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Do Public Subsidy Schemes Foster Innovation and Competitiveness in Energy-Intensive Industries?

Heli Koski
ETLA Economic Research, Finland
heli.koski@etla.fi

Maria Wang
ETLA Economic Research, Finland
maria.wang@etla.fi

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Abstract

This study evaluates the impacts of public subsidies on firms in energy-intensive industries, focusing on R&D subsidies and compensation subsidies. Using firm-level data from Finnish energy-intensive industries between 2010 and 2022, it examines how these subsidies influence firm competitiveness and innovation outcomes. Compensation subsidies, designed to alleviate the additional electricity costs imposed by the EU Emissions Trading Scheme (ETS) on firms operating in certain energy-intensive industries, and to enhance their international competitiveness show no significant effects on employment, value added, or labor productivity. R&D subsidies, instead, demonstrate a substantial positive impact on innovation. Specifically, R&D subsidies significantly increase the citation stocks of climate change mitigation technology patents filed with the United States Patent and Trademark Office (USPTO). Total patent citation stocks associated with the European Patent Office (EPO) and USPTO also show statistically significant growth.

Tiivistelmä

Edistävätkö energiaintensiivisen teollisuuden tuet innovaatioita ja kilpailukykyä?

Tässä tutkimuksessa tarkastellaan yritystukien vaikutuksia energiaintensiivisten toimialojen yrityksiin Suomessa. Yritystason aineistoa vuosilta 2010–2022 käytetään analysoimaan sitä, miten t&k-tuet ja kompensaatiotuet ovat vaikuttaneet yritysten kilpailukykyyn ja innovaatioihin. Kompensaatiotuilla, joiden tarkoituksena on helpottaa EU:n päästökaupan aiheuttamia lisäkustannuksia sähkön hinnassa tietyillä energiaintensiivisillä teollisuuden aloilla toimiville yrityksille ja lisätä niiden kilpailukykyä kansainvälisillä markkinoilla, ei havaittu merkittäviä vaikutuksia työllisyyteen, jalostusarvoon tai työvoiman tuottavuuteen. Sen sijaan t&k-tuilla oli positiivinen vaikutus yritysten innovaatiotuotoksiin. T&k-tuet lisäsivät merkittävästi ilmastonmuutoksen hillintään liittyvien patentoitujen teknologioiden viittausten kertymiä Yhdysvaltain patentti- ja tavaramerkkivirastolta (USPTO) haetuissa patenteissa. Euroopan patenttivirastossa (EPO) sekä USPTO:n kokonaispatenttien viittausvarannot kasvoivat myös tilastollisesti merkitsevästi.

Ph.D. (Econ.) **Heli Koski** is a Research Director at ETLA Economic Research.

Ph.D. (Econ.) **Maria Wang** is a Researcher at ETLA Economic Research.

KTT **Heli Koski** on Elinkeinoelämän tutkimuslaitoksen tutkimusjohtaja.

FT **Maria Wang** on Elinkeinoelämän tutkimuslaitoksen tutkija.

Keywords: Firm subsidy, R&D subsidies, EU ETS, Competitiveness, Green innovation, Patents

Asiasanat: Yritystuet, T&k-tuet, EU ETS, Kilpailukyky, Vihreät innovaatiot, Patentit

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1 Introduction

Understanding the impacts of public support measures on firms operating in energy-intensive industries is critical for designing effective policies that balance environmental goals with industrial renewal and competitiveness. Governments across Europe have implemented targeted subsidy programs to assist these industries in addressing the implications of climate-related regulations, such as increased carbon costs, and to encourage innovation. For instance, in Finland, firms in energy-intensive industries—central to achieving climate policy goals—rank among the largest recipients of public subsidies. Despite their significance, the effects of these public support measures on firm-level outcomes remain insufficiently understood, leaving policymakers with limited evidence to inform effective policy design. This study focuses on two key types of subsidies: R&D subsidies and compensation subsidies.

R&D subsidies, aimed at stimulating innovation and technological progress, have been extensively studied, with a large body of literature demonstrating their impact on both firms' R&D expenditures and innovation outputs, such as patents (Howell, 2017; Bronzini and Piselli, 2016; Fornaro et al., 2020; Gök and Edler, 2012). Within this extensive research, a growing literature focuses specifically on the impact of R&D subsidies on green innovation, highlighting the pivotal role of government support in fostering environmentally sustainable technologies.

For instance, Battarelli et al. (2023), using aggregate-level data across 40 advanced and emerging market economies and five economic sectors from 2000 to 2021, find that climate change policies — particularly non-market-based measures such as R&D subsidies — significantly increase green patenting, with effects that strengthen over time. Howell (2017) similarly shows that R&D grants in clean energy sectors boost patenting, venture capital financing, and firm survival rates, though these effects are less pronounced in conventional energy technologies. Rentocchini et al. (2023), analyzing patents granted by the USPTO between 2005 and 2015 linked to procurement contracts or research grants with U.S. funding agencies, demonstrate that government-supported clean technologies generate substantial knowledge spillovers. Their findings indicate that clean technology patents associated with public R&D programs have a 26% higher citation rate than non-supported technologies, underscoring the long-term impact of technology-push policies on subsequent innovations.

While evidence on the innovation impacts of R&D subsidies is substantial, studies focusing on energy-related subsidies, such as compensation subsidies, remain relatively limited. Compensation subsidies, including the EU ETS indirect cost compensation subsidy and its successor, Electrification Aid, aim to mitigate the financial burden of carbon pricing for energy-intensive firms by offsetting electricity cost increases under the EU Emissions Trading Scheme (EU ETS). Although the EU ETS itself has been extensively studied and shown to reduce emissions with minimal competitiveness losses (Colmer et al., 2024; Dechezleprêtre et al., 2023; Bayer and Aklin, 2020; Marin et al., 2018), the firm-level impacts of associated subsidies remain underexplored. The only studies on the EU ETS indirect cost compensation subsidy that we are aware of are Ferrara & Giua (2022), who analyze the subsidy with EU-wide firm-level data and find no notable effects on turnover per worker and the value of total assets per employees, and Wang (2024), who finds no significant effects of the compensation subsidy on plant-level gross production, employment, or worker compensation with Finnish data. The longer-term and broader effects of compensation subsidies, particularly in conjunction with newer programs like Electrification Aid, have yet to be fully examined.

This study contributes to the literature by analyzing both the innovation impacts of R&D subsidies and the competitiveness impacts of compensation subsidies, focusing on firms in energy-intensive industries. Our analysis of R&D subsidies emphasizes their influence on total patent citation stocks and green patent citation stocks, providing insights into how these programs foster environmentally sustainable innovations. For compensation subsidies, we extend the analysis to a longer time series than Wang (2024) and include Electrification Aid to assess their effectiveness in supporting firm competitiveness. Methodologically, we employ state-of-the-art econometric models that address complexities of exploring the impacts of government subsidies such as staggered or heterogenous treatment timing, recurring subsidies, and potential lagged effects of subsidies. This framework enables a comprehensive evaluation of the causal impacts of these programs.

Using firm-level data from Finnish energy-intensive industries between 2010 and 2022, our analysis reveals distinct impacts of compensation and R&D subsidies. Compensation subsidies, aimed at offsetting carbon pricing-related costs, show no measurable effect on key performance indicators such as employment, value added, or labor productivity. In contrast, R&D subsidies significantly enhance innovation outcomes. These subsidies substantially increase the citation stocks of climate change mitigation technology patents filed with the USPTO, with pronounced effects observed consecutively for five years following the subsidy. Moreover, total patent citation stocks associated with the European Patent Office (EPO) exhibit consistent and statistically significant growth post-subsidy, while increases in environment-specific EPO patent citation stocks, though evident, are statistically inconclusive due to high data variation.

The remainder of this paper is organized as follows. Section 2 provides the institutional background, detailing the subsidy schemes for energy-intensive industries in Finland. Section 3 describes the data used in the analysis. Section 4 outlines the empirical strategy employed to evaluate the impacts of the subsidies. Section 5 presents the empirical findings, and Section 6 concludes with a discussion of the results and their policy implications.

2 Institutional background

This section provides institutional background on the various subsidy schemes available for firms in energy intensive industries in Finland. Our empirical analysis focuses on two key types of subsidies: i) the EU ETS indirect cost compensation subsidy and its follow-up subsidy, Electrification Aid, and ii) R&D subsidies. Firms may simultaneously receive different types of subsidies, making it essential to understand the broader context when analyzing their effects.

