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Preface

With the Paris Agreement of 2016, 189 nations signed a legally binding document to keep global warming below 2°C, and to pursue efforts to limit the temperature increase to 1.5°C. It was recognized that this would reduce climate change impacts substantially. All signatories submitted "Intended Nationally Determined Contributions" (INDCs) where they specified their national emission reduction goals and pathways to achieve them. However, the INDCs submitted for the Paris Agreement "imply a median warming of 2.6-3.1 degrees Celsius by 2100" (Rogelj et al. 2016). A temperature increase by 2°C would already carry a very high risk for systems such as the Arctic sea ice and coral reefs. For a warming of 3°C above pre-industrial levels though, we are expected to face extensive losses of biodiversity and ecosystems; accelerated economic damages; and a high risk for abrupt and irreversible changes ("tipping points"), such as the melting of the Greenland ice sheet and the accompanying sea level rise (IPCC 2014b).

The Paris Agreement stipulates that countries can update and strengthen their contributions, and some have already done so. Most INDCs, however, do not even provide clear policies on how to achieve their targets. It is therefore obvious that further policies and large investment shifts are necessary to stay below 2°C warming, let alone 1.5°C (Rogelj et al. 2018). This thesis studies the economic implications of (expected) future climate policies.

To assess the economic effects of climate action, a typical first approach is to measure the cost of avoiding emissions from an engineering perspective. For instance, replacing coal-fired power generation with large-scale solar photovoltaic (PV) systems incurs an estimated cost of 28$ per avoided ton of CO_2 as of 2017 (in 2017 $) (Gillingham and Stock 2018). However, private costs can change over time and space, and emissions abatement has more effects than just private costs – it can even have economic benefits beyond reducing the damages of climate change. It is therefore important to consider systemic, dynamic, and expectation effects of climate policies as well. The installation of solar PV, for instance, requires changes in the design of power markets, and in the skills and intermediate inputs needed to run these new energy systems. Since the available natural and economic resources may differ between regions, these changes imply heterogeneous effects. Furthermore, dynamic effects need to be considered. The development and installation of solar PV leads to economies of scale, learning-by-doing effects, and innovation spillovers, reducing the future cost of avoiding emissions (Gillingham and Stock 2018). Finally, the cost of future abatement crucially depends on investment decisions taken today (Erickson et al. 2015; IPCC 2014a; IRENA 2017a), and therefore on expectations about future policies. Given the inherent uncertainties in the political economy process, it is by no means clear that all actors believe in the enforcement of the Paris Agreement.

Using different models and data sources, this thesis examines and connects some of these aspects. It sheds light on future policies and their broader economic implications; on how investors' expectations of climate policies are shaped by the political process; and on investors' strategies to deal with climate policy risk. When assessing the economic consequences of future climate policy, one guiding idea of this thesis is the role of economic input factors. It can therefore also be read as a story on the enabling factors of decarbonization, touching upon capital allocation, availability of skilled labor, and green technology.

The first and second chapters look at financial markets and their expectations of climate policy. It is part of the core business of financial markets to price in expectations about the future. However, researchers, activists, central banks, and investors themselves have voiced the concern that the "transition risk" due to climate policy may not be fully priced in. The resulting delay in investment shifts can lead to a lock-in of fossil infrastructure, and make the transition to clean capital more expensive (Erickson et al. 2015; IRENA 2017b). Moreover, a sudden devaluation of assets following stricter climate regulation could then lead to substantial losses in financial markets, implying a risk for financial stability (van der Ploeg and Rezai 2020; Battiston et al. 2017; Batten et al. 2016; European Systemic Risk Board 2016a; HSBC 2012). It is therefore vital to understand what shapes investors' expectations with respect to climate policies, and how they deal with transition risks.

Chapter 1 aims to answer the question what investors' priors are regarding future climate policy, and how these priors are changed by new information. It tracks the evolution of a climate-related policy proposal in Germany and the reactions in financial markets. Following pressure from lobby groups and coalition partner politicians, the proposal was transformed from a carbon pricing instrument to a compensation scheme: Companies would receive payments for not running their emission-intensive power plants. Compensations have been suggested in various climate policy contexts, such as to enable international climate agreements, reduce the cost of emission reductions, prevent carbon leakage, and avoid stranded assets (Harstad 2012; Peterson and Weitzel 2014; Collier and Venables 2014). In the context at hand, compensations were an attempt to reconcile different interests. Such political economy processes are not rare: investors have good reasons to expect a “bail-out”. Chapter 1 thus highlights how the expectation of a compensation can cause financial markets to remain in fossil investments.

The second chapter studies a particular type of transition risk: technological risk. Innovation for clean technologies is a key component of worldwide decarbonization, and innovation today crucially influences future abatement cost. To align with climate goals, technological change is likely more relevant than own emission reductions in some sectors (e.g., automotive). Do financial markets expect and address technological risk? To answer this question, Chapter 2 turns to the active role of institutional investors, such as asset managers or pension funds, in the context of climate action. With their large owner shares and dedicated personnel, institutional investors can influence firms via direct conversations, or change voting outcomes in annual meetings. They can also be conducive to innovation efforts by bridging times of costly R&D investments which affect firm performance in the short run (Aghion et al. 2013; Bushee 1998). A growing literature provides evidence for successful engagement in environmental contexts (Dyck et al. 2019; Dimson et al. 2015; Azar et al. 2020). These outcomes seem to reflect the concern about transition risk that many institutional investors have expressed. According to a recent survey, 84% of investors consider technological risk to be financially relevant today or within the next 5 years (Krueger et al. 2020). Using patents in *green* and *fossil* technologies as outcome variables, Chapter 2 thus tests whether institutional investors have an impact on the *direction* of firms’ innovation.

The third chapter shifts the focus to future policy implementation. It looks at a case where an individual region plans to take climate action in its own hands and decarbonize its energy sector until 2035. The aim of the study was to develop a model to quantify the regional economic effects of such an endeavor, taking into account inter-industry linkages via intermediate goods. Together with further interdisciplinary analyses, the results of this study are feeding into the policy process in the region.[1] Beyond this direct use in local policymaking, the regional analysis provides a helpful case study for ambitious policies based on precise local data on natural resource availability and regional economic structures.

[1] See also the “INOLA tool for value added and employment effects”, `https://inola-region.de/hp877/INOLA-Tool-fuer-Wertschoepfungs-und-Beschaeftigungseffekte.htm`.

The chapter provides a methodological framework to study value added and employment effects of increased investments in renewable energy sources. Previous studies have largely focused on the initial impacts of the investment only, and ignored crowding-out effects. In our approach, we explicitly model the use phase of the new investments as well as scarcity of factors of production. Chapter 3 therefore draws attention to the availability and mobility of labor and capital as enabling factors for energy system transformations. The analysis is a useful case study in the current Covid-19 recession. To counter the effects of Covid-19 measures, (green) fiscal stimulus programs are being designed. Since the study models energy policy as exogenous increased investment in renewables, the implications are comparable to those of economic stimulus programs. These should therefore address non-financial barriers to renewables expansion, e.g. skilled labor shortage; be aware of the spatially heterogeneous conditions and effects; and address the mobility of labor between sectors and regions.

In the following, I provide an overview of each chapter.

Chapter 1, co-authored by Suphi Sen,[2] explores whether and how investors price in the risk of asset stranding due to specific climate policies. We exploit the gradual development of a climate policy proposal in Germany which targeted the most emission-intensive type of electricity production: lignite-fired power plants. If they are phased out, both the power plants as well as the lignite deposits situated next to them become stranded assets. We investigate how the steps in the policy process have affected the market valuation of firms active in electricity production from lignite. In a short-run event study analysis, we examine whether there are abnormal returns associated with the events. To ensure identification of the event effect, we control for contemporaneous shocks at the firm and industry level, and we test different counterfactuals, i.e. the market index and a synthetic control group.

We find that investors did not react to announcements of the initial “climate levy” proposal, which was directed at stranding lignite assets by charging an extra fee on carbon emissions (Stage 1). When the proposal was turned into a compensation mechanism (Stage 2), paying plant owners for not running their units, this did not have a significant effect on stock valuations either. Only announcements that the compensation mechanism might not go through due to violating state aid rules (Stage 3) resulted in a significant and negative reaction. This suggests that investors have already priced in the stranded asset risk, but they also expect

[2] Chapter 1 has been published in the Journal of Environmental Economics and Management (Sen and von Schickfus 2020).

a compensation mechanism for the affected firms. We further support this interpretation by showing strong reactions in electricity future markets to the initial proposal, indicating that it surprised participants in these markets; the non-reaction in stock markets can best be explained by compensation expectations.

