	Great Britain	143	3.75	44.87
GRC	Greece	135	3.54	48.40
HUN	Hungary	130	3.40	51.81
ISR	Israel	128	3.35	55.16
ITA	Italy	130	3.40	58.56
JPN	Japan	110	2.88	61.45
KOR	Korea	130	3.40	64.85
LTU	Lithuania	130	3.40	68.26
LVA	Latvia	139	3.64	71.90
NOR	Norway	143	3.75	75.64
NZL	New Zealand	128	3.35	78.99
POL	Poland	143	3.75	82.74
PRT	Portugal	133	3.48	86.22
SVK	Slovakia	136	3.56	89.79
SVN	Slovenia	130	3.40	93.19
SWE	Sweden	130	3.40	96.60
TUR	Turkey	130	3.40	100.00
Total		3818	100.00	

Source: OECD

TABLE AII. List of variables

Variable	Definition	Unit
RDbusiness	Privately funded expenditures on research and development	National currency, millions
RDsub	Publicly funded expenditures on research and development	National currency, millions
PCM	Price cost margin, $\frac{Net\ operating\ surplus}{Gross\ output} \times 100$	Percent
PCMsq	Price cost margin squared	Percent squared
Valueadded	Industry value added	National currency, millions
Indg	Percentage changes in gross output, $(\frac{Gross\ output_t}{Gross\ output_{t-1}} - 1) \times 100$	Percent
Interestrate	Long-term interest rates on government bonds with time to maturity of 10 year	Percent
Skills	Average labor costs per employee, $\frac{Total\ labor\ costs}{Number\ of\ employees}$	National currency, millons
Inflation	Annual inflation, measured as changes in the consumer price index	Percent

TABLE AIII. List of industries

Industry
Accommodation and food service activities (i)
Administrative and support service activities (n)
Agriculture, forestry and fishing (a)
Construction (f)
Electricity, gas and water supply; sewerage, waste management and remediation activities (d-e)
Financial and insurance activities (k)
Information and communication (j)
Manufacturing (c)
Mining and quarrying (b)
Professional, scientific and technical activities (m)
Real estate activities (l)
Transportation and storage (h)
Wholesale and retail trade, repair of motor vehicles and motorcycles (g)

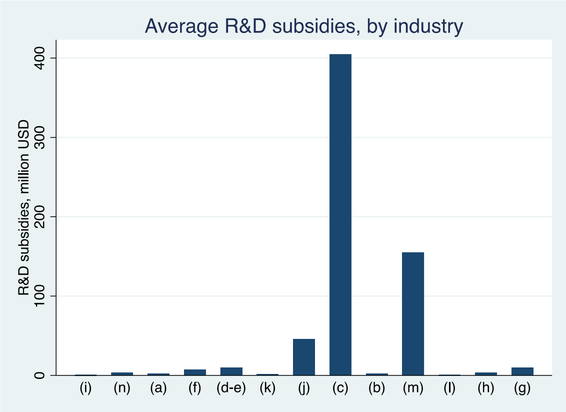

FIG AI. Source: OECD.

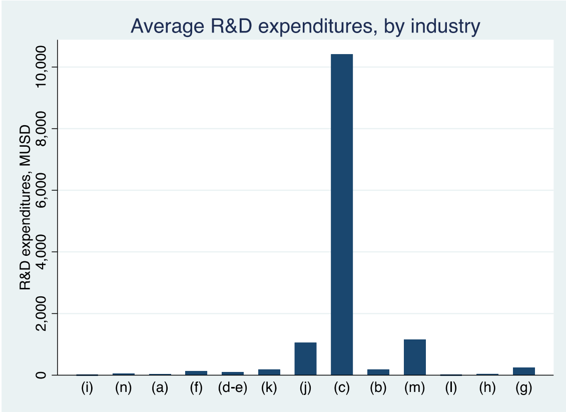

FIG AII. Source: OECD.