2.1 Subsidy schemes for energy intensive industries in Finland

EU ETS indirect cost compensation subsidy and Electrification Aid

The EU ETS indirect cost compensation subsidy is an EU-wide scheme implemented in 10 member states, including Finland, in the mid-2010s. It was designed to compensate for the indirect costs incurred by energy-intensive industries due to the European Union Emissions Trading System (EU ETS). These indirect costs stem from higher electricity prices driven by the carbon pricing mechanism, as electricity producers were expected to pass on the emission costs into their final prices. The subsidy aimed to preserve the global competitiveness of EU producers by mitigating the financial burden of increased electricity costs. Eligibility was typically restricted to sectors at risk of carbon leakage, where elevated energy costs could incentivize relocating production to regions with less stringent climate policies.

The eligible sectors for the compensation subsidy are listed in Table 1. It also lists the changes that the successor of the compensation subsidy, called Electrification aid, added. The subsidy amounts have been calculated with formulas that take into account e.g., production levels (past ones for the compensation subsidy and current ones for the Electrification Aid) and the EU ETS emission allowance prices.

The compensation subsidy scheme ended in Finland in 2021. It faced criticism for primarily benefiting large firms that did not necessarily require financial support and for failing to incentivize energy efficiency improvements or greener production methods. Additionally, in Finland, it was unclear whether firms' electricity costs risen during the majority of the subsidy period.

Table 1: Eligible sectors for the compensation subsidy

Industries and sub-industries eligible for the compensation subsidy	NACE Rev. 2	Note
Mining of iron ore	0710	Not eligible for the Electrification Aid
Mining of chemical and fertiliser minerals	0891	Not eligible for the Electrification Aid
Preparation and spinning of cotton-type fibres	1310	
Manufacture of leather clothes	1411	
Manufacture of paper and paperboard	1712	
Manufacture of other inorganic basic chemicals	2013	
Manufacture of other organic basic chemicals	2014	
Manufacture of fertilizers and nitrogen compounds	2015	
Manufacture of man-made fibres	2060	
Manufacture of basic iron and steel and of ferro-alloys, incl. seamless steel tubes	2410	
Aluminium production	2442	
Lead, zinc and tin production	2443	
Copper production	2444	
Following subsector of Manufacture of pulp:	1711	Whole section 17 eligible for the Electrification Aid
Mechanical pulp		
Following subsectors of Manufacture of plastics in primary forms:	2016	Only polyethylene glycols and other polyether alcohols in primary forms eligible for Electrification aid
Linear high-density polyethylene		
High-density polyethylene		
Low-density polyethylene		
Polyvinyl chloride		
Polycarbonate		
Polypropylene		
Additional industries that are eligible for the Electrification Aid	**NACE Rev. 2**	
Manufacture of refined petroleum products	1920	
Other non-ferrous metal production	2445	
Casting of iron	2451	
Following subsections of Manufacture of industrial gases:	2011	
Hydrogen		
Inorganic oxygen compounds of non-metals		
Following subsections of Manufacture of glass fibres:	2314	
Glass fiber mats		
Glass fiber thin sheets		

In 2022, a new subsidy scheme called the Aid for electrification of energy-intensive industries (also known as Electrification Aid) replaced the previous compensation subsidy system. Unlike its predecessor, the Electrification Aid is calculated based on current production levels rather than historical production from a reference period. Additionally, it introduces a requirement that at least 50% of the subsidy must be allocated to development measures aimed at increasing the proportion of renewable energy or enhancing energy efficiency, reducing greenhouse gas emissions, or advancing electrification. The eligible industries also changed slightly, as shown in Table 1. Despite these changes, the primary recipients of the subsidy remain largely the same firms as under the previous scheme.

R&D subsidies

In Finland, research and development (R&D) subsidies for firms have been available since the 1980s. Initially managed by Tekes (the Finnish Funding Agency for Technology and Innovation, established in 1983), the administration of these subsidies transitioned in 2018 when Tekes merged with Finpro to form Business Finland. Operating under the Ministry of Economic Affairs and Employment, Business Finland now oversees a wide array of R&D funding programs.

R&D subsidies aim to promote technological advancement, enhance competitiveness, and address market failures. These subsidies typically target projects involving significant uncertainty or risk, particularly those focused on developing innovative products, services, or processes. As the primary provider of green subsidies in Finland, Business Finland also aims at advancing sustainability and environmental objectives through dedicated funding initiatives (Kässi, 2024). Beyond environmental objectives, its comprehensive support for firms underscores a broader policy framework designed to drive technological progress and strengthen competitiveness across sectors.

Other support measures

In addition to compensation, electrification, and R&D subsidies, several other support measures are available for firms in energy-intensive industries in Finland. These include tax incentives and investment grants. We provide a brief overview of these programs, the impacts of which are not analyzed in this paper.

Tax incentives play a significant role in Finland's energy-related subsidy framework**.** *A tax refund system for energy-intensive companies* was introduced in the late 1990s as part of a broader strategy to enhance industrial competitiveness while complying with European Union regulations on state aid and environmental protection. In 2011, this system underwent a major expansion in response to increased excise tax rates on coal, natural gas, oil, and electricity (Laukkanen et al., 2019). Prior to the reform, companies were eligible for a tax refund if their energy excise tax expenditure exceeded 3.7% of the value added in production. Following the reform, the threshold was reduced to just 0.5%.

According to the Finnish Tax Administration, energy-intensive companies were eligible for an excise tax refund amounting to 85% of the portion of excise duties that exceeded 0.5% of the company's added value in the accounting year 2020. However, only the amount exceeding €50,000 under this calculation was refunded. The eligibility criteria for tax refunds will become stricter in the coming years, with excise duties paid in 2025 no longer refundable to energy-intensive companies.

The Energy Aid program is one of the most significant **investment grant schemes** related to energy use in Finland. Administered jointly by the Ministry of Economic Affairs and Employment and Business Finland, the program has supported investments in innovative energy technologies, renewable energy production, and energy efficiency improvements. Typical beneficiaries include projects focusing on wind power, solar energy, bioenergy, and energy storage systems. Business Finland is responsible for awarding aid when the eligible costs are below €5 million, while the Ministry of Economic Affairs and Employment handles decisions for larger projects. The program provides funding for up to 30% of eligible costs for investment projects and up to 40% for assessment projects.

The Energy Aid program dates to 1996, when it was first introduced by the Ministry of Trade and Industry. In 2008, this ministry merged with the Ministry of Labour to form the current Ministry of Economic Affairs and Employment. Over the years, the program has been redefined in terms of the types of projects eligible for funding and the annual budget allocations. Despite these adjustments, the program has remained relatively consistent in its overall structure and purpose.

In 2024, the guidelines for granting Energy aid were revised, excluding investments in renewable energy production and energy efficiency improvements for buildings from eligibility. Additionally, the government budget allocated for new applications dropped significantly, from €283.1 million in 2023 to just €68.6 million in 2024. This marks a sharp decline compared to 2022, when the total aid for new projects amounted to €390.8 million, highlighting a substantial reduction in funding over recent years.

3 Data and descriptive statistics

3.1 Data

3.1.1 Firm performance metrics

The dataset employed in this study encompasses Finnish firm-level data from 2010 to 2022, providing detailed insights into firm performance metrics and the subsidies granted to firms. Our analysis concentrates on sectors characterized by high energy intensity, specifically the manufacture of paper and paper products, coke and refined petroleum products, chemicals and chemical products, other non-metallic mineral products, and basic metals, corresponding to NACE Rev. 2 codes 17, 19, 20, 23, and 24, respectively.

The primary metrics used to assess firm performance in the context of the compensation subsidy analysis were sourced from the Asiakastieto database, a comprehensive repository of Finnish company data. These metrics include the number of employees, value added, and value added per employee. **The number of employees** serves as a measure of the firm's size and its capacity for labor. **Value added**, calculated as the difference between the firm’s revenue and its intermediate consumption, reflects the firm’s economic contribution to the economy. **Value added per employee**, in turn, serves as a measure of labor productivity, providing insights into the efficiency with which the firm utilizes its workforce.

The impact of R&D subsidies was assessed based on their effects on innovation output, proxied by patenting activity. Patent data were extracted from the Patentinspiration database, covering applications filed with the USPTO (United States Patent and Trademark Office) and the EPO (European Patent Office) during 2010–2022. Green patents were specifically identified to evaluate the environmental dimension of innovation. EPO and USPTO patent filings were chosen as they provide a measure of innovation with international relevance. EPO patents offer protection across multiple European countries, making them particularly valuable for firms targeting broader regional markets. USPTO patents, on the other hand, secure intellectual property rights in the United States, one of the world’s largest and most competitive markets. Together, these filings reflect Finnish firms' ambitions to safeguard and commercialize their innovations on a global scale.

We utilize patent citations rather than merely counting patent applications, as prior research indicates that a substantial proportion of patents hold negligible economic value. Patent citations serve as a proxy for a patent's significance within the technological landscape; a higher number of citations suggests that subsequent innovations have built upon the patented technology, implying greater importance and value. Prior research has established a significant positive correlation between patent citations and the economic value of inventions. For instance, Harhoff et al. (1999) and Gambardella et al. (2008) found that patent citations correlate with survey-based profit measures from the associated inventions.