With our research, we contribute to the literature on financial markets and transition risk. Our paper is the first to look at the role that individual climate policies play for investors' expectations. More importantly, we find two results which are relevant for the discussion on stranded asset risk and climate policy design. First, we conclude that financial market investors seem to follow the climate policy process. The concern that investors may be "blind" to carbon risk (Leggett 2014) can therefore be allayed somewhat. However, our second result shows how investors trust in political economy and lobbying success, and that they expect firms to be compensated for stranded assets. Therefore, financial markets are still likely to misallocate resources instead of channelling them away from fossil assets.

Compensations, then, are almost a self-fulfilling prophecy: if they are expected, they will be necessary in order to avoid larger shocks. It is therefore essential for policymakers and researchers alike to understand the interaction between policy making and investors' expectations when designing climate policies aimed at fostering a transition to clean capital. A credible commitment to non-compensation, combined with a clear pathway toward clean capital, may be a way to avoid macro shocks as well as costly compensation payments.

Chapter 2 uses an international firm-level panel to test for the impact of institutional investors on climate-relevant innovation in firms. Policy-accelerated technological change entails a risk for firms relying on fossil-related technological knowledge. The question of Chapter 2 is whether institutional investors address this technological risk as part of their climate risk strategies.

Institutional investors play an increasingly large role in equity markets, and have been shown to affect the firms they invest in through *engagement*: they can exert influence on management appointments, strategic decisions, and even CO_2 emissions and environmental, social and governance (ESG) ratings (Appel et al. 2018; Dimson et al. 2015; Dyck et al. 2019; Azar et al. 2020). Many large investors have joined initiatives for sustainable or responsible investment; according to a recent survey, the concern about technological risk is relevant for their risk assessments, and their preferred strategy to deal with this risk is to engage with firms (Krueger et al. 2020).

Contributing to the literature on climate risk in financial markets, the analysis in Chapter 2 is only the second paper to empirically assess the effects of institutional owners' engagement on climate-relevant outcomes in firms.[3] I add to this literature by using *green* and *fossil* innovation as an outcome measure, and thus providing insights on investors' awareness of technological risk.

Using an international panel covering 1,261 firms over the years 2009-2018, I employ a dynamic panel data approach in the spirit of Aghion et al. (2016). Patenting depends on previous knowledge, knowledge spillovers, and R&D efforts; the share of institutional ownership is added as an additional explanatory variable. The model includes firm fixed effects using the pre-sample mean method (Blundell et al. 1999). To control for patent quality, I focus on granted patents filed at one of the main patenting offices (EU, US, Japan). To account for potential bias through endogenous selection of investors, I apply a control function approach. A firm's institutional ownership share is instrumented by the inclusion of the firm in a large stock index.

Despite robust evidence for increased overall innovation with more institutional ownership, I find no evidence for institutional owners' influence on green or fossil patenting, neither in the energy nor in the transport sector. This also holds for investor types for which we would expect a stronger interest in the issue, such as signatories of the UN Principles for Responsible Investment (UN PRI) initiative. Green innovation is found to be positively associated with climate-related topics mentioned in firms' conference calls with investors. It is difficult to interpret this as a causal effect. Nevertheless, the result shows that there is sufficient variation in the data to measure a nonzero relationship between the importance of climate issues in firms, and firms' green innovation activities. I therefore conclude that the insignificant effect of institutional owner shares can likely be interpreted as a zero effect. The timing of the analysis may still be an issue: Climate risk has probably not been at the top of investors' minds especially in the beginning of my sample. Since the awareness for climate risk has been increasing in the last years, repeating the analysis in the future may deliver different results.

[3] The only other paper to do so – to the best of the author's knowledge – is Azar et al. (2020), who measure the influence of the Big Three index investors (BlackRock, Vanguard, and State Street) on firm-level carbon emissions.

Chapter 3, co-authored by Ana Maria Montoya Gómez and Markus Zimmer,[4] analyzes the economic effects of regional decarbonization efforts. The subject of our research is the southern German "Bavarian Oberland" region ($\sim$400,000 inhabitants), which has set itself the target of meeting their electricity and heat consumption with own renewable sources by 2035. This commitment requires substantial investments in renewable energy and storage capacity as well as energy efficiency measures. We consider both the installation and the use phase of the required investments and examine their effects on regional value added and employment divided in three qualification levels (low-skilled, medium-skilled and high-skilled employment).

We model energy policy as an exogenous increase in investment in renewable energy sources, and otherwise assume a finite availability of factors of production (capital and labor). Based on the Rybczynski theorem, we use the approach developed by Fisher and Marshall (2011) and Benz et al. (2014) to calculate an international Rybczynski matrix, which yields sectoral changes in output for an increase in factors of production. The main channel of these effects are the direct and indirect (via intermediates) factor requirements of the different sectors: following an endowment change in one specific factor, all other factors need to reallocate between sectors for maximum aggregate output.

Our two main contributions are to apply this methodology to the energy context, and to adjust it to the regional level. First, to use the methodology for an energy-economic question, we combine disaggregated economic data for the energy sector and incorporate the assumption of sector-specific capital. This allows us to calculate Rybczynski effects of four capital types, i.e., capital specific to four renewable energy technologies. Second, we produce a multiregional input-output table (consisting of the three districts of the region, and the rest of Germany) including a disaggregated energy sector. We also adapt the methodology to improve its performance in a regional context. In combination, this enables us to quantify the effects of additional investment in renewables specifically for the Oberland region.

With this approach, we go beyond traditional input-output multiplier analysis often used in regional economic analyses, where any investment creates additional demand, but no crowding-out or reallocation of resources takes place. We argue that such reallocation effects are important, and that it is relevant to know which sectors or regions may be negatively affected. We also highlight the importance of considering both the investment and the operation phase in an analysis of economic effects. Our methodology offers a relatively easy way

[4] This paper is available in the CESifo Working Paper Series (Montoya Gómez et al. 2020).

to model effects of factor scarcity and could be used for many other regional-economic and energy-economic applications.

We find that the three districts in the Oberland region benefit from investments towards the regional energy transition, both in terms of additional value added and employment. The benefits vary by district mostly due to availability of natural resources and location of relevant intermediate input providers. Yet, the overall positive development comes at the expense of value added and employment in the rest of Germany. Moreover, our analysis shows that medium-skilled employment increases most across all scenarios. Due to the low labor intensity of renewable power generation, the employment results are mostly driven by sectors providing intermediate inputs, most notably construction and trade. This finding shows the importance of medium-skilled, sector-specific labor for a successful energy transition. In our model, the additionally required labor force can be drawn from the rest of the country. In case of an economy-wide investment increase in renewables, this possibility would be limited.

In summary, this thesis assesses the economic implications of future climate policy, with a particular focus on the required input factors for the transition to a Paris-aligned world. It provides insights on capital allocation mechanisms and investment effects, shows the importance of skilled labor to complement investments, and examines the influence of future policy expectations on green innovation. By highlighting the role of these enabling factors and of expectations, especially for capital allocation in financial markets, it calls for an early commitment to (specific) climate policies. In addition, against the current background of the Covid-19 recession and the ensuing economic stimulus packages, the insights of this thesis on limiting factors besides investment money are relevant for the design of stimulus programs which deliver for the economy as well as for the climate.

Keywords:	Stranded assets, climate policy, expectations, utilities, event study, green innovation, patents, panel analysis, green finance, climate risk, intangible assets, institutional investors, renewable energy, crowding-out, regional economics, input-output analysis
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1 Climate Policy, Stranded Assets, and Investors' Expectations

1.1 Introduction

As early as 2012, global financial services companies drew attention to the risk of coal investments becoming stranded as a consequence of the 2°C "carbon budget."[1] This carbon budget specifies the maximal amount of cumulative carbon emissions that can be emitted without surpassing a 2°C temperature increase above the preindustrial levels (Meinshausen et al. 2009; Allen et al. 2009). Therefore, climate policies might render fossil-fuel assets worthless prior to the end of their economic life time. We study whether the current market valuation of companies owning fossil fuel assets reflect this risk of stranding assets.[2] A failure to price in this risk can lead to costly consequences for the whole economy. First, the resulting misallocation of capital due to delayed divestment could render the transition to clean capital more expensive (IPCC 2014a; IRENA 2017a). Second, a sudden and unexpected tightening of carbon emission policies (Batten et al. 2016) or sudden changes in expectations in the presence of tipping points (Krugman 1991) can lead to abrupt repricing of fossil fuel assets. This situation can result in a negative supply shock through changes in energy use and second-round effects in financial markets.[3] Financial institutions such as the Bank of England, the Dutch Central Bank (DNB), the Inter-American Development Bank (IDB), and the European Systemic Risk Board (ESRB) have identified the mispricing of stranded asset risk as a potential systemic risk and threat to financial stability.[4]

[1] For example, see the report by HSBC on "Coal and Carbon. Stranded Assets: Assessing the Risk," picking up on the 2011 report by the Climate Tracker Initiative on "Unburnable Carbon – Are the World's Financial Markets Carrying a Carbon Bubble?"

