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The Impact of a Reversal of R&D Tax Credit Schemes on Innovation Output

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Abstract

This paper examines the effect of scaling back R&D tax credit schemes on the innovativeness of an economy. While prior research has tended to find a positive link between indirect R&D subsidies and an economy's innovation output when a subsidy was enacted or increased, the effects of a reverse case, where R&D tax incentives are abandoned or reduced, remains largely unexamined. Using a 2010 Taiwanese R&D tax policy reform that led to a decrease in the R&D tax credit rate, this paper attempts to fill this research gap. Employing both a difference-in-difference and a difference-in-difference-in-difference analysis, as well as their corresponding event studies, I find no adverse effect of reducing the R&D tax credit rate on the innovativeness of Taiwanese industries at the aggregated level and only limited adverse effects on the industry level. The results from this study lend support to the notion of R&D persistence and have important implications for policymakers to rethink R&D tax credit schemes as a temporary measure to boost R&D activity rather than a long-term policy tool.

Keywords: Output Additionality, R&D persistence, R&D subsidies, SII, Tax credit
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I. Introduction

There is widespread consensus among economists that technological change and innovation significantly contribute to the level of productivity, the rate of economic growth and consequently, the standard of living within an economy (Czarnitzki & Hussinger, 2018). As technological change is oftentimes introduced through advances in research and development[1] which may be underprovided given various market failures, it comes as no surprise that most industrialised countries dedicate significant amounts of public resources to support private R&D. Policies to support private R&D usually occur via two main channels, direct subsidies and tax incentives, the latter of which seem to have recently gained popularity: While in 1996, only 12 OECD countries provided some form of R&D tax incentives, in 2020, 32 out of 37 OECD countries gave preferential tax treatment to business R&D expenditure (Appelt, Bajgar, Criscuolo, & Galindo-Rueda, 2020).

The usefulness of R&D tax incentives has traditionally been challenged on the basis that tax incentives have limited scope for identifying and supporting projects with the highest expected social return that would not be realised in the absence of public support and the fact that tax incentives may adversely affect R&D project decisions made by firms (Appelt, Bajgar, Criscuolo, & Galindo-Rueda, 2016). Existing research has thus directed its focus on the impact of public R&D support programs on firms' R&D input, output, or behaviour, with the largest chunk of prior research dedicated to input additionality. Most of these studies have found positive effects, reaching the consensus that the introduction of R&D tax subsidies, or their expansion, enhances both R&D expenditures of firms and R&D output. However, reverse situations where a policy instrument is scaled back rather than introduced or intensified remain largely unexplored. Given the theoretical plausibility of firms displaying R&D persistence, examining the effects of a reversal of public R&D support is a very interesting line of inquiry.

In this paper, I evaluate the impact of a 2010 Taiwanese tax reform, that led to a reduced R&D tax credit rate. The Statute for Industrial Innovation[2] marked the first time the Taiwanese government greatly reduced R&D tax benefits, replacing the previously existing combination of a volume- and increment-based tax credit scheme with a tax credit rate of 35% (50% in case the incremental portion applied to the beneficiary) with a purely volume-based scheme with a

[1] Henceforth referred to as R&D.
[2] Henceforth referred to as SII.

flat tax credit rate of 15%. While the SII was written to apply to all industries, an industry-specific legislation act impeded its applicability to the Taiwanese biotech and new pharmaceuticals industry, which as a result, was the only industry to continue enjoying the previous, more generous R&D tax incentives. I exploit this divergent applicability of the SII to estimate the effect of a reversal in the R&D tax credit rate using a difference-in-difference and a difference-in-difference-in-difference regression approach that compares innovation output as measured by patent applications before and after the introduction of the SII and its reduced tax credit rate. My estimates are based on the identifying assumption that post-implementation changes in patent applications beyond those that occurred for the control industry are due to the reduced tax credit rate. My main result is that most industries exposed to the new, reduced R&D tax credit rate did not, on average, apply for fewer patents than the unaffected control industry. A series of subsequently performed event studies also find no lagging or leading effects of the SII that might have been unobservable within the binary setting of the basic difference-in-difference and difference-in-difference-in-difference analyses.

Finally, I extend my analysis to further include a proxy for direct subsidies in a series of robustness checks to examine whether any potential effect of the reduced R&D tax credit rate on the number of patent applications might have been offset through direct government subsidies. While I find a positive effect of the proxy variable, which indicates a positive relation between direct subsidies and innovation output, I do not find direct subsidies to have offset the effect of the reduced tax credit rate. Furthermore, I find no significant changes to the amount of direct subsidies following the introduction of the SII. My robustness checks thus confirm my findings from the main analysis.

Apart from contributing to the understanding of the link between tax incentives and R&D output, examining the effect of a reversal in R&D tax credits rates is also of significant importance to policymakers, providing a helpful reference for the formulation and revision of R&D tax policies. Proving the lack of persistence of the impact of tax incentive policies on R&D output may encourage policymakers to reassess the necessity of continuous R&D tax credit policies, thus improving the allocative efficiency of public funds.

The rest of this paper is organised as follows. Section II gives an overview of the existing literature on the effect of R&D tax incentives. Section III presents Taiwan's economic development and R&D policies. In Section IV, I describe the data. Section V lays out the

identification strategy and estimating equations. Section VI estimates the effect of the SII's reduced R&D tax credit rate. In Section VII, I examine an alternative explanation for the observed effects through a series of robustness checks. Section VIII interprets the findings. Sections IX and X discuss the paper's limitations and possible paths for future research. Section XI concludes.

II. Literature Review on Public Support for R&D

There exists an extensive literature on public R&D tax policies, which mostly focuses on the effect of introducing or enhancing existing R&D support. However, the effect of a reversal of an existing tax policy remains largely unexamined. Thus, this paper will contribute to the literature by examining the effect of a 2010 Taiwanese tax reform, which led to a decrease in the R&D tax credit rate, on innovativeness as measured by R&D output. To the best of my knowledge, this is one of the first papers to do this. Understanding the implications of a reversal of R&D tax policies will not only extend the existing literature on the link between R&D tax credit incentives and innovation output but is also of great importance to policymakers to improve the allocative efficiency of public resources.

A. Literature on the Effectiveness of Public Support for R&D

Recognizing the importance of R&D subsidies for an economy's prosperity and international competitiveness, most governments in industrialised countries attempt to support R&D efforts through a variety of institutional and financial incentives[3]. Institutional R&D incentives encompass all policies that indirectly affect expected R&D returns by improving the conditions within which firms engage in R&D activities. Classic examples of institutional incentives include the provision of public goods used as inputs in the production of innovations or an effective patenting system to address appropriability problems stemming from spillovers from R&D activities (Center for Economic Research and Environmental Strategy, 2005). However, institutional incentives on their own are often considered insufficient or too blunt of a tool to generate the socially optimal level of R&D. Hence most countries provide additional measures taking the form of various financial incentives. Unlike institutional incentives, financial incentives directly affect firms' anticipated net returns from investing in R&D. There exist two

[3] For a detailed explanation of the economic rationale for public intervention in private R&D, please refer to Appendix 2: Market Imperfections and the Need for Public R&D Support.

forms of financial incentives: Direct government funding and indirect fiscal incentives. The primary difference between these two policy tools runs in their execution. Direct government funding is usually accompanied by a government-directed project choice, either because the government spends the funds directly or because the funds are distributed via grants to firms for specific projects or research areas. Indirect fiscal incentives, on the other hand, allow firms more freedom in choosing their projects (David, Hall, & Toole, 2000; Bronzini & Piselli, 2016). Among indirect financial incentives are tax allowances, exemptions, deductions, or credit. While tax allowances, exemptions and deductions effectively subtract from the tax base before the tax liability is computed, reducing the taxable amount before assessing the tax, a tax credit is an amount subtracted directly from the tax liability after the liability has been computed (Appelt, Bajgar, Criscuolo, & Galindo-Rueda, 2016).

Whether and to what extent public support for private firms' R&D is effective has been widely examined in prior empirical studies. Here, the existing economic literature has been particularly interested in investigating whether the so-called incentive effect of public R&D support after its introduction or enhancement is observed in practice. In general, this line of research has focussed on measuring the spillover effects generated by public R&D support on private for-profit firms' R&D activities. These spillover effects are referred to as additionality effects and are divided into three sub-types: Input additionality, output additionality and behavioural additionality (Czarnitzki & Debackere, 2016; Ghazinoory & Hashemi, 2021). While results on the effect of direct subsidies have been mixed, results from empirical studies on tax subsidies have tended to find a positive link between the tax subsidy and firms' R&D input and output[4]. Interestingly, however, the potential impact of a reduction rather than an implementation or increase in R&D subsidies remains largely unexamined.

A1. Input Additionality

Prior research efforts have primarily focused on input additionality, which refers to spillover effects that generate more R&D inputs, such as private R&D investment, tangible assets, or R&D employees (Bronzini & Piselli, 2016; Bodas Freitas, Castellaci, Fontana, & Malerba, 2017; Ghazinoory & Hashemi, 2021).

[4] As it is not the focus of this paper, I eclipse the topic of direct government subsidies in this literature review. For an overview of studies focussing on the effects of direct R&D subsidies, both David, Hall and Toole (2000) and Zúñiga-Vicente et al. (2014) provide a great summary.

The main research question has been to investigate whether public support for R&D leads to crowding-out or crowding-in of private R&D efforts. Full crowding-out occurs when subsidies are perfect substitutes for private funds and thus decrease firms' net R&D expenditure by the full amount of the public R&D support (Boeing, 2016). Conversely, crowding-in refers to a situation where public support for R&D encourages additional privately funded R&D activities (Zúñiga-Vicente, Alonso-Borrego, Forcadell, & Galán, 2014). From a theoretical point of view, arguments for both complementarity and substitutability can be made. On the one hand, since public R&D subsidies reduce the marginal costs and increase the profitability of R&D projects, they could constitute a stimulus to firms to begin R&D projects or increase the resources they allocate to their R&D activities. On the other hand, public support for R&D could reduce private R&D efforts, as the firms could substitute their financing with public funding on projects that they would have realised even in the absence of public support (García-Quevedo, 2004).

Empirical studies on input additionality typically gauge the effect of R&D tax subsidies by estimating the private R&D price elasticity, which refers to the percentage change in R&D resulting from the tax relief for every percentage change in its after-tax price. Alternatively, studies have used the incrementality ratio, which measures the change in R&D investment per unit of foregone tax revenue spent on R&D fiscal incentives. Most existing studies find that R&D tax incentives result in additional R&D investment (Appelt, Bajgar, Criscuolo, & Galindo-Rueda, 2016). Surveying econometric evidence from over 20 empirical studies published between 1983 and 1998, Hall and van Reenen (2000) find substantial evidence that tax credits have a positive effect on R&D spending by firms. Similarly, Bloom et al. (2002) use data of a sample of nine OECD countries from over 18 years between 1979 to 1997 to analyse the effect of fiscal incentives on the level of R&D investment. Controlling for country-specific characteristics, world macro shocks and other policy influences, the authors conclude tax incentives to be an effective tool to increase R&D intensity, with a 10% decrease in the cost of R&D stimulating a rise of R&D spending of just over 1% in the short run and around 10% in the long run. Carrying out a meta-regression analysis, Castellacci and Lie (2015) also find input additionality effects of R&D tax incentives. However, the authors further find additionality effects to diverge between industries, with larger effects observed for low-tech industries. Concerning effect size, Parsons and Phillips (2007) collect estimates from a broad range of studies undertaken in OECD countries between 1990 – 2006. Within this paper, the authors calculate a median long-run elasticity of R&D of -1.09, which implies that a 1%

decrease in the price of R&D as induced through tax incentives would lead to a 1.09% increase in R&D investment. More recent estimates from the OECD are broadly consistent with this conclusion (Appelt, Bajgar, Criscuolo, & Galindo-Rueda, 2016).

A2. Output Additionality

Output additionality, which are the spillover effects that generate more R&D outputs such as increases in productivity and innovative products or services, has received far less attention than input additionality (Ghazinoory & Hashemi, 2021). This may at first come as a surprise as innovation outputs likely represent the end goal of most public support for private R&D activities. The reason for this may lie in the evaluation approach employed in many studies, which is built on the knowledge production framework where innovation is assumed to be a function of a set of innovative inputs such as R&D investment, the number of researchers, or human capital. According to this approach, incentives are supposed to enhance innovation outputs if they affect innovation inputs. Nevertheless, a public programme might affect innovation outputs even when private R&D investments or other innovation inputs remain unchanged.

Examining the impact of R&D tax credits on innovation activities of Canadian manufacturing firms, Czarnitzki, Hanel and Rosa (2011) find positive effects on the direct output of R&D activities such as a higher number of product innovations and increased sales shares of new and improved products. Cappelen, Raknerud and Rybalka (2012) examine the effects of a Norwegian government-introduced tax-based R&D incentive on the likelihood of innovation and patenting. The authors find that projects benefitting from R&D tax credits resulted in the development of new production processes but did not appear to generate new products for the market or patenting. Dechezleprêtre et al. (2016) exploit a policy reform in the UK which raised the size threshold under which firms could access the more generous tax regime for small and medium-sized enterprises and find large positive effects of the tax scheme on both R&D activity and patents. Nilson, Raknerud and Iancu (2020) study the effects of direct and indirect R&D subsidies on outcome variables related to output, employment, labour productivity and profitability in Norway. The authors find no statistically significant output additionality for firms that regularly engage in R&D activities but find positive output additionality for firms that have not previously conducted R&D activities.

A3. Behavioural Additionality

Behavioural additionality refers to changes in the way firms conduct R&D in response to a public policy. It is a line of research that has only received nominal attention. During the early 2000s, however, there have been a series of empirical studies conducted under the sponsorship of the OECD's Working Party on Innovation and Technology Policy (TIP). Reviewing the evidence obtained through these studies suggests that several behavioural additionality effects can be encouraged through public R&D support. Amongst these effects were the accelerated completion of business R&D projects, expanded project scale and scope, greater involvement in R&D collaborations, a greater likelihood to pursue follow-up projects and improved management (OECD, 2006).

B. R&D Persistence

While the existing literature on the effectiveness of R&D tax subsidies has widely found a positive effect on R&D input, output, and firm behaviour, these studies have almost exclusively focussed on cases where the R&D subsidy was first introduced or amended in a way that increased R&D tax benefits to the recipient firms. The reverse case where R&D tax subsidies have been scaled back has remained largely unexamined.

From a theoretical perspective, the effect of a reduction in R&D subsidies is not clear cut as a simple reversal to a negative effect on R&D is not a given due to firms' potential R&D persistence. In the presence of R&D persistence, firms would be less sensitive to a decrease in R&D subsidies as they are rigid regarding their R&D efforts. The existing theoretical literature discusses several conceptually distinct reasons for the existence of R&D persistence: A first potential reason is related to the idea that success breeds success, meaning that past R&D successes are likely to positively affect future R&D outcomes as they influence firms' choice probabilities regarding R&D activities. A second reason for R&D persistence stems from the use of knowledge that has been accumulated from the performance of R&D activities, regardless of whether these activities have been successful or not. As firms engage in R&D activities, they not only gain insights that might spur future R&D efforts but also develop the necessary organisational competencies to successfully carry out future research projects thus, effectively increasing the probability of future R&D successes. Large sunk costs associated with R&D activities constitute a third potential reason for R&D persistence. Firms conducting R&D typically incur costs from technological adaptation, organisational changes and the

training or hiring of qualified R&D personnel. These costs would be irredeemable if firms did not realise any R&D successes. Therefore, firms may have an incentive to continuously invest in R&D to increase the probability of recovering their initial investments (Triguero & Córcoles, 2013). Finally, a continuous improvement of processes and products through advancements in R&D may be of long-term strategic importance to firms experiencing competitive pressures (Duguet & Monjon, 2004; Yang, Huang, & Chang, 2021). Several prior empirical studies have shown R&D persistence to exist for countries such as Germany (Peters, 2009), the Netherlands (Raymond, Mohnen, Palm, & Schim van der Loeff, 2010) and Spain (Triguero & Córcoles, 2013).

C. Contribution

As outlined in the above review of the existing literature on R&D tax subsidies, there exists a clear gap in research concerning the effect of a reduction in R&D tax subsidies on R&D, especially on R&D output. To the best of my knowledge, only two empirical studies have examined this issue, both focussing exclusively on the effect of the subsidy reversal on R&D input and both coming to differing conclusions. Chen and Lie (2018) examine the same 2010 tax reform used in this paper to analyse its impact on R&D input. Using a multivariate regression model and a DD analysis, the authors find an adverse effect of the reduced R&D tax credit rate both on corporate R&D expenditure, as well as on firm value. Contrary to Chen and Lie (2018), Yang, Huang and Chang (2021) employ a multivariate regression model controlling for firm characteristics and find no overall significant effect on firms' R&D expenditure. However, the authors find considerable differences in the treatment effect of the R&D tax reversal on R&D spending between R&D-intensive and less R&D-intensive firms. However, as outlined in the section on output additionality, R&D spending is unlikely to constitute a policy goal in itself. The prime interest is rather the output of the R&D efforts as there might be factors enhancing or mitigating the effects of the policy other than pure R&D expenditure. In this empirical study, I will thus make use of the 2010 Taiwanese tax reform, which led to a reduction in Taiwan's R&D tax credit rate and will examine its effect on R&D output. By focussing on output additionality rather than input additionality I hope to be able to better examine the effects of such a policy reversal and to fill the identified research gap.

III. Context and Description of the 2010 Taiwanese Tax Reform

As one of the so-called Asian tigers, Taiwan has undergone rapid economic growth since the 1960s, which has significantly impacted the composition of its GDP. Initially an economy heavily reliant on the agricultural sector, the share of manufacturing industries in Taiwan's GDP increased significantly during the 1950s and 1960s due to the rapid growth of food processing, textiles, and electrical manufacturing. The 1970s saw a decline in the importance of these industries and a relative increase in industries such as petrochemicals, metals, and machinery, which was subsequently followed by the development of the information and technology industry. During the 1980s, Taiwan's economic development began to enter the technology-intensive stage. This period has been marked by strong government support for applied technological development, most notably through fiscal incentive schemes (Mah, 2015).

The first important fiscal incentive scheme for investors was the Statutory Encouragement of Investment (SEI) which was in place between 1961 and 1990 and available to both domestic as well as foreign companies. The primary goal of the SEI was to encourage investment into areas considered vital for economic development. Which areas were considered to be "vital" changed throughout the program: During the 1960s, the focus was on encouraging the establishment and enlargement of exporting industries, on capital-intensive industries during the 1970s, and on encouraging technology-intensive industries in the 1980s. The corporate income tax rate for ordinary productive enterprises was reduced in 1977 from 30% to 25%, while important, productive industries were eligible for a corporate income tax ceiling of 22% in 1981 and 20% since 1987 (Mah, 2015).

In 1990, the Taiwanese government decided to discontinue the encouragement of targeted products and industries. Consequently, substantial modifications were made to the system of tax incentives and the specific industry-oriented SEI was replaced with the Statute for the Upgrading of Industry (SUI) in 1991. The SUI was one of the most important tax incentives to promote industrial R&D, technological upgrading, and economic development in Taiwan. Unlike its predecessor, the SUI did not provide special tax treatment to specific industries but provided tax benefits to all industries for certain types of investments, which included investments into R&D and manpower training. Within the SUI Art. 5, 6, 8 and 9 are the key articles pertaining to tax incentives, including accelerated depreciation. Of particular interest

for this paper is Art. 6 of the SUI, which lists the rules for R&D tax credits and describes the SUI's tax policy as a combination of volume and increment-based schemes. According to the volume-based scheme, 35% of R&D expenditure could be claimed in tax credits against the total payable amount for five years. Moreover, the tax credits included an incremental share, which was equal to 50% of the increase in R&D if the current year's R&D expenditure exceeded the average for the previous two years (Yang, Huang, & Hou, 2012; Mah, 2015; Chen & Li, 2018). Yang, Huang and Hou (2012) found that the steadily increasing trend of R&D expenditure in Taiwan was accompanied by an accelerating trend for using R&D tax credits since the late 1990s which suggests that firms conducting R&D actively used this fiscal incentive. Despite the increase in R&D expenditures by private firms since the 1990s, the SUI's generous tax incentives have been the subject of criticism due to three main reasons: Firstly, the SUI contributed to a moderate share of the annual total tax revenue loss incurred by the government of Taiwan, leading to a deterioration in Taiwan's fiscal budget (Chen & Li, 2018). Secondly, R&D investments were widely recognized as intangible assets of the firm or the R&D performer. This was considered particularly valid for high-tech firms, which were argued to be able to maintain their R&D momentum regardless of tax credit provisions. Thirdly, developed countries often provide credit rates lower than Taiwan's 35% to 50% tax credit rate or subsidize only incremental R&D expenditure, which again questions the necessity of Taiwan's generous tax credit scheme (EY, 2013 - 2019; Yang, Huang, & Chang, 2021). These considerations eventually led the Taiwanese government to repeal the SUI.

Following the phase-out of the SUI, the Statute for Industrial Innovation (SII) was enacted in 2010 and first implemented in tax returns in 2012. Compared to its predecessor, the SII is more function-oriented and has a focus on encouraging innovative activity. One specific feature of the SII is the considerable reduction in the tax credit rate and tax deduction period. The SII cancels most tax incentives except for the R&D tax credit, which is reduced to a flat rate of 15% without any increments. Hence, the introduction of the SII revised the combination of volume- and increment-based schemes in the SUI to a purely volume-based scheme with a much lower tax credit rate. Art. 10 of the SII states that a company can receive tax credits of up to 15% of its total R&D expenditure against the total payable amount of corporate tax in the year that the tax is incurred. This tax credit is capped at 30% of the total payable tax and cannot be carried forward to subsequent years. This constituted the first time the Taiwanese government greatly reduced the tax incentive for firms' R&D expenditures (Chen & Gupta, 2017; Chen & Li, 2018).

It is to note that while the SII was written to apply to all industries, there is one industry, namely the biotech and new pharmaceuticals industry, that remains unaffected by the implementation of the SII through a previously implemented industry-specific legislation act. The Act for the Development of Biotech and New Pharmaceuticals Industry is the only legislation act that enabled a specific industry to continue to enjoy the SUI's tax incentives after the SUI was replaced with the SII in 2010. Art. 3 of the act, which was implemented in 2007 and recently extended until 2031, defines the biotech and new pharmaceuticals industry as the industry that deals in new drugs, high-risk medical devices and emerging biotech and pharmaceutical products to be used by human beings, animals and plants (Laws & Regulations Database of the Republic of China, 2007; Chen & Li, 2018)[5]. The empirical study in this paper will make use of the discrepancy in the applicability of the SII to the Taiwanese biotech and new pharmaceuticals industry and other Taiwanese industries to gauge the effect that the implementation of the SII, and its connected lower R&D tax credit rate, had on the R&D output of Taiwanese industries.

IV. Data

A. Data Sources and Data Preparation

My main data source is the number of patent applications under the Patent Cooperation Treaty[6] from the OECD database, which lists patents by country and by international patent classification[7]. The IPC, in turn, organises patents according to the different areas of technology to which they pertain. I then group the individual IPC codes according to their NACE category, which is a statistical classification of economic activities, to form meaningful industry groups. To group IPC codes into their corresponding NACE categories, I mainly rely on the Concordance IPCV8-NACE Rev. 2 published by Eurostat (2015). In a limited number of cases, I deviate from the Concordance IPCV8-NACE Rev. 2 to better capture Taiwan's definition of the biotech and new pharmaceuticals industry[8]. Organising the patents by NACE

[5] The term "new drugs" refers to drugs that contain a new ingredient or have a new pharmaceutical effect or a new administration method as verified by the central competent authorities. "High-risk medical devices" are class III medical devices or a type of class II medical devices requiring clinical trial for approval. Examples of such high-risk medical devices include pacemakers, coronary stents, or artificial heart valves. Finally, "emerging biotech and pharmaceutical products are biotech or pharmaceutical items defined as emerging with strategic development direction (Laws & Regulations Database of the Republic of China, 2007).
[6] Henceforth referred to as PCT.
[7] Henceforth referred to as IPC.
[8] Appendix 3: IPC and NACE Rev. 2 outlines this grouping of the IPCs into NACE Rev. 2 categories and notes on deviations from the Eurostat conversion table.

category reduces the number of patent groups from over 600 IPC subclasses to 20 industries. Finally, to allow for a more straightforward interpretation of regression estimators, the natural logarithm of patent counts will be used in the analysis. For calculation purposes, I assume a minimum annual number of 0.0001 patents for each industry.