In our analysis, we normalize patent citations by dividing each patent's citation count by the average citation count of all patents granted in the same year, with separate calculations performed for patents granted by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO). This method accounts for annual variations in citation practices and ensures that our analysis reflects the relative impact of each patent within its cohort. Additionally, this normalization addresses the issue of citation lag, where newer patents have had less time to accumulate citations compared to older ones, thereby providing a more accurate assessment of a patent's significance over time.

In our analysis, **patent citation stocks** serve as the dependent variable, capturing the cumulative nature of intellectual property and intangible capital and accounting for the time lags inherent in innovation processes, where the effects of R&D investments emerge gradually.

The value of the patent stock in year *t* is calculated as follows:

$$K_{it} = (1 - \delta_{it})^{*} K_{it-1} + I_{it}$$

where δ_{it} represents the annual depreciation rate of patent stocks, and I_{it} denotes the number of patent applications filed in year t. Consistent with prior studies, we applied a 15% annual depreciation rate to account for the gradual decline in the economic value of existing patents over time (e.g., Hall & MacGarvie, 2010). Given the absence of a long pre-sample patent history in our data, we used an annual growth rate of 8% (as, e.g., in Hall et al. (2007) to estimate the value of knowledge stock for the first observation year. In other words, for 2010, we calculated the patent citation stock was calculated as $I_{it}/(\delta_{it} + g)$, where g is set to 8%.

Additionally, we constructed separate stocks for green patent citation stocks to evaluate environmentally relevant technological advancements.

3.1.2 Subsidy data

Our dataset provides comprehensive annual records of the various types of subsidies received by the Finnish energy-intensive companies from 2012 to 2022. Our primary focus is on compensation subsidies and electrification aid, as they enable the construction of a quasi-experimental design with data from both before and after their implementation. By including all recipients of these subsidies, the dataset enables a comprehensive evaluation of their impacts.

Additionally, we examine the effects of R&D subsidies among the sample of firms in energy-intensive industries, which include both grants and loans. Business Finland also administers Energy Aid for projects with eligible costs below 5 million euros, designed to enhance energy efficiency and promote the adoption of renewable energy solutions, thereby supporting a transition to a low-carbon economy. These Energy Aid grants are included in our data. However, as over 50 percent of firms receiving Business Finland's subsidies did so in the first observation year, establishing causal impacts of these subsidies is more challenging.

To control for the impacts of other types of subsidies, our data also includes the energy tax refunds granted by the Finnish Tax Office. The only relevant type of subsidy that is not included in our data is the Energy Aid for projects above the 5-million-euro threshold, as those have been granted by the Ministry of Economic Affairs and Employment and have only been made publicly available from 2020 onwards. In 2020-2022, the largest recipients of this specific aid were mostly in power generation, which would not be applicable in our analysis in any case.

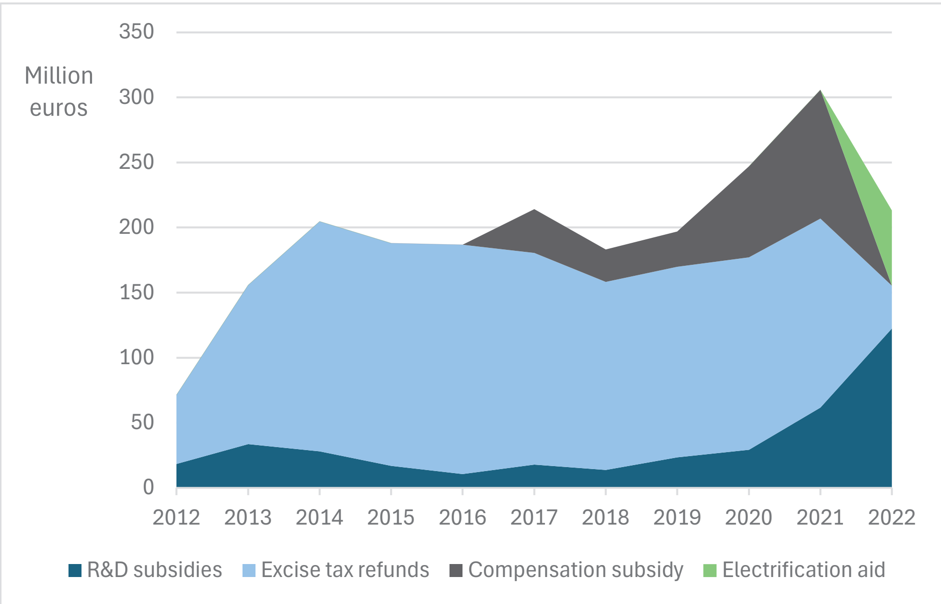

Figure 1: Business subsidies allocated to sample energy-intensive companies in Finland, 2012-2022

Figure 1 illustrates he distribution of business subsidies allocated to our sample of firms in energy-intensive industries in Finland between 2012 and 2022. Throughout the 2010s, excise tax refunds constituted the largest individual form of subsidy. The overall volume of subsidies exhibited a steady upward trend during this decade, reaching its peak in 2021. However, in 2022, the total subsidy amount declined following the discontinuation of compensation subsidies and a reduction in excise tax refunds. Despite this decrease, the cumulative subsidy level in 2022 remained more than double that of 2012.

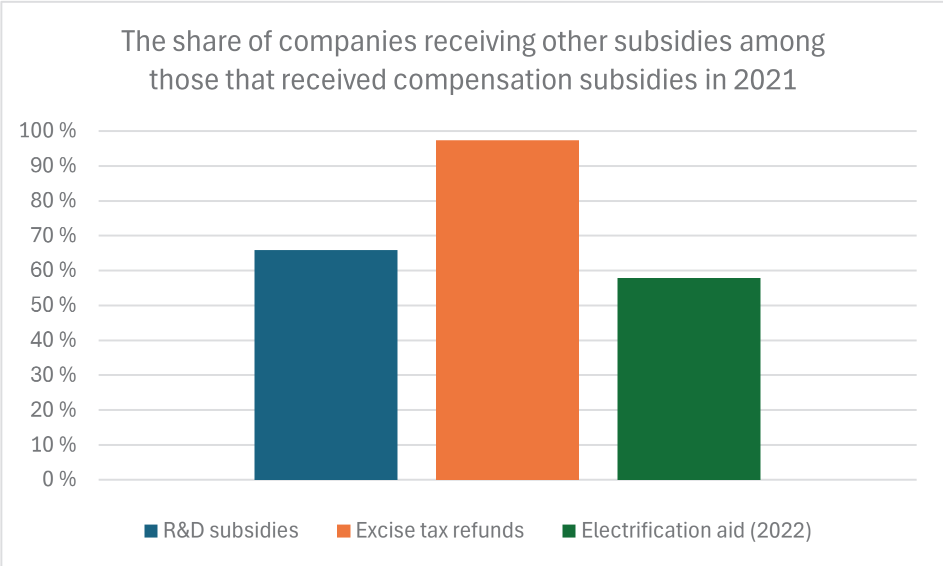

Figure 2: The share of companies receiving other subsidies during 2012-2022 among those that received compensation subsidies

Figure 2 illustrates that firms receiving compensation subsidies frequently benefited from additional government support throughout the sample period. Nearly all energy-intensive companies receiving compensation subsidies also secured excise tax refunds, with over two-thirds additionally obtaining R&D subsidies. Furthermore, approximately 60 percent of these firms took advantage of the Electrification Aid introduced in 2022 for energy-intensive industries.

3.1.3 Matching

To ensure the robustness of the causal estimates, we employ nearest neighbor matching using Mahalanobis distance. This matching technique helps in constructing a control group that is statistically similar to the treated group, thereby reducing selection bias and improving the validity of our results. The matching is done separately for the analysis of compensation subsidy/electrification aid and R&D subsidies. It is performed with replacement to ensure that as many as possible treated firms get matched with control firms.

3.1.3.1 Electrification aid data

When analyzing the impacts of the compensation subsidy and its successor Electrification aid, we have data from both before and after the subsidy period began. This allows us to use pre-treatment means of various variables for the matching process. The pre-treatment period is defined as the time preceding the introduction of the compensation subsidy scheme in 2016.

The pre-treatment variables used for matching include the number of employees and revenue, with matching conducted within sectors to ensure comparability across firms operating in the same industry. These variables are selected based on their strong correlation with subsidy receipt, reflecting the role of firm size in determining eligibility or access to subsidies. Each treated firm is matched with the five nearest control firms that did not receive any subsidies during the study period.

Table 2 presents descriptive statistics for the original dataset and the matched sample, with mean values calculated for the pre-treatment period. The data reveal that compensation subsidy recipients are predominantly large firms. However, after matching, the differences in firm size and other characteristics between treated and control firms are notably reduced, enhancing the comparability of the two groups.