[2] See Caldecott (2017) for various definitions of the term "stranded assets".

[3] Weyzig et al. (2014) analyze the risk associated with the carbon bubble, and conclude that a slow and uncertain transition to clean energy is likely to be costlier than a quick transition.

[4] See Batten et al. (2016), Schotten et al. (2016), Caldecott et al. (2016), and European Systemic Risk Board (2016a). Bank of England governor Mark Carney warns "..., once climate change becomes a defining issue for financial stability, it may already be too late" (speech given at Lloyd's of London, September 9, 2015). To mitigate the risk, the Finance Ministers and Central Bank Governors of the Group of Twenty (G20) requested the Financial Stability Board to create an industry-led Task Force on Climate-Related Financial Disclosures (TCFD 2017). The private sector is becoming increasingly aware and active as well, with, for example, the rating agency Moody's announcing that it will analyze firms' carbon transition risk in its credit ratings (Moody's 2016).

Therefore, we analyze the interaction between investors' expectations and the development of climate policies. Investors' reactions to new policies depend on their prior expectations, which, in turn, are shaped by previous policies. This interaction is central to the current paper: What are investors' priors regarding stranded asset risk, and (how) do these priors change when climate policy proposals are announced? In particular, we analyze (i) whether investors have already priced in expected losses due to the carbon budget, (ii) whether they only respond to concrete policies, and (iii) whether they expect firms to be financially compensated for stranded assets. To answer these questions, we exploit the gradual development of a climate policy proposal in Germany targeting lignite assets and investigate how adjustments of this proposal have affected the market valuation of firms active in electricity production. We find that investors did not react to announcements of the initial "climate levy" proposal, which was directed at stranding lignite assets by charging an extra fee on carbon emissions (Stage 1). Investors also did not respond when the proposal transformed into a compensation mechanism (Stage 2), paying plant owners for not running their units. Only announcements that the compensation mechanism may not go through due to violating state aid rules (Stage 3) resulted in a significant and negative reaction. Our findings show that investors do care about the stranded asset risk, but with an expectation of a compensation mechanism.

Our analysis starts from the notion that the evolution of climate policies and the expectations of investors are interrelated. First, climate policies and policy proposals provide signals that shape how the investors percieve the stranded asset risk. For instance, setting a price on CO_2 emissions or imposing a cost on fossil resource extraction[5] can reduce demand, slow down investment in fossil infrastructure, and cause asset stranding. Alternatively, policies addressing fossil-fuel reductions may compensate fossil-fuel owners for leaving their reserves unburned. For example, Harstad (2012) proposed that, in the absence of a global climate agreement, "the coalition's best policy is to simply buy foreign deposits and conserve them".[6] Second, investors' reactions to policy signals depend on their prior expectations regarding the likelihood of asset stranding and the credibility of climate policy announcements. For example, they may have already devalued assets following information on the carbon budget implied by the Paris Agreement, or they may find it difficult to translate the concept of a carbon

[5] For instance, by reducing subsidies or imposing taxes on production, exports, or capital rents (Faehn et al. 2014; Richter et al. 2015; Sinn 2008).

[6] Such as the failed compensation attempt for the oil under Yasuni National Park in Ecuador. Compensation mechanisms have been suggested in various contexts, such as to enable an international climate agreement, reduce the cost of emission reductions, prevent carbon leakage, and avoid stranded assets (Harstad 2012; Peterson and Weitzel 2014; Collier and Venables 2014).

budget into stranded asset risk.[7] In the latter case, they would wait for further information on climate policies with clear asset stranding implications. Even the announcement of climate policies does not necessarily lead investors to reassess the likeliness of asset stranding, if they expect a compensation mechanism. The policy proposal we investigate provides the opportunity to disentangle the effects of these policy signals and expectations. By tracking the stock market response to different stages of the proposal, we can draw conclusions about investors' prior expectations and how they evolved in the course of the policy's development.

Our baseline estimation strategy is a short-run event study analysis. We investigate whether there are abnormal returns to the assets of three publicly listed energy companies that can be associated with the three stages of the policy proposal.[8] The pattern in the reactions to the different stages of the proposal helps us to identify whether an individual event surprised the investors. Furthermore, we test for effects in the power futures market to establish surprise empirically. Finally, we provide anectodal evidence for our empirical findings on the presence of surprise. We provide an extensive robustness analysis related to the identification of the event effects. First, we conduct placebo tests for the nonevent days just prior to the event days to verify the model's performance in predicting the counterfactual returns. Second, as an alternative to using a market price index to control for average market conditions, we estimate a synthetic portfolio aiming to produce a counterfactual control unit.[9] These estimations show that our results are not driven by the endogeneity of the market price index to the event shocks. Third, in order to control for industry-wide shocks, we use an energy utility company without any lignite-related assets as the control unit, leading to a difference-in-differences estimation of abnormal returns. Finally, by using a news search engine, we identify a small number of potentially confounding events and verify that our results are not driven by these events.

Our paper contributes to the literature on empirical assessments of market reactions to emission reduction policies, often in the form of event studies. Lemoine (2017) and Di Maria et al. (2014) find that market players do act in anticipation of demand-side policies. Ramiah et al. (2013) and Linn (2010) show that stock investors react to announcements of national

[7] See Rook and Caldecott (2015) for how a wide range of cognitive biases in the decision-making process of oil industry managers can hamper risk perceptions and exacerbate the risk of asset stranding.

[8] Short-run event study methodology has been a widely employed approach in identifying how specific events affect asset returns. See MacKinlay (1997) for a comprehensive description of event study methodology.

[9] See Abadie and Gardeazabal (2003) and Abadie et al. (2010) for the synthetic control approach. We apply this approach to the classic short-run event study methodology. See Guidolin and La Ferrara (2007) for a similar approach.

carbon emission pledges or the introduction of emission trading programs, respectively. Koch et al. (2016) find evidence that regulatory events drove EU ETS allowance prices. In the German power market context, Oberndorfer et al. (2013) investigate the stock market effects of voluntary actions such as the inclusion of firms in a sustainability stock index. However, to date, investor expectations with regard to specific policies directed at stranding assets or to compensation mechanisms have not been studied.

There are few papers investigating empirically how investors price in unburnable carbon risk. Batten et al. (2016) conclude that the announcement of the Paris Agreement in December 2015 had a positive effect on the valuation of renewable energy companies, but no significant effect on fossil fuel companies. Mukanjari and T. Sterner (2018) report similar results both for the Paris Agreement and the U.S. presidential election in 2016. Griffin et al. (2015) find that the publication of the Meinshausen et al. (2009) article in *Nature* led to a statistically significant, yet fairly small, reduction in the stock returns of oil and gas firms. They mention several reasons why this effect might be so small. One reason is investors' expectations with respect to technological developments: this is what Byrd and Cooperman (2016) examine, concluding that investors are aware of the relevance of carbon capture and storage (CCS) in allowing continued carbon use, but that they have already priced in stranded asset risk. A second potential reason is that investors are more concerned with specific energy policies, which is what this article examines in detail.

The remainder of the paper is organized as follows: Section 1.2 describes the development of the specific German policy proposal and the affected companies. In Section 1.3, we present a theoretical discussion on the potential effects of the proposed policies. In Section 1.4, we present different scenarios with regard to investors' expectations. The empirical methodology is outlined in Section 1.5, and Section 1.6 presents the main results. We present the robustness tests in Section 1.7. Section 1.8 presents a general discussion of our results, and Section 1.9 concludes.

1.2 Event description

We track investors' reactions to each of the three steps in the development of a German climate policy proposal known as the "climate levy" (Klimabeitrag) that was first publicly announced in March 2015. The development of this proposal provides a convenient empirical setting for investigating investors' expectations. Each stage in the development of this proposal represents a different event within our analysis. The first stage of the policy development, the introduction of the climate levy proposal, was designed to retire lignite assets. The second stage is the amendment of the proposal to include a compensation mechanism. In the third stage, the compensation mechanism came under official scrutiny for being inconsistent with the EU state aid rules.

Event study methodology is a widely employed approach to analyze the effects of regulatory changes or policy announcements (Lamdin 2001). In regulatory event studies, it is necessary to identify the potential dates on which new information might have changed investors' expectations (Binder 1985a). We extensively examined several news search engines to identify the date on which the related information regarding each stage of the proposal might have been publicized in the media. In the next stage, we carefully searched for (i) prior events which might have led to information leakages, and (ii) later events which might represent an additional piece of information for investors' assessment. Our search resulted in three or four announcement dates for each stage. Table 1.1 presents the stages of the policy proposal and the announcement dates in their chronological order. In the remainder of this section, we describe the proposal development, our strategy to establish surprise for each of the stages of the proposal, and some important characteristics of the affected companies.

