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Implications of tax incentives and tax complexity

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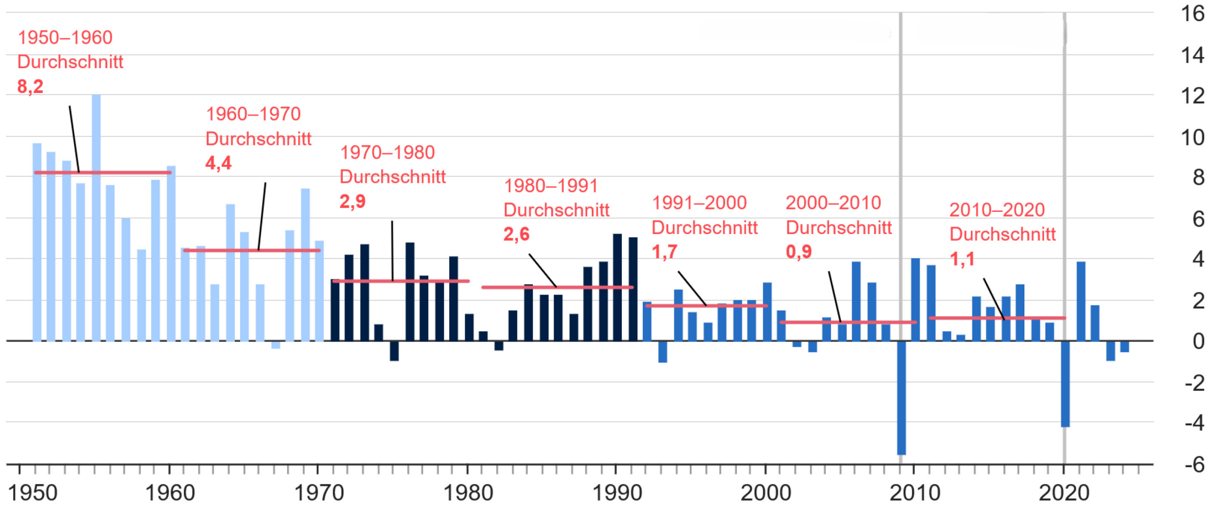
With Love to my family:
Mum, Dad, Marina, Eva-Maria, Florian,
and my Grandparents

Preface

Economic growth in Germany has slowed markedly in recent decades. Following a period of uninterrupted economic expansion since the 1950s, with growth rates of up to 12.1%, gross domestic product subsequently recorded an average growth rate of up to 6.4% in the following decades (Statistisches Bundesamt, 2025). However, in more recent years, GDP growth slowed steadily with an average annual increase of only around 1% between 2000 and 2020 (see Figure I).

Figure I: Economic growth: Gross domestic product adjusted for price changes, change compared to the previous year in percentage.



Source: Statistisches Bundesamt, 2025a

This substantial decline in growth is attributable, on the one hand, to cyclical economic factors. The German economy is recovering only slowly from the shocks triggered by the global COVID-19 pandemic and Russia's war of aggression against Ukraine. On the other hand, the slowdown in growth is increasingly rooted in structural inefficiencies. These include, in particular, increased bureaucratic burdens due to reporting and documentation requirements, shortcomings in the education system, rising labor costs, the transition toward climate neutrality, as well as deficiencies in infrastructure, the legal system, and the tax framework.

In order to ease the burden on companies and enhance Germany's attractiveness as a business location, measures must be taken to stimulate private investment and innovation (Eichfelder, 2024; Schmidt, 2025; Hardeck and Heckemeyer, 2023; Hantzsch, 2025).

Accordingly, a draft law for an immediate tax investment program to strengthen Germany's position as a business location was published on June 3, 2025 (Deutscher Bundestag, 2025). The measure includes the extension of declining-balance depreciation for movable assets, the stepwise reduction of the corporate income tax rate, and the expansion of the Research Allowance Act. These measures are intended to provide targeted investment incentives for companies in order to foster economic growth and improve Germany's attractiveness as a business location.

It is evident that tax incentives have the capacity to function as an ancillary instrument with the potential to promote investment. Business decisions not only depend on the availability of labor or land, infrastructure, networks, and legal stability, but also their tax consequences (Eichfelder, 2024). As Hardeck and Heckemeyer (2023) emphasize, the expansion of corporate reporting and disclosure obligations with the aim of reducing tax avoidance is likely to result in increased tax compliance costs. This development is presumably intended to increase competitive pressure on Germany as a business location, where rising costs are expected to lead to a decline in investment activity. In addition, administrative procedures in Germany detract from the country's appeal. Lengthy tax audits and mutual agreement procedures, as well as extended assessment periods and processing times, negatively affect Germany's competitiveness (Eichfelder, 2024; Hardeck and Heckemeyer, 2023).

It has been shown that tax incentives constitute an appropriate instrument for enhancing the attractiveness of a business location. Beyond their fiscal effects, tax incentives can stimulate private (corporate) investment and thereby improve additional location-specific factors. The dissertation examines various structural for measures aimed at increasing the attractiveness of a country as a business location. Chapters 1 and 2 demonstrate that tax incentives can exert a significant influence on firms' investment decisions. These measures aim to foster corporate growth potential, prevent overinvestment, and thereby contribute to job creation. Chapter 1 outlines a tax incentive for automation, which is of critical relevance for Germany as the world's second-largest automobile producer. Chapter 2 focuses on tax incentives for corporate research and development activities. Reducing the cost of research and development is intended to increase firms' investment capacity, with the objective of promoting innovation and productivity. With regard to research expenditures in artificial intelligence, digitalization, and data security, Germany exhibits a considerable lag compared with the United States and China. Preserving the international competitiveness of Germany as a business location, as well as that of the firms operating there, is therefore of central importance. In this context, the contribution provides insight into the applicability of tax incentives in the area of research and development.

As an additional structural measure - alongside the implementation of tax incentives - Chapter 3 discusses the establishment of appropriate tax frameworks conducive to an investment-friendly environment. Chapter 3 shows that complex tax regulations increase firms' costs and thereby reduce firm value. This, in turn, engenders diminished investment levels, encompassing those into research and development, thereby constraining firms' growth potential.

The following section describes the content of the three chapters introduced. The first chapter analyzes the impact of tax incentives for automation on corporate investment, investment quality, and employees. In 2018, South Korea reduced a tax credit for automation investments by 2% for medium-sized and large companies, still maintaining the credit for small companies. A difference-in-differences approach based on this quasi-experiment is used to analyze the causal effect of this reduction on firms' investment. The analysis draws on robot data from the International Federation of Robotics (IFR) and firm-level data from the *Orbis* database (Bureau van Dijk). The results indicate a significant decline in automation investments in the affected industries following the reform, accompanied by an increase in employment within the affected firms. Further firm-level analyses reveal heterogeneity: firms with liquidity constraints reduced overall investment, while firms without such constraints reallocated resources toward more productive uses. Finally, the study finds that such tax credits had previously led to inefficient overinvestment in automation.

In addition to the provision of tax incentives for automation, the existence of tax incentives for research and development has been demonstrated to result in increased investment by companies. This, in turn, has been shown to contribute to the promotion of Germany's attractiveness as a business location. Hence, the draft law of June 3, 2025 (Deutscher Bundestag, 2025) explicitly aims to promote innovation and productivity in companies by expanding tax incentives for research in Germany. The expansion of the research allowance provides additional investment incentives for companies to remain internationally competitive. Chapter 2 of this dissertation focuses on the specific design of the research allowance as an instrument for promoting investment in research and development (R&D). With the introduction of the research allowance in December 2020, companies became able to deduct eligible R&D expenditures from their income or corporate tax liabilities as an indirect tax incentive. Since its introduction, approximately 33,840 applications have been submitted for around 42,231 projects, predominantly by small and medium-sized enterprises (SMEs). To assess the effectiveness of indirect tax incentives for research, the existing literature on their impact was reviewed. It shows that indirect research incentives increase firms' R&D expenditures, employment, and wages in R&D-related positions. The number of newly developed products, more efficient production processes, patent applications, and productivity also rise as a result of indirect tax incentives for research.

Furthermore, the short- and long-term consequences of such incentives are evaluated descriptively based on innovation data from the Federal Ministry of Research, Technology, and Space. The research allowance has led to an increase in R&D expenditure; however, the target set by the federal government at the time of the law's introduction - R&D spending amounting to 3.5% of GDP - has not yet been achieved. Nevertheless, the introduction of the research allowance has resulted in greater innovation, as measured by new product developments, patent applications, and increased business productivity.

However, providing direct investment incentives alone is not sufficient; the existing tax system must also be structured in a way that supports their effectiveness (Giese et al., 2025). Amberger et al., 2025 demonstrate that tax incentives for investment are less effective in the context of complex tax systems. The authors examine the responsiveness of corporate investment to changes in the corporate tax rate, as well as differences in the complexity of tax systems across countries. Their findings suggest that firms are less sensitive to changes in the corporate tax rate when the tax system is more complex. This illustrates that tax complexity diminishes policymakers' ability to influence economic growth. In order to assess the effectiveness of tax incentives, it is therefore necessary to analyze not only the tax incentives themselves but also consider the complexity of the tax system, which I do in the third chapter of this dissertation.

Devereux et al. (2016) show that large multinational enterprises rank tax uncertainty - closely linked to tax complexity - among the three most important location factors. The complexity of the regulatory framework intensified as well. In recent years, the German tax system became considerably more complex. In 2010, there were approximately 1,670 laws comprising 43,086 individual provisions, whereas by 2024 the number had risen to approximately 1,792 laws with 52,468 individual provisions. This represents an increase of 122 laws and roughly 18% more individual provisions over the past 14 years (Deutscher Bundestag, 2020c). The index developed by Hoppe et al. (2023) maps the evolution of tax complexity over time. A rise in tax complexity measures has been observed over time, which is indicative of an increase in tax complexity in an international context.

Chapter 3 of this dissertation evaluates how country-level tax complexity is reflected in firms' market values. The analysis uses data from companies listed in the MSCI World Index, employing a two-way fixed effects regression model. The analysis shows that tax complexity not only increases expenses and compliance costs at the firm level, but also reduces the market value of publicly listed companies. Consequently, an increase in complexity leads to a decline in firms' market value. If the level of complexity had remained constant over the observation period, companies' total market capitalization would have been approximately 2% higher - equivalent to around US$900 billion. Further analyses reveal that this negative effect is particularly pronounced for regulations targeting tax avoidance and in tax assessment procedures. At the firm level, the adverse effect is stronger for companies with limited opportunities for international profit shifting, weak corporate governance, or low internal information quality. In addition to the effects on investment, there are further negative implications, such as lower corporate growth potential and reduced spending on research and development. This paper therefore provides new insights into the economic costs of tax complexity, contributing to the design of a more efficient and equitable tax system and the improvement of tax policy efficiency.

Finally, the relative importance of taxes in corporate investment decisions must also be considered. Compared to other location factors, it remains unclear whether the importance of taxation in determining location attractiveness has been overestimated. Once the publication bias has been revised, the influence of taxes on business decisions becomes more moderated (Eichfelder, 2024).[1] An analysis of location factors confirms that other determinants driven by private or public investment have a greater impact on location attractiveness than taxation (Eichfelder et al., 2022). This finding underscores the notion that the impact of taxation on corporate investment decisions cannot be definitively ascertained. It therefore necessitates further empirical investigation, which this dissertation provides.

[1] See as well: Neiser, 2021; Gechert and Heimberger, 2022; Knaisch and Pöschel, 2023; Pöschel, 2023.

1 Investment Effects of a Quasi-Robot Tax: Evidence from South Korea‡

1.1 Introduction

Automation in industrial processes and services has advanced rapidly in recent years. The number of annual industrial robot installations in Asia increased from 199,481 units in 2016 to 380,078 units in 2021 - a 90% increase in five years. Robots have become attractive partly because current tax practices favor their use. While regular employees must pay income tax on their employment income, robots face no similar tax on their "income". This tax treatment encourages firms to adjust their production processes towards automation.

In response to these trends, several countries (e.g., the USA, Canada, New Zealand, and Poland) are discussing the implementation of a tax on industrial robots, commonly referred to as a "robot tax". A robot tax would not only remove the preferential tax treatment of industrial robots but also compensate countries for lost income tax revenues. Governments could use the additional funds to retrain workers who lose their jobs to automation, as Bill Gates suggested.[3] However, opponents argue that taxing robots could stifle innovation and discourage firms from adopting new technologies, thereby reducing productivity growth and competitiveness. Additionally, there are concerns about the complexity of designing and implementing such a tax, particularly when it comes to defining what qualifies as a "robot" and measuring its economic contribution.

Despite the growing interest in the idea of a robot tax, there is almost no empirical evidence on the real effects of incentivizing or disincentivizing automation investment via

‡ Chapter 1 is unpublished joint work with Svea Holtmann (University of Mannheim), Jae Cho (HEC Lausanne), Reinald Koch (Catholic University Eichstätt-Ingolstadt) and Dominika Langenmayr (Catholic University Eichstätt-Ingolstadt, WU Vienna, CESifo). The author of this dissertation was responsible for a significant portion of the empirical data collection and the analysis of earlier drafts of the paper. In addition, she wrote the first draft of the paper and contributed to its subsequent revisions.

3 See: https://qz.com/911968/bill-gates-the-robot-that-takes-your-job-should-pay-taxes.

taxes. We aim to provide some guidance on these effects by exploiting a reform in South Korea that reduced a long-standing tax credit on automation investments. For decades, South Korean firms benefited from a tax credit that applied to new investments in automated systems, including industrial robots. The 2018 reform reduced the tax credit available to larger firms and those that are part of a large business group. By effectively increasing the cost of automation for some firms, the reform can be interpreted as a quasi-robot tax and serves as a natural experiment that allows us to evaluate the potential impacts of a robot tax.

Understanding how tax regulations affect firms' real investment decisions is central to accounting research, as it connects tax policy to firms' resource allocation and reporting behavior. Recent studies highlight the importance of examining such real effects of tax regulation on corporate actions (see, e.g., Lester and Olbert, 2025). By focusing on the potential consequences of a robot tax, this paper contributes to this emerging line of research at the intersection of taxation, accounting, and real economic outcomes.

It is particularly worthwhile to study the investment effects of a quasi-robot tax (or a tax credit targeted at automation) because they are likely distinct from those of broader tax incentives. Corporate tax rates influence the cost of capital for all types of investment, and general tax credits or accelerated depreciation provisions usually affect a wide range of assets. In contrast, the quasi-robot tax directly impacts a narrowly defined category of investment. This specificity may result in different overall investment responses, as firms weigh the unique costs and benefits of automation relative to other capital expenditures. Furthermore, such targeted measures could lead to substitution effects, prompting firms to shift resources between automation and other forms of investment in ways that broader policies do not. Finally, the consequences of discouraging automation - such as a shift toward more labor-intensive production and potential changes in investment efficiency - are of particular interest. Our analysis speaks directly to these margins by examining both the quantity and the composition of investment, as well as related consequences on employment and firm performance.

In the first part of our empirical analysis, we investigate whether the quasi-robot tax (i.e., the reduction in the tax credit) led to a decline in robot adoption within South Korea. We employ two identification strategies to examine this effect. First, we combine industry-level data on robot installations from the International Federation of Robotics (IFR) with firm-level financial data from *Orbis*. Using the *Orbis* data, we construct a measure of industry-level exposure to the reform based on the share of firms affected by the tax credit reduction. The policy change applied only to large and medium-sized firms, as well as to small firms affiliated with a large business group. We find that industries with a higher share of treated firms experienced significantly lower robot adoption following the reform. As a complementary analysis, we also test the effect on industry-level robot installations in a cross-country difference-in-differences (DiD) setting. We find that Korean industries decreased robot installations by 28% relative to their Japanese counterparts following the reform.

Second, we directly leverage the firm-level data, which enables us to implement a DiD design. As the *Orbis* data do not include direct measures of automation investments, we use investment in fixed tangible and intangible assets as proxy. The firm-level analysis corroborates the industry-level findings. On average, treated firms reduced their investment in tangible and intangible fixed assets (relative to total assets) by approximately 3%-points relative to unaffected firms.

In the second part of the analysis, we further explore the firm-level data to examine indirect effects of the reform and heterogeneity in firm responses. Specifically, we assess whether firms increased their reliance on labor to compensate for reduced automation. The existing literature draws no clear picture, as to whether robots and employees are substitutes or complements. Some studies find that robots substitute for human labor, particularly in routine and manual tasks, leading to job displacement and reduced wages (Frey and Osborne, 2017; Acemoglu and Restrepo, 2020; Bonfiglioli et al., 2024; Giuntella et al., 2024; Bessen et al., 2025). Conversely, other research suggests that robots complement human workers by enhancing productivity and creating new employment opportunities without reducing overall employment levels (Autor, 2015; Graetz and Michaels, 2018; Dauth et al., 2021). Our findings contribute to this debate by providing firm-level evidence that supports the substitutability between robots and employees. We find evidence of a positive effect on firm-level employment in the sub-sample of less financially constrained firms, suggesting that robots and employees act as substitutes here; the average effect in the full sample is, however, statistically indistinguishable from zero.

While we observe that the reduction in the tax credit lowers the *quantity* of investment, it may also affect the *quality* of investment. A generous tax credit can induce overinvestment by encouraging firms to adopt automation technologies that are not necessarily productivity-enhancing. If so, scaling back the credit could improve allocative efficiency. Alternatively, the tax credit might have been necessary to overcome firms' reluctance to adopt new technologies, and its removal could exacerbate underinvestment. Moreover, the reduced credit implies that firms have less cash on hand, which could constrain investment, especially for financially constrained firms. To examine this, we use current and future turnover and profit as proxies for investment quality. We find positive effects among financially unconstrained firms, suggesting that the pre-reform tax incentive may have led to inefficient overinvestment in automation. No such effect is observed among financially constrained firms.

Taken together, our results suggest that the quasi-robot tax had asymmetric effects across firms, depending on their financial constraints. Unconstrained firms appear to have substituted away from robot investments toward other production technologies involving additional labor. This reallocation was accompanied by gains in investment quality. By contrast, financially constrained firms responded by cutting overall investment, with no comparable offsetting effects on employment or investment quality. These findings also imply that when tax incentives explicitly favor automation, countries may inadvertently encourage overinvestment in robotics, leading to inefficient capital allocation and potentially exacerbating disparities between financially constrained and unconstrained firms.

Our study is related to the large literature on how firm-level tax incentives influence investment decisions (see Jacob, 2022, for a survey). Lower corporate tax rates (Dobbins and Jacob, 2016; Giroud and Rauh, 2019; Coles et al., 2022; Link et al., 2024) and more generous depreciation allowances (Wielhouwer and Wiersma, 2017; Zwick and Mahon, 2017; Maffini et al., 2019; Ohrn, 2019; Garrett et al., 2020; Curtis et al., 2021) increase investment, but may decrease investment quality (Eichfelder et al., 2023). Effect sizes vary significantly, depending, e.g., on financial constraints (Zwick and Mahon, 2017; Dobbins and Jacob, 2016) or losses (Edgerton, 2010). Ohrn (2018) and Lester (2019) study the U.S. Domestic Production Activities Deduction Act, which allows firms to deduct part of income related to domestic production, and both find substantial investment responses. These papers studied broad-based tax incentives that lowered the cost for all or for most forms of investment, whereas we focus on a tax credit aimed only at a specific type of capital, automation investment.

We also contribute to this literature by providing novel evidence on how financial constraints shape firm-level responses to tax-based investment incentives. Zwick and Mahon (2017) show that financially constrained firms are 1.5 to 2.6 times more responsive to bonus depreciation than their less constrained counterparts. Orihara and Suzuki (2023) confirm the finding of a stronger investment response by more constrained firms to temporary investment incentives in a Japanese firm panel. Our findings extend this insight by demonstrating that financial frictions not only affect the magnitude of investment responses but also influence the underlying adjustment mechanisms and potential substitution patterns across input factors. In this sense, our findings also speak to the literature on the determinants of over- and underinvestment and investment efficiency (Biddle and Hilary, 2006; Biddle et al., 2009).

Furthermore, we contribute to the literature on the implications and the optimal design of robot taxation (see Bastani and Waldenström, 2024, for a survey of this largely theoretical literature). As the reduction in the tax credit is similar to the introduction of a robot tax, we can provide some empirical insights on the implications that the introduction of a robot tax would have.[4] Lastly, a concurrent working paper by Kang et al. (2024) also examines the South Korean reform. They document reduced robot adoption and some reallocation toward labor, but focus mainly on labor market and welfare effects from an economics perspective. For the subgroup of firms with revenues between 50 and 200 billion Korean Won, they find that employment increases by about 3.8%, while earnings per worker decrease. In contrast, our study takes an accounting perspective and centers on firms' real investment behavior and the implications of tax regulation for investment efficiency. We show how the reform reduced automation investment, triggered partial substitution toward labor, and affected the quality of investment. Unlike Kang et al. (2024), we provide evidence that scaling back tax incentives mitigated inefficient overinvestment in automation and improved investment quality among less financially constrained firms.[5] Together, the two studies offer complementary perspectives on the consequences of a quasi- robot tax: Kang et al. (2024) from a labor economics viewpoint, and this paper from an accounting perspective that links tax regulation to firms' real decisions.[6]

[4] Previous theoretical literature (see, e.g., Guerreiro et al., 2022; Thuemmel, 2023) discusses whether robots should be taxed and generally finds that taxing robots can reduce income inequality, increase welfare, and mitigate negative effects of automation on routine workers. These studies suggest that robot taxes could have positive effects on redistribution and welfare. Conversely, Mazur (2019) warns of potential negative effects, such as stifling innovation. Englisch (2018) argues that taxing shareholders or capital returns might be a more efficient approach than taxing robots directly.

[5] There are also methodological differences: The identification in Kang et al. (2024) relies largely on the revenue thresholds, whereas in our sample often the membership in a corporate group decides whether a firm is treated.

[6] Hirvonen et al. (2022) study a subsidy for technology adoption in Finland. They find that the subsidy induced firms to use new technologies to produce new types of output rather than replace workers with technologies within the same type of production.

Our paper proceeds as follows. Section 1.2 describes the institutional setting in South Korea and derives our hypotheses. We present the data in Section 1.3 and discuss the empirical strategy in Section 1.4. Section 1.5 presents our empirical findings. Section 1.6 concludes.

1.2 Institutional Setting and Hypotheses Development

1.2.1 Institutional Setting

Industrial robots in South Korea. South Korea is one of the global leaders in automation. In the 1980s and 1990s, the South Korean government prioritized technological advancement within its economic development strategy, recognizing the importance of automation for transforming the manufacturing sector. Industrial robots have played a central role in this process. In this context, a “robot” is an “automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed or mobile for use in industrial automation applications” (based on ISO 8373:2012, which is also the definition used by the IFR).

According to the IFR, South Korea was an early adopter of industrial robots, with 5,462 of them newly installed in 1993 - comparable to the 10,492 installed in the substantially larger U.S. in the same year. While the country was always at the forefront of using robots in production, their use really took off around 2010, when new robot installations in South Korea caught up with those in Japan, also a substantially larger country (see Figure 1.1).

Today, robots are common in many industries. The use of robots is especially common in the electronics (e.g., household appliances, semiconductors, LEDs, solar cells) and automotive industries. In 2021, the average robot density in the manufacturing sector worldwide was around 141 newly installed robots per 10,000 employees. South Korea was the leading country with 1,000 robots per 10,000 employees, followed by Singapore (670 robots per 10,000 employees), Japan (399 robots per 10,000 employees), and Germany (397 robots per 10,000 employees) (IFR Statistical Department, 2022).

The automation tax credit. Investing in automation, particularly in industrial robots, involves significant costs for firms. Depending on the size and function of a robot, these investment costs can range from $20,000 to $400,000 per unit (EVS Tech Co. LTD, 2023).[7] To help local firms manage these substantial costs and strengthen their international competitiveness, the South Korean government introduced a tax credit for productivity-enhancing investments in 2002. The credit, codified in Article 24 of the Restriction of Special Taxation Act, applies to new investments in automated systems, including industrial robots.[8]

The credit is granted in the year the robot is purchased. Its generosity depends on firm size: small firms receive the highest rate, with 7% of the acquisition cost reimbursed by the government. Until 2017, medium-sized entities qualified for a 5% credit and large entities for a 3% credit.[9] From 2018 onward, these rates were reduced to 3% and 1%, respectively (see Panel A of Table 1.1). The credit directly lowers the corporate income tax liability. If the liability is insufficient in the year of purchase, unused amounts can be carried forward for up to five years.

In addition to the automation credit, South Korea offers several other investment-related tax credits. However, if a firm claims the automation tax credit, which is by far the most important, it cannot simultaneously claim another investment-type tax credit (such as an energy-saving or safety facility investment credit) for the same asset. Using tax return data, Kang et al. (2024) show that for manufacturing firms, the automation credit exceeded all other investment credits combined (amounting to roughly 430 million USD in 2019).[10] They also find that around 5% of small firms and almost 25% of large firms used the credit. Among users, the benefit corresponded to 5.2% to 15% of total tax payable, depending on firm size. Thus, the

[7] The average price of robots produced in Korea remained stable at around 22,000 USD in the years around the reform (2017–2019) (IFR Statistical Department, 2022).
[8] For an excerpt from the list of assets eligible for this tax credit, see Table 1.A.1 in the appendix.
[9] The category of "medium" sized firms has existed only since 2015. Before that, firms were either small or "non-small" (i.e., large).
[10] In addition, the variation we exploit is specific to the tax credit for automation investments.

tax credit for automation investment is substantial, making it plausible that its reduction affects investment behavior.

Firm size definitions. South Korea applies a relatively broad definition of small- and medium-sized entities, based on two criteria: (1) firm size and (2) firm independence. Regarding firm size, a firm qualifies as a small firm if it has (1a) turnover below 80 - 140 billion Won (about USD 72 - 145 million in 2018, depending on the industry) and (1b) total assets below 500 billion Won (about USD 450 million).[11]

Regarding firm independence, a firm qualifies as a small firm if it (2a) does not belong to a business group subject to mutual investment or debt guarantee restrictions, (2b) is not owned by a corporation with total assets of 500 billion KRW or more, and (2c) none of its affiliates exceed the small firm thresholds.

A medium-sized entity is one that does not qualify as a small firm but whose turnover in the previous three years is below 300 billion Won (about USD 270 million). Firms that qualify as neither small nor medium-sized entities are classified as large.

Small firm status will determine treatment in our empirical analysis.

[11] The thresholds are 80 billion Won for beverages and medical industries, 100 billion Won for food, tobacco, textile, wood, chemicals, electronics, and automobile industries, and 150 billion Won for clothing, metal, electric appliances, and furniture.

TABLE 1.1:
Automation investment tax credit and comparison for tax benefits

Panel A: Change in tax credit

	Small	Middle	Large
2017	7%	5%	3%
2018	7%	3%	1%

Panel B: Example calculation

	Until 2017	From 2018
Pre-tax income	400,000	400,000
Preliminary tax (24%)	96,000	96,000
Investment in automation	100,000	100,000
Tax credit	5% = 5,000	3% = 3,000
Final tax payment	91,000	93,000

Panel C: Comparison of tax benefits under different regimes

Year	Tax credit (3%)	Tax credit (5%)	Straight-line (10 yrs)	Bonus depreciation (40%)
1	5,400	7,400	2,400	11,040
2	2,400	2,400	2,400	1,440
3	2,400	2,400	2,400	1,440
4	2,400	2,400	2,400	1,440
5	2,400	2,400	2,400	1,440
6	2,400	2,400	2,400	1,440
7	2,400	2,400	2,400	1,440
8	2,400	2,400	2,400	1,440
9	2,400	2,400	2,400	1,440
10	2,400	2,400	2,400	1,440
Total tax benefit	**27,000**	**29,000**	**24,000**	**24,000**
PV of total tax benefit	**22,459**	**24,459**	**19,459**	**21,275**

Notes: Panel A shows the change in the automation investment tax credit before and after the 2018 reform. Panel B illustrates an example calculation for a firm investing 100,000 in automation. Panel C compares the total and present value (PV) of tax benefits under different regimes: A 3% tax credit, a 5% tax credit, straight-line depreciation over ten years and 40% bonus depreciation. We assume an investment of 100,000, a corporate tax rate of 24%, and a discount rate of 5%. Tax benefits are assumed to be realized at the beginning of the fiscal year.

The reform. In 2018, South Korea reduced the automation investment tax credit by two percentage points for medium-sized and large firms, with the change applying to all fiscal years after December 31, 2017.[12] This reduction has been described in the media as the introduction of a "robot tax."[13]

The reform stemmed from a broader political shift that was unrelated to firms' automation activities. Following the impeachment of the president in March 2017, the new government, in office from May 2017, introduced a series of policy changes that diverged sharply from those of the previous administration. A central goal of these new policies was to reduce inequality and enhance tax fairness. To achieve this, the government rolled back tax reductions for large corporations, aiming to improve the competitive position of small and medium-sized firms. This approach enabled these firms to compete more effectively with larger firms, and consequently, the reduction in tax credits for new automation investments was applied irrespective of firms' existing automation levels.[14]

This setting provides a suitable natural experiment. A central requirement for a DiD design is the exogeneity of the policy change. In this case, the reduction in tax credits was politically motivated rather than driven by firms' investment behavior, making it plausibly exogenous to firm-level automation decisions. This allows us to isolate the causal effect of the quasi-robot tax on investment outcomes.

Panel B of Table 1.1 illustrates the immediate impact of the reform. For a medium- sized firm with pre-tax income of \$400,000 and an automation investment of \$100,000, the tax credit

[12] During our observation period, South Korea offered several other tax credits, including those for safety facilities, research and development, job creation, and energy and environmental initiatives. The credit for safety facilities was also reduced by two percentage points from 2018 onward. While we know the distribution of robots across industries, we do not observe the distribution of safety investments. Assuming equal distribution, the reduced credit for safety investments would matter relatively more in low-robot industries.

[13] See, e.g., The Korea Times, The Telegraph, Mashable, or The New York Times.

[14] Other measures included raising the top income tax rate, increasing capital gains taxation for major shareholders, reducing R&D credits for large firms, tightening inheritance and gift tax deductions, and increasing taxation of rental income.

fell from 5% ($5,000) to 3% ($3,000). As a result, the firm's final tax liability increased from $91,000 to $93,000. This simple example shows how the reform effectively raised the tax cost of robot adoption.

An important feature of the Korean tax credit is that it is granted in addition to regular tax depreciation. Unlike bonus depreciation schemes, which mainly accelerate the timing of deductions, the Korean credit provides an immediate and permanent tax benefit. Panel C of Table 1.1 compares four regimes: a 3% tax credit, a 5% tax credit, straight-line depreciation over ten years, and 40% bonus depreciation. We assume an asset with acquisition costs of $100,000 and a ten-year useful life,[15] a corporate tax rate of 24%, and a discount rate of 5%. The table reports yearly tax benefits, as well as their totals and present values. Both the 5% and the 3% credit yield larger benefits than 40% bonus depreciation. The reason is straightforward: tax credits reduce the tax burden on top of regular depreciation, whereas bonus depreciation only shifts deductions forward in time without changing their total amount. The difference is less pronounced once we account for discounting, but the credits still provide a larger present value benefit. Notably, even the reduced 3% credit after the reform yields a larger benefit than 40% bonus depreciation, which is typically considered a generous tax incentive. Also the effect of moving from a 5% to a 3% tax credit - as in the 2018 reform - is more pronounced than introducing a 40% bonus depreciation.

1.2.2 Hypotheses

We derive three hypotheses regarding the effects of reducing the automation tax credit in South Korea. These hypotheses address robot investments, the broader response of firms in terms of production and employment (and how these may vary depending on financial constraints), and the quality of investments following the reform.

[15] Fixed assets in South Korea are depreciated over four to twelve years. For industrial robots, the usual period is five years. We assume ten years here and, hence, underestimate the absolute benefits of linear depreciation. See EY (2024).

The first question we address is how the reduction in the automation tax credit affects investments in robots. The reduced tax credit makes automation investments more expensive for the affected firms. Standard economic theory suggests that increasing the cost of capital goods, such as robots, reduces the quantity of investment. However, it is not necessarily obvious that the impact on robot investments will be large, given that firms may have already committed to a technological trajectory that involves automation. On the other hand, embedded in a broader policy shift, the reform likely influenced firms' expectations of future economic policy. Gallemore et al. (2025) provide evidence of particularly strong investment responses to reforms of this kind.

The impact of the tax credit reduction might differ depending on firm characteristics. Larger, financially unconstrained firms might continue to invest despite higher costs, while financially constrained firms may be unable to do so and reduce investment more sharply.

Therefore, we formulate the following hypothesis:

Hypothesis 1: *The reduction in the automation tax credit in South Korea led to a decrease in investments in robots. Financially constrained firms reduce investment by more than financially unconstrained firms.*

The second question concerns how firms adjust more broadly to the increased cost of automation. If robot investments become less attractive due to the reduced tax credit, firms may respond by compensating through other means, such as hiring more employees. The direction of this response is not obvious, and previous empirical evidence has found mixed results.

On the one hand, robots may enhance overall productivity and be complementary to labor and other inputs (Autor, 2015; Graetz and Michaels, 2018). In this case, reducing automation may force firms to scale back production overall, and we would expect no increase in employment or other types of investment. On the other hand, robots may act as substitutes for workers (Acemoglu and Restrepo, 2020; Frey and Osborne, 2017). Then, reducing robot investment could lead firms to hire more employees to maintain production.

The ability to make such adjustments likely depends on financial constraints. Firms with sufficient internal or external funds may flexibly reallocate resources when robot investment becomes less attractive: for example, by hiring more workers or investing in alternative technologies. In contrast, with the lower tax credit, financially constrained firms face both higher costs of automation and reduced internal liquidity, which they cannot easily replace with external finance. Prior work shows that financially constrained firms respond more strongly to tax incentives (Zwick and Mahon, 2017) and are less likely to innovate and slower to adopt new technologies (Hall and Lerner, 2010; Brown et al., 2012). These findings suggest that financial capacity not only determines the magnitude of investment responses but also whether firms can substitute away from robots toward other inputs.

We, therefore, formulate the following hypothesis:

Hypothesis 2: *Following the reduction in the automation tax credit, financially unconstrained firms compensate the reduced use of robots by hiring more employees, whereas financially constrained firms do not.*

The final question concerns the *quality* of automation investments. In a setting without taxes or externalities, firms should invest efficiently, allocating capital to those investment projects with the highest marginal returns. However, investment tax credits lower the user cost of capital, potentially encouraging firms to overinvest in subsidized assets, including industrial robots, even when their marginal productivity is low. Such distortions may lead firms to adopt automation technologies beyond the economically efficient point. Removing the tax credit restores market-based investment signals, potentially prompting firms to allocate capital more efficiently.

We expect this reallocation effect to be strongest for financially unconstrained firms, who are able to adjust their input mix and reoptimize after the reform. In contrast, constrained firms may be unable to substitute or reallocate capital, and may even loose productivity if the lost credit makes them even more financially constrained. As a result, the net impact of the reform on investment quality is likely to vary with financial constraints.

We form the following hypothesis:

Hypothesis 3: *The reduction in the automation tax credit increased the quality of investments among financially unconstrained firms, but not among financially constrained firms.*

1.3 Data and Descriptives

1.3.1 Robot Data

The first database we use is provided by the International Federation of Robotics (IFR). It contains information on new installations and the operational stock[16] of industrial robots by country and industry[17] since 1993 for about 80 countries worldwide. The data availability differs across countries. All major industrial robot suppliers report information on new installations to the IFR (primary source). This primary source is supplemented with data submitted by national robotics associations, which also report to the IFR (secondary source). As a result, the data covers almost the whole population of robot installations.

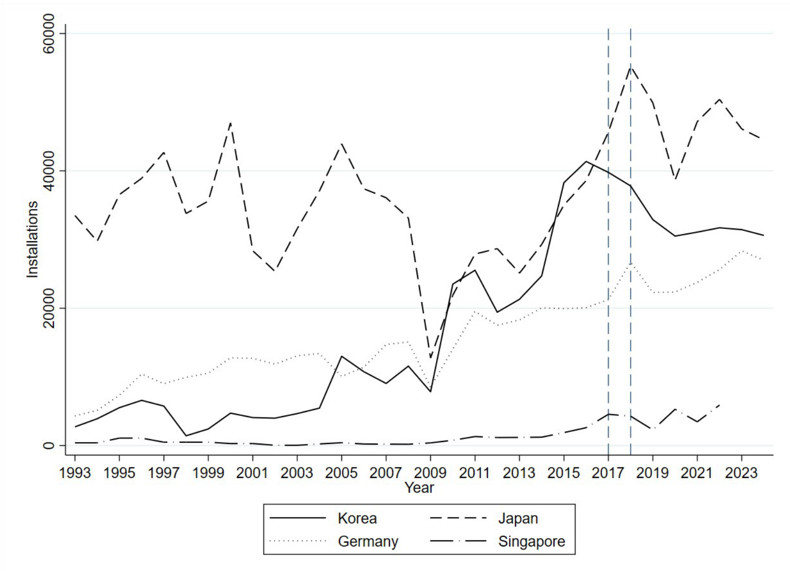
Figure 1.1 shows IFR data on newly installed industrial robots in Korea, Singapore, Japan, and Germany - the four countries with the highest robot density over the period 1993 to 2021. In South Korea, we observe a pronounced decrease in newly installed robots starting in

[16] The operational stock, according to the IFR, measures the number of robots currently deployed.

[17] In addition to agriculture, forestry, fishing (A-B), mining and quarrying (C) and manufacturing (D) the industry classes included electricity, gas, water supply (E), construction (F) and education, research (P). The industry class 'manufacturing' is additionally subdivided into smaller sub-areas. In total, there are 31 different industry classifications.

2017 when the tax reform was announced. In the other countries, the number of newly installed robots stays roughly constant. Especially in Japan, the volatility of robot installations is high.

FIGURE 1.1: Robot Installations in Leading Robot Countries



Notes: The graph shows newly installed industrial robots for Korea and three other leading countries over a time period from 1993-2021. Installations in absolute numbers. Vertical lines indicate the announcement of the tax reform (2017) and the implementation (2018). Data from the IFR.

1.3.2 Orbis

The second database we use is the *Orbis* database provided by Moody's. This database contains firm-level balance sheet data as well as stakeholder information for more than 45 million private and listed entities worldwide. For our analysis, we create a balanced sample and use only unconsolidated financial statement information for entities in South Korea from 2014 to 2021. We also remove entities that report negative total assets or negative employee numbers. We further drop observations with inconclusive information on ownership structure.[18] We drop entities from the following industries: "Mining and Quarrying", "Agriculture, Forestry, Fishing", "Electricity, Gas, Water Supply", "Construction", and "Education, Research and

[18] More specifically, we drop firms where we have information on the global ultimate owner (GUO) of an entity, but the entity is classified as "Independent Co" or "Single location". We also drop observations that are classified as "Controlled subsidiaries" but for which we have no information on the GUO.

Development". Finally, we remove observations if EBIT exceeds 300 billion Korean Won (roughly 230 million USD), since firms with a tax base above this threshold experienced a change in the corporate income tax rate in 2018.