Table 2: Descriptive statistics for compensation subsidy matching

	All data		After matching
Variable	Treated	Control	Control
Number of firms	42	1,686	61
Mean number of employees	823.9	24.00	209.12
Mean revenue (mil)	813.68	22.69	225.68
Mean value added (mil)	140.93	3.11	25.84
Mean value added / employee	156,899.82	66,462.82	127,838.01

Our empirical approach relies on the parallel trends assumption, which requires that, in the absence of treatment (i.e., receiving the subsidy), the treated and control firms would have followed similar developmental trajectories. To assess the validity of this assumption, we examine pre-treatment trends in the data. Figure 3 provides a graphical analysis for this purpose: the top row displays the means of our dependent variables across years, while the bottom row presents the same variables indexed to the base year 2015, the year prior to the introduction of the subsidy system.

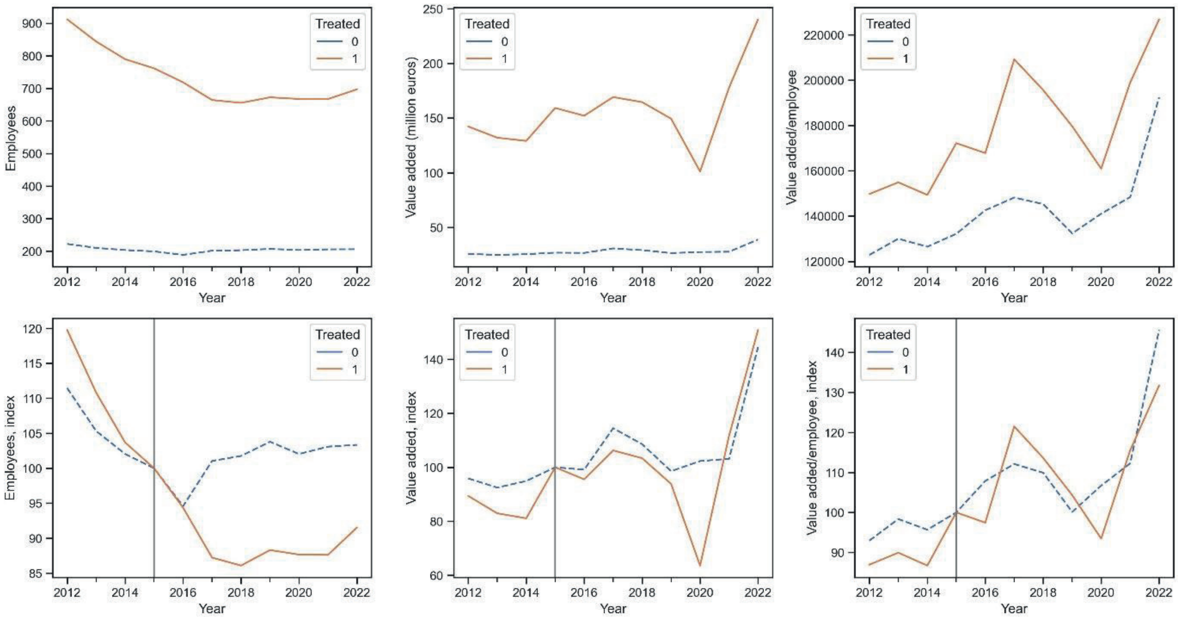

Figure 3: Data trends with matched data

As shown in Figure 3, the trends during the pre-treatment period align closely, supporting the validity of the parallel trends assumption. Notably, in 2020, firms receiving subsidies experienced a sharper decline in value added compared to non-recipients. This drop is likely attributable to the COVID-19 pandemic, which seems to have disproportionately impacted the subsidy recipient firms.

3.1.3.2 R&D subsidy data

Our data on R&D subsidies spans the entire period from 2010 to 2022. As treatment data is available for the full timeframe, matching is performed using covariates calculated across the entire observation period rather than limited to pre-treatment characteristics. Specifically, we employ the number of employees and revenue as covariates, computing their mean values over all available years. Additionally, a firm's estimated propensity to patent and its industry are included as covariates in the matching analysis.

The propensity to patent is estimated using a probit model, where the dependent variable is a dummy indicating whether a firm has applied for a patent from the USPTO or EPO (1) or not (0). The explanatory variables include firm size, industry, and foreign ownership, which are selected based on their established relevance in the literature. Firm size and industry are widely recognized as key determinants of a firm's propensity to patent (Hall & Ziedonis, 2001; Link & Scott, 2018), while foreign ownership has been shown to influence patenting through access to international resources and knowledge networks (Criscuolo & Martin, 2009).

Following the estimation, the predicted probabilities from the probit model are used as a measure of each firm's propensity to patent. These estimated probabilities are then incorporated as a covariate in the matching analysis to account for firm-level heterogeneity in innovation activity. By doing so, we ensure that treated and control firms are comparable not only in observable characteristics like size and revenue but also in their underlying likelihood to engage in patenting.

Table 3: Descriptive statistics for R&D subsidy matching

	All data		After matching		
Variable	Treated	Control	Treated	Control	Control with innovation activities
Number of firms	286	1,431	280	401	57
Mean number of employees	174.20	12.20	176.39	32.17	71.39
Mean revenue (mil)	158.21	14.55	158.68	16.91	51.62
Mean value added (mil)	26.27	2.40	26.32	3.45	7.68
Mean value added / employee	92,890.11	78,775.30	93,149.74	81,379.47	77,055.59

Table 3 presents the mean values of key variables before and after matching for R&D subsidies, calculated across the entire observation period. During the matching process, six treated firms were excluded due to the lack of sufficiently close matches in the data, and the statistics are recalculated for the matched sample. The rightmost column of Table 3 provides statistics for a subsample restricted to firms with identifiable innovation-related activities, i.e. firms that have received R&D subsidies, have reported R&D expenditures in financial statements, or hold patents during the observation period. This restriction allows the analysis to focus on firms with demonstrated innovative activities.

Matching has reduced the difference between the treated and control firms, but there is still a relatively large difference in the sizes of the firms. Despite this, our empirical approach is robust to such differences, as long as the parallel trends assumption holds.

In this case, the parallel trends assumption cannot be visually tested due to subsidies being granted throughout the entire observation period. To address this, the empirical strategy incorporates placebo periods prior to the staggered adoption of subsidy recipiency, allowing for a robustness check of the assumption.

4 Empirical strategy

The compensation subsidy data spans periods both before and after the subsidy was introduced, enabling the use of a traditional difference-in-differences approach. However, the allocation of the compensation subsidies is somewhat staggered, as not all firms began receiving the subsidy in the first year, and some ceased to receive it at later points. This is particularly evident with the introduction of the Electrification Aid system, which adjusted the eligibility criteria. These staggered starts and the presence of "leavers" must therefore be accounted for in the empirical design.

In contrast, R&D subsidies were in place well before the start of our observation period. These subsidies are not necessarily granted to the same firms continuously; instead, firms may receive them intermittently, creating both "leavers" and "joiners" over time.

We employ a difference-in-differences approach designed to accommodate heterogeneous treatment effects, following the methodology recently developed by De Chaisemartin and D'Haultfoeuille (2024). This flexible approach allows for binary, discrete, or continuous treatments, accounts for potential lagged effects of the treatment on the outcome and accommodates treatments that persist over time as well as cases where firms exit and re-enter the treatment status.

The treatment effect is specified as follows:

$$\delta_{g,\ell} = E[Y_{g,F_g-1+\ell} - Y_{g,F_g-1+\ell}(D_{g,1}, \dots, D_{g,1}) \mid \boldsymbol{D}],$$

where:

- g is a group with the same period one treatment,
- $Y_{g,t}(d_1, \dots, d_t)$ is the potential outcome of g at period t, and d_t is the treatment,
- $\ell \in \{1, \dots, T_g - F_g + 1\}$ are the periods from one to the maximum number of event-study effects. T_g denotes the last period where there is still a group with the same period-one treatment as g and whose treatment has not changed since the start of the panel, and F_g is the first period at which group g's treatment changes.

As outlined by De Chaisemartin and D'Haultfoeuille (2024), the treatment effect is defined as "the expected difference between group g's actual outcome at $F_g - 1 + \ell$ and its counterfactual "status quo" outcome if its treatment had remained equal to its period-one value from period one to $F_g - 1 + \ell$". De Chaisemartin and D'Haultfoeuille (2024) refer to this estimated effect as the "actual-versus-status-quo" (AVSQ) effect for group g. This term is a refined variant of the average treatment effect on the treated, ATT.

In designs where the treatment is binary and groups can join and then leave treatment, the treatment effect becomes

$$\delta_{g,\ell} = E\left[Y_{g,F_g-1+\ell}(\mathbf{0}_{F_{g-1}}, \mathbf{1}_{E_g-F_g+1}, \mathbf{0}_{F_g-1+\ell-E_g}) - Y_{g,F_g-1+\ell}(\mathbf{0}_{F_{g-1+\ell}}) \mid \boldsymbol{D}\right],$$

where $F_g - 1 + \ell > E_g$.