Stage 1: Climate levy proposal - uncompensated policy: In March 2015, the German Ministry of Economy and Energy presented its first proposal of the climate levy legislation. This proposal suggests charging an extra levy on CO_2 emissions from all power generating units older than 20 years whose emissions exceed a certain yearly threshold (a levy-free allowance). The aim of the proposal was to save 22 million tons of CO_2, as Germany needed to cut emissions from the electricity sector by that amount in order to reach its national emission reduction targets. The climate levy proposal directly targeted the stranding of assets by focusing on old units and incentivizing non-use if the allowance is exceeded. The excess levy was to be applied independently of technology. Therefore, the most emission-intensive energy carrier, lignite, would have been the most, or the only one, affected.[10]

German lignite power plants are designed to provide base load electricity. They are all situated next to mines, since lignite is essentially not transported over long distances due to the high

[10] For the details and implications of the climate levy, see, e.g., Peterson (2015), Bundesministerium für Wirtschaft und Energie (2015), and Oei et al. (2015). Lignite provided 24% of German electricity production in 2014.

Table 1.1 : Event Dates

No	Date	Events and Announcements
		Stage 1: Climate levy proposal
(1a)	March 20	First news on climate levy proposal
(1b)	March 26	Climate levy proposal presented in parliament
(1c)	May 19	Ministry provides new, less stringent proposal for climate levy
		Stage 2: Security reserve proposal
(2a)	May 23[a]	IG BCE trade union presents proposal of turning lignite plants into capacity reserve
(2b)	May 28	Media reports that Ministry is positively considering the IG BCE proposals
(2c)	June 24	Minister debating between two options: climate levy and security reserve. Coalition summit will decide on July 1
(2d)	July 2	Press reports: Coalition summit decided on security reserve
		Stage 3: State aid assessments
(3a)	July 23[b]	Academic service of German Parliament assesses security reserve as violating EU state aid rules
(3b)	August 14	Media reports on the state aid assessment
(3c)	September 14	European Commission considers state aid procedure

[a] The date of Announcement (2a) corresponds to Saturday. In our estimations, we take its announcement date as the following Monday. Note that events (2a) and (2b) are very close and may overlap depending on the event window.

[b] This is the date of the report; it seems that the media reports on August 14 were the first public news on this topic.

transport cost per energy content. Often, operators of lignite power plants own and operate the mines. Thus, if the power plant is not run, then the fuel input of the plant is left in the ground. Consequently, a policy targeting CO_2 emissions from lignite strands the power plant assets as well as their fuel resources.

The climate levy proposal was the first stage of the policy development and we classify this proposal as an "uncompensated policy." Unsurprisingly, the proposal sparked protest among industry, trade unions, and politicians. In response, the Ministry presented an amended proposal in May 2015, permitting operators to transfer the allowances to other installations, and allowing some flexibility in the levy price. However, this was not enough to placate the levy's opponents.

Stage 2: Security reserve proposal – compensated policy: Only a few days later, the trade union for mining, chemicals, and energy (IG BCE) presented its own proposal, which was to turn six Gigawatts of lignite capacity into a capacity reserve. That is, they suggested to take this capacity out of the regular electricity market, pay them for holding capacity ready, and use the capacity only in the case of unexpected shortfalls. This marks the beginning of the second stage of the policy development. Following IG BCE statements that the Ministry was positively considering this alternative proposal (May 28), various newspapers reported that the climate levy would not be introduced (June 6). On June 24, Minister Gabriel declared that both options were currently on the table for discussion and that the coalition summit would decide. On July 2, 2015, the federal coalition decided at its energy summit not to introduce the climate levy, but a security reserve (Sicherheitsbereitschaft, literally security readiness[11]), mothballing 2.7 Gigawatts of capacity.[12] The targeted units were equivalent to 13% of installed lignite capacity and were supposed to be compensated for their foregone revenues (to be financed via network fees) until they were gradually decommissioned.

Stage 3: State aid assessments – challenge to the compensation: It turned out that the compensation proposal had to overcome another hurdle, which brings us to the third stage. In July 2015, the German Parliament academic service concluded that the security reserve could violate EU state aid rules. *Spiegel online* was the first to report this state aid assessment on August 14, stating that it could cause the security reserve plans to fail. On September 14, the European Commission announced that it was considering a state aid procedure on the security reserve plans. We classify this news as a "challenge to the compensation".

Surprise. Event studies aim to understand whether investors use new information revealed by an event (surprise) in their valuation of firms. In the absence of any confounding events, a significant market reaction indicates that the announcement of interest contains a surprise element. On the other hand, absence of reaction might simply mean that the announcement does not constitute a surprise. Our empirical design is a novel approach which helps to understand the nature of surprise element in the announcements by tracking reactions to a sequence of related events. The idea is that, significant reactions for some events inform us about the expectations of investors in certain periods, which can be useful to figure out the expectations of investors before and/or after a related event with no market reaction. This indirect information can be helpful to understand whether an event with no market reaction did contain a surprise element or not.

In such a sequential event study analysis, it might be important to establish surprise for the first announcement, as there is no previous event to track a change in expectations. Press

[11] The term "capacity reserve" (Kapazitätsreserve) described another mechanism in the energy market legislation and thus could not be used to describe the mothballing of lignite power plants.
[12] The term "mothballing" is used for power plants (or any other production facilities) that are not in operation, but preserved for potential future use.

reports on the first announcement of the proposal give interesting insights. According to the weekly newspaper *Der Spiegel*, the first public news on the climate levy proposal were the result of a leak a couple of days before the official presentation of the proposal (see Table 1.1). Minister Gabriel, of the Social Democrats (SPD), had not even informed the coalition partner (the Christian Democrats, CDU) about the proposal. Irritated by this "rush" without prior consultation, the CDU called off a planned meeting of energy experts from both parties.[13] If not even all government members were aware of the proposal, it is unlikely that markets had prior knowledge of it. In Appendix A.1, we show that this point is supported by the googling trends for the term "Klimabeitrag" (climate levy) in Germany between January and September 2015. The patterns show that this was not a marginal topic — we observe a general public interest in the issue coinciding with the event dates we identified. The term "Klimabeitrag" became a trend only after the first news on the proposal which we identified. The search pattern does suggest that the first announcement of the proposal came as a surprise. The details are provided in Appendix A.1.

After presenting our baseline results in Section 1.6, we empirically establish whether there is a surprise or not for all stages of the policy proposal by following three strategies: (i) analyzing a sequence of related events as explained earlier, (ii) providing an extensive analysis to rule out that significant market reactions are not driven by confounding events, and (iii) tracking the intensity of market activity for electricity futures, based on the idea that the initial proposal would result in a significant reduction in baseload electricity capacity after 2016. The third strategy turns out to be particularly useful in establishing surprise for the initial stage. Our empirical findings on the presence of surprise are in line with the anecdotal evidence presented previously.

Companies. We focus on the three publicly listed German companies that were active in the lignite business in 2015: RWE AG, E.ON SE, and EnBW AG.[14] The climate levy proposal targeted plants older than 20 years and was intended to be implemented in 2017. Considering the share of each firm's lignite plants that were commissioned before 1997 in its overall electricity generation capacity, RWE was the most lignite-intensive electricity producer. The share of lignite plants older than 20 years in RWE's total capacity was 31% by 2015. For E.ON, this

[13] See `http://www.spiegel.de/wirtschaft/service/gabriel-neue-klimaschutzabgabe-fuer-kohlekraftwerke-geplant-a-1024554.html`.

[14] Two more firms were operating with lignite: Vattenfall GmbH and Mibrag mbH. As they are not publicly listed, we cannot consider them in the event study.

share would have been 8%.[15] On the other hand, EnBW holds shares only in one plant that was commissioned in 1999 and thus the policy proposal would not affect EnBW. Moreover, in contrast to RWE, which largely owns the lignite mines next to its plants, E.ON and EnBW only operate the power plants and buy the fuel from a mine operator. Therefore, their stranded asset risk is limited to their power plants, whereas RWE would have had to strand its fossil assets as well.

While the climate levy proposal did not target specific plants (apart from selecting by age), the security reserve proposal clearly specified the individual plants scheduled for mothballing.[16] Of the three publicly listed companies, only RWE was affected by this bill: two of its units in Frimmersdorf were scheduled to be mothballed on October 1, 2017, two units in Niederaußem on October 1, 2018, and one unit in Neurath on October 1, 2019. The final decommissioning is always scheduled for four years later. Nevertheless, E.ON was impacted by the coalition decision on the security reserve because it implied that the climate levy would not be introduced. All announcements related to a potential state aid procedure against compensation plan are relevant for all lignite-owning companies because they introduce uncertainty about future policies.