As described in Section 1.2, a firm is treated by the Korean tax reform if it is not classified as a small firm.[19] In line with the Korean tax code, we classify an entity as small if it does not exceed the industry-specific turnover thresholds, and it does not exceed the size threshold for total assets of 500 billion Korean Won (about 380 million USD). Additionally, an entity has to be independent to be classified as small. We classify an entity as independent if its global ultimate owner (GUO) is Korean and does not exceed the firm size thresholds.[20]

Table 1.2 shows the summary statistics for all considered variables for our baseline firm-level regression analysis based on a matched sample presented in Section 1.4.

[19] We drop all entities that change their firm size status during our observation period.

[20] We do not have information on the size of non-Korean global GUOs. Thus, for simplicity, we assume a Korean entity not to be a small firm if its GUO is a non-Korean company. The underlying assumption is that foreign ownership is an indicator for a larger corporate group that exceeds the Korean small firm threshold.

TABLE 1.2: Descriptive Statistics

	N	Mean	1%	50%	99%	SD
Gross Investment$_{it}$	20,288	0.06	-0.23	0.00	1.02	0.36
Net Investment$_{it}$	20,288	0.04	-0.26	-0.00	0.97	0.35
Employees$_{it}$	16,233	175	3	70	1,469	528
Staff Expenses$_{it}$ *(million KRW)*	20,236	3,341	80	1,517	23,162	5,012
Turnover$_{it}$ *(million KRW)*	20,273	76,606	1,032	22,761	736,894	161,703
Turnover/Assets$_{it}$	20,273	1.36	0.05	1.09	5.74	1.15
GrossProfit$_{it}$ *(million KRW)*	20,276	13,230	-1,350	4,447	131,507	26,688
Total Assets$_{it}$ *(million KRW)*	20,288	70,053	1,133	23,611	658,781	130,702
Age$_{it}$	20,288	20.24	4.00	19.00	37.00	9.01
HPI$_{it}$	20,288	-2.60	-4.29	-2.65	-0.40	0.86
Cash$_{it}$ *(million KRW)*	20,267	6,770	2	1,300	79,705	24,592
RD Expenses Intensity$_{jt}$	20,288	0.15	0.00	0.22	0.40	0.12
Installations$_{jt}$ *(absolute)*	20,288	913	0	75	16,783	2,904

Notes: This table presents summary statistics of our firm-level data for our matched sample. See Table 1.A.2 in the appendix for variable definitions. The average exchange rate in our sample period is about 1,300 Korean Won (KRW) per U.S. dollar. Yearly data from 2014 to 2021. Data from Orbis, the International Federation of Robotics, and the OECD.

1.4 Empirical Strategy

1.4.1 Industry- and Country-Level Analyses

The only available direct data on the use of industrial robots is provided by the industry-level statistics data from the IFR. Accordingly, we begin our empirical analysis of the reform's impact on automation investment at the industry level. Here, we exploit both within-country variation in exposure to the reform, adopting an intensity-to-treat design, and cross-country variation in a DiD design.

Within-country setting. For the within-country design, we use *Orbis* data to calculate the share of Korean firms in each industry that were directly affected by the tax credit reduction ($Share\ Treated_j$) prior to the reform.

Our within-country regressions are specified as follows:

$$\text{Installations}_{jt} = \alpha_1(Share\ Treated_j \times \text{Post}_t) + \eta_j + \zeta_t + \epsilon_{jt}, \tag{1}$$

where the dependent variable $Installations_{jt}$ is the number of robot installations in industry j in year t. We estimate two specifications of Equation (1). In the first, we use a Poisson pseudo-maximum likelihood (PPML), in the second, we estimate an OLS regression.[21]

In all specifications, our primary variable of interest is the interaction between $Share\ Treated_j$ and the post-reform indicator $Post_t$, which equals one for years 2018 and onward, and zero otherwise. This interaction term captures differential changes in robot installations across industries with varying treatment intensities following the implementation of the tax credit reduction. Under Hypothesis 1, we expect a negative estimate for α_1, indicating that industries with higher treatment intensity experienced a relative decline in robot installations after the reform.

We operationalize treatment intensity in two ways. First, we use the continuous variable $Share\ Treated^{cont}{}_j$, which measures the share of treated firms in each industry. Treated firms are those not classified as small and therefore affected by the reduction in the automation tax credit. Second, we use the binary indicator $Share\ Treated^{bin}{}_j$, which equals one if industry j is in the top two quintiles of the $Share\ Treated^{cont}{}_j$ distribution and zero if it is in the bottom two quintiles. Observations in the middle quintile are excluded.

[21] In robustness tests, we also estimate a zero-inflated Poisson, or estimate OLS using the dependent variable $Installations\ Scaled_{jt}$, defined as the share of robot installations in industry j relative to the total number of installations in year t (see Section 1.5.3).

All specifications include industry fixed effects (η_j) and year fixed effects (ζ_t), and standard errors are clustered at the industry level.

Cross-country setting. For the cross-country setting, we use Japanese industries as the control-group in our DiD framework. We estimate the following equation:

$$\text{Installations}_{jct} = \beta_1(Korea_c \times \text{Post}_t) + \gamma_{jt} + \epsilon_{jct}, \tag{2}$$

where $Korea_c$ is a binary indicator that equals one if the industry-year observation relates to firms from South Korea. All other variables are defined as before. We include industry-year fixed effects and cluster at the country-industry level in this specification. We chose Japan as the control country as both countries share a similarly high robot density (see Figure 1.1) and have similar GDP per capita, employment and unemployment rates.[22]

1.4.2 Firm-Level Analyses

To ensure comparability between treated and control firms, all firm-level regressions are estimated on a matched sample. We implement Coarsened Exact Matching (CEM) to construct a balanced panel of comparable treated and untreated observations. Firms are matched based on their pre-reform average levels of total assets, staff expenses, and investment in fixed assets adjusted for depreciation. In addition, we match on firm age and require exact matches on industry affiliation and legal form.[23] By coarsening continuous variables into data-driven intervals and performing exact matches on categorical attributes, CEM produces strata in which treated and control firms are directly comparable across all observed pre-treatment characteristics.[24]

[22] In 2018, GDP per capita was 42,142 USD in Japan and 43,044 USD in South Korea; unemployment rate was 2.5% in Japan and 3.8 in South Korea. Data from the World Bank.

[23] While firm size is one criterion for small-firm classification, treatment status in practice often hinges on firm independence (i.e., whether a firm belongs to a business group). As a result, matching on total assets does not mechanically determine treatment and remains appropriate for balancing treated and control firms on pre-reform characteristics.

[24] We use Sturges' rule to determine binning intervals and construct strata with equal numbers of treated and control observations.

DiD Setting. We employ a DiD design on this matched sample to identify the impact of the reduced tax credit for automation investments.[25] We examine three sets of outcomes: investment (Hypothesis 1), employment (Hypothesis 2), and investment quality (Hypothesis 3). The design compares treated and control firms in Korea before and after the reform. Formally, we estimate:

$$Outcome_{it} = \delta_1(Treatment_i \times Post_t) + \gamma X_{jt} + \eta_i + \zeta_t + \epsilon_{it}, \quad (3)$$

where the coefficient δ_1 captures the treatment effect of the reform. The variable $Treatment_i$ is an indicator equal to one if firm i is affected by the tax credit reduction, i.e., if a firm does not qualify as a small firm prior to the reform.[26] The post-reform indicator $Post_t$ equals one for all years from 2018 onward, and zero otherwise. The interaction $Treatment_i \times Post_t$ is our main variable of interest. As a control variable X_{jt}, we include the industry-level intensity of R&D expenditures, obtained from OECD data. This accounts for contemporaneous changes affecting innovation and capital investment. All regressions include firm fixed effects η_i to absorb time-invariant firm characteristics and year fixed effects ζ_t to control for macroeconomic shocks. Standard errors are clustered at the firm level.

We use several outcome variables to test our three hypothesis.

To test Hypothesis 1, we would ideally use firm-level data on automation investments. As no such data are available, we proxy automation investment by the change in tangible and intangible fixed assets. Intangible assets, such as software, can be bundled with robots, and form part of broader digitalization and automation strategies.[27] Accordingly, our dependent variable $Outcome_{it}$ is defined either as the change in tangible and intangible fixed assets plus

[25] A regression discontinuity design (RDD) is not feasible in our setting for two reasons. First, treatment status is determined by a combination of characteristics (firm size and group affiliation), rather than a single sharp cutoff. Second, there is insufficient density of observations around the relevant size thresholds to credibly estimate local effects.
[26] See Section 1.2 for the official definition of small firms under Korean law.
[27] See Brynjolfsson et al. (2021) for evidence on the complementarity between automation and intangible capital.

depreciation, scaled by lagged total assets (*Gross Investment*$_{it}$); or as the change in tangible and intangible fixed assets excluding depreciation, also scaled by lagged total assets (*Net Investment*$_{it}$). Table 1.A.2 in the appendix provides detailed variable definitions.

To examine Hypothesis 2, we focus on two employment measures. The natural logarithm of the number of employees (*Ln(Employees)*$_{it}$) captures adjustments in headcount, while staff expenses (*Ln(Staff Expenses)*$_{it}$) reflect changes in both the number of employees as well as their typical wages. Using both variables allows us to get some insight into the wage structure of newly hired employees.

For Hypothesis 3, we consider six measures of investment quality: the logarithms of turnover, gross profit, and EBIT. These outcomes capture both the scale and efficiency of investment. Turnover provides information on firms' sales growth, while EBIT and gross profit proxy for operating performance. Scaling by assets accounts for firm size, allowing us to measure whether investments translate into higher productivity relative to resources employed.[28] These choices follow Eichfelder et al. (2023), who also study turnover and profit-based measures.[29]

IV analysis. While the DiD design identifies the direct effect of the reform, it does not establish whether subsequent changes in investment quality are indeed caused by changes in robot investment. To address this, we complement our baseline analysis with an instrumental

[28] An alternative outcome measure would be total factor productivity (TFP). We do not use it here because the tax reform directly affects both assets and employment, which are themselves inputs in the standard estimation of TFP. Any observed change in TFP would thus partly reflect the mechanical effect of altered factor inputs rather than a genuine change in underlying productivity, making it difficult to interpret TFP (the residual of an estimated production function) as a separate outcome.

[29] Eichfelder et al. (2023) also examine leads. This is not feasible in our DiD setting, but we address leads later in the IV analysis.

variables (IV) strategy. This approach allows us to isolate the impact of reform-induced changes in investment on firm outcomes and to examine the time structure of these effects.[30]

Specifically, we use the reform as an exogenous instrument for investment. In the first stage, we estimate the effect of the reform on investment,

$$Gross\ Investment_{it} = \theta_1 Treatment\ On_{it} + \eta_i + \zeta_t + \epsilon_{it}, \tag{4}$$

where $Gross\ Investment_{it}$ is defined as the change in tangible and intangible fixed assets plus depreciation, scaled by lagged total assets. $Treatment\ On_{it}$ equals one for treated firms in the post-reform period. The specification includes firm fixed effects η_i, year fixed effects ζ_t, and clusters standard errors at the firm level.

In the second stage, we use the fitted values $Gross\ \widehat{Investment_{it}}$ to estimate the impact of reform-induced changes in investment on firm outcomes,

$$Outcome_{it} = \phi_1\ Gross\ \widehat{Investment_{it}} + \eta_i + \zeta_t + \nu_{it}. \tag{5}$$

We use the same outcome variables as above to measure investment quality. To capture dynamics, we estimate effects for the contemporaneous year as well as one- and two-year leads.

The IV analysis thus complements our baseline DiD estimates by linking changes in firm outcomes directly to investment responses. We now turn to our results.

[30] We view labor adjustments as part of the investment transmission channel rather than a separate pathway. Firms respond to the reform by reallocating resources between automation and labor. Thus, changes in employment are a direct consequence of altered investment decisions, not an independent source of variation affecting turnover or profits.

1.5 Empirical Results

1.5.1 Investment Effects

We begin our empirical analysis by examining how the reduction in the automation investment tax credit affected robot installations by Korean firms (Hypothesis 1).

Industry-level results: Within-Korea setting. We begin by testing whether industries in Korea with greater exposure to the 2018 reduction in the automation tax credit experienced larger declines in robot adoption. Exposure is measured at the industry level using the pre-reform share of firms that do not qualify as small firms ("treated" firms). We interact this exposure with a post-reform indicator for years 2018 - 2021 and estimate two sets of specifications: (i) Poisson pseudo–maximum likelihood (PPML) regressions of the count of new robot installations with industry and year fixed effects; and (ii) OLS regressions in levels with the same fixed effects. To gauge sensitivity to functional form and to emphasize treatment contrast, we implement two measures of exposure: a continuous share (Columns (1) and (3) of Table 1.3) and a binary indicator that equals one for industries in the top two quintiles of the exposure distribution and zero for those in the bottom two quintiles (Columns (2) and (4)).

Across all four specifications in Table 1.3, the interaction term is negative and statistically significant, indicating that more exposed industries curtailed robot installations more strongly after the reform. The magnitudes are economically meaningful. In the OLS specification with the continuous exposure measure (Column (3)), a one–percentage-point higher pre-reform treated-firm share is associated with 33 fewer robot installations in the post period, which corresponds to roughly 4.2% of the pre-reform sample average. Using the binary specification, the PPML estimate in Column (2) implies that, conditional on fixed effects, post-reform installations in high-exposure industries are about $1 - \exp(-1.447) \approx 76\%$ lower than in low-exposure industries.

Thus, industries with a larger pre-reform share of firms affected by the credit reduction cut robot adoption more sharply after 2018. While the within-country design has the advantage of ruling out confounding factors from cross-country differences, its interpretation relies fully on differences in the intensity of treatment. To complement this evidence, we next turn to a DiD framework that compares Korean industries to their Japanese counterparts.

Industry-level results: Korea vs. Japan We next exploit a cross-country DiD design that compares robot installations in Korean industries to those in Japan, a country with similar levels of robot density and economic development (see eq. (1)). Treatment is defined at the country level, with Korean industries exposed to the reform while Japanese industries serve as the control group.

Results are reported in Columns (5) and (6) of Table 1.3. Across both PPML and OLS specifications, the interaction term $Korea_c \times Post_t$ is negative, indicating that robot adoption in Korea fell relative to Japan after the reform. The coefficient is statistically significant in the PPML specification (Column 5) and marginally insignificant in the OLS specification (Column 6). The PPML estimate implies that Korean industries installed about 30.2% fewer robots per year than their Japanese counterparts in the post-reform period. The OLS coefficient points in the same direction, corresponding to a decline of roughly 547 installations per industry-year, although the coefficient is imprecisely estimated.

These magnitudes are economically large and broadly consistent with prior evidence on investment responses to changes in bonus depreciation and other tax incentives. For example, Zwick and Mahon (2017) estimate that a 20 percentage point increase in bonus depreciation raised investment in eligible assets by between 10% and 17%. Similarly, Eichfelder et al. (2023) find that eliminating a 40% bonus depreciation led to a 17% to 20% decline in investment.

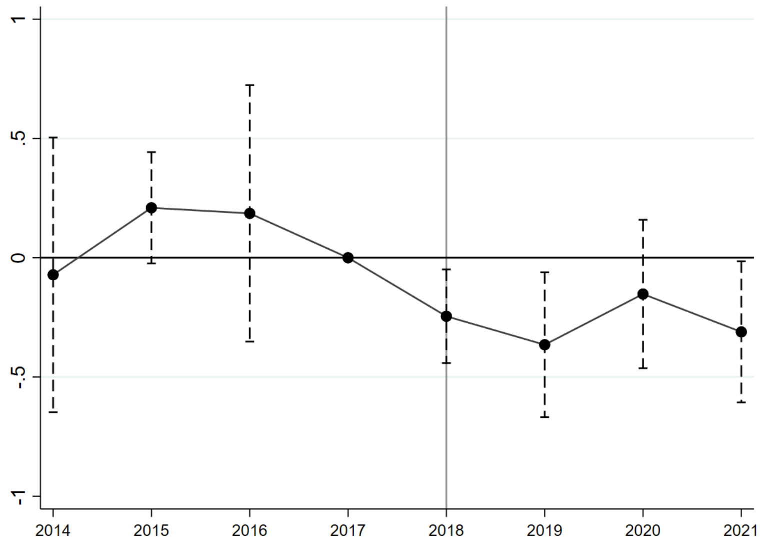
TABLE 1.3:
Industry-Level Results: Robot Installations

	Within Korea				Korea vs. Japan	
	PPML		OLS		PPML	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Share Treated$^{cont}{}_{i}$ *$Post_t$	-0.075**		-33.018*			
	(0.031)		(18.026)			
Share Treated$^{bin}{}_{j}$ *$Post_t$		-1.447**		-1118.280**		
		(0.620)		(516.700)		
$Korea_c$*$Post_t$					-0.360**	-547.323
					(0.166)	(344.100)
Industry FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	No	No
Year-Industry FE	No	No	No	No	Yes	Yes
Observations	224	176	248	200	338	384
Pseudo R^2	0.81	0.76			0.86	
Adjusted R^2			0.64	0.43		0.68

Notes: Estimated effects of the 2018 reform on industry-level investment. Columns (1)-(4) apply a within-Korea setting, Columns (5)-(6) apply a cross-country setting and compare Korea with Japan. The dependent variable is $Installations_{cjt}$, the absolute number of newly installed robots in country c (for Columns (5) and (6)) in industry j in year t. *Share Treated*$^{cont}{}_{j}$ measures the average pre-reform share of treated firms in each industry. *Share Treated*$^{bin}{}_{j}$ is a binary indicator that equals one if industry *j* is in the top two quintiles of the *Share Treated*$^{cont}{}_{j}$ distribution and zero if it is in the bottom two quintiles. $Korea_c$ is a binary indicator that equals one for Korean industry-year observation and zero for Japanese industry-year observations. $Post_t$ is an indicator variable equal to one after the implementation of the reform, thus after December 31, 2017. Columns (1)-(2) and (5)-(6) apply a PPML approach, Columns (3)-(4) apply an OLS approach. Specifications differ in their fixed effects as indicated. Standard errors are given in parentheses and are clustered at the industry level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from the International Federation of Robotics and Orbis database of Moody's.

The event study plot in Figure 1.2 lends support to the validity of the design. It shows parallel pre-trends in robot installations between Korean and Japanese industries before 2018, and a persistent decline in Korea following the reform. This pattern reinforces the interpretation that the observed cross-country differences capture the causal effect of the quasi-robot tax.

FIGURE 1.2: Industry-Level Results: Event Study Korea vs. Japan



Notes: Graph shows coefficient estimates from an event study specification which compares robot installations between Korea (treated) and Japan (control). Coefficients are from regressions that replace the post indicator with year dummies, capturing annual differences between installations in Korea and Japan. Bars indicate 90% confidence intervals with standard errors clustered at the country-industry level. Yearly data from 2014 to 2021 from the International Federation of Robotics.

Industry-level results: Robustness We conduct three robustness checks to assess the stability of our industry-level results in the within-country setting. First, to address the large number of observations with zero installation, we re-estimate the PPML specifications using a zero-inflated Poisson (ZIP) model. Second, we implement OLS regressions where the dependent variable is the share of robot installations in industry *j* relative to total installations in year *t* ($Installations\ Scaled_{jt}$), thereby normalizing outcomes across industries and years. Third, we augment our baseline models with additional industry-level controls constructed from firm-level *Orbis* data to account for potential compositional changes in firm characteristics. The results, reported in Table 1.A.3 in the Appendix, consistently show negative and statistically significant effects of the reform on robot installations in exposed Korean industries.

Firm-level results. We complement the industry-level analysis with firm-level regressions based on data from *Orbis*. As the dataset does not contain robot-specific investment information, we use broader measures of investment as proxies. Following the DiD strategy outlined in Section 1.4, we regress investment on the interaction of $Treatment_i$ with a post-reform indicator. The dependent variable is either gross investment - defined as the change in tangible and intangible assets plus depreciation, scaled by lagged total assets - or net investment, which is constructed analogously but net of depreciation.

Table 1.4 reports the results. Columns (1) - (3) use gross investment as the dependent variable, while Columns (4) - (6) use net investment. Specifications gradually increase in stringency: Columns (1) and (4) include only year fixed effects; Columns (2) and (5) add firm fixed effects and an industry-level control for R&D intensity; Columns (3) and (6) include industry-by-year fixed effects. Across all six specifications, the estimated treatment effect is negative and highly significant. Coefficients are very similar across specifications (between −0.026 and −0.028), implying that treated firms reduced investment relative to total assets by about 3 percentage points relative to the control group. In economic terms, this corresponds to roughly eight percent of the standard deviation of the investment rate in the sample.

TABLE 1.4:
Firm-Level Results: Investment

	Gross Investment			*Net Investment*		
	(1)	(2)	(3)	(4)	(5)	(6)
$Treatment_i$	-0.028***	-0.028***	-0.028***	-0.026***	-0.026***	-0.026***
$*Post_t$	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Controls	No	Yes	No	No	Yes	No
Company FE	No	Yes	Yes	No	No	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes
Observations	20,288	20,288	20,288	20,288	20,288	20,288
Adjusted R^2	0.004	0.087	0.092	0.003	0.054	0.058

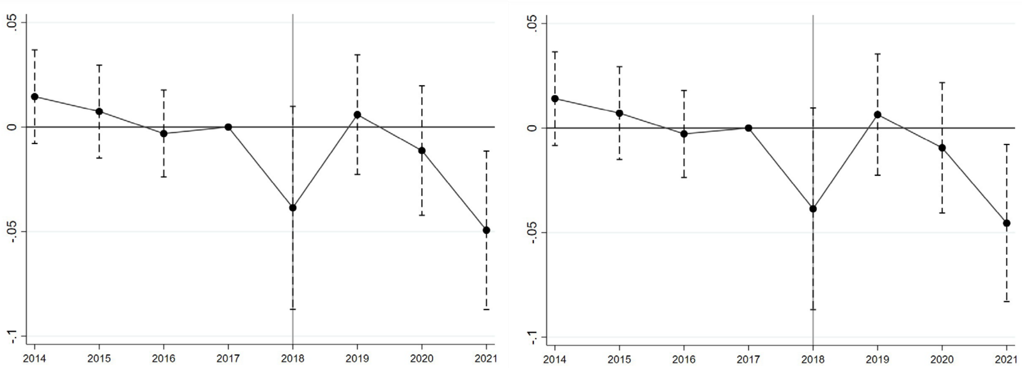
Notes: Estimated effects of the 2018 reform on firm-level investment in Korea. The dependent variable in Columns (1)–(3) is gross investment (change in tangible and intangible fixed assets plus depreciation, scaled by lagged total assets). Columns (4)–(6) use net investment (change in tangible and intangible fixed assets net of depreciation, scaled by lagged total assets). $Treatment_i$ indicates firms affected by the reduced tax credit. $Post_t$ is an indicator variable equal to one after the implementation of the reform, thus after December 31, 2017. Columns (2), (3), (5), and (6) include industry-level R&D intensity as a control. Specifications differ in their fixed effects as indicated. Standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis and the OECD.

Moreover, the estimates suggest that lower robot investment was not fully offset by substitution into other forms of capital. In untabulated robustness checks that separate tangible and intangible assets, we confirm that the negative investment effect is driven by tangible fixed assets, with no significant change in intangibles.

Figure 1.3 shows the corresponding event study estimates. Both for gross and net investment, treated and control firms follow largely parallel pre-trends up to 2017, supporting the validity of the design. In the reform year 2018, investment by treated firms drops sharply relative to the control group, consistent with the baseline regression results. In subsequent years, the coefficients fluctuate: the gap narrows in 2019 and 2020, but then again becomes larger and also statistically significant in 2021. This pattern points to an immediate investment response to the reform, followed by varying adjustments taking place across firms. This may suggest the presence of heterogeneous effects, an issue we investigate more systematically in the next section by splitting firms into two subgroups according to the financial constraints they face.

FIGURE 1.3: Firm-Level Results: Event Studies for Investment

(A) *Gross Investment* (B) *Net Investment*



Notes: Event study estimates of the reform effect on firm-level investment. Panel (A) shows gross investment (tangible and intangible fixed assets plus depreciation scaled by lagged total assets). Panel (B) shows net investment (tangible and intangible fixed assets net of depreciation scaled by lagged total assets). Coefficients are from regressions that replace the post indicator with year dummies, capturing annual differences between treated and control firms. Bars indicate 95% confidence intervals with standard errors clustered at the firm level. Yearly data from 2014 to 2021 from Orbis and the OECD.

1.5.2 Heterogeneity and Adjustment Mechanisms

We next investigate whether firms' responses to the quasi-robot tax vary with their degree of financial constraints, and whether such heterogeneity gives rise to adjustment along other margins such as employment and the quality of investment. The premise is that a firm's financial position shapes its ability to adjust investment behavior when faced with a less favorable tax treatment of automation.

To capture financial constraints, we stratify firms using the Hadlock–Pierce Index (Hadlock and Pierce, 2010). The index is a parsimonious measure based solely on firm size and age: larger and older firms are classified as less constrained, while smaller and younger firms are classified as more constrained. In practice, the index is constructed as a linear combination of the logarithm of firm assets and firm age (with a squared assets term), where higher values indicate greater financial constraints. Because it does not rely on financial statement variables that may themselves respond to investment choices, the index is less prone to endogeneity concerns than alternative proxies. We split the sample at the median value of the index to distinguish financially constrained from unconstrained firms.

We test two remaining hypotheses not already addressed in the previous section. First, financially unconstrained firms should be able to maintain overall investment levels by substituting away from automation toward other forms of capital, potentially including more labor input (Hypothesis 2). Second, such substitution may be associated with improvements in investment quality (Hypothesis 3). By contrast, financially constrained firms are expected to have limited scope for adjustment and to reduce investment overall.

We test these hypotheses in three steps: we first compare the investment effects across constrained and unconstrained firms, then analyze substitution into employment, and finally assess whether the reform altered the quality composition of investment.

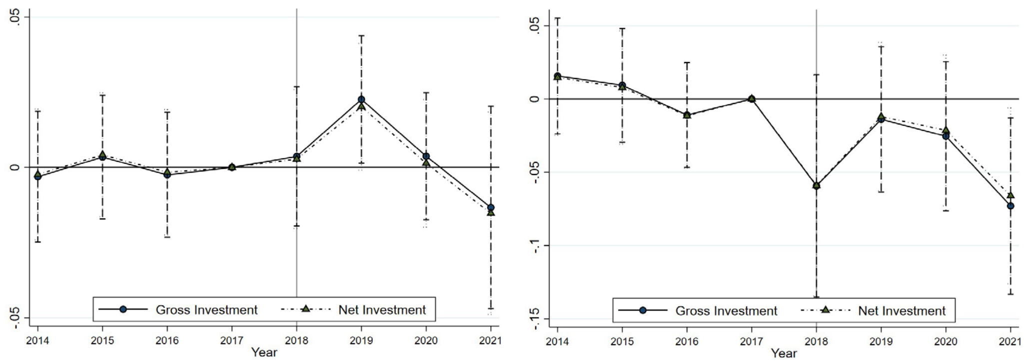
Heterogeneity by financial constraints. We begin the heterogeneity analysis by re-estimating the firm-level investment regressions separately for financially constrained and unconstrained firms. Results are shown in Table 1.A.4 in the appendix (DiD estimates) and Figure 1.4 (event study plots). The patterns align closely with our hypotheses. Among financially constrained firms (above-median Hadlock–Pierce Index), treatment effects are negative and statistically significant, ranging from -5.0% to -5.5% of total assets. These estimates are about twice as large as the average effect in the full sample, suggesting that the reduction in the tax credit tightened existing liquidity constraints and forced these firms to cut overall investment.

For financially unconstrained firms, by contrast, we estimate an insignificant (and even slightly positive) treatment effect. This indicates that these firms were able to reallocate resources: rather than reducing overall investment, they appear to have substituted away from automation toward other forms of capital spending.

The event study plots in Figure 1.4 corroborate this interpretation. Pre-reform trends are parallel in both subsamples. After the reform, however, investment paths diverge: financially constrained firms display a sustained contraction in investment, while unconstrained firms maintain or even expand their investment activity. This expansion may partly reflect a temporary reallocation of resources and production processes, requiring new or adapted machinery despite the overall reduction in automation incentives.

FIGURE 1.4: Firm-Level Results: Financial Constraints and Investment

(A) *Low HPI* (B) *High HPI*



Notes: Event study estimates of the reform effect on firm-level investment for a sample split between financially unconstrained and financially constrained firms. Panel (A) compares net investment (change in tangible and intangible assets net of depreciation, scaled by lagged total assets) and gross investment between treated and control firms among financially unconstrained firms (Low HPI). Panel (B) presents the same for financially constrained firms (High HPI). Financial constraints are measured using the Hadlock-Pierce Index (HPI); the sample is split at the median. Bars indicate 95% confidence intervals. Yearly data from 2014 to 2021 from Orbis and the OECD.

Employment effects. We next examine whether reduced automation incentives translated into changes in labor demand. The regressions follow the same firm-level DiD framework as in the investment analysis, with the dependent variable defined either as the natural logarithm of the number of employees or the logarithm of staff expenses. Table 1.5 reports results for the full sample and separately for financially constrained and unconstrained firms.[31]

[31] The number of observations is smaller for the employment outcomes because employment information is not available for all firms in the full sample used for the investment outcomes.

For the full sample, we find no significant change in employment. Among financially constrained firms, employment likewise remains unaffected. By contrast, unconstrained firms increase headcount significantly after the reform: Column (2) suggests an average rise of about 4% relative to control firms. The corresponding effect on staff expenses, however, is smaller and statistically insignificant. This divergence between headcount and staff expenses indicates that unconstrained firms primarily expanded employment at the lower end of the wage or skill distribution. The results are consistent with Hypothesis 2, which posits that financially unconstrained firms substitute away from automation and toward more labor-intensive production when incentives to invest in robots weaken.

Event study plots in Appendix Figure 1.A.1 support this interpretation. Employment trends in the pre-reform period are parallel across treatment and control firms in both subsamples. After 2018, however, trajectories diverge: employment remains flat among financially constrained firms but increases steadily among unconstrained firms, with statistically significant differences emerging from 2019 onward. These results underscore that labor substitution effects in response to the reform are concentrated among firms that did not face financial constraints.

TABLE 1.5:
Firm-Level Results: Employment

	Ln(Employees)$_{it}$			*Ln(Staff Expenses)$_{it}$*		
	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment$_i$	0.020	0.043**	0.019	-0.003	0.013	-0.004
**Post$_t$*	(0.017)	(0.022)	(0.028)	(0.016)	(0.019)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,076	9,472	6,604	16,076	9,472	6,604
Adjusted R^2	0.95	0.95	0.93	0.94	0.94	0.91

Notes: Estimated effects of the 2018 reform on firm-level employment in Korea. The dependent variable in Columns (1)–(3) is the natural logarithm of the number of employees; Columns (4)–(6) use the logarithm of staff expenses. *Treatment$_i$* equals one for firms affected by the reduced robot tax credit. *Post$_t$* is an indicator variable equal to one after the implementation of the reform, thus after December 31, 2017. Columns (2) and (5) report results for financially unconstrained firms (Low HPI) and Columns (3) and (6) for constrained firms (High HPI), where firms are classified based on the Hadlock–Pierce Index (HPI) of financial constraints and split at the sample median. All specifications include industry-level R&D intensity as a control as well as firm and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis and the OECD.

Investment quality. Lastly, we examine whether the reform affected not only the quantity but also the quality of firm-level investment. One concern is that the automation tax credit may have induced overinvestment in robots, possibly beyond firms' privately optimal level. By reducing this distortion, the reform could have shifted resources toward more productive uses, thereby improving subsequent firm performance. We expect this mechanism to be particularly relevant for financially unconstrained firms, which are better able to reallocate investment across capital categories (Hypothesis 3).

Table 1.6 summarizes the results for different measures of investment quality. We measure investment quality with different measures of firm performance, i.e., turnover, EBIT, and gross profit. The estimated effects display strong heterogeneity. Among financially constrained firms, we find no statistically significant effect of reform-induced investment changes on any performance measure. By contrast, financially unconstrained firms show robust positive responses: turnover, EBIT, and gross profit all increase significantly in the years following the reform.

TABLE 1.6:
Firm-Level Results: Investment Quality

	Ln(Turnover)$_{it}$			*Ln(Gross Profit)$_{it}$*			*Ln(EBIT)$_{it}$*		
	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment$_i$	0.011	0.056**	0.013	-0.002	0.056*	-0.013	0.060*	0.171***	0.032
**Post$_t$*	(0.018)	(0.026)	(0.025)	(0.020)	(0.031)	(0.029)	(0.035)	(0.059)	(0.051)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,273	9,699	10,574	19,861	9,456	10,405	17,001	8,029	8,972
Adjusted R²	0.94	0.93	0.90	0.89	0.86	0.83	0.78	0.72	0.63

Notes: Estimated effects of the 2018 reform on firm-level investment quality in Korea for the following measures of performance*: Ln(Turnover)$_{it}$, Ln(Gross Profit)$_{it}$, Ln(EBIT)$_{it}$*. *Treatment$_i$* equals one for firms affected by the reduced robot tax credit. *Post$_t$* is an indicator variable equal to one after the implementation of the reform, thus after December 31, 2017. Columns labelled "Low HPI" refer to financially unconstrained firms, and "High HPI" to constrained firms, based on the Hadlock-Pierce Index split at the sample median. All specifications include industry-level R&D intensity as a control as well as firm and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis and the OECD.

As a complementary exercise, we implement an instrumental variables strategy to isolate the causal effect of reform-induced investment changes on subsequent firm performance. The instrument exploits the treatment assignment directly, ensuring that we capture only variation in outcomes driven by changes in investment. This approach has two advantages: it allows us to trace effects dynamically over the two years following the reform, and it provides a cleaner interpretation of investment as the underlying transmission channel.

The IV results, reported in Appendix Table 1.A.5, reinforce the heterogeneity documented above. For financially constrained firms, reform-induced reductions in investment have no discernible impact on turnover or profitability in either the reform year or the subsequent two years. For unconstrained firms, by contrast, most of the estimates show large and statistically significant positive effects on all outcomes. Turnover and gross profit increase immediately in the reform year, and the gains persist into years $t+1$ and $t+2$, though becoming gradually smaller and statistically weaker. EBIT appears to increase only in years $t + 1$ and $t + 2$.

In sum, the reform triggered very different responses across firms. Financially constrained firms cut back on investment, and we find no evidence that these losses were offset by additional employees. Unconstrained firms, by contrast, restructured their spending: they scaled back automation but compensated with other forms of investment, hired additional - likely lower-wage-workers, and achieved improvements in investment quality. The results show that financial flexibility was decisive for how firms adjusted to the quasi-robot tax.

1.5.3 Robustness Tests

In this section, we assess the robustness of our main firm-level regression results. For each robustness check, we re-estimate the investment regressions for the full sample, as well as separately for financially constrained and unconstrained firms. In addition, we report the corresponding employment and investment quality regressions for the two subsamples to verify whether the observed heterogeneity in second-order effects remains consistent.

Our first robustness check uses a consistent sample for investment and employment outcomes across all specifications, rather than varying the sample depending on the availability of the respective dependent variables. This consistent sample comprises around 80% of the full investment-analysis sample. As shown in Table 1.A.6, most of our baseline findings remain intact. In particular, we continue to find a negative investment effect only among more financially constrained firms, while the positive employment effect continues to be concentrated among the less constrained firms. Moreover, the positive second-order effects on turnover growth among less constrained firms become even more pronounced in this restricted sample.

Our second robustness test addresses the potential confounding effects of the COVID-19 pandemic, which overlaps with the post-reform period. We are relatively confident that our results are not substantially biased by this coincidence, as our identification strategy is mostly based on within-country variation across Korean firms. Thus, issues would only arise if treated and non-treated firms responded differentially to the pandemic. In addition, the macroeconomic impact of COVID-19 in South Korea was relatively modest compared to other advanced economies. In contrast to many European countries or the U.S., South Korea did not impose a nationwide lockdown in 2020. Instead, the government relied on aggressive testing, contact tracing, and quarantine only for confirmed cases. Thus, manufacturing plants and offices generally remained open, though many firms adopted remote work or staggered shifts voluntarily. As a result, real GDP declined by just 0.7% in 2020.

Nevertheless, we formally test the sensitivity of our results by excluding the year 2020 - the peak of the pandemic - from the sample. The results of this exercise, reported in Table 1.A.7, confirm the stability of our main conclusions.

Our third robustness check uses an alternative proxy to measure financial constraints. Instead of the Hadlock-Pierce Index, we use the logarithm of cash to proxy financial constraints. We present the results in Table 1.A.8, confirming the negative effects on investment as well as the positive effect of employment and investment quality for financially unconstrained firms.

Our final robustness check restricts the sample to firms that were, on average, profitable during the pre-reform period. This restriction mitigates concerns that loss-making firms may have responded differently to the reform due to limited tax liabilities, which could distort the effective value of the automation tax credit. The results, shown in Table 1.A.9, are fully consistent with our baseline findings. The investment response to the reform remains negative for financially constrained firms, while unconstrained firms continue to exhibit offsetting positive effects on employment and investment quality.

1.6 Conclusion

Our study analyses the impact of the reduction of a long-standing “productivity improvement” tax credit on the investment and employment behavior of South Korean firms. We argue that the reduction in this tax credit, which largely encouraged investment in industrial robots, can be interpreted as a quasi-robot tax. In 2018, Korea decreased the tax credit for large and medium-sized firms, but not for small firms.

Exploiting this natural experiment, we first show that reducing tax incentives for automation leads to a decline in both robot investment and broader production activities. Industries with a higher share of affected firms experienced a sharper drop in robot installations, and treated firms reduced their investment in fixed assets by about three percentage points relative to unaffected firms. Second, we find that financially unconstrained firms responded to the reduced incentive for automation by hiring additional employees, while financially constrained firms did not. This substitution toward labor suggests that robots and workers are, on average, substitutes in production. Third, our evidence indicates that scaling back the tax credit improved investment efficiency among financially unconstrained firms. These firms reallocated resources toward more productive uses, leading to gains in turnover, profitability, and gross profit, whereas financially constrained firms cut investment without such offsetting benefits.

Thus, a policy that was designed to encourage innovation may have led to unproductive capital allocation. Our analysis is, however, based on the South Korean context, which is characterized by exceptionally high robot density and long-standing automation policies. The extent of overinvestment we document may therefore be specific to this environment. In economies where automation is less pervasive, diminishing returns to robot investment may be weaker, and the effects of comparable tax reforms could differ.

Our study directly informs the ongoing global debate on the feasibility and implications of robot taxation. By providing empirical evidence on the economic effects of a robot tax-like policy, we bridge the gap between theoretical discussions and real-world outcomes. Our results highlight the inherent trade-offs: while robot taxes may generate fiscal revenue and, under some circumstances, reduce inequality, they also discourage investment in robots and distort firms' capital allocation decisions.

In the South Korean setting, we find that reducing automation incentives improved investment quality, suggesting that very generous, narrowly targeted tax credits can lead to inefficient overinvestment. From a policy perspective, this implies that broad-based, technology-neutral tax systems are less distortionary than selective incentives or taxes focused on specific technologies such as robots. If automation were to cause large-scale displacement of workers in the future, a robot tax might become a relevant instrument for redistribution. At present, however, we do not observe such widespread labor market disruptions and thus little need for a robot tax.