In this case, groups exit treatment at various times, so the effect $\delta_{g,\ell}$ reflects the impact of being treated for a varying number of periods. For example, one group might have been treated for $E_g - F_g + 1$ periods (the time they were in treatment) and then ceased receiving treatment $F_g - 1 + \ell - E_g$ periods before the outcome is measured. The effect can be interpreted as the average effect of having been exposed to a higher level of treatment for ℓ periods.

The above interpretation of the treatment effects applies to both subsidy analyses, as firms can enter and exit subsidy programs at different points in time.

The dependent variables examined differ between the analyses of the effects of compensation subsidies and R&D subsidies, reflecting the distinct objectives of each program. Compensation subsidies are intended to enhance the competitiveness of recipient firms. Accordingly, the key dependent variables in our analysis include the number of employees, value added, and value added per employee. In contrast, R&D subsidies aim to foster innovation, which may be reflected in increased patenting activity. Therefore, for the analysis of R&D subsidies, the dependent variables are patent citation stocks from the EPO and USPTO. To address data skewness and facilitate interpretation, the dependent variables in both of our subsidy analyses are log-linearized.

Given that treated and control firms remained somewhat different after matching, particularly in terms of firm size, we also estimate models including various background characteristics as explanatory variables. The control variables in our analysis of the compensation subsidy are the size of the firm (binned, e.g. 50-249 employees), the cumulative sum of all R&D subsidies that the firm has received, the cumulative aggregate value of additional (or "extra") emission allowances allocated to the firm, and the yearly value of refunds received from energy taxes.

Many firms in our sample receive multiple types of subsidies simultaneously and may also participate in the EU ETS, so these variables are included to control for overlapping retaining and renewing subsidy schemes and to isolate the specific effect of the compensation subsidy.

In the analysis of the impacts of R&D subsidies, the control variables include the number of employees and a binary indicator for foreign ownership. Additionally, we account for the total value of energy-related subsidies or benefits, defined as the sum of the compensation subsidy, energy tax refunds, and extra emission allowances. The total amount of these subsidies may influence the effectiveness of R&D subsidies by shaping firms' financial constraints and investment decisions. Including this aggregate measure may help to isolate the specific impacts of R&D subsidies from those of other financial support.

Patenting activities are likely to differ substantially across sectors due to variation in innovation intensity, market dynamics, technological opportunities, and the stage of innovation, and therefore incorporating sector-specific trends is essential to ensure more accurate estimation of the effects of R&D subsidies. While these trends are particularly relevant for patent-related analysis, they are included for the analysis of the compensation subsidy as well, to provide a comprehensive comparison across model specifications.

5 Results

5.1 Compensation subsidy & Electrification aid

We report the empirical findings concerning the impacts of the compensation subsidy and the Electrification Aid in Table 4. The results are reported using three different model specifications: column (1) excludes control variables, column (2) includes the control variables outlined in the previous section, and column (3) incorporates the control variables and allows for the sector-specific trends.

Regarding the model in column (3), the sample that is used to study the compensation subsidy is relatively small, and as such different trends in each sector may not be clear. Additionally, it is worth noting that when the sector-specific trends are allowed, the placebo effect in year -1 becomes statistically significant for value added and value added per employee. This could indicate some anticipatory effects, particularly since the firms applied for the subsidy a year before receiving it. However, these results should be interpreted with caution due to the small number of firms within each sector. For these reasons, our main specification is the model with control variables but no varying sector trends in column (2).

Table 4: Estimation results for the effects of the compensation subsidy

Dependent variables	(1) No control variables	(2) Control variables	(3) Control variables + trends
Ln number of employees			
t+1	-0.0381**	-0.0390	-0.0175
	(0.0186)	(0.0247)	(0.0339)
t+2	-0.0920**	-0.0731*	-0.0615
	(0.0375)	(0.0412)	(0.0556)
t+3	-0.0915**	-0.0295	-0.0202
	(0.0430)	(0.0502)	(0.0693)
t+4	-0.0836	-0.0852*	-0.0952
	(0.0514)	(0.0472)	(0.0617)
t+5	-0.0679	0.0142	-0.00117
	(0.0660)	(0.0562)	(0.0648)
Overall effect	-0.0759*	-0.0440	-0.0401
	(0.0398)	(0.0374)	(0.0478)
Ln value added			
t+1	0.0475	0.0587	0.0807*
	(0.0676)	(0.0760)	(0.0477)
t+2	-0.0463	-0.0420	-0.0125
	(0.0981)	(0.0981)	(0.0832)
t+3	-0.0874	-0.119	0.00927
	(0.0932)	(0.0994)	(0.142)
t+4	-0.163*	-0.201*	-0.0805
	(0.0992)	(0.116)	(0.116)
t+5	-0.208	-0.149	-0.00618
	(0.131)	(0.127)	(0.123)
Overall effect	-0.0899	-0.0888	-0.000624
	(0.0780)	(0.0803)	(0.0700)
Ln value added per employee			
t+1	0.0903	0.105	0.140***
	(0.0677)	(0.0751)	(0.0465)
t+2	0.0595	0.0462	0.0770
	(0.0939)	(0.0938)	(0.0722)
t+3	0.00126	-0.0379	0.0910
	(0.0892)	(0.0913)	(0.123)
t+4	-0.0835	-0.124	-0.000708
	(0.0942)	(0.102)	(0.105)
t+5	-0.111	-0.108	0.0192
	(0.130)	(0.132)	(0.115)
Overall effect	-0.00647	-0.0213	0.0676
	(0.0747)	(0.0752)	(0.0545)
Observations	1023	1023	1023

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 4 visualizes the results of our main specification. The red vertical lines are the confidence intervals. As can be seen, the placebo effects are not statistically significant, which supports the parallel trends assumption.

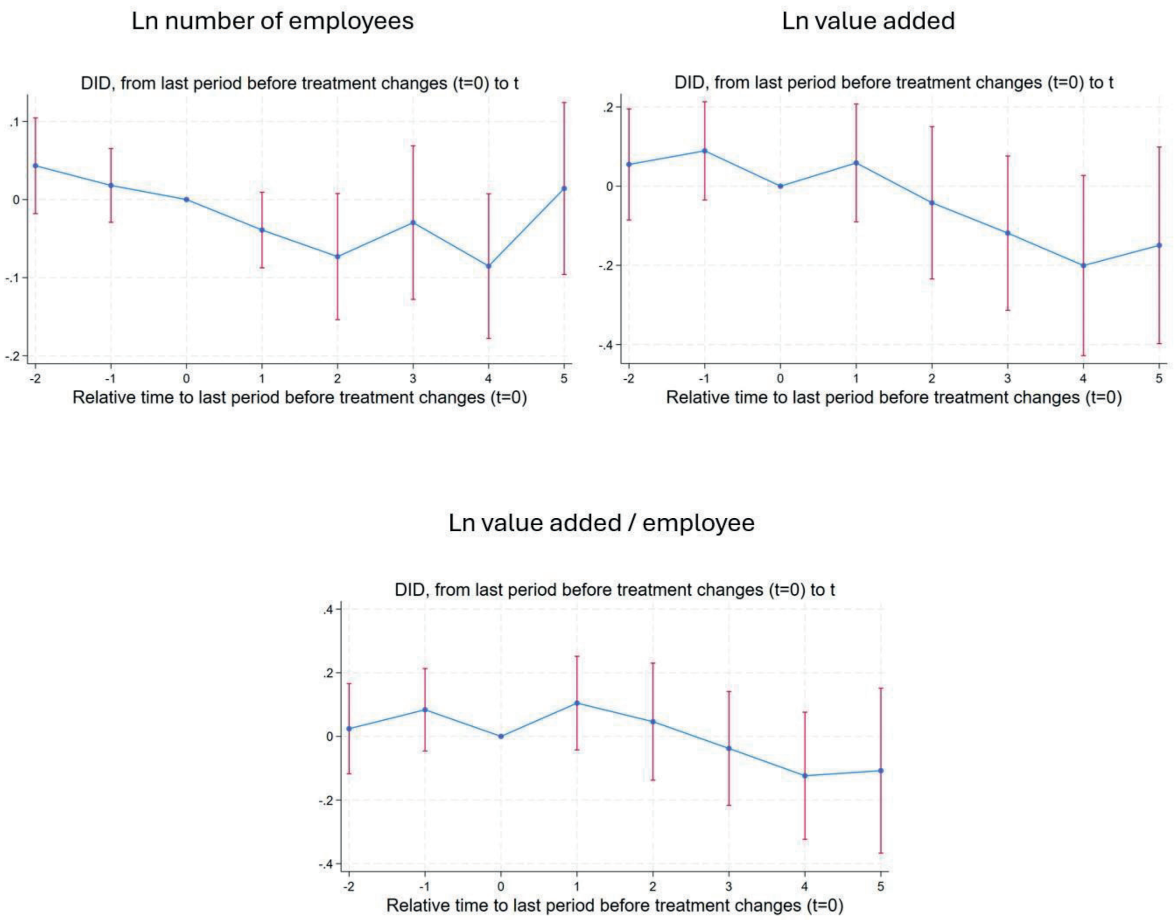

Figure 4: Compensation subsidy results with the main specification

Overall, the findings suggest that the compensation subsidy did not have statistically significant impacts on any of the dependent variables. While some years show negative effects on the number of employees at the 10% significance level, this level is not considered a strong indicator of significance. Without the control variables, this effect is more significant. The controls include the binned firm size with five different size categories (0-9, 10-49, 50-249, 250-499 and 500+ employees), which is naturally correlated with the number of employees. Nevertheless, including this control variable considers the possible differences in employment characteristics within firms of different sizes.