1.3 Theory

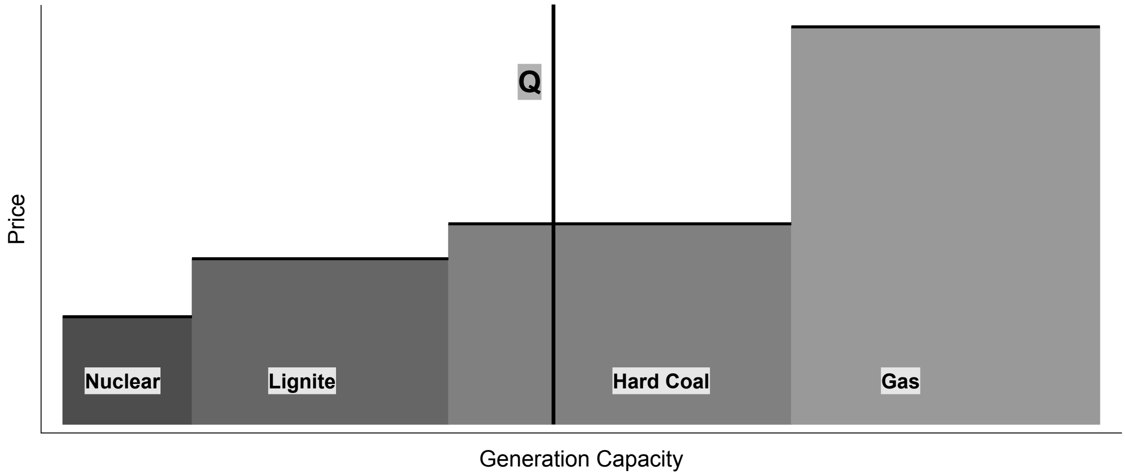
In this section, we use a simple theoretical setup in order to provide intuition for the potential effects of the proposed policies and give a feeling for the magnitude of their effects on the profits of the firms. We focus on RWE for brevity. In the following, we start by describing the economic environment, how we map this environment to data, and our policy scenarios. Finally, we present the theoretical predictions from our scenario analyses.

1.3.1 Environment

We assume that demand is fully inelastic and firms operate in a perfectly competitive market. Each firm determines output by maximizing profits subject to the capacities of their plants. The number of plants owned by a firm and their generation capacities are exogenous. In this setting, the so-called merit order of various technologies determines the supply curve, such that the capacity with lower marginal cost of producing power has priority in meeting the demand for

[15] The underlying data for these calculations is described in the next section.
[16] See Table A.2 in the Appendix for a list of units to be transferred into the security reserve.

Figure 1.1 : Electricity supply and demand



Notes: This figure illustrates the demand and supply curves implied by our theoretical setup. The technologies are ranked by their average variable costs calculated from IEA (2015).

energy. In our baseline analysis, we assume that the marginal cost of producing electricity is constant and technology specific. Generated electricity from renewables has priority in meeting electricity demand, because renewable electricity generation is characterized by low operating costs and high volatility in its capacity utilization. Therefore, market clears where conventional power capacity meets the residual load given by total load minus electricity generation from renewables.

We illustrate this theoretical framework in Figure 1.1, where Q stands for hourly residual demand. We rank the conventional technologies by their average variable costs (AVC), which we obtain from the IEA report "Projected Costs of Generating Electricity 2015" (IEA 2015).[17] The IEA's data imply that nuclear comes first in the supply schedule, followed by lignite, hard coal, and gas. We provide further details about the AVCs in the next subsection. Appendix A.2.2 presents further empirical evidence supporting the merit order of these conventional technologies.

In the depicted situation, the marginal technology is hard coal, such that the market equilibrium is determined by the marginal cost of producing power from hard coal. The inframarginal technologies are nuclear and lignite, which operate at their full capacity. They become marginal technologies at hours with low residual load. The gas capacity operates at peak-load hours when the residual demand is high.

[17] See Tables 3.9, 3.10, and 3.11 in IEA (2015).

1.3.2 Estimation of the merit order curve

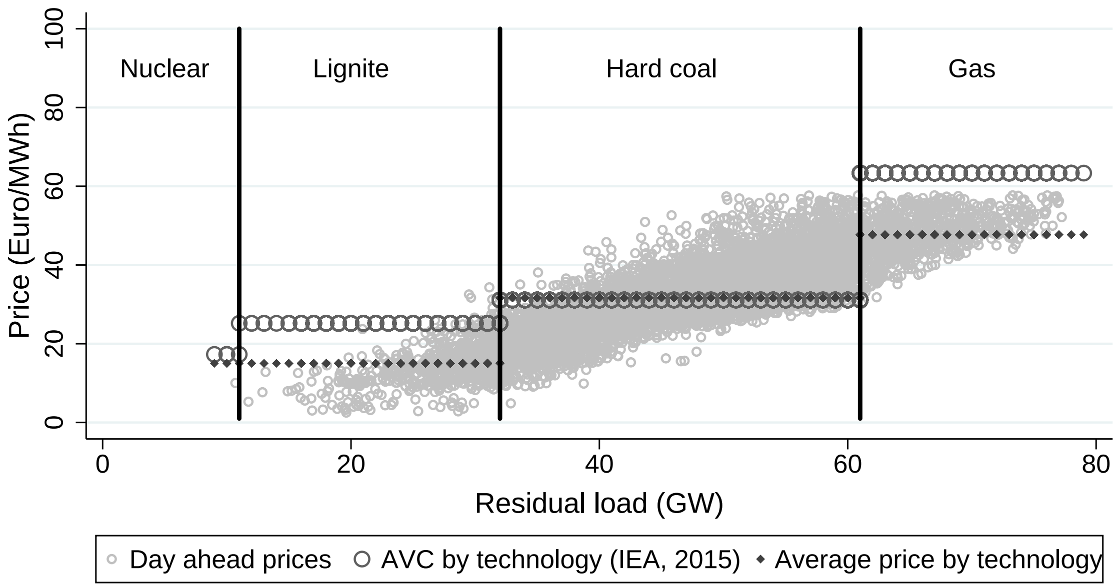
In this section, we describe how we map our economic environment to data. We conduct this analysis in two steps. First, we determine the ranking of conventional technologies in the supply schedule as breifly explained in the previous subsection. Second, we estimate technology specific supply curves by using data on market prices. Next, we explain each of these steps in detail.

As we will illustrate later in this section, our policy scenarios mainly change the ranking of some part of the lignite capacity in the supply schedule. Therefore, we need to be able to identify which generation capacities are subject to our policy shocks. Unfortunately, we do not have the required data to achieve this identification at the level of capacity unit or at the plant level. However, our assumption of technology-specific constant marginal cost enables this analysis in two ways. First, we can rank the conventional technologies by their AVCs from the IEA data. Second, as the marginal cost is assumed to be constant for each technology, which part of the lignite capacity is replaced by the shock is irrelevant. The AVCs based on the IEA data are depicted in Figure 1.2.[18] We impose the illustrated ranking of conventional technologies throughout our analysis. However, we do not prefer to use the AVCs themselves as an approximation for the merit order curve. The reason is that the AVCs are not completely in line with the market outcomes within our theoretical framework, which we show in the following.

Under an inelastic demand assumption, the functional relation between electricity prices and residual load traces a supply curve.[19] Figure 1.2 also presents the observed prices and the average prices within each technological supply range.[20] The average price where hard coal is assumed to be the marginal technology is quite close to the AVC of hard coal. However, there are considerable differences between the AVCs and the average prices in the case of lignite and gas. Therefore, we conduct our analysis with the average prices by maintaining

[18] In calculating these average variable costs, we include the fuel, carbon, and operational and maintenance costs reported in IEA (2015). However, we set the carbon price to \$10 per tonne of CO_2 which is a rough approximation of the ETS price in 2015, instead of a \$30 per tonne of CO_2 carbon price assumed by IEA. The range of technological capacities are given by their net installed generation capacities obtained from the website of Fraunhofer Institute for Solar Energy Systems (ISE). See https://www.energy-charts.de/index.htm.
[19] See, for example, Bessembinder and Lemmon (2002) and Cludius et al. (2014) for estimations of electricity supply curve from data on market outcomes.
[20] We obtain the residual load and price data at hourly resolution from the Open Energy Modeling Initiative (OEMI 2019). The prices are the day-ahead prices in the European Energy Exchange (EEX) for the German power market. Appendix A.2.1 presents further details about this dataset.

Figure 1.2 : Electricity prices and residual load



Notes: This figure illustrates the hourly prices and residual loads in 2015 for Germany. The prices are the day-ahead prices in the EEX market, which are truncated at the upper and lower 2nd percentiles. The technologies are ranked by their AVCs, which we obtain from IEA (2015). The residual-load range that is met by a specific technology is determined by the generation capacities of technologies. The residual load is given by total load minus generated electricity from renewables.

the technology-specific constant marginal cost assumption. We discuss the implications of this assumption later in this section, and provide results from relaxing it in Appendix A.2.4.