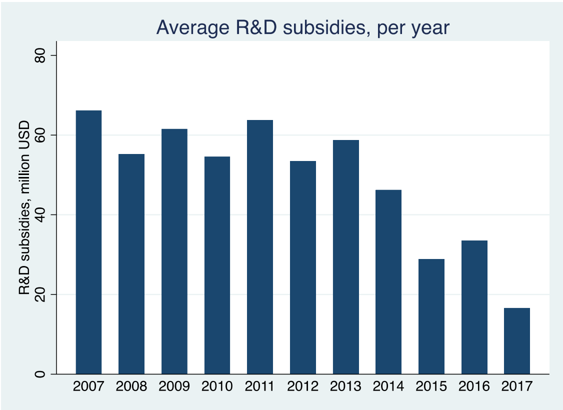

FIG AIII. Source: OECD.

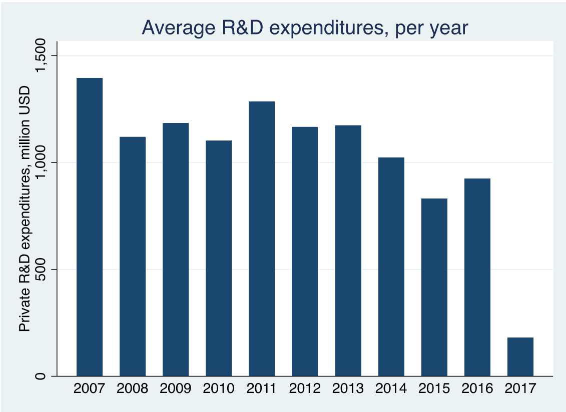

FIG AIV. Source: OECD.

TABLE AIV. Correlation Matrix

e(V)	RD business	RDsub	RDsub* PCM	RDsub* PCMsq	PCM	PCMsq	Valu	L.valu	GDP	ind_g	INT	Skills	Infl	_cons
RDbusiness	1.000													
RDsub	-0.0914	1.0000												
RDsub*PCM	-0.4453	0.4651	1.0000											
RDsub*PCMsq	0.4719	-0.4620	-0.6222	1.0000										
PCM	0.3587	-0.0458	-0.3081	0.2831	1.0000									
PCMsq	-0.1796	-0.3040	0.1216	0.0147	-0.5751	1.0000								
Valu	0.2131	-0.3041	-0.1130	-0.0244	-0.5365	0.0493	1.0000							
L.valu	-0.3743	-0.3042	0.2804	-0.3930	0.0276	-0.1909	-0.3394	1.0000						
GDP	-0.3274	-0.3043	0.3418	-0.0886	-0.0272	0.2321	-0.2819	0.1250	1.0000					
ind_g	-0.0149	-0.3044	0.2052	-0.3598	-0.1238	-0.0764	-0.0673	0.6643	-0.1344	1.0000				
INT	-0.1624	-0.3045	-0.0231	0.1670	-0.2282	0.2399	0.1067	-0.3472	0.1724	-0.1942	1.0000			
Skills	0.1248	-0.3046	-0.4099	0.1802	0.1700	-0.3407	-0.0531	0.0152	-0.3541	0.2241	0.1107	1.0000		
Infl	-0.2299	-0.3047	0.1714	-0.0128	-0.3615	0.1204	0.1443	0.2143	0.2317	0.2114	0.1200	0.1830	1.0000	
_cons	-0.2852	-0.3048	0.2481	-0.1209	-0.4312	0.1782	0.1528	0.3711	0.3466	0.3967	0.0418	0.1337	0.9032	1.0000