Although the estimated coefficients are predominantly negative, the large standard errors reduce the precision of these estimates. The estimation method does not display the direct effects of control variables; however, a comparison between columns (1) and

(2) shows minimal differences. Notably, including control variables reduces the statistical significance of the effects, suggesting that factors such as firm size partially influence the outcomes. This is the most visible with the number of employees, as noted.

With some possible negative effects on employment numbers, the results overall show that the compensation subsidy did not produce positive outcomes on the performance metrics analyzed. This result suggests that the subsidy has not been effective in its intended purpose of improving firm competitiveness.

5.2 R&D subsidies

Next, we present the findings on the impacts of R&D subsidies in

Table 6. The results are reported using the same three specifications as in Table 4. As discussed above, column (3) represents the most appropriate specification, as it allows for sector-specific trends, which are crucial given the substantial variation in patenting activities across sectors.

The estimation results reveal that R&D subsidies significantly increase the total number of USPTO patent filings, including patents related to climate change mitigation technologies. Additionally, all EPO patent filings begin to rise starting from the third year after the subsidy, with the overall effect being both positive and statistically significant. However, no statistically significant effects are observed for EPO climate change mitigation technology patents. This could partly be due to the relatively low volume of patenting activity in this category, resulting in insufficient observations to achieve significant results. Table 5 provides the number of observations with some patenting activity for each patent type, and the count for EPO green patents is notably lower compared to other categories.

Table 5: Statistics for the patent stock values

Group		USPTO	USPTO: green patents	EPO	EPO: green patents
Treated	Mean	0.64	0.32	0.90	0.84
	Standard deviation	4.63	3.78	6.46	10.05
	Obs with positive values	463	141	227	92
Control	Mean	0.16	0.01	0.22	0.03
	Standard deviation	1.78	0.26	2.47	0.61
	Obs with positive values	131	7	114	22

Table 6: Estimation results for the effects of R&D subsidies

Dependent variables	(1) No control variables	(2) Control variables	(3) Control variables + ind trends
Ln USPTO			
t+1	0.224***	0.283***	0.298***
	(0.0712)	(0.0688)	(0.0860)
t+2	0.367***	0.479***	0.524***
	(0.128)	(0.127)	(0.199)
t+3	0.431***	0.600***	0.672***
	(0.155)	(0.152)	(0.228)
t+4	0.565***	0.814***	0.802***
	(0.192)	(0.185)	(0.261)
t+5	0.596**	0.877***	0.804***
	(0.238)	(0.226)	(0.306)
Overall effect	0.751***	1.041***	1.090***
	(0.242)	(0.235)	(0.357)
Ln USPTO: green patents			
t+1	0.138**	0.159***	0.183***
	(0.0596)	(0.0572)	(0.0679)
t+2	0.132	0.163*	0.174*
	(0.0974)	(0.0951)	(0.103)
t+3	0.291**	0.316***	0.313**
	(0.122)	(0.117)	(0.122)
t+4	0.528***	0.532***	0.429***
	(0.160)	(0.143)	(0.136)
t+5	0.558***	0.628***	0.469***
	(0.193)	(0.184)	(0.170)
Overall effect	0.543***	0.594***	0.543***
	(0.199)	(0.187)	(0.196)
Ln EPO			
t+1	-0.0223	-0.00358	0.0212
	(0.0611)	(0.0591)	(0.0536)
t+2	0.153	0.235*	0.283*
	(0.138)	(0.134)	(0.164)
t+3	0.463**	0.598***	0.831***
	(0.200)	(0.192)	(0.193)
t+4	0.550**	0.724***	0.803***
	(0.246)	(0.233)	(0.214)
t+5	0.559*	0.824***	0.892***
	(0.297)	(0.280)	(0.305)
Overall effect	0.547*	0.765***	0.935***
	(0.293)	(0.279)	(0.291)
Ln EPO: green patents			
t+1	0.0386	0.0391	0.0439
	(0.0343)	(0.0329)	(0.0295)
t+2	0.0990	0.105	0.117
	(0.0752)	(0.0743)	(0.0746)
t+3	0.222*	0.225*	0.320
	(0.120)	(0.119)	(0.199)
t+4	0.241	0.222	0.249
	(0.165)	(0.161)	(0.211)
t+5	0.274	0.263	0.239
	(0.191)	(0.189)	(0.220)
Overall effect	0.290	0.285	0.335
	(0.180)	(0.177)	(0.233)
Observations	7430	7430	7430

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Since we use the logarithmic form of the dependent variables, the effects are expressed as percentage differences. In difference-in-difference analyses, log-transformed dependent variables indicate differences in growth rates between the treated and control groups (McConnell, 2024). Our empirical approach compares both the differences with the untreated control group and with switchers, leading to a slightly different interpretation. Specifically, our results approximate the differences in the growth rates of patent stocks when firms receive subsidies versus when they do not.

For instance, in the case of the total effect on USPTO green patents, the interpretation is that receiving the subsidy increases the normalized patent citation stocks by $(e^{0.543} - 1) * 100\% = 72\%$ compared to when the firms do not receive subsidies. The effects of the subsidies are therefore significant in relative terms. In the case of all USPTO patents, the difference is 197%, and for all EPO patents it is 155%. To provide additional context, Table 5**Error! Reference source not found.** presents the mean values for each type of patent stock. The larger growth rates observed for subsidy recipients suggest that the differences between recipients and non-recipients will become even more pronounced over time.

As illustrated in Figure 5, the placebo effects in the estimations concerning the impacts of R&D subsidies were statistically insignificant, reinforcing the robustness of the results.

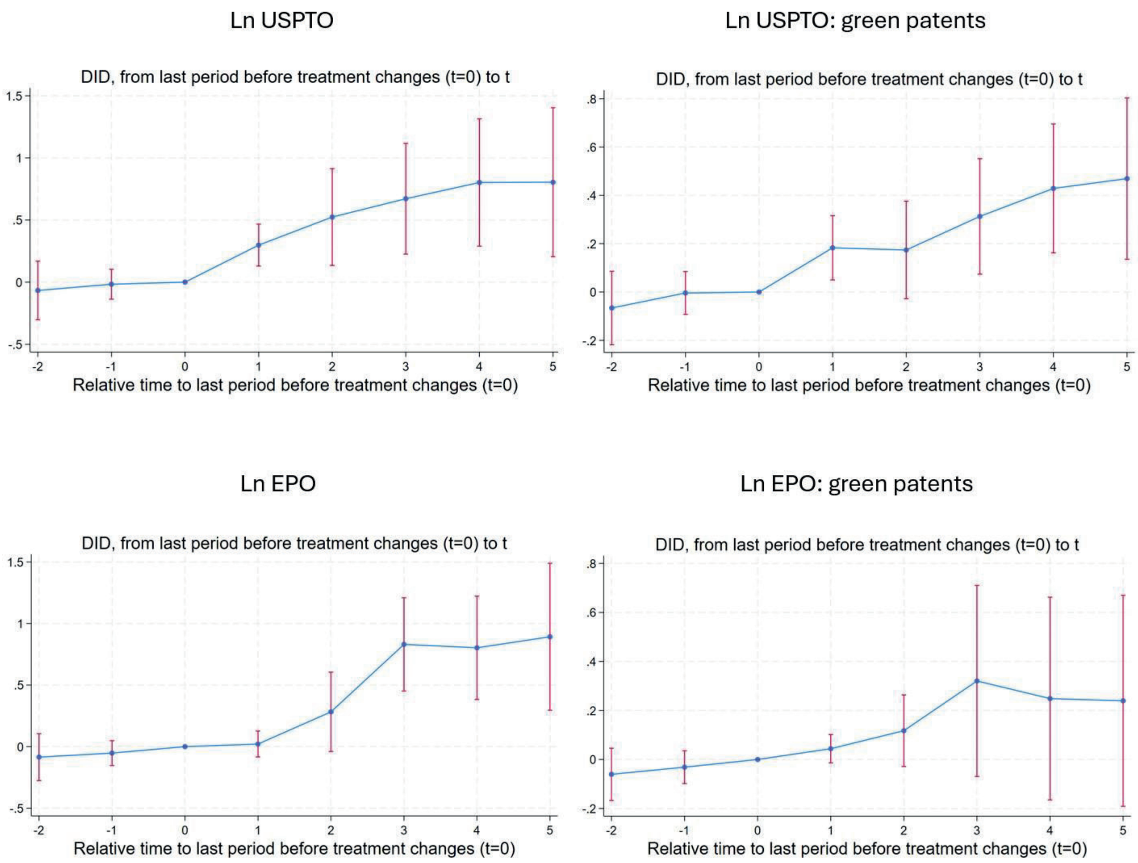

Figure 5: R&D subsidy results with the main specification

6 Conclusions

This study investigated the economic impacts of subsidies allocated on energy-intensive firms in Finland, focusing on the following primary types: EU ETS indirect cost compensation and the Electrification Aid, and R&D subsidies. The analysis offers insights into the effectiveness of these measures in enhancing competitiveness, fostering innovation, and facilitating the transition to a low-carbon economy.