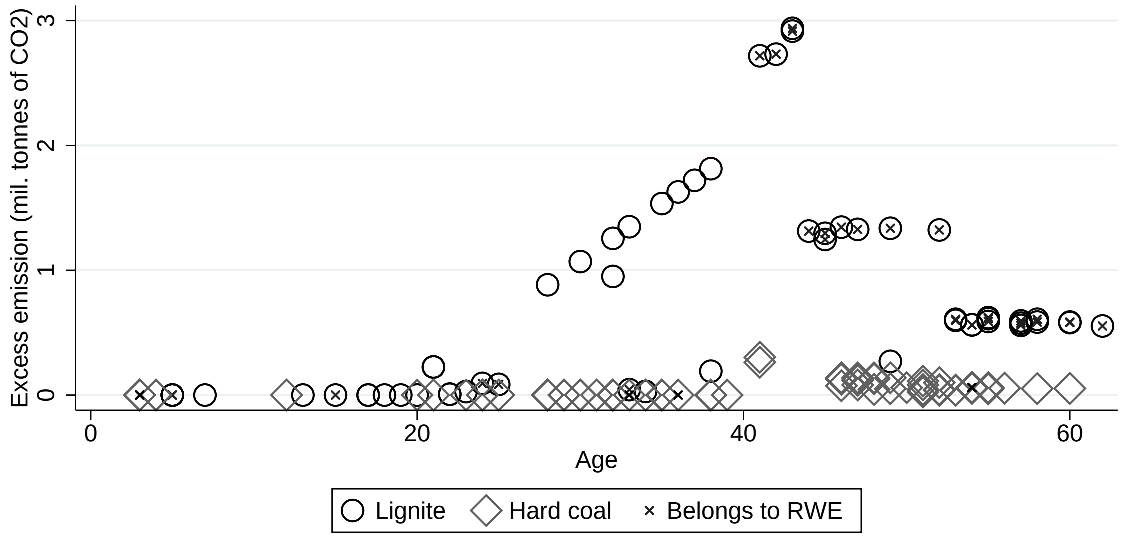
One obvious problem in Figure 1.2 is that there are not enough observations for the nuclear capacity, which means that it is rarely the marginal (price-setting) technology. We circumvent this problem by assuming that its marginal cost is equal to the minimum of the predicted supply curve for other technologies, which corresponds to that of lignite capacity.

1.3.3 Policy shocks

We go on by quantifying the policy shocks to the economic environment described in the previous subsection. The climate levy would apply to annual emissions in excess of 7 million tonnes of CO_2 per GW installed capacity by plants over 20 years old. The cost of exceeding this limit was as high as 20 Euros per tonne of CO_2. The levy-free emissions would be lower for older plants, leading to a cap of 3 million tonnes for plants over 40 years old.[21] We use the

[21] See Oei et al. (2015) for further details.

Figure 1.3 : Excess emission by plants subject to the climate levy



Notes: This figure plots the level of excess emissions in 2015 from each plant in Germany against their ages. Diamonds indicate hard coal plants, and circles indicate lignite plants. The plants of RWE are crossed. There are three more plants over 70 years old. They are not shown in this figure for clarity. They have very low or zero excess emissions, and they do not belong to RWE.

2014 plant level data from the Federal Network Agency (Bundesnetzagentur), which provides the nameplate capacities of each plant in Germany together with their construction dates. In our calculations related to RWE, we take into account the plants owned by RWE Generation SE, RWE Innogy GmbH, and RWE Power AG.

We assume that the levy-free emission level for 21 and 41 year-old plants are 7 million and 3 million tonnes of CO_2, respectively. We apply linear interpolation to obtain in-between values. In our scenario analysis, we assume that the climate levy applies to emissions above these estimated limits. We also assume that emission per capacity is constant for each technology, and calculate hourly emissions by using the annual data on emissions per installed net capacity provided at the ISE website. The results from these calculations are presented in Figure 1.3, where each point represents a plant. Lignite plants are indicated with circles, hard coal plants are indicated with diamonds, and the plants of RWE are crossed. The vertical axis indicates excess emissions of a plant that is subject to the fee.

There are two noteworthy observations in Figure 1.3: First, the hard coal capacity is almost unaffected. Second, the share of the affected capacity of RWE in overall affected capacity is very high. Based on our calculations, 48 out of 58 lignite plants and 73 out of 79 hard coal plants were over 20-years old by 2017. However, the policy is hardly binding for the hard coal capacity as the average emissions from hard coal plants per GW-installed capacity were 3.4 million tonnes of CO_2 in 2015. According to our calculations, the levy would be binding for less than 4% of the hard coal capacity. Therefore, we ignore this point in our analysis. On the other hand, the average emissions from lignite plants per GW installed capacity were 7.5 million tonnes of CO_2. As a result, 29% of the lignite capacity would be subject to the climate levy. Taking into account the average emissions per MWh of generation from lignite plants, the marginal cost of affected lignite plants would increase by 28 Euros/MWh.[22] This fee would apply to 41% of RWE's lignite capacity.

The merit order effect of the climate levy is indirect through the resulting change in prices. On the other hand, the security reserve proposal implies a direct change in the merit order. This policy scenario phases out 2.7 GW lignite capacity and moves it into a security reserve. In our analysis, we ignore the latter implication and simply remove this capacity from the supply schedule.[23]

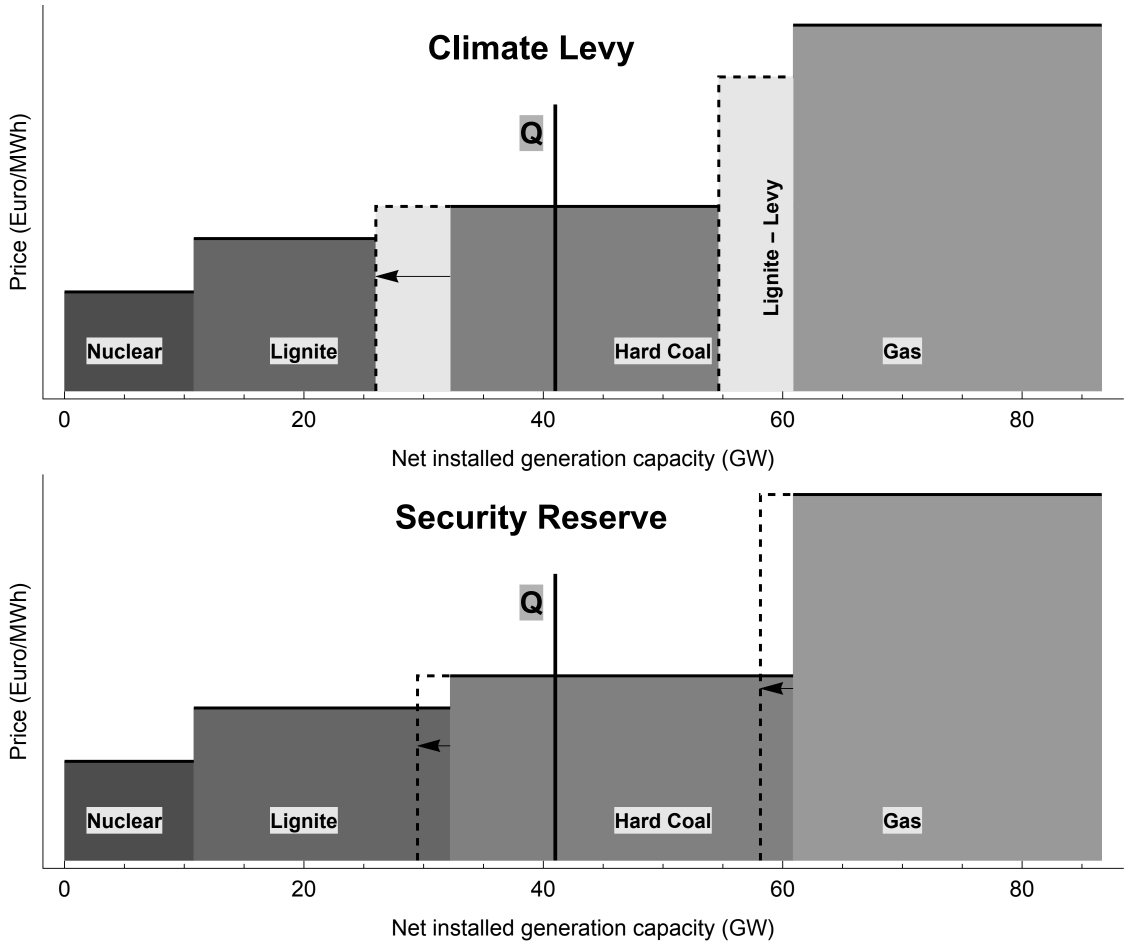
1.3.4 Merit order effects

Next, we explain how our policy shocks affect the estimated supply curve. Figure 1.4 illustrates the implications of our policy scenarios on the supply curve. In this figure, the capacities that are affected by the policies and the generation capacity by technology are based on our dataset. On the other hand, we set the cost levels in order to clarify the exposition. However, the illustration preserves all the qualitative implications of our calculations. The average residual demand for conventional power capacity in 2015 is indicated with Q. The figure shows that, hard coal is the marginal technology at the average demand. This is in line with the higher variability of generation from hard coal plants in Germany. We support this result with further empirical evidence in Appendix A.2.2.[24]