For the later performed robustness checks, I use OECD data on business expenditures on R&D from government sources (GBERD) to proxy for direct R&D subsidies. The data is at the NACE industry level and is expressed in 2015 dollars, thus ensuring constant prices and purchasing power parity (PPP). To transform GBERD into GBERD per capita, I then use population data from both the World Bank and the National Statistics of the Republic of China (Taiwan).

B. Patent Applications as a Proxy for R&D Output

The use of patent-based indicators as a measure for R&D output is commonly used in economic studies as the close relationship between patents and innovative output is widely recognized, and patents are a rich source of data (OECD, 2001). However, there are no best practices for using indicators from patent data. The following section will thus explain the use of patent counts as the dependent variable in this study in more detail and draw attention to some of the benefits and shortcomings of using patent counts as a proxy for R&D output.

From a statistical point of view, patent indicators encompass a series of advantages: They have a close link to innovation as there are few major innovations that have not been patented. Furthermore, patents cover a broad range of technologies and provide a wealth of data. However, patents are also subject to certain drawbacks as indicators of R&D activity. Most importantly, not all R&D results are patentable, and the propensity to patent varies between countries and industries. Therefore, filings can only serve as a proxy for R&D output, without being a perfect measure for innovation. Furthermore, the value distribution of patents is skewed as many patents have no industrial application and thus no value to society, whereas others are of substantial value. Given this heterogeneity, patent counts that assume patents to be of equal or comparable value might be misleading as an indicator. Finally, differences in patent regulations across countries and changes in patent law may make a direct comparison difficult. However, carefully choosing the data source and the patent office under which the patent is filed will allow controlling for these weaknesses to at least some extent (OECD, 2001).

To avoid biases associated with purely national statistics, this study will use the number of patent applications filed under the PCT as its output variable. The PCT allows patent applicants to simultaneously seek protection for an innovation in currently 153 contracting states without having to apply for a patent at each national patent authority (OECD, 2001). As the purpose of this study is to identify the impact of a cut in R&D tax credits on R&D output, I will use the patent application date as the reference date for a patent. Since the application date is closer to the actual invention date, it is a more appropriate indicator than patent grants. In other words, the patent application occurs closer to the change in the R&D tax credit policy, requiring a shorter observation period for the empirical study.

V. Identification Strategy and Estimating Equations

The previously mentioned discrepancy in the applicability of the SII to the Taiwanese biotech and new pharmaceuticals industry and other Taiwanese industries provides a quasi-experimental setting that allows for examining the effect of the reduction in tax credits on R&D output in Taiwan. This section will detail the methodology, by first introducing the identification strategy before detailing the empirical model employed in this study.

A. Identification Strategy

A fundamental difficulty in any policy evaluation, as one of the processes in making causal inference, stems from the fact that one cannot observe what would have happened in the absence of the policy. One common way to deal with this problem is to use quasi-experiments, which are experiments that lack random assignments of units into treatment and control groups but that apart from this non-randomness are similar in purpose and structural attributes to randomized experiments (Shadish, Cook, & Campbell, 2002). In the case of Taiwan, where the treatment is the reduction in R&D tax credits under the SII, there is a non-random assignment of industries into the treatment and control group. The treatment group consists of industries that are affected by the SII's reduction in tax credits, while the control group consists of the one industry that is not affected, the biotech and new pharmaceuticals industry.

There are several possible ways in which to perform policy evaluations using a quasi-experimental design. This study will make use of the difference-in-difference (DD) analysis and event study to analyse the effect of the introduction of the SII on the R&D output of

Taiwanese firms[9]. My main outcome of interest is the number of patent applications. The first difference compares this outcome across treated industries and the biotech and new pharmaceuticals industry, which acts as the control industry. If the change in outcome that occurs within the control industry before and after the policy change occurred can successfully capture the effect of other relevant factors, which I assume to be similar to the treatment group, I can estimate the pure effect of the reduced R&D tax credit rate (Ho, 2006). The Taiwanese biotech and new pharmaceuticals industry is a useful control group for the SII's reduced R&D tax credit rate as it would have been exposed to all other economic events and changes happening in Taiwan during the observation period, but remained unaffected by the SII program.

Additionally to the DD analysis, I will repeat the analysis employing the difference-in-difference-in-difference (DDD) method using the Republic of Korea as another control group. The DDD method is an extension of the DD method that allows for the comparison of differences between the treated and untreated industries between an economy subject to the 2010 tax reform and one that remains unaffected. Using a DDD approach has the advantage that it may help to difference out potential biases in the DD estimators. Simply comparing the treated Taiwanese industries to the untreated Taiwanese biotech and new pharmaceuticals industry does run the risk of low validity in the event of unobserved inter-industry spill-overs or trends.

B. The Parallel Trends Assumption

Both the DD and DDD method rely on the assumption that the difference between the treatment and control groups observed in the base period would have been maintained absent the treatment. While this so-called parallel trends assumption cannot be observed and thus tested for, it is possible to support this assumption by testing for parallel trends before the treatment took place. This can be done both graphically and formally.

B1. Testing for Parallel Pre-Trends in a Difference-in-Difference Setting

For the formal test of parallel pre-trends in the DD setting, I regress the output variable patents per industry and year (with the eight years of data being years 1 to 8) for the years prior to the

[9] Other common statistical methods include the matching method, the instrumental variable (IV) method and the regression discontinuity design (RDD).

reduction in tax credits (2004-2011) on industry dummies and a year variable as well as their interaction term. If pre-trends are truly parallel, then the estimates for the double-interaction terms should be zero. I will run two pre-tests, one basic DD pre-test, which groups industries into treatment and control industries and one detailed DD pre-test which includes the treatment industries individually, by including a dummy variable for each NACE industry.

Table 1 below gives the regression output for the basic DD pre-test. The coefficient estimate for the double-interaction term is very close to zero, with the null hypothesis that the true estimate of the double-interaction variable is zero not being rejected at the conventional levels of significance.

Table 1 - Testing for Parallel Pre-Trends - Basic DD

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	3.04 (2.65)	0.252
Not_C21	-3.21 (2.72)	0.240
Year	0.14 (0.52)	0.787
Not_C21 * Year	0.02 (0.54)	0.963
Observations	160	
R^2 / R^2 adjusted	0.050 / 0.032	

Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2004-2011). Each observation corresponds to the log of the number of patent applications by industry and year. The eight years included in the pre-test are coded as Years 1 to 8. Not_C21 refers to all industries other than the control industry (biotech and new pharmaceuticals). Standard errors are in parentheses.

Table 1: Testing for Parallel Pre-Trends – Basic DD[10]

[10] C21 is the NACE Rev.2 code that most closely resembles Taiwan's definition of the biotech and new pharmaceuticals industry. Not_C21 thus constitutes all industries that are not the biotech and new pharmaceuticals industry, or in other words, all industries within the treatment group. For a full overview of what IPC codes are combined under which NACE industry, please refer to Appendix 3: IPC and NACE Rev. 2.

I perform a similar formal pre-test at a less aggregated level, including industries individually rather than grouped into treatment and control group. As shown in Table 2, the double-interaction terms are again not significant. I find that I do not reject the null hypothesis of parallel trends. However, for some double interaction terms, the estimate, while not significant, is quite far away from zero, thus warranting a further investigation. Using the graphical approach, I observe slightly diverging trends or strong fluctuations in the pre-intervention period for the industries C101112 – Manufacture of Food, Beverages and Tobacco Products, C161718 – Manufacture of Wood, Cork and Paper Products as well as Printing, C19 – Manufacture of Coke and Refined Petroleum, C24 – Manufacture of Basic Metals, C30 - Manufacture of Other Transport Equipment, F42 – Civil Engineering and J62 – Computer Programming, Consultancy and Related Activities[11]. While none of the interaction terms pertaining to these industries is significant and most diverging trends are very small, I will exclude these industries from all further detailed DD analyses, where I examine the impact of the SII at the industry-level to avoid potential biases.

[11] The graphical approach is included in Appendix 4.1: Graphical Approach.

Table 2 - Testing for Parallel Pre-Trends – Detailed DD (Excerpt of Regression Output)

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
C101112 * Year	0.18 (0.52)	0.734
C131415 * Year	0.06 (0.52)	0.909
C161718 * Year	-0.15 (0.52)	0.776
C19 * Year	0.46 (0.52)	0.380
C20 * Year	-0.04 (0.52)	0.935
C22 * Year	0.06 (0.52)	0.910
C23 * Year	0.11 (0.52)	0.835
C24 * Year	-0.40 (0.52)	0.448
C25 * Year	-0.06 (0.52)	0.911
C26 * Year	-0.03 (0.52)	0.958
C27 * Year	0.00 (0.52)	0.996
C28 * Year	-0.07 (0.52)	0.889
C29 * Year	-0.09 (0.52)	0.864
C30 * Year	0.17 (0.52)	0.745
C31 * Year	0.10 (0.52)	0.851
C32 * Year	0.03 (0.52)	0.955
F42 * Year	-0.27 (0.52)	0.599
F43 * Year	0.05 (0.52)	0.920
J62 * Year	0.37 (0.52)	0.484
Observations	160	
R^2 / R^2 adjusted	0.639 / 0.522	

Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2004-2011). Each observation corresponds to the log of the number of patent applications by industry and year. The eight years included in the pre-test are coded as Years 1 to 8. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. Standard errors are in parentheses.

Table 2: Testing for Parallel Pre-Trends - Detailed DD (Excerpt of Regression Output)[12]

[12] The full regression output for the parallel pre-trends test can be found in Appendix 4: Testing for Parallel Pre-trends (DD) using the Graphical and Formal Approach.

B2. Testing for Parallel Pre-Trends in a Difference-in-Difference-in-Difference Setting

Similarly to the DD method, the DDD approach assumes parallel trends. However, parallel trends in the DD setting do not necessarily translate to parallel trends within a DDD setting as for the DDD analysis, parallel trends have to hold for the differences between the two DD analyses. The existence of parallel pre-trends can again be tested using both a graphical and a formal approach. I use a formal approach for testing parallel pre-trends akin to the one performed above. I again run two pre-tests, one basic DDD pre-test, which groups industries into treatment and control industries and one detailed DDD pre-test which includes the treatment industries individually, by including a dummy variable for each NACE industry.

Table 3 below gives the regression output for the basic DDD pre-test. The coefficient estimate for the double-interaction term is very close to zero, with the null hypothesis that the true estimate of the triple-interaction variable is zero not being rejected at the conventional levels of significance. I again perform a similar formal pre-test at a less aggregated level, including industries individually rather than grouped into treatment and control groups. As shown in Table 4, the triple-interaction terms are again close to zero and not significant. I find that I do not reject the null hypothesis of parallel trends[13]. However, for the industries C101112 – Manufacture of Food, Beverages and Tobacco Products, C161718 – Manufacture of Wood, Cork and Paper Products as well as Printing, C19 – Manufacture of Coke and Refined Petroleum, C24 – Manufacture of Basic Metals, F42 – Civil Engineering and J62 – Computer Programming, Consultancy and Related Activities, the estimates are further away from zero. Combining the insights from this formal approach with the insights gained from the graphical approach leads me to exclude these industries from all further detailed DDD analyses, where I examine the impact of the SII at the industry-level[14].

[13] The full regression output for the parallel pre-trends test can be found in Appendix 5.2: Formal Approach.
[14] The graphical approach is included in Appendix 5.1: Graphical Approach.

Table 3 - Testing for Parallel Pre-Trends - Basic DDD

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	5.68 (2.03)	**0.005**
Not_C21	-1.77 (2.08)	0.397
Year	0.13 (0.40)	0.748
CountryDummy	-2.64 (2.87)	0.359
Not_C21 * Year	0.01 (0.41)	0.973
Not_C21 * CountryDummy	-1.44 (2.95)	0.625
Year * CountryDummy	0.01 (0.57)	0.982
(Not_C21 * Year) * CountryDummy	0.01 (0.58)	0.985
Observations	320	
R^2 / R^2 adjusted	0.390 / 0.376	

Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2004-2011). Each observation corresponds to the log of the number of patent applications by region, industry and year. The eight years included in the pre-test are coded as Years 1 to 8. Not_C21 refers to all industries other than the control industry (biotech and new pharmaceuticals). CountryDummy[15] is a dummy variable that takes on a value of 1 for an observation from Taiwan, and a value of 0 for an observation from Korea. Standard errors are in parentheses.

Table 3: Testing for Parallel Pre-Trends - Basic DDD[16]

[15] The term "CountryDummy" is used to distinguish between Taiwan and the Republic of Korea. Readers be advised that throughout this study the term "country" carries no political connotation and is to be understood exclusively as reference for an economy.

[16] C21 is the NACE Rev.2 code that most closely resembles Taiwan's definition of the biotech and new pharmaceuticals industry. Not_C21 thus constitutes all industries that are not the biotech and new pharmaceuticals industry, or in other words, all industries within the treatment group. For a full overview of what IPC codes are combined under which NACE industry, please refer to Appendix 3: IPC and NACE Rev. 2.

Table 4 - Testing for Parallel Pre-Trends – Detailed DDD (Excerpt of Regression Output)

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(C101112 * Year) * CountryDummy	0.24 (0.52)	0.646
(C131415 * Year) * CountryDummy	0.07 (0.52)	0.901
(C161718 * Year) * CountryDummy	-0.09 (0.52)	0.861
(C19 * Year) * CountryDummy	0.36 (0.52)	0.488
(C20 * Year) * CountryDummy	-0.04 (0.52)	0.945
(C22 * Year) * CountryDummy	0.06 (0.52)	0.916
(C23 * Year) * CountryDummy	0.09 (0.52)	0.865
(C24 * Year) *CountryDummy	-0.47 (0.52)	0.368
(C25 * Year) * CountryDummy	-0.08 (0.52)	0.877
(C26 * Year) * CountryDummy	-0.06 (0.52)	0.903
(C27 * Year) * CountryDummy	-0.05 (0.52)	0.931
(C28 * Year) * CountryDummy	-0.03 (0.52)	0.956
(C29 * Year) * CountryDummy	-0.15 (0.52)	0.770
(C30 * Year) * CountryDummy	0.07 (0.52)	0.887
(C31 * Year) * CountryDummy	0.13 (0.52)	0.805
(C32 * Year) * CountryDummy	0.02 (0.52)	0.964
(F42 * Year) * CountryDummy	-0.23 (0.52)	0.658
(F43 * Year) * CountryDummy	0.10 (0.52)	0.853
(J62 * Year) * CountryDummy	0.27 (0.52)	0.601
Observations	320	
R^2 / R^2 adjusted	0.802 / 0.737	

Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2004-2011). Each observation corresponds to the log of the number of patent applications by region, industry and year. The eight years included in the pre-test are coded as Years 1 to 8. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. CountryDummy is a dummy variable that takes on a value of 1 for an observation from Taiwan, and a value of 0 for an observation from Korea. Standard errors are in parentheses.

Table 4: Testing for Parallel Pre-Trends – Detailed DDD (Excerpt of Regression Output)

C. Empirical Strategy

In a first step, the effect of exposure to the SII's reduction in R&D tax credits is estimated by the following DD model

$$\ln(p_{it}) = \alpha + \beta * I_i * SII + \gamma * I_i + \delta * SII + \varepsilon_{it}$$

Equation 1: DD Model

where $\ln(p_{it})$ is the natural logarithm of the outcome variable of interest corresponding to industry i in year t, I_i is an indicator variable for the industry, which takes a value of 0 for the biotech and new pharmaceuticals industries and a value of 1 for other industries and SII is the post-treatment dummy, taking on a value of 0 for observations before the implementation of the SII and a value of 1 for observations after the implementation. I will use the year 2012 as the implementation year of the SII, as this was the first year the new R&D tax policy was implemented in firms' tax returns. The key variable of interest within this estimation is the DD estimator β, which measures the average impact of the SII's reduced R&D tax credit rate after its introduction.

I will complement this analysis with an event study to examine whether there are potential effects of the implementation of the SII that occur before or after the implementation of the SII. The reason for this is that while the SII was first implemented in tax returns in 2012, it was already introduced in 2010 and announced to firms prior to this date. It is thus possible, that firms adjusted their R&D activities in anticipation of the introduction of the SII. Similarly, it is possible that firms had a delayed response to the introduction of the SII as R&D activities constitute medium- to long-term decisions and can thus not be immediately adjusted. An event study thus allows to uncover the timing of any potential effects in a way that a conventional DD does not. The dynamic effect of the introduction to the SII is estimated by the following model

$$\ln(p_{it}) = \alpha + \sum_{j=2}^{8} \beta_j * (I_i * Lag\ j)_t + \sum_{k=0}^{7} \gamma_k * (I_i * Lead\ k)_t + \delta * I_i + \lambda_t + \varepsilon_{it}$$

Equation 2: DD Event Study Model

where $\ln(p_{it})$ once again is the natural logarithm of the outcome variable of interest corresponding to industry i in year t, I_i is an indicator variable for the industry and $(Lag\ j)_t$ and $(Lead\ k)_t$ are binary variables indicating the number of years before and after the introduction of the SII respectively. $J = 8$ and $K = 7$ lags and leads are included respectively, with a single lag variable being omitted to capture the baseline difference between industries subject to the SII's reduced R&D tax credit rate and industries not subjected to the policy change. The baseline omitted case is the first lag, where $j = 1$. Finally, λ_t indicates the year fixed effects and ε_{it} is the unobserved error term. The main parameters of interest within this estimation are the dynamic DD estimators β_j and γ_k (Clarke & Schythe, 2020).

In a second step, I will expand upon the DD analysis and its corresponding event study, by using a DDD approach, where I compare the double difference between the treated and untreated Taiwanese industries (see DD analysis above) to the same double difference in the Republic of Korea, which did not introduce the SII program. This allows me to ensure that any true effect of the SII's reduced tax credit rate is not hidden or distorted due to industry spillovers. The Republic of Korea[17] is useful as a control group as both Korea and Taiwan, as so-called Asian tigers, underwent similar economic development during the last decades. Additionally, Korea has established a mature R&D tax incentive regime through the Tax Incentives Limitation Law (TILL), which was enacted in 1999. The country currently provides various R&D incentives to encourage R&D activities, most notably its R&D tax credit rate, which amounts to 2% of current R&D expenses for large firms, 8% for medium-scale companies and 25% for small-and-medium-sized enterprises (Ministry of Strategy and Finance, Korea, 2012; EY, 2013 - 2019).

The effect of exposure to the SII's reduction in R&D tax credits is estimated by the following DDD model

$$\ln(p_{itc}) = \alpha + \beta * I_i * SII * T + \gamma * I_i * SII + \delta * I_i * T + \theta * SII * T + \vartheta * I_i + \rho * SII + \sigma * T + \varepsilon_{it}$$

Equation 3: DDD Model

[17] Henceforth referred to as Korea.

where T is a binary variable with a value of 0 for an observation from Korea and a value of 1 for an observation from Taiwan. The interpretation of the remaining variables remains the same as for the DD model detailed in Equation 1 above. The key variable of interest within this estimation is the DDD estimator β, which measures the average impact of the SII's reduced R&D tax credit rate after its introduction. I will once more complement this analysis with an event study to uncover potentially leading or lagging effects of the implementation of the SII. The dynamic effect of the introduction to the SII is estimated by the following model

$$\ln(p_{itc}) = \alpha + \sum_{j=2}^{8} \beta_j * (I_i * Lag\ j * T)_t + \sum_{k=0}^{7} \gamma_k * (I_i * Lead\ k * T)_t + \sum_{j=2}^{8} \delta_j * (I_i * Lag\ j)_t + \sum_{k=0}^{7} \theta_k * (I_i * Lead\ k)_t + \sum_{j=2}^{8} \vartheta_j * (Lag\ j * T)_t + \sum_{k=0}^{7} \mu_k * (Lead\ k * T)_t + \rho * I_i * T + \varphi * I_i + \omega * T + \lambda_t + \varepsilon_{it}$$

Equation 4: DDD Event Study Model

I will run two versions of the DD and DDD models each: First, a basic estimation which simply groups industries into the biotech and new pharmaceuticals industry and all other industries[18] and a more detailed estimation which includes the treated industries individually. In the case of the basic estimation, the industry indicator variable I_i will take a value of 0 for the unaffected biotech and new pharmaceuticals industry and a value of 1 for all other industries. In the case of the detailed estimations, the industry indicator variable I_i will still take a value of 0 for the unaffected biotech and new pharmaceuticals industry but I will include an individual dummy variable for each included industry. This set-up will allow me to first identify the overall effect of the reduced tax credit rate before examining whether there exist differences in the impact of the SII's R&D tax credit rate reduction amongst industries.

[18] That is industries being subject to the SII's R&D tax credit.

VI. Results and Interpretation

A. Difference-in-Difference (DD) Analysis and Event Study

In a first step, I run the basic DD model as specified in Equation 1, where the industry indicator I_i takes a value of 0 for the control group, the by the SII unaffected biotech and new pharmaceuticals industry, and a value of 1 for all other industries. The regression output for the basic DD analysis is presented in Table 5 below.

Table 5 - Regression Output Basic DD

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	3.68 (1.16)	**0.002**
IndustryDummy	-3.09 (1.19)	**0.010**
SII	0.96 (1.70)	0.573
IndustryDummy * SII	-0.37 (1.75)	0.832
Observations	300	
R^2 / R^2 adjusted	0.053 / 0.044	

Notes: The regression output is for the basic DD model as specified in Equation 1. Each observation corresponds to the log of the number of patent applications by industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 5: Regression Output Basic DD

The coefficient estimate for the industry dummy I_i is negative and significant at the 1%-level of significance. This implies that before the introduction of the SII and its associated lower tax credit rate, the treated industries already tended to have a lower number of patent applications than the control industry. The post-treatment dummy *SII* is positive, which would imply an increase in the average number of patent applications from the control industry after the SII intervention. However, this estimate is not significant at the conventional levels of significance, thus excluding it from further assessment. Finally, the key variable of interest, the DD estimator,

which indicates how much the average number of patent applications has changed for the treated industries after the intervention in the form of the SII, is negative. This would imply a decrease in the average number of patent applications for the treated industries after the SII was introduced. However, the DD estimator is not significant, so that no negative effect of the reduced tax credit rate can be concluded from this regression output. Additionally, as indicated by the model's low adjusted R-squared value, the fit of the model is poor, meaning that I am not able to explain much of the variation observed in the data with the basic DD model employed.

To ensure that no lagged or leading effects of the implementation of the SII are masked due to the binary nature of the initial basic DD analysis, that only compares the average number of patent applications in the pre- and post-intervention period, I expand on this basic DD analysis with an event study by including year-fixed effects instead of the post-treatment dummy *SII*. The double interaction terms are presented in Table 6 below. None of the interaction estimates are significant, both for the years before and after the SII was introduced, which negates any changes or trends following or preceding the intervention. This suggests that overall, the SII and its associated reduction in the R&D tax credit rate had no lagging or leading effect on innovation output by Taiwanese firms. This conclusion is further supported by the fact that the event study has an adjusted R-squared lower than the basic DD model. In fact, the adjusted R-squared value is below zero, which suggests that the model employed in this study does not fit the data better than an intercept-only model. This indicates that the interaction variables do not help to explain the variation within the dependent variable. These findings are further visualised in Figure 1 below, which plots the estimates for the interaction terms together with their 95%-confidence intervals over time.