Appendix 1.A

TABLE 1.A.1: Eligible Goods for the Tax Credit for Productivity Enhancement

Category	Scope of Application
1. Facilities for automated production and control of automated production	A. Computers for designing and manufacturing products and computers, peripheral devices (limited to workstations for computer-aided design (CAD) and computer-aided manufacturing (CAM), auxiliary storage, printers, plotters, workstations, modems, terminals, interfaces, and constant voltage power supply systems) and software for the management of business information to receive orders, deliveries, sales, etc. B. Work process control machines or systems for automatic control of manufacturing facilities and parts of such machines or systems: • Facilities operated with programmable logic controllers (PLC) and numerical control systems (NC or CNC) • Robot controllers and unit devices related to computer-integrated manufacturing systems (CIM) • Hydropneumatic valves, hydraulic valves, air compressors, and hydropneumatic actuators C. Machines or facilities equipped with microprocessors or numerical control systems automatically controlling the main work process or function of such machines or facilities. D. Manufacturing or processing systems assembled with two or more machines automatically controlled (including FMC, FMS, and Transfer Line). E. Automatic warehouse systems and loaders/unloaders for safekeeping, storing, and releasing raw materials, parts, and finished products. F. Distributed control systems, integrated information display systems, uninterrupted power supply systems, control valves, signal transmitters, and peripheral devices. G. Automatic control systems, systems for synthesis chemical reaction, and peripheral equipment. *- Continued on next page -*

2. Processing facilities and facilities for quality improvement	A. Facilities for the processing of semiconductors and facilities for the formation of high-purity silicon materials, including facilities for cutting and etching wafers, facilities for shaping circuits, and equipment for packing and assembling chips. B. Wire elongating machines, wire stranding machines, wire winding machines, taping machines equipped with controllers; equipment for removing electrodes and magnetic poles; equipment for air-conditioning, including vacuum, clean, and explosion-proof equipment and equipment for hermetic sealing; equipment for coating, evaporation, and filming; equipment for exposing, developing, etching, and trimming; and equipment for surface-washing, grinding, chamfering, and laminating. C. High-Speed spinning equipment with a spin speed of at least 6,000 meters per minute and manufacturing equipment for high-strength, high-functional fibers. (...)

TABLE 1.A.2: Description of Variables

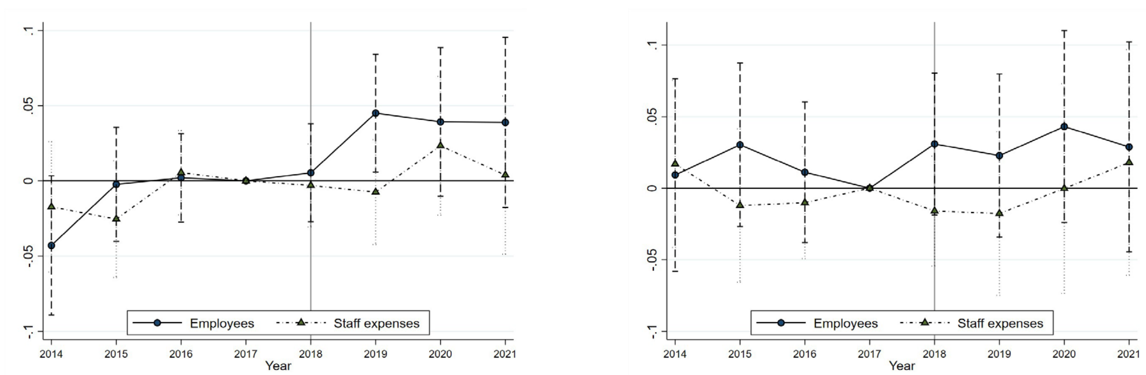
Variable	Definition	Source
Age$_{it}$	Years since incorporation.	Orbis
Cash$_{it}$	Cash.	Orbis
Cashflow$_{it}$	Cashflow.	Orbis
Employees$_{it}$	Number of employees.	Orbis
Gross Investment$_{it}$	Change in fixed assets compared to previous year adjusted for depreciations relative to total assets in the previous year. Gross Investment$_{it}$ = (Fixed Assets − l.Fixed Assets + *Depreciations*)/l.Total Assets.	Orbis
Gross Profit$_{it}$	Gross Profit.	Orbis
HPI$_{it}$	Hadlock & Pierce Index according to Hadlock and Pierce (2010): $HPI = -0.737 * Size + 0.043 * Size^2 - 0.040 * Age$. In line with Hadlock and Pierce (2010), *Size* is the logarithm of total assets in million USD. *Age* is capped at 37.	Orbis
Installations$_{jt}$	Number of new robot installations in industry *j* in year *t*.	IFR
Installations Scaled$_{jt}$	Share of robot installations in industry *j* relative to the total number of installations in year *t*.	IFR
Korea$_c$	Binary treatment indicator. 1 for Korean observations, 0 for Japanese observations.	Orbis
Net Investment$_{it}$	Change in fixed assets compared to previous year relative to total assets in the previous year. Net Investment$_{it}$ = (Fixed Assets - l.Fixed Assets) / l.Total Assets.	Orbis
Post$_t$	Binary treatment indicator. 1 for post-reform observations (2018-2021); 0 for pre-reform observations (2014-2017).	Orbis
RD Expenses Intensity$_{jt}$	R&D Expenses per industry divided by R&D expenses in all industries.	OECD
Share Treated$^{cont}_j$	Percentage share of treated firms in industry *j* prior to the reform.	Orbis
Share Treated$^{bin}_j$	Binary treatment indicator based on the industry's position in the distribution of average robot adoption intensity before the reform. 1 if the industry's pre-treatment mean share of treated firms is in the 4th or 5th quintile; 0 if it is in the 1st or 2nd quintile.	Orbis
Staff Expenses$_{it}$	Staff expenses / costs of employment.	Orbis
Total Assets$_{it}$	Total assets.	Orbis
Treatment$_i$	Indicator variable equal to one if firm *i* is affected by the tax credit reduction, i.e., if a firm does not qualify as a small firm prior to the reform. 0 otherwise.	Orbis
Treatment On$_{it}$	Binary indicator. 1 for treated observations in the post-reform period. 0 otherwise.	Orbis
Turnover$_{it}$	Turnover / Sales.	Orbis

TABLE 1.A.3:
Industry-Level Results: Robustness

	ZIP		Share		PPML	
	(1)	(2)	(3)	(4)	(5)	(6)
Share Treated$^{cont}_{i}$ *$*Post_t$*	-0.053* (0.030)		-0.001* (0.001)		-0.087** (0.034)	
Share Treated$^{bin}_{i}$ *$*Post_t$*		-0.777* (0.431)		-0.032** (0.015)		-1.515** (0.661)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	Yes
Observations	248	200	248	200	224	176
Pseudo R^2					0.82	0.77
Adjusted R^2			0.64	0.42		

Notes: Robustness tests for the estimated effects of the 2018 reform on industry-level investment. The dependent variable in Columns (1)-(2) and (5)-(6) is $Installations_{jt}$, the absolute number of newly installed robots in industry j in year t. The dependent variable in Columns (3)-(4) is $Installations\ Scaled_{jt}$ the number of newly installed robots in industry j in year t divided by the number of installed robots across all industries in year t. *Share Treated*$^{cont}_{j}$ measures the average pre-reform share of treated firms in each industry. *Share Treated*$^{bin}_{j}$ is a binary indicator that equals one if industry j is in the top two quintiles of the *Share Treated*$^{cont}_{j}$ distribution and zero if it is in the bottom two quintiles. $Post_t$ is an indicator variable equal to one after the implementation of the reform, thus after December 31, 2017. Columns (1)-(2) apply a zero-inflated Poisson approach, Columns (3)-(4) apply an OLS approach with the share of robot installations being the dependent variable, Columns (5)-(6) apply a PPML approach with additional control variable which vary at an industry-year level (we include total assets, turnover growth and the number of employees scaled by total assets at an industry-year level). All Columns include industry and year fixed effects. Standard errors are given in parentheses and are clustered at the industry level (for ZIP, we report robust standard errors as clustering is not possible.). ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from the International Federation of Robotics and Orbis database of Moody's.

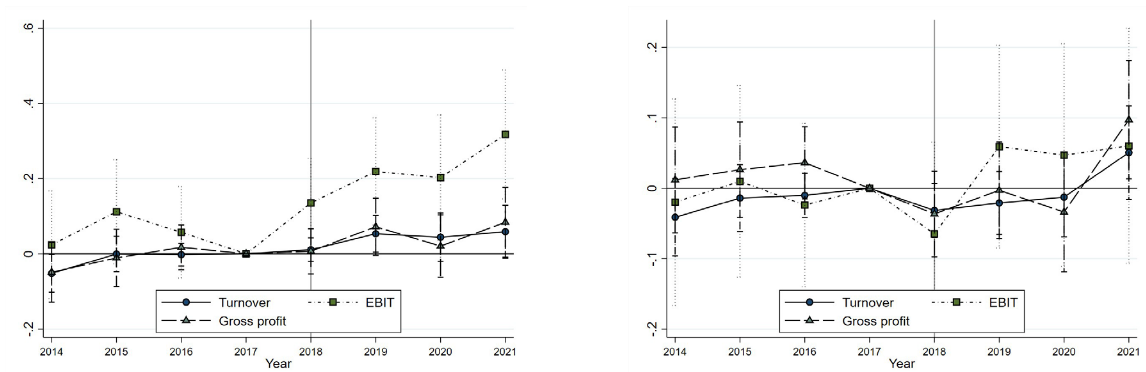
FIGURE 1.A.1: Firm-Level Results: Event Studies for Employment



(A) Low HPI (B) High HPI

Notes: Event study estimates of the reform effect on firm-level employment for a sample split between financially unconstrained and financially constrained firms. The dependent variables are the logarithm of the number of employees and the logarithm of staff expenses. All graphs compare employment outcomes between treated and control firms. Panel (A) focuses on financially unconstrained firms (Low HPI), Panel (B) focuses on financially constrained firms (High HPI). Financial constraints are measured using the Hadlock-Pierce Index; the sample is split at the median. Bars indicate 95% confidence intervals. Yearly data from 2014 to 2021 from Orbis and the OECD.

FIGURE 1.A.2: Firm-Level Results: Event Studies for Investment Quality



(A) Low HPI (B) High HPI

Notes: Event study estimates of the reform effect on firm-level investment quality measures for a sample split between financially unconstrained and financially constrained firms. The dependent variables are the logarithms of turnover, EBIT, and gross profit. All graphs compare investment quality outcomes between treated and control firms. Panel (A) focuses on financially unconstrained firms (Low HPI), Panel (B) focuses on financially constrained firms (High HPI). Financial constraints are measured using the Hadlock-Pierce Index; the sample is split at the median. Bars indicate 95% confidence intervals. Yearly data from 2014 to 2021 from Orbis and the OECD.

TABLE 1.A.4:
Firm-Level Results: Investment by Financial Constraints

	Gross Investment		*Net Investment*	
	Low HPI	High HPI	Low HPI	High HPI
	(1)	(2)	(3)	(4)
*Treatment$_i$ *Post$_t$*	0.003	-0.055***	0.001	-0.050***
	(0.008)	(0.016)	(0.008)	(0.015)
Controls	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	9,704	10,584	9,704	10,584
Adjusted R^2	0.10	0.05	0.06	0.02

Notes: Estimated effects of the 2018 reform on firm-level investment in Korea for a sample split. The dependent variable in Columns (1)–(2) is gross investment (change in tangible and intangible fixed assets plus depreciation, scaled by lagged total assets). Columns (3)–(4) use net investment (change in tangible and intangible fixed assets net of depreciation, scaled by lagged total assets). *Treatment$_i$* indicates firms affected by the reduced tax credit. *Post$_t$* is an indicator variable equal to one after the implementation of the reform, thus after December 31, 2017. Columns (1) and (3) report results for financially unconstrained firms (Low HPI) and Columns (2) and (4) for constrained firms (High HPI), where firms are classified based on the Hadlock–Pierce Index (HPI) of financial constraints and split at the sample median. All columns include industry-level R&D intensity as a control and include firm and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis and the OECD.

TABLE 1.A.5:
Firm-Level Results: Investment Quality - IV

Panel A: Financially Unconstrained (Low HPI)

	Invest	*Outcome$_t$*			*Outcome$_{t+1}$*			*Outcome$_{t+2}$*		
		Turnover	Gross Profit	EBIT	Turnover	Gross Profit	EBIT	Turnover	Gross Profit	EBIT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment On$_{it}$	0.003									
	(0.007)									
$\widehat{Invest}$		23.656***	21.413**	-626.582***	7.659**	8.436**	27.320***	4.740*	3.002	20.768**
		(0.004)	(0.035)	(0.001)	(0.016)	(0.038)	(0.001)	(0.078)	(0.417)	(0.020)
Observations	11,912	11,907	11,610	9,823	10,419	10,150	8,517	8,930	8,685	7,236
F-Stat	0.19									

Panel B: Financially Constrained (High HPI)

	Invest	*Outcome$_t$*			*Outcome$_{t+1}$*			*Outcome$_{t+2}$*		
		Turnover	Gross Profit	EBIT	Turnover	Gross Profit	EBIT	Turnover	Gross Profit	EBIT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment On$_{it}$	-0.049***									
	(0.014)									
$\widehat{Invest}$		-0.444	0.154	-0.530	-0.618	-0.343	-1.060	-0.837	-0.646	-0.878
		(0.516)	(0.516)	(0.844)	(0.568)	(0.664)	(0.939)	(0.552)	(0.691)	(0.968)
Observations	11,912	11,902	11,687	10,049	10,418	10,232	8,754	8,930	8,770	7,459
F-Stat	11.97									

Notes: Estimated effects of the 2018 reform on firm-level investment quality measures in Korea for an IV approach and a sample split between financially unconstrained (Low HPI) and financially constrained (High HPI) firms. Column (1) presents the first stage, where the dependent variable is gross investment (change in tangible and intangible fixed assets plus depreciation, scaled by lagged total assets). *Treatment On$_{it}$* is an indicator variable that equals one for treated observations in the post-reform period. Columns (2)-(10) present estimates of the second stage for different measures of investment quality dynamically over time. The dependent variable in Columns (2), (5), and (8) is the logarithm of turnover, the dependent variable in Columns (3), (6) and (9) is the logarithm of EBIT, and the dependent variable in Columns (4), (7), and (10) is the logarithm of gross profit. Columns (2)-(4) refer to outcome variables in the reform year, Columns (5)-(7) in t + 1 and Columns (8-10) in t + 2. Panel A reports results for financially unconstrained firms (Low HPI) and Panel B for constrained firms (High HPI), where firms are classified based on the Hadlock–Pierce Index (HPI) of financial constraints and split at the sample median. All columns include firm and year fixed effects. R^2 is not meaningful in instrumental-variables regressions. For Panel A, Anderson–Rubin are given in parentheses as we have a weak instrument (F-Stat: 0.19). For Panel B, standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis.

TABLE 1.A.6:
Firm-Level Results: Robustness Test Consistent Sample

Panel A: Investment and Employment

	Gross Investment			*Ln(Employees)$_{it}$*		
	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI
	(1)	(2)	(3)	(4)	(5)	(6)
*Treatment$_i$ *Post$_t$*	-0.017	0.006	-0.043*	0.019	0.043*	0.017
	(0.011)	(0.008)	(0.022)	(0.017)	(0.022)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,916	9,372	6,544	15,916	9,372	6,544
Adjusted R^2	0.17	0.08	0.16	0.95	0.95	0.93

Panel B: Investment Quality

	Ln(Turnover)$_{it}$			*Ln(Gross Profit)$_{it}$*			*Ln(EBIT)$_{it}$*		
	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment$_i$	0.022	0.058**	0.009	0.020	0.056*	0.001	0.081**	0.179***	-0.001
**Post$_t$*	(0.019)	(0.025)	(0.030)	(0.023)	(0.030)	(0.037)	(0.041)	(0.058)	(0.064)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,063	9,467	6,596	15,699	9,230	6,469	13,312	7,841	5,471
Adjusted R^2	0.94	0.93	0.90	0.88	0.86	0.81	0.76	0.72	0.63

Notes: Estimated effects of the 2018 reform on firm-level investment, employment, and investment quality for a consistent sample for investment and employment outcomes. Panel A displays results for investment and employment outcomes, Panel B displays results for investment quality outcomes. For each variable, the first column presents results for the full sample and the following two columns present results for financially unconstrained (Low HPI) and financially constrained (High HPI) firms separately. For variable definitions, see Table 1.A.2 in the appendix. Firms are classified based on the Hadlock–Pierce Index (HPI) of financial constraints and split at the sample median. All columns include firm and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis.

TABLE 1.A.7:
Firm-Level Results: Robustness Test Without 2020

Panel A: Investment and Employment

	Gross Investment			*Ln(Employees)it*		
	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI
	(1)	(2)	(3)	(4)	(5)	(6)
$Treatment_i*Post_t$	-0.032***	0.005	-0.052***	0.016	0.042**	0.010
	(0.011)	(0.008)	(0.018)	(0.016)	(0.020)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,752	8,491	9,261	14,163	8,305	5,858
Adjusted R^2	0.10	0.07	0.09	0.95	0.95	0.93

Panel B: Investment Quality

	Ln(Turnover)it			*Ln(Gross Profit)it*			*Ln(EBIT)it*		
	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Treatment_i$	0.020	0.056**	0.004	0.022	0.060**	0.001	0.071*	0.167***	-0.009
$*Post_t$	(0.018)	(0.024)	(0.029)	(0.023)	(0.030)	(0.035)	(0.041)	(0.058)	(0.065)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,111	8,291	5,820	13,802	8,099	5,703	11,789	6,933	4,856
Adjusted R^2	0.95	0.94	0.90	0.88	0.86	0.81	0.76	0.72	0.63

Notes: Estimated effects of the 2018 reform on firm-level investment, employment, and investment quality for a sample without the year 2020. Panel A displays results for investment and employment outcomes, Panel B displays results for investment quality outcomes. For each variable, the first column presents results for the full sample and the following two columns present results for financially unconstrained (Low HPI) and financially constrained (High HPI) firms separately. For variable definitions, see Table 1.A.2 in the appendix. Firms are classified based on the Hadlock–Pierce Index (HPI) of financial constraints and split at the sample median. All columns include firm and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis.

TABLE 1.A.8:
Firm-Level Results: Robustness Test with Alternative Financial Constraints Measures

Panel A: Investment and Employment

	Gross Investment			*Ln(Employees)it*		
	Full Sample	High Cash	Low Cash	Full Sample	High Cash	Low Cash
	(1)	(2)	(3)	(4)	(5)	(6)
*Treatment$_i$ *Post$_t$*	-0.028***	0.006	-0.047***	0.020	0.038*	0.003
	(0.009)	(0.008)	(0.015)	(0.017)	(0.021)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,288	10,200	10,088	16,118	9,494	6,624
Adjusted R^2	0.09	0.11	0.08	0.95	0.95	0.92

Panel B: Investment Quality

	Ln(Turnover)it			*Ln(Gross Profit)it*			*Ln(EBIT)it*		
	Full Sample	High Cash	Low Cash	Full Sample	High Cash	Low Cash	Full Sample	High Cash	Low Cash
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment$_i$	0.011	0.048*	0.004	-0.002	0.051*	-0.024	0.060*	0.157***	0.040
**Post$_t$*	(0.018)	(0.027)	(0.026)	(0.020)	(0.031)	(0.031)	(0.035)	(0.056)	(0.058)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,273	10,190	10,083	19,861	9,975	9,886	17,001	8,624	8,377
Adjusted R^2	0.94	0.92	0.93	0.89	0.87	0.83	0.78	0.72	0.67

Notes: Estimated effects of the 2018 reform on firm-level investment, employment, and investment quality using the logarithm of cash as an alternative measure for financial constraints. Panel A displays results for investment and employment outcomes, Panel B displays results for investment quality outcomes. For each variable, the first column presents results for the full sample and the following two columns present results for financially constrained (Low Cash) and financially unconstrained (High Cash) firms separately. For variable definitions, see Table 1.A.2 in the appendix. Firms are classified based on the logarithm of cash and split at the sample median. All columns include firm and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis.

TABLE 1.A.9:
Firm-Level Results: Robustness Test without Loss-making Firms

Panel A: Investment and Employment

	Gross Investment			*Ln(Employees)$_{it}$*		
	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI
	(1)	(2)	(3)	(4)	(5)	(6)
*Treatment$_i$ *Post$_t$*	-0.035***	0.006	-0.060***	0.025	0.053**	0.024
	(0.010)	(0.007)	(0.015)	(0.017)	(0.021)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,856	8,512	9,344	14,097	8,333	5,764
Adjusted R^2	0.08	0.08	0.08	0.95	0.95	0.93

Panel B: Investment Quality

	Ln(Turnover)$_{it}$			*Ln(Gross Profit)$_{it}$*			*Ln(EBIT)$_{it}$*		
	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI	Full Sample	Low HPI	High HPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment$_i$	0.008	0.066**	0.004	-0.004	0.079**	-0.029	0.074**	0.227***	0.017
**Post$_t$*	(0.018)	(0.027)	(0.025)	(0.020)	(0.031)	(0.030)	(0.036)	(0.060)	(0.052)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,848	8,508	9,340	17,665	8,386	9,279	15,970	7,548	8,422
Adjusted R^2	0.95	0.93	0.91	0.91	0.87	0.85	0.79	0.72	0.65

Notes: Estimated effects of the 2018 reform on firm-level investment, employment, and investment quality for a sample without firms who on average made a loss prior to the reform. Panel A displays results for investment and employment outcomes, Panel B displays results for investment quality outcomes. For each variable, the first column presents results for the full sample and the following two columns present results for financially unconstrained (Low HPI) and financially constrained (High HPI) firms separately. For variable definitions, see Table 1.A.2 in the appendix. Firms are classified based on the logarithm of HPI and split at the sample median. All columns include firm and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. ***, ** and * label statistical significance at 1%, 5% and 10% level, respectively. Yearly data from 2014 to 2021 from Orbis.

2 Die Forschungszulage: Erfolgreiche Stärkung des Innovationsstandorts Deutschland?*

2.1 Einleitung

Neben der geopolitischen Zeitenwende, dem demographischen Wandel und dem Klimawandel stellen die vernachlässigten Standortfaktoren die Treiber für das verringerte Wachstum und die Produktivität in Deutschland dar. Dabei bedarf es dringend benötigte Investitionen im Bereich der Digitalisierung und der Künstlichen Intelligenz. Neben dem Ausbau der digitalen Infrastruktur, der Datenverarbeitung und Speicherung müssen ebenso die Digitalisierung der öffentlichen Verwaltung und die Förderung der Entwicklung von Fachkräften im Umgang mit Künstlicher Intelligenz weiter vorangetrieben werden. Zusätzlich sind weitere Investitionen im Bereich des Klimaschutzes und der Energieversorgung, der Infrastruktur und Mobilität, dem Gesundheitswesen und der Medizintechnik, sowie der Industrie und Produktion erforderlich. Um all diese notwendigen Investitionen gewährleisten zu können, werden umfangreiche finanzielle Mittel benötigt. Gleichwohl stagnierte das Wachstum der deutschen Wirtschaft bereits vor Beginn der COVID-Pandemie und verharrt seit her auf diesem Niveau (Statistisches Bundesamt, 2024). Gerade dieses schwache Wachstum reduziert den fiskalischen Spielraum bei gleichzeitigen erhöhten Bedarf an gezielten Investitionen. Zusätzlich führen knapp bemessene Bundeshaushalte zur Verschärfung der Situation. Neben der Schuldenbremse müssen ebenfalls die Stabilitätsziele eingehalten werden, sodass eine nachhaltige Priorisierung der Haushaltsausgaben erfolgen muss. Dies führt zur Notwendigkeit der effizienteren Ausgestaltung von Steueranreizen, um einen möglichst hohen Nutzen je eingesetztem öffentlichen Mittel zu erzielen.

Auch im internationalen Vergleich müssen die entsprechenden Rahmenbedingungen für Beschäftigung, Investition und Innovation verbessert werden. Dabei wird eine geringere

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* Das Kapitel 2 ist ein Beitrag in Alleinautorenschaft.

Steuerbelastung für die Unternehmen, mehr Bürokratieabbau und stärkere Investitionsanreize gefordert. Infolgedessen soll speziell der Investitionsförderung in Forschung und Entwicklung durch Einführung einer Forschungszulage im Dezember 2020 besondere Bedeutung zukommen. (Wünnemann, 2025; Hardeck und Heckemeyer, 2023; BMWK, 2025a; Bundesregierung, 2025). Konkret sollte durch die Einführung einer Forschungszulage die Ausgaben in Forschung und Entwicklung auf mindestens 3,5% des Bruttoinlandsprodukts gesteigert werden. Die Ausweitung dieser Ausgaben hilft den Unternehmen im internationalen Wettbewerb standhalten zu können und eröffnet die Möglichkeit der Ansiedelung neuer Unternehmen (Deutscher Bundestag, 2019).

Der vorliegende Beitrag verfolgt das Ziel, die Wirkungsweise der deutschen Forschungszulage zu analysieren und auf Basis gesamtwirtschaftlicher Datenauswertungen zu beurteilen, ob die Ausgestaltung des Instruments die bei seiner Einführung formulierten Ziele der Bundesregierung erreicht. Auf Grundlage der theoretischen Befunde erfolgt anschließend eine datenbasierte Analyse der Zielerreichung, mit der dieser Beitrag die bestehende Literatur um eine deskriptiv gestützte Bewertung der deutschen Forschungszulage ergänzt und gegebenenfalls Ansatzpunkte für eine präzisere Ausrichtung des Förderinstruments aufzeigt.

Dabei wird zunächst die Rechtslage vor Einführung der Forschungszulage der Rechtslage nach Einführung gegenübergestellt (Vgl. Kapitel 2.2). Vor Dezember 2020 konnte eine Förderung lediglich direkt über verschiedene Forschungs- und Entwicklungsprogramme der einzelnen Bundesländer erfolgen. Mit Einführung der Forschungszulage existiert nun auch in Deutschland eine indirekte steuerliche Forschungsförderung, welche auf Antrag mehrfach je Unternehmen genehmigt werden kann.

Um beurteilen zu können, ob die Forschungszulage ein geeignetes Instrument zur Investitionsförderung in Forschung und Entwicklung ist, muss die Ausgestaltung der Zulage und deren ökonomische Wirkung auf die Unternehmen analysiert werden. Demnach werden in Kapitel 2.3 vorhandene Studien zu den Effekten einer indirekten steuerlichen Förderung im

Allgemeinen auf Unternehmen ausgewertet, um Rückschlüsse auf eine sinnvolle Ausgestaltung einer Forschungszulage ziehen zu können. Zu beachten sind dabei, die durch die Bundesregierung gesetzten Ziele beim Erlass des Referentenentwurfs. Neben dem Ziel der Erhöhung der Ausgaben für Forschung und Entwicklung wurde ebenso vereinbart mehr Innovation und eine gesteigerte Produktivität der Unternehmen zu erreichen. Folglich werden die Studien explizit auf diese drei Kernbereiche hin analysiert.

Auch in Bezug auf die deutsche Forschungszulage im Speziellen muss die Erreichung der gesetzten Ziele überprüft werden und mögliche Änderungen der Ausgestaltung der Forschungszulage diskutiert werden (Vgl. Kapitel 2.4). Hierfür werden deskriptive Auswertungen der Innovationsdaten des Bundesministeriums für Forschung, Technologie und Raumfahrt im Hinblick auf mögliche kurz- und langfristigen Folgen der Forschungszulage erstellt. So führt die bisherige Ausgestaltung der Zulage zwar zu einer Erhöhung der Aufwendungen für Forschung und Entwicklung, das gesetzte Ziel von 3,5% des Bruttoinlandsprodukts konnte dabei aber nicht erreicht werden. Darüber hinaus folgt aus der Einführung der deutschen Forschungszulage mehr Innovation, gemessen an neuen Produktentwicklungen und Patentanmeldungen, ebenso wie eine gestiegene unternehmerische Produktivität. Eine veränderte Ausgestaltung der Zulage durch eine separate Förderung von kleinen und mittleren Unternehmen und großen Unternehmen, eine Output-orientierte Förderung oder gesonderte Fördersätze für arbeitsplatzschaffende Forschungsprojekte würden die Zielerreichung weiter verbessern (Vgl. Kapitel 2.5).

Zusammenfassend ergänzt dieser Beitrag die Literatur zur indirekten steuerlichen Forschungsförderung, indem die vorhandene Literatur hinsichtlich der Ausgestaltung der deutschen Forschungsförderung analysiert wird und veränderte Ausgestaltungsmöglichkeiten diskutiert werden. Dies könnte zukünftig die Politik bei der weiteren Entwicklung von Investitionsförderprogrammen für Forschung und Entwicklung unterstützen.

2.2 Rechtslage und Motive der Forschungszulage

2.2.1 Rechtslage vor Einführung der Forschungszulage

Zur Finanzierung der Ausgaben in Forschung- und Entwicklung, haben die Unternehmen neben der internen Finanzierung ebenso die Möglichkeit der Nutzung öffentlicher Mittel. Dabei erfolgt die öffentliche Finanzierung über eine direkte Förderung, die auf Antrag für die einzelnen Forschungsprojekte erteilt werden kann. Als Alternative dazu ist es möglich, eine indirekte Förderung der Forschungstätigkeit zu erlangen, welche meist als eine steuerliche Förderung ausgestaltet ist. Dieses Instrument der steuerlichen Forschungsförderung steht den Unternehmen in nahezu allen OECD Ländern zur Verfügung. So förderten Frankreich, Großbritannien und Japan mehr als die Hälfte der gesamten öffentlichen Forschungsmittel durch eine indirekte Förderung. Die USA und Schweden hingegen bevorzugen eine überwiegend direkte projektbezogene Forschungsförderung. (EFI Gutachten, 2022). Auch Deutschland verwendete die gesamten öffentlichen Mittel zur Förderung projektbezogener Forschungsvorhaben, denn vor Einführung der Forschungszulage im Jahr 2020 existierte keine Möglichkeit zur indirekten (steuerlichen) Forschungsförderung (EFI Gutachten, 2022; EFI Gutachten, 2019; Dreßler und Schwechel, 2020; OECD, 2024).

Infolgedessen konnten deutsche Unternehmen in den Jahren vor der Forschungszulage lediglich die direkte (Projekt-) Förderung anhand verschiedener Förderprogramme in Anspruch nehmen. Neben den verschiedenen Forschungs- und Entwicklungsförderungsprogrammen der einzelnen Bundesländer, wurde vermehrt das Zentrale Innovationsprogramm des Mittelstandes (ZIM) genutzt. Das ZIM ist ein Bundesprogramm zur Förderung marktorientierter Forschungsprojekte zur Unterstützung der Innovationskraft des Mittelstands, um Wertschöpfungspotenziale zu erschließen und damit volkswirtschaftliches Wachstum zu fördern. Begünstigt sind neben den Kosten für das forschenden Personal auch weitere Projektkosten und Kosten für Aufträge an Dritte (ZIM, 2025). Dabei können speziell kleine und mittlere Unternehmen mit einer Betriebsstätte oder Niederlassung in Deutschland, ebenso wie

Forschungseinrichtungen einen Antrag (auch elektronisch) auf Forschungsförderung beim Bundesministerium für Wirtschaft und Klimaschutz (BMWK) stellen. Als begünstigtes Förderprogramm gilt ein Projekt, welches mindestens die Definition der experimentellen Entwicklung gemäß § 2 Nr. 86 AGVO (siehe Anhang 2.A.1) entspricht. Zudem müssen die Grundsätze der Wirksamkeit und Sparsamkeit eingehalten werden. Die Förderung erfolgt als Anteilsfinanzierung in Form eines Projektzuschusses, dessen Fördersätze mit steigender Unternehmensgröße absinkt. Eine genaue Darstellung der einzelnen Fördersätze können dabei Anhang 2.A.2 entnommen werden (BMWK, 2024).

2.2.2 Allgemeines zur Forschungszulage

Mit Veröffentlichung des Gesetzes[33] zur steuerlichen Förderung von Forschung und Entwicklung am 14. Dezember 2019 wurde die Erweiterung der bereits bestehenden Projektförderlandschaft um eine steuerliche Forschungsförderung beabsichtigt. Ziel war es dabei, nicht nur den Unternehmensstandort Deutschland zu fördern, sondern ebenfalls die Investitionsentscheidungen der Unternehmen im internationalen Wettbewerb zu verbessern. Hierbei sollten speziell kleine und mittlere Unternehmen von einer Forschungsförderung profitieren, um selbst mehr Investitionen in die eigene Forschung und Entwicklung zu tätigen (Deutscher Bundestag, 2019).

Daneben fördert die Einführung der Forschungszulage zusätzliche Investitionen der Unternehmen in Forschung und Entwicklung. Diese Investitionen sind notwendig, um Innovation zu fördern und langfristiges Wachstum und Beschäftigung in Deutschland zu sichern. Zudem hat die Einführung einer steuerlichen Forschungsförderung auch positive Effekte auf die Unternehmen selbst. So führt die Einführung einer Forschungszulage neben der Steigerung der Produktivität auch zu mehr Wettbewerbsfähigkeit auf Unternehmensebene.

[33] Um eine deutliche Abgrenzung zu den anderen steuerlichen Regelungen zu schaffen, sind die einzelnen Vorschriften zur Gewährung der Forschungszulage in einem gesonderten Gesetz, welches als steuerliches Nebengesetz zum Einkommen- und Körperschaftssteuergesetz dient, geregelt (Deutscher Bundestag, 2019).

Durch die höheren Investitionen in Forschung und Entwicklung generieren die Unternehmen selbst oder aus der Zusammenarbeit mit öffentlichen Forschungseinrichtungen neues Wissen. Darüber hinaus können Unternehmen weiteres Wissen durch die Tätigkeit der Wettbewerber ableiten, welche für die eigene Innovationstätigkeit genutzt werden kann. In diesen Zusammenhang ergeben sich auch positive Spill-Over-Effekte auf Patentanmeldungen ebenso wie auf Unternehmen ohne eigene Forschungstätigkeiten (Deutscher Bundestag, 2019).

Die Inanspruchnahme der Forschungsförderung erfolgt als Steuergutschrift, sodass die Forschungszulage auf die festgesetzte Einkommen- oder Körperschaftsteuer angerechnet werden kann (§ 10 Abs. 1 FZulG). Dabei dient der Forschungszulagenbescheid als Grundlagenbescheid für die Einkommen- oder Körperschaftsteuerfestsetzung (§ 10 Abs. 3 FZulG). Zudem soll eine Auszahlung über die festgesetzte Steuer hinaus möglich sein, sodass es bei Unternehmen im Verlustjahr zu einer vollständigen Ausbezahlung der Zulage kommen kann (Deutscher Bundestag, 2019a).

Im Hinblick auf die Ausgestaltung der einzelnen steuerlichen Forschungsförderungen existieren zwei Möglichkeiten. Bei einer volumenbasierten steuerlichen Förderung werden die gesamten Aufwendungen für Forschung und Entwicklung berücksichtigt, wohingegen die inkrementelle lediglich den Zuwachs der Aufwendungen im Vergleich zum Referenzjahr heranzieht. Die deutsche Forschungszulage ist als volumenbasierte steuerliche Förderung konzipiert, da alle begünstigten Aufwendungen für Forschung und Entwicklung berücksichtigt werden, nicht nur die Zunahme dieser Aufwendungen im Verhältnis zum Vorjahr. Dabei gelten neben allen Personalkosten ebenso die Anschaffung von Vermögensgegenständen und andere Ausgaben im Bereich der Forschung und Entwicklung als begünstigte Aufwendungen (Spengel et al., 2017; EU Report, 2014). Der Vergleich mit anderen Ländern zeigt, dass die Umsetzung anhand der volumenbasierten Förderung häufiger verwendet wird. Neben den USA wendet Italien als einziges europäisches Land, eine inkrementelle Förderung an. Generell ist aber auch die Kombination aus beiden Variationen möglich, sodass Spanien, Portugal, Irland, Japan und die Tschechische Republik zu der volumenbasierten ebenso eine inkrementelle steuerliche Forschungsförderung anbietet. Um zu entscheiden, ob eine volumenbasierte oder inkrementelle Förderung in Frage kommt, hängt von der Intention der Unternehmen ab. Ein Unternehmen, welches noch keine Forschungs- und Entwicklungstätigkeiten ausübt, ist indifferent zwischen einer volumenbasierten und einer inkrementellen Förderung. Solche Unternehmen investieren in Forschung und Entwicklung, solange der Nettogegenwartswert der Steuergutschrift gleich hoch bleibt. Bei Unternehmen, die bereits aktiv in Forschung und Entwicklung investieren führt eine inkrementelle Steuergutschrift nur dann zu einer Staatsersparnis, wenn die Forschungsförderung sinkt. Im Vergleich der Elastizitäten bezüglich der Nutzerkosten des eingesetzten Kapitals beider Systeme, ergibt sich kein wesentlicher Unterschied (Spengel et al., 2017; EU Report, 2014; Lokshin und Mohnen, 2012). Auch die empirische Literatur zeigt keine einheitliche Empfehlung, welches der beiden Systeme vorrangig zu wählen ist (EU Report, 2014). Lester und Warda (2014) verdeutlichen, dass bei steigenden Forschungs- und Entwicklungsausgaben die Effizienz beider Systeme in etwa vergleichbar ist. Der Vorteil einer inkrementellen gegenüber einer volumenbasierten Gestaltung liegt zunächst in ihrer höheren Kosteneffizienz. Während eine inkrementelle Förderung ausschließlich auf marginale Ausgaben abzielt – also auf jene Investitionen, die tatsächlich durch die Subvention zusätzlich angeregt werden –, subventioniert eine volumenbasierte Förderung auch infra-marginale Ausgaben, die Unternehmen ohnehin getätigt hätten. Dadurch entstehen bei einer inkrementellen Förderung pro zusätzlich induziertem Euro für Forschung und Entwicklung geringere Steuerverluste, vorausgesetzt, die Forschungs- und Entwicklungsausgaben der Unternehmen steigen nicht an. Planen die Unternehmen jedoch ohnehin mit steigenden Forschungs- und Entwicklungsausgaben, verliert die inkrementelle Förderung ihre ursprüngliche Wirkung. Ein wachsender Anteil des natürlichen Ausgabenzuwachses wird automatisch förderfähig, obwohl dieser nicht durch den Anreiz ausgelöst wurde. Damit nähert sich das inkrementelle System funktional einem volumenbasierten an, da in beiden Fällen zunehmend sämtliche Ausgaben subventioniert werden – nicht nur die zusätzlich induzierten. Infolgedessen sinkt bei normalem Wachstum der Forschungs- und Entwicklungsausgaben die Kosteneffizienz einer inkrementellen Ausgestaltung.

Als mögliche Nachteile einer inkrementellen Förderung ist einerseits die Verzerrung der Investitionsplanung zu nennen. Falls Unternehmen Forschungsprojekte über mehrere Jahre planen, schränkt eine inkrementelle Betrachtung die Zeitplanung anhand des maximal möglichen Abzugsbetrags der Forschungs- und Entwicklungsaufwendungen ein. Solche Projekte müssen dann ggf. über einen länger als zu Beginn geplanten Zeithorizont ausgeführt werden. Andererseits erfordert das inkrementelle System einen höheren administrativen Aufwand, was wiederum zu höheren Folgekosten führen kann (EU Report, 2014).