Appendix II: Sensitivity analysis

TABLE AV. Sensitivity to Excluding Individual Countries

	(1) AUS	(2) AUT	(3) BEL	(4) CAN	(5) CHE	(6) CHL	(7) CZE	(8) DEU	(9) ESP
Ln(*RDbusiness*$_{it-1}$)	0.194	0.194	0.194	0.194	0.194	0.194	0.159	0.194	0.194
	(0.204)	(0.204)	(0.204)	(0.204)	(0.204)	(0.204)	(0.276)	(0.204)	(0.204)
Ln(*RDsub*$_{it}$)	0.0743**	0.0743**	0.0743**	0.0743**	0.0743**	0.0743**	0.0508	0.0743**	0.0743**
	(0.0357)	(0.0357)	(0.0357)	(0.0357)	(0.0357)	(0.0357)	(0.0461)	(0.0357)	(0.0357)
Ln(*RDsub)*PCM*$_{it}$	0.000546	0.000546	0.000546	0.000546	0.000546	0.000546	0.000824	0.000546	0.000546
	(0.00233)	(0.00233)	(0.00233)	(0.00233)	(0.00233)	(0.00233)	(0.00186)	(0.00233)	(0.00233)
Ln(*RDsub)*PCMsq*$_{it}$	2.24e-05	2.24e-05	2.24e-05	2.24e-05	2.24e-05	2.24e-05	9.06e-06	2.24e-05	2.24e-05
	(6.44e-05)	(6.44e-05)	(6.44e-05)	(6.44e-05)	(6.44e-05)	(6.44e-05)	(4.87e-05)	(6.44e-05)	(6.44e-05)
PCM$_{it}$	-0.00194	-0.00194	-0.00194	-0.00194	-0.00194	-0.00194	-0.00417	-0.00194	-0.00194
	(0.0193)	(0.0193)	(0.0193)	(0.0193)	(0.0193)	(0.0193)	(0.0211)	(0.0193)	(0.0193)
PCMsq$_{it}$	7.91e-05	7.91e-05	7.91e-05	7.91e-05	7.91e-05	7.91e-05	0.000121	7.91e-05	7.91e-05
	(0.000342)	(0.000342)	(0.000342)	(0.000342)	(0.000342)	(0.000342)	(0.000314)	(0.000342)	(0.000342)
Constant	-3.873	-3.873	-3.873	-3.873	-3.873	-3.873	-7.402	-3.873	-3.873
	(9.097)	(9.097)	(9.097)	(9.097)	(9.097)	(9.097)	(11.69)	(9.097)	(9.097)
Observations	782	782	782	782	782	782	688	782	782

Notes: Standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Source: OECD

TABLE AV. *(continued)* Sensitivity to Excluding Individual Countries

	(10) EST	(11) IN	(12) FRA	(13) GBR	(14) GRC	(15) HUN	(16) IS	(17) ITA	(18) JPN
Ln($RDbusiness_{it-1}$)	0.194	0.191*	0.192	0.150	0.194	0.203	0.194	0.202*	0.248
	(0.204)	(0.111)	(0.126)	(0.127)	(0.204)	(0.125)	(0.204)	(0.116)	(0.201)
Ln($RDsub_{it}$)	0.0743**	0.0698*	0.0821**	0.0872**	0.0743**	0.0640*	0.0743**	0.0692**	0.0968
	(0.0357)	(0.0364)	(0.0378)	(0.0382)	(0.0357)	(0.0327)	(0.0357)	(0.0341)	(0.0729)
Ln($RDsub$)*PCM_{it}	0.000546	0.000931	0.000668	0.00195	0.000546	-6.70e-05	0.000546	0.000999	-0.00304
	(0.00233)	(0.00232)	(0.00249)	(0.00217)	(0.00233)	(0.00234)	(0.00233)	(0.00215)	(0.00564)
Ln($RDsub$)*$PCMsq_{it}$	2.24e-05	2.59e-05	2.78e-05	1.95e-05	2.24e-05	2.77e-05	2.24e-05	2.23e-05	0.000133
	(6.44e-05)	(6.08e-05)	(7.07e-05)	(6.99e-05)	(6.44e-05)	(8.06e-05)	(6.44e-05)	(6.25e-05)	(0.000122)
PCM_{it}	-0.00194	-0.0110	-0.000202	-0.00398	-0.00194	0.00193	-0.00194	-0.00935	0.00738
	(0.0193)	(0.0167)	(0.0162)	(0.0156)	(0.0193)	(0.0157)	(0.0193)	(0.0165)	(0.0217)
$PCMsq_{it}$	7.91e-05	0.000155	1.97e-05	0.000104	7.91e-05	5.31e-05	7.91e-05	0.000247	-6.41e-05
	(0.000342)	(0.000353)	(0.000376)	(0.000416)	(0.000342)	(0.000297)	(0.000342)	(0.000403)	(0.000562)
Constant	-3.873	-1.838	-3.841	-3.418	-3.873	-1.997	-3.873	-2.210	2.326
	(9.097)	(8.134)	(8.619)	(10.57)	(9.097)	(9.302)	(9.097)	(10.89)	(10.44)
Observations	782	709	745	714	782	709	782	723	733