Table 6 – Excerpt of Regression Output Basic DD Event Study

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
IndustryDummy * Lag_8	0.22 (4.91)	0.965
IndustryDummy * Lag_7	-0.20 (4.91)	0.967
IndustryDummy * Lag_6	-0.41 (4.91)	0.934
IndustryDummy * Lag_5	1.34 (4.91)	0.786
IndustryDummy * Lag_4	0.31 (4.91)	0.949
IndustryDummy * Lag_3	0.53 (4.91)	0.915
IndustryDummy * Lag_2	0.16 (4.91)	0.974
IndustryDummy *Implementation_Year	1.18 (4.91)	0.810
IndustryDummy * Lead_1	0.35 (4.91)	0.944
IndustryDummy * Lead_2	0.45 (4.91)	0.928
IndustryDummy * Lead_3	-0.58 (4.91)	0.905
IndustryDummy * Lead_4	-0.77 (4.91)	0.875
IndustryDummy * Lead_5	-0.29 (4.91)	0.952
IndustryDummy * Lead_6	-1.22 (4.91)	0.804
Observations	300	
R^2 / R^2 adjusted	0.083 / -0.015	

Notes: The regression output is for the basic DD event study as specified in Equation 2. Each observation corresponds to the log of the number of patent applications by industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Lags and leads refer to the number of years before or after the implementation of the SII respectively. Standard errors are in parentheses.

Table 6: Excerpt of Regression Output Basic DD Event Study[19]

[19] The full regression output including the estimates for the year-fixed effects for the event study is included in Appendix 6: Regression Output DD Analyses and Corresponding Event Studies

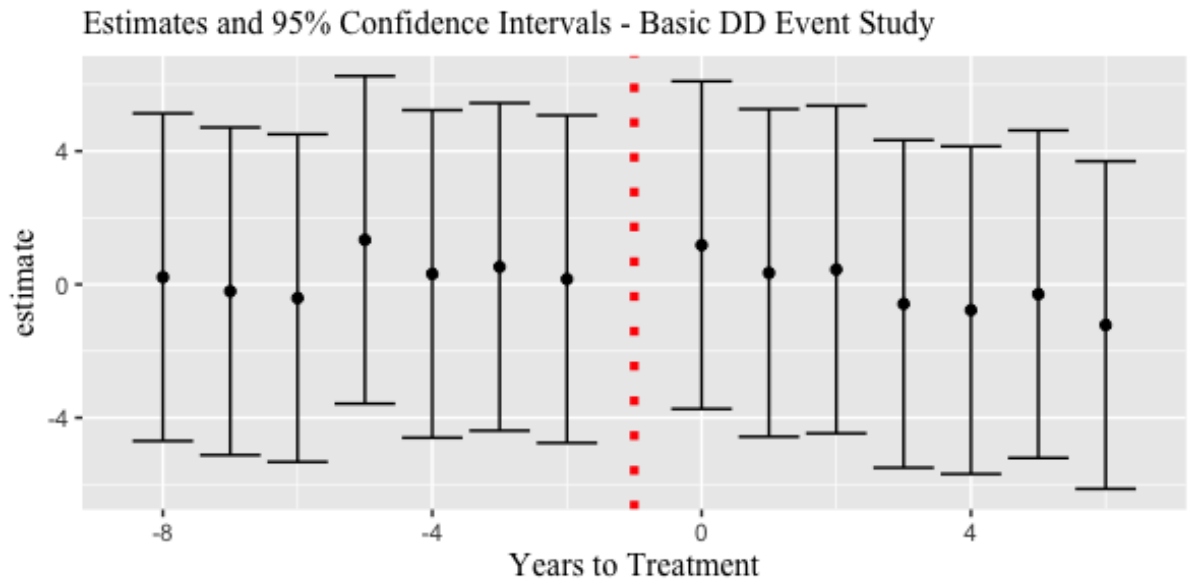


Figure 1: Estimates and 95%-Confidence Intervals Basic DD Event Study

Thus, I did not find any significant effects of the SII and its reduced R&D tax credit rate on R&D output as measured by patent applications at the aggregate level. However, as industries likely vary in both their R&D intensity and R&D maturity, it is possible that the SII's reduced R&D tax credit rate did have an effect at the industry level. I thus repeat the analysis using the detailed DD model to examine whether there exist individual industries that were affected by the reduced R&D tax credit rate.

The double-difference estimates based on Equation 2 are presented in Table 7[20]. The double difference estimates are non-significant for most industries, which is in line with the findings from the previously performed basic DD analysis and event study according to which the SII's reduced R&D tax credit rate did not have a significant impact on R&D output. However, for four industries, namely C25 – Manufacture of Fabricated Metal Products except Machinery and Equipment, C29 – Manufacture of Motor Vehicles, Trailers and Semi-Trailers, C31 – Manufacture of Furniture and F43 – Specialised Construction Activity, the estimates are negative and significant at the 10% level of significance. This suggests an adverse effect of the SII's reduced R&D tax credit rate on R&D output in these industries. Further examining the effect by conducting a simple event study with only these affected industries, reveals that the

[20] The full regression output is included in Appendix 6: Regression Output DD Analyses and Corresponding Event Studies.

largest increase in the differences between the number of patent applications for the control industry and industries C25, C29, C31 and F43 occurs in year 3 after the intervention[21].

Table 7 – Excerpt of Regression Output Detailed DD

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
C131415 * SII	0.10 (0.42)	0.820
C20 * SII	-0.43 (0.42)	0.302
C22 * SII	-0.27 (0.42)	0.516
C23 * SII	-0.58 (0.42)	0.165
C25 * SII	-0.78 (0.42)	0.066
C26 * SII	-0.26 (0.42)	0.528
C27 * SII	-0.48 (0.42)	0.251
C28 * SII	-0.60 (0.42)	0.154
C29 * SII	-0.84 (0.42)	**0.047**
C31 * SII	-1.07 (0.42)	**0.011**
C32 * SII	-0.29 (0.42)	0.495
F43 * SII	-0.79 (0.42)	0.060
Observations	195	
R^2 / R^2 adjusted	0.872 / 0.854	

Notes: The regression output is for the detailed DD model as specified in Equation 1. Each observation corresponds to the log of the number of patent applications by industry and year. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. Only industries for which the null hypothesis of parallel pre-trends could not be rejected are included in the analysis. SII refers to the post-treatment dummy. Standard errors are in parentheses.

Table 7: Excerpt of Regression Output Detailed DD

[21] The full regression output of the performed event study, as well as a graphical representation of its findings are included in Appendix 6: Regression Output DD Analyses and Corresponding Event Studies.

Thus, while I did not find a significant effect of the SII and its reduced R&D tax credit rate on the number of patent applications at the aggregate level, the subsequently performed detailed DD analysis suggests that some individual industries might have been adversely affected by the reduced R&D tax credit rate. I follow up on this observation, by expanding the analysis to a DDD setting.

B. Difference-in-Difference-in-Difference (DDD) Analysis and Event Study

The DD analysis performed in the previous section did not find significant effects of the SII at the aggregate level and only found a significantly negative effect for a limited number of industries. To ensure that the true effect of the SII's reduced R&D tax credit rate is not hidden due to inter-industry spillovers I further examine the issue using a DDD approach, where I compare the double difference between the treated and untreated Taiwanese industries (see DD analysis above) to the same double difference in the Republic of Korea, which did not introduce the SII tax reform.

The regression output for the basic DDD analysis is presented in Table 8 below. Both the industry dummy and the Taiwan dummy are negative and significant at the 10% and 5% levels of significance respectively. This implies that the treatment industries tended to be on average less likely to apply for a patent than the biotech and new pharmaceuticals industry before the SII was implemented. Similarly, Taiwanese industries overall tended to apply for fewer patents than their Korean counterparts prior to the intervention. The key variable of interest, the DDD estimator, is negative but not significant meaning that the difference between the two DDs did not change significantly between the pre- and the post-intervention periods. This is in line with the findings from the basic DD analysis performed in the previous section and suggests once more that at the aggregate level, the SII and its associated lower R&D tax credit rate did not have a significant effect on the number of patent applications. It is noteworthy to observe, that extending the initial DD estimation to a DDD estimation also largely increased the model's overall significance as seen from the larger adjusted R-squared value. The DDD model is thus, able to explain a greater portion of the variation observed in the dataset than the basic DD model.

The complementary basic DDD event study confirms the insights obtained from the basic DDD, as none of the triple difference estimators presented in Table 9 are significant, and no trend

regarding the development of the DDD estimates over time exists. This insight is further illustrated in Figure 2 below, which shows stable estimates for both the pre- and post-intervention period that are close to zero throughout the observation period.

Table 8 – Regression Output Basic DDD

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	6.26 (0.90)	**<0.001**
IndustryDummy	-1.70 (0.92)	0.066
Taiwan	-2.58 (1.27)	**0.043**
SII	0.72 (1.32)	0.587
IndustryDummy * Taiwan	-1.39 (1.31)	0.288
IndustryDummy * SII	-0.01 (1.35)	0.997
Taiwan * SII	0.25 (1.86)	0.896
(IndustryDummy * Taiwan) * SII	-0.37 (1.91)	0.849
Observations	600	
R^2 / R^2 adjusted	0.404 / 0.397	

Notes: The regression output is for the basic DDD model as specified in Equation 3. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Taiwan is a dummy variable, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 8: Regression Output Basic DDD

Table 9 - Excerpt of Regression Output Basic DDD Event Study

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(IndustryDummy * Taiwan)* Lag_8	0.34 (5.39)	0.949
(IndustryDummy * Taiwan)* Lag_7	-0.25 (5.39)	0.964
(IndustryDummy * Taiwan)* Lag_6	-0.37 (5.39)	0.945
(IndustryDummy * Taiwan)* Lag_5	1.39 (5.39)	0.797
(IndustryDummy * Taiwan)* Lag_4	0.33 (5.39)	0.952
(IndustryDummy * Taiwan) * Lag_3	0.57 (5.39)	0.916
(IndustryDummy * Taiwan) * Lag_2	0.07 (5.39)	0.990
(IndustryDummy * Taiwan)* Implementation_Year	1.13 (5.39)	0.834
(IndustryDummy * Taiwan) * Lead_1	0.34 (5.39)	0.949
(IndustryDummy * Taiwan) * Lead_2	0.43 (5.39)	0.936
(IndustryDummy * Taiwan) * Lead_3	-0.65 (5.39)	0.903
(IndustryDummy * Taiwan) * Lead_4	-0.70 (5.39)	0.897
(IndustryDummy * Taiwan) * Lead_5	-0.23 (5.39)	0.965
(IndustryDummy * Taiwan) * Lead_6	-1.07 (5.39)	0.843
Observations	600	
R^2 / R^2 adjusted	0.422 / 0.359	

Notes: The regression output is for the basic DDD event study as specified in Equation 4. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Taiwan is a dummy variable, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. Lags and leads refer to the number of years before or after the implementation of the SII respectively. Standard errors are in parentheses.

Table 9: Excerpt of Regression Output Basic DDD Event Study[22]

[22] The full regression output is included in Appendix 7: Regression Output DDD Analyses and Corresponding Event Studies

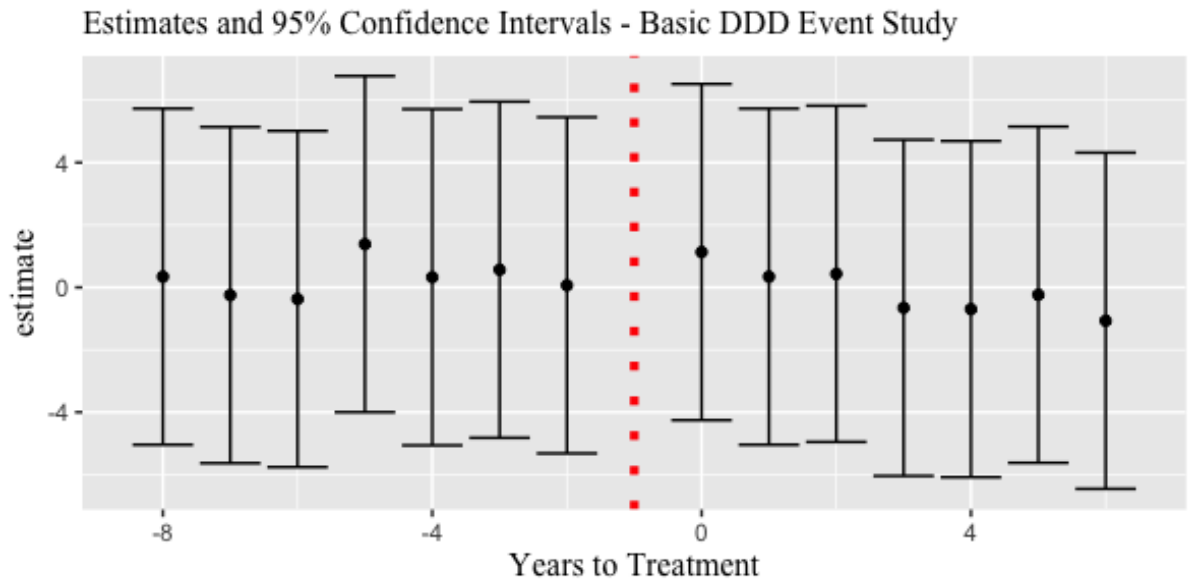


Figure 2: Estimates and 95% Confidence Intervals - Basic DDD

I will again also run a more detailed DDD analysis to ensure that aggregating industries did not mask trends within industry groups and to examine whether the negative effect of the SII observed for some industries in the previous DD setting is also observed in a DDD setting.

The triple-difference estimates of the impact of the SII's reduced R&D tax credit rate, based on Equation 3 are presented in Table 10 below. I again find the triple-difference estimates to be non-significant for most industries, which is in line with the findings from the previously performed basic DDD analysis and event study according to which the SII's reduced R&D tax credit rate did not have a significant impact on R&D output. However, similarly to the detailed DD analysis performed in the previous section, where industries were included individually rather than as one treated group, the detailed DDD reveals that the SII had a significantly negative effect for some industries, namely C25 – Manufacture of Fabricated Metal Products except Machinery and Equipment, C29 – Manufacture of Motor Vehicles, Trailers and Semi-Trailers and C31 – Manufacture of Furniture. Interestingly, industry F43 – Specialised Construction Activities, which was found to be negatively affected by the SII's reduced tax credit rate in the DD setting, is non-significant in the DDD setting. This suggests that the relative increase in the difference in patent applications between this industry and the biotech and new pharmaceuticals industry was not only observed in Taiwan, but also in Korea, which in turn implies that the SII's reduced R&D tax credit rate cannot be the cause for this effect.

Table 10 – Excerpt of Regression Output Detailed DDD

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(C131415 * Taiwan) * SII	0.45 (0.49)	0.359
(C20 * Taiwan) * SII	-0.55 (0.49)	0.255
(C22 * Taiwan) * SII	-0.18 (0.49)	0.713
(C23 * Taiwan) * SII	-0.74 (0.49)	0.128
(C25 * Taiwan) * SII	-0.88 (0.49)	0.071
(C26 * Taiwan) * SII	-0.27 (0.49)	0.585
(C27 * Taiwan) * SII	-0.64 (0.49)	0.192
(C28 * Taiwan) * SII	-0.41 (0.49)	0.397
(C29 * Taiwan) * SII	-0.96 (0.49)	0.050
(C30 * Taiwan) * SII	-0.67 (0.49)	0.168
(C31 * Taiwan) * SII	-0.97 (0.49)	**0.048**
(C32 * Taiwan) * SII	-0.38 (0.49)	0.432
(F43 * Taiwan) * SII	-0.54 (0.49)	0.270
Observations	420	
R^2 / R^2 adjusted	0.957 / 0.950	

Notes: The regression output is for the detailed DDD model as specified in Equation 3. Each observation corresponds to the log of the number of patent applications by region, industry and year. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. Only industries for which the null hypothesis of parallel pre-trends could not be rejected are included in the analysis. Taiwan is a dummy variable, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII refers to the post-treatment dummy. Standard errors are in parentheses.

Table 10: Excerpt of Regression Output Detailed DDD[23]

However, industries C25, C29 and C31 remain significantly negative affected by the SII and its associated lower R&D tax credit rate. Repeating the DDD event study for these affected

[23] The full regression output is included in Appendix 7: Regression Output DDD Analyses and Corresponding Event Studies

industries, reveals that while none of the triple-difference estimates is individually significant, a slight dip in the estimate can be observed for year 3 after the intervention[24]. This is consistent with the corresponding event study for affected industries performed in the DD section above.

Thus, my findings in the DDD analysis mirror the findings from the DD analysis. While I do not find a significant effect of the SII and its reduced R&D tax credit rate on the number of patent applications at the aggregate level, the subsequently performed detailed DDD analysis suggests that some individual industries might have been adversely affected by the reduced R&D tax credit rate.

C. Findings

At the aggregate level, both the DD and DDD estimations do not find the introduction of the SII that led to a reduction in Taiwan's R&D tax credit rate to significantly affect innovation output as measured by patent applications. This also largely holds for estimations at the industry level (as done in the detailed DD and DDD estimations), although three treated industries displayed a significant decrease in the number of patent applications relative to the control industry[25]. This suggests that for these three industries, the reduction in R&D tax credits led to a relative decrease in R&D output. However, it is to note that adverse effects were not significant in the subsequently performed event studies and that the post-treatment observation period is short. Consequently, as of now, it is difficult to fully judge whether the observed negative effect will persist or whether this is a temporary effect.

VII. Robustness checks

A. Control Variable and Model

As previously discussed, one important issue regarding the definition of treatment and control groups in a quasi-experimental setting is that the population affected by the policy change is not randomly selected. This means that the treatment and control groups may not be equivalent but systematically different. While I found parallel trends in the number of patent applications for both the DD and the DDD analysis before the introduction of the SII, there might exist

[24] The full regression output of the event study with industries C25, C29 and C31 as well as a graphical representation of the triple-difference estimates is included in Appendix 7: Regression Output DDD Analyses and Corresponding Event Studies.

[25] C25 – Manufacture of Fabricated Metal Products except Machinery and Equipment, C29 – Manufacture of Motor Vehicles, Trailers and Semi-Trailers and C31 – Manufacture of Furniture.

changes in R&D policies that I am unaware of. If not accounted for, a change in the control group might not be able to properly measure the effect from other relevant factors. Following Woolridge (2013), I will thus add a covariate to the DDD analyses performed above to ensure that the analyses were not subject to omitted variable bias[26].

A reasonable control variable to include is GBERD, which is a measure of business expenditure for R&D activities from government sources within a specific industry. As outlined in the literature review above, countries typically employ two broad financial tools when attempting to encourage R&D activity: Indirect subsidies and direct subsidies. While the previous analyses have attempted to measure the change in R&D output due to Taiwan's 2010 tax reform, thus focussing on indirect subsidies, I now include GBERD by industry in the model to account for direct government incentives aimed at encouraging R&D activity that took place during the roll-out of the SII. The variable will be lagged, as there is to expect time gap between a firm receiving financial support and registering its R&D output as a patent. As a first step, I include GBERD in the DDD analyses as well as the corresponding event studies.

$$\ln(p_{itc}) = \alpha + \beta * I_i * SII * T + \gamma * I_i * SII + \delta * I_i * T + \theta * SII * T + \vartheta * I_i + \rho * SII + \sigma * T + \zeta GBERD_{ict-1} + \varepsilon_{it}$$

Equation 5: Robustness Check - DDD Model

$$\ln(p_{itc}) = \alpha + \sum_{j=2}^{5} \beta_j * (I_i * Lag\ j * T)_t + \sum_{k=0}^{6} \gamma_k * (I_i * Lead\ k * T)_t + \sum_{j=2}^{5} \delta_j * (I_i * Lag\ j)_t + \sum_{k=0}^{6} \theta_k * (I_i * Lead\ k)_t + \sum_{j=2}^{5} \vartheta_j * (Lag\ j * T)_t + \sum_{k=0}^{6} \mu_k * (Lead\ k * T)_t + \rho * I_i * T + \varphi I_i + \omega T + \lambda_t + \zeta GBERD_{ict-1} + \varepsilon_{it}$$

Equation 6: Robustness Check - DDD Event Study

where $GBERD_{ict-1}$ refers to the covariate being added. Similarly, to the main analysis above, I will again perform both a basic and a detailed estimation. However, due to limited data

[26] As the DD model and its connected event studies were unable to explain the variation observed in the data, I will exclude them from the following robustness checks and will instead focus on the more significant DDD model and event study.

availability, the robustness checks can only be performed for a shorter time period spanning the years 2006 to 2018 and on a limited set of industries[27].

B. Estimations

As Table 11 illustrates, GBERD per capita is positive and significant at the 1% level of significance. This implies that industries that have higher R&D expenditures financed with funds from government sources tend to apply more often for a patent. Comparing the initial DDD model and the DDD model employed for this robustness check, it is clear that the sign of the remaining coefficient estimates did not change. Most importantly, once GBERD is included as a proxy for direct government funding, the key variable of interest, the DDD estimator, both increases and becomes less significant. This suggests that the exclusion of GBERD did not hide an adverse effect of the SII. Breaking the analysis down to the industry level leads to similar insights. While GBERD per capita is significant, the triple interaction estimates measuring the effect of the SII on the number of patent applications tend to become less negative and less significant. This especially holds for industry C25 – Manufacture of Fabricated Metal Products, except Machinery and Equipment, which was previously identified as one of the industries that experienced a decline in the number of patent applications following the introduction of the SII. Controlling for GBERD per capita renders the triple-difference estimate for this industry less negative and non-significant, which suggests that the SII's reduced R&D tax credit rate did not have a significantly negative effect on the industry's R&D output as measured using the number of patent applications[28].

Performing the corresponding event study and graphing the coefficients for the triple interaction terms over time reveals no significant leading or lagging effects[29]. Graphing the robust estimates against the estimates obtained from the initial basic DDD event study, as done in Figure 3, reveals that the estimates closely align with the ones obtained from the initial DDD analysis and no significant lagging or leading effects of the SII's introduction are to be found.

[27] Industries F42 – Civil Engineering and F43 – Specialised Construction Activities are excluded due to limited data availability.
[28] The output for the detailed regression is included in Appendix 8: Regression Output Robustness Checks.
[29] The full regression output of the event study is included in Appendix 8: Regression Output Robustness Checks.

Table 11 - Regression Output Basic DDD (Robustness Check)

Dependent variable: log(number of patent applications by region, industry and year)				
	Basic DDD		**Robustness Check for Basic DDD**	
Predictors	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	6.26 (0.90)	**<0.001**	5.41 (0.93)	**<0.001**
IndustryDummy	-1.70 (0.92)	0.066	-1.55 (0.95)	0.105
Taiwan	-2.58 (1.27)	**0.043**	-1.95 (1.31)	0.137
SII	0.72 (1.32)	0.587	0.41 (1.31)	0.752
IndustryDummy * Taiwan	-1.39 (1.31)	0.288	-1.34 (1.34)	0.318
IndustryDummy * SII	-0.01 (1.35)	0.997	-0.17 (1.34)	0.901
Taiwan * SII	0.25 (1.86)	0.896	0.44 (1.85)	0.814
(IndustryDummy * Taiwan) * SII	-0.37 (1.91)	0.849	-0.16 (1.90)	0.935
GBERD_per_capita			0.46 (0.05)	**<0.001**
Observations	600		478	
R^2 / R^2 adjusted	0.404 / 0.397		0.496 / 0.487	

Notes: The left-hand column replicates the regression output of the basic DDD analysis. The right-hand column presents the regression output for the robustness check, based on Equation 5. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Due to limited data availability, the industries F42 – Civil Engineering and F43 – Specialised Construction activities were excluded from the robustness check. Taiwan is a dummy variable, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 11: Regression Output Basic DDD – Robustness Check

Table 12 – Excerpt of Regression Output Basic DDD Event Study (Robustness Check)

Dependent variable: log(number of patent applications by region, industry and year)

	Basic DDD Event Study		**Robustness Check for Basic DDD Event Study**	
Predictors	*Estimates*	*p*	*Estimates*	*p*
(IndustryDummy * Taiwan)* Lag_5	1.39 (5.39)	0.797	1.22 (4.16)	0.770
(IndustryDummy * Taiwan)* Lag_4	0.33 (5.39)	0.952	0.47 (4.15)	0.911
(IndustryDummy * Taiwan)* Lag_3	0.57 (5.39)	0.916	0.66 (4.15)	0.874
(IndustryDummy * Taiwan)* Lag_2	0.07 (5.39)	0.990	0.49 (4.15)	0.906
(IndustryDummy * Taiwan) * Implementation_Year	1.13 (5.39)	0.834	1.64 (4.15)	0.693
(IndustryDummy * Taiwan)* Lead_1	0.34 (5.39)	0.949	0.45 (4.15)	0.913
(IndustryDummy * Taiwan)* Lead_2	0.43 (5.39)	0.936	0.52 (4.15)	0.900
(IndustryDummy * Taiwan)* Lead_3	-0.65 (5.39)	0.903	-0.37 (4.15)	0.929
(IndustryDummy * Taiwan)* Lead_4	-0.70 (5.39)	0.897	-0.50 (4.15)	0.905
(IndustryDummy * Taiwan)* Lead_5	-0.23 (5.39)	0.965	0.15 (4.15)	0.971
GBERD_per_capita			0.46 (0.05)	**<0.001**
Observations	600		478	
R^2 / R^2 adjusted	0.422 / 0.359		0.506 / 0.455	

Notes: The left-hand column replicates the regression output of the basic DDD event study. The right-hand column presents the regression output for the corresponding robustness check, based on Equation 6. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII. Due to limited data availability, the industries F42 – Civil Engineering and F43 – Specialised Construction activities were excluded from the robustness check.