2.2.2.1 Anspruchsberechtigung

Die Forschungszulage steht grundsätzlich allen Unternehmen zu, die eine Steuerpflicht in der Einkommen- oder Körperschaftsteuer begründen.[34] Dabei ist die Größe und die Art der Tätigkeit der Unternehmen unerheblich, es wird lediglich auf die Erzielung von Gewinneinkünften abgestellt (§ 1 Abs. 1 FZulG). Auch für Mitunternehmerschaften besteht die Möglichkeit der Nutzung der Forschungszulage. Die Forschungszulage steht der Mitunternehmerschaft selbst zu, nicht den einzelnen Mitunternehmern, was zu einer Durchbrechung des Transparenzprinzips führt. Zudem verweist § 1 Abs. 2 FZulG bei Mitunternehmerschaften speziell auf Gewinneinkünfte im Sinne des § 15 Abs. 1 EStG. Dies würde Mitunternehmerschaften mit selbständigen oder land- und forstwirtschaftlichen Einkünften vom Anspruch auf die Forschungszulage ausschließen. Die Systematik des Gesetzes verlangt jedoch eine Begünstigung für alle Gewinneinkünfte, sodass eine teleologische Extension notwendig und folgerichtig wäre (Deutscher Bundestag, 2019c; Dreßler und Schwechel, 2020). Nach aktuellem Stand der Rechtsprechung existiert

[34] Auch für optierte Gesellschaften i.S.d. § 1a KStG ist ein Antrag zum Erhalt der Forschungszulage möglich. Nicht jedoch für Unternehmen, die der Allgemeinen Gruppenfreistellungsverordnung unterliegen (AGVO).

diesbezüglich noch keine richterliche Entscheidung, sodass eine teleologische Auslegung weiterhin notwendig ist.

Ebenso erfolgt keine Unterscheidung, ob eine unbeschränkte oder allgemein beschränkte Steuerpflicht im Inland begründet werden muss. Dies führt zu einer Erweiterung der Anspruchsberechtigung der Forschungszulage auf ausländische Unternehmen mit inländischen Gewinneinkünften, nicht jedoch per se zu einer Erweiterung des Anwendungsbereichs auf ausländische Betriebsstätten von im Inland steuerpflichtigen Unternehmen. Wurde die Doppelbesteuerung der Betriebsstättengewinne durch die Anrechnungsmethode beschränkt, gehören diese Einkünfte weiterhin zum Welteinkommen des Steuerpflichtigen und fallen unter den Anwendungsbereich des Forschungszulagengesetztes. Im Gegensatz dazu gehören Betriebsstättengewinne, die anhand der Freistellungsmethode im Inland steuerfrei gestellt wurden, nicht zum Anwendungsbereich. Gleiches gilt für Anspruchsberechtigte, die von der Besteuerung befreit sind. Hierzu zählen neben den Universitäten auch anderen gemeinnützige Institutionen mit Tätigkeiten im Bereich der Wissenschaft. Gerade solche Institutionen könnten aber wesentlich von der Forschungszulage profitieren, sodass eine Förderung dennoch beantragt werden kann, falls die Institution einen wirtschaftlichen Geschäftsbetrieb oder einen Betrieb gewerblicher Art innehat. Im Rahmen dieser Institutionen kommt es neben Forschungskooperationen mit Unternehmen, Forschungsinstituten oder Universitäten, ebenso zu Auftragsforschungen durch Dritte. Gemäß § 2 Abs. 4 FZulG werden auch solche Projekte durch die Forschungszulage unterstützt. Dabei muss bei den Kooperationen jedes Mitglied selbst und bei der Auftragsforschung der Auftraggeber die Voraussetzungen der Zulage erfüllen und diese entsprechend beantragen. Zudem erfolgt eine betragsmäßige Einschränkung der abzugsfähigen Aufwendungen auf 60% des durch den Auftragnehmer gezahlten Entgelts (§ 3 Abs. 4 FZulG). Zu beachten ist ferner, dass § 2 Abs. 4 FZulG keine eigene Anspruchsberechtigung neben § 1 Abs. 1 FZulG begründet, sondern die Vorschriften gerade zur Steuerfreiheit bei Universitäten weiterhin Anwendung finden (Deutscher Bundestag, 2019c; Birkholz und Hagemann, 2019; Dreßler und Schwechel, 2020; Mirbach und Werth, 2024). Als Ergänzung wurde gem. § 2 Abs. 5 FZulG die Auftragsforschung auch auf Auftragsnehmer mit Ansässigkeit in anderen EU oder EWR-Staaten erweitert, um nicht gegen die europäische Dienstleistungsfreiheit zu verstoßen (Deutscher Bundestag, 2019a; Deutscher Bundestag, 2019b; Meyering et al., 2020).

Der sachliche Anwendungsbereich der Forschungszulage umfasst die Grundlagenforschung, die industrielle Forschung und die experimentelle Entwicklung (§ 2 Abs. 1 FZulG). Dabei erfolgt die genaue Definition der einzelnen Teilbereiche gem. § 9 Abs. 1 FZulG anhand des Art. 2 Ziffer 84 bis 86 der AGVO (Vgl. Anhang 2.A.1). Im Falle von Abgrenzungsfragen werden die oben genannten Definitionen erweitert um die Merkmale des Frascati Handbuchs der OECD. Nach dieser Definition ergeben sich konkret fünf Merkmale, um sachlich ein begünstigungsfähiges Forschungs- und Entwicklungsvorhaben zu definieren (OECD, 2018; Dreßler und Schwechel, 2020). So muss das Vorhaben auf die Gewinnung neuer Erkenntnisse ausgelegt sein (Neuartigkeit), basierend auf originäre, nicht offensichtliche Konzepte und Hypothesen (Schöpferisch), sowie in Bezug auf das Endergebnis ungewiss sein (Ungewissheit). Darüber hinaus sollen diese Vorhaben einem Plan folgen, budgetiert sein (Systematik) und zu Ergebnissen führen, die reproduziert werden können (Übertragbarkeit) (OECD, 2018; Birkholz und Hagemann, 2019; Dreßler und Schwechel, 2020).

Eine klare Abgrenzung muss jedoch zwischen der begünstigten (experimentellen) Entwicklung und der nicht begünstigten Entwicklung von Produkten zur Vermarktung erfolgen. Die experimentelle Entwicklung kann Teil der Marktentwicklung sein, jedoch endet diese sobald die oben genannten Kriterien nicht mehr zutreffen. Alle Aufwendungen nach Abschluss der experimentellen Entwicklung können dann nicht mehr im Rahmen der Forschungszulage gefördert werden. Gleiches gilt für Entwicklungen, welche zum reibungslosen Funktionieren von Produktsystemen generiert wurden gem. § 2 Abs. 2 FZulG (OECD, 2018)

In Bezug auf den zeitlichen Anwendungsbereich legt das Gesetz fest, dass eine

Förderung der Forschungs- und Entwicklungsausgaben erst nach dem Tag des Inkrafttretens des Forschungszulagengesetzes erfolgen kann (§ 8 Abs. 1 FZulG). Dies erscheint folgerichtig, da die Forschungszulage einen Anreiz setzen soll, dass Unternehmen zusätzliche Investitionen in die eigenen Forschungs- und Entwicklungstätigkeit einsetzen (Birkholz und Hagemann, 2019; Trage et al., 2019).

2.2.2.2 Förderungsfähige Aufwendungen und Höhe der Forschungszulage

Falls Unternehmen den sachlichen Anwendungsbereich erfüllen und in ein begünstigtes Forschungs- und Entwicklungsvorhaben investieren, werden nicht die gesamten anfallenden Ausgaben gefördert. Die förderfähigen Aufwendungen sind auf die dem Lohnsteuerabzug unterliegenden Arbeitslöhne mit Sozialversicherungsbeiträgen beschränkt (§ 3 Abs. 1 FZulG; § 38 Abs. 1 EStG; § 3 Nr. 62 EStG).[35] Dies hat zur Folge, dass die Forschungsförderung durch die Zulage gänzlich unabhängig vom Gewinn gewährt werden kann. Zu beachten ist, dass solche Lohnkosten, die von Dritten bezahlt werden, nicht förderfähige Aufwendungen sind, denn der Anspruchsberechtigte hatte hier keinen wirtschaftlichen Aufwand zu tragen (Deutscher Bundestag, 2019; Birkholz und Hagemann, 2019).

Darüber hinaus darf die Forschungszulage nur für Personal beantragt werden, für welches eine direkte Zuordnung zu Forschungs- und Entwicklungstätigkeiten möglich ist. Folglich können Aufwendungen für nicht forschendes Personal, wie Reinigungskräfte, Bürosachbearbeiter oder nicht forschende Führungskräfte nicht mitberücksichtigt werden (Deutscher Bundestag, 2019).[36] Die Unternehmen können dem forschenden Personal auch solche Arbeitnehmer zu ordnen, für welche aufgrund der Zuweisung des Besteuerungsrechts durch Doppelbesteuerungsabkommen in Deutschland keine Lohnsteuer einbehalten wurde (sog. Grenzpendler oder Grenzgänger). Solche Grenzpendler werden unter Vorliegen aller anderen Voraussetzungen des § 3 Abs. 1 FZulG den inländisch steuerpflichtigen

[35] Dies gilt auch für Gesellschafter oder Anteilseigner, welche einen schuldrechtlichen Vertrag mit der Kapitalgesellschaft geschlossen haben (§ 3 Abs. 1 S. 3 FZulG).
[36] Hier ist das Unternehmen verpflichtet eine nachprüfbare, eindeutige und zeitnahe Dokumentation zu führen.

Arbeitnehmern gleichgestellt (§ 3 Abs. 2 FZulG). Zu berücksichtigen ist hier auch die offene Formulierung, sodass keine Einschränkung für den Fall der Arbeitslöhne in einer ausländischen Betriebsstätte eines inländischen Arbeitsgebers vorhanden ist (Deutscher Bundestag, 2019; Trage et al., 2019). Folgt man den Vorschriften zur Berücksichtigung der Arbeitslöhne zur Berechnung der Bemessungsgrundlage, so können speziell Einzelunternehmer keine Aufwendungen geltend machen. Da Einzelunternehmer keine Verträge mit sich selbst abschließen können (§ 181 BGB), sind die Kosten der eigenen Arbeitsleistung nicht als Betriebsausgabe abzuziehen. Um jedoch den forschenden Einzelunternehmer dennoch zu unterstützen, existiert in § 3 Abs. 4 FZulG die Möglichkeit einer fiktiven Stundenlohnpauschale. So kann der Einzelunternehmer einen Stundenlohn von 40 € für begünstigte Forschungs- und Entwicklungstätigkeiten bei maximal 40 Wochenstunden, also insgesamt höchstens 1.600 € wöchentlich ansetzen.[37] Gleiches gilt bei Mitunternehmerschaften durch zivilrechtlich wirksame Vereinbarungen (§ 3 Abs. 3 FZulG).

Zusätzlich existiert eine allgemeine Obergrenze bei der Ermittlung der Bemessungsgrundlage. So dürfen die im Wirtschaftsjahr maximal möglichen förderfähigen Aufwendungen 2 Mio. € nicht übersteigen (§ 3 Abs. 5 FZulG). Dabei ist die Grenze bei verbunden Unternehmen insgesamt zu berücksichtigen (§ 3 Abs. 6 FZulG), wohingegen bei Forschungskooperationen jedem Kooperationspartner diese Grenze zusteht (§ 3 Abs. 7 FZulG).

Die Höhe der Forschungszulage bemisst 25% der in § 3 FZulG ermittelten Bemessungsgrundlage, was bei einer Obergrenze der Bemessungsgrundlage von 2 Mio. € zu einer Forschungszulage von maximal 500.000 € je Anspruchsberechtigten je Wirtschaftsjahr führt (§ 4 Abs. 1 FZulG). Mithin kann der Höchstbetrag auf mehrere begünstigungsfähigen Vorhaben verteilt werden (Mohaupt, 2019). Prinzipiell erlaubt § 7 Abs. 1 FZulG eine Förderung

[37] Mit 40 € je Stunde wurde die Stundenlohnpauschale zwar im Verhältnis zum Referentenentwurf angehoben, betragsmäßig erfolgte die Festsetzung aber immer noch unter den geforderten Höchstbetrag von 55 €. Somit bleibt die Angemessenheit der Höhe des Stundenlohns für Einzel- und Mitunternehmer weiterhin fragwürdig (Meyering et al., 2020).

durch die Forschungszulage zusätzlich neben Projektförderungen und staatlichen Beihilfen. Dabei dürfen Aufwendungen aber nicht kumuliert verwertet werden, was dazu führt, dass die Aufwendungen entweder in die steuerliche Förderung oder in die alternative Förderung mit eingezogen werden können. Zuletzt existiert gem. § 4 Abs. 2 FZulG eine absolute Obergrenze für alle staatliche gewährten Beihilfen von 15 Mio. € (Deutscher Bundestag, 2019; Haase et al., 2020).

2.2.2.3 Antragsverfahren

Der Antrag zum Erhalt der Forschungszulage erfolgt über ein zweistufiges Verfahren. Die Forschungszulage kann nur durch Antrag des Anspruchsberechtigten gewährt werden (§ 5 Abs. 1 FZulG). Für den Antrag ist eine entsprechende Bescheinigung der zuständigen Stelle notwendig (§ 5 Abs. 3 FZulG; § 6 Abs. 1 FZulG), welche fachlich prüft, ob die Anspruchsvoraussetzungen für ein förderfähiges Vorhaben im Sinne des Forschungszulagengesetzes vorliegen. Diese Bescheinigung ist dann Grundlagenbescheid für die Festsetzung der Forschungszulage (Deutscher Bundestag, 2019). Der entsprechende Antrag mit Bescheinigung ist beim zuständigen Betriebsstättenfinanzamt des jeweiligen Anspruchsberechtigten einzureichen (§ 5 Abs. 1 FZulG). Dabei kann der Antrag nach Ablauf des Wirtschaftsjahres unmittelbar ohne Einhaltung der Steuererklärungsfristen gestellt werden, ein fertiger Jahresabschluss muss nicht vorliegen (§ 5 Abs. 1 FZulG). Zudem entsteht der Anspruch auf die Forschungszulage nicht erst mit Antragstellung, sondern bereits mit Verursachung der Aufwendungen für das Forschungsprojekt (Haas et al., 2020). Folglich kommt nur eine Abschnittsbetrachtung in Frage, sodass ein Forschungsprojekt auch über mehrere Jahre gefördert werden kann (Deutscher Bundestag, 2019).

2.2.2.4 Nachträgliche Änderungen des Forschungszulagengesetzes

Das Forschungszulagengesetz wurde nach Einführung am 14. Dezember 2019 durch das zweite Corona-Steuerhilfegesetz und das Wachstumschancengesetz vom 28. März 2024 geändert. Eine schon mehrfach geforderte Erhöhung der Bemessungsgrundlage wurde erstmals mit dem zweiten Corona-Steuerhilfegesetz von bisher 2 Mio. € auf 4 Mio. € umgesetzt. Mit dem Wachstumschancengesetz vom 28. März 2024 erhöht sich die Bemessungsgrundlage erneut auf 10 Mio. € (§ 3 Abs. 4 FZulG). Dieser Wert scheint in Anbetracht des Ziels der Förderung von kleinen und mittleren Unternehmen eher nichtzutreffend gewählt. Die Gesetzesbegründung legt jedoch nahe, dass nun nicht mehr nur kleine und mittlere Unternehmen, sondern auch größere Unternehmen von der Forschungszulage profitieren sollen. Demzufolge ist die erweiterte Bemessungsgrundlage auf 10 Mio. € folgerichtig (Deutscher Bundestag, 2020b). Um aber dennoch das Ziel der Förderung der Ausweitung eigener Forschungsausgaben für kleine und mittlere Unternehmen zu betonen, erfolgte eine Ausweitung der Höhe der Forschungszulage von 25% auf 35% speziell für kleine und mittlere Unternehmen. Der Fördersatz für größere Unternehmen verbleibt derweilen bei 25% (§ 4 Abs. 1 FZulG). Die notwendigen Größenbedingungen zur Einteilung sind dabei dem Art. 2 Abs. 1 AGVO zu entnehmen (Mirbach und Werth, 2024; Schumann, 2021).

Weitere Änderungen durch das Wachstumschancengesetz vom 28. März 2024 sind die Erhöhung des fiktiven Stundenlohns der Einzel- und Mitunternehmer von 40 € je Arbeitsstunde auf 70 € (§ 3 Abs. 3 S. 2 FZulG), ebenso wie die Erweiterung des Anteils an förderfähigen Aufwendungen im Rahmen der Auftragsforschung von 60% auf 70% (§ 3 Abs. 4 S. 2 FZulG). Zudem wurde eine Ausweitung auf investive Aufwendungen gem. § 3 Abs. 3a FZulG vorgenommen. Dabei umfassen investive Aufwendungen abnutzbare bewegliche Wirtschaftsgüter des Anlagevermögens, welche für die Forschungs- und Entwicklungstätigkeiten erforderlich und ausschließlich eigenbetrieblich genutzt werden. Eine genaue Erläuterung der Wertminderungsberechnung befindet sich in § 3 Abs. 3a S. 3 f. FZulG.

Durch den kürzlich vorgestellten Entwurf des Gesetzes für ein steuerliches Investitionssofortprogramm zur Stärkung des Wirtschaftsstandorts Deutschland vom 04. Juni 2025 soll auch in Bezug auf das Forschungszulagengesetz Änderungen bewirkt werden. Dabei soll speziell der Wirtschaftsstandort Deutschland gefördert und das Wachstum und die

Innovation beschleunigt werden (Deutscher Bundestag, 2019). Zur Umsetzung dieser Ziele, wird die Forschungszulage um einen pauschalen Aufwand in Höhe von 20% der förderfähigen Aufwendungen für Gemein- und Betriebskosten berücksichtigt (§ 3 Abs. 3b FZulG-E in Deutscher Bundestag, 2025). Zudem sieht der Gesetzesentwurf eine weitere Erhöhung der Obergrenze der Bemessungsgrundlage von 10 Mio. € auf 12 Mio. € vor. Diese Ausweitung setzt nicht nur den Anreiz, weiter in Forschung und Entwicklung zu investieren, sondern unterstützt speziell jetzt auch größere Unternehmen hier intensiver tätig zu werden. Das zeigt auch die Entwicklung des Gesetzes von einer speziellen Forschungsförderung für kleine und mittlere Unternehmen, hin zu einer Förderung aller Unternehmen in Deutschland (§ 3 Abs. 5 FZulG-E in Deutscher Bundestag, 2025; Deutscher Bundestag, 2019a).

2.3 Allgemeine Wirkung von Forschungsförderungen

Im Rahmen dieses Kapitels werden die allgemeinen Auswirkungen einer steuerlichen Forschungsförderung genauer erläutert. Zunächst werden die Wirkungen auf die Forschungs- und Entwicklungsaufwendungen der Unternehmen analysiert. Dabei ist zwischen den Sachausgaben für Forschung und Entwicklung (Kapitel 2.3.1) und den Lohnkosten für forschendes Personal (Kapitel 2.3.2) zu unterscheiden. Im Folgenden wird die vorhandene Literatur bezüglich der Effekte einer steuerlichen Forschungsförderung auf Innovationen (Kapitel 2.3.3) ebenso wie auf die Produktivität von Unternehmen (Kapitel 2.3.4) ausgewertet. Diese Ausführungen dienen als Grundlage, um im weiteren Verlauf der Arbeit empirische Befunde zur Wirkung der deutschen Forschungszulage (Kapitel 2.4) und deren konkreten Ausgestaltung (Kapitel 2.5) genauer erläutern zu können.

2.3.1 Auswirkungen auf Forschungs- und Entwicklungsaufwendungen

2.3.1.1 Aufnahme von Forschungstätigkeiten durch steuerliche Förderungen

Die Einführung einer indirekten steuerlichen Forschungsförderung sollte zu einer Ausweitung der Anzahl an Unternehmen, welche Forschungs- und Entwicklungsaktivitäten ausüben, führen. So kann die steuerliche Förderung einerseits die Unternehmen darauf hinweisen, dass die bereits ausgeführten Aktivitäten für Forschung und Entwicklung einer Förderung unterliegen. Durch die Beseitigung der Unkenntnis der Unternehmen hinsichtlich des Vorhandenseins einer steuerlichen Forschungsförderung, setzt die steuerliche Förderung den Anreiz vermehrt in Forschung und Entwicklung zu investieren. Zu beachten ist aber auch, dass die Unternehmen trotz Kenntnis über die mögliche Förderung eine solche nicht in Anspruch nehmen wollen. Neben hohen administrativen Kosten existiert auf Seiten der Unternehmen auch eine gewisse Unsicherheit in der Anwendung einer indirekten Forschungsförderung. (Spengel et al., 2017).

Andererseits führt eine steuerliche Forschungsförderung zu niedrigeren Kosten im Bereich der Forschung und Entwicklung, was Unternehmen generell dazu veranlassen kann, erstmalig in Forschungs- und Entwicklungsaktivitäten zu investieren. Durch die Förderung verringern sich die Kosten so, dass Unternehmen, für die eine Investition in Forschung und Entwicklung bisher nicht profitabel war, nun vermehrt Kapital in diesem Bereich einsetzen sollten. Dabei tätigen die Unternehmen vermehrt solche Investitionen immer dann, wenn deren erwarteten Erträge höher sind als die damit verbundenen Kosten. Führen die Investitionen in Forschung und Entwicklung über einen längeren Zeitraum zu Erträgen, so folgen weitere dynamische Effekte für das Unternehmen. Folglich werden neben der Investitionsentscheidung auch generell strategische Überlegungen initiiert, welche zu einer Neuausrichtung des Geschäftsmodells innerhalb des Unternehmens führen kann. Peters et al. (2013) haben diesen Effekt genauer untersucht. Die Investitionen in Forschung und Entwicklung führen langfristig zu Innovationen, was zu einer Steigerung der Produktivität und zu künftigen Gewinnen führt. Dieser Effekt zeigt sich durch die Analyse der Ausgaben für Forschung und Entwicklung auf den Unternehmenswert. Dabei resultieren die niedrigeren Aufwendungen[38] in einem steigenden Unternehmenswert, sodass die Unternehmen die (erstmalige) Investition in Forschung und

[38] Gemeint sind die um die steuerliche Forschungsförderung geminderten internen Aufwendungen der Unternehmen; insgesamt führt die Forschungsförderung zu einem höheren Investitionsvolumen.

Entwicklung tätigen werden. Demzufolge steigt bei einer Reduktion der Forschungs- und Entwicklungskosten um 20% der Anteil der beteiligten Unternehmen in Forschung und Entwicklung nach fünf Jahren um ca. 1,3%, was zu einem Produktivitätsanstieg von ca. 0,2% der Unternehmen führt (Peters et al., 2013).

2.3.1.2 Ausweitung vorhandener Forschungstätigkeiten durch steuerliche Förderungen

Eine Einführung einer Forschungsförderung kann nicht nur die erstmalige Aufnahme von Forschungs- und Entwicklungsaktivitäten begünstigen, sondern auch auf die Ausweitung der Aufwendungen bereits investierender Unternehmen Einfluss haben. So zeigt die empirische Literatur, dass die durch die steuerliche Förderung geminderten Kosten von 10% zu höheren Investitionen in Forschung und Entwicklung führen. Dabei verstärkt sich der Effekt mit jedem folgenden Jahr nach der Einführung einer steuerlichen Förderung. Neben der Elastizität kann als alternatives Maß zur Analyse der B-Index[39] verwendet werden, welcher die Attraktivität der steuerlichen Rahmenbedingungen für Investitionen in Forschung und Entwicklung misst. Je geringer dieser Wert ist, desto eher führen steuerliche Förderinstrumente zu einer Investition. Auch der B-Index zeigt, dass ein positiver Zusammenhang zwischen der steuerlichen Forschungsförderung und der Ausgaben in diesem Bereich besteht (Spengel et al., 2017; EU Report, 2014).

Bei Betrachtung einzelner Länder zeigt sich ebenfalls ein Anstieg der Aufwendungen nach Einführung einer steuerlichen Förderung. So belegt die Analyse der OECD-Staaten, dass über alle Länder hinweg die Einführung einer Steuergutschrift zu mehr Investitionen in Forschung und Entwicklung führt. Im Rahmen dieses Vergleichs zeigt sich, dass Länder wie Belgien, Norwegen, Portugal und Schweden höhere Zunahmeraten aufweisen als Australien,

[39] Der B-Index ist ein Maßstab, der die Auswirkungen eines Steuersystems auf die Entscheidung der Unternehmen in Forschung und Entwicklung zu investieren, aufzeigt. Dabei wird der B-Index als Barwert des Vorsteuergewinns berechnet, den ein Unternehmen erzielen muss, um die Kosten einer anfänglichen Forschung und Entwicklungsinvestition zu decken und die anfallenden Steuern zu zahlen. Je niedriger der Index, desto größer ist der Anreiz für ein Unternehmen, in Forschung und Entwicklung zu investieren (Warda, 2001; McFetridge und Warda, 1983).

die Tschechische Republik und Frankreich. Im Verhältnis zu Deutschland besitzt Belgien eine ähnliche steuerliche Forschungsförderung. Die Analyse der Auswirkungen einer steuerlichen Forschungsförderung in Belgien zeigt, dass eine Senkung der Kosten um 1% mit einem Anstieg der unternehmerischen Forschungs- und Entwicklungsinvestitionen um rund 2% verbunden ist. Darüber hinaus investieren die Unternehmen im Durchschnitt etwa 3,50 € zusätzlich in Forschung und Entwicklung pro erhaltenen Euro an steuerlichen Förderungen (Appelt et al., 2020; Dumont, 2017). Dieser positive Zusammenhang ist relativ stark ausgeprägt, entspricht aber weitestgehend der aktuellen Literatur für Schätzungen von steuerlichen Forschungsförderungen auf Unternehmensebene. Dabei ergeben sich solche starken positiven Effekte ebenfalls für die USA (Rao, 2016; Melnik und Smyth, 2024), für Großbritannien (Dechezlepretre et al., 2023; Guceri und Liu, 2017), für Norwegen (Benediktow et al., 2018) und für China (Jia und Ma, 2017).

Da gerade in Bezug auf Innovationen multinationale Unternehmen von großer Bedeutung sind, haben Knoll et al. (2021) den Einfluss von steuerlichen Anreizen auf die Forschungs- und Entwicklungstätigkeiten dieser Unternehmer untersucht. Dabei ist zu erkennen, dass multinationale europäische Unternehmen die Investitionen in Tochtergesellschaften in Ländern mit großzügigen Steuergutschriften sukzessive erhöhen, wohingegen die Investitionen in solchen Ländern mit geringerer steuerlicher Forschungsförderung reduziert werden. Es kommt zu einer grenzüberschreitenden Verlagerung der Forschungs- und Entwicklungsausgaben nicht jedoch zu einer allgemeinen Ausweitung der Forschungs- und Entwicklungstätigkeiten.[40]

Einer der maßgeblichen Gründe für die Einführung einer steuerlichen Forschungsförderung ist die spezielle Förderung der Investitionen in Forschung und Entwicklung von kleinen und mittleren Unternehmen. Dabei zeigten neben Guceri et al. (2015)

[40] Weitere Analysen zur grenzüberschreitenden Verlagerung von Forschungs- und Entwicklungstätigkeiten führten Wilson, 2009; Montmartin/Herrera, 2015; Akcigit et al., 2018; Corrado et al., 2015 durch.

und Lokshin und Mohnen (2012) auch Caiumi (2010), dass speziell kleine und mittlere Unternehmen stärker auf steuerliche Förderungen reagieren. Mögliche Gründe hierfür können die stärker vorherrschenden Kreditbeschränkungen der kleinen und mittleren Unternehmen im Verhältnis zu größeren Unternehmen sein (Kasahara et al., 2014; Kobayashi, 2014). Lester und Warda (2014) bestätigen diese Heterogenität, denn die steuerliche Forschungsförderung wird mit zunehmendem Wachstum der Unternehmen ineffizient. Demzufolge ist es notwendig, dass gesonderte Regelungen bezüglich der Steueranreize für kleine und mittlere Unternehmen und große Unternehmen erfolgen (Lester und Warda, 2018).

2.3.2 Wirkungen auf die Lohnkosten für Personal in Forschung und Entwicklung

Darüber hinaus hat die Einführung einer indirekten steuerlichen Förderung für Forschungstätigkeiten Auswirkungen auf die Beschäftigung und die Lohnkosten von Mitarbeitern in Forschung und Entwicklung. Durch die Einführung einer steuerlichen Forschungsförderung sind die Unternehmen in der Lage mehr Forschungsaktivitäten zu betreiben, wofür aber mehr Personal benötigt wird. Mit steigender Nachfrage steigen auch die Preise für dieses Personal, also die Löhne der forschenden Mitarbeiter. Goolsbee (1998) entdeckte als Erster den positiven Zusammenhang zwischen steigenden Forschungs- und Entwicklungsausgaben und dem Anstieg der Gehälter für forschendes Personal.[41] Weiterführende Studien untersuchten diesen Effekt genauer und fanden für Dänemark einen positiven Anstieg um ca. 33.000 Kronen je 100.000 Kronen Steuervergünstigung (Hægeland und Møen, 2010) und für die Niederlande einen Anstieg der Lohnkosten um ca. 0,2% (Lokshin und Mohnen, 2013). Ebenfalls einen Anstieg konnte Dumont (2013) für Belgien feststellen. Hier führte eine ein Euro höhere Subvention zu einem Lohnanstieg von ca. 0,15%. Darüber hinaus beeinflusst die steuerliche Forschungsförderung nicht nur die Löhne und Gehälter für

[41] Durch die Auswertung staatlicher Ausgaben für Forschung und Entwicklung in den USA für einen Zeitraum von 1968-1994 konnte Goolsbee zeigen, dass eine Steigerung der Forschungs- und Entwicklungsausgaben um 10% in einem unmittelbaren Anstieg der Löhne um 1% und um eine weitere Steigung um 2% in den nächsten 4 folgenden Jahren resultiert. Eine Nichtberücksichtigung dieser Auswirkung könnte zu einer Überschätzung der öffentlichen Förderung von Forschung und Entwicklung um 30% - 50% führen.

forschendes Personal positiv, sondern auch solche anderen Mitarbeiter der Unternehmen. So zeigten Carbonnier et al. (2022), dass in Frankreich ca. die Hälfte des durch Steuergutschriften generell erzeugten Überschusses auf die Arbeitslöhne umgelegt werden. Dabei profitieren hochqualifizierte Beschäftigte eher von den Überschüssen als weniger qualifizierte Mitarbeiter.

2.3.3 Effekt einer steuerlichen Förderung auf Innovationen

Eine steuerliche Forschungsförderung sollte nicht nur die Ausgaben für Forschung und Entwicklung ausweiten, sondern ebenfalls positive Effekte auf die Innovation haben. Durch eine solche indirekte steuerliche Forschungsförderung wird die finanzielle Belastung der Unternehmen gemindert, sodass diese mehr Liquidität zur Verfügung haben, um Forschungs- und Entwicklungsaktivitäten zu fördern. Somit ist es speziell kleinen und mittleren Unternehmen möglich mehr in solche Tätigkeiten zu investieren und dadurch die Entwicklung von neuen Produkten und damit von Innovation zu fördern. Ebenso geht die Investition in Forschung und Entwicklung einher mit einer hohen Unsicherheit und einem hohen Risiko. Die Unternehmen können bei Beginn der Investition noch nicht eindeutig wissen, ob sich ein Mehrwert aus dieser Investition für das Unternehmen ergibt. Im Rahmen einer steuerlichen Förderung können diese Kosten entsprechend aufgeteilt werden und die Unternehmen für einen Teil der Unsicherheit und des Risikos entschädigt werden. Darüber hinaus enthalten die Regelungen zu steuerlichen Forschungsförderungen den Anreiz die Zusammenarbeit von Unternehmen und Institutionen zu fördern. So können in Forschungskooperationen nicht nur die Ressourcen gemeinsam nutzen, sondern auch Synergieeffekte aus den unterschiedlichen Kompetenzen erzielt werden. Dies führt zu einer beschleunigten Forschungs- und Entwicklungstätigkeit, was wiederum die Innovation zügiger voranbringen kann (Melnik und Smyth, 2024; Hu et al., 2025).

Der Effekt der steuerlichen Forschungsförderung auf die Innovation kann anhand der erweiterten Entwicklung neuer Produkte gemessen werden. Dabei zeigte Czarnitzki et al. (2011), dass Unternehmen, welche eine Forschungsförderung in Anspruch nehmen mehr

Produktinnovationen ebenso wie höhere Verkäufe neuer und verbesserter Produkte aufzeigen. Die Förderung steigert hierbei nicht nur die Einführung neuer Produkte auf den heimischen Markt, sondern auch weltweit. Zudem kann die steuerliche Förderung dazu beitragen neue Produktionsprozesse zu entwickeln (Cappelen et al., 2012).

Daneben wird die Erweiterung der Innovation durch die steuerliche Forschungsförderung üblicherweise anhand der erhöhten Anmeldung neuer Patente ermittelt. Dabei zeigt sich in der herrschenden Literatur ein positiver Zusammenhang zwischen einer Förderung und der Anmeldung neuer Patente. Diesen zeigten Ernst et al. (2011) für die EU, Westmore (2013) für die OECD Länder, Hu et al. (2025) für China und Melnik und Smyth (2024) für die USA.

Durch eine Forschungsförderung sollen speziell kleine und mittlere Unternehmen profitieren und selbst vermehrt in die eigene Forschungs- und Entwicklungstätigkeit investieren. Ist die steuerliche Forschungsförderung also ein adäquates Konzept, um genau dieses Ziel zu erreichen, muss sich speziell bei den kleinen und mittleren Unternehmen ein Anstieg der Patentdaten zeigen. Eine genaue Analyse der Heterogenität zeigt, dass die Patentzahlen für kleine und mittlere Unternehmen durch eine steuerliche Forschungsförderung ansteigen. Dechezlepretre et al. (2023) belegten, dass eine volumenbasierte Forschungsförderung der kleinen und mittleren Unternehmen in Großbritannien zu einer um 75% höheren Anmeldequote der Patente führt. Im Gegensatz dazu analysierten Melnik und Smyth (2024) die Patentanmeldungen für große amerikanische Unternehmen, welche eine Bilanzsumme über 5 Mrd. USD aufweisen. Dabei verdeutlichte diese Analyse, dass der positive Effekt der steuerlichen Forschungsförderung und der Anmeldequote für große Unternehmen nicht auftritt. Als Melnik und Smyth (2024) jedoch die Größe der Unternehmen entsprechend anpassten, um nun die Auswirkungen der Förderung für kleine und mittlere Unternehmen in den USA zu testen, konnte hier der positive Zusammenhang belegt werden. Das weist eindeutig daraufhin, dass speziell kleine und mittlere Unternehmen von einer steuerlichen

Forschungsförderung profitieren können.

Zuletzt zeigten Ernst et al. (2014), dass bei europäischen Unternehmen die Steuergutschrift zwar die Anzahl der Neuanmeldungen der Patente erhöht, jedoch keinen signifikanten (positiven) Einfluss auf die Qualität der Patente aufweisen. Dies erscheint folgerichtig, da Steueranreize die Input-Seite (Sachausgaben für Forschung und Entwicklung) erhöhen, die Patentqualität jedoch eine Komponente des Outputs der Forschungs- und Entwicklungsinvestitionen darstellt. Lediglich die Besteuerung von Patenteinkünften zeigt einen signifikant negativen Einfluss auf die Patentqualität. So führt eine Erhöhung des Steuersatzes auf Patenteinkünfte um 10% zu einer Reduktion der Patentqualität um 5,6%. Demzufolge kann der positive Einfluss auf die Patent Qualität nur bei Patent Boxen wieder dargelegt werden (EU Report, 2014).

2.3.4 Wirkung der steuerlichen Förderung auf die Produktivität von Unternehmen

Die steuerliche Forschungsförderung steigert nicht nur die Innovationstätigkeit von Unternehmen, sondern wirkt sich zudem positiv auf die Produktivität aus. Dabei kann die Produktivität der Unternehmen einerseits durch eine erhöhte Produktinnovation beeinflusst werden. Mit zunehmender Innovation entwickeln die Unternehmen effizientere Produkte, für welche die Nachfrage aufgrund des positiven Mehrwerts immer weiter ansteigt. Diese steigende Nachfrage erhöht die unternehmerische Produktivität (EU Report, 2014).

Anderseits führt mehr Innovation nicht nur zu verbesserten Produkten, sondern auch zu einem effizienteren Produktionsprozess. Durch effektive Prozesse mindern die Unternehmen die Kosten der Produktion bei gleichzeitiger Erhöhung des Produktoutputs. Die Produktivität der Unternehmen steigt. Zudem generieren die Mehrverkäufe höhere Umsätze, welche nach Kostenabzug zu mehr variablen Kapital der Unternehmen führt. Dieses Kapital resultiert in einer erhöhten unternehmerischen Investitionstätigkeit beispielsweise in Forschungs- und Entwicklungsprojekte (EU Report, 2014).

Die empirische Literatur bestätigt diesen positiven Zusammenhang zwischen der

Forschungsförderung und der Produktivität von Unternehmen. So zeigt Rammer et al. (2022) durch Auswertung der Daten des Mannheimer Innovationspanel, dass mit 10% höheren Ausgaben für Forschung und Entwicklung die Produktivität der Unternehmen um 0,21% ansteigt. Diese Produktivitätszunahme ist besonders hoch in wissensintensiven und forschungsintensiven Dienstleistungsindustrien. Auch Caiumi (2011) bestätigt, dass durch eine Forschungsförderung die Produktivität der Unternehmen insgesamt ansteigt. Dabei ist der Anstieg speziell für den unteren Rand der Produktivitätsverteilung höher als für den oberen Rand der Verteilung.

Die Schätzung der Effekte einer steuerlichen Forschungsförderung auf die Produktivität von Unternehmen kann ebenfalls anhand der Total-Factor-Productivity (TFP) erfolgen. Brasch et al. (2021) verifizierten durch das TFP einen positiven Effekt einer Forschungsförderung auf die Produktivität. Darüber hinaus zeigen Brasch et al. (2021) die Auswirkungen der steigenden Produktivität auf die Haushaltseinkommen und die Gesamtbeschäftigung. Mit steigender Produktivität sinken die Grenzkosten der Unternehmen was zu einem Absinken der Erzeugerpreise und des Verbraucherpreisindex führt. Bei gleichbleibendem Nominallohn steht den Verbraucher ein höherer Reallohn zur Verfügung. Zudem zeigt sich, dass bei zunehmender Produktivität die Gesamtbeschäftigung sinkt. Die Unternehmen benötigen bei effizienteren Produktionsprozessen zum Erhalt des bisherigen Produktivitätsniveaus nicht mehr die gleiche Anzahl an Arbeitnehmern, die Gesamtbeschäftigung sinkt.

Zuletzt analysierten Cappelen et al. (2012), dass eine steuerliche Forschungsförderung den gleichen Effekt auf die Produktivität der Unternehmen hat, als eine nicht steuerlich basierte Forschungsförderung.