Notes: Standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Source: OECD

TABLE AV. *(continued)* Sensitivity to Excluding Individual Countries

	(19) KOR	(20) LTU	(21) LVA	(22) NOR	(23) NZL	(24) POL	(25) PRT	(26) SVK	(27) SVN
Ln($RDbusiness_{it-1}$)	0.234	0.194	0.230*	0.181	0.194	0.179	0.204	0.202	0.119
	(0.280)	(0.204)	(0.119)	(0.114)	(0.204)	(0.111)	(0.192)	(0.209)	(0.181)
Ln($RDsub_{it}$)	0.0695**	0.0743**	0.0737*	0.0962***	0.0743**	0.0759**	0.0753*	0.0629*	0.0733**
	(0.0335)	(0.0357)	(0.0391)	(0.0352)	(0.0357)	(0.0346)	(0.0442)	(0.0323)	(0.0349)
Ln($RDsub)*PCM_{it}$	0.00164	0.000546	0.000520	0.00110	0.000546	0.000469	0.000283	0.00162	7.99e-05
	(0.00234)	(0.00233)	(0.00232)	(0.00219)	(0.00233)	(0.00231)	(0.00221)	(0.00186)	(0.00210)
Ln($RDsub)*PCMsq_{it}$	-3.51e-05	2.24e-05	2.60e-05	8.44e-06	2.24e-05	2.81e-05	3.43e-05	1.77e-05	2.93e-05
	(6.08e-05)	(6.44e-05)	(6.61e-05)	(7.08e-05)	(6.44e-05)	(6.32e-05)	(6.02e-05)	(7.12e-05)	(6.68e-05)
PCM_{it}	-0.00212	-0.00194	-0.00643	-0.00452	-0.00194	-0.00514	0.00391	-0.0103	0.00271
	(0.0153)	(0.0193)	(0.0168)	(0.0176)	(0.0193)	(0.0175)	(0.0176)	(0.0197)	(0.0166)
$PCMsq_{it}$	-8.85e-06	7.91e-05	0.000117	0.000187	7.91e-05	0.000145	4.68e-05	0.000134	3.38e-05
	(0.000294)	(0.000342)	(0.000355)	(0.000380)	(0.000342)	(0.000370)	(0.000308)	(0.000362)	(0.000321)
Constant	-9.193	-3.873	-4.294	-4.846	-3.873	-2.593	4.035	-2.617	-4.792
	(12.78)	(9.097)	(8.043)	(8.094)	(9.097)	(9.464)	(13.23)	(11.41)	(14.44)
Observations	705	782	775	694	782	761	710	751	749

Notes: Standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Source: OECD

TABLE AV. *(continued)* Sensitivity to Excluding Individual Countries

	(28) SWE	(29) TUR
Ln(*RDbusiness*$_{it-1}$)	0.194	0.194
	(0.204)	(0.204)
Ln(*RDsub*$_{it}$)	0.0743**	0.0743**
	(0.0357)	(0.0357)
Ln(*RDsub)*PCM*$_{it}$	0.000546	0.000546
	(0.00233)	(0.00233)
Ln(*RDsub)*PCMsq*$_{it}$	2.24e-05	2.24e-05
	(6.44e-05)	(6.44e-05)
PCM$_{it}$	-0.00194	-0.00194
	(0.0193)	(0.0193)
PCMsq$_{it}$	7.91e-05	7.91e-05
	(0.000342)	(0.000342)
Constant	-3.873	-3.873
	(9.097)	(9.097)
Observations	782	782