Table 12: Excerpt of Regression Output Basic DDD Event Study (Robustness Check)

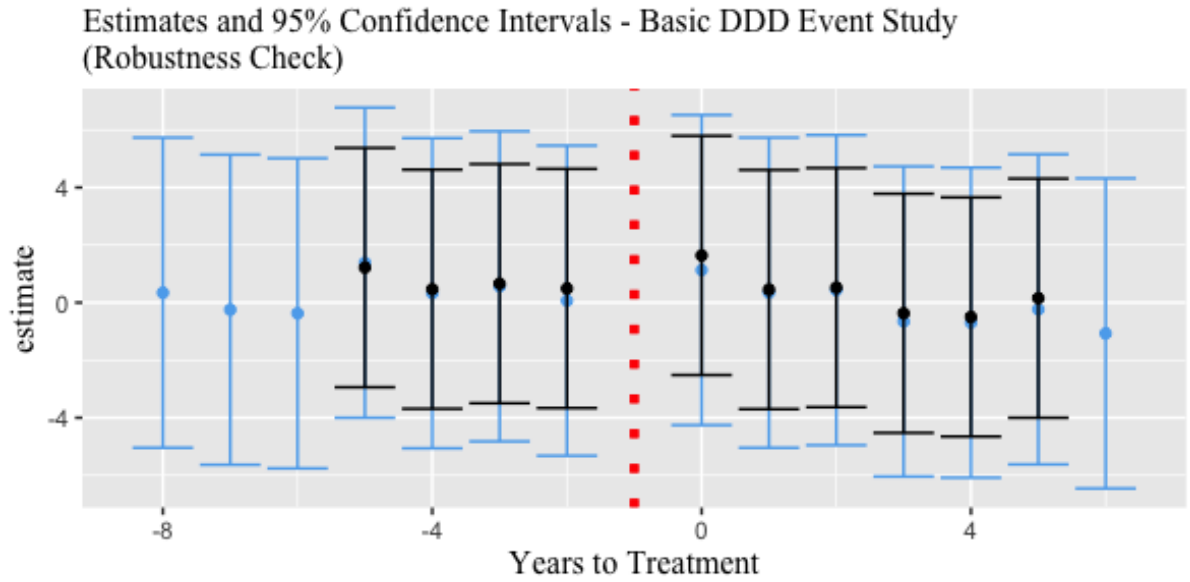


Figure 3: Estimates and 95% Confidence Intervals - Robust Event Study Basic DDD[30]

Thus, the results obtained from the robustness checks confirm the findings from the main analysis above: There were no significant effects of the SII's reduced R&D tax credit rate to be observed at the aggregate level and no effects for most industries. However, in both the basic and detailed DDD analyses and event studies, I have found GBERD per capita to be significant and positive, which suggests that government-financed business expenditures in R&D are positively correlated with R&D output as measured by patents. This might mean that all or part of the effect of the SII's reduced R&D tax credit rate could potentially be offset with more generous direct subsidies. To check whether this is the case, I will thus run a final DDD analysis and event study, using GBERD per capita as the dependent variable using the following two estimations[31].

$$GBERD_{itc} = \alpha + \beta * I_i * SII * T + \gamma * I_i * SII + \delta * I_i * T + \theta * SII * T + \vartheta * I_i + \rho * SII + \sigma * T + \varepsilon_{it}$$

Equation 7: Robustness Check - DDD Model with GBERD as Output Variable

[30] Figure 3: Estimates and 95% Confidence Intervals - Robust Event Study Basic DDD includes both the estimates obtained from the previously performed basic DDD as well as the estimates from its robustness check. The former are coloured in a light blue, while the latter are drawn in black.

[31] Performing a formal pre-test mirroring the tests performed in V. B. The Parallel Trends Assumption to test for parallel pre-trends with respect to GBERD per capita, I fail to reject the null hypothesis of parallel trends, with the coefficient on the triple interaction term being both close to zero and insignificant. The full regression output of the pre-test is included in Appendix 8: Regression Output Robustness Checks.

$$GBERD_{itc} = \alpha + \sum_{j=2}^{5} \beta_j * (I_i * Lag\ j * T)_t + \sum_{k=0}^{6} \gamma_k * (I_i * Lead\ k * T)_t$$
$$+ \sum_{j=2}^{5} \delta_j * (I_i * Lag\ j)_t + \sum_{k=0}^{6} \theta_k * (I_i * Lead\ k)_t + \sum_{j=2}^{5} \vartheta_j * (Lag\ j * T)_t$$
$$+ \sum_{k=0}^{6} \mu_k * (Lead\ k * T)_t + \rho * I_i * T + \varphi I_i + \omega T + \lambda_t + \varepsilon_{it}$$

Equation 8: Robustness Check - DDD Event Study with GBERD as Output Variable

If the interaction terms are significant, this would imply a change in the amount of GBERD which is used as a proxy of direct R&D subsidies that coincides with the implementation of the SII.

The regression output for the basic DDD using GBERD per capita as the dependent variable is presented in Table 13 below. The DDD estimator for this analysis is slightly negative and not significant, which implies that overall, the amount of GBERD per capita has not increased for the treated industries following the introduction of the SII. Repeating the analysis at the industry level further reveals that no significant increases in the amount of GBERD per capita occurred for individual industries either[32]. Only two of the triple-difference estimators in this detailed DDD robustness check are significant: C25 – Manufacture of Fabricated Metal Products, except Machinery and Equipment and C30 – Manufacture of Other Transport Equipment. However, both estimates were negative which suggests a decrease in direct subsidies as proxied for by using GBERD per capita. Hence, it does not appear to be the case that Taiwan did attempt to offset the effects of a reduced R&D tax credit rate with more generous direct R&D subsidies.

[32] The regression output for the industry level regression is included in Appendix 8: Regression Output Robustness Checks.

Table 13 - Regression Output Robustness Check Basic DDD using GBERD as Dependent Variable

Dependent variable: GBERD_per_capita by region, industry and year		
Predictors	*Estimates*	*p*
(Intercept)	2.17 (0.84)	**0.010**
IndustryDummy	-0.33 (0.86)	0.704
Taiwan	-1.38 (1.19)	0.249
SII	0.26 (1.19)	0.828
IndustryDummy * SII	0.38 (1.22)	0.753
Taiwan * SII	-0.37 (1.68)	0.825
IndustryDummy * Taiwan	0.05 (1.22)	0.965
(IndustryDummy * Taiwan)* SII	-0.26 (1.73)	0.879
Observations	478	
R^2 / R^2 adjusted	0.147 / 0.135	

Notes: Regression output is for the DDD robustness check model as specified in Equation 7. Each observation corresponds to the amount of GBERD per capita expressed in constant 2015 US-dollars by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Taiwan is a dummy variable, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 13: Regression Output Robustness Check Basic DDD using GBERD as Dependent Variable

A quick note on industry C25 – Manufacture of Fabricated Metal Products, except Machinery and Equipment: The previous robustness checks where GBERD per capita was included as a control variable rather than the dependent variable already revealed that once the regression controls for GBERD the effect of the SII's reduced R&D tax credit rate on the industry's

number of patent applications becomes non-significant. Finding industry C25's triple-difference estimate in this detailed DDD robustness check (which uses GBERD per capita as the output variable) to be negative and significant suggests that the adverse effect of the SII that was identified in the main analysis above is potentially due to the decrease in direct government subsidies rather than the SII's reduced R&D tax credit rate.

The subsequently performed event study, whose estimates for the triple interaction terms are graphically represented in Figure 4 below, further confirms that there were no significant changes to the level of GBERD per capita in the years preceding and following the introduction of the SII. Thus, the performed robustness checks support the findings from the main analysis, according to which the SII and its reduced R&D tax credit rate did not largely affect innovation output as measured by the number of patent applications.

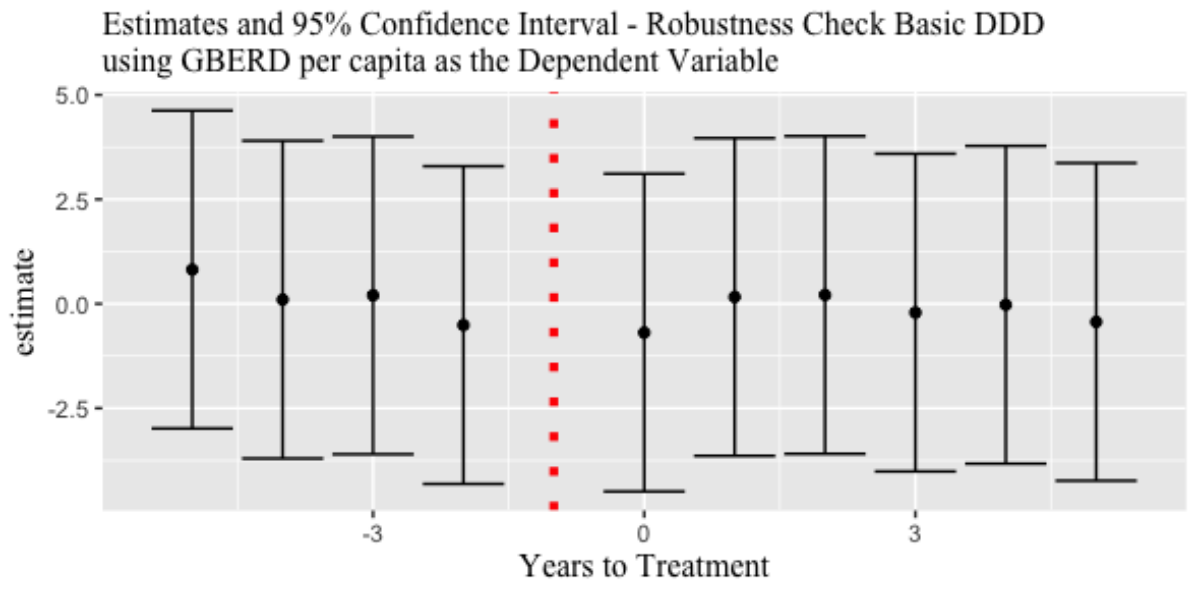


Figure 4: Estimates and 95% Confidence Interval - Robustness Check Basic DDD using GBERD per capita as the Dependent Variable

Table 14 - Excerpt of Regression Output Robustness Check Basic DDD using GBERD as Dependent Variable

Dependent variable: GBERD_per_capita by region, industry and year		
Predictors	*Estimates*	*p*
(IndustryDummy * Taiwan) * Lag_5	0.82 (3.80)	0.830
(IndustryDummy * Taiwan) * Lag_4	0.10 (3.80)	0.979
(IndustryDummy * Taiwan) * Lag_3	0.20 (3.80)	0.958
(IndustryDummy * Taiwan) * Lag_2	-0.51 (3.80)	0.893
(IndustryDummy * Taiwan) * Implementation_Year	-0.69 (3.80)	0.856
(IndustryDummy * Taiwan) * Lead_1	0.16 (3.80)	0.966
(IndustryDummy * Taiwan) * Lead_2	0.21 (3.80)	0.956
(IndustryDummy * Taiwan) * Lead_3	-0.21 (3.80)	0.956
(IndustryDummy * Taiwan) * Lead_4	-0.02 (3.80)	0.995
(IndustryDummy * Taiwan) * Lead_5	-0.43 (3.80)	0.909
Observations	478	
R^2 / R^2 adjusted	0.153 / 0.069	

Notes: Regression output for the detailed DDD robustness check model as specified in Equation 7. Each observation corresponds to the amount of GBERD per capita expressed in constant 2015 US-dollars by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Due to limited data availability, the industries F42 – Civil Engineering and F43 – Specialised Construction activities were excluded from the robustness check. Taiwan is a dummy variable, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. Lags and leads refer to the number of years before or after the implementation of the SII respectively. Standard errors are in parentheses.

Table 14: Excerpt of Regression Output Robustness Check Basic DDD using GBERD as Dependent Variable[33]

[33] The full regression output for the event study is included in Appendix 8: Regression Output Robustness Checks

C. Findings

The insights gained from the robustness checks performed within this section are in line with the findings from the main analysis. Including GBERD per capita as a proxy for direct government subsidies does only marginally affect the estimates obtained through the DDD analysis and corresponding event study. When it did affect the triple-difference estimates it mostly increased the estimates or lowered their significance, thus reducing some of the previously estimated effects of the SII's reduced R&D tax credit rate on R&D output.

VIII. Interpretation

Within this study, I have only found a limited impact of the SII's reduced R&D tax credit rate on industries' R&D output as measured by the number of patent applications. There was no significant effect of the SII on R&D output at the aggregate level. Furthermore, for most individual industries the double- or triple-difference estimates measuring the impact of the SII on R&D output have been non-significant. The estimates for industries that were initially significant mostly turned insignificant once the initial DD analysis was expanded to a DDD analysis or once GBERD was included to control for changes in direct R&D subsidies. Out of the 20 NACE industries initially included in the analysis, only two, namely the industries C29 – Manufacture of Motor Vehicles, Trailers and Semi-Trailers and C31 – Manufacture of Furniture remained consistently negatively affected by the introduction of the SII. Unlike Chen and Lie (2018) I thus did not find overall significant adverse effects of the SII's reduced R&D tax credit rate. Neither did I find clear differences in the treatment effect according to R&D-intensity as Yang, Huang and Chang did in their 2021 paper. Furthermore, as too few and very different industries were adversely affected by the lower R&D tax credit rate it is at this point not possible to draw conclusions about the characteristics of the industries which might have caused these negative effects or to make a judgement on whether there likely is an unobserved omitted variable unconnected to the SII which drives this negative effect.

The absence of any significantly negative effect of the lower R&D tax credit rate on Taiwan's R&D output that is observed for most industries, implies that these industries are able to maintain their R&D output even in the face of a substantially reduced R&D tax credit rate. Thus, while previous studies have shown R&D tax subsidies to boost innovation output after their introduction or their enhancement, the apparent R&D persistence found in this study casts doubt on their continuous necessity. It appears that once industries have reached a certain level

of R&D intensity, and along with it, R&D maturity or are under competitive pressure to continuously innovate, industries are no longer reliant on R&D tax credits to uphold their R&D activities.

For policymakers, this implies that R&D tax subsidies may not be an adequate tool to enhance R&D activity for a prolonged period but may rather be seen as a temporary tool to boost R&D activity in the short run. As R&D tax credits are an expensive policy tool due to the loss in tax revenue they cause, once R&D levels have been increased to the level where R&D persistence will appear, the effectiveness of existing tax credits should be reviewed, and the subsidies potentially scaled back. However, this review should be carefully conducted. While the effect of scaling back R&D tax incentives was found to be mostly non-significant, the nature of the empirical study in this paper was not able to draw conclusions on how quickly the effect of R&D tax credits wane or whether some industries reach R&D persistence sooner than others.

IX. Limitations

The empirical methods used in this paper are not without shortcomings as this section will highlight.

First, the use of patent counts as a proxy for R&D output may be limiting. While patent counts are an established measure of firm innovativeness, it needs to be acknowledged that as a proxy, it only captures parts of a firm's R&D efforts. Some innovations may not be patentable, and the propensity to patent an innovation may differ across countries or industries. Furthermore, there persists a natural heterogeneity of patent values, with some patents having no industrial application and thus no value to society, whereas others are of substantial value. Using only patent counts as an indicator, which amounts to the implicit assumption that all patents are of equal or comparable value, may be misleading (OECD, 2001). There may be other potential indicators for R&D output such as innovations in terms of sales or costs reductions. To ensure the use of such an indicator to compare innovativeness across countries and industries, one option would be to construct a country- or industry-level index that would combine different innovation measures.

Second, there are also limitations regarding the estimation itself. While quasi-experimental settings allow for a manipulable cause that occurs before the effect is measured, the non-

randomness of this approach usually creates less compelling support for counterfactual inferences, as the control group may differ from the treatment group in systematic, that is non-random, ways other than the presence of the treatment. Some of the ways in which control groups differ from the treatment group may be alternative explanations for the observed effect. Therefore, ruling them out is a key concern when using a quasi-experimental research design. While this paper has attempted to address this issue through a series of robustness checks, the prime difficulty here is that alternative explanations are rarely ever completely identifiable in advance, are often particular to the context studied, with the methods needed to account for them potentially varying between alternative explanations and studies (Shadish, Cook, & Campbell, 2002; Ho, 2006). Hence, it might be possible that there exist alternative, non-identified explanations for the observed outcome. This in turn would imply that the internal validity of this study which is relying on a quasi-experimental setting may be reduced.

Third, the dataset used in this analysis is very small, with only up to 600 observations included in the analysis. As the standard error of an analysis decreases in sample size, more data inputs would have lent less variation and thus more precision to the results.

Fourth, the length of the observation period limits the insights gained from the analysis. With only seven years in the post-intervention period, it is not yet clear whether the drop observed for the industries C29 – Manufacture of Motor Vehicles, Trailers and Semi-Trailers and C31 – Manufacture of Furniture will persist. Additionally, the short observation period did not allow for implementing a robustness model with a higher-order lag structure in the robustness checks. A future replication of this analysis would give more freedom in assessing different hypotheses regarding the time lag and might provide different insights.

X. Future Research

The findings from this study support the theoretical notion of R&D efforts being persistent in the event of scaled back R&D tax incentives. To the best of my knowledge very few empirical analyses on this topic have been conducted, and those that exist exclusively focus on input additionality. Thus, further studies, potentially using different proxy variables for R&D output, longer data observation periods or a different R&D tax credit cutting policy to the one examined in this study are needed to validate the findings of this study. Given that the relationship between tax credit rate and patents likely differs in strength across R&D intensive

and less R&D intensive firms, repeating this study at the firm level might also reveal more interesting patterns of the effects of scaled-back tax incentives and may yield more insights into the formulation of future R&D policies. I do hope that this study helps to encourage future research to expand upon the empirical analysis in this paper and hopefully to other policy settings to investigate further the impact of reversed R&D tax subsidies on innovation output and the pace at which R&D tax subsidies become potentially obsolete.

XI. Conclusion

The effect of an introduction or enhancement of R&D tax subsidies on R&D has been widely examined in previous empirical studies, with most studies finding at least some kind of positive effect on R&D input and output. However, the reverse question, whether a decrease in R&D tax subsidies harms R&D activities, remains largely unexplored. Proving the persistence of positive effects of R&D tax subsidies on R&D activities, however, is highly relevant to policymakers to both justify and fine-tune R&D policies. This study set out to fill this research gap by exploiting the reversal of a Taiwanese R&D tax incentive scheme which led to a reduction in the R&D tax credit rate. Using panel data on the number of annual PCT patent applications, I find no significant effects of this policy reversal both at the aggregate level and for the large majority of individual NACE industries. Given that prior empirical evidence found significantly positive effects on the introduction or intensification of R&D tax subsidies, these findings suggest that these positive effects do not endure as industries develop R&D persistence.

These findings provide several policy implications. First, while tax subsidies may initially boost R&D activities, they are not an adequate tool to enhance R&D activity for a prolonged period as their effect wanes. Tax subsidies thus appear to be a policy tool that should be used to increase R&D maturity within industries in the short run. Once a certain level of R&D maturity and thus R&D persistence has been reached, the effectiveness of existing tax subsidies should be reviewed and potentially be scaled back. However, further research is needed to better understand at what rate R&D tax subsidies lose effectiveness over time to pinpoint when existing policies should be reversed. Similarly, further firm-level research is needed to increase policymakers understanding of how to best revise R&D tax policies.

References

Aguiar, L., & Gagnepain, P. (2017). European cooperative R&D and firm performance: Evidence based on funding differences in key actions. *International Journal of Industrial Organization, 53*, 1-31.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics - An Empiricist's Companion.* Princeton, New Jersey: Princeton University Press.

Appelt, S., Bajgar, M., Criscuolo, C., & Galindo-Rueda, F. (2016). R&D Tax Incentives: Evidence on design, incidence and impacts. *OECD Science, Technology and Industry Policy Papers*(No. 32).

Appelt, S., Bajgar, M., Criscuolo, C., & Galindo-Rueda, F. (2020). *Effectiveness of R&D tax incentives in OECD economies.* Retrieved October 31, 2021, from voxeu.org: https://voxeu.org/article/effectiveness-rd-tax-incentives-oecd-economies

Arrow, K. J. (1962). Economic Welfare and the Allocation of Resources for Invention. In U.-N. B. Research, & C. o. Council, *The Rate and Direction of Inventive Activity: Economic and Social Factors* (pp. 609-626). Princeton University Press.

Berger, P. G. (1993). Explicit and Implicit Tax Effects of the R&D Tax Credit. *Journal of Accounting Research*, 131-171.

Bérubé, C., & Mohnen, P. (2009, February). Are firms that receive R&D subsidies more innovative? *Canadian Journal of Economics, 42*(1), 206-225.

Bloom, N., Griffith, R., & Van Reenen, J. (2002). Do R&D tax credits work? Evidence from a panel of countries 1979-1997. *Journal of Public Economics*, 1-31.

Bodas Freitas, I., Castellaci, F., Fontana, R., & Malerba, F. (2017). Sectors and the additionality effects of R&D tax credits: A cross-country microeconometric analysis. *Research Policy, 46*, 57-72.

Boeing, P. (2016). The allocation and effectiveness of China's R&D subsidies - Evidence from listed firms. *Research Policy, 45*, 1774-1789.

Branstetter, L., & Sakakibara, M. (1998, June). Japanese Research Consortia: A Microeconometric Analysis of Industrial Policy. *The Journal of Industrial Economics, 46*(2), 207-233.

Bronzini, R., & Iachini, E. (2014). Are Incentives for R&D Effective? Evidence from a Regression Discontinuity Approach. *American Economic Journal: Economic Policy, 6*(4), 100-134.

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

Cameron, G. (1996, February). *Innovation and Economic Growth.* London, UK: Center for Economic Performance, London School of Economics and Political Science.

Cappelen, Å., Raknerud, A., & Rybalka, M. (2012). The effects of R&D tax credits on patenting and innovations. *Research Policy, 41*, 334-345.

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

Center for Economic Research and Environmental Strategy. (2005). *The Impact of R&D State aid and its appraisal on the level of EU research expenditures in the context of the Barcelona European Council Objectives.* Athens, Greece: Center for Economic Research and Environmental Strategy.