2.4 Empirische Befunde zur Wirkung der deutschen Forschungszulage

Der folgende Abschnitt soll die empirischen Befunde zur Wirkung der deutschen Forschungszulage analysieren darlegen. Zunächst wird die Inanspruchnahme durch die antragstellenden Unternehmen (Kapitel 2.4.1.1) sowie die regionale Verteilung der antragsstellenden Unternehmen (Kapitel 2.4.1.2) ausgewertet. Im Anschluss werden die kurzfristigen Auswirkungen (Kapitel 2.4.2) sowie die mittel- und langfristigen Effekte der Forschungszulage (Kapitel 2.4.3) im Detail analysiert. Grundlage der Auswertung bilden Daten des Bundesministeriums für Forschung, Technologie und Raumfahrt zu Forschungs- und Entwicklungsausgaben, Beschäftigtenstrukturen, Innovationsleistungen und zur Produktivität der geförderten Unternehmen.

2.4.1 Inanspruchnahme der Forschungszulage

2.4.1.1 Personenbezogene Nutzung der Forschungszulage

Im Rahmen des Bundesprogramms ZIM wurden für die Jahre 2015 bis 2019 ca. 2.749 Einzelprojekte und ca. 11.918 Kooperationsprojekte bewilligt. Diese Projekte bezogen sich überwiegend auf die Technologiefelder der Produktion, der Elektrotechnik und der Werkstofftechnologien und umfassten für 2015 bis 2019 ca. 2,708 Mio. € Fördermittel (BMWK, 2025b).[42] Für den Zeitraum nach Einführung der Forschungszulage zeigt sich ein deutlicher Rückgang der bewilligten Förderprojekte des ZIM von ca. 37% auf 1.737 für Einzelprojekte und um ca. 18% auf 9.764 für Kooperationsprojekte. Die hierfür notwendigen Fördermittel verringerten sich um ca. 2% auf 2,657 Mio. € (BMWK, 2025b). Der Rückgang zeigt, dass die indirekte Forschungsförderung durch die Forschungszulage zunehmend in Anspruch genommen wird. Dabei führte die Einführung der Forschungszulage zu einem Anstieg der gestellten Anträge von 4.500 im Jahr 2021 auf 6.600 Anträge im Jahr 2022, was einer Zunahme von ca. 46% entspricht (Finger et al., 2023). Diese Tendenz wird unterstützt durch die unterschiedlichen Bewilligungsquoten der Förderung des ZIM und der Forschungszulage. So weist die direkte Forschungsförderung des ZIM eine Bewilligungsquote von ca. 65% auf, wohingegen die Anträge der Forschungszulage zu ca. 75% bis 80% bewilligt oder teilbewilligt wurden. Dieser hohe Anteil an Bewilligungen spiegelt die verlässliche

[42] Bei entsprechender Aufteilung nach Bundesländern wurden die meisten Fördermittel in Baden-Württemberg bewilligt, gefolgt von Sachsen, Nordrhein-Westfalen und Bayern. Am wenigstens Fördermittel verbrauchte Bremen, Schleswig-Holstein und Saarland (BMWK, 2025: ZIM Statistik Stand Dez. 2024).

Planbarkeit der indirekten Forschungsförderung durch die Forschungszulage wider, was zu einer bevorzugten Nutzung der Forschungszulage führt.

Zudem zeigt sich eine Komplementarität der direkten Projektförderung zur indirekten Forschungsförderung. Demnach hat jedes zweite Unternehmen, welches die Forschungszulage nutzt, zuvor noch keine direkte Forschungsförderung in Anspruch genommen. (EFI Gutachten, 2024; Finger et al., 2023; Rammer, 2023).

Eine Analyse der Anträge auf Erteilung einer Forschungszulage der zuständigen Bescheinigungsstelle zeigt, dass in den ersten zehn Monaten nach Einführung der Forschungszulage insgesamt 2.417 Anträge gestellt wurden. Dabei stellten die kleinen Unternehmen[43] mit ca. 638 Anträgen ebenso wie die großen Unternehmen mit ca. 653 Anträgen jeweils ein Drittel aller Anträge. Die Kleinstunternehmen und die mittleren Unternehmen reichen jeweils ca. 20% aller Anträge bei der Bescheinigungsstelle ein. In Hinblick auf die deutsche Unternehmenslandschaft[44] zeigt sich, dass die großen Unternehmen in etwa gleich viele Anträge gestellt haben als auch die kleinen Unternehmen, wobei diese großen Unternehmen weniger als 1% der gesamten Unternehmen in Deutschland ausmachen (Deutscher Bundestag, 2021).

Die Förderung der kleinen und mittleren Unternehmen wurde durch das Wachstumschancengesetz weiter betont, indem hier der Fördersatz ausschließlich für kleine und mittleren Unternehmen erhöht wurde (Deutscher Bundestag, 2021). Neue Antragsdaten legen nahe, dass dies zu einer Veränderung der Struktur antragsstellender Unternehmen geführt hat. So sind seit Einführung der Forschungszulage im Dezember 2019 bis März 2025 laut Bescheinigungsstelle ca. 33.840 Anträge mit ca. 42.231 Vorhaben beantragt worden. Hinsichtlich der antragsstellenden Unternehmen zeigt sich, dass Kleinstunternehmen und

[43] Definition der Unternehmensgrößen: Kleinstunternehmen bis 9 Beschäftigte, kleine Unternehmen bis 49 Beschäftigte, mittlere Unternehmen bis 249 Beschäftigte und große Unternehmen über 249 Beschäftigte.

[44] Aufteilung der Unternehmerlandschaft in Deutschland im Jahr 2021: Kleinstunternehmen 2.946.649 (ca. 86,91%), kleine Unternehmen 354.317 (ca. 10,45%), mittlere Unternehmen 73.034 (ca. 2,15%) und große Unternehmen 16.704 (ca. 0,49%).

kleine Unternehmen jeweils ca. ein Drittel der Anträge stellen, wohingegen mittlere Unternehmen ca. ein Fünftel und große Unternehmen nur noch ca. 14% beantragen. Anhand dieser Veränderung ist erkennbar, dass die Nachbesserung der Forschungszulage durch das Wachstumschancengesetz die ursprüngliche Zielsetzung der Bundesregierung besser abbildet.[45] So stellen jetzt überwiegend kleine und mittleren Unternehmen einen Antrag auf Forschungsförderung, wohingegen gerade die großen Unternehmen deutlich weniger Anträge stellen (Bescheinigungsstelle Forschungszulage, 2025).

Eine Analyse der einzelnen Wirtschaftszweige der antragsstellenden Unternehmen verdeutlicht eine hohe Akzeptanz der neuen Forschungszulage, da nur vereinzelte Sektoren keinen Antrag auf Erteilung einer Forschungszulage gestellt haben. Dabei stellten die meisten Anträge der Sektor Maschinenbau (Nr. 28) mit ca. 491 Anträgen, gefolgt von der Erbringung von Dienstleistungen der Informationstechnologie (Nr. 62) mit ca. 318 Anträgen und mit ca. 209 Anträgen der dritt größte antragsstellende Sektor die Forschung und Entwicklung (Nr. 72).[46] Keine Anträge hingegen stellen Sektoren wie die Herstellung von Bekleidung (Nr. 14), die Beherbergung (Nr. 55), das Veterinärwesen (Nr. 75) und das Sozialwesen (Nr. 88) (Deutscher Bundestag, 2021).

Zur Bearbeitung der Anträge wird im Durchschnitt ca. 65,5 Tage benötigt. Hierbei liegt die Zeitdauer zu Beginn des zehnmonatigen Betrachtungszeitraums bei ca.81,1 Tagen, welche sich bis zum Ende hin auf ca. 36,6 Tage reduziert (Deutscher Bundestag, 2021).

Nach Prüfung der Bescheinigungsstelle über ein begünstigtes Forschungsvorhaben erteilt diese ein Bescheid an den Antragsteller. In den ersten zehn Monaten wurden alle gestellten Anträge mit ca. 80% positiv beschieden. Dabei erfolgte keine wesentliche

[45] Möglich wäre auch ein zeitlicher Effekt, d.h. kleine Unternehmen können aufgrund von finanziellen oder personellen Mitteln zeitlich verzögert einen Antrag stellen. Genaue Evaluationen zur Wirkungsanalyse der Forschungszulage wurde durch das Bundesministerium in Auftrag gegeben (Rammer, 2025).

[46] Eine Auswertung der Sektoren für Anträge des gesamten Zeitraums seit Einführung bis März 2025 bestätigt, dass die wesentlichsten Industriezweige weiterhin die Erbringung von Dienstleistungen der Informationstechnologie und der Maschinenbau sind (Bescheinigungsstelle Forschungszulage, 2025).

Abweichung hinsichtlich der Unternehmensgröße – über die gesamte deutsche Unternehmenslandschaft hinweg wurden nur ca. ein Fünftel aller Anträge abgelehnt. Dies zeigt auch, dass obwohl kleine und mittlere Unternehmen nicht die finanziellen Ressourcen aufweisen trotzdem nicht weniger Negativbescheide erhalten als größere Unternehmen. Einer der wesentlichen Gründe für eine Ablehnung des Antrags ist die Nicht-Erfüllung der erforderlichen Kriterien zum Vorliegen eines begünstigten Forschungsprojekts (Deutscher Bundestag, 2021).

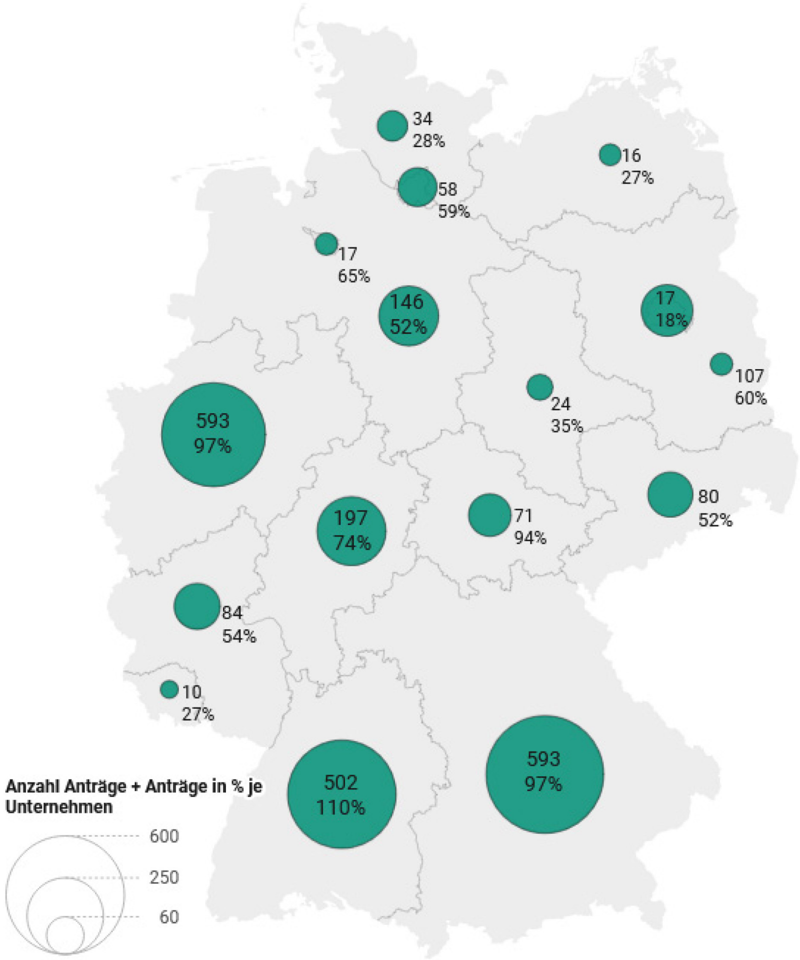
2.4.1.2 Regionale Verteilung der Forschungszulage

Eine Einteilung der eingegangenen Anträge auf eine Forschungszulage kann nicht nur anhand der einreichenden Unternehmen erfolgen, sondern ebenfalls geographisch (siehe Abbildung 2.1). So zeigt die regionale Verteilung innerhalb Deutschlands, dass innerhalb der ersten zehn Monate nach Einführung der Forschungszulage die meisten Anträge (ca. 461) in Nordrhein-Westfalen gestellt wurden. Mit ca. 593 Anträge weist Bayern die zweit größte Antragsdichte auf, gefolgt von Baden-Württemberg mit ca. 502 Anträgen. Am wenigsten Anträge hat die Bescheinigungsstelle aus Brandenburg (17 Anträge), Bremen (17 Anträge) und dem Saarland (10 Anträge) erhalten (Deutscher Bundestag, 2021).

Ein Vergleich mit der Anzahl der Unternehmen je Bundesland zeigt, dass generell die Bundesländer mit der höchsten Antragsanzahl auch die höchste Anzahl an Unternehmen aufweisen. In Nordrhein-Westfalen stimmt die regionale Verteilung der Unternehmen mit der Anzahl der Anträge überein, denn ca. 20% der Unternehmen Deutschlands sind in Nordrhein-Westfalen angesiedelt und stellen ca. 20% der gesamten Anträge. Dem gegenüber werden mehr Zulagen in Bayern und Baden-Württemberg beantragt, als der dortigen Anzahl an Unternehmen entspricht. So stellen die Unternehmen in Bayern, welche ca. 18% der gesamten Unternehmen Deutschlands umfassen, etwa 25% der Anträge und in Baden-Württemberg (mit ca. 14% der gesamten Unternehmen Deutschlands) ca. 21% der Anträge. Demzufolge entsteht eine überproportionale Antragstellung im Verhältnis der angesiedelten Unternehmen für Bayern in

Höhe von 137% und für Baden-Württemberg in Höhe von 154%. Im Gegensatz dazu werden in Brandenburg um ca. 25% sowie im Saarland und Mecklenburg-Vorpommern um ca. 40% zu wenig Anträge gestellt. (Deutscher Bundestag, 2021; Statistisches Bundesamt, 2021).

ABBILDUNG 2.1: Anzahl der gestellten Anträge je Bundesland in den ersten zehn Monaten nach Einführung der Forschungszulage



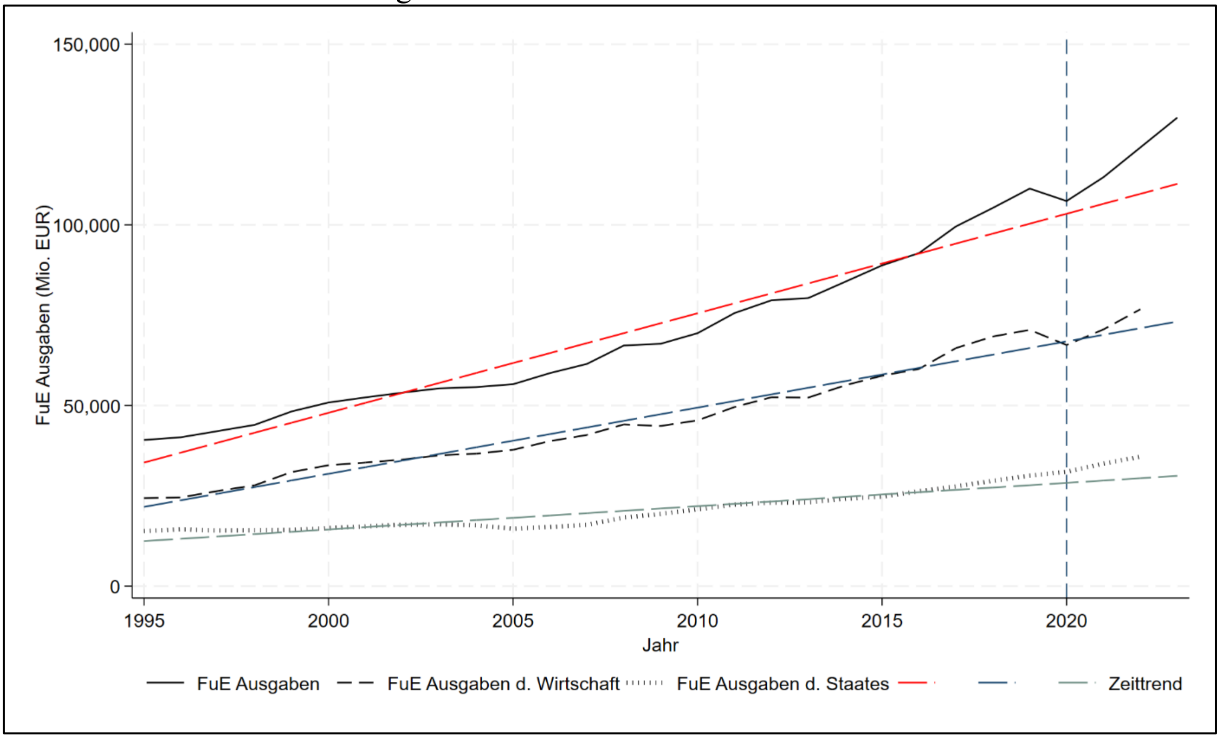
(*Quelle:* Deutscher Bundestag, 2021).

2.4.2 Kurzfristige Folgen der Forschungszulage

2.4.2.1 Aufwendungen für Forschung und Entwicklung

Mit Einführung der Forschungszulage am 14. Dezember 2019 hat sich die Bundesregierung das Ziel der Förderung der Ausgaben für Forschungs- und Entwicklungstätigkeiten gesetzt. Die Forschungszulage, ausgestaltet als steuerliche Förderung, führt zu einer geminderten Steuerbelastung und somit zu mehr Liquidität der Unternehmen in eigene Forschungs- und Entwicklungsaktivitäten zu investieren. Die Abbildung 2.2 zeigt diesen Effekt der ansteigenden Ausgaben für Forschung und Entwicklung nach der Einführung der Forschungszulage. Dabei erhöhten sich die Aufwendungen von ca. 107 Mio. € in 2020 auf ca. 130 Mio. € in 2023. Zudem verdeutlicht die Abbildung, dass der Wirtschaftssektor nicht nur generell in etwa doppelt so hohe Investitionen tätigt als der Staatssektor, sondern auch, dass solche Ausgaben der Wirtschaft deutlich stärker ansteigen.

ABBILDUNG 2.2: Gesamtausgaben für Forschung und Entwicklung von 1995-2023 mit Aufteilung nach Wirtschafts- und Staatssektoren

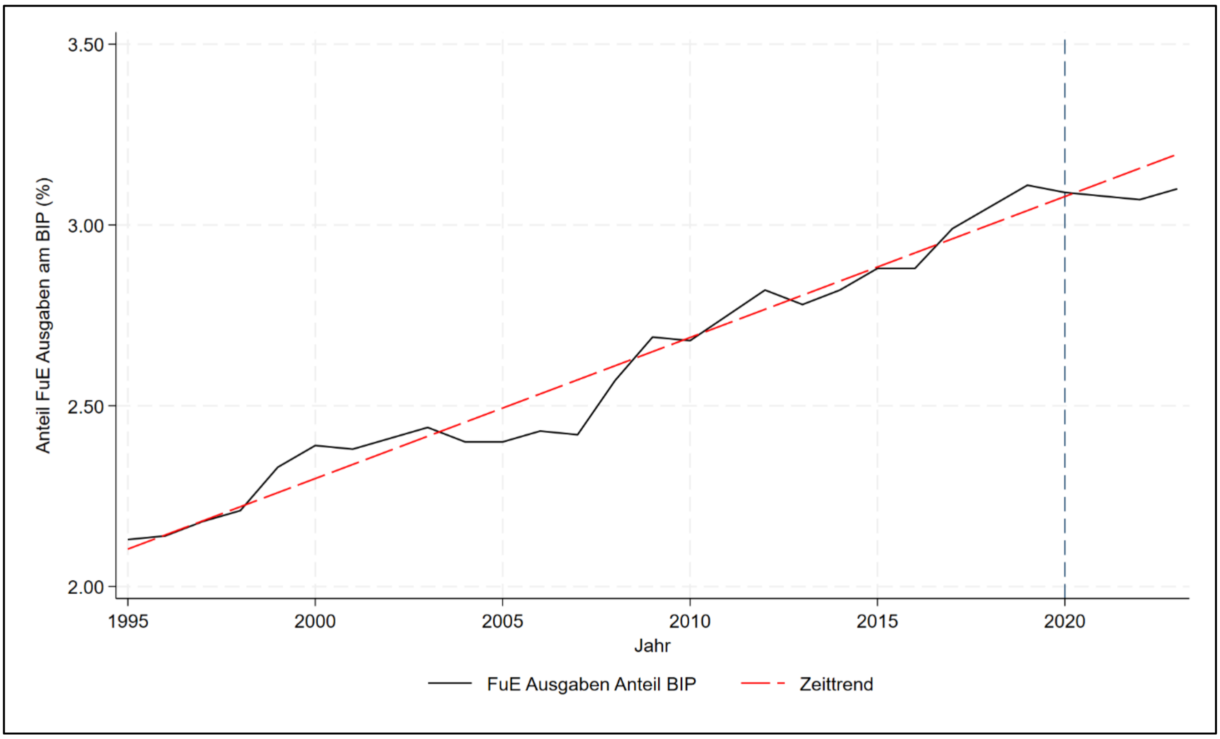


(*Quelle:* eigene Darstellung auf Grundlage der Daten des BMFTR).

Ein konkret formuliertes Ziel der Forschungszulage ist, die Aufwendungen für Forschung und Entwicklung auf jährlich 3,5% des Bruttoinlandsprodukts zu steigern. Ein Vergleich der Bruttoinlandsausgaben mit dem Bruttoinlandsprodukt in Abbildung 2.3 zeigt bereits 2019 ein Absinken der Aufwendungen für Forschung und Entwicklung. Dieser Rückgang ist vermutlich auf die COVID Pandemie zurückzuführen. Auch die Einführung der Forschungszulage konnte diesen abwärts Trend nicht aufhalten, sodass die Forschungs- und Entwicklungsausgaben gemessen am Bruttoinlandsprodukt weiter absinken. Erst ab 2022 ist ein erneuter Anstieg zu erkennen, welcher jedoch unterhalb des Vor-COVID-Niveaus liegt.

Dabei wird das Ziel einer jährlichen Investition von mindestens 3,5% des Bruttoinlandsprodukts nicht erreicht. Die getätigten Ausgaben liegen für die Jahre nach Einführung der Forschungszulage im Bereich zwischen 3,05% und 3,1%.

ABBILDUNG 2.3: Bruttoinlandsausgaben für Forschung und Entwicklung von 1995-2023 als Anteil am Bruttoinlandsprodukt



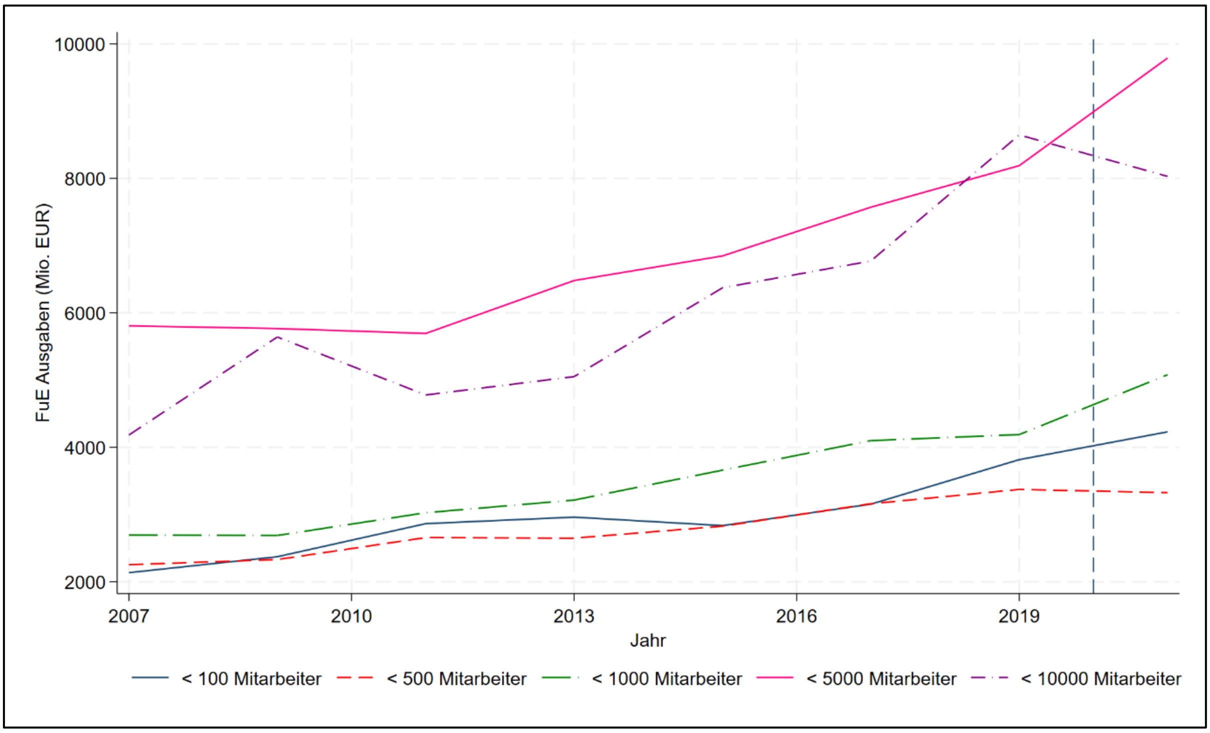
(*Quelle:* eigene Darstellung auf Grundlage der Daten des BMFTR).

Eine geographische Analyse der Forschungs- und Entwicklungsausgaben je Bundesland illustriert, dass gerade solche Bundesländer mit einer Vielzahl an Anträge für die Forschungszulage einen deutlicheren Zuwachs an Forschungs- und Entwicklungsausgaben verzeichnen. Folglich zeigt sich aber auch, dass in Bundesländern mit relativ wenig Anträgen keine Auswirkungen auf Investitionen in Forschung und Entwicklung existieren (Vgl. Abbildung 2.A.3 im Anhang).

Die Bundesregierung betonte im Regierungsentwurf zur Forschungszulage die besondere Förderfähigkeit von kleinen und mittleren Unternehmen. Durch eine steuerliche Förderung sollten gerade diese Unternehmen mehr Liquidität zur Verfügung haben, um in die eigenen Forschungs- Entwicklungsaktivitäten investieren zu können. Eine Analyse der unternehmerischen Ausgaben für Forschung und Entwicklung nach Beschäftigtengrößenklassen (Vgl. Abbildung 2.4) legt nahe, dass die Forschungszulage einen Einfluss auf die Veränderung der Aufwendungen gehabt haben könnte. So steigen speziell bei den kleineren und mittleren Unternehmen die Forschungs- und Entwicklungsaufwendungen nach Einführung der Forschungszulage an. Darüber hinaus zeigt sich ein Rückgang der Aufwendungen für Forschung und Entwicklung bei den großen Unternehmen, also solchen Unternehmen mit mehr als 10.000 Mitarbeitern. Zunächst sollten speziell kleine und mittlere Unternehmen von der Forschungszulage profitieren. Erst mit Änderung des Forschungszulagengesetzes durch das Wachstumschancengesetz betonte die Bundesregierung die Erweiterung der konkreten Förderung auch auf die großen Unternehmen. Eine spezielle Förderung der kleinen und mittleren Unternehmen fällt demzufolge weg, sodass bei Auswertung der künftigen Daten auch die großen Unternehmen einen Anstieg der Forschungs- und Entwicklungsausgaben aufzeigen sollten.

Zudem zeigt Abbildung 2.4 für alle Unternehmensgruppen einen Anstieg der Ausgaben bereits ab 2019, was auf mögliche Ankündigungseffekte hindeuten kann. Ein Antrag für die Forschungszulage kann entweder direkt vor, während oder nach Durchführung eines Forschungsvorhabens gestellt werden. Demzufolge können Unternehmen bereits in Erwartung der Einführung einer Forschungszulage im Jahr 2019 die Ausgaben für Forschung und Entwicklung gesteigert haben.

ABBILDUNG 2.4: Unternehmerische Ausgaben für Forschung und Entwicklung von 2007-2021 unterteilt anhand von Beschäftigungszahlen



(*Quelle:* eigene Darstellung auf Grundlage der Daten des BMFTR).

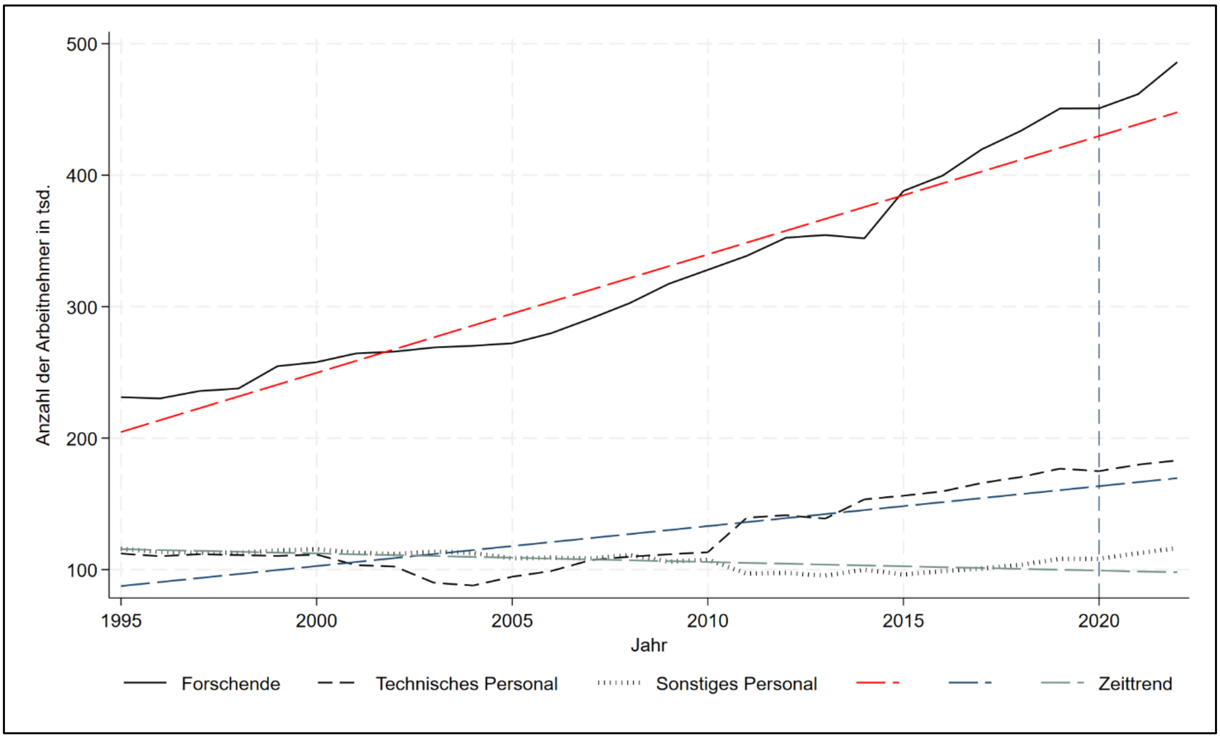
Die Abbildung 2.A.4 im Anhang bestätigt diesen positiven Zusammenhang auch für einzelne Wirtschaftszweige. Ein Vergleich der drei Sektoren mit den meistgestellten Anträgen auf eine Forschungszulage demonstriert nicht nur für den Wirtschaftszweig Forschung und Entwicklung einen deutlichen Anstieg der Aufwendungen, sondern auch für den Bereich der Information und Kommunikation.

2.4.2.2 Anzahl der Arbeitnehmer in einem Unternehmen

Ein Teil der Aufwendungen für Forschung und Entwicklung umfasst auch die Kosten für das forschende Personal. Mit einer steuerlichen Förderung entsteht den Unternehmen mehr Liquidität, um in eigene Forschungsprojekte zu investieren. Um die eigene Forschung weiter voranzubringen benötigen die Unternehmen nicht nur die notwendige Liquidität, sondern auch forschende Mitarbeiter. Demzufolge sollten nach Einführung der Forschungszulage die Anzahl forschender Mitarbeiter ansteigen. In Abbildung 2.5 zeigt sich ein Anstieg der Anzahl der Arbeitnehmer im forschenden Bereich gegenüber dem technischen oder dem sonstigen Personal. Dabei steigt die Anzahl der forschenden Mitarbeiter von ca. 450.000 in 2020 auf ca.

486.000 in 2022, was einer gesamten Zunahme von ca. 72% der Mitarbeiter aller drei Bereiche entspricht. Dem gegenüber nahm die Anzahl der Mitarbeiter im technischen und sonstigen Bereich zusammen nur um ca. 14.000 zu. Zu beachten ist, dass der Rückgang der forschenden Mitarbeitenden im Jahr 2019 – vermutlich verursacht durch die COVID-19-Pandemie – zwar im Jahr 2020 wieder leicht kompensiert wird, dieser Anstieg jedoch lediglich die bereits zuvor bestehende Trendentwicklung fortsetzt. Erst ab 2021 zeigt sich ein Zuwachs, der über die üblichen Steigerungsraten der Vorjahre hinausgeht. Dennoch bleibt festzuhalten, dass das Niveau der Zeit vor der COVID-Pandemie bislang nicht vollständig erreicht wurde.

ABBILDUNG 2.5: Anzahl der Arbeitnehmer von 1995-2022



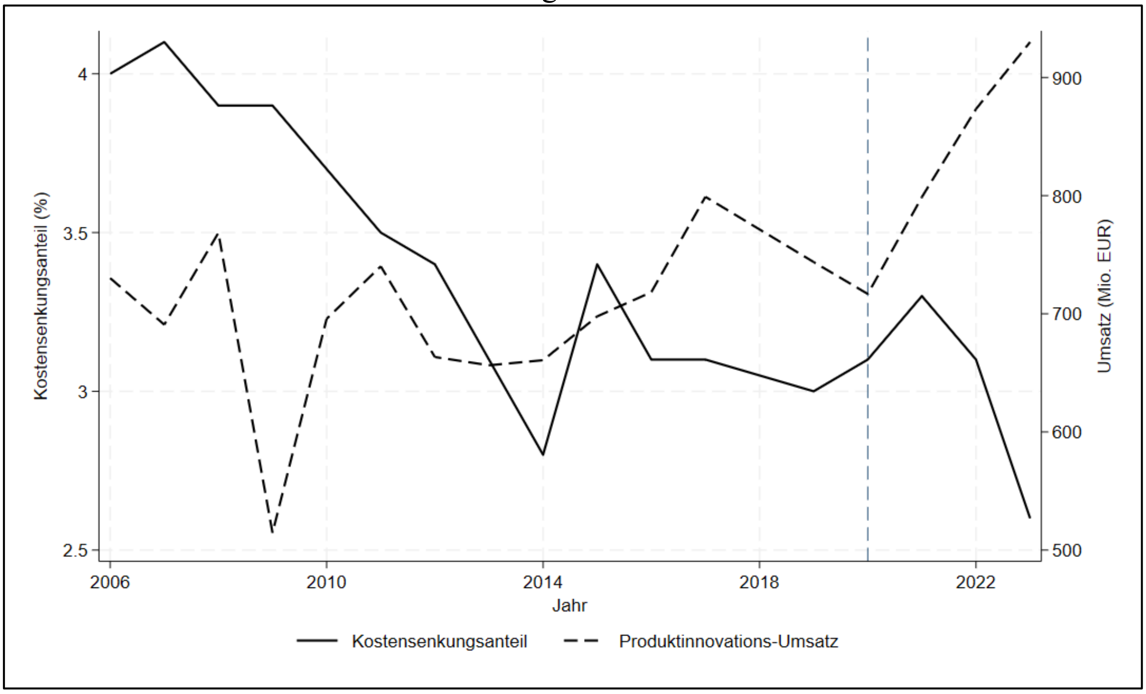
(*Quelle:* eigene Darstellung auf Grundlage der Daten des BMFTR).

2.4.3 Mittel- bis langfristige Folgen der Forschungszulage

2.4.3.1 Innovationsleistungen der Unternehmen

Die Einführung einer Forschungszulage hat Auswirkungen auf die Innovationsleistungen von Unternehmen. So führt eine steuerliche Forschungsförderung nicht nur zur Entwicklung neuer Produkte, sondern auch zu einer effizienteren Gestaltung von Produktionsprozessen. Mithilfe der Forschungszulage können die Unternehmen mehr finanzielle Mittel zur Entwicklung neuer Produkte verwenden, was zu einer größeren Anzahl an Produktinnovationen führt. Als direkte Folge dieser vermehrten Innovationsaktivität können Unternehmen neue Marktbereiche erschließen und ihre Umsätze aus Produktinnovationen signifikant steigern. Wie in Abbildung 2.6 auf der rechten Achse dargestellt, zeigt sich ein deutlicher Anstieg der Umsätze aus neuen Produktinnovationen nach Einführung der Forschungszulage, was den positiven Effekt der Zulage auf die Unternehmensumsätze betont. Zudem zeigt Abbildung 2.6 auf der linken Achse den Kostensenkungsanteil der Unternehmen im Produktionsprozess. Neben neuen Produkten fördert die Forschungszulage aber auch die Entwicklung kosteneffizienterer Produktionsprozesse. Aufgrund dieser verbesserten Produktionswege erhalten die Unternehmen einen Kostenvorteil je produzierten Gut. Demzufolge steigt nach Einführung der Forschungszulage der Kostensenkungsanteil an. Die Abbildung 2.6 verdeutlicht aber auch, dass der Kostensenkungsanteil nach kurzem Anstieg wieder absinkt. Dies könnte auf mögliche Gewöhnungseffekte schließen lassen. Die zuvor kosteneffiziente Produktion gilt in Zeiten schnellen technologischen Wandels nach einigen Monaten, als veraltet und damit als weniger effizient als zu Beginn. Der Kostensenkungsanteil sinkt.

ABBILDUNG 2.6: Kostensenkungsanteil durch Prozessinnovationen und mit Produktinnovationen generierte Umsatz von 2006-2023



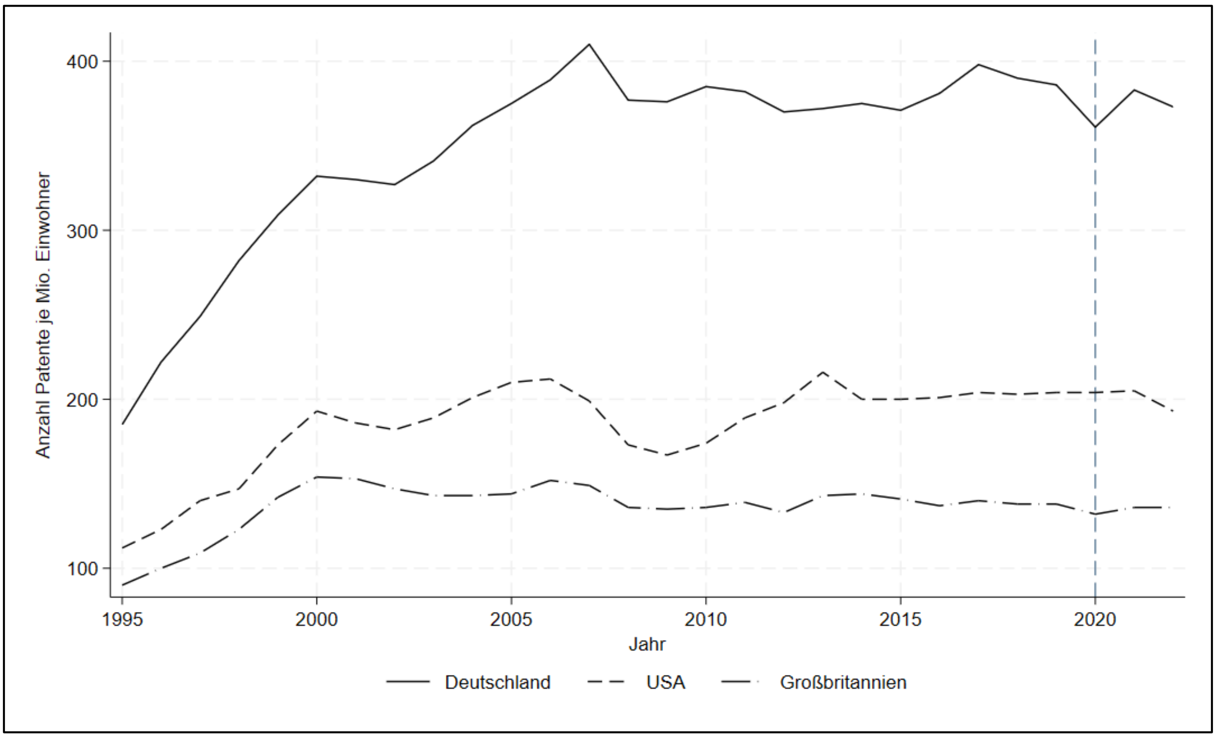
(*Quelle:* eigene Darstellung auf Grundlage der Daten des BMFTR).