Our results indicate that the EU ETS indirect cost compensation subsidy and its successor, Electrification Aid, did not lead to statistically significant improvements in the economic outcomes of recipient firms. The estimated impacts on employment, value added, and labor productivity were negative, albeit mostly not statistically significant. These findings suggest that the subsidies may not have effectively achieved their objectives of enhancing competitiveness and preserving jobs in energy-intensive industries.

Several factors may explain the lack of measurable impacts. First, the wide confidence intervals highlight sample size limitations, which may have hindered the detection of small effects. Second, the subsidies might have primarily served as financial support than as drivers of efficiency or innovation. Notably, the compensation subsidy faced criticism for its design lacking incentives for greener production methods or energy efficiency enhancements. Although Electrification Aid sought to address these issues by requiring at least 50% of the subsidy to fund development measures, its short implementation period limited our ability to assess its long-term impacts.

In contrast, the analysis of R&D subsidies yielded more encouraging results. R&D subsidies were associated with a statistically significant increase in climate change mitigation technology patent citation stocks for patents filed with the USPTO. In addition, total USPTO and EPO patent citation stocks demonstrated significant growth across the examined years, indicating broader support for innovation.

These findings underscore the greater potential of R&D-focused policies to drive long-term economic and technological advancements compared to compensatory support measures. While the R&D subsidies demonstrated positive impacts on innovation, the EU ETS indirect cost compensation and Electrification Aid failed to significantly enhance competitiveness, raising questions about their efficiency and design. This suggests that alternative mechanisms, such as direct incentives for energy efficiency and greener production methods, may be more effective in achieving policy goals.

This study acknowledges certain limitations, particularly regarding sample size and data availability for studying the impacts of compensation subsidies. Despite these constraints, the findings underscore the need for more targeted funding strategies that align subsidies with both environmental and economic objectives. To maximize their effectiveness, subsidies should be carefully designed and subject to evaluation to ensure their alignment with sustainability goals. Policymakers should prioritize evidence-based approaches, iterative assessments of subsidy programs, and adaptive frameworks to ensure that subsidies effectively support industrial renewal and sustainable economic growth.

References

Battarelli, L., Furceri, D., Pizzuto, P. & Shakoor, N. (2023). Environmental Policies and Innovation in Renewable Energy. IMF Working Paper 2023/180, International Monetary Fund, Washington, DC.

Bayer, P. & Aklin, M. (2020). The European Union Emissions Trading System reduced CO2 emissions despite low prices. *Proceedings of the National Academy of Sciences, 117*(16), 8804–8812.

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

Colmer, J., Martin, R., Muuls, M., & Wagner, U. (2024). Does pricing carbon mitigate climate change? Firm-level evidence from the European Union Emissions Trading Scheme. *The Review of Economic Studies*. In press.

Criscuolo C. & Martin R. (2009). Multinationals and U.S. productivity leadership: Evidence from Great Britain. *The Review of Economics and Statistics*, 91(2), 263–281.

De Chaisemartin, C., & D'Haultfœuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *The Review of Economics and Statistics*, 2024, 1–45.

Dechezleprêtre, A., Nachtigall, D., & Venmans, F. (2023). The joint impact of the European Union emissions trading system on carbon emissions and economic performance. *Journal of Environmental Economics and Management*, 118, 102758.

Ferrara, A. R. & Giua, L. (2022). Indirect cost compensation under the EU ETS: A firm-level analysis. *Energy Policy, 165*, 112989.

Fornaro, P., Koski, H., Pajarinen, M. & Ylhäinen, I. (2020). Evaluation of Tekes R&D funding to the European Commission. *Impact Study, Business Finland Report 3/2020*.

Gök, A. & Edler, J. (2012). The use of behavioural additionality evaluation in innovation policy making. *Research Evaluation*, 21(4): 306-318.

Hall, B.H. & MacGarvie, M. (2010). The private value of software patents. *Research Policy* 39, 994–1009.

Hall, B. H., Thoma, G., & Torrisi, S. (2007). The market value of patents and R&D: Evidence from European firms. *Academy of Management Proceedings*, *2007*(1), 1–6.

Hall B.H. & Ziedonis, R.H. (2001). The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979–1995. *Rand Journal of Economics* 32, 101–28.

Harhoff, D., Gambardella, A. & Verspagen, B. (2008). The value of European patents. CEPR Discussion Papers 6848.

Harhoff, D., Narin, F. & Vopel, K. (1999). Citation frequency and the value of patented inventions. *The Review of Economics and Statistics, 81*(3): 511-15.

Howell S.T. (2017). Financing innovation: Evidence from R&D grants. American Economic Review, 107(4), 1136-1164.

Kässi, O. (2024). Vihreän siirtymän ja digitalisaation tuet Suomessa. ETLA Raportti No 147.

Laukkanen, M., Ollikka K. and Tamminen, S. (2019). The impact of energy tax refunds on manufacturing firm performance: Evidence from Finland's 2011 energy tax reform. Publications of the Government's analysis, assessment and research activities 2019:32.

Link, A.N. & Scott, J.T. (2018). Propensity to patent and firm size for small R&D-intensive firms. *Review of Industrial Organization* 52, 561–587.

Marin, G., Marino, M. & Pellegrin, C.(2018). The impact of the European Emission Trading Scheme on multiple measures of economic performance. *Environmental and Resource Economics*, *71*, 551–582.

McConnell, B. (2024). Can't See the Forest for the Logs: On the Perils of Using Difference-in-Differences With a Log-Dependent Variable. Working Paper.

Rentocchini, F., Vezzani, A. & Montresor, M. (2023), Walking the Green Line: Government Sponsored R&D and Clean Technologies, JRC Working Papers on Corporate R&D and Innovation series No 01/2023, European Commission, JRC133670.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics, 225(2).

Wang, M. (2024). Does compensating firms for indirect carbon costs work? Evidence from Finnish manufacturing. *Journal of Finnish Economic Analysis, 1*(2024).

Appendix

Robustness checks

Compensation subsidy effects: alternative econometric method

As an alternative empirical approach, we employ the Event Study Interact methodology developed by Sun and Abraham (2021) to analyze the effects of the Electrification Aid. The Event Study Interact approach is suited for examining dynamic treatment effects in settings with staggered adoption of the treatment. It extends the standard event study framework by allowing for interaction effects and addressing potential biases arising from differential timing of treatment adoption.

The core specification of the Event Study Interact model can be represented as follows:

$$Y_{it} = \alpha_i + \gamma_t + \sum\nolimits_{g \in K} \beta_k D_{it}^k + \sum\nolimits_{g \in K} \delta_k D_{it}^k X_{it} + \epsilon_{it}$$

where

- Y_{it} is the outcome variable for unit i at time t,
- α_i represents unit fixed effects,
- γ_t represents time fixed effects,
- D_{it}^k is an indicator variable that equals 1 if unit i is k periods away from treatment at time t, and 0 otherwise,
- The set K collects disjoint sets g of relative periods $k \ \in [-T, T]$. Some relative periods are allowed to be excluded from the specification to avoid multicollinearity. The excluded set is denoted with $g^{excl} = \{k : k \ / \in \cup_{g \in K} \ g\}$,
- X_{it} is a vector of covariates that may interact with the treatment effect,
- ϵ_{it} is the error term.

The coefficients β_k capture the average treatment effects at different time periods relative to the treatment event. The interaction terms, captured by δ_k, allow for heterogeneous treatment effects conditional on covariates.

The control variables X_{it} that are included in our analysis are the same as in the main specification.