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

Chen, M.-C., & Gupta, S. (2017). The incentive effects of R&D tax credits: An empirical examination in an emerging economy. *Journal of Contemporary Accounting & Economics, 13*, 52-68.
Chen, M.-C., & Li, H.-Y. (2018). The effects and economic consequences of cutting R&D tax incentives. *China Journal of Accounting Research, 11*, 367-384.
Clarke, D., & Schythe, K. T. (2020). Implementing the Panel Event Study. *IZA Discussion Papers*, IZA DP No. 13524.
Cohen, W. M., & Levinthal, D. A. (1989). Innovation and Learning: The two faces of R&D. *The Economic Journal, 99*, 569-596.
Conlisk, J. (1969). A Neoclassical Growth Model with Endogenously Positioned Technical Change Frontier. *The Economic Journal, 79*(314), 348-362.
Czarnitzki, D., & Debackere, K. (2016). *Towards a portfolio of additionality indicators.* Retrieved September 5, 2021, from OECD: https://www.oecd.org/sti/081%20-%20Blue%20Sky%20ADD%20Paper%20Submitted.pdf
Czarnitzki, D., & Hussinger, K. (2018). Input and output additionality of R&D subsidies. *Applied Economics, 50*(12), 1324-1341.
Czarnitzki, D., Hanel, P., & Rosa, J. M. (2011). Evaluating the impact of R&D tax credits on innovation: A microeconometric study on Canadian firms. *Research Policy, 40*, 217-229.
Dasgupta, P., & Stiglitz, J. (1980). Industrial Structure and the Nature of Innovative Activities. *The Economic Journal, 90*(358), 266-293.
David, P. A., Hall, B. H., & Toole, A. A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy, 29*, 497-529.
Dechezleprêtre, A., Einiö, E. M., Nguyen, K.-T., & Van Reenen, J. (2016). *Do Tax Incentives For Research Increase Firm Innovation? An RD Design for R&D.* Retrieved October 31, 2021, from National Bureau of Economic Research: http://www.nber.org/papers/w22405
Duguet, E., & Monjon, S. M. (2004). Is Innovation Persistent at the Firm Level? An Econometric Examination Comparing the Propensity Score and Regression Methods. *SSRN Electronic Journal*.
Eurostat. (2015). *Patent Statistics: Concordance IPC V8 - NACE REV.2*. Eurostat.
EY. (2013 - 2019). *Worldwide R&D incentives reference guide.* Retrieved November 10, 2021, from ey.com: https://www.ey.com/en_gl/tax-guides/tax-guide-library-archive
García-Quevedo, J. (2004). Do Public Subsidies Complement Business R&D? A Meta-Analysis of the Econometric Evidence. *Kyklos, 57*, 87-102.
Ghazinoory, S., & Hashemi, Z. (2021). Do tax incentives and direct funding enhance innovation input and output in high-tech firms. *Journal of High Technology Management Research, 32*.
Hair, J., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). Multiple Regression Analysis. In J. Hair, W. C. Black, B. J. Babin, & R. E. Anderson, *Multivariate Data Analysis.* Harlow, UK: Pearson Education Limited.
Hall, B., & Van Reenen, J. (2000). How effective are fiscal incentives for R&D? A review of the evidence. *Research Policy, 29*, 449-469.
Ho, Y. (2006). Evaluating the Effectiveness of State R&D Tax Credits. Retrieved from https://core.ac.uk/download/pdf/12208858.pdf
Kaldor, N., & Mirrlees, J. A. (1962). A New Model of Economic Growth. *The Review of Economic Studies, 29*(3), 174-192.

Klette, T. J., Møen, J., & Griliches, Z. (2000). Do subsidies to commercial R&D reduce market failures? Microeconometric evaluation studies. *Research Policy, 29*, 471-495.
Laws & Regulations Database of the Republic of China. (2007, July 4). *Article content: Act For The Development Of Biotech And New Pharmaceuticals Industry.* Retrieved October 9, 2021, from law.moj.gov.tw: https://law.moj.gov.tw/ENG/LawClass/LawAll.aspx?pcode=J0040046
Mah, J. S. (2015). R&D policies and development of technology-intensive industries of Taiwan. *Progress in Development Studies, 15*(2), 125-138.
Ministry of Strategy and Finance, Korea. (2012). *KOREAN TAXATION.* Retrieved October 31, 2021, from https://english.moef.go.kr: https://english.moef.go.kr/upload/eco/2012/07/FILE_9AF96F_20120724140314_2.pdf
Nelson, R. R. (1959, June). The Simple Economics of Basic Scientific Research. *Journal of Political Economy, 67*(3), 297-306.
Nilson, Ø. A., Raknerud, A., & Iancu, D.-C. (2020). Rublic R&D support and firm performance: A multivariate dose-response analysis. *Research Policy, 49*.
OECD. (2001). *Using Patent Counts for Cross-Country Comparisons of Technology Output.* Retrieved September 30, 2021, from oecd.org: https://www.oecd.org/sti/35520805.pdf
OECD. (2006). *Government R&D Funding and Company Behaviour - Measuring Behavioural Additionality.* OECD.
Olden, A., & Møen, J. (2020). The Triple Difference Estimator. *No 2020/1, Discussion Papers, Norwegian School of Economics, Department of Business and Management Science*.
Parsons, M., & Phillips, N. (2007). *An Evaluation of the Federal Tax Credit for Scientific Research and Experimental Development.* Retrieved October 31, 2021, from publications.gc.ca: https://publications.gc.ca/collections/collection_2008/fin/F21-8-2007-8E.pdf
Perloff, J. M. (2015). *Microeconomics* (7th Edition ed.). Harlow, UK: Pearson Education Limited.
Peters, B. (2009). Persistance of innovation: stylised facts and panel data evidence. *Journal of Technological Transformation, 34*, 226-242.
Raymond, W., Mohnen, P., Palm, F., & Schim van der Loeff, S. (2010). Persistence of Innovation in Dutch Manufacturing: Is it Spuriou? *The Review of Economics and Statistics, 92*(3), 495-504.
Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy, 98*(5), 71-102.
Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference.* Boston: Houghton Mifflin.
Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics, 39*(3), 312-320.
Swenson, C. (1992). Some tests of the incentive effects of the research and experimentation tax credit. *Journal of Public Economics, 49*, 203-218.
Szücs, F. (2020). Do research subsidies crowd out private R&D of large firms? Evidence from European Framework Programmes. *Research Policy, 49*(3).
Trading Economics. (2021). *Taiwan Exports*. Retrieved November 21, 2021, from tradingeconomics.com: https://tradingeconomics.com/taiwan/exports
Triguero, Á., & Córcoles, D. (2013). Understanding innovation: An analysis of persistence for Spanish manufacturing firms. *Research Policy, 42*, 340-352.
Woolridge, J. M. (2013). *Introductory Econometrics - A Modern Approach* (5th Edition ed.). Boston, MA: Cengage.

Yang, C.-H., Huang, C.-H., & Chang, W.-H. (2021, April). Does Reduction in the Tax Credit Rate Retard R&D Activity? Evidence from Taiwan's R&D Credit Reform in 2010. *Contemporary Economic Policy, 39*(2), 398-415.

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

Zúñiga-Vicente, J. Á., Alonso-Borrego, C., Forcadell, F. J., & Galán, J. I. (2014). ASSESSING THE EFFECT OF PUBLIC SUBSIDIES ON FIRM R&D INVESTMENT. *Journal of Economic Surveys, 28*(1), 36-67.

Appendices

Appendix 1: Abbreviations

Art.	Article
DD	Difference-in-difference
DDD	Difference-in-difference-in-difference
et al.	et alii; et aliae; et alia
Eurostat	European Statistical Office
GBERD	Business expenditure for R&D from government sources
GDP	Gross domestic product
IPC	International Patent Classification
IV	Instrumental variable
MCC	Marginal cost of capital
MRR	Marginal rate of return
NACE	Nomenclature statistique des activités économiques dans la Communauté européene
OECD	Organisation for Economic Cooperation and Development
PCT	Patent Cooperation Treaty
PPP	Purchasing power parity
RDD	Regression discontinuity design
R&D	Research and development
TILL	Tax Incentives Limitation Law
SEI	Statutory Encouragement of Investment
SII	Statute for Industrial Innovation
SUI	Statute for the Upgrading of Industry

Appendix 2: Market Imperfections and the Need for Public R&D Support

The primary argument used by economists to justify public support of R&D is that of the persistence of market imperfections that in a freely competitive market would cause the R&D equilibrium level to be below the socially optimal level (Zúñiga-Vicente, Alonso-Borrego, Forcadell, & Galán, 2014; Szücs, 2020). This theoretical rationale for systematic underinvestment in R&D activities dates back to the seminal works of Nelson (1959) and Arrow (1962b), who were amongst the first to argue that the three classical reasons for non-optimal resource allocation in a perfectly competitive market, namely inappropriability, uncertainty and indivisibility, are likely to apply to the case of R&D.

Incomplete Appropriability of R&D efforts

One of the most well-known and most widely accepted causes for market imperfections concerning R&D arises from the traditional public good characteristics exhibited by knowledge. Knowledge generated from a firm's R&D efforts is not perfectly exclusive, as the use of knowledge in any productive way is bound to reveal it at least partially to third parties not involved in the R&D activity. The spread of knowledge to third parties is also likely to be furthered due to the mobility of personnel among firms within the same industry or sector. Thus, because at least a part of the knowledge created through a firm's R&D efforts spills over to other economic agents, other agents can free ride, in other words, benefit from another firm's R&D efforts without paying for them (Aguiar & Gagnepain, 2017).

To now show why its public goods characteristics cause R&D to be underprovided by competitive markets, it is important to recall that the social marginal benefit of a private good is the same as the marginal benefit to the economic agent who consumes the good. The market demand for private goods is the horizontal sum of the individual demand curves of the economic agents in the market. In contrast, the social marginal benefit of a public good is the sum of the marginal benefit of each economic agent who consumes the good. Because a public good is both non-rival and non-exclusive, several economic agents can derive utility from the same unit of the good. In this case here, the same unit of knowledge. Consequently, the social demand curve for a public good is the vertical sum of the demand curves of the individual economic agents. Acting individually, the R&D conducting firm always provides less knowledge than would be socially optimal, as it does not take the positive externalities provided to other agents into account when making its R&D decisions (Perloff, 2015). Consequently, the incentive for a private for-profit firm to be the investing agent is too low to reach the socially

optimal level. The argument for public intervention now goes that in a classical Pigouvian tax context, public intervention could reduce the extent of the market imperfection (Arrow, 1962; Cerulli, 2010; Zúñiga-Vicente, Alonso-Borrego, Forcadell, & Galán, 2014; Czarnitzki & Debackere, 2016).

Indivisibility

A second cause for market imperfections associated with R&D is that of the indivisibility of R&D output. Knowledge and information are characterised by increasing returns to scale. This is because once a unit of knowledge or information is created, it can be used multiple times regardless of the scale of production. Since the same unit can be used multiple times by the same or by a different user, the cost of its production is not dependent on the scale on which it is used. Generating knowledge or information is thus associated with high initial fixed costs for establishing an economic unit capable of producing the unit of knowledge or information. However, once produced, the marginal cost of providing a unit of knowledge or information is far below the average cost of producing this unit. Hence, from a welfare perspective, the knowledge or information derived from R&D efforts should be available free of charge, except for the cost of transmitting the knowledge or the information to another party. While this would ensure optimal utilisation of the information, it would provide little incentive to private for-profit firms to engage in R&D activities (Czarnitzki & Debackere, 2016).

Capital Market Imperfections

A third reason that has been raised to explain the underinvestment in R&D activities are capital market imperfections. R&D efforts are extremely risky activities for firms to engage in because it is impossible to a priori know whether R&D efforts will lead to the desired output. Furthermore, the degree of market success of any potential innovations is equally uncertain (Nelson, 1959). Hence, to undertake an R&D project, a firm must be willing to bear the inherent risks. Assuming economic agents to be risk-averse, firms will discriminate against risky projects, which leads to a suboptimal allocation of risk (Nelson, 1959; Czarnitzki & Debackere, 2016). This uncertainty issue multiplies if firms face financial constraints due to a lack of internal resources. Adding to the inherent uncertainty of R&D projects come stark information asymmetries between the innovating firm and external lenders, which gives rise to adverse selection and moral hazard that might discourage external investors. Furthermore, compared to physical capital, the intangible nature of R&D means that R&D cannot be used as collateral in credit negotiations. These circumstances can then lead to a higher cost of external finance due

to the requirements of a risk premium or even to finance rationing. Thus, firms will be prompted to put more weight on internal funds to conduct their R&D (Zúñiga-Vicente, Alonso-Borrego, Forcadell, & Galán, 2014). However, this preference for internal funds implies that only large and diversified corporations will be able to bear the risks associated with innovation and that smaller or younger firms will be restricted in their ability to engage in R&D activities (Nelson, 1959; Arrow K., 1962; Bronzini & Piselli, 2016). Consequently, systematic underinvestment in R&D activities may occur.

Appendix 3: IPC and NACE Rev. 2

IPC Section	Section Name
A	Human Necessities
B	Performing Operations; Transporting
C	Chemistry; Metallurgy
D	Textiles; Paper
E	Fixed Constructions
F	Mechanical Engineering; Lighting; Heating; Weapons; Blasting
G	Physics
H	Electricity

Table 15: IPC Categories by Section

NACE Code	Name of NACE Rev. 2 Category	IPC codes included in the NACE Rev. 2 Category	Deviations from the Concordance IPCV8-NACE Rev. 2 published by Eurostat in 2015
C10	Manufacture of Food Products	A23J A01H A01J A21D A23B A23C A23D A23F A23G A23J A23K A23L1/* A23L3/* A23P C12J C13B C13F C13J C13K	
C11	Manufacture of Beverages	A23L2/* C12C C12F C12G C12H	
C12	Manufacture of Tobacco Products	A24B A24D A24F	
C13	Manufacture of Textiles	D04D D04G D04H D06C D06J D06M D06N D06P D06Q	
C14	Manufacture of Wearing Apparel	A41B A41C A41D A41F	
C15	Manufacture of Leather and Related Products	A43V A43C B68B B68C	
C16	Manufacture of Wood and of Products of Wood and Cork, except furniture; Manufacture of Articles of Straw and Plaiting Materials	B27D B27H B27M B27N	
C17	Manufacture of Paper and Paper Products	B42F D21C D21H D21J	

C18	Printing and Reproduction of Recorded Media	B41M B42D B44F	
C19	Manufacture of Coke and Refined Petroleum Products	C10G C10L	
C20	Manufacture of Chemicals and Chemical Products	A01N A01P A61Q A62D B01J B09B B09C B27K C01B C01C C01D C01F C01G C02F C05B C05C C05D C05F C05G C06B C06C C06D C07B C07C C07F C07G C08B C08F C08G C08H C08J C08K C08L C09B C09C C09D C09F C09G C09H C09J C09K C10B C10C C10H C10J C10K C10M C10N C11B C11C C11D C12S C14C C23F C23G C25B C40B D01C D01F D06L F17C F17D F25J F42B F42D G21F	
C21	Manufacture of Basic Pharmaceutical Products and Pharmaceutical Preparations	A61K A61P C07D C07H C07J C07K C12N A61N A61F A61M	The codes A61N, A61F, A61M are not in Eurostat's definition of the industry. These codes are however included to better reflect on Taiwan's industry definition of the biotech and new pharmaceutical industry
C22	Manufacture of Rubber and Plastic Products	B29B B29C B29D B60C B67D C08C	
C23	Manufacture of Other Non-Metallic Mineral Products	B28B B28C B32B C03B C03C C04B E03D	
C24	Manufacture of Basic Metals	B21C B22D C21B C21C C21D C22B C22C C22F C25C C25F G21H	
C25	Manufacture of Fabricated Metal Products, except Machinery and Equipment	A01L A44B A47H B21G B22F B63G C23D C25D E05B E05C E05D E05F E06B F16B F16T F17B F22B F22G F24J F27D F41A F41B F41C F41F F41G F41H F41J F42C G21B G21C G21D G21J	
C26	Manufacture of Computer, Electronic and Optical Products	B81B B81C B82B B82Y C30B F15C G01B G01C G01D G01F G01H G01J G01K G01L G01M G01N G01Q G01R G01S G01V G01W G02B	Eurostat includes the code A61N in this category. However, to better

		G02C G02F G03B G03C G03H G04B G04C G04D G04F G04G G04R G05B G05F G06C G06D G06E G06F G06G G06J G06N G06T G08B G08C G09C G11C G12B G21K H01C H01F H01G H01J H01L H01Q H01S H03B H03C H03D H03F H03G H03H H03J H03K H03L H03M H04B H04H H04J H04K H04L H04M H04N H04Q H04R H04S H04W H05G H05H H05K	match Taiwan's industry definition of the biotech and new pharmaceutical industry this IPC has been included under C21.
C27	Manufacture of Electrical Equipment	A21B A45D A47G A47J A47L B01B B60M B61L D06F E06C F21H F21K F21L F21M F21P F21Q F21S F21V F21W F21Y F24B F24C F24D F25C F25D G08G G10K H01B H01H H01K H01M H01P H01R H01T H02B H02G H02H H02J H02K H02M H02N H02P H02S H05B H05C	
C28	Manufacture of Machinery and Equipment N.E.C.	A01B A01C A01D A01F A01G A01K A01M A21C A22B A22C A23N A24C A41H A42C A43D A47K A62C B01D B01F B02B B02C B03B B03C B03D B04C B05B B05C B05D B06B B07B B07C B08B B21B B21D B21F B21H B21J B21K B21L B22C B23B B23C B23D B23F B23G B23H B23K B23P B23Q B24B B24C B24D B25B B25C B25D B25F B25G B25H B25J B26B B26D B26F B27B B27C B27F B27G B27J B27L B28D B30B B31B B31C B31D B31F B33Y B41B B41C B41D B41F B41G B41J B41K B41L B41N B42B B42C B43M B44B B44C B60S B61B B65B B65C B65F B65G B65H B66B B66C B66D B66F B67B B67C B68F C10F C12L C13C C13D C13G C13H C14B C23C D01B D01D D01G D01H D02G D02H D02J D03C D03D D03J D04B D04C D05B D05C D06B D06G D06H D21B D21D D21F D21G E01C E01D E01F E01H E02C E02D E02F E05G E21B E21C E21D E21F F01B F01C F01D F01K F01M F01N F01P F02C F02G F02K F03B F03C F03D F03G F04B F04C F04D F04F F15B F15D F16C F16D F16F F16G F16H F16K F16M F16N F16P F22D F23B F23C F23D F23G F23H F23J F23K	

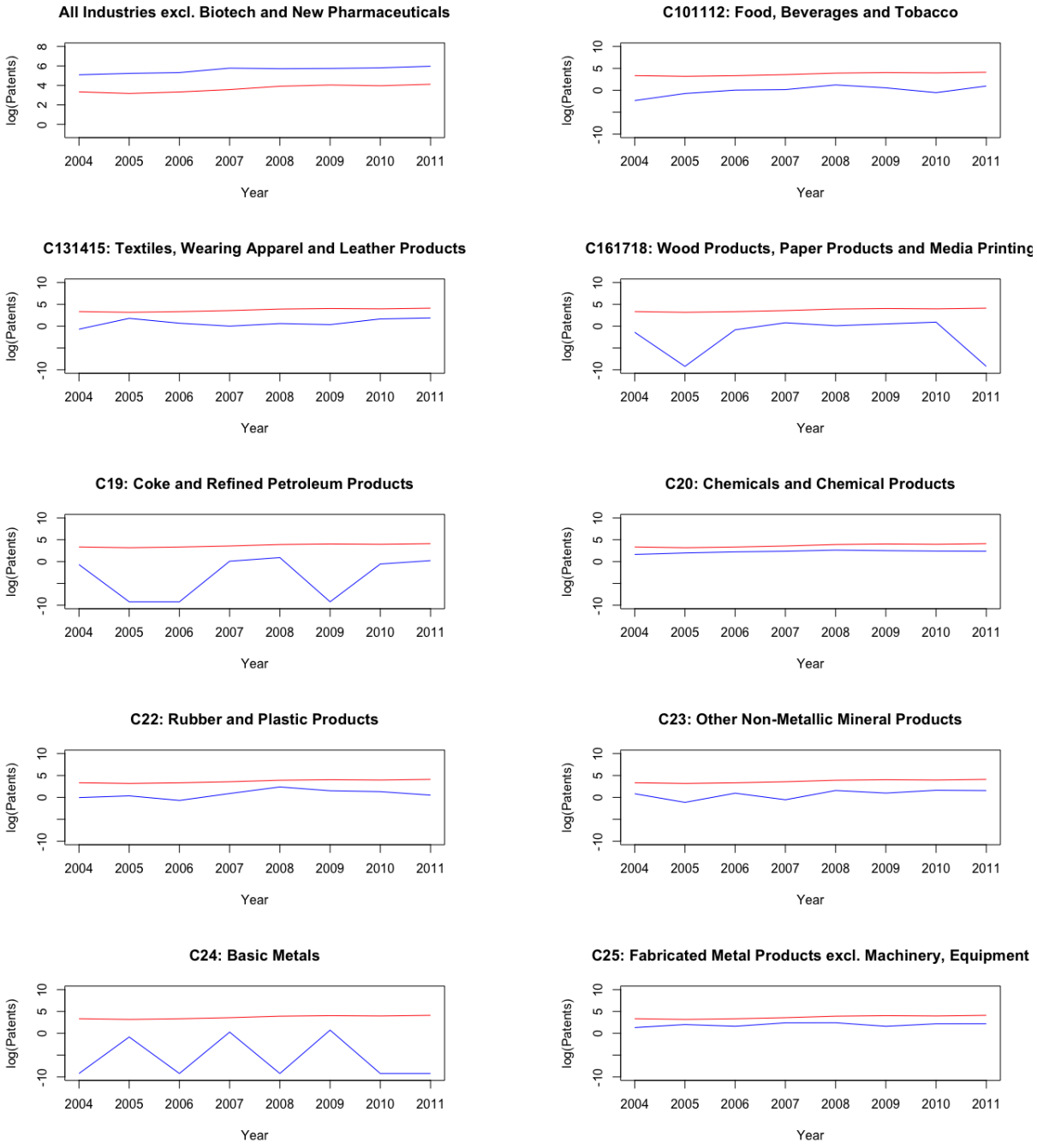
		F23L F23M F23N F23R F24F F24H F25B F26B F27B F28B F28C F28D F28F F28G G01G G03G G05D G05G G06K G06M G07B G07C Go7D G07F G07G G09D G09G G10L G11B H05F	
C29	Manufacture of Motor Vehicles, Trailers and Semi-Trailers	B60B B60D B60G B60H B60J B60K B60L B60N B60P B60Q B60R B60T B60W B62D F01L F02B F02D F02F F02M F02N F02P F16J G01P	
C30	Manufacture of Other Transport Equipment	B60F B60V B61C B61D B61F B61G B61H B61J B61K B62C B62H B62J B62K B62L B62M B63B B63C B63H B63J B64B B64C B64D B64F B64G E01B F03H	
C31	Manufacture of Furniture	A47B A47C A47D A47F	
C32	Other Manufacturing	A45F A61G A63G B62B G10F A41G A42B A44C A45B A45C A46B A46D A61B A61C A61D A61H A61J A61L A62B A63B A63C A63D A63F A63H A63J A63K B01L B04B B43K B43L B44D B65D B68G C06F C12M D07B F16L F23Q G01T G03D G03F G09B G09F G10B G10C G10D G10G G10H G21G	Eurostat includes the codes A61F and A61M in this category. However, to better match Taiwan's industry definition of the biotech and new pharmaceutical industry this IPC has been included under C21.
F42	Civil Engineering	E02B E03B E03C	
F43	Specialised Construction Activities	E03F E04B E04C E04D E04F E04G E04H	
J62	Computer Programming, Consultancy and Related Activities	G06Q	

Table 16: Concordance Table IPC V8 - NACE Rev.2
Adapted from (Eurostat, 2015)

Appendix 4: Testing for Parallel Pre-trends (DD) using the Graphical and Formal Approach

Appendix 4.1: Graphical Approach

Below, the trends in the number of applications for patents over time are graphed for each industry group. The red line represents the control group (Industry C21: Biotech and New Pharmaceuticals), treated industries are represented in blue.