2.4.3.2 Patentanmeldungen

Die Innovationsleistung der Unternehmen kann aber auch anhand von Patentanmeldungen gemessen werden. So zeigt Abbildung 2.7 die Anzahl der Patentanmeldungen je eine Million Einwohner. Dabei werden solche Patente abgetragen, die beim Europäischen Patentamt oder bei der World Intellectual Property Organization (WIPO) angemeldet worden sind. Zu erkennen ist, dass die Rückläufigkeit der Patentanmeldungen in den Vorjahren nach Einführung der Forschungszulage beseitigt wird. Die Anmeldezahlen der Patente steigt auf ca. 383 je Mio. Einwohner in Deutschland für 2021 an. Ein Vergleich mit den USA und Großbritannien zeigt, dass während in Deutschland die Patentanmeldungen zunehmen, bleiben die Anmeldungen in den USA und Großbritannien in etwa gleich oder sinken sogar ab. Zu beachten ist jedoch, dass die Möglichkeit einer zeitlichen Verzögerung von mehreren Jahren zwischen der Beantragung der Forschungszulage und der Erteilung eines Patents besteht (Ernst et al., 2011; Dechezlepretre et al., 2016). Deshalb kann bei diesem Anstieg kein konkreter kausaler Zusammenhang zwischen der Einführung der

Forschungszulage und der Zunahme der Patentdaten angenommen werden.

ABBILDUNG 2.7: Anzahl der weltmarktrelevanten Patente von 1995-2022

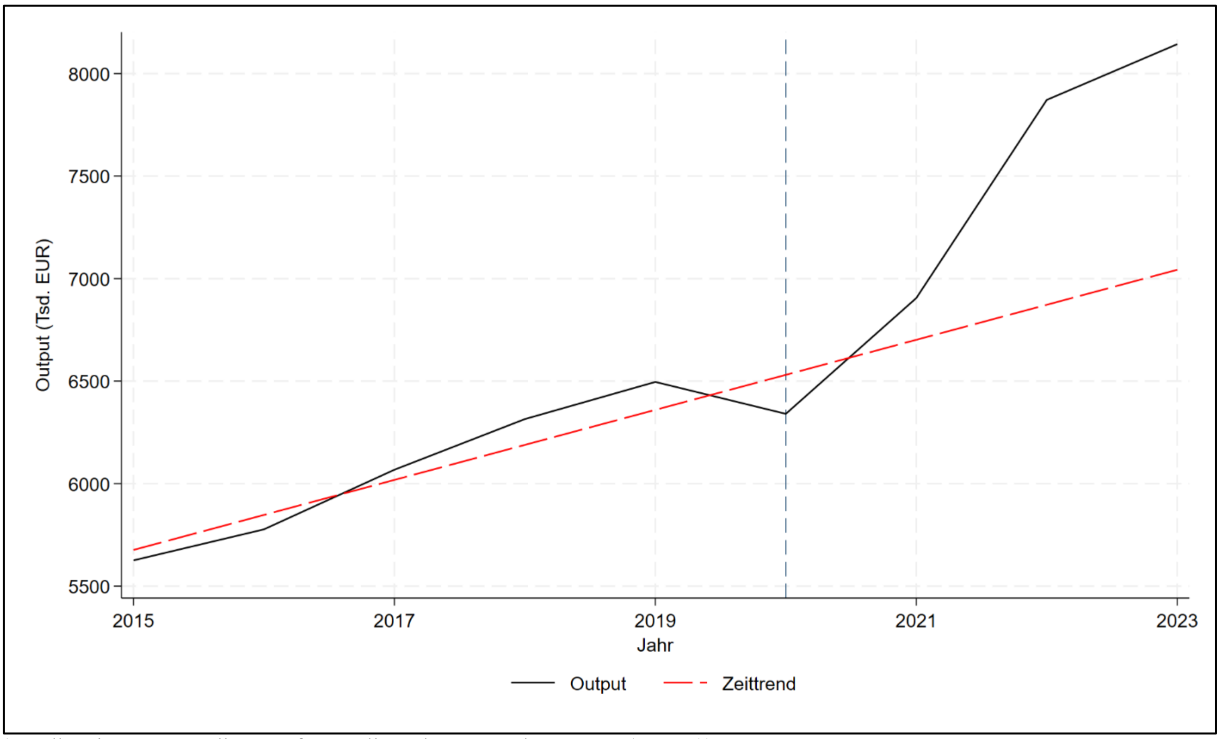


(*Quelle:* eigene Darstellung auf Grundlage der Daten des BMFTR).

2.4.3.3 Unternehmerische Produktivität

Die erhöhte Innovationsleistung der Unternehmen durch die Forschungszulage beeinflusst positiv deren Produktivität. Durch erhöhte Umsätze aus Produktinnovationen oder dem Kostensenkungsanteil aus effizienteren Produktionsprozessen können die Unternehmen deren Output bei gleichbleibendem Input erhöhen. Die Produktivität der Unternehmen nimmt zu. Die Abbildung 2.8 zeigt genau diesen Effekt. Die Einführung der Forschungszulage führt zu einem Anstieg des Outputs der Unternehmen von ca. 6 Mio. € in 2020 auf ca. 8 Mio. € in 2023.

ABBILDUNG 2.8: Produktivität gemessen am Output der Unternehmen von 2015-2023



(*Quelle:* eigene Darstellung auf Grundlage der Daten der OECD (STAN)).

2.5 Kritische Einordnung der Ausgestaltung der deutschen Forschungszulage

Die Bundesregierung hat die Forschungszulage als volumenbasierte steuerliche Förderung initiiert, um die Nachteile einer inkrementellen Ausgestaltung zu umgehen. Dabei war eines der wesentlichen Ziele die Ausweitung der Investitionen in die eigenen Forschungs- und Entwicklungsaktivitäten. Durch die Einführung einer steuerlichen Förderung erweitert sich das Investitionsvolumen der Unternehmen, sodass diese vermehrt in Forschung und Entwicklung investieren können. Neben den empirischen Befunden in Kapitel 2.3.1.1 zeigen die deskriptiven Auswertungen der Abbildung 2.2 ebenfalls diesen positiven Zusammenhang der deutschen Forschungszulage und der Erweiterung der Ausgaben für Forschung und Entwicklung. So investierte der Wirtschaftssektor nach Einführung der deutschen Forschungszulage etwa doppelt so viel als der Staatssektor. Als konkretes Ziel wurde dabei eine Steigerung der Aufwendungen auf jährlich 3,5% des Bruttoinlandsprodukts formuliert. Eine Auswertung der Daten des Bundesministeriums diesbezüglich zeigen, dass der Anteil der Forschungs- und Entwicklungsausgaben am Bruttoinlandsprodukt bei ca. 3% liegen (Vgl.

Abbildung 2.3). Folglich konnten zwar die Ausgaben gesteigert werden, das konkrete Ziel der Erweiterung auf 3,5% des Bruttoinlandsprodukts wurde jedoch verfehlt. Mögliche Gründe hierfür könnten neben der zeitlichen Verzögerung zwischen Antragstellung und Genehmigung der Forschungszulage ebenfalls die Ausgestaltung der Zulage sein. So sind die Kriterien, um eine steuerliche Förderung zu erhalten relativ strikt formuliert (§ 2 FZulG), sodass ggf. nicht alle Unternehmen diese erfüllen können. Zudem erhalten die Unternehmen auch nur für die erste Phase der Forschung- und Entwicklung entsprechende Förderungen, für alle weiteren Tätigkeiten bis zur Marktentwicklung oder für das Produktionssystem entfallen diese (§ 2 Abs. 2 FZulG). Mit Ausweitung der Begünstigten Vorhaben auch auf diesen Teil der Forschung und Entwicklung könnten die Aufwendungen nochmals gesteigert werden und dadurch ggf. die Ausgaben auf die 3,5% des Bruttoinlandsprodukts angehoben werden.

Zudem sollten speziell die kleinen und mittleren Unternehmen durch die Forschungszulage unterstützt werden, um eine effektive Erweiterung der Ausgaben für Forschung und Entwicklung zu tätigen. Dies konnte durch die Umsetzung der Forschungszulage als eine steuerliche Förderung erreicht werden (Vgl. Abbildung 2.4). Lester und Warda (2018) betonten jedoch, dass eine spezielle getrennte Regelung für kleine und mittlere Unternehmen und große Unternehmen zu einem effizienteren Einsatz der Forschungszulage führen würde. Dabei wird die steuerliche Förderung ineffizienter je größer die Unternehmen sind, sodass eine getrennte Ausgestaltung der Forschungszulage zu einer erweiterten Förderung der kleinen und mittleren Unternehmen führen kann. Eine solche getrennte Regelung erfolgte in der ersten Gesetzesfassung vom 14. Dezember 2019 noch nicht. Erst mit Änderung durch das Wachstumschancengesetz entsteht ein gesonderter Fördersatz für die kleinen und mittleren Unternehmen in Höhe von 35% im Verhältnis zu den großen Unternehmen, welche bei einem Fördersatz von 25% verbleiben (§ 4 Abs. 1 FZulG).

Mit steigenden Ausgaben für Forschung und Entwicklung benötigen die Unternehmen mehr forschendes Personal, um diese Tätigkeiten ausführen zu können. Diese Zunahme an forschendem Personal wurde in Abbildung 2.5 dargestellt. Darüber hinaus führen zunehmende Ausgaben für Forschung und Entwicklung nicht nur zu einem Anstieg der Anzahl an Arbeitnehmern, sondern ebenfalls zu steigenden Gehältern in einem Unternehmen. Dabei steigen nicht nur die Personalkosten für die Mitarbeiter im Bereich der Forschung und Entwicklung an, sondern für die gesamten Beschäftigten des Unternehmens (Carbonnier et al., 2022). Zu beachten ist jedoch, dass die Löhne eher für höherqualifizierte Berufsgruppen ansteigen, wohingegen die weniger qualifizierten Mitarbeiter keinen Lohnanstieg verzeichnen können. Hier zeigt sich ein Nebeneffekt der Ausgestaltung der Forschungszulage, welcher höherqualifizierte Mitarbeiter bevorzugt behandelt. Diese Differenzierung steigert zwar kurzfristig die Produktivität und das Wachstum, führt jedoch auf Gesellschaftsebene zu einer erweiterten Chancenungleichheit.

Als weiteres Ziel formulierte die Bundesregierung in der Gesetzesbegründung die Förderung der Innovation deutscher Unternehmen. Durch die Nutzung einer steuerlichen Forschungsförderung erweitern die Unternehmen die Innovationstätigkeiten, was neben der zunehmenden Entwicklung neuer Produkte ebenso in einer erhöhten Anzahl an Patentanmeldungen resultiert. So zeigt Abbildung 2.6, dass nach Einführung der Forschungszulage der Umsatz durch neu entwickelte Produkte ebenso wie der Kostensenkungsanteil ansteigt. Demnach führte die Umsetzung der Forschungszulage zunächst zu einer erweiterten Innovationstätigkeit der Unternehmen. Zu beachten ist jedoch, dass nach kurzer Zeit der Kostensenkungsanteil wieder absinkt. Ein möglicher Grund hierfür ist der Gewöhnungseffekt der Unternehmen, welcher durch eine Ausweitung der steuerlichen Förderung auf den Produktionsprozess der neu entwickelten Produkte geschmälert werden kann. Als zweiter Maßstab für steigende Innovationstätigkeit der Unternehmen wird eine steigende Anzahl angemeldeter Patente verwendet (Vgl. Abbildung 2.7). So zeigt sich, dass die Forschungszulage zwar Innovation fördert, die angemeldeten Patente aber wohl nicht zu sehr wesentlichen Neuerungen führen. Dies kann an einer Verlagerung des Fokus von Innovation auf strategische unternehmerische Entscheidungen liegen. So kann einerseits die Qualität der Patente beeinflusst werden durch die Reallokation des Innovationsaufwands in andere Länder aufgrund spezieller Patent-Box-Regelungen (Baumann et al., 2018). Andererseits priorisieren die Unternehmen eher die Anzahl der patentierten Erfindungen anstelle deren Qualität, um im Wettbewerb zu bestehen. Eine veränderte Ausgestaltung der Forschungszulage könnte den Fokus auf die Qualität der Innovation lenken, anstelle der Quantität der angemeldeten Patente. Dabei könnten einerseits differenzierte Fördersätze je nach Innovation eingeführt werden, d.h. beispielsweise höhere Förderungen für bestimmte risikoreiche Innovationen (Mohnen et al., 2017). Andererseits könnte die Implementierung von Output orientierter Förderung durch Patentprämien, welche nach Zitierhäufigkeit oder Kommerzialisierung der Patente ausgezahlt werden, zu einer Erhöhung der Qualität der angemeldeten Patente führen.

Zuletzt fördert die Forschungszulage die Produktivität der Unternehmen (Vgl. Abbildung 2.8). Mit sinkenden Kosten für die Forschungs- und Entwicklungstätigkeiten können die Unternehmen bei gleichbleibendem Input einen höheren Output generieren, die Produktivität steigt. Zu beachten ist, dass auch hier Nebeneffekte aus der Produktivitätsförderung entstehen. So zeigt sich ein positiver Zusammenhang zwischen der Forschungszulage und einem Anstieg der Reallöhne, jedoch ein negativer Effekt auf die Gesamtbeschäftigung. Dieser negative Effekt kann durch entsprechende Förderungen der Unternehmen in Weiterbildungsmaßnahmen abgeschwächt werden (Lokshin und Mohnen, 2013). Auch wäre ein höherer Fördersatz für arbeitsplatzschaffende Forschungs- und Entwicklungsprojekte möglich.

2.6 Fazit

Mit Einführung der Forschungszulage wurde die bisherige direkte Forschungsförderung um eine indirekte Forschungsförderung ergänzt. Dabei kann diese Förderung ab Einführung des Gesetzes am 14. Dezember 2020 von allen Unternehmen in Deutschland beantragt werden, insofern ein begünstigtes Forschungs- und Entwicklungsvorhaben gem. § 2 FZulG vorliegt.

Prinzipiell erfolgt eine Forschungsförderung nur im Rahmen der Grundlagenforschung oder experimenteller Entwicklungen, sodass weitergehende Forschungsbereiche hin zur Marktentwicklung oder Produktionsprozessen nicht umfasst werden. Als abzugsfähige Aufwendungen gelten die Bruttolohnkosten des forschenden Personals oder die Stundenlohnpauschale des forschenden Einzelunternehmers bis zur Obergrenze gem. § 3 FZulG. Durch Einreichung der Bescheinigung auf Förderfähigkeit wird der Antrag auf Zulage genehmigt, sodass die Förderung direkt von der nächsten Einkommen- oder Körperschaftssteuerlast abgezogen wird.

Die Forschungszulage wird vermehrt von kleinen und mittleren Unternehmen in Anspruch genommen, welche ca. zwei Drittel aller Anträge auf Forschungszulage stellen. Eine Geographische Betrachtung zeigt, dass die meisten Anträge von Unternehmen in Nordrhein-Westfalen, gefolgt von Baden-Württemberg und Bayern beantragt werden. Bundesländer wie Brandenburg, Bremen und das Saarland nutzten die Forschungszulage hingegen selten.

Die Bundesregierung hat mit Einführung der Forschungszulage unterschiedliche Ziele verfolgt. Eines der wesentlichsten Ziele war die Erweiterung der Ausgaben für Forschung und Entwicklung. Als konkreten Vorsatz wurde dabei eine Erhöhung der jährlichen Ausgaben auf 3,5% des Bruttoinlandsprodukts gesetzt. Durch eine steuerliche Förderung sollen die Unternehmen mehr Liquidität zur Verfügung haben, um in eigene Forschungs- und Entwicklungsvorhaben zu investieren. Eine Auswertung der Forschungs- und Entwicklungsdaten Deutschlands des Bundesministeriums für Forschung, Technologie und Raumfahrt zeigt auf, dass mit Einführung der Forschungszulage zwar die Ausgaben für Forschung und Entwicklung zunehmen, jedoch die 3,5% des Bruttoinlandsprodukts nicht erreicht werden konnten.

Auch bezüglich der Beschäftigung zeigt sich die Erfüllung der Zielsetzung. So sollte die Forschungszulage die Beschäftigung sichern. Durch die Einführung der steuerlichen Forschungsförderung konnte mehr forschendes Personal eingestellt werden, welches höhere

Löhne und Gehälter ausbezahlt bekommt. Als positiver Zusatzeffekt zeigte sich, dass höhere Löhne des forschenden Personals auch zu höheren Löhnen aller anderen Mitarbeiter führen kann.

Zudem sollte die Forschungszulage konkret Innovation und Wachstum beschleunigen. Die Ausweitung der Produktinnovation, die erhöhte Patentanmeldungen sowie die effizienteren Produktionsprozesse führten zu einer erhöhten Produktivität der Unternehmen. So konnte durch die Forschungszulage nicht nur die Innovation gesteigert werden, sondern auch der Output der Unternehmen positive beeinflusst werden.

Auch wenn die getätigten Auswertungen auf einen positiven Zusammenhang der Forschungszulage auf die gesteckten Ziele der Bundesregierung hindeuten, so zeigen einige Graphiken auch, dass diese positiven Effekte nach längerer Zeit wieder abflachen. Deshalb muss im bestehenden Forschungszulagengesetz nochmal konkret geprüft werden, ob die derzeitige Ausgestaltung der Forschungszulage auch zu langanhaltenden positiven Effekten für den Innovationsstandort Deutschland führt.

Anhang 2.A

TABELLE 2.A.1: Definition der Forschungs- und Entwicklungstätigkeiten

Grundlagenforschung	Experimentelle oder theoretische Arbeiten, die in erster Linie dem Erwerb neuen Grundlagenwissens ohne erkennbare direkte kommerzielle Anwendungsmöglichkeiten dienen.
Industrielle Forschung	Planmäßiges Forschen oder kritisches Erforschen zur Gewinnung neuer Kenntnisse und Fertigkeiten mit dem Ziel, neue Produkte, Verfahren oder Dienstleistungen zu entwickeln oder wesentliche Verbesserungen bei bestehenden Produkten, Verfahren oder Dienstleistungen herbeizuführen. Hierzu zählen auch die Entwicklung von Teilen komplexer Systeme und unter Umständen auch der Bau von Prototypen in einer Laborumgebung oder in einer Umgebung mit simulierten Schnittstellen zu bestehenden Systemen wie auch von Pilotlinien, wenn dies für die industrielle Forschung und insbesondere die Validierung von technologischen Grundlagen notwendig ist.
Experimentelle Entwicklung	Erwerb, Kombination, Gestaltung und Nutzung vorhandener wissenschaftlicher, technischer, wirtschaftlicher und sonstiger einschlägiger Kenntnisse und Fertigkeiten mit dem Ziel, neue oder verbesserte Produkte, Verfahren oder Dienstleistungen zu entwickeln. Dazu zählen zum Beispiel auch Tätigkeiten zur Konzeption, Planung und Dokumentation neuer Produkte, Verfahren und Dienstleistungen. Die experimentelle Entwicklung kann die Entwicklung von Prototypen, Demonstrationsmaßnahmen, Pilotprojekte sowie die Erprobung und Validierung neuer oder verbesserter Produkte, Verfahren und Dienstleistungen in einem für die realen Einsatzbedingungen repräsentativen Umfeld umfassen, wenn das Hauptziel dieser Maßnahmen darin besteht, im Wesentlichen noch nicht feststehende Produkte, Verfahren oder Dienstleistungen weiter zu verbessern. Die experimentelle Entwicklung kann die Entwicklung von kommerziell nutzbaren Prototypen und Pilotprojekten einschließen, wenn es sich dabei zwangsläufig um das kommerzielle Endprodukt handelt und dessen Herstellung allein für Demonstrations- und Validierungszwecke zu teuer wäre. Die experimentelle Entwicklung umfasst keine routinemäßigen oder regelmäßigen Änderungen an bestehenden Produkten, Produktionslinien, Produktionsverfahren, Dienstleistungen oder anderen laufenden betrieblichen Prozessen, selbst wenn diese Änderungen Verbesserungen darstellen sollten.

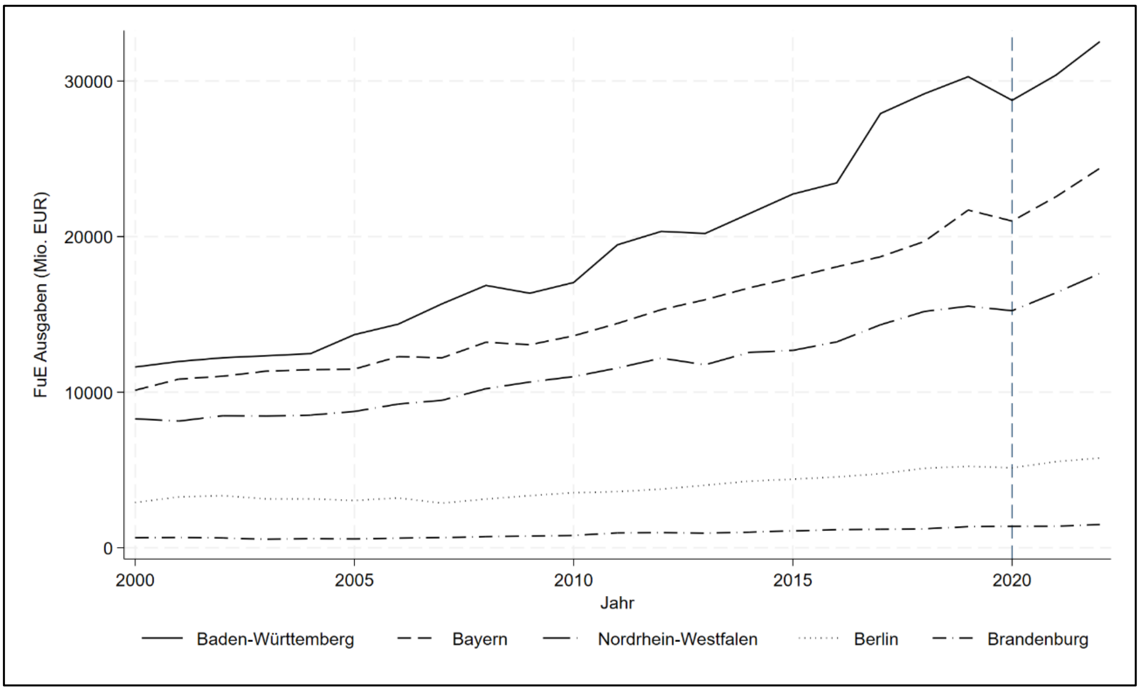
(*Quelle:* Art. 2 Ziffer 84 bis 86 der Allgemeinen Gruppenfreistellungsverordnung (AGVO)).

TABELLE 2.A.2: Fördersätze des Projektzuschusses für ZIM

Unternehmensgröße	**Einzel-projekte**	**Kooperations-projekte**	**Kooperationsprojekte mit ausländischen Partnern**
Kleine Unternehmen in strukturschwachen Regionen (Landkreise im GRW)	45 Prozent	55 Prozent	60 Prozent
Kleine junge Unternehmen (Gründung < 10 Jahre)	45 Prozent	50 Prozent	60 Prozent
Kleine Unternehmen (< 50 Arbeitnehmer)	40 Prozent	45 Prozent	55 Prozent
Mittlere Unternehmen (< 250 Arbeitnehmer)	35 Prozent	40 Prozent	50 Prozent
Mittlere Unternehmen (< 500 Arbeitnehmer)	25 Prozent	30 Prozent	40 Prozent
Mittlere Unternehmen (< 1.000 Arbeitnehmer)	---	30 Prozent	40 Prozent

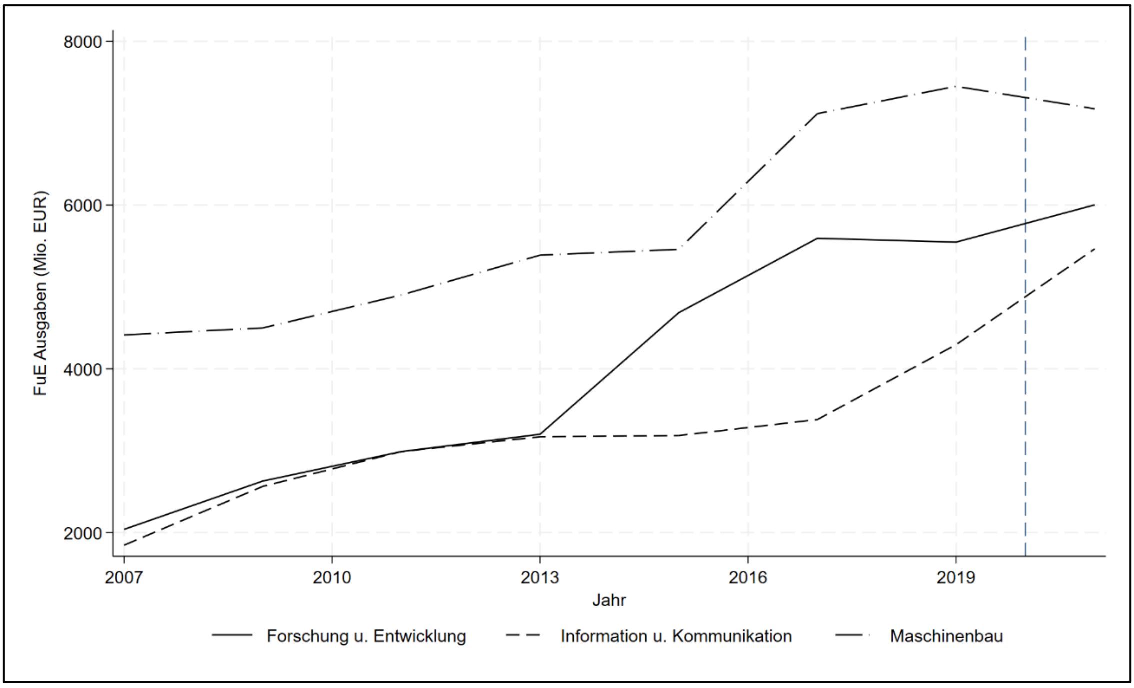
(*Quelle:* BMWK, 2024.)

ABBILDUNG 2.A.3: Ausgaben für Forschung und Entwicklung von 2000-2021 aufgeteilt nach Bundesländern mit der höchsten und niedrigsten Rate an Antragstellungen



(*Quelle:* eigene Darstellung auf Grundlage der Daten des BMFTR).

ABBILDUNG 2.A.4: Bundesausgaben für Forschung und Entwicklung von 2007-2021 aufgeteilt nach den Industriesektoren mit den meistgestellten Anträgen



(*Quelle:* eigene Darstellung auf Grundlage der Daten des BMFTR).

3 Tax Complexity and Firm Value[♣]

3.1 Introduction

Globalization, along with the recent rise of digitization and artificial intelligence, has complicated business models. These developments can inhibit policymakers' efforts to design tax systems that ensure compliance by taxpayers while also supporting economic growth. As a result, the complexity of tax regulations and tax processes has grown rapidly in recent years (Devereux, 2016; Asen, 2021; Harst et al., 2023; Hoppe et al., 2023). Leading experts increasingly warn of the rising tax complexity in today's international business environment, as reflected in the following two statements.

> *For 2024, the biggest impact is the increasingly burdensome and complex tax reporting and data collection requirements taxpayers must meet.*
>
> Amanda Tickel, Deloitte Global Leader, Tax & Legal Policy, Economics Week, 16 August 2024

> *Canadians are wasting money and losing productivity to deal with recent tax changes. ... What was very apparent, however, is that practitioners' tolerance level for the voluminous amounts of change and complexity is at a breaking point.*
>
> Andy Holloway, Postmedia Breaking News, 20 August 2024

Survey evidence by Devereux et al. (2016) shows that senior tax professionals in large multinational firms consider tax uncertainty, closely linked to tax complexity, to be among the top three location factors, mattering more than the statutory tax rate. Yet relatively little is known about the economic consequences of tax complexity for firms. In contrast to other forms of regulatory complexity—such as firm entry regulation - where the effects on entrepreneurship, firm growth, profitability, and risk are well documented (Calomiris et al., 2024; Kalmenovitz, 2023: Trebbi et al., 2023), research on the implications of tax complexity for firms remains scarce. Studies suggest that complex tax systems can impose costs on firms

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[♣] Chapter 3 is based on unpublished joint work with Reinald Koch (Catholic University Eichstätt-Ingolstadt) and Caren Sureth-Sloane (Paderborn University, WU Vienna). The author of this dissertation was responsible for data collection, data preparation, and the conduct and evaluation of the analyses. In addition, the author drafted the first version of the paper and contributed to its further development.

(e.g., higher compliance burdens and the obscuring of tax planning opportunities, Zwick, 2021; Amberger et al., 2025) while also offering benefits (e.g., new tax planning opportunities, Laplante et al., 2019; Diller et al., 2025). Cross-country studies further indicate that complexity arising from tax regulations might offer strategic tax planning advantages for firms while complexity in tax processes can have particularly harmful effects (Hoppe et al., 2023; Euler et al., 2024). This multifaceted nature of tax complexity leaves the net impact on firm value unclear.

This study is the first to assess the overall costs and benefits of tax complexity for firms as well as its effect on the market value of large public firms. We further investigate which types of tax regulations and processes drive this effect, identify the kinds of firms that benefit or suffer most, and assess whether the effect persists or dissipates. In short, we assess firms' ability to adapt to tax complexity.

What do we know so far about the economic effects of tax complexity on firms? Several studies examine effects on corporate investment and location decisions. Edmiston et al. (2003), Mueller and Voget (2012), and Lawless (2013) show that tax complexity deters foreign direct investment (FDI), a finding that Zagler (2023) extends to developing countries. Euler et al. (2024) document that complexity in tax procedures mostly explain these adverse investment effects.

Zwick (2021) attributes the low uptake of loss carryback refunds by U.S. firms to the high complexity of the relevant regulation. Amberger et al. (2025) similarly show that tax complexity damps the responsiveness of corporate investment to tax incentives introduced through changes in tax rates. Complementing this perspective, Campbell et al. (2025) demonstrate that tax complexity affects capital markets. Exploiting the largely unexpected increase in tax complexity resulting from the U.S. Tax Cuts and Jobs Act, they analyze insider trading and find evidence of heightened market uncertainty, increased information asymmetry, and greater insider trading profitability following this law's enactment. While these findings primarily highlight the costs of tax complexity, Laplante et al. (2019) show that firms may also exploit tax complexity for strategic gain: their findings on the classification of R&D tax credit-related expenses suggest that complexity can be used to secure tax benefits. Euler et al. (2024) demonstrate positive implications of complexity in tax regulations centered around large multinationals.

Research also links increased complexity to increased investment in tax expertise. Bustos et al. (2022) show that Chilean firms responded to new anti-profit shifting legislation by demanding more external tax advisory services. Similarly, Giese et al. (2024) find that the complexity of tax processes leads to higher staffing of local tax departments in European multinationals. In contrast, complex tax regulations appear less manageable internally and instead lead to greater tax uncertainty.

In sum, although tax complexity is commonly viewed as imposing costs, it may also create strategic opportunities for firms, leaving its net impact on firm value ultimately an empirical matter. This study assesses the net impact of tax complexity on firm value. Specifically, we examine how tax complexity influences the market value of firms in the MSCI World Index over the period 2016 to 2022. Our approach allows us to capture costs and benefits - a broader perspective than the literature, which has so far focused on investment and tax incentives. We further investigate how these costs and benefits vary with firm characteristics, such as profit-shifting potential, internal governance quality, and the quality of internal information systems. Lastly, we assess whether firms adapt to complex tax regulations and procedures.

Our primary measure of tax complexity is the Tax Complexity Index developed by Hoppe et al. (2023). It offers three key advantages for our analysis. First, it distinguishes between complexity in the tax code and in the tax processes, allowing us to analyze the different dimensions. Second, the index is compiled biennially using a consistent and transparent methodology, enabling the application of panel regression techniques. Third, it is based on survey responses from experienced tax professionals. This subjective perspective is particularly valuable, as it captures perceived complexity - an aspect we hypothesize to influence firm behavior and consequently market valuation. To test the robustness of our results, we also employ the PwC Paying Taxes Score, developed by Djankov et al. (2010) and used, for example, by Amberger et al. (2025).

Our study yields four main findings. First, we find that firms facing higher tax complexity have, on average, a smaller market value. A one standard deviation increase in tax complexity, comparable to the rise experienced in the United States following the Tax Cuts and Jobs Act, corresponds to an average decline in firm value of approximately 2.6%. Complexity in both the tax code and tax framework significantly reduces firm values; the effect for the tax code complexity is, however, about 60% larger. This finding holds in several robustness tests, including the use of an alternative tax complexity measure, the use of a first-differences regression model, an alternative clustering of standard errors, and in an event study design analyzing the implementation of the Anti Tax Avoidance Directive (ATAD) in Europe. Further analysis reveals that complexity arising from anti-BEPS provisions (e.g., transfer pricing and CFC rules) significantly depresses firm value. Among the framework components, only post-filing complexity, pertaining to audits and appeals, exerts a robust negative effect.

Second, we document substantial heterogeneity in the effect of tax complexity across firms. We hypothesize that firms with greater tax planning opportunities may be able to navigate or even benefit from complexity. We test this by stratifying firms based on their tax planning potential, proxied by the share of foreign subsidiaries, the prevalence of affiliates in tax havens, and the statutory tax burden. Our results support this hypothesis. We find that the adverse valuation effects of tax code complexity are strongest among firms with low tax planning capacity. We also find that firms with weak information environments and weak governance are hurt more by tax complexity.

Third, we examine the temporal dynamics of the relationship between tax complexity and firm values by including one- or two-year lags of tax complexity in our models. The results suggest that firms may adapt to increased tax complexity, consistent with learning effects. Nevertheless, tax framework complexity continues to exert a persistent negative influence, indicating that some frictions are not easily mitigated.

Fourth, we analyze how tax complexity affects firm value by using alternative outcome variables. We find that higher tax code complexity is associated with lower current year return-on-assets and slower sales growth, while complexity in both the code and tax processes reduces R&D intensity. These results point to suppressed firm growth and less innovation as likely transmission channels.

Our findings have implications for policymakers. We provide the first comprehensive evidence that tax complexity imposes significant net costs on firms, reducing firm value on average. And this effect is sizeable. Based on our estimates, if all countries had maintained their 2016 levels of tax complexity, the aggregate market capitalization of firms in our sample would have been approximately 2% or almost 900 billion USD higher in 2022.

Although new regulations often aim to enhance fairness and limit tax avoidance, they also impose compliance burdens that can unintentionally distort capital markets. Our research demonstrates that these adverse effects dominate potential benefits and weigh heavily on firms with limited opportunities for international tax planning - precisely those that were not the primary targets of many recent anti-tax avoidance reforms. In addition, firms with efficient internal processes and governance mechanisms are not - or at least not as much - harmed by tax system complexity. Our results further indicate that firms can adapt to high levels of tax code complexity. Frequent changes of a complex tax code are, therefore, particularly harmful to them.

3.2 Theoretical Background and Hypotheses

Firm value is commonly modeled as the (risk-adjusted) present value of a firm's expected future cash flows (Brealey et al., 2020). In this framework, tax complexity may affect both the expected after-tax cash flows and the discount rate applied to them. The direction of the effect of tax complexity on after-tax cash flows is theoretically ambiguous. Tax complexity is likely associated with higher compliance burdens (Mueller and Voget, 2012; Marcuss et al., 2013) and administrative costs such as those associated with calculating tax liabilities, producing documentation, and interacting with tax authorities (Edmiston, 2003). Related costs decrease cash flows.

On top of these direct costs, tax complexity may affect tax avoidance and related costs and benefits, leaving its direction theoretically ambiguous. First, high complexity may obscure potential planning strategies, particularly for less sophisticated firms. Second, tax complexity may be associated with unclear tax regulations, which may create new possibilities for tax planning (Krause, 2000; Tran-Nam et al., 2016). In a cross-country setting, these additional tax planning opportunities may also result from a lack of international coordination of complex tax rules. Third, tax complexity may also affect fairness perceptions, with a potential effect on the tax morale (Blesse et al., 2019).

Empirical studies provide evidence for both directions of the relationship. Laplante et al. (2019) document that firms strategically classify expenses to exploit loosely defined R&D tax credits. Euler et al. (2024) find more foreign direct investments by large multinationals in countries with complex tax codes. Saptono et al. (2024) find a positive relationship between tax complexity and tax evasion in a cross-country context. Conversely, Amberger et al. (2025) find that firms' investment sensitivity to tax rate incentives declines with complexity, and Zwick (2021) shows that higher tax complexity reduces the likelihood of firms claiming loss refunds. Relatedly, Osswald and Sureth-Sloane (2024) demonstrate that tax complexity-related risks, like administrative inefficiencies, reduce the effectiveness of tax loss incentives in encouraging risky investments.

In addition to these cash flow effects, tax complexity may affect the discount rate applied in the firm value model. Higher complexity is generally associated with greater tax uncertainty (Devereux et al., 2016, 2022), particularly when it stems from complex rules that cannot be fully mitigated by increasing internal tax resources (Giese et al., 2024). Studies document that increased tax risk is associated with greater firm risk (Guenther et al., 2017), higher cost of equity (Hutchens and Rego, 2015), and ultimately lower firm value. For instance, Drake et al. (2019) estimate that a one standard deviation increase in tax risk reduces Tobin's Q by approximately 2%.

Given the ambiguous impact of tax complexity on after-tax cash flows and the stronger evidence for an upward pressure on the cost of capital, we propose the following hypothesis:

Hypothesis 1: *Higher tax complexity is associated with a reduction in firm value.*

We test this relationship for overall tax complexity as well as for tax code and tax framework complexity and their specific subcategories. Next, we consider heterogeneity in this relationship. Specifically, we argue that firms may be less harmed by tax complexity if they can exploit its potential benefits or are, in general, better able to process complex tax information.