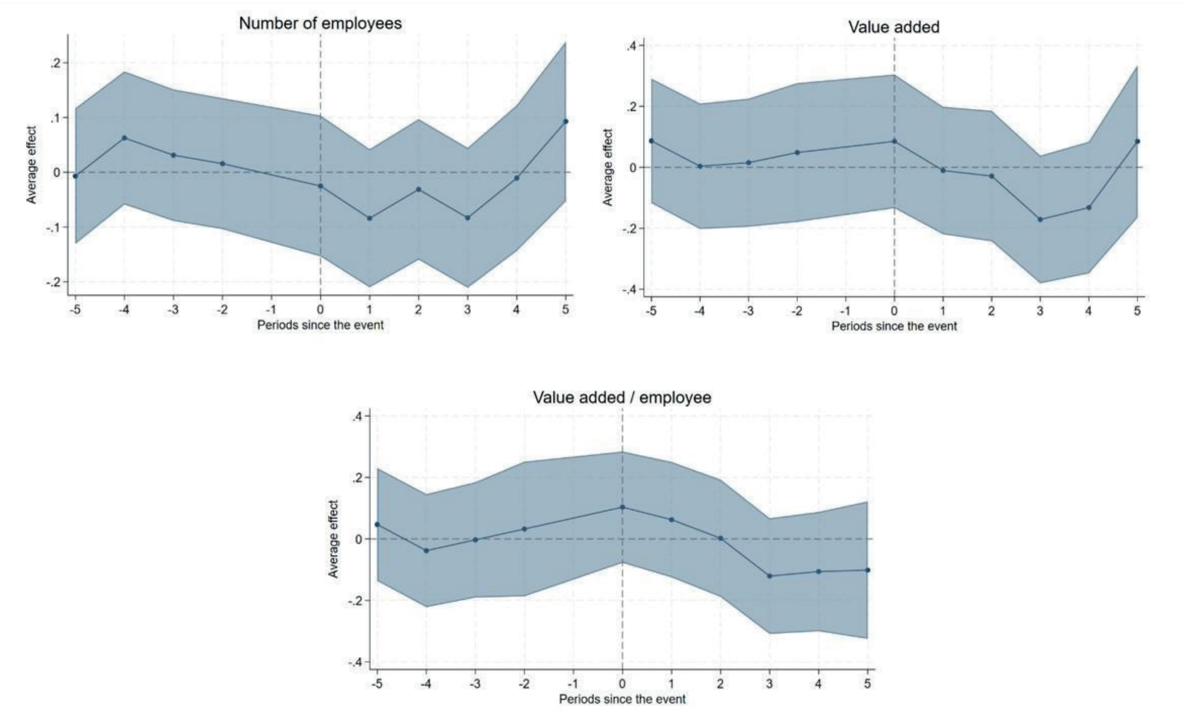

Figure A1: Event study graphs

As illustrated in Figure A1 and Table A1, the findings align closely with our main specification, indicating that the compensation subsidy does not exhibit any statistically significant impact on the dependent variables.

Table A1: Detailed results for the event study interact analysis

	(1) Ln number of employees	(2) Ln value added	(3) Ln value added / employee
Compensation subsidy	-0.0236	-0.0286	-0.0268
	(0.0503)	(0.0829)	(0.0739)
Energy tax returns (mil)	0.00878**	0.00729	-0.00148
	(0.00382)	(0.00557)	(0.00499)
Cum sum of BF subsidies (mil)	-0.00321	0.00924	0.0133**
	(0.00381)	(0.00590)	(0.00528)
Cum value of emission allowances (mil)	-0.00484	-0.0161	-0.0118
	(0.00862)	(0.0124)	(0.0111)
Size	0.583***	0.398***	-0.0618
	(0.0264)	(0.0490)	(0.0438)
Observations	1,019	754	754

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Dependent variables in levels

Tables A2 and A3 present our estimation results using dependent variables in levels rather than logarithms. As shown, the results remain consistent with this alternative method. For the compensation subsidy, Table A2 indicates no significant impacts, aligning with the findings from our main specification.

Table A3 displays the results for the R&D subsidy analysis. Once again, the results exhibit similar signs and significance levels as those in the main specification. The only exception is for USPTO patents, where the estimated coefficients are not statistically significant. These results are interpreted as the differences in patent stock growth when firms receive subsidies.

For context, the mean USPTO patent stock is 0.64 for the treated group and 0.16 for the control group, suggesting that the overall effect of 1.57 would represent a relatively large impact, consistent with our main findings. However, in this case, the large standard errors render the effect statistically insignificant.

Table A2: Compensation subsidy results

Dependent variables	(1) No controls	(2) Control variables	(3) Control variables + trends
Number of employees			
t+1	-62.80	-62.95	-62.71
	(43.69)	(43.56)	(42.23)
t+2	-84.77*	-91.66	-92.95*
	(50.57)	(59.22)	(56.48)
t+3	-77.40	-106.4*	-107.1*
	(49.16)	(64.04)	(62.04)
t+4	-86.54	-114.1*	-113.2*
	(54.54)	(69.03)	(67.42)
t+5	-95.32*	-84.69*	-80.12
	(56.71)	(51.47)	(51.50)
Overall effect	-82.81	-93.76	-93.04*
	(51.32)	(57.82)	(56.22)
Value added (million euros)			
t+1	54.23	61.82	59.07***
	(37.19)	(45.82)	(9.214)
t+2	-5.373	-12.49	-31.81
	(12.65)	(19.07)	(31.73)
t+3	-27.97*	-59.05*	-62.73*
	(16.15)	(31.74)	(34.92)
t+4	-28.59	-58.73	-59.82
	(26.87)	(42.20)	(44.42)
t+5	19.12	27.94	13.24
	(22.15)	(23.33)	(34.56)
Overall effect	3.236	-7.019	-15.36
	(14.75)	(19.72)	(20.86)
Value added per employee			
t+1	29,215*	33,264*	39,447***
	(14,908)	(18,126)	(8,789)
t+2	12,234	8,871	10,434
	(13,726)	(13,950)	(24,777)
t+3	10,682	-2,416	7,238
	(12,287)	(13,829)	(13,773)
t+4	10,755	-1,958	5,394
	(14,775)	(18,143)	(20,872)
t+5	9,865	12,945	5,707
	(26,639)	(27,560)	(26,280)
Overall effect	15,074	10,737	14,372
	(9,174)	(9,417)	(9,480)
Observations			

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: R&D subsidy results

Dependent variables	(1) No control variables	(2) Control variables	(3) Control variables + ind trends
USPTO			
t+1	0.147	0.200*	0.204
	(0.113)	(0.111)	(0.139)
t+2	0.341	0.445	0.500
	(0.311)	(0.299)	(0.380)
t+3	0.505	0.720	1.057*
	(0.497)	(0.473)	(0.613)
t+4	0.908	1.278	1.314
	(0.899)	(0.850)	(0.898)
t+5	1.267	1.614*	1.667
	(0.939)	(0.925)	(1.210)
Overall effect	1.020	1.377	1.570
	(0.878)	(0.842)	(1.061)
USPTO: green patents			
t+1	0.0596*	0.0341	0.0707***
	(0.0354)	(0.0329)	(0.0247)
t+2	0.198	0.174	0.150**
	(0.140)	(0.135)	(0.0677)
t+3	0.265*	0.180	0.317***
	(0.145)	(0.120)	(0.111)
t+4	0.433	0.216	0.219*
	(0.294)	(0.172)	(0.118)
t+5	0.599*	0.458*	0.396**
	(0.341)	(0.250)	(0.165)
Overall effect	0.503*	0.344*	0.392**
	(0.267)	(0.191)	(0.160)
EPO			
t+1	0.340	0.464**	0.355**
	(0.207)	(0.208)	(0.146)
t+2	0.968*	1.187**	0.919*
	(0.531)	(0.535)	(0.542)
t+3	1.875**	2.368***	2.143***
	(0.749)	(0.778)	(0.816)
t+4	2.133**	3.064***	1.976**
	(0.976)	(1.059)	(0.979)
t+5	3.097**	4.208**	2.496**
	(1.476)	(1.652)	(1.213)
Overall effect	2.748**	3.669***	2.660**
	(1.189)	(1.270)	(1.214)
EPO: green patents			
t+1	0.296	0.248	0.0383
	(0.209)	(0.203)	(0.105)
t+2	0.370	0.333	0.0500
	(0.291)	(0.286)	(0.178)
t+3	0.486*	0.376*	0.287
	(0.266)	(0.228)	(0.211)
t+4	1.047	0.743	0.282
	(0.670)	(0.517)	(0.227)
t+5	1.458	1.269	0.456*
	(0.949)	(0.835)	(0.254)
Overall effect	1.189*	0.964	0.359
	(0.716)	(0.629)	(0.325)
Observations	7430	7430	7430

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Tel. +358-9-609 900
www.etla.fi
firstname.lastname@etla.fi

Arkadiankatu 23 B
FIN-00100 Helsinki