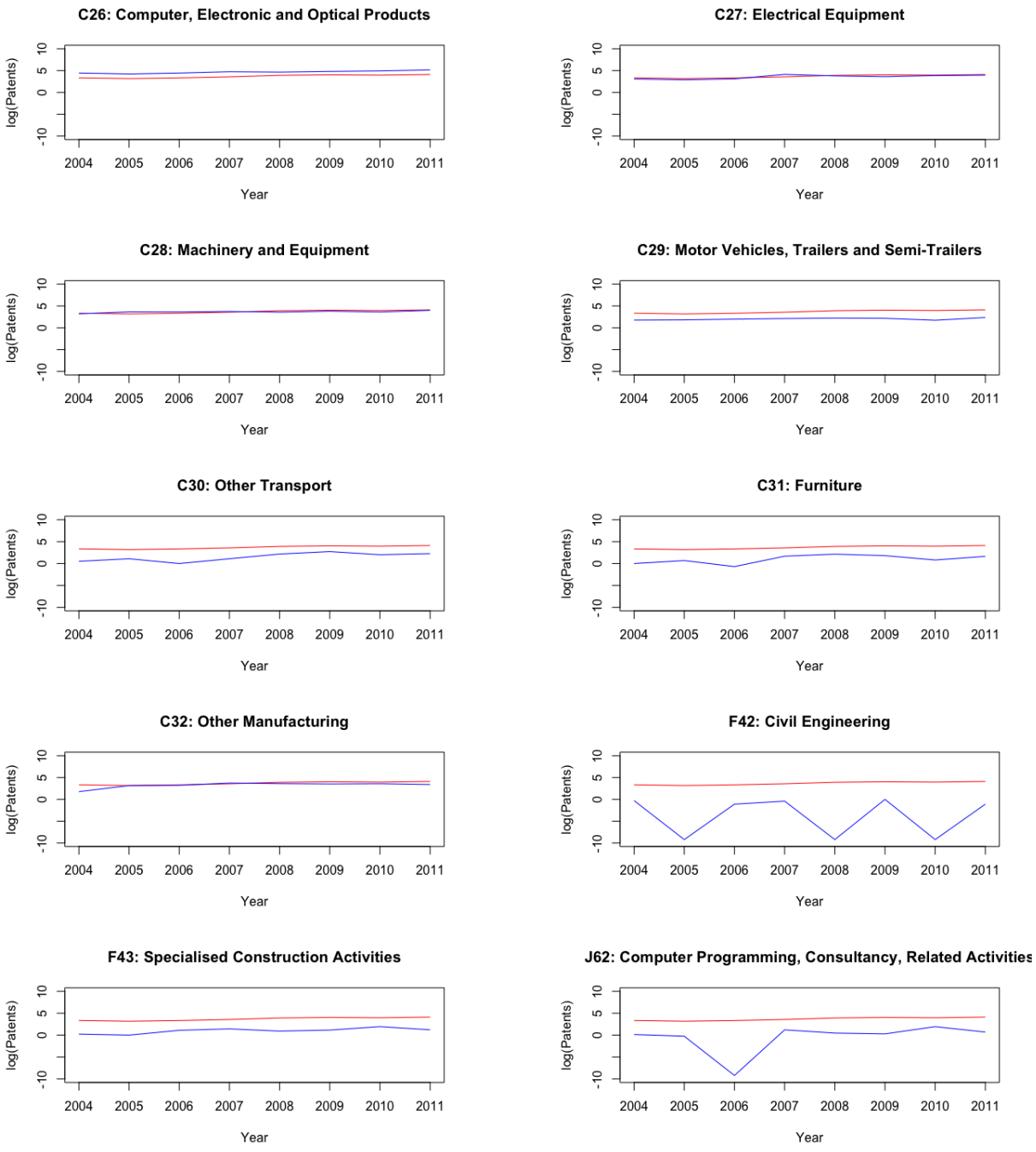


Figure 5: Testing for Parallel Pre-Trends (DD) - Graphical Approach

Appendix 4.2: Formal Approach

Testing for Parallel Pre-Trends - Basic DD

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	3.04 (2.65)	0.252
Not_C21	-3.21 (2.72)	0.240
Year	0.14 (0.52)	0.787
Not_C21 * Year	0.02 (0.54)	0.963
Observations	160	
R^2 / R^2 adjusted	0.050 / 0.032	

Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2004-2011). Each observation corresponds to the log of the number of patent applications by industry and year. The eight years included in the pre-test are coded as Years 1 to 8. Not_C21 refers to all industries other than the control industry (biotech and new pharmaceuticals). Standard errors are in parentheses.

Table 17: Regression Output - Testing for Parallel Pre-Trends Basic DD

Testing for Parallel Pre-Trends - Detailed DD

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	3.04 (1.86)	0.105
C101112	-4.57 (2.63)	0.085
C131415	-3.17 (2.63)	0.231
C161718	-5.31 (2.63)	**0.046**
C19	-9.21 (2.63)	**0.001**
C20	-1.23 (2.63)	0.641
C22	-3.17 (2.63)	0.231
C23	-3.44 (2.63)	0.194
C24	-7.63 (2.63)	**0.004**
C25	-1.46 (2.63)	0.579
C26	1.11 (2.63)	0.673
C27	-0.14 (2.63)	0.958
C28	0.30 (2.63)	0.910
C29	-1.26 (2.63)	0.632
C30	-2.96 (2.63)	0.263
C31	-3.11 (2.63)	0.239
C32	-0.56 (2.63)	0.831
F42	-6.26 (2.63)	**0.019**
F43	-2.92 (2.63)	0.270
J62	-5.92 (2.63)	**0.026**
Year	0.14 (0.37)	0.701
C101112 * Year	0.18 (0.52)	0.734
C131415 * Year	0.06 (0.52)	0.909
C161718 * Year	-0.15 (0.52)	0.776

C19 * Year	0.46 (0.52)	0.380
C20 * Year	-0.04 (0.52)	0.935
C22 * Year	0.06 (0.52)	0.910
C23 * Year	0.11 (0.52)	0.835
C24 * Year	-0.40 (0.52)	0.448
C25 * Year	-0.06 (0.52)	0.911
C26 * Year	-0.03 (0.52)	0.958
C27 * Year	0.00 (0.52)	0.996
C28 * Year	-0.07 (0.52)	0.889
C29 * Year	-0.09 (0.52)	0.864
C30 * Year	0.17 (0.52)	0.745
C31 * Year	0.10 (0.52)	0.851
C32 * Year	0.03 (0.52)	0.955
F42 * Year	-0.27 (0.52)	0.599
F43 * Year	0.05 (0.52)	0.920
J62 * Year	0.37 (0.52)	0.484
Observations	160	
R^2 / R^2 adjusted	0.639 / 0.522	

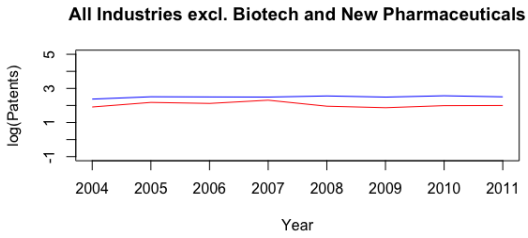
Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2004-2011). Each observation corresponds to the log of the number of patent applications by industry and year. The eight years included in the pre-test are coded as Years 1 to 8. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. Standard errors are in parentheses.

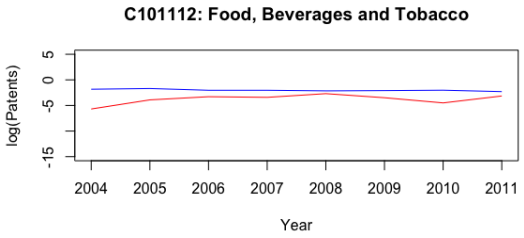
Table 18: Estimates for Parallel Pre-trend Test – Detailed DD

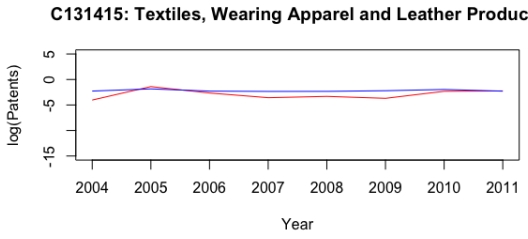
Appendix 5: Testing for Parallel Pre-trends (DD) using the Graphical and Formal Approach

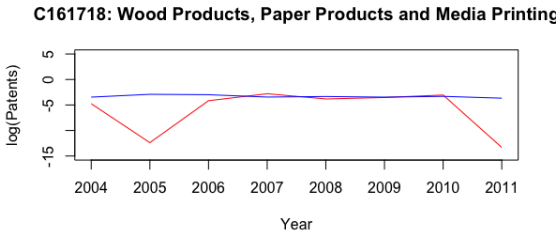
Appendix 5.1: Graphical Approach

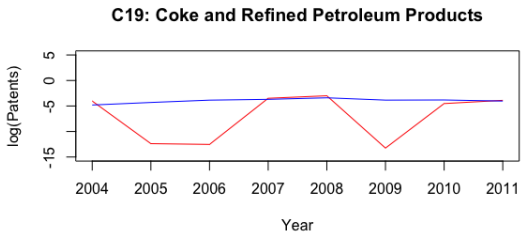
Below, the trends in the differences in the number of applications for patents over time are graphed for each industry group. The red line represents the Taiwan, Korea is represented in blue.

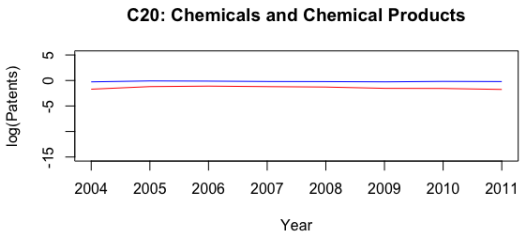


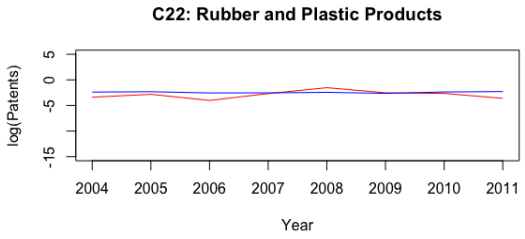


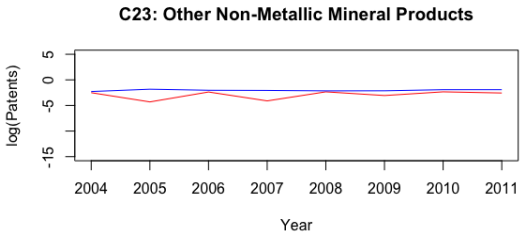


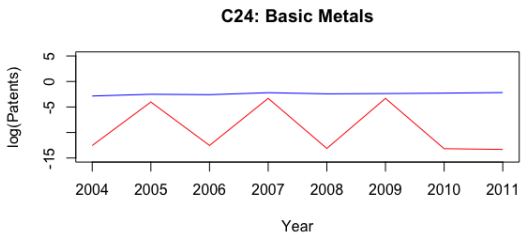


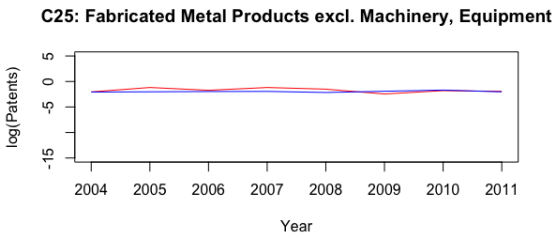












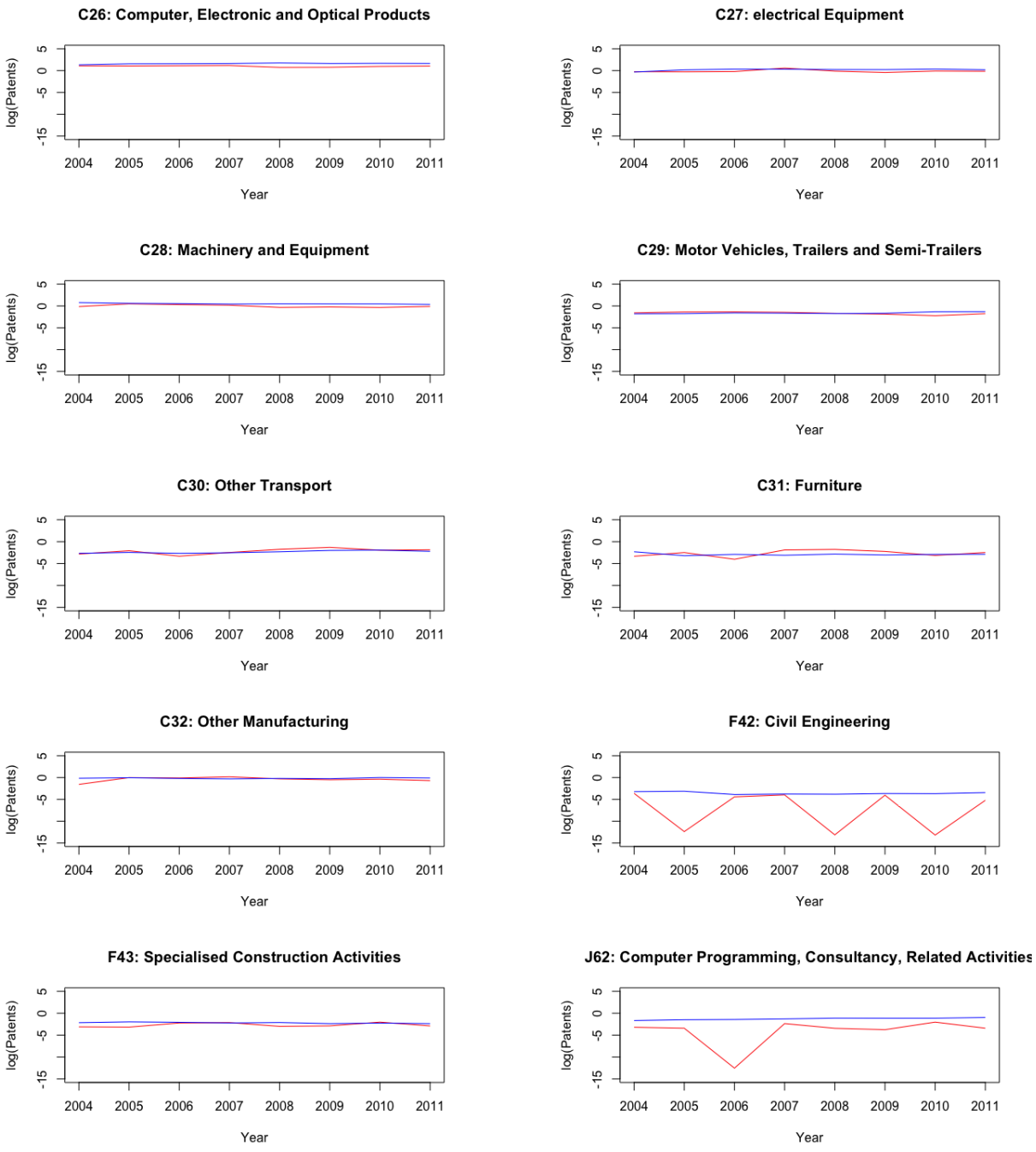


Figure 6: Testing for Parallel Pre-Trends (DDD) - Graphical Approach

Appendix 5.2: Formal Approach

Testing for Parallel Pre-Trends - Basic DDD

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	5.68 (2.03)	**0.005**
Not_C21	-1.77 (2.08)	0.397
Year	0.13 (0.40)	0.748
CountryDummy	-2.64 (2.87)	0.359
Not_C21 * Year	0.01 (0.41)	0.973
Not_C21 * CountryDummy	-1.44 (2.95)	0.625
Year * CountryDummy	0.01 (0.57)	0.982
(Not_C21 * Year) * CountryDummy	0.01 (0.58)	0.985
Observations	320	
R^2 / R^2 adjusted	0.390 / 0.376	

Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2004-2011). Each observation corresponds to the log of the number of patent applications by region, industry and year. The eight years included in the pre-test are coded as Years 1 to 8. Not_C21 refers to all industries other than the control industry (biotech and new pharmaceuticals). CountryDummy[34] is a dummy variable that takes on a value of 1 for an observation from Taiwan, and a value of 0 for an observation from Korea. Standard errors are in parentheses.

Table 19: Testing for Parallel Pre-Trends - Basic DDD

[34] The term "CountryDummy" is used to distinguish between Taiwan and the Republic of Korea. Readers be advised that throughout this study the term "country" carries no political connotation and is to be understood exclusively as reference for an economy.

Testing for Parallel Pre-Trends - Detailed DDD

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	5.68 (1.32)	**<0.001**
C101112	-1.74 (1.87)	0.352
C131415	-2.16 (1.87)	0.247
C161718	-3.07 (1.87)	0.102
C19	-4.41 (1.87)	**0.019**
C20	-0.17 (1.87)	0.928
C22	-2.46 (1.87)	0.189
C23	-2.13 (1.87)	0.255
C24	-2.76 (1.87)	0.140
C25	-2.08 (1.87)	0.267
C26	1.43 (1.87)	0.445
C27	-0.03 (1.87)	0.987
C28	0.71 (1.87)	0.703
C29	-1.89 (1.87)	0.312
C30	-2.78 (1.87)	0.138
C31	-2.76 (1.87)	0.141
C32	-0.19 (1.87)	0.920
F42	-3.39 (1.87)	0.071
F43	-1.99 (1.87)	0.287
J62	-1.70 (1.87)	0.364
Year	0.13 (0.26)	0.622
CountryDummy	-2.64 (1.87)	0.159
C101112 * Year	-0.06 (0.37)	0.866
C131415 * Year	-0.01 (0.37)	0.988

C161718 * Year	-0.06 (0.37)	0.877
C19 * Year	0.10 (0.37)	0.794
C20 * Year	-0.01 (0.37)	0.987
C22 * Year	0.00 (0.37)	0.992
C23 * Year	0.02 (0.37)	0.958
C24 * Year	0.07 (0.37)	0.840
C25 * Year	0.02 (0.37)	0.951
C26 * Year	0.04 (0.37)	0.922
C27 * Year	0.05 (0.37)	0.897
C28 * Year	-0.04 (0.37)	0.905
C29 * Year	0.06 (0.37)	0.863
C30 * Year	0.10 (0.37)	0.796
C31 * Year	-0.03 (0.37)	0.933
C32 * Year	0.01 (0.37)	0.987
F42 * Year	-0.04 (0.37)	0.908
F43 * Year	-0.05 (0.37)	0.903
J62 * Year	0.09 (0.37)	0.803
C101112 * CountryDummy	-2.83 (2.64)	0.285
C131415 * CountryDummy	-1.01 (2.64)	0.703
C161718 * CountryDummy	-2.24 (2.64)	0.396
C19 * CountryDummy	-4.80 (2.64)	0.070
C20 * CountryDummy	-1.06 (2.64)	0.688
C22 * CountryDummy	-0.71 (2.64)	0.788
C23 * CountryDummy	-1.31 (2.64)	0.620
C24 * CountryDummy	-4.87 (2.64)	0.066
C25 * CountryDummy	0.61 (2.64)	0.817
C26 * CountryDummy	-0.32 (2.64)	0.905

C27 * CountryDummy	-0.11 (2.64)	0.968
C28 * CountryDummy	-0.41 (2.64)	0.875
C29 * CountryDummy	0.63 (2.64)	0.812
C30 * CountryDummy	-0.18 (2.64)	0.946
C31 * CountryDummy	-0.35 (2.64)	0.893
C32 * CountryDummy	-0.37 (2.64)	0.888
F42 * CountryDummy	-2.87 (2.64)	0.278
F43 * CountryDummy	-0.93 (2.64)	0.725
J62 * CountryDummy	-4.22 (2.64)	0.111
Year * CountryDummy	0.01 (0.37)	0.973
(C101112 * Year) * CountryDummy	0.24 (0.52)	0.646
(C131415 * Year) * CountryDummy	0.07 (0.52)	0.901
(C161718 * Year) * CountryDummy	-0.09 (0.52)	0.861
(C19 * Year) * CountryDummy	0.36 (0.52)	0.488
(C20 * Year) * CountryDummy	-0.04 (0.52)	0.945
(C22 * Year) * CountryDummy	0.06 (0.52)	0.916
(C23 * Year) * CountryDummy	0.09 (0.52)	0.865
(C24 * Year) *CountryDummy	-0.47 (0.52)	0.368
(C25 * Year) * CountryDummy	-0.08 (0.52)	0.877
(C26 * Year) * CountryDummy	-0.06 (0.52)	0.903
(C27 * Year) * CountryDummy	-0.05 (0.52)	0.931
(C28 * Year) * CountryDummy	-0.03 (0.52)	0.956
(C29 * Year) * CountryDummy	-0.15 (0.52)	0.770
(C30 * Year) * CountryDummy	0.07 (0.52)	0.887
(C31 * Year) * CountryDummy	0.13 (0.52)	0.805
(C32 * Year) * CountryDummy	0.02 (0.52)	0.964
(F42 * Year) * CountryDummy	-0.23 (0.52)	0.658

(F43 * Year) * CountryDummy	0.10 (0.52)	0.853
(J62 * Year) * CountryDummy	0.27 (0.52)	0.601
Observations	320	
R^2 / R^2 adjusted	0.802 / 0.737	

Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2004-2011). Each observation corresponds to the log of the number of patent applications by region, industry and year. The eight years included in the pre-test are coded as Years 1 to 8. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. CountryDummy[35] is a dummy variable that takes on a value of 1 for an observation from Taiwan, and a value of 0 for an observation from Korea. Standard errors are in parentheses.

Table 20: Testing for Parallel Pre-Trends - Detailed DDD

[35] The term "CountryDummy" is used to distinguish between Taiwan and the Republic of Korea. Readers be advised that throughout this study the term "country" carries no political connotation and is to be understood exclusively as reference for an economy.

Appendix 6: Regression Output DD Analyses and Corresponding Event Studies

Regression Output Basic DD

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	3.68 (1.16)	**0.002**
IndustryDummy	-3.09 (1.19)	**0.010**
SII	0.96 (1.70)	0.573
IndustryDummy * SII	-0.37 (1.75)	0.832
Observations	300	
R^2 / R^2 adjusted	0.053 / 0.044	

Notes: The regression output is for the basic DD model as specified in Equation 1. Each observation corresponds to the log of the number of patent applications by industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 21: Regression Output Basic DD

Regression Output Basic DD Event Study

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	4.12 (3.39)	0.225
IndustryDummy	-3.34 (3.48)	0.338
Lag_8	-0.78 (4.79)	0.871
Lag_7	-0.94 (4.79)	0.844
Lag_6	-0.79 (4.79)	0.869
Lag_5	-0.55 (4.79)	0.909
Lag_4	-0.20 (4.79)	0.966
Lag_3	-0.08 (4.79)	0.987
Lag_2	-0.15 (4.79)	0.975
Implementation_Year	-0.14 (4.79)	0.977
Lead_1	0.07 (4.79)	0.989
Lead_2	0.34 (4.79)	0.944
Lead_3	0.90 (4.79)	0.851
Lead_4	0.97 (4.79)	0.840
Lead_5	0.88 (4.79)	0.855
Lead_6	0.66 (4.79)	0.891
IndustryDummy * Lag_8	0.22 (4.91)	0.965
IndustryDummy * Lag_7	-0.20 (4.91)	0.967
IndustryDummy * Lag_6	-0.41 (4.91)	0.934
IndustryDummy * Lag_5	1.34 (4.91)	0.786
IndustryDummy * Lag_4	0.31 (4.91)	0.949
IndustryDummy * Lag_3	0.53 (4.91)	0.915
IndustryDummy * Lag_2	0.16 (4.91)	0.974
IndustryDummy *Implementation_Year	1.18 (4.91)	0.810

IndustryDummy * Lead_1	0.35 (4.91)	0.944
IndustryDummy * Lead_2	0.45 (4.91)	0.928
IndustryDummy * Lead_3	-0.58 (4.91)	0.905
IndustryDummy * Lead_4	-0.77 (4.91)	0.875
IndustryDummy * Lead_5	-0.29 (4.91)	0.952
IndustryDummy * Lead_6	-1.22 (4.91)	0.804
Observations	300	
R^2 / R^2 adjusted	0.083 / -0.015	

Notes: The regression output is for the basic DD event study as specified in Equation 2. Each observation corresponds to the log of the number of patent applications by industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Lags and leads refer to the number of years before or after the implementation of the SII respectively. Standard errors are in parentheses.