As discussed above, it is unclear whether tax complexity facilitates or constrains tax planning. In the international context, complexity may result from regulatory inconsistencies and a lack of coordination across jurisdictions (Zangari et al., 2017; Hoppe et al., 2023). These inconsistencies - most pronounced in transfer pricing - simultaneously create tax planning opportunities and expose firms to such risks as double taxation (Arena et al., 2021; Diller et al., 2025). Firms can partially mitigate these risks if they are experienced and have the capacity to navigate many tax systems; use measures such as advance pricing agreements, mutual agreement procedures, or other dispute resolution mechanisms; or exploit tax system differentials. We therefore expect that the costs and benefits of tax complexity differ across firms. We pose two hypotheses. First, we assume - based on the above arguments - that tax complexity creates more profit shifting opportunities than it obscures. Accordingly, firms with a high potential for international profit shifting should be less harmed by tax complexity. Hence, we hypothesize:

> **Hypothesis 2a**: *The negative effect of tax complexity on firm value strengthens when a firm's profit shifting potential is low.*

Second, beyond planning opportunities, the ability to manage tax complexity also depends on a firm's processing capacity. One direct measure is internal information quality, as used by Gallemore and Labro (2015) and McGuire et al. (2018). Their findings show that firms with higher information quality face lower effective tax rates and lower tax risk. We expect these firms to better identify planning opportunities in complex systems and better mitigate associated risks.

Relatedly, firm size also likely matters. Larger firms maintain better-staffed tax departments and allocate more resources to external advisors. Since many tax compliance and planning costs are fixed, they can benefit from economies of scale. This view is supported by Amberger et al. (2025) and Zwick (2021), who find that the costs of tax complexity decrease with firm size - at least in the context of domestic planning. However, larger firms may also face greater scrutiny from tax authorities (Epple and Zelenitz, 1981) and the public (Baker et al., 1998), especially when engaging in aggressive international tax planning. Their broader and more complex operations may also make compliance more challenging.

Another important moderator is internal governance strength. According to Desai and Dharmapala (2006), managers of poorly governed firms may use tax planning to extract private benefits. Indeed, Desai and Dharmapala (2009) and Wilson (2009) show that tax avoidance enhances firm value only in well-governed firms, and Goh et al. (2016) highlight the role of strong external monitoring. If complex rules provide more cover for managerial opportunism, weak governance may amplify agency costs. In this sense, Campbell et al. (2025) show that firm insiders have benefited, at the cost of external shareholders, from the jump in tax complexity caused by the U.S. Tax Cuts and Jobs Act.

Together, these considerations motivate the following hypothesis:

Hypothesis 2b: *The negative effect of tax complexity on firm value strengthens when a firm's capacity to process complex information is low—that is, when internal information quality is low, firm size is small, or governance standards are weak.*

Finally, we explore whether the adverse consequences of tax complexity attenuate as firms and managers learn to navigate that complexity. We posit that learning occurs both passively - through continued exposure to complex rules - and actively - through organizational adaptation. Firms may adjust by hiring additional internal tax staff (Giese et al., 2024) or engaging more external advisors (Bustos et al., 2022), particularly personnel with experience in dealing with similar rules. Over time, uncertainty may also decline as ambiguity in new rules is resolved through case law or administrative guidance.

Hypothesis 3: *The negative consequences of tax complexity for firm value diminish over time due to firm learning and adaptation.*

We also analyze whether the effects for the hypotheses differ across different kinds or subcategories of tax complexity. We expect that firms' ability to navigate and adapt to complexity differs between complex tax regulations and tax processes and across specific regulations and processes, but we have no clear prediction in what direction.

3.3 Empirical Design

Our empirical analysis primarily relies on a two-way fixed effects regression model, as specified in Equation (1):

$$ln\,(q_{it}) = \beta_1 TaxComplexity_{it} + \beta_2 STR_{it} + \beta_3 AvgETR_{ct} + \varphi\, Controls_{it} + \gamma\, Controls_{ct} + \eta_i + \sigma_t + \varepsilon_{it}. \quad (1)$$

Following the literature (Desai and Dharmapala, 2009; Bryant-Kutcher et al., 2012; Jacob and Schuett, 2020), we use Tobin's Q (q_{it}) as our baseline measure to capture the market valuation of firms. We define q_{it} as the ratio of the market value of equity (measured as shares outstanding times the stock price at the balance sheet date) plus the book value of total liabilities, to the book value of total assets:

$$q_{it} = (Book\ Value\ of\ Total\ Liabilities_{it} + Market\ Value\ of\ Equity_{it}) / (Book\ value\ of\ Total\ Assets_{it}), \quad (2)$$

with $Market\ Value\ of\ Equity_{it} = Number\ of\ Shares_{it} \times Share\ Price_{it}$, of firm *i* in year *t*. Given the skewed distribution of q_{it}, we use its natural logarithm in our regressions.

The key independent variable is the level of tax complexity faced by each firm across its global operations, denoted as $TaxComplexity_{it}$. We use the Tax Complexity Index (TCI) developed by Hoppe et al. (2023) as our primary measure. We compute the firm-level tax complexity as the average of the TCI across all group entity locations, weighted by the number of entities in each country, using subsidiary data from *Orbis*.[47]

The TCI captures the perceived complexity of a country's corporate income tax system and comprises two subindices: tax code complexity ($TaxCodeComplexity_{it}$) and tax framework complexity ($TaxFrameworkComplexity_{it}$). It is based on a global survey of senior local tax

[47] The Tax Complexity Index has been updated every two years since 2016. We use the average value for the years *t+1* and *t-1* in all years where no index value is available.

experts from 20 major tax service firms and networks. The tax code complexity index reflects the regulatory complexity of 15 corporate income tax provisions,[48] evaluated across five drivers: ambiguity and interpretation, change, computation, detail, and record keeping. The tax framework complexity index reflects procedural complexity in five areas: guidance, law enactment, payment and filing, audits, and appeals.[49]

We analyze tax complexity at different levels of aggregation. Beyond the overall TCI and the two main subindices, we construct more granular indices: three subcategories of tax code complexity (*anti-BEPS-complexity*$_{it}$, *domestic corporate group complexity*$_{it}$, and *other regulations*$_{it}$) and two subcategories of tax framework complexity (*pre-filing*$_{it}$ and *post-filing*$_{it}$ processes). This allows us to identify the specific regulations and processes that drive the association between tax complexity and firm value. We also test the robustness of our results using alternative tax complexity proxies, including the PwC *PayingTaxesScore*$_{it}$ (Djankov et al., 2010) and the *TaxCompetitiveIndex*$_{it}$ by the Tax Foundation.

To isolate the effect of tax complexity, we control for two additional tax system characteristics. First, we include *STR*$_{it}$, the statutory corporate tax rate, computed as the weighted average across all group entity locations. This controls for the documented downward trend in tax rates over time, which contrasts with the rising trend in tax complexity. Second, we include *AvgETR*$_{ct}$, the average GAAP effective tax rate in the firm's headquarters country and year. This accounts for the potential confounding effect of increasing tax rule restrictiveness, such as the adoption of anti-BEPS legislation, which may simultaneously increase complexity and limit tax planning opportunities. This country-level average mitigates firm-level endogeneity and avoids filtering out firm-specific tax avoidance behavior.

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[48] These 15 regulations cover additional taxes, (alternative) minimum tax, capital gains taxation, CFC rules, taxation of corporate reorganization, depreciation allowances, dividend taxation, general anti-avoidance rules, group taxation, taxation of interest income, investment incentives, loss offsets, royalties, statutory tax rates, and transfer pricing. For details, see Hoppe et al. (2023).

[49] Each of these framework dimensions is composed based on a set of specific more granular tax complexity-relevant issues. For details, see Hoppe et al. (2023).

We also include firm controls commonly used in the literature to account for nontax determinants of firm value: return on assets (ROA_{it}), sales growth ($Growth_{it}$), leverage ($Leverage_{it}$), capital intensity ($CapitalIntensity_{it}$), and firm size, measured as the natural logarithm of total assets ($Size_{it}$). Country-level macroeconomic controls include inflation ($Inflation_{ct}$), GDP growth ($GDPGrowth_{ct}$), and six dimensions from the World Governance Indicators. Detailed variable definitions are provided in Appendix Table 3.A.3.

We rely on the same regression model also to test Hypotheses 2a, 2b, and 3. For Hypotheses 2a and 2b, we examine firm heterogeneity by splitting the sample based on firm characteristics. In Hypothesis 2a, we test whether the negative effect of tax complexity on firm value is mitigated in firms with greater profit-shifting potential. We conduct a median split using the share of foreign affiliates ($International_i$) or the share of tax haven affiliates ($TaxHaven_i$) as proxies for profit shifting potential. Assuming that firms with a high expected tax burden have more potential and more pressure for using international profit shifting, we also estimate specifications where we include interactions of tax complexity and proxies for the expected average tax burden of the group.

For Hypothesis 2b, we test whether the negative effect of tax complexity is less pronounced in firms with greater ability to process complex information. Following Gallemore and Labro (2015), we use E*arnings Announcement Speed* as a proxy for internal information quality and firm size as an additional indicator. We again use a median split approach. To measure internal governance strength, we rely on the presence of a board-level corporate governance committee or the use of performance-based executive compensation.

For Hypothesis 3, we include one-year or two-year lags of tax complexity to test for potential learning effects - i.e., whether firms can adapt to complexity.[50]

[50] We do not include both lags into the same regression to mitigate potential multicollinearity in the case of stable levels of tax complexity.

3.4 Data

Our sample consists of firms listed in the MSCI World Stock Index over the period of 2016 to 2022.[51] The MSCI World Index includes 1,515 of the largest publicly traded firms across 23 developed countries, representing approximately 90% of total market capitalization in these economies and covering a wide range of sectors and regions. The index includes firms headquartered in North America, Europe, Asia, and the Pacific region.

We collect stock prices and financial statement data from Refinitiv. We exclude observations from the banking, insurance, and other financial sectors as well as firm-year observations with negative pre-tax net income. We further restrict the sample to firm-years with complete ownership data and nonmissing values for all dependent and independent variables. These filters result in a final sample of 6,344 firm-year observations for 1,055 unique firms. Appendix Table 3.A.1 provides a detailed overview of sample selection, while Appendix Table 3.A.2 reports the geographic distribution of firms in our final sample.

We obtain data on the Tax Complexity Index from taxcomplexity.org and data on statutory corporate tax rates and the Tax Fairness Index from the Tax Foundation. Country tax haven status is identified using the consolidated list reported by Bennedsen and Zeume (2017). Additional country macroeconomic and governance indicators are sourced from the World Bank. Data on affiliate locations - used to compute firm-specific average values of tax complexity and statutory tax rates - are retrieved from *Orbis*.

Figure 3.1 displays the development of our main independent variables - tax complexity and its two types and their subcategories - over time. In the upper section of Figure 3.1, we show the average development of overall tax complexity and its two types - tax code and tax framework complexity - in the headquarters countries of our sample firms. All three lines show, in general, an upwards trend. Whereas tax framework complexity increases continuously over

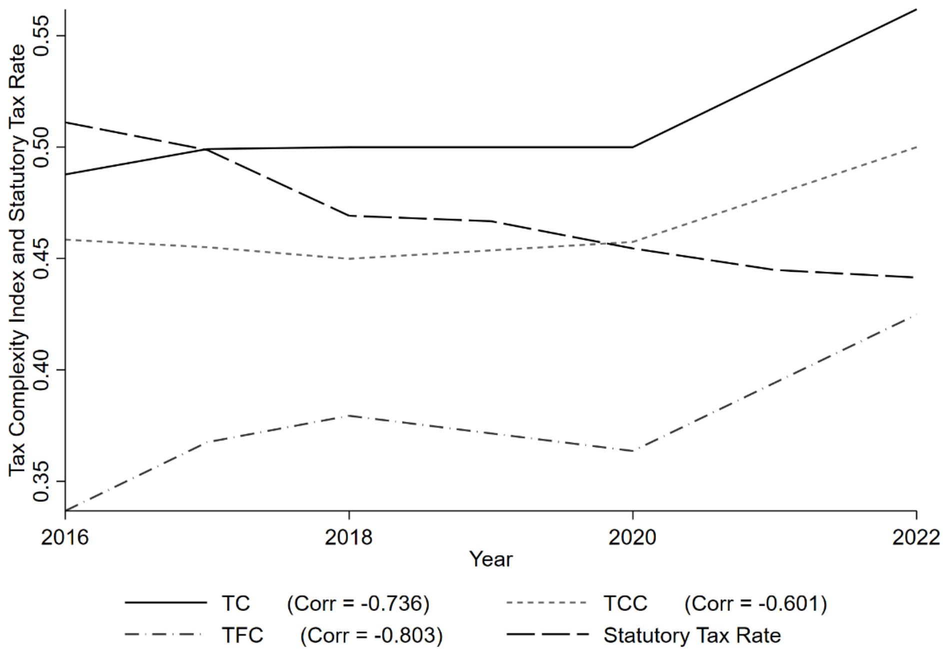
[51] We refer to the current composition of the index for the selection of firms. We do not expect that survivorship bias affect our findings.

our sample period, tax code complexity starts to rise only after 2020. Both kinds of tax complexity are negatively correlated with the headquarters country's statutory tax rates, as we also learn from the upper graph of Figure 3.1.

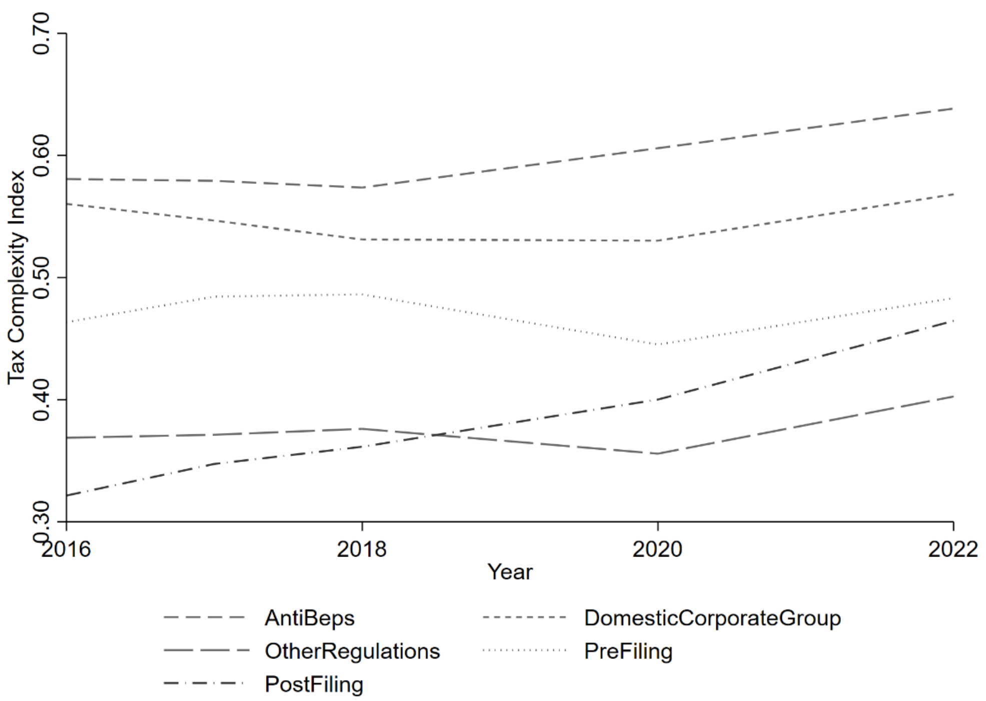
In the lower graph of Figure 3.1, we show time trends for five subcategories of tax code and tax framework complexity. We learn from this graph that the time trends in both types of tax complexity relate to specific regulations and processes, namely the $\textit{anti-BEPS complexity}_{it}$ and $\textit{post-filing}_{it}$ procedures (i.e., audits and appeals).

FIGURE 3.1: Development of Different kinds and subcategories of Tax Complexity. (A) Different kinds of Tax Complexity. (B) Different subcategories of Tax Complexity.

(A) Different kinds of Tax Complexity



(B) Different subcategories of Tax Complexity



Notes: This figure illustrates the development of Tax Complexity Index as well as its to kinds and subcategories used in this paper over the sample period. Each line depicts the unweighted average of tax complexity in the headquarter countries of our sample. The definitions of subcategories of tax complexity are given in Table 3.A.3.

Table 3.1 presents descriptive statistics for all variables used in our final regression analyses.

TABLE 3.1:
Descriptive Statistics

	N	Mean	SD	P5	P95
	(1)	(2)	(3)	(4)	(5)
$ln\ q_{it}$	6344	0.727	0.639	-0.064	1.944
$TaxComplexity_{it}$	6344	0.384	0.029	0.331	0.430
$TaxCodeComplexity_{it}$	6344	0.501	0.038	0.444	0.561
$TaxFrameworkComplexity_{it}$	6344	0.264	0.026	0.217	0.302
$TaxComplexity\_HQ_{ct}$	6344	0.373	0.052	0.270	0.450
$TaxCodeComplexity\_HQ_{ct}$	6344	0.495	0.068	0.330	0.580
$TaxFrameworkComplexity\_HQ_{ct}$	6344	0.247	0.042	0.170	0.310
$anti\text{-}BEPS\text{-}complexity_{it}$	6344	0.543	0.041	0.475	0.607
$domestic\ corporate\ group\ complexity_{it}$	6344	0.497	0.041	0.439	0.557
$other\ regulations_{it}$	6344	0.411	0.059	0.313	0.500
$EU\ AntiBEPS\ Complexity_{it}$	6344	0.001	0.010	-0.007	0.011
$pre\text{-}filing_{it}$	6344	0.265	0.035	0.204	0.325
$post\text{-}filing_{it}$	6344	0.263	0.032	0.218	0.316
STR_{it}	6344	0.274	0.039	0.229	0.365
STR_HQ_{ct}	6344	0.275	0.057	0.190	0.389
$AvgETR_{ct}$	6344	0.232	0.294	0.116	0.416
ROA_{it}	6344	0.086	0.062	0.020	0.206
$Growth_{it}$	6344	0.801	27.64	-0.547	1.737
$Leverage_{it}$	6344	0.280	0.208	0.003	0.572
$CapitalIntensity_{it}$	6344	0.476	0.233	0.153	0.914
$Size_{it}$	6344	23.41	1.268	21.39	25.58
$GDPgrowth_{ct}$	6344	1.687	2.984	-4.147	5.945
$Inflation_{ct}$	6344	2.188	2.332	-0.190	7.041
$Accountability_{ct}$	6344	1.094	0.287	0.845	1.557
$PoliticalStability_{ct}$	6344	0.549	0.441	-0.036	1.115
$GovernmentEffectiveness_{ct}$	6344	1.480	0.235	1.231	1.863
$RegulatoryQuality_{ct}$	6344	1.494	0.244	1.189	1.879
$RuleofLaw_{ct}$	6344	1.500	0.224	1.297	1.839
$Corruption_{ct}$	6344	1.435	0.354	1.020	2.068
$PayingTaxesScore_{it}$	6344	0.158	0.027	0.125	0.200
$\Delta MarketCap_{it}$	6230	0.104	0.245	-0.261	0.522
$TaxCompetitiveIndex_{ct}$	6315	60.98	5.150	55.10	70.39
$yield_{it}$	6344	0.096	0.072	0.018	0.240
$uncertainty_{it}$	4702	0.017	0.021	0.001	0.057
$growth_{it}$	5479	0.039	0.081	-0.057	0.164
$innovation_{it}$	6344	0.017	0.034	0.000	0.090
$investment_{it}$	3588	19.66	1.791	16.73	22.45
$TaxComplexity\ adj_{it}$	6344	0.376	0.043	0.290	0.443
$TaxCodeComplexity\ adj_{it}$	6344	0.497	0.056	0.364	0.569
$TaxFrameworkComplexity\ adj_{it}$	6344	0.252	0.036	0.189	0.308
$Ln(Total\ Fixed\ Assets)_{it}$	5754	22.13	1.629	19.39	24.67
$Ln(Employees)_{it}$	6091	9.849	1.532	7.246	12.20
$EBIT\_sc_{it}$	5603	0.105	0.074	0.028	0.252
$Ln(Total\ Revenue)_{it}$	6342	22.86	1.314	20.75	25.08
$Earnings\ Announcement\ Speed_{it}$	5219	-0.258	2.025	-1.118	-0.082

Notes: This table shows summary statistics for all dependent and independent variables.

3.5 Empirical Results

3.5.1 Baseline Results

We present the results of our baseline regression analysis in Table 3.2, where we estimate Equation 1 to test whether tax complexity is, on average, negatively associated with firm value (Hypothesis 1).

TABLE 3.2:
Baseline Results

	(1)	(2)	(3)	(4)	(5)
	$ln\ q_{it}$	$ln\ q_{it}$	$ln\ q_{it}$	$ln\ q_{it}$	$ln\ q_{it}$
$TaxComplexity_{it}$		-0.8956***			
		(-3.49)			
$TaxCodeComplexity_{it}$			-0.6198***		-0.4761*
			(-2.86)		(-1.90)
$TaxFrameworkComplexity_{it}$				-0.5703**	-0.3760
				(-2.29)	(-1.32)
STR_{it}	-0.0828	-0.3065	-0.2633	-0.2136	-0.3077
	(-0.48)	(-1.55)	(-1.35)	(-1.11)	(-1.54)
$AvgETR_{ct}$	-0.0249***	-0.0250***	-0.0257***	-0.0243***	-0.0251***
	(-2.92)	(-2.93)	(-3.04)	(-2.83)	(-2.95)
ROA_{it}	1.7904***	1.7808***	1.7851***	1.7826***	1.7812***
	(11.46)	(11.39)	(11.40)	(11.41)	(11.39)
$Growth_{it}$	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(6.15)	(5.86)	(6.01)	(5.94)	(5.90)
$Leverage_{it}$	0.0516	0.0530	0.0541	0.0511	0.0532
	(0.71)	(0.73)	(0.74)	(0.70)	(0.73)
$CapitalIntensity_{it}$	-0.0793	-0.0833	-0.0840	-0.0800	-0.0834
	(-0.98)	(-1.03)	(-1.04)	(-0.98)	(-1.03)
$Size_{it}$	-0.2316***	-0.2329***	-0.2320***	-0.2329***	-0.2328***
	(-7.48)	(-7.47)	(-7.46)	(-7.49)	(-7.47)
$GDPgrowth_{ct}$	0.0076***	0.0081***	0.0080***	0.0079***	0.0081***
	(3.98)	(4.24)	(4.19)	(4.13)	(4.24)
$Inflation_{ct}$	0.0054**	0.0044*	0.0045*	0.0051**	0.0045*
	(2.19)	(1.83)	(1.90)	(2.07)	(1.88)
$Accountability_{ct}$	0.0672	0.0500	0.0513	0.0541	0.0463
	(1.16)	(0.87)	(0.88)	(0.94)	(0.80)
$PoliticalStability_{ct}$	-0.0784***	-0.0812***	-0.0813***	-0.0790***	-0.0811***
	(-3.54)	(-3.65)	(-3.67)	(-3.55)	(-3.64)
$GovernmentEffectiveness_{ct}$	0.0034	0.0183	0.0251	-0.0003	0.0176
	(0.07)	(0.36)	(0.49)	(-0.01)	(0.35)
$RegulatoryQuality_{ct}$	0.0559	0.0783*	0.0529	0.0871**	0.0742*
	(1.28)	(1.86)	(1.23)	(2.04)	(1.70)
$RuleofLaw_{ct}$	-0.0309	-0.0426	-0.0519	-0.0234	-0.0421
	(-0.42)	(-0.58)	(-0.71)	(-0.32)	(-0.58)
$Corruption_{ct}$	-0.0606	-0.0212	-0.0349	-0.0345	-0.0236
	(-1.05)	(-0.35)	(-0.59)	(-0.58)	(-0.39)
Observations	6,344	6,344	6,344	6,344	6,344
Adj. R^2	0.9211	0.9213	0.9212	0.9212	0.9212
Firm & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents results for the effect of tax system complexity on firm value. The samples in all columns include observations for the years 2016 to 2022. The dependent variable is $ln\ q_{it}$, measured as the natural log of Tobin's Q. The main independent variable of interest is the firm-year specific average level of tax complexity. It is captured either by the overall Tax Complexity Index (*TaxComplexity*$_{it}$) or by its two subcategories reflecting separately the complexity of tax regulations (*TaxCodeComplexity*$_{it}$) or the complexity of tax processes (*TaxFrameworkComplexity*$_{it}$). All regressions include firm and year fixed effects. All variables are defined in Table 3.A.3. We report t-statistics in parenthesis, based on standard errors clustered by firm. ***, **,and * denote significance at the 1%, 5%, and 10% levels, respectively.

Specification (1) reports a reduced-form model that includes only the control variables but no tax complexity measures. This serves as a benchmark to evaluate the incremental explanatory power of tax complexity. The estimated coefficients for the control variables are largely consistent with expectations. The natural logarithm of Tobin's Q is positively associated with firm profitability and growth, whereas we estimate a negative coefficient for firm size—suggesting that larger firms trade at lower valuation multiples. Among the country-level controls, $GDPGrowth_{ct}$ and $Inflation_{ct}$ are positively associated with firm value, whereas firms located in countries with weaker political stability tend to have lower market valuations.

We also include two tax burden proxies to account for potential overlap with tax complexity. STR_{it} is the weighted average of statutory tax rates across all jurisdictions where the firm operates, while $AvgETR_{ct}$ captures the average GAAP effective tax rate of all firms headquartered in the same country and year - a broader proxy for the local tax burden. As anticipated, we find a statistically significant negative coefficient for $AvgETR_{ct}$, whereas STR_{it} is not statistically significant in this specification.

In Specifications (2) to (5), we introduce different proxies for tax complexity. In Specification (2), we begin with the overall tax complexity score. The statistically significant coefficient of -0.896 supports Hypothesis 1, indicating that higher levels of tax complexity are associated with lower firm valuations. The effect is also economically meaningful: a one standard deviation increase in average tax complexity is associated with a reduction in Tobin's Q of approximately 2.6%. Such a jump in tax complexity was experienced, for example, in the United States after the implementation of the 2017 Tax Cuts and Jobs Act. This magnitude is comparable to that of a one standard deviation increase in the tax burden measures, suggesting that tax complexity and tax burden similarly influence firm valuation.

The results in Specification (2) underscore the importance of including tax complexity in firm valuation models. Compared to the benchmark model in Specification (1), the addition of tax complexity leads to a marked increase in the estimated effect of STR_{it}, highlighting the potential for omitted variable bias when analyses of the tax burden–valuation relationship ignore complexity.

We further disaggregate the two main kinds of tax complexity—tax code complexity and tax framework complexity - in Specifications (3) through (5). When each component is included separately in Specifications (3) and (4), we find that both are negatively associated with firm value. However, the effect of tax code complexity is more pronounced and more statistically significant. Specifically, a one standard deviation increase in average tax code complexity is associated with a 2.4% decline in Tobin's Q, whereas the corresponding effect of tax framework complexity is almost 40% smaller.

This finding aligns with the evidence of Giese et al. (2024), who show that firms can—at least partially - mitigate the harms of tax framework complexity through greater investment in tax personnel and compliance resources. In contrast, the burdens imposed by tax code complexity, such as the intricacy and opacity of statutory provisions, are less easily offset. This distinction is further confirmed in Specification (5), which includes both subcomponents simultaneously. In this model, only tax code complexity retains a statistically significant negative coefficient.

We conduct a series of robustness tests, presenting the results in Table 3.3. The first four tests address potential concerns about our primary independent variable by employing alternative measures of tax system complexity. First, we substitute $TaxComplexity_{it}$ with the PwC $PayingTaxesScore_{it}$, as a proxy for the administrative burden of tax compliance across countries (Djankov et al., 2010; Amberger et al., 2025). The estimated coefficient remains negative and statistically significant, with the effect size approximately doubling relative to our baseline specification. Second, we examine the Tax Foundation's $TaxCompetitiveIndex_{it}$, which is designed to capture the overall competitiveness and neutrality of a country's tax system. While this index may be correlated with complexity, it is not a direct measure. Consistent with this distinction, we find no statistically significant association between the Tax Competitiveness

Index and firm value, reinforcing the importance of using a more targeted proxy for tax complexity.

TABLE 3.3:
Robustness Tests

		(1)	(2)	(3)
Dependent variable (if not otherwise stated)		$ln\ q_{it}$	$ln\ q_{it}$	$ln\ q_{it}$
Category of Tax Complexity		TC_{it}	TCC_{it}	TFC_{it}
(1) PwC Paying Taxes Score	$TaxComplexity_{it}$	-1.9868***		
		(-3.02)		
	Observations	6,344		
	Adj. R^2	0.9212		
(2) Tax Competitive Index	$TaxComplexity_{it}$	-0.0601		
		(-0.92)		
	Observations	6,315		
	Adj. R^2	0.9204		
(3) Headquarter country TC	$TaxComplexity\_HQ_{ct}$	-0.6764***	-0.4168***	-0.5262***
		(-3.96)	(-3.18)	(-3.00)
	Observations	6,344	6,344	6,344
	Adj. R^2	0.9216	0.9214	0.9214
(4) 70% Firm average/ 30% Headquarter country TC	$TaxComplexity\_adj_{it}$	-0.6900***	-0.4458***	-0.4966**
		(-3.55)	(-2.92)	(-2.50)
	Observations	6,344	6,344	6,344
	Adj. R^2	0.9213	0.9212	0.9212
(5) First Difference Estimator	$\Delta TaxComplexity_{it}$	-0.7401**	-0.9129***	0.1368
		(-2.50)	(-3.54)	(0.53)
	Observations	5,048	5,048	5,048
	Adj. R^2	0.3189	0.3203	0.3181
(6) Clustering at country-level	$TaxComplexity_{it}$	-0.8956***	-0.6198**	-0.5703
		(-2.86)	(-2.28)	(-1.29)
	Observations	6,344	6,344	6,344
	Adj. R^2	0.9213	0.9212	0.9212
(7) Dependent variable: ΔMarketCap$_{it}$	$TaxComplexity_{it}$	-0.8012***	-0.6985***	-0.4921**
		(-3.19)	(-3.09)	(-2.48)
	Observations	6,225	6,225	6,225
	Adj. R^2	0.3510	0.3511	0.3504

Notes: This table presents results of seven robustness tests for the baseline regressions in Table 3.2. If not otherwise specified, the dependent variable is $ln\ q_{it}$, measured as the natural log of Tobin's Q. The main independent variable of interest is the firm-year specific average level of tax complexity. If not otherwise specified, it is captured either by the overall Tax Complexity Index ($TaxComplexity_{it}$, *TC*) in the first column or by its two subcategories reflecting separately the complexity of tax regulations ($TaxCodeComplexity_{it}$, *TCC*) or the complexity of tax processes ($TaxFrameworkComplexity_{it}$, *TFC*) in columns 2 and 3. All regressions include firm and year fixed effects and the set of control variables used in Table 3.2. The first two robustness tests use the $Paying\ Taxes\ Score_{it}$ (PwC/Worldbank) and $Tax\ Competitiveness\ Index_{it}$ (Tax Foundation) as alternative measures of tax complexity. In (3) we refer to the headquarter country's level of tax complexity. In (4) we use a weighted definition of $TaxComplexity_{it}$, reflecting the firm-average (70%) and the headquarter country's (30%) level of tax complexity. In (5) we consider all dependent and independent variables in first differences. In (6) we cluster standard errors at the headquarter country-level. In (7) we use an alternative definition of the dependent variable. All variables are defined in Table 3.A.3. We report t-statistics in parenthesis, based on standard errors clustered by firm. ***, **,and * denote significance at the 1%, 5%, and 10% levels, respectively.

Our main measure assumes that tax complexity at all firm locations contributes equally to the tax planning environment. However, given that corporate tax departments are often located at the firm's headquarters, we re-estimate our baseline model using two alternative specifications: one based solely on the headquarters country's tax complexity and another using a weighted index combining 70% group-average tax complexity and 30% headquarters-specific tax complexity. In both cases, the coefficients remain negative and statistically significant, with magnitudes comparable to our baseline results. These findings indicate that our results are insensitive to the weighting of tax complexity across jurisdictions.

In the remaining robustness tests, we address methodological concerns related to model specification and measurement. Specifically, we re-estimate our regression model using first differences rather than levels, cluster standard errors at the country level rather than the firm level, and replace the dependent variable with the relative change in market capitalization ($\Delta MarketCap_{it}$) instead of the natural logarithm of Tobin's Q. The results based on market capitalization changes are fully consistent with our baseline findings. However, when estimating the model in first differences or clustering standard errors at the country level, we observe statistically significant effects only for the overall tax complexity index and the code complexity component. The coefficient on framework complexity, in contrast, becomes insignificant in these specifications. These findings further underscore that code complexity influences firm value while framework complexity does not.

We now turn to a more granular analysis to identify which specific subcategories of tax complexity matter most for publicly listed firms. This analysis seeks to disentangle the effects of complexity stemming from particular tax regulations and administrative processes. We disaggregate tax code complexity into three subcategories: (i) *anti-BEPS complexity*$_{it}$, which captures the intricacy of six regulatory areas aimed at curbing base erosion and profit shifting; (ii) *domestic corporate group complexity*$_{it}$, which reflects the complexity of four regulatory items specific to national corporate groups; and (iii) *complexity of other regulations*$_{it}$, covering all aspects not captured by the first two. For tax framework complexity, we distinguish between the complexity of *pre-filing*$_{it}$ processes and *post-filing*$_{it}$ processes (e.g., audits, appeals).

Specifications (1) through (5) of Table 3.4 include each subcategory individually, while Specification (6) includes all of them simultaneously. The results suggest that the overall effect of tax complexity on firm value is primarily driven by *anti-BEPS complexity*$_{it}$ and *post-filing*$_{it}$ processes. While *domestic corporate group complexity*$_{it}$ exhibits a significant negative association with firm value when considered in isolation, its effect becomes statistically insignificant when all subcomponents are included—indicating potential overlap or shared explanatory power with other forms of complexity.

TABLE 3.4:
Subcategories of Tax Complexity

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$\ln q_{it}$	$\ln q_{it}$	$\ln q_{it}$	$\ln q_{it}$	$\ln q_{it}$	$\ln q_{it}$
anti-BEPS-complexity$_{it}$	-0.5869***					-0.5101*
	(-4.22)					(-1.94)
domestic group complexity$_{it}$		-0.5262**				-0.1853
		(-2.17)				(-0.55)
other regulations$_{it}$			0.1314			0.5383
			(0.46)			(1.34)
pre-filing$_{it}$				-0.1870		0.8037**
				(-0.72)		(2.47)
post-filing$_{it}$					-0.6131***	-0.8154***
					(-3.77)	(-3.23)
Observations	6,344	6,344	6,344	6,344	6,344	6,344
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.9212	0.9213	0.9210	0.9210	0.9214	0.9215

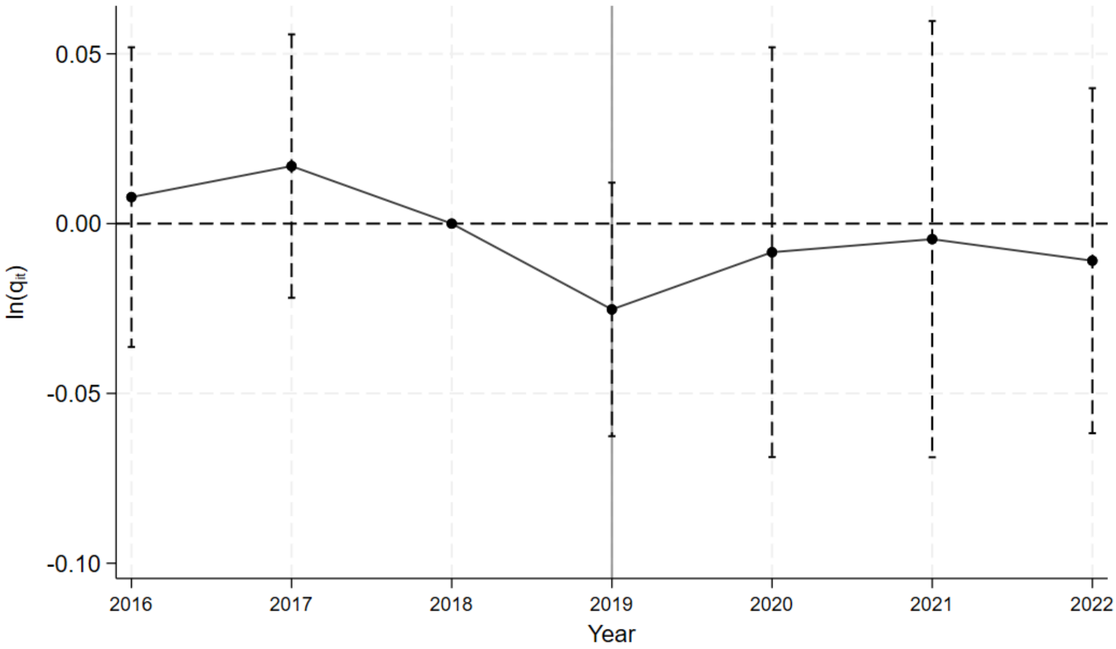
Notes: This table presents results for the effect of subcategories of tax system complexity on firm value. The samples in all columns include observations for the years 2016 to 2022. The dependent variable is $\ln q_{it}$, measured as the natural log of Tobin's Q. The main independent variable of interest is the firm-year specific average of a category of tax system complexity. The *anti-BEPS-complexity$_{it}$* reflects the complexity of the following regulations: of *cfcrules*, *generalantiavoidance*, *interest*, *royalties*, *dividends*, *transferpricing*. The *domestic corporate group complexity$_{it}$* reflects the complexity of the following regulations: *capitalgains*, *corporatereogranization*, *grouptreatment*, *lossoffset*. *Other regulations$_{it}$* reflect the complexity of the following regulations: *additionaltaxes*, *alternativeminimumtax*, *depreciation*, *investmentincentives*, *statutorytaxrates*..*Pre-filing$_{it}$* reflects the complexity of the following processes: *guidance*, *enactment*, *paymentfiling*. *Post-filing$_{it}$* reflects the complexity of the following processes: *audits*, *appeals*. All regressions include firm and year fixed effects and the set of control variables used in Table 3.2. All variables are defined in Table 3.A.3. We report t-statistics in parenthesis, based on standard errors clustered by firm. ***, **,and * denote significance at the 1%, 5%, and 10% levels, respectively.

To further examine the effect of anti-BEPS tax code complexity, we conduct an event study around the adoption of the EU Anti-Tax Avoidance Directive in 2019. This directive serves as a quasi-exogenous shock to tax code complexity, as it was mandated at the EU level and did not result from individual country policy choices. We calculate, for each firm, the change in anti-BEPS tax code complexity between 2018 and 2019 attributable solely to its EU-based affiliates, excluding changes from non-EU jurisdictions.