The climate levy scenario leads to a drastic change in the merit order curve as illustrated in the first panel of Figure 1.4. A considerable hard coal capacity replaces the affected lignite capacity, which leads to a higher average cost of meeting the average load. The affected lignite

[22] We obtain emission and generation data for lignite plants from the ISE charts, and calculate average emissions per MWh of generation.
[23] See Table A.2 in Appendix A.2.3 for the list of units to be transferred into the security reserve.
[24] Also see the charts presented on the website of ISE for the variability of generation (`https://www.energy-charts.de/index.htm`).

Figure 1.4 : Merit order effects



Notes: This figure illustrates the effects of the proposed policies. Affected capacities and generation capacities are based on the 2015 data for Germany. Marginal costs are not based on data, but chosen to clarify the exposition. The first panel illustrates how the climate levy relocates a significant amount of lignite capacity on the merit order curve. The second panel illustrates the phase-out plan due to the security reserve proposal. Q is the average hourly load in 2015.

capacity is now ranked just prior to the gas capacity on the merit order curve. The second panle illustrates the effect of security reserve proposal. It phases out 2.7 GW of lignite capacity. As a result, the hard coal and gas capacities shift left on the supply schedule.

These policy scenarios do not affect the market price at the average load instant. Hence, at the average load, there is no profit change for the capacity ranges that are unaffected by the policy, but there is a negative profit effect due to the replacement of the affected lignite capacity with hard coal capacity. We present the profit effects at each load instant in the following subsection.

1.3.5 Profits

We calculate the overall profit effects by assuming that the total profit from each technological capacity is shared among firms based on their technology-specific capacity shares. Figure 1.5 displays the density of hourly load over 2015 and the absolute change in RWE's profits at each load value. When we calculate the profits for each value of load, and take weighted average with respect to its density, we find that the climate levy causes 18% profit loss on average, and the security reserve scenario results in 5% average loss in profits.

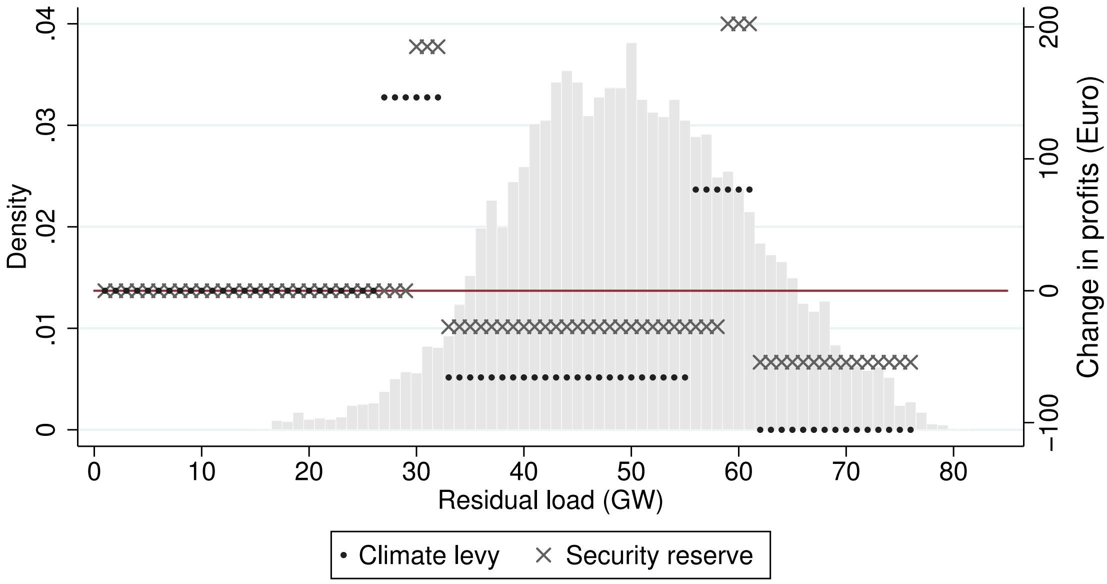
Figure 1.5 depicts the profit effects at each level of hourly demand, which can be summarized in three categories: First, there is no change in the profits at the hours when the marginal technology is nuclear or unaffected lignite capacity. Second, at the load instants where the shift in the supply curve causes a change in the marginal technology, the firm makes positive profits from running its infra-marginal units. For example, the nuclear capacity runs with much higher absolute profits at these hours. There are two occasions of positive profits: one is where the lignite capacity is replaced by the hard coal capacity, and the other one is where the hard coal capacity is replaced by either the lignite capacity in the climate levy scenario, or the gas capacity in the security reserve scenario. The density of such hours is less than half of that of an hour with the average load. Hence, although the positive profit effects are high at these load instants, their weights are small. Third, the profits are negative for all other values of load which covers the mass and the right tail of the distribution.

A noteworthy point in Figure 1.5 is related to the hours where the hard coal capacity is replaced. At those hours, there are two countervailing effects on the profits. First, the post-policy prices are higher, leading to positive profits from infra-marginal technologies. Second, the post-policy marginal cost of the capacity where hard coal replaces lignite is higher, which exerts a negative pressure on the profits. The net effect seems to be positive for both scenarios. However, it is much smaller for the climate levy scenario. The reason is that the marginal cost of affected lignite capacity is not much higher than the marginal cost of the replaced hard coal capacity.

1.3.6 Remarks and summary

The security reserve proposal includes a compensation for the affected capacity. The proposed compensation amounts to 1.61 billion Euros for the five years that this capacity is used as

Figure 1.5 : Profit effects



Notes: This figure illustrates the density of hourly load over 2015 and the absolute change in hourly profits at each load value due to climate levy and security reserve scenarios. The residual load is given by total load minus generated electricity from renewables.

a security reserve just prior to their scheduled decommissioning dates. According to our calculations, the implied subsidy rate of the compensation is 13.38 Euro/MWh.[25] This means that the policy compensates the decline in profits due to each unit of retired capacity at this rate. The 13.38 Euro/MWh subsidy for RWE's retired capacity compensates half of its profit loss at the average-demand, which can be seen in Figure 1.5. The net effect of the security reserve policy on RWE's total profits is a slight increase in profits by less than 1%.

To summarize, our theoretical analysis predicts that (i) the climate levy proposal in the first stage leads to an 18% loss in the RWE's profits, and (ii) the retirement of lignite plants in the security reserve scenario results in 5% profit loss, which is fully restored with a compensation. In the third stage of the proposal, the security reserve scenario faced a legal challenge that the compensation plan could be against the EU state aid rules. This event increased the probability of an uncompensated policy, such as the climate levy in the first stage.

[25] We assume that the decommissioning dates provided in Table A.2 in Appendix A.2.3 are binding independent of the policy, and the compensation is paid for the energy that the capacity in the security reserve can produce for the five years just prior to their scheduled decommissioning dates.

In our analysis, we assume constant marginal cost per technology, and use the average prices to approximate the merit order curve. An alternative way is to allow for non-constant marginal costs by fitting technology-specific lines to the market data. We prefer the former method for three reasons. First, it is much easier to illustrate the effect of these policy scenarios on the supply schedule, which is the main goal of the current section. Second, each capacity unit of lignite would have different marginal cost under non-constant marginal cost assumption, whereas we do not have data to identify the lignite units affected by the climate levy. This point is not important under a constant marginal cost assumption. Third, the estimations of a linear supply curve suffers from simultaneity. As a result, estimated slopes based on market data can be biased. Proper estimation of the supply curve is beyond the scope of our paper. With a positively-sloped supply curve, however, the policy shocks lead to an increase in prices at each point that the supply curve shifts to left. An increase in equilibrium prices affects profits positively, in particular for infra-marginal nuclear and lignite capacities. Therefore, relaxing the constant marginal cost per technology assumption might yield lower profit effects in absolute terms. We illustrate this effect in Appendix A.2.4 based on a naive supply curve estimation.