Table 22: Regression Output Basic DD Event Study

Regression Output Detailed DD

Dependent variable: log(number of patent applications by industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	3.68 (0.20)	**<0.001**
C131415	-2.90 (0.29)	**<0.001**
C20	-1.42 (0.29)	**<0.001**
C22	-2.90 (0.29)	**<0.001**
C23	-2.95 (0.29)	**<0.001**
C25	-1.73 (0.29)	**<0.001**
C26	0.99 (0.29)	**0.001**
C27	-0.12 (0.29)	0.664
C28	-0.03 (0.29)	0.917
C29	-1.66 (0.29)	**<0.001**
C31	-2.67 (0.29)	**<0.001**
C32	-0.43 (0.29)	0.137
F43	-2.68 (0.29)	**<0.001**
SII	0.96 (0.30)	**0.001**
C131415 * SII	0.10 (0.42)	0.820
C20 * SII	-0.43 (0.42)	0.302
C22 * SII	-0.27 (0.42)	0.516
C23 * SII	-0.58 (0.42)	0.165
C25 * SII	-0.78 (0.42)	0.066
C26 * SII	-0.26 (0.42)	0.528
C27 * SII	-0.48 (0.42)	0.251
C28 * SII	-0.60 (0.42)	0.154
C29 * SII	-0.84 (0.42)	**0.047**
C31 * SII	-1.07 (0.42)	**0.011**

C32 * SII	-0.29 (0.42)	0.495
F43 * SII	-0.79 (0.42)	0.060
Observations	195	
R^2 / R^2 adjusted	0.872 / 0.854	

Notes: The regression output is for the detailed DD model as specified in Equation 1. Each observation corresponds to the log of the number of patent applications by industry and year. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. Only industries for which the null hypothesis of parallel pre-trends could not be rejected are included in the analysis. SII refers to the post-treatment dummy. Standard errors are in parentheses.

Table 23: Regression Output Detailed DD

Regression Output Basic DD Event Study including Industries C25, C29, C31 and F43 only

	Patents	
Predictors	*Estimates*	*p*
(Intercept)	4.12 (0.77)	**<0.001**
IndustryDummy	-2.27 (0.86)	**0.012**
Lag_8	-0.78 (1.09)	0.480
Lag_7	-0.94 (1.09)	0.392
Lag_6	-0.79 (1.09)	0.472
Lag_5	-0.55 (1.09)	0.619
Lag_4	-0.20 (1.09)	0.853
Lag_3	-0.08 (1.09)	0.945
Lag_2	-0.15 (1.09)	0.889
Implementation_Year	-0.14 (1.09)	0.901
Lead_1	0.07 (1.09)	0.951
Lead_2	0.34 (1.09)	0.759
Lead_3	0.90 (1.09)	0.413
Lead_4	0.97 (1.09)	0.380
Lead_5	0.88 (1.09)	0.425
Lead_6	0.66 (1.09)	0.551
IndustryDummy * Lag_8	-0.25 (1.22)	0.841
IndustryDummy * Lag_7	0.22 (1.22)	0.858
IndustryDummy * Lag_6	-0.06 (1.22)	0.963
IndustryDummy * Lag_5	0.60 (1.22)	0.623
IndustryDummy * Lag_4	0.28 (1.22)	0.820
IndustryDummy * Lag_3	-0.09 (1.22)	0.941
IndustryDummy * Lag_2	-0.03 (1.22)	0.979
IndustryDummy *Implementation_Year	-0.13 (1.22)	0.915

IndustryDummy * Lead_1	-0.28 (1.22)	0.817
IndustryDummy * Lead_2	-0.42 (1.22)	0.735
IndustryDummy * Lead_3	-1.08 (1.22)	0.382
IndustryDummy * Lead_4	-1.04 (1.22)	0.397
IndustryDummy * Lead_5	-0.99 (1.22)	0.424
IndustryDummy * Lead_6	-1.57 (1.22)	0.205
Observations	75	
R^2 / R^2 adjusted	0.778 / 0.635	

Notes: The regression output is for the DD event study as specified in Equation 2. However, the dataset is restricted to only include the industries found to be significant in the detailed DD analysis (C25, C29, C31 and F43) and the biotech and new pharmaceuticals industry as control industry. Each observation corresponds to the log of the number of patent applications by industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Lags and leads refer to the number of years before or after the implementation of the SII respectively. Standard errors are in parentheses.

Table 24: Regression Output Basic DD - Event Study including only the affected industries C25, C29, C31 and F43.

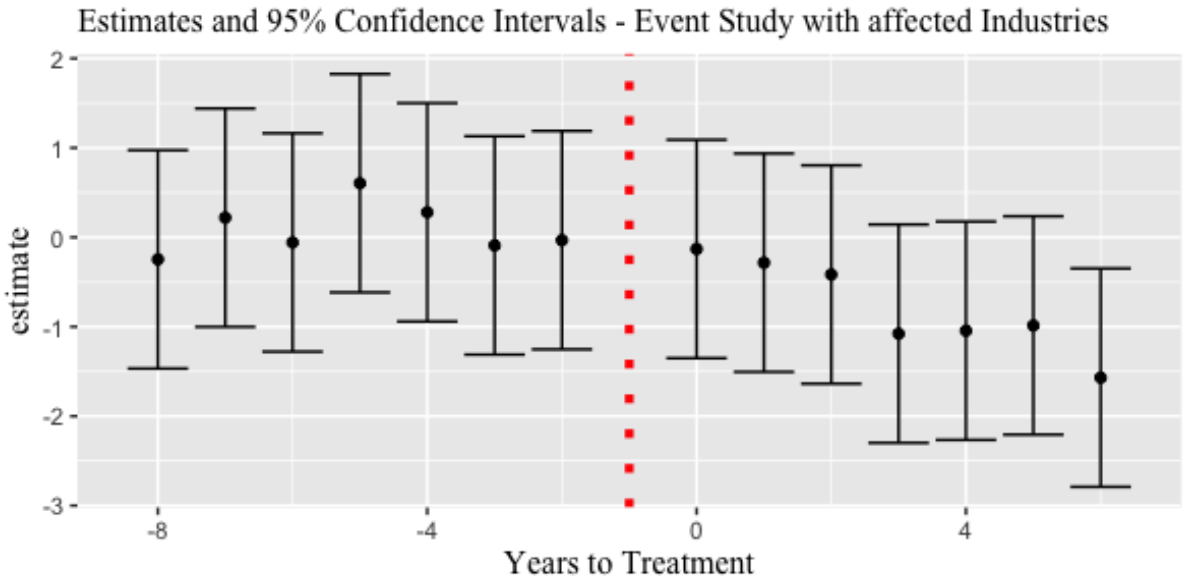


Figure 7: Estimates and 95% Confidence Intervals - Event Study with affected Industries

Appendix 7: Regression Output DDD Analyses and Corresponding Event Studies

Regression Output Basic DDD

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	6.26 (0.90)	**<0.001**
IndustryDummy	-1.70 (0.92)	0.066
Taiwan	-2.58 (1.27)	**0.043**
SII	0.72 (1.32)	0.587
IndustryDummy * Taiwan	-1.39 (1.31)	0.288
IndustryDummy * SII	-0.01 (1.35)	0.997
Taiwan * SII	0.25 (1.86)	0.896
(IndustryDummy * Taiwan) * SII	-0.37 (1.91)	0.849
Observations	600	
R^2 / R^2 adjusted	0.404 / 0.397	

Notes: The regression output is for the basic DDD model as specified in Equation 3. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 25: Regression Output Basic DDD

Regression Output Basic DDD Event Study

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	6.68 (2.63)	**0.011**
IndustryDummy	-1.69 (2.69)	0.531
Taiwan	-2.57 (3.71)	0.490
Lag_8	-0.92 (3.71)	0.804
Lag_7	-0.81 (3.71)	0.827
Lag_6	-0.56 (3.71)	0.880
Lag_5	-0.38 (3.71)	0.918
Lag_4	-0.32 (3.71)	0.931
Lag_3	-0.24 (3.71)	0.948
Lag_2	-0.14 (3.71)	0.971
Implementation_Year	0.11 (3.71)	0.976
Lead_1	0.14 (3.71)	0.970
Lead_2	0.16 (3.71)	0.966
Lead_3	0.26 (3.71)	0.945
Lead_4	0.44 (3.71)	0.905
Lead_5	0.45 (3.71)	0.904
Lead_6	0.50 (3.71)	0.893
IndustryDummy * Lag_8	-0.13 (3.81)	0.974
IndustryDummy * Lag_7	0.04 (3.81)	0.991
IndustryDummy * Lag_6	-0.04 (3.81)	0.992
IndustryDummy * Lag_5	-0.05 (3.81)	0.990
IndustryDummy * Lag_4	-0.01 (3.81)	0.998
IndustryDummy * Lag_3	-0.04 (3.81)	0.992
IndustryDummy * Lag_2	0.09 (3.81)	0.981

IndustryDummy *Implementation_Year	0.05 (3.81)	0.990
IndustryDummy * Lead_1	0.00 (3.81)	1.000
IndustryDummy * Lead_2	0.01 (3.81)	0.997
IndustryDummy * Lead_3	0.07 (3.81)	0.985
IndustryDummy * Lead_4	-0.08 (3.81)	0.984
IndustryDummy * Lead_5	-0.06 (3.81)	0.988
IndustryDummy * Lead_6	-0.15 (3.81)	0.969
Taiwan * Lag_8	0.14 (5.25)	0.978
Taiwan * Lag_7	-0.13 (5.25)	0.980
Taiwan * Lag_6	-0.23 (5.25)	0.965
Taiwan * Lag_5	-0.16 (5.25)	0.975
Taiwan * Lag_4	0.12 (5.25)	0.982
Taiwan * Lag_3	0.17 (5.25)	0.975
Taiwan * Lag_2	-0.02 (5.25)	0.998
Taiwan *Implementation_Year	-0.25 (5.25)	0.962
Taiwan * Lead_1	-0.07 (5.25)	0.989
Taiwan * Lead_2	0.18 (5.25)	0.973
Taiwan * Lead_3	0.64 (5.25)	0.902
Taiwan * Lead_4	0.52 (5.25)	0.921
Taiwan * Lead_5	0.43 (5.25)	0.935
Taiwan * Lead_6	0.16 (5.25)	0.976
IndustryDummy * Taiwan	-1.65 (3.81)	0.665
(IndustryDummy * Taiwan)* Lag_8	0.34 (5.39)	0.949
(IndustryDummy * Taiwan)* Lag_7	-0.25 (5.39)	0.964
(IndustryDummy * Taiwan)* Lag_6	-0.37 (5.39)	0.945
(IndustryDummy * Taiwan)* Lag_5	1.39 (5.39)	0.797
(IndustryDummy * Taiwan)* Lag_4	0.33 (5.39)	0.952

(IndustryDummy * Taiwan) * Lag_3	0.57 (5.39)	0.916
(IndustryDummy * Taiwan) * Lag_2	0.07 (5.39)	0.990
(IndustryDummy * Taiwan)* Implementation_Year	1.13 (5.39)	0.834
(IndustryDummy * Taiwan) * Lead_1	0.34 (5.39)	0.949
(IndustryDummy * Taiwan) * Lead_2	0.43 (5.39)	0.936
(IndustryDummy * Taiwan) * Lead_3	-0.65 (5.39)	0.903
(IndustryDummy * Taiwan) * Lead_4	-0.70 (5.39)	0.897
(IndustryDummy * Taiwan) * Lead_5	-0.23 (5.39)	0.965
(IndustryDummy * Taiwan) * Lead_6	-1.07 (5.39)	0.843
Observations	600	
R^2 / R^2 adjusted	0.422 / 0.359	

Notes: The regression output is for the basic DDD event study as specified in Equation 4. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. Lags and leads refer to the number of years before or after the implementation of the SII respectively. Standard errors are in parentheses.

Table 26: Regression Output Basic DDD Event Study

Regression Output Detailed DDD

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	6.26 (0.17)	**<0.001**
C131415	-2.19 (0.24)	**<0.001**
C20	-0.20 (0.24)	0.405
C22	-2.44 (0.24)	**<0.001**
C23	-2.04 (0.24)	**<0.001**
C25	-1.97 (0.24)	**<0.001**
C26	1.59 (0.24)	**<0.001**
C27	0.19 (0.24)	0.429
C28	0.51 (0.24)	**0.029**
C29	-1.60 (0.24)	**<0.001**
C30	-2.35 (0.24)	**<0.001**
C31	-2.90 (0.24)	**<0.001**
C32	-0.16 (0.24)	0.494
F43	-2.19 (0.24)	**<0.001**
Taiwan	-2.58 (0.24)	**<0.001**
SII	0.72 (0.24)	**0.003**
C131415 * Taiwan	-0.71 (0.33)	**0.033**
C20 * Taiwan	-1.23 (0.33)	**<0.001**
C22 * Taiwan	-0.46 (0.33)	0.165
C23 * Taiwan	-0.91 (0.33)	**0.007**
C25 * Taiwan	0.25 (0.33)	0.457
C26 * Taiwan	-0.60 (0.33)	0.071
C27 * Taiwan	-0.31 (0.33)	0.350
C28 * Taiwan	-0.54 (0.33)	0.103

C29 * Taiwan	-0.06 (0.33)	0.857
C30 * Taiwan	0.15 (0.33)	0.642
C31 * Taiwan	0.23 (0.33)	0.496
C32 * Taiwan	-0.27 (0.33)	0.422
F43 * Taiwan	-0.49 (0.33)	0.140
C131415 * SII	-0.35 (0.34)	0.307
C20 * SII	0.12 (0.34)	0.727
C22 * SII	-0.09 (0.34)	0.785
C23 * SII	0.16 (0.34)	0.646
C25 * SII	0.11 (0.34)	0.760
C26 * SII	0.00 (0.34)	0.998
C27 * SII	0.15 (0.34)	0.658
C28 * SII	-0.19 (0.34)	0.584
C29 * SII	0.11 (0.34)	0.739
C30 * SII	0.05 (0.34)	0.874
C31 * SII	-0.11 (0.34)	0.755
C32 * SII	0.10 (0.34)	0.780
F43 * SII	-0.26 (0.34)	0.455
Taiwan * SII	0.25 (0.34)	0.477
(C131415 * Taiwan) * SII	0.45 (0.49)	0.359
(C20 * Taiwan) * SII	-0.55 (0.49)	0.255
(C22 * Taiwan) * SII	-0.18 (0.49)	0.713
(C23 * Taiwan) * SII	-0.74 (0.49)	0.128
(C25 * Taiwan) * SII	-0.88 (0.49)	0.071
(C26 * Taiwan) * SII	-0.27 (0.49)	0.585
(C27 * Taiwan) * SII	-0.64 (0.49)	0.192
(C28 * Taiwan) * SII	-0.41 (0.49)	0.397

(C29 * Taiwan) * SII	-0.96 (0.49)	0.050
(C30 * Taiwan) * SII	-0.67 (0.49)	0.168
(C31 * Taiwan) * SII	-0.97 (0.49)	**0.048**
(C32 * Taiwan) * SII	-0.38 (0.49)	0.432
(F43 * Taiwan) * SII	-0.54 (0.49)	0.270
Observations	420	
R^2 / R^2 adjusted	0.957 / 0.950	

Notes: The regression output is for the detailed DDD model as specified in Equation 3. Each observation corresponds to the log of the number of patent applications by region, industry and year. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. Only industries for which the null hypothesis of parallel pre-trends could not be rejected are included in the analysis. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII refers to the post-treatment dummy. Standard errors are in parentheses.

Table 27: Regression Output Detailed DDD

Regression Output Basic DDD Event Study including Industries C25, C29 and C31 only

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	6.68 (0.77)	**<0.001**
IndustryDummy	-2.07 (0.89)	**0.024**
Lag_8	-0.92 (1.09)	0.402
Lag_7	-0.81 (1.09)	0.461
Lag_6	-0.56 (1.09)	0.608
Lag_5	-0.38 (1.09)	0.727
Lag_4	-0.32 (1.09)	0.770
Lag_3	-0.24 (1.09)	0.825
Lag_2	-0.14 (1.09)	0.901
Implementation_Year	0.11 (1.09)	0.918
Lead_1	0.14 (1.09)	0.900
Lead_2	0.16 (1.09)	0.885
Lead_3	0.26 (1.09)	0.814
Lead_4	0.44 (1.09)	0.685
Lead_5	0.45 (1.09)	0.683
Lead_6	0.50 (1.09)	0.650
Taiwan	-2.57 (1.09)	**0.022**
IndustryDummy * Lag_8	0.01 (1.26)	0.993
IndustryDummy * Lag_7	-0.26 (1.26)	0.839
IndustryDummy * Lag_6	-0.09 (1.26)	0.946
IndustryDummy * Lag_5	-0.16 (1.26)	0.899
IndustryDummy * Lag_4	-0.17 (1.26)	0.891
IndustryDummy * Lag_3	-0.14 (1.26)	0.914
IndustryDummy * Lag_2	0.10 (1.26)	0.936

IndustryDummy *Implementation_Year	-0.00 (1.26)	0.998
IndustryDummy * Lead_1	0.02 (1.26)	0.985
IndustryDummy * Lead_2	-0.00 (1.26)	1.000
IndustryDummy * Lead_3	0.10 (1.26)	0.938
IndustryDummy * Lead_4	-0.07 (1.26)	0.954
IndustryDummy * Lead_5	-0.10 (1.26)	0.934
IndustryDummy * Lead_6	-0.29 (1.26)	0.816
IndustryDummy * Taiwan	0.01 (1.26)	0.993
Lag_8 * Taiwan	0.14 (1.54)	0.926
Lag_7 * Taiwan	-0.13 (1.54)	0.931
Lag_6 * Taiwan	-0.23 (1.54)	0.883
Lag_5 * Taiwan	-0.16 (1.54)	0.916
Lag_4 * Taiwan	0.12 (1.54)	0.940
Lag_3 * Taiwan	0.17 (1.54)	0.914
Lag_2 * Taiwan	-0.02 (1.54)	0.992
Implementation_Year *Taiwan	-0.25 (1.54)	0.872
Lead_1 * Taiwan	-0.07 (1.54)	0.964
Lead_2 * Taiwan	0.18 (1.54)	0.908
Lead_3 * Taiwan	0.64 (1.54)	0.678
Lead_4 * Taiwan	0.52 (1.54)	0.736
Lead_5 * Taiwan	0.43 (1.54)	0.782
Lead_6 * Taiwan	0.16 (1.54)	0.919
(IndustryDummy * Lag_8) * Taiwan	-0.27 (1.78)	0.880
(IndustryDummy * Lag_7) * Taiwan	0.64 (1.78)	0.721
(IndustryDummy * Lag_6) * Taiwan	-0.22 (1.78)	0.904
(IndustryDummy * Lag_5) * Taiwan	0.71 (1.78)	0.691
(IndustryDummy * Lag_4) * Taiwan	0.58 (1.78)	0.747

(IndustryDummy * Lag_3) * Taiwan	0.01 (1.78)	0.995
(IndustryDummy * Lag_2) * Taiwan	-0.44 (1.78)	0.808
(IndustryDummy * Implementation_Year) * Taiwan	-0.21 (1.78)	0.905
(IndustryDummy * Lead_1) * Taiwan	-0.46 (1.78)	0.795
(IndustryDummy * Lead_2) * Taiwan	-0.40 (1.78)	0.825
(IndustryDummy * Lead_3) * Taiwan	-1.06 (1.78)	0.554
(IndustryDummy * Lead_4) * Taiwan	-1.16 (1.78)	0.518
(IndustryDummy * Lead_5) * Taiwan	-0.84 (1.78)	0.639
(IndustryDummy * Lead_6) * Taiwan	-1.51 (1.78)	0.400
Observations	120	
R^2 / R^2 adjusted	0.910 / 0.821	

Notes: The regression output is for the DDD event study as specified in Equation 4. However, the dataset is restricted to only include the industries found to be significant in the detailed DDD analysis (C25, C29 and C31) and the biotech and new pharmaceuticals industry as control industry. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. Lags and leads refer to the number of years before or after the implementation of the SII respectively. Standard errors are in parentheses.

Table 28: Regression Output Basic DDD Event Study including Industries C25, C29 and C31 only

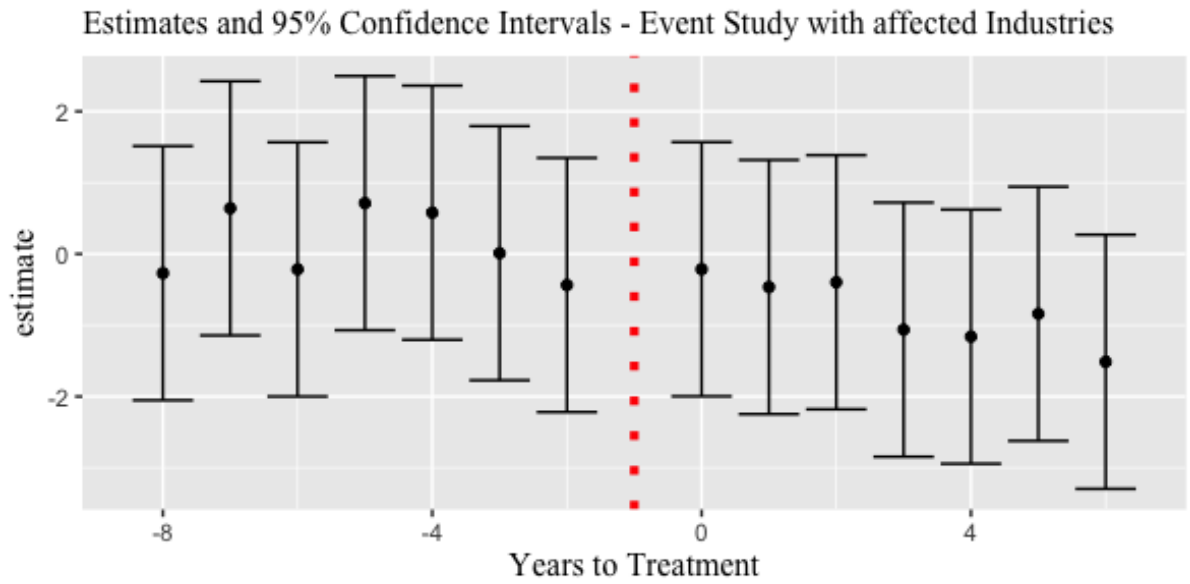


Figure 8: Estimates and 95% Confidence Intervals - Event Study with affected Industries

Appendix 8: Regression Output Robustness Checks

Regression Output Basic DDD (Robustness Check)

Dependent variable: log(number of patent applications by region, industry and year)				
	Basic DDD		**Robustness Check for Basic DDD**	
Predictors	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	6.26 (0.90)	**<0.001**	5.41 (0.93)	**<0.001**
IndustryDummy	-1.70 (0.92)	0.066	-1.55 (0.95)	0.105
Taiwan	-2.58 (1.27)	**0.043**	-1.95 (1.31)	0.137
SII	0.72 (1.32)	0.587	0.41 (1.31)	0.752
IndustryDummy * Taiwan	-1.39 (1.31)	0.288	-1.34 (1.34)	0.318
IndustryDummy * SII	-0.01 (1.35)	0.997	-0.17 (1.34)	0.901
Taiwan * SII	0.25 (1.86)	0.896	0.44 (1.85)	0.814
(IndustryDummy * Taiwan) * SII	-0.37 (1.91)	0.849	-0.16 (1.90)	0.935
GBERD_per_capita			0.46 (0.05)	**<0.001**
Observations	600		478	
R^2 / R^2 adjusted	0.404 / 0.397		0.496 / 0.487	

Notes: For comparison purposes, the left-hand column replicates the regression output of the previously performed basic DDD analysis. The right-hand column presents the regression output for the corresponding robustness check, based on Equation 5. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Due to limited data availability, the industries F42 – Civil Engineering and F43 – Specialised Construction activities were excluded from the robustness check. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 29: Regression Output Basic DDD (Robustness Check)

Regression Output Basic DDD Event Study (Robustness Check)

Dependent variable: log(number of patent applications by region, industry and year)

	Basic DDD Event Study		**Robustness Check for Basic DDD Event Study**	
Predictors	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	6.68 (2.63)	**0.011**	5.54 (1.66)	**0.001**
IndustryDummy	-1.69 (2.69)	0.531	-1.65 (1.70)	0.333
Taiwan	-2.57 (3.71)	0.490	-2.17 (2.34)	0.355
Lag_8	-0.92 (3.71)	0.804		
Lag_7	-0.81 (3.71)	0.827		
Lag_6	-0.56 (3.71)	0.880		
Lag_5	-0.38 (3.71)	0.918	-0.44 (2.86)	0.878
Lag_4	-0.32 (3.71)	0.931	-0.25 (2.86)	0.929
Lag_3	-0.24 (3.71)	0.948	-0.19 (2.86)	0.949
Lag_2	-0.14 (3.71)	0.971	0.03 (2.86)	0.992
Implementation_Year	0.11 (3.71)	0.976	0.21 (2.86)	0.941
Lead_1	0.14 (3.71)	0.970	-0.02 (2.86)	0.994
Lead_2	0.16 (3.71)	0.966	0.00 (2.86)	0.999
Lead_3	0.26 (3.71)	0.945	0.34 (2.86)	0.906