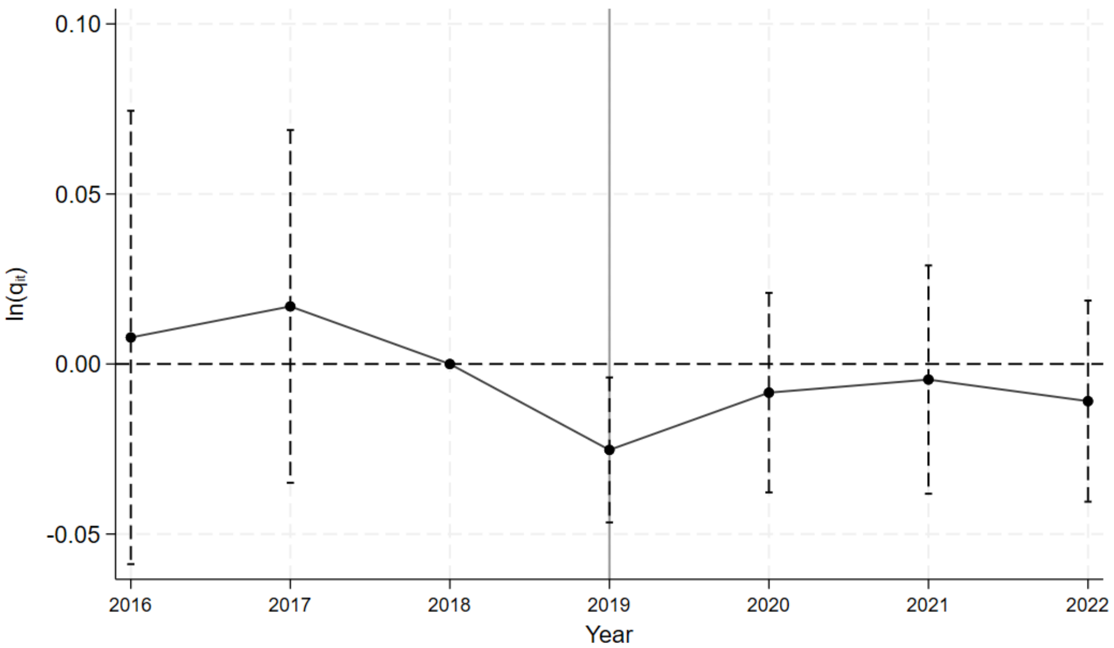
Our treatment group consists of firms that experienced an increase in EU anti-BEPS complexity during this period, while the control group includes firms that saw a decrease. We exclude firms with no change in EU anti-BEPS complexity (typically those without EU affiliates) and firms headquartered in the EU (to mitigate confounding effects from domestic policy responses or headquarters bias). Results from this analysis are presented in Figure 3.2, using standard errors clustered at both the firm and country levels.

FIGURE 3.2: Event Study: ATAD Implementation in the EU (2019). (A) Clustering at firm level. (B) Clustering at country level.

(A) Clustering at firm level:



(B) Clustering at country level:



Notes: This figure shows the results of an event study analyzing the effects of implementing the ATAD I directive in the European Union in 2019. We estimate Equation 1 but replace *TaxComplexity$_{it}$* by the interaction term *Treat$_i$*Year$_t$*, which is depicted in the two graphs (the upper graph clusters standard errors at the firm level, the lower graph at the headquarter country level). *Treat$_i$* is equal to one if *EU AntiBEPS Complexity$_{it}$* has increased from 2018 to 2019, and zero otherwise. The definition of *EU AntiBEPS Complexity$_{it}$* is provided in Table 3.A.3. We disregard all firms headquartered in the European Union and all firms for which the *EU AntiBEPS Complexity$_{it}$* has not changed from 2018 to 2019.

The event study results indicate no evidence of pre-trends, suggesting that anticipation is unlikely to drive the observed effects. In the treatment group, we detect a statistically significant decline in firm value in 2019, coinciding with the directive's implementation - at least when standard errors are clustered at the country level. In subsequent years, the interaction terms between the treatment indicator and year dummies remain negative but statistically insignificant, suggesting that the effect of increased $\textit{anti-BEPS complexity}_{it}$ may be temporary. These findings further support the notion that heightened regulatory complexity can have immediate, though possibly short-lived, adverse effects on firm valuation.

3.5.2 Heterogeneity Analyses

We now examine firm heterogeneity in the relationship between tax complexity and firm value to better understand whether tax complexity systematically creates winners and losers. In Hypotheses 2a and 2b, we posit that firms with (1) greater opportunities for international profit shifting, (2) stronger internal information systems/governance standards, or (3) larger size are less harmed by tax system complexity.

Building on the literature, we argue that tax complexity may open additional avenues for tax planning - particularly through international profit shifting. As a result, any negative valuation effects should weaken for firms better positioned to exploit planning opportunities. To test this, we conduct two complementary sets of analyses.

First, we follow Amberger et al. (2025) by interacting tax complexity measures with proxies for firms' tax planning incentives: the group's average statutory tax burden (STR_{it}) and the average effective tax rate of firms headquartered in the same country and year ($AvgETR_{ct}$). We hypothesize that firms facing higher tax burdens have greater incentives to engage in international tax planning and are thus less harmed by tax complexity. Results reported in Table 3.5 support this prediction. While the baseline effect of tax code complexity remains negative and statistically significant, the interaction terms with both STR_{it} and $AvgETR_{ct}$ are positive and significant, indicating an attenuation of the adverse effect. In contrast, we find no significant interaction effects for tax framework complexity (or for the overall complexity index), suggesting that this kind of complexity is less directly tied to international tax planning strategies.

TABLE 3.5:
Heterogeneity: Profit Shifting Potential I

	(1)	(2)	(3)
Category of Tax Complexity	*TC_{it}*	*TCC_{it}*	*TFC_{it}*
Section A: Interaction of Tax Complexity$_{it}$ and STR$_{it}$			
$TaxComplexity_{it}$	-2.0948	-4.1568***	3.5627***
	(-1.64)	(-3.76)	(2.91)
$TaxComplexity_{it}$ x STR_{it}	4.3666	13.2690***	-14.6625***
	(0.98)	(3.32)	(-3.43)
Observations	6,344	6,344	6,344
Firm & Year FE	YES	YES	YES
Controls	YES	YES	YES
Adj. R-sq	0.9213	0.9214	0.9213
Section B: Interaction of Tax Complexity$_{it}$ and AvgETR$_{ct}$			
$TaxComplexity_{it}$	-0.9802***	-0.7374***	-0.4570*
	(-3.65)	(-3.33)	(-1.80)
$TaxComplexity_{it}$ x $AvgETR_{ct}$	0.4270	0.5966**	-0.4736
	(0.98)	(2.44)	(-1.21)
Observations	6,344	6,344	6,344
Firm & Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adj. R^2	0.9213	0.9212	0.9212

Notes: In this table we assess how the association between tax complexity and firm value is moderated by the firm-level tax burden. To this end, we include interactions of *$TaxComplexity_{it}$* and *STR_{it}* in Section A and interactions of *$TaxComplexity_{it}$* and *$AvgETR_{ct}$* in Section B. The samples in all columns include observations for the years 2016 to 2022. The dependent variable is *$ln\ q_{it}$*, measured as the natural log of Tobin's Q. The main independent variables of interest are the firm-year specific average level of tax complexity and the respective interactions. Tax complexity is captured either by the overall Tax Complexity Index (*$TaxComplexity_{it}$, TC*) in the first column or by its two subcategories reflecting separately the complexity of tax regulations (*$TaxCodeComplexity_{it}$, TCC*) or the complexity of tax processes (*$TaxFrameworkComplexity_{it}$, TCF*) in column 2 and 3. All regressions include firm and year fixed effects and the set of control variables used in Table 3.2. All variables are defined in Table 3.A.3. We report t-statistics in parenthesis, based on standard errors clustered by firm. ***, **,and * denote significance at the 1%, 5%, and 10% levels, respectively.

Second, we conduct subsample analyses based on two direct proxies for firms' profit-shifting potential: the share of foreign subsidiaries (*$International_i$*) and the share of tax haven affiliates (*$TaxHaven_i$*). Using a median split, we re-estimate our baseline model (Equation 1) separately for firms above and below the median of each variable and report the results in Table 3.6. We find that statistically significant negative effects of both the overall complexity index and tax code complexity are confined to firms with below-median levels of foreign or tax haven affiliates. For firms with higher international presence and thus greater profit-shifting potential, the estimated coefficients are much smaller (or even positive) and statistically insignificant. Results for tax framework complexity are directionally consistent but notably weaker.

TABLE 3.6:
Heterogeneity: Profit Shifting Potential II

	(1)	(2)	(3)
Dependent variable	*ln* q_{it}	*ln* q_{it}	*ln* q_{i}
Kind of Tax Complexity	TC_{it}	TCC_{it}	TFC_{it}
Section A: Sample split: Share of foreign affiliates			
Below Median (Obs. 3,162)			
TaxComplexity$_{it}$	-0.7414***	-0.5647**	-0.4081
	(-2.84)	(-2.43)	(-1.40)
Adj. R^2	0.9298	0.9298	0.9297
Above Median (Obs. 3,182)			
TaxComplexity$_{it}$	0.1000	-0.0430	0.2206
	(0.15)	(-0.08)	(0.37)
Adj. R^2	0.9165	0.9165	0.9165
Section B: Sample split: Share of tax haven affiliates			
Below Median (Obs. 3,161)			
TaxComplexity$_{it}$	-0.9810***	-0.7077***	-0.6131**
	(-3.63)	(-2.83)	(-2.30)
Adj. R^2	0.9380	0.9487	0.986
Above Median (Obs. 3,183)			
TaxComplexity$_{it}$	-0.6198	-0.5132	-0.3886
	(-1.08)	(-1.19)	(-0.70)
Adj. R^2	0.9064	0.9064	0.9064

Notes: In this table we assess how the association between tax complexity and firm value differs in subsamples with different potential for international profit shifting. To this end, we split the sample according to the firm-level share of foreign subsidiaries (Section A) and according to the firm-level share of tax haven affiliates (Section B). The samples in all columns include observations for the years 2016 to 2022. The dependent variable is $ln\ q_{it}$, measured as the natural log of Tobin's Q. The main independent variable of interest is the firm-year specific average level of tax complexity. It is captured either by the overall Tax Complexity Index (*TaxComplexity*$_{it}$, TC_{it}) in the first column or by its two subcategories reflecting separately the complexity of tax regulations (*TaxCodeComplexity*$_{it}$, TCC_{it}) or the complexity of tax processes (*TaxFrameworkComplexity*$_{it}$, TCF_{it}) in column 2 and 3. All regressions include firm and year fixed effects and the set of control variables used in Table 3.2. All variables are defined in Table 3.A.3. We report t-statistics in parenthesis, based on standard errors clustered by firm. ***, **,and * denote significance at the 1%, 5%, and 10% levels, respectively.

Together, these findings strongly support Hypothesis 2a, indicating that firms with more opportunities for international tax planning are less harmed by complex tax systems. From a policy perspective, this challenges a widely cited rationale for increasing tax complexity - namely, to deter tax avoidance and promote fairness. On the contrary, our results suggest that complexity may instead entrench disparities by benefiting more internationally mobile firms, potentially placing domestically oriented ones at a competitive disadvantage.

We further hypothesize in Hypothesis 2b that firms vary in their capacity to manage tax complexity, particularly in their ability to process complex information. We expect that larger firms possess better internal tax departments and benefit from economies of scale in navigating complex tax systems. A more direct proxy for a firm's information-processing capacity is the speed of earnings announcements, as proposed by Gallemore and Labro (2015), which captures the timeliness of internal reporting. Additionally, we predict that firms with weaker governance may be less harmed by tax complexity. The rationale is that complex tax regulations may offer greater scope for managerial discretion or rent extraction, potentially benefiting insiders at the expense of shareholders (Campbell et al., 2025).

We test these predictions through subsample analyses based on firm size, earnings announcement speed, and governance characteristics. The results of these tests are reported in Table 3.7. Contrary to our expectations, we find no evidence that larger firms are less harmed by tax complexity. In fact, the results suggest that the negative valuation effects are more pronounced among firms in the top size tertile. These firms may be more exposed to tax complexity due to the scope of their operations or may be held to higher compliance expectations.

By contrast, our other results support the theoretical predictions—particularly in relation to tax framework complexity and the overall tax complexity index. As reported in Table 3.7, firms with below-median *Earnings Announcement Speed* and those lacking a dedicated *Corporate Governance Board Committee* or *Performance-based Compensation* exhibit significantly larger negative effects of tax complexity. These findings imply that highly complex tax systems place a premium on strong internal governance and information systems and that firms with these capabilities can better mitigate the associated costs.

TABLE 3.7:
Heterogeneity: Information Processing Capacity

	(1)	(2)	(3)
Dependent variable	$ln\ q_{it}$	$ln\ q_{it}$	$ln\ q_{i}$
Kind of Tax Complexity	TC_{it}	TCC_{it}	TFC_{it}
Section A: Sample split: Corporate Governance Board Committee			
No CGBC (Obs. 2,666)			
$TaxComplexity_{it}$	-1.1441**	0.2384	-1.4076***
	(-2.53)	(0.61)	(-3.80)
Adj. R^2	0.9175	0.9172	0.9180
With CGBC (Obs. 3,469)			
$TaxComplexity_{it}$	-0.1897	-0.3628	0.2371
	(-0.57)	(-1.22)	(0.63)
Adj. R^2	0.9283	0.9284	0.9283
Section B: Sample split: Performance-based Compensation			
No performance-based compensation (Obs. 341)			
$TaxComplexity_{it}$	-3.3390*	2.9991**	-3.4394**
	(-1.97)	(2.14)	(-2.58)
Adj. R^2	0.9330	0.9326	0.9351
With performance based compensation (Obs. 5,776)			
$TaxComplexity_{it}$	-0.7936***	-0.5320**	-0.5346**
	(-2.91)	(-2.37)	(-2.03)
Adj. R^2	0.9245	0.9244	0.9244
Section C: Sample split: Earnings Announcement Speed			
Below Median (Obs. 2,648)			
$TaxComplexity_{it}$	-1.2318***	-0.4571	-1.2510***
	(-3.34)	(-1.27)	(-3.37)
Adj. R^2	0.9251	0.9247	0.9252
Above Median (Obs. 2,571)			
$TaxComplexity_{it}$	-0.9185**	-0.9322***	-0.0868
	(-2.02)	(-2.78)	(-0.18)
Adj. R^2	0.9183	0.9185	0.9181
Section D: Sample split: Firm Size			
Below Median (Obs. 3,183)			
$TaxComplexity_{it}$	-0.7398*	-0.5818*	-0.3130
	(-1.73)	(-1.80)	(-0.72)
Adj. R^2	0.8997	0.8997	0.8995
Above Median (Obs. 3,161)			
$TaxComplexity_{it}$	-1.2876***	-0.8217***	-1.0182***
	(-4.83)	(-3.26)	(-4.56)
Adj. R^2	0.9274	0.9276	0.9277

Notes: In this table we assess how the association between tax complexity and firm value differs in subsamples with different capacity for processing complex information. To this end, we split the sample according to the existence of a Corporate Governance Board Committee (Section A) and Performance-Based Compensation (Section B) as well as according to the Earnings Announce Speed (Section C) and Firm Size (Section D). The samples in all columns include observations for the years 2016 to 2022. The dependent variable is $ln\ q_{it}$, measured as the natural log of Tobin's Q. The main independent variable of interest is the firm-year specific average level of tax complexity. It is captured either by the overall Tax Complexity Index ($TaxComplexity_{it}$, TC_{it}) in the first column or by its two subcategories reflecting separately the complexity of tax regulations ($TaxCodeComplexity_{it}$, TCC_{it}) or the complexity of tax processes ($TaxFrameworkComplexity_{it}$, TCF_{it}) in column 2 and 3. All regressions include firm and year fixed effects and the set of control variables used in Table 3.2. All variables are defined in Table 3.A.3. We report t-statistics in parenthesis, based on standard errors clustered by firm. ***, **,and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.5.3 Analyses of dynamics over time

So far, our analysis has focused on the contemporaneous relationship of tax complexity and firm value, specifically, the effect of tax complexity on firm value at the end of the same year. However, this static regression design may overlook that the consequences of complex tax regulations and tax processes may evolve.

There are at least two reasons to expect a dynamic relationship. First, the introduction of new regulations and processes may entail one-time implementation costs, such as those resulting from introducing the global minimum tax or country-by-country reporting. These initial burdens suggest that newly introduced tax complexity may be costlier than persistent tax complexity that firms have incorporated into their routines. Second, firms may need time to adjust their tax planning strategies to new regulations, particularly when the exact application of these new rules is unclear. As a result, potential benefits from newly introduced planning opportunities may only materialize with a delay. We therefore predict, in Hypothesis 3, that the negative effects of tax complexity diminish over time.

To explore these dynamics, we augment our regression model by including one-year or two-year lags of the tax complexity variables in addition or instead of the current-year variables (see Table 3.8). These additional regression analyses reveal distinct temporal patterns of tax code and tax framework complexity. We find consistently negative coefficients of a similar (or even larger) size for the lagged values of tax framework complexity, suggesting that tax process complexity exerts persistent negative effects on firm value.

Conversely, the impact of $TaxCodeComplexity_{it}$ appears more transitory. We find a statistically significant negative effect of $TaxCodeComplexity_{it}$ only for the current value, whereas we estimate even a positive (albeit statistically insignificant) coefficient for its two-year lag. These findings indicate that, while tax processes complexity imposes enduring costs for firms, tax code complexity may become more manageable over time, as firms learn to navigate the complexities in the tax code.

TABLE 3.8:
Dynamic Effects of Tax Complexity

	(1)	(2)	(3)	(4)
Dependent variable	$\ln q_{it}$	$\ln q_{it}$	$\ln q_{it}$	$\ln q_{it}$
Section A: Tax Complexity Index				
$TaxComplexity_{it}$	-0.5995*	-1.1914***		
	(-1.87)	(-3.68)		
$TaxComplexity_{it-1}$	-0.3473		-0.7031***	
	(-1.28)		(-2.60)	
$TaxComplexity_{it-2}$		-0.7957**		-0.3256
		(-2.24)		(-0.95)
Observations	5,474	4,324	5,474	4,324
Firm & Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.9286	0.9379	0.9285	0.9376
Section B: Tax Code Complexity				
$TaxCodeComplexity_{it}$	-0.7083***	-0.7286***		
	(-2.68)	(-2.80)		
$TaxCodeComplexity_{it-1}$	0.3254		-0.0605	
	(1.15)		(-0.24)	
$TaxCodeComplexity_{it-2}$		0.1895		0.5326*
		(0.61)		(1.88)
Observations	5,474	4,324	5,474	4,324
Firm & Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.9285	0.9379	0.9284	0.9377
Section C: Tax Framework Complexity				
$TaxFrameworkComplexity_{it}$	0.0243	-0.6983**		
	(0.09)	(-2.33)		
$TaxFrameworkComplexity_{it-1}$	-0.7935***		-0.7805***	
	(-3.54)		(-3.22)	
$TaxFrameworkComplexity_{it-2}$		-1.3189***		-1.0987***
		(-4.82)		(-4.14)
Observations	5,474	4,324	5,474	4,324
Firm & Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.9286	0.9381	0.9286	0.9380

Notes: In this table we assess time properties of the association between tax complexity and firm value. To this end, we add one-year or two-year lags of tax complexity to the regression. The samples in columns 1 and 3 include observations for the years 2017 to 2022, the samples in columns 2 and 4 include observations for the years 2018 to 2022. The dependent variable is $\ln q_{it}$, measured as the natural log of Tobin's Q. The main independent variable of interest is the firm-year specific average level of tax complexity. It is captured either by the overall Tax Complexity Index ($TaxComplexity_{it}$, TC_{it}) in Section A or by its two subcategories reflecting separately the complexity of tax regulations ($TaxCodeComplexity_{it}$, TCC_{it}) or the complexity of tax processes ($TaxFrameworkComplexity_{it}$, TCF_{it}) in Sections B and C. All regressions include firm and year fixed effects and the set of control variables used in Table 3.2. All variables are defined in Table 3.A.3. We report t-statistics in parenthesis, based on standard errors clustered by firm. ***, **,and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.5.4 Additional Analyses on Effect Channels

Finally, we investigate potential real effects associated with tax complexity that may explain its negative impact on firm value. Drawing on the literature, we consider three potential channels: (i) direct compliance costs that reduce current profitability, (ii) increased tax uncertainty that raises firm risk, and (iii) dampened investment, which may constrain long-term growth.

To explore these mechanisms, we re-estimate Equation 1 using alternative dependent variables. In Section A of Table 3.9, we use return on assets ($yield_{it}$) as a proxy for profitability. Section B employs the standard deviation of the return on assets (uncertainty_{it}) to capture firm risk. In Section C, we examine sales growth ($growth_{it}$), followed by R&D intensity ($innovation_{it}$) in Section D, and investment in tangible fixed assets ($investment_{it}$) in Section E. For each model, we adapt the set of control variables to reflect the respective outcome variable, in line with standards established in the literature.

TABLE 3.9:
Effect Channels

Kind of Tax Complexity		(1) TC_{it}	(2) TCC_{it}	(3) TFC_{it}
Section A	**Dep. variable:**	**yield$_{it}$**	**yield$_{it}$**	**yield$_{it}$**
	TaxComplexity$_{it}$	-0.1201**	-0.1263**	-0.0461
		(-2.13)	(-2.40)	(-1.13)
	Observations	6,084	6,084	6,084
	Adj. R^2	0.7436	0.7437	0.7433
Section B	**Dep. variable:**	**uncertainty$_{it}$**	**uncertainty$_{it}$**	**uncertainty$_{it}$**
	TaxComplexity$_{it}$	-0.0118	-0.0050	-0.0171
		(-0.66)	(-0.34)	(-1.00)
	Observations	4,697	4,697	4,697
	Adj. R^2	0.2165	0.2164	0.2166
Section C	**Dep. variable:**	**growth$_{it}$**	**growth$_{it}$**	**growth$_{it}$**
	TaxComplexity$_{it}$	-0.1854*	-0.2343**	0.0232
		(-1.78)	(-2.33)	(0.29)
	Observations	5,472	5,472	5,472
	Adj. R^2	0.1753	0.1760	0.1747
Section D	**Dep. variable:**	**innovation$_{it}$**	**innovation$_{it}$**	**innovation$_{it}$**
	TaxComplexity$_{it}$	-0.0263**	-0.0192**	-0.0128*
		(-2.49)	(-2.19)	(-1.66)
	Observations	3,809	3,809	3,809
	Adj. R^2	0.9578	0.9578	0.9578
Section E	**Dep. variable:**	**investment$_{it}$**	**investment$_{it}$**	**investment$_{it}$**
	TaxComplexity$_{it}$	-2.4603	-1.6014	-1.7363
		(-0.99)	(-0.71)	(-1.01)
	Observations	3,530	3,530	3,530
	Adj. R^2	0.6320	0.6320	0.6320

Notes: In this table we assess what potential real responses of firms may explain the valuation effect of tax complexity. We estimate Equation 1 using the following alternative dependent variables: *yield$_{it}$*, is the net income divided by total assets; *uncertainty$_{it}$*, is the standard deviation of future yields for current and the next two years; *growth$_{it}$* is the Compound Annual Growth Rate of total revenue for current and the next two years; *innovation$_{it}$* is the firm's R&D expenses divided by total assets; *investment$_{it}$* is the natural log of the change in tangible fixed assets. The samples in all columns include observations for the years 2016 to 2022. The main independent variable of interest is the firm-year specific average level of tax complexity. It is captured either by the overall Tax Complexity Index (*TaxComplexity$_{it}$*, *TC_{it}*) in Column (1) or by its two subcategories reflecting seperately the complexity of tax regulations (*TaxCodeComplexity$_{it}$*, *TCC_{it}*) or the complexity of tax processes (*TaxFrameworkComplexity$_{it}$*, *TCF_{it}*) in Columns (2) and (3). All regressions include firm and year fixed effects. All regressions include the set of control variables from Table 3.2, subject to some modifications in firm controls to account for the nature of the dependent variables. In Section A, we additionally include the *Ln(fixed assets)$_{it}$* and *ln (employees)$_{it}$*, but disregard *ROA$_{it}$*, *Size$_{it}$* and *CapitalIntensity$_{it}$*. In Section B, we additionally include the *EBIT_sc$_{it}$*, but disregard *ROA$_{it}$*. In Section C, we disregard *ROA$_{it}$* and *Growth$_{it}$*. In Section D, we include *investment$_{it}$*, but disregard *ROA$_{it}$* and *Growth$_{it}$*. In Section E, we include *Ln(revenue)$_{it}$*, but disregard *Size$_{it}$* and *Growth$_{it}$*. All variables are defined in Table 3.A.3. We report t-statistics in parenthesis, based on standard errors clustered by firm. ***, **,and * denote significance at the 1%, 5%, and 10% levels, respectively.

Our findings suggest that the harm of tax complexity on firm value cannot be attributed to a single dominant channel. We find that overall tax complexity is significantly negatively associated with both return on assets and sales growth and that these effects are primarily driven by the tax code complexity. This aligns with the overall stronger valuation effect that we find for this subcategory of tax complexity throughout this paper. Moreover, for all three kinds of tax complexity - overall, tax code, and tax framework - we observe a significant negative association with R&D intensity. This suggests that complex tax regulations and processes may discourage firms from engaging in forward-looking, innovative activities.

In contrast, we find no robust evidence linking tax complexity to firm risk or to investment in tangible assets. However, when we incorporate interaction terms between tax complexity and the average statutory tax rates (STR_{it}), we observe additional nuances.[52] Specifically, the interaction between STR_{it} and tax framework complexity yields a positive and statistically significant coefficient, indicating that it is tax framework complexity that particularly moderates the sensitivity of investment to the tax rate. In other words - and extending Amberger et al. (2025) - we show that firms appear to respond less to tax incentives when faced with more complex tax processes, which may dilute the effectiveness of tax policy as an investment lever.

Taken together, these findings indicate that tax complexity - particularly that resulting from complex tax regulations - is associated with negative real responses of firms. The identified negative firm value effects are primarily driven by reduced growth opportunities - reflected in lower profitability and sales growth - and less R&D, rather than by increased perceived risk.

3.6 Conclusion

Our study documents the significant impact of tax system complexity on the market value of firms listed on the MSCI World stock index. We demonstrate that high tax complexity can reduce firm values, particularly through complex anti-BEPS regulations and complex post-filing processes.

Our study is the first to empirically document this effect and to quantify its magnitude. According to our estimations, an increase in average tax complexity by one standard deviation,

[52] These results are untabulated.

similar to what was experienced by the United States after the enactment of the TCJA, reduces firm values on average by about one percent. We also assess the overall loss in market capitalization based on our findings. If all countries would have retained their tax complexity scores from the year 2016, the overall market capitalization of the firms in our sample would have been approximately 2% or almost 900 billion USD higher in 2022. In most of our tests, the negative value implications of complex tax regulations turn out worse than those of complex tax procedures.

We also show that tax complexity unevenly affects the values of firms. The negative effects are stronger for firms with a limited potential for tax-motivated profit shifting, like firms with low statutory tax rates or few foreign or tax haven affiliates. Tax complexity is also particularly harmful for firms with weak governance and weak internal information quality.

These findings have important implications for both policymakers and corporate managers. Policymakers must carefully weigh the benefits of new tax regulations against the additional burdens of increased complexity. While aiming to enhance tax fairness and curb tax avoidance, they should consider the unintended negative consequences on corporate value. These negative effects seem to be temporary if complexity results from tax regulations, but complex tax procedures seem to have a longer-lasting, though smaller, effect. Frequent changes of tax regulations may thus be particularly costly for firms.

For corporate managers, understanding the nuances of tax complexity is crucial for strategic planning and investing. Firms would be well advised to anticipate the costs associated with complex tax systems and adapt their strategic decisions accordingly.

Ultimately, our research contributes to the broader discourse on international tax policy by highlighting the delicate balance between regulatory objectives and economic efficiency. As tax systems evolve, further empirical research is essential to refine understanding of the economic effects of tax complexity and to guide the design of better and more equitable tax policies. This study lays the groundwork for future investigations into the interplay between tax complexity, corporate behavior, and economic outcomes, emphasizing the need for a nuanced approach to tax policy reform.

Appendix 3.A

Table 3.A.1: Sample Selection

1,451 Firms over 7 Years		10,157
Excluding Banks, Insurances and Other Financials	./.	1,554
Excluding Negative Net Income Before Taxes	./.	863
Excluding Incomplete Data for ownership information	./.	455
Excluding: Sample Baseline Regression	./.	941
Final Sample		**6,344**

Notes: This table describes the sample selection process for the sample used in the baseline regressions.

Table 3.A.2: Geographic Distribution of the Sample

Code	*Country*	*Firms*	*Observations*
AU	Australia	37	211
AT	Austria	3	17
BE	Belgium	6	38
CA	Canada	57	306
CN	China	1	3
DK	Denmark	10	65
FI	Finland	11	66
FR	France	46	273
DE	Germany	44	265
HK	Hong Kong	23	143
IE	Ireland	18	115
IL	Israel	4	21
IT	Italy	14	80
JP	Japan	193	1,229
NL	Netherlands	18	106
NZ	New Zealand	6	42
NO	Norway	9	51
PT	Portugal	3	19
ES	Spain	17	88
SE	Sweden	21	134
CH	Switzerland	34	213
GB	United Kingdom	57	329
US	United States	423	2,530
		1,055	6,344

Notes: This table reports the number of firms and observations per headquarter country.

Table 3.A.3: Variable Definitions

Variables	Definition	Source
ln q$_{it}$	Natural log of Tobin's Q of firm *i* in year *t*, measured by the total of equity market value and total liabilities book value, divided by total assets book value.	Refinitiv
TaxComplexity$_{it}$	Firm-wide average of the Tax Complexity Index by Hoppe et al. (2023) of firm *i* in year *t*, weighted with the number of subsidiaries per locations.	taxcomplexity.org, Orbis
TaxCode Complexity$_{it}$	Firm-wide average of the Tax Code Complexity by Hoppe et al. (2023) of firm *i* in year *t*, weighted with the number of subsidiaries per locations. .	taxcomplexity.org, Orbis
TaxFramework Complexity$_{it}$	Firm-wide average of the Tax Framework Complexity by Hoppe et al. (2023) of firm *i* in year *t*, weighted with the number of subsidiaries per locations. .	taxcomplexity.org, Orbis
TaxComplexity_HQ$_{ct}$	Tax Complexity Index by Hoppe et al. (2023) in the headquarter country of firm *i* in year *t*.	taxcomplexity.org
TaxCode Complexity_HQ$_{ct}$	Tax Code Complexity by Hoppe et al. (2023) in the headquarter country of firm *i* in year *t*.	taxcomplexity.org
TaxFramework-Complexity_HQ$_{ct}$	Tax Framwork Complexity by Hoppe et al. (2023) in the headquarter country of firm *i* in year *t*.	taxcomplexity.org
anti-BEPS-complexity$_{it}$	Firm-wide average of six dimension of Tax Code Complexity by Hoppe et al. (2023) of firm *i* in year *t*, weighted with the number of subsidiaries per locations. The dimensions are *cfcrules, generalantiavoidance*, *dividends*, *interest*, *royalties* and *transferpricing*.	taxcomplexity.org, Orbis
domestic corporate group complexity$_{it}$	Firm-wide average of four dimension of Tax Code Complexity by Hoppe et al. (2023) of firm *i* in year *t*, weighted with the number of subsidiaries per locations. The dimensions are *capialgains*, *corporatereogranization*, *grouptreatment* and *lossoffset*.	taxcomplexity.org, Orbis
other regulations$_{it}$	Firm-wide average of five dimensions of Tax Code Complexity by Hoppe et al. (2023) of firm *i* in year *t*, weighted with the number of subsidiaries per locations. The dimensions are *additionaltaxes*, *alternativeminimumtax*, *depreciation*, *investmentincentives* and *statutorytaxrates*.	taxcomplexity.org, Orbis
pre-filing$_{it}$	Firm-wide average of three dimensions of Tax Framework Complexity by Hoppe et al. (2023) of firm *i* in year *t*, weighted with the number of subsidiaries per locations. The dimensions are *guidance*, *enactment*, and *paymentfiling*.	taxcomplexity.org, Orbis
post-filing$_{it}$	Firm-wide average of two dimensions of Tax Framework Complexity by Hoppe et al. (2023) of firm *i* in year *t*, weighted with the number of subsidiaries per locations. The dimensions are *audits* and *appeals*.	taxcomplexity.org, Orbis
STR$_{it}$	Firm-wide average of the statutory corporation tax rate of firm *i* in year *t*, weighted with the number of subsidiaries per locations. .	Tax Foundation, Orbis

Variables	Definition	Source
STR_HQ_{ct}	Statutory corporation tax rate in the headquarter country of firm *i* in year *t*.	Tax Foundation
$AvgETR_{ct}$	Average GAAP effective tax rate of country *c* in year *t* as measured by tax expense divided by profit before tax.	Refinitiv
ROA_{it}	Net income of firm *i* in year *t*, divided by total assets.	Refinitiv
$Growth_{it}$	Current year sales of firm *i* in year *t* minus prior year sales, divided by prior year sales.	Refinitiv
$Leverage_{it}$	Total liabilities of firm *i* in year *t*, divided by total assets.	Refinitiv
$CapitalIntensity_{it}$	Fixed assets of firm *i* in year *t*, divided by total assets.	Refinitiv
$Size_{it}$	Natural log of total assets of firm *i* in year *t*.	Refinitiv
$GDPgrowth_{ct}$	Annual percentage growth rate of GDP at market prices based on constant local currency of country *c* in year *t*.	World Bank
$Inflation_{ct}$	Inflation of country *c* in year *t*, as measured by the annual growth rate of the GDP implicit deflator.	World Bank
$Accountability_{ct}$	Dimension of the WWGI of country *c* in year *t*. Reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.	www.govindicators.org
Political $Stability_{ct}$	Dimension of the WWGI of country *c* in year *t*. Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism.	www.govindicators.org
Government $Effectiveness_{ct}$	Dimension of the WWGI of country *c* in year *t*. Reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.	www.govindicators.org
Regulatory $Quality_{ct}$	Dimension of the WWGI of country *c* in year *t*. Reflects perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	www.govindicators.org
$RuleofLaw_{ct}$	Dimension of the WWGI of country *c* in year *t*. Reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	www.govindicators.org
$Corruption_{ct}$	Dimension of the WWGI of country *c* in year *t*. Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.	www.govindicators.org

Variables	Definition	Source
ΔMarketCap$_{it}$	Annual growth rate in market capitalization at the firm level measured as the first difference of the firm's market value over its lagged value.	Refinitiv
PayingTaxes Score$_{it}$	The inverse of the firm-wide average of the PwC Paying Taxes Score of firm *i* in year *t*. This measure is based on a survey that the World Bank, in cooperation with PwC, conducted annually from 2004 to 2021.	PwC World Bank Doing Business Survey
TaxCompetitive Index$_{it}$	The inverse of the firm-wide average of the Tax Competitive Index of firm *i* in year *t*. The Tax Foundation ranks countries based on the competitiveness and neutrality of their tax systems.	Tax Foundation
Tax Complexity adj$_{it}$	Firm-wide average of the Tax Complexity Index by Hoppe et al. (2023) of firm *i* in year *t*, combining 70% for the headquarter and 30% for the subsidiaries	taxcomplexity.org
International$_{i}$	Number of international located subsidiaries of firm *i* scaled by the total number of subsidiaries.	Orbis
TaxHaven$_{i}$	Number of tax haven subsidiaries defined in accordance with Bennedsen & Zeume (2017) of firm *i* scaled by the total number of subsidiaries.	Orbis
Corporate Governance Board Committee	The dummy variable is assigned a value of one having a corporate governance board committee and zero otherwise.	Refinitiv
Performance based Compensation	The dummy variable is assigned a value of 1 if the firm has a policy for performance-oriented compensation that is effective in attracting and retaining senior executives and board members.	Refinitiv
Earnings Announcement Speed	This variable is employed to measure the time span between the conclusion of the financial year and the subsequent announcement of the dividend distribution, standardized to years.	Refinitiv
EU AntiBEPS Complexity$_{it}$	Firm-wide average of five dimensions of Tax Code Complexity by Hoppe et al. (2023) of firm *i* in year t, weighted with the number of subsidiaries per location. The dimensions are *cfcrules, generalantiavoidance*, *interest*, *royalties* and *transferpricing*. Only the complexity of regulations at EU locations is considered; the complexity at all other locations is set to zero.	taxcomplexity.org, Orbis
yield$_{it}$	Net income of firm *i* in year *t*, divided by total assets.	Refinitiv
uncertainty$_{it}$	The volatility of operating profitability, measured as the standard deviation of EBIT scaled by total assets.	Refinitiv
growth$_{it}$	The firm's revenue growth between year *t*-1 and *t*, calculated as the change in the natural logarithm of total revenue, divided by two.	Refinitiv
innovation$_{it}$	R&D expenditures of firm *i* in year *t*, divided by total assets.	Refinitiv

Variables	Definition	Source
$investment_{it}$	The natural logarithm of the difference between the firm's fixed tangible assets and their lagged value in year *t*.	Refinitiv
$Ln(Total\ Fixed\ Assets)_{it}$	Natural log of fixed assets of firm *i* in year *t*.	Refinitiv
$EBIT\_sc_{it}$	EBIT of firm *i* in year *t*, divided by total assets.	Refinitiv
$Ln(Total\ Revenue)_{it}$	Natural log of total revenue of firm *i* in year *t*.	Refinitiv

Conclusion

This dissertation examines the effects of tax incentives on corporate investment and innovation with a view to increasing Germany's competitiveness, economic growth, and attractiveness as a business location. It analyzes various policy instruments designed to ease the burden on firms, promote investment and innovation, and create additional growth potential. The analyses are conducted on two levels. The first level examines support through tax incentives, evaluated using a difference-in-differences approach in Chapter 1 and descriptive analyses in Chapter 2. The second level investigates investment and innovation incentives that arise from a more efficient design of the tax system, as discussed in Chapter 3 through a two-way fixed effects model.

The dissertation demonstrates that carefully designed tax incentives can foster corporate investment and growth potential, thereby contributing to overall economic growth. Chapter 1, in particular, provides insights into the effects of tax incentives on automation. The reduction of the tax credit for automated equipment leads to a decline in corporate investment in such technologies. At the same time, some firms reduce their overall investment, whereas financially stronger and more creditworthy firms substitute these investments with other, more productive forms of capital. This reaction indicates that tax incentives for investment do not necessarily lead to optimal investment decisions. If incentives are too generously subsidized, they may result in overinvestment - i.e., in a level of automation exceeding what is economically efficient for firms. Accordingly, Chapter 1 provides evidence that tax incentives can also create distortions. Moreover, tax incentives do not inherently enhance corporate efficiency. Factors such as firm structure, financial capacity, and market conditions shape the productivity of tax incentives. Consequently, tax incentives must be carefully differentiated and calibrated to achieve their intended effects. Chapter 2 reinforces this insight in the context of R&D tax incentives. It outlines explicit options for adjusting the current design of the German R&D tax credit to ensure better alignment with the policy objectives originally pursued by the legislature. It is evident that, even in this context, the incentive must be specifically and precisely designed to provide firms with long-term planning certainty and stability regarding expected costs.

The complexity of the tax system likewise affects corporate investment decisions and Germany's attractiveness as a business location. Chapter 3 shows that higher tax complexity is associated with lower growth potential, reduced investment, and diminished expenditure on research and development. Thus, the negative effects of complexity extend well beyond mere investment restraint. It must also be noted that a complex tax system diminishes the effectiveness of tax incentives. The study therefore provides quantitative evidence for policymakers by highlighting the net costs that firms incur due to intricate tax rules and administrative requirements, and by underscoring the importance of reducing complexity in future tax reforms. In addition, in order to pursue multiple concurrent objectives - such as preventing tax avoidance, promoting investment and innovation, and ensuring tax equity - it is essential that tax incentives be designed in a balanced and targeted manner.

Overall, this dissertation provides new insights into the effects of tax incentives on investment promotion and the economic costs of complex tax legislation. The results can help foster corporate investment and innovation, thereby stimulating economic growth. The promotion of an investment-friendly environment is expected to enhance Germany's attractiveness as a business location, thereby promoting economic growth and ensuring its continued international competitiveness in the future.

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