Notes: Standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Source: OECD

TABLE AVI. Sensitivity to Excluding Individual Industries

	(1) i	(2) n	(3) a	(4) f	(5) d-e	(6) k	(7) j	(8) c	(9) b
Ln($RDbusiness_{it-1}$)	0.246*	0.193	0.199	0.0659	0.144	0.167	0.188*	0.175	0.250**
	(0.129)	(0.169)	(0.257)	(0.0708)	(0.110)	(0.215)	(0.113)	(0.110)	(0.113)
Ln($RDsub_{it}$)	0.0579*	0.0815**	0.0804**	0.0785*	0.0621*	0.0878**	0.0759**	0.0756*	0.0694
	(0.0346)	(0.0400)	(0.0341)	(0.0402)	(0.0330)	(0.0373)	(0.0366)	(0.0409)	(0.0586)
Ln($RDsub$)*PCM_{it}	0.000428	0.000977	0.000258	-0.000293	0.00143	0.00114	0.000582	0.000675	0.000417
	(0.00211)	(0.00244)	(0.00250)	(0.00242)	(0.00217)	(0.00251)	(0.00223)	(0.00217)	(0.00478)
Ln($RDsub$)*$PCMsq_{it}$	3.64e-05	1.71e-05	3.01e-05	5.43e-05	2.63e-05	1.48e-05	2.32e-05	2.15e-05	6.25e-05
	(6.26e-05)	(7.46e-05)	(0.000102)	(6.02e-05)	(6.05e-05)	(6.19e-05)	(6.82e-05)	(6.20e-05)	(9.36e-05)
PCM_{it}	0.00139	-0.000496	0.0102	-0.00452	-0.00796	-0.00351	-0.0103	0.00358	-0.00615
	(0.0165)	(0.0159)	(0.0187)	(0.0171)	(0.0150)	(0.0218)	(0.0146)	(0.0170)	(0.0284)
$PCMsq_{it}$	9.74e-05	3.70e-07	1.63e-05	-6.11e-05	0.000144	0.000138	0.000181	6.75e-05	0.000232
	(0.000362)	(0.000408)	(0.000304)	(0.000251)	(0.000259)	(0.000310)	(0.000336)	(0.000256)	(0.000514)
Constant	-1.959	-3.718	-5.411	-7.056	0.852	-3.110	-2.139	-2.416	-1.494
	(11.00)	(11.91)	(11.91)	(6.514)	(7.746)	(22.24)	(9.264)	(7.588)	(9.485)
Observations	769	720	716	702	711	751	696	692	733

Notes: Standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Source: OECD

TABLE AVI. *(continued)* Sensitivity to Excluding Individual Industries

	(10) m	(11) l	(12) h	(13) g
Ln(*RDbusiness*$_{it-1}$)	0.219	0.175	0.211*	0.232**
	(0.255)	(0.122)	(0.125)	(0.113)
Ln(*RDsub*$_{it}$)	0.0733**	0.0778***	0.0720**	0.0708**
	(0.0366)	(0.0302)	(0.0324)	(0.0345)
Ln(*RDsub)*PCM*$_{it}$	7.55e-05	0.00180	0.00128	0.000403
	(0.00235)	(0.00162)	(0.00185)	(0.00238)
Ln(*RDsub)*PCMsq*$_{it}$	3.67e-05	-6.44e-05	1.55e-05	3.40e-05
	(6.73e-05)	(4.96e-05)	(5.85e-05)	(6.41e-05)
PCM$_{it}$	-0.00500	-0.00149	4.92e-05	-0.00523
	(0.0196)	(0.0142)	(0.0142)	(0.0154)
PCMsq$_{it}$	4.59e-05	0.000227	9.84e-05	0.000149
	(0.000293)	(0.000380)	(0.000241)	(0.000251)
Constant	-2.022	-6.369	-3.452	-3.478
	(12.65)	(7.745)	(7.545)	(7.033)
Observations	707	752	727	708

Notes: Standard errors in parentheses * p<.10, ** p<.05, *** p<.01. Source: OECD