Lead_4	0.44 (3.71)	0.905	0.62 (2.86)	0.828
Lead_5	0.45 (3.71)	0.904	0.48 (2.86)	0.868
Lead_6	0.50 (3.71)	0.893		
IndustryDummy * Lag_8	-0.13 (3.81)	0.974		
IndustryDummy * Lag_7	0.04 (3.81)	0.991		
IndustryDummy * Lag_6	-0.04 (3.81)	0.992		
IndustryDummy * Lag_5	-0.05 (3.81)	0.990	0.31 (2.94)	0.917
IndustryDummy * Lag_4	-0.01 (3.81)	0.998	0.24 (2.94)	0.935
IndustryDummy * Lag_3	-0.04 (3.81)	0.992	0.10 (2.94)	0.973
IndustryDummy * Lag_2	0.09 (3.81)	0.981	-0.04 (2.94)	0.990
IndustryDummy * Implementation_Year	0.05 (3.81)	0.990	-0.17 (2.94)	0.953
IndustryDummy * Lead_1	0.00 (3.81)	1.000	0.06 (2.94)	0.983
IndustryDummy * Lead_2	0.01 (3.81)	0.997	0.14 (2.94)	0.961
IndustryDummy * Lead_3	0.07 (3.81)	0.985	-0.05 (2.94)	0.986
IndustryDummy * Lead_4	-0.08 (3.81)	0.984	-0.12 (2.94)	0.967
IndustryDummy * Lead_5	-0.06 (3.81)	0.988	-0.26 (2.94)	0.928
IndustryDummy * Lead_6	-0.15 (3.81)	0.969		

Taiwan * Lag_8	0.14 (5.25)	0.978		
Taiwan * Lag_7	-0.13 (5.25)	0.980		
Taiwan * Lag_6	-0.23 (5.25)	0.965		
Taiwan * Lag_5	-0.16 (5.25)	0.975	0.38 (4.05)	0.926
Taiwan * Lag_4	0.12 (5.25)	0.982	0.35 (4.05)	0.931
Taiwan * Lag_3	0.17 (5.25)	0.975	0.50 (4.05)	0.902
Taiwan * Lag_2	-0.02 (5.25)	0.998	0.08 (4.05)	0.984
Taiwan * Implementation_Year	-0.25 (5.25)	0.962	-0.06 (4.05)	0.988
Taiwan * Lead_1	-0.07 (5.25)	0.989	0.51 (4.05)	0.900
Taiwan * Lead_2	0.18 (5.25)	0.973	0.76 (4.05)	0.851
Taiwan * Lead_3	0.64 (5.25)	0.902	1.04 (4.05)	0.797
Taiwan * Lead_4	0.52 (5.25)	0.921	0.83 (4.05)	0.838
Taiwan * Lead_5	0.43 (5.25)	0.935	0.85 (4.05)	0.834
Taiwan * Lead_6	0.16 (5.25)	0.976		
IndustryDummy * Taiwan	-1.65 (3.81)	0.665	-1.82 (2.40)	0.450
(IndustryDummy * Taiwan) * Lag_8	0.34 (5.39)	0.949		
(IndustryDummy * Taiwan) * Lag_7	-0.25 (5.39)	0.964		

(IndustryDummy * Taiwan) * Lag_6	-0.37 (5.39)	0.945		
(IndustryDummy * Taiwan) * Lag_5	1.39 (5.39)	0.797	1.22 (4.16)	0.770
(IndustryDummy * Taiwan) * Lag_4	0.33 (5.39)	0.952	0.47 (4.15)	0.911
(IndustryDummy * Taiwan) * Lag_3	0.57 (5.39)	0.916	0.66 (4.15)	0.874
(IndustryDummy * Taiwan) * Lag_2	0.07 (5.39)	0.990	0.49 (4.15)	0.906
(IndustryDummy * Taiwan) * Implementation_Year	1.13 (5.39)	0.834	1.64 (4.15)	0.693
(IndustryDummy * Taiwan) * Lead_1	0.34 (5.39)	0.949	0.45 (4.15)	0.913
(IndustryDummy * Taiwan) * Lead_2	0.43 (5.39)	0.936	0.52 (4.15)	0.900
(IndustryDummy * Taiwan) * Lead_3	-0.65 (5.39)	0.903	-0.37 (4.15)	0.929
(IndustryDummy * Taiwan) * Lead_4	-0.70 (5.39)	0.897	-0.50 (4.15)	0.905
(IndustryDummy * Taiwan) * Lead_5	-0.23 (5.39)	0.965	0.15 (4.15)	0.971
(IndustryDummy * Taiwan) * Lead_6	-1.07 (5.39)	0.843		
GBERD_per_capita			0.46 (0.05)	**<0.001**
Observations	600		478	
R^2 / R^2 adjusted	0.422 / 0.359		0.506 / 0.455	

Notes: For comparison purposes, the left-hand column replicates the regression output of the previously performed basic DDD event study. The right-hand column presents the regression output for the corresponding robustness check, based on Equation 6. Each observation corresponds to the log of the number of patent applications by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Due to limited data availability, the industries F42 – Civil Engineering and F43 – Specialised Construction activities were excluded from the robustness check. Taiwan is a dummy,

taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. Lags and leads refer to the number of years before or after the implementation of the SII respectively.. Standard errors are in parentheses.

Table 30: Regression Output Basic DDD Event Study (Robustness Check)

Regression Output Detailed DDD (Robustness Check)

Dependent variable: log(number of patent applications by region, industry and year)				
	Detailed DDD		**Robustness Check for Detailed DDD**	
Predictors	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	6.26 (0.17)	**<0.001**	6.26 (0.18)	**<0.001**
C131415	-2.19 (0.24)	**<0.001**	-2.12 (0.24)	**<0.001**
C20	-0.20 (0.24)	0.405	-0.31 (0.24)	0.192
C22	-2.44 (0.24)	**<0.001**	-2.37 (0.24)	**<0.001**
C23	-2.04 (0.24)	**<0.001**	-1.91 (0.24)	**<0.001**
C25	-1.97 (0.24)	**<0.001**	-1.86 (0.24)	**<0.001**
C26	1.59 (0.24)	**<0.001**	1.06 (0.35)	**0.003**
C27	0.19 (0.24)	0.429	0.29 (0.23)	0.221
C28	0.51 (0.24)	**0.029**	0.14 (0.27)	0.601
C29	-1.60 (0.24)	**<0.001**	-1.61 (0.24)	**<0.001**
C30	-2.35 (0.24)	**<0.001**	-2.23 (0.24)	**<0.001**
C31	-2.90 (0.24)	**<0.001**	-2.79 (0.24)	**<0.001**
C32	-0.16 (0.24)	0.494	-0.08 (0.24)	0.730
F43	-2.19 (0.24)	**<0.001**		
Taiwan	-2.58 (0.24)	**<0.001**	-2.49 (0.24)	**<0.001**
SII	0.72 (0.24)	**0.003**	0.52 (0.23)	**0.028**
C131415 * Taiwan	-0.71 (0.33)	**0.033**	-0.81 (0.33)	**0.015**
C20 * Taiwan	-1.23 (0.33)	**<0.001**	-1.09 (0.34)	**0.001**
C22 * Taiwan	-0.46 (0.33)	0.165	-0.43 (0.33)	0.198
C23 * Taiwan	-0.91 (0.33)	**0.007**	-0.84 (0.33)	**0.012**
C25 * Taiwan	0.25 (0.33)	0.457	0.12 (0.33)	0.715
C26 * Taiwan	-0.60 (0.33)	0.071	-0.29 (0.38)	0.443
C27 * Taiwan	-0.31 (0.33)	0.350	-0.34 (0.33)	0.307

C28 * Taiwan	-0.54 (0.33)	0.103	-0.26 (0.36)	0.470
C29 * Taiwan	-0.06 (0.33)	0.857	-0.08 (0.33)	0.805
C30 * Taiwan	0.15 (0.33)	0.642	0.16 (0.33)	0.625
C31 * Taiwan	0.23 (0.33)	0.496	0.26 (0.33)	0.442
C32 * Taiwan	-0.27 (0.33)	0.422	-0.20 (0.33)	0.556
F43 * Taiwan	-0.49 (0.33)	0.140		
C131415 * SII	-0.35 (0.34)	0.307	-0.27 (0.33)	0.418
C20 * SII	0.12 (0.34)	0.727	0.05 (0.33)	0.890
C22 * SII	-0.09 (0.34)	0.785	-0.05 (0.33)	0.885
C23 * SII	0.16 (0.34)	0.646	0.15 (0.33)	0.649
C25 * SII	0.11 (0.34)	0.760	-0.06 (0.34)	0.871
C26 * SII	0.00 (0.34)	0.998	-0.10 (0.33)	0.755
C27 * SII	0.15 (0.34)	0.658	0.01 (0.33)	0.967
C28 * SII	-0.19 (0.34)	0.584	-0.13 (0.33)	0.704
C29 * SII	0.11 (0.34)	0.739	0.10 (0.33)	0.760
C30 * SII	0.05 (0.34)	0.874	-0.14 (0.34)	0.692
C31 * SII	-0.11 (0.34)	0.755	0.03 (0.33)	0.939
C32 * SII	0.10 (0.34)	0.780	0.11 (0.33)	0.745
F43 * SII	-0.26 (0.34)	0.455		
Taiwan * SII	0.25 (0.34)	0.477	0.29 (0.33)	0.383
(C131415 * Taiwan) * SII	0.45 (0.49)	0.359	0.57 (0.47)	0.222
(C20 * Taiwan) * SII	-0.55 (0.49)	0.255	-0.47 (0.47)	0.323
(C22 * Taiwan) * SII	-0.18 (0.49)	0.713	-0.21 (0.47)	0.655
(C23 * Taiwan) * SII	-0.74 (0.49)	0.128	-0.75 (0.47)	0.109
(C25 * Taiwan) * SII	-0.88 (0.49)	0.071	-0.60 (0.47)	0.205
(C26 * Taiwan) * SII	-0.27 (0.49)	0.585	-0.17 (0.47)	0.711
(C27 * Taiwan) * SII	-0.64 (0.49)	0.192	-0.50 (0.47)	0.290

(C28 * Taiwan) * SII	-0.41 (0.49)	0.397	-0.33 (0.47)	0.476
(C29 * Taiwan) * SII	-0.96 (0.49)	0.050	-0.85 (0.47)	0.070
(C30 * Taiwan) * SII	-0.67 (0.49)	0.168	-0.48 (0.47)	0.311
(C31 * Taiwan) * SII	-0.97 (0.49)	**0.048**	-0.83 (0.47)	0.076
(C32 * Taiwan) * SII	-0.38 (0.49)	0.432	-0.48 (0.47)	0.303
(F43 * Taiwan) * SII	-0.54 (0.49)	0.270		
GBERD_per_capita			0.07 (0.03)	**0.028**
Observations	420		312	
R^2 / R^2 adjusted	0.957 / 0.950		0.968 / 0.961	

Notes: For comparison purposes, the left-hand column replicates the regression output of the previously performed detailed DDD analysis. The right-hand column presents the regression output for the corresponding robustness check, based on Equation 5. Each observation corresponds to the log of the number of patent applications by region, industry and year. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. Only industries for which the null hypothesis of parallel pre-trends could not be rejected are included in the analysis. Due to limited data availability, the industries F42 – Civil Engineering and F43 – Specialised Construction activities were excluded from the robustness check. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 31: Regression Output Detailed DDD (Robustness Check)

Testing for Parallel Pre-Trends – Basic DDD (GBERD Robustness Check)

Dependent variable: log(number of patent applications by region, industry and year)		
Predictors	*Estimates*	*p*
(Intercept)	6.05 (2.42)	**0.013**
Not_C21	-1.75 (2.48)	0.481
Year	0.10 (0.62)	0.868
CountryDummy	-2.75 (3.42)	0.422
Not_C21 * Year	0.02 (0.64)	0.979
Not_C21 * CountryDummy	-1.13 (3.51)	0.747
Year * CountryDummy	0.05 (0.88)	0.958
(Not_C21 * Year) * CountryDummy	-0.05 (0.90)	0.953
Observations	240	
R^2 / R^2 adjusted	0.381 / 0.362	

Notes: The pre-test uses OECD data on the number of annual patent applications per industry for the eight years before the SII was implemented in tax returns in 2012 (2006-2011). Each observation corresponds to the log of the number of patent applications by region, industry and year. The eight years included in the pre-test are coded as Years 1 to 6. Not_C21 refers to all industries other than the control industry (biotech and new pharmaceuticals). CountryDummy[36] is a dummy variable that takes on a value of 1 for an observation from Taiwan, and a value of 0 for an observation from Korea. Standard errors are in parentheses.

Table 32: Testing for Parallel Pre-Trends – Basic DDD (GBERD Robustness Check)

[36] The term "CountryDummy" is used to distinguish between Taiwan and the Republic of Korea. Readers be advised that throughout this study the term "country" carries no political connotation and is to be understood exclusively as reference for an economy.

Regression Output Robustness Check Basic DDD using GBERD as Dependent Variable

Dependent variable: GBERD_per_capita by region, industry and year		
Predictors	*Estimates*	*p*
(Intercept)	2.17 (0.84)	**0.010**
IndustryDummy	-0.33 (0.86)	0.704
Taiwan	-1.38 (1.19)	0.249
SII	0.26 (1.19)	0.828
IndustryDummy * SII	0.38 (1.22)	0.753
Taiwan * SII	-0.37 (1.68)	0.825
IndustryDummy * Taiwan	0.05 (1.22)	0.965
(IndustryDummy * Taiwan) * SII	-0.26 (1.73)	0.879
Observations	478	
R^2 / R^2 adjusted	0.147 / 0.135	

Notes: Regression output is for the DDD robustness check model as specified in Equation 7. Each observation corresponds to the amount of GBERD per capita expressed in constant 2015 US-dollars by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 33: Regression Output Robustness Check Basic DDD using GBERD as Dependent Variable

Regression Output Robustness Check Detailed DDD using GBERD as Dependent Variable

Dependent variable: GBERD_per_capita by region, industry and year		
Predictors	*Estimates*	*p*
(Intercept)	2.17 (0.32)	**<0.001**
C131415	-1.65 (0.46)	**<0.001**
C20	1.58 (0.46)	**0.001**
C22	-1.48 (0.46)	**0.001**
C23	-1.83 (0.46)	**<0.001**
C25	-1.36 (0.46)	**0.003**
C26	8.31 (0.46)	**<0.001**
C27	-0.20 (0.46)	0.669
C28	4.47 (0.46)	**<0.001**
C29	0.89 (0.46)	0.053
C30	-0.69 (0.46)	0.131
C31	-2.15 (0.46)	**<0.001**
C32	-1.41 (0.46)	**0.002**
Taiwan	-1.38 (0.46)	**0.003**
SII	0.26 (0.46)	0.570
C131415 * Taiwan	1.16 (0.65)	0.073
C20 * Taiwan	-1.62 (0.65)	**0.013**
C22 * Taiwan	0.91 (0.65)	0.158
C23 * Taiwan	1.10 (0.65)	0.089
C25 * Taiwan	0.89 (0.65)	0.168
C26 * Taiwan	-5.60 (0.65)	**<0.001**
C27 * Taiwan	-0.17 (0.65)	0.794
C28 * Taiwan	-4.20 (0.65)	**<0.001**
C29 * Taiwan	-1.41 (0.65)	**0.030**

C30 * Taiwan	0.10 (0.65)	0.872
C31 * Taiwan	1.37 (0.65)	**0.034**
C32 * Taiwan	1.01 (0.65)	0.119
C131415 * SII	0.05 (0.65)	0.939
C20 * SII	1.15 (0.65)	0.075
C22 * SII	-0.09 (0.65)	0.887
C23 * SII	-0.10 (0.65)	0.875
C25 * SII	2.30 (0.65)	**<0.001**
C26 * SII	1.12 (0.65)	0.085
C27 * SII	0.77 (0.65)	0.234
C28 * SII	0.07 (0.65)	0.917
C29 * SII	-0.24 (0.65)	0.713
C30 * SII	2.59 (0.65)	**<0.001**
C31 * SII	-0.25 (0.65)	0.694
C32 * SII	0.41 (0.65)	0.530
Taiwan * SII	-0.37 (0.65)	0.563
(C131415 * Taiwan) * SII	0.16 (0.91)	0.857
(C20 * Taiwan) * SII	-1.20 (0.91)	0.189
(C22 * Taiwan) * SII	0.16 (0.91)	0.859
(C23 * Taiwan) * SII	0.22 (0.91)	0.810
(C25 * Taiwan) * SII	-2.10 (0.91)	**0.022**
(C26 * Taiwan) * SII	-0.76 (0.91)	0.403
(C27 * Taiwan) * SII	-0.59 (0.91)	0.521
(C28 * Taiwan) * SII	0.17(0.91)	0.850
(C29 * Taiwan) * SII	0.24 (0.91)	0.793
(C30 * Taiwan) * SII	-2.45 (0.91)	**0.008**
(C31 * Taiwan) * SII	0.37 (0.91)	0.687

(C32 * Taiwan) * SII	-0.22 (0.91)	0.812
Observations	312	
R^2 / R^2 adjusted	0.924 / 0.909	

Notes: Regression output for the detailed DDD robustness check model as specified in Equation 7. Each observation corresponds to the amount of GBERD per capita expressed in constant 2015 US-dollars by region, industry and year. Industries other than the control industry (biotech and new pharmaceuticals) are indicated by their three-figure NACE code. Only industries for which the null hypothesis of parallel pre-trends could not be rejected are included in the analysis. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea. SII is the post-treatment dummy. Standard errors are in parentheses.

Table 34: Regression Output Robustness Check Detailed DDD

Regression Output Robustness Check Basic DDD using GBERD as Dependent Variable

Dependent variable: GBERD_per_capita by region, industry and year		
Predictors	*Estimates*	*p*
(Intercept)	1.85 (1.51)	0.222
IndustryDummy	-0.13 (1.55)	0.934
Taiwan	-1.11 (2.14)	0.605
Lag_5	0.73 (2.62)	0.780
Lag_4	0.47 (2.62)	0.859
Lag_3	0.48 (2.62)	0.854
Lag_2	0.25 (2.62)	0.923
Implementation_Year	0.40 (2.62)	0.880
Lead_1	0.95 (2.62)	0.716
Lead_2	0.94 (2.62)	0.720
Lead_3	0.43 (2.62)	0.870
Lead_4	0.23 (2.62)	0.931
Lead_5	0.54 (2.62)	0.836
IndustryDummy * Lag_5	-0.78 (2.69)	0.773
IndustryDummy * Lag_4	-0.50 (2.69)	0.853
IndustryDummy * Lag_3	-0.25 (2.69)	0.925
IndustryDummy * Lag_2	0.31(2.69)	0.907
IndustryDummy * Implementation_Year	0.52 (2.69)	0.848
IndustryDummy * Lead_1	-0.09 (2.69)	0.972
IndustryDummy * Lead_2	-0.24 (2.69)	0.928
IndustryDummy * Lead_3	0.31 (2.69)	0.909
IndustryDummy * Lead_4	0.14 (2.69)	0.958
IndustryDummy * Lead_5	0.48 (2.69)	0.858
Taiwan * Lag_5	-0.92 (3.71)	0.805

Taiwan * Lag_4	-0.26 (3.71)	0.945
Taiwan * Lag_3	-0.47 (3.71)	0.900
Taiwan * Lag_2	0.03 (3.71)	0.993
Taiwan * Implementation_Year	-0.16 (3.71)	0.966
Taiwan * Lead_1	-1.01 (3.71)	0.786
Taiwan * Lead_2	-1.01 (3.71)	0.786
Taiwan * Lead_3	-0.61 (3.71)	0.870
Taiwan * Lead_4	-0.41 (3.71)	0.911
Taiwan * Lead_5	-0.66 (3.71)	0.859
IndustryDummy * Taiwan	-0.05 (2.20)	0.984
(IndustryDummy * Taiwan) * Lag_5	0.82 (3.80)	0.830
(IndustryDummy * Taiwan) * Lag_4	0.10 (3.80)	0.979
(IndustryDummy * Taiwan) * Lag_3	0.20 (3.80)	0.958
(IndustryDummy * Taiwan) * Lag_2	-0.51 (3.80)	0.893
(IndustryDummy * Taiwan) * Implementation_Year	-0.69 (3.80)	0.856
(IndustryDummy * Taiwan) * Lead_1	0.16 (3.80)	0.966
(IndustryDummy * Taiwan) * Lead_2	0.21 (3.80)	0.956
(IndustryDummy * Taiwan) * Lead_3	-0.21 (3.80)	0.956
(IndustryDummy * Taiwan) * Lead_4	-0.02 (3.80)	0.995
(IndustryDummy * Taiwan) * Lead_5	-0.43 (3.80)	0.909
Observations	478	
R^2 / R^2 adjusted	0.153 / 0.069	

Notes: Regression output for the detailed DDD robustness check model as specified in Equation 7. Each observation corresponds to the amount of GBERD per capita expressed in constant 2015 US-dollars by region, industry and year. The IndustryDummy indicates whether an industry was subject to the SII, taking a value of 1 for an observation from a treated industry, and a value of 0 for an observation from the untreated biotech and new pharmaceuticals industry. Due to limited data availability, the industries F42 – Civil Engineering and F43 – Specialised Construction activities were excluded from the robustness check. Taiwan is a dummy, taking a value of 1 for an observation from Taiwan and a value of 0 for an observation from Korea.

Lags and leads refer to the number of years before or after the implementation of the SII respectively. Standard errors are in parentheses.

Table 35: Regression Output Robustness Check Basic

Appendix 9: Overview of Model Components

p_{itc}	Outcome variable: Patents per region, industry and year
SII	Post-treatment dummy in the basic DD and DDD model, which takes the value of 0 for observations from before the SII was implemented in 2012 and the value of 1 for observations after the SII's implementation.
$Lag\ j$	Year fixed effects prior to the intervention
$Lead\ k$	Year fixed effects after the intervention
I_{ciy}	An indicator variable for the industry. Depending on the regression run, this is an indicator that groups industries into biotech and new pharmaceuticals and all other industries (Basic DD and DDD) or into NACE Rev.2 categories (Detailed DD and DDD)
T_{ciy}	A dummy, which takes the value of 0 for observations from Korea and the value of 1 for observations from Taiwan.
$GBERD$	Business expenditure in R&D with funds from government sources. This is used as a proxy for direct R&D subsidies. Additional covariate in the robustness checks.

Table 36: Overview of Regression Variables

Appendix 10: Overview of Variable Coding

$CountryDummy$	The term country dummy is used to distinguish between Taiwan and the Republic of Korea. Within this study the term "country" carries no political connotation and is to be understood exclusively as reference for an economy.
$C21$	Proxy for the control industry: Biotech and New Pharmaceuticals
$GBERD$	Business expenditure in R&D with funds from government sources. This is used as a proxy for direct R&D subsidies. Additional covariate in the robustness checks.
$IndustryDummy$	The indicator variable for the industry. Depending on the regression run, this is an indicator that groups industries into biotech and new pharmaceuticals and all other industries (Basic DD and DDD) or into NACE Rev.2 categories (Detailed DD and DDD)
Lag_j	Dummy variable indicating j years before the intervention in year 2012.
$Lead_k$	Dummy variable indicating k years after the intervention in year 2012.
SII	Post-treatment dummy in the basic DD and DDD model, which takes the value of 0 for observations from before the SII was implemented in 2012 and the value of 1 for observations after the SII's implementation.
$Taiwan$	The dummy, which takes the value of 0 for observations from Korea and the value of 1 for observations from Taiwan.

Table 37: Overview of Variable Coding