1.4 Potential reactions and investors’ priors

We will draw conclusions about investors’ initial beliefs from their reactions to the different stages of the policy development. Table 1.2 outlines plausible belief updating scenarios. *Scenario 0* is no reaction: here, investors simply do not care about stranded asset risk and do not react to any policy proposals or related news. In *Scenario 1*, the investors’ prior is that unburnable carbon is of no concern. However, they do care about stranded asset risk induced by specific policies, and react to such news. They are positively surprised by the compensation mechanism and negatively by its challenge. In *Scenario 2*, investors have already priced in stranded asset risk due to unburnable carbon: for example, they are aware of a nationwide or worldwide emission reduction target and have already considered this overall target in their firm valuation. Therefore, a policy introduced to achieve the target does not impact their valuation of the affected firms. However, the compensation mechanism is unexpected for these investors and they value it positively.[26] When the compensation is challenged, they

[26] Note that in this case, we would not expect a positive reaction for E.ON: only RWE receives compensation payments, and investors are not concerned about introduction of the uncompensated policy in this scenario, as they have already priced in general unburnable carbon risk.

Table 1.2 : Scenarios for investors' priors and reactions

	Scenarios	**Reactions to...**		
		Uncompensated policy	Compensated policy	Challenge to compensation
0	Don't care	0	0	0
1	Have not priced in stranded asset risk before, but react to policies	$-$	$+$	$-$
2	Have priced in expected loss, but are surprised by compensation	0	$+$	$-$
3	Have priced in expected loss and compensation	0	0	$-$

adjust their valuation downward again. Finally, in *Scenario 3*, investors do care about stranded asset risk, but they expect firms to be compensated. When the Ministry announces the uncompensated policy, they already expected a policy move and they still expect a subsequent compensation to follow. Therefore, they do not believe that the announcement will affect the firms economically, and show no reaction. The compensation plans are not surprising, either, and investors do not adjust their firm valuation. However, the challenge of the compensation is a surprise, and causes investors to adjust firms' values downward.

Table 1.2 lists the scenarios that we find likely and logically consistent. It is not a complete list of potential reactions and potential interpretations for each event. Note that, absence of surprise is already one part of the story in some of our scenarios. We provide a detailed analysis related to the surprise content of the events in Section 1.6 after presenting our results.

1.5 Empirical methods

We conduct a short-run event study analysis where we investigate whether there are abnormal returns associated with the events. Consider the following specification to estimate the normal market performance of a single asset: $r_t = X_t\beta + \epsilon_t$, where r_t is the continuously compounded return of the asset at the trading date t, which is the daily change in the logarithm of asset prices. The normal performance of the asset is predicted by the vector of covariates X_t. The coefficient vector (β) and the error term (ϵ_t) are asset specific. We assume that the errors are independent drawings from a normal distribution with mean zero and constant variance, such that $\epsilon_t \sim$ NID$(0, \sigma^2)$. We provide extensive specification tests and robustness checks on the NID assumption.

Event study approach is based on comparing realized returns on the event date with normal returns. The normal return, which is an estimate of $\mathsf{E}[r_t|X_t]$, is the predicted return given by $\hat{r}_t = X_t\hat{\beta}$. We define the relative time index $\tau = t - T$ to measure the distance to the event date T in terms of trading days. Then, the abnormal returns (AR) are given by $\gamma_{T+\tau} = r_{T+\tau} - \mathsf{E}[r_{T+\tau}|X_{T+\tau}]$, and their estimates are the prediction errors, given by $\hat{\gamma}_{T+\tau} = r_{T+\tau} - \hat{r}_{T+\tau}$.

The null hypothesis that the event does not have an effect over the event window is formulated as H_0: $\sum_{\tau=-h}^{\tau=h} \gamma_{T+\tau} = 0$, where h is the half-width of the event window. Hence, the event window spans the $L = 2h + 1$ trading days from $t = T - h$ to $t = T + h$. The sum over the abnormal returns gives the cumulative abnormal return (CAR).

In order to apply the classical t-test, the variance of the CAR can be calculated as $var(CAR) = \iota' V \iota$, where V is the $L \times L$ covariance matrix of abnormal returns and ι is an $L \times 1$ vector of ones. The variance of prediction errors has two components: sampling uncertainity in the estimation of the model parameters and the error uncertainty. If the estimation sample is sufficiently large, one can ignore the sampling uncertainty. Although the sampling uncertainity in our application is small and does not affect any of our results, we do not ignore it. Sampling uncertainty causes serial correlation among abnormal returns. Hence, V has non-zero off-diagonal elements. Its influence is typically very small in short-run event studies, which is the case in our application too. In all our estimations, taking the correlation structure into account does not lead to any visible differences. When the off-diagonal elements are taken as zero, $var(CAR) = \sum_{\tau=-h}^{\tau=h} var(\gamma_{T+\tau})$, where $var(\gamma_{T+\tau})$ is given by $var(\hat{r}_{T+\tau}) + \sigma^2$. The first term is due to sampling uncertainity, and the second term is the error variance.

To interpret the AR as the event effect, the required assumption is that the model is correctly specified such that the predicted returns for the event window are the counterfactual returns to the asset in the absence of the event. The choice of the covariate set is generally motivated by well-known statistical and theoretical models of asset returns. We provide an extensive robustness analysis with respect to this choice. In our baseline estimations, we simply use a constant and returns to a market performance index (the so-called market model), which is generally considered sufficient for short-run event studies (Campbell et al. 1997).

Valid estimation requires that the normal market performance is uncorrelated with the event-induced abnormal returns. To control for potential feedback from the event to the normal market performance, the common approach is to exclude the event window observations in the estimation of expected returns. Given that abnormal returns are simply the prediction errors, the natural choice for the estimation window is to use the observations prior to the event window, potentially leaving a gap between the end of the estimation sample and the beginning of the event window, which we call the "pseudo window". In the absence of any other event, the pseudo-window abnormal returns are expected to be insignificant. We conduct performance tests for the predictive power of our model by calculating L-days CARs for each date in the pseudo window as if an event has occurred on that date.

The most important threat to identification of the event effect is the presence of other contemporaneous shocks in the event window. There are several ways to control for such potential biases. First, when there is a limited number of assets or announcements, it is feasible to review the news around the event dates. We undertake this approach by using a news search engine and we identify a small number of such potential confounding events, which will be discussed in Section 1.7.2. Second, the event window should be kept reasonably small to rule out other asset-specific events around the event window. Third, the market model can capture the average effect of market-wide shocks via the market price index. However, the market price index is not a proper counterfactual control unit because the event-affected units might participate in this portfolio, leaving the price index endogenous to the event shock. Also, the weights of the market index are not intended to produce a control unit for the affected company, but to reflect the average market conditions. In order to take care of this concern, we apply a synthetic control approach which allows choosing assets to create a counterfactual portfolio and estimating their weights.[27] We provide a detailed description of this approach in Appendix A.4.

To control for industry-wide shocks, we use EnBW as the control unit, a company in the same industry but without any relevant lignite asset. Therefore, a priori, we do not expect the series of events subject to our analysis to have any effect on EnBW. This gives a difference-in-differences estimate of the abnormal returns by removing biases from industry-wide shocks to returns to asset i.[28] We provide a technical description of this approach in Appendix A.4.

[27] See Abadie and Gardeazabal (2003) for the synthetic control estimation. See, for example, Guidolin and La Ferrara (2007) for an application of synthetic control estimation in an event study analysis. An alternative approach might be to use a different market index. This approach is less preferable, since our goal is to capture the common shocks in the market that are most relevant for the subject firms.

[28] In terms of the synthetic control approach, this can be considered as assigning a weight of 1 to EnBW and 0 to all other assets in the donor pool.

When there are more than one announcement, testing H_0 amounts to testing the significance of average cumulative abnormal returns (ACAR) over the announcements. Index different announcements with $j = 1, .., J$, and denote the corresponding announcement date with T_j. Therefore, $\tau = 0$ at $t = T_j$ for all j. In these estimations, we use announcement specific estimation windows located at a common distance to the announcement dates. The average abnormal return (AAR) at distance τ is given by $(1/J)\sum_{j=1}^{J}\gamma_{j,T_j+\tau}$, and its variance is given by $(1/J^2)\sum_{j=1}^{J}Var(\gamma_{j,T+\tau})$. The ACAR and its variance can be calculated as described previously by using the AARs and their variances (Campbell et al. 1997).

1.6 Baseline results

We employ data on three publicly listed German energy utilities, namely E.ON, RWE, and EnBW. Their stock prices and all other data are from Thomson Reuters Datastream, unless otherwise noted. To calculate market returns, we use the DAX, a performance index consisting of the 30 major German companies trading on the Frankfurt stock exchange. In the estimations presented in the main text, the covariate set includes a constant and the market return, which is generally considered to be sufficient for short-run event studies (Campbell et al. 1997). In the Appendix, we provide robustness tests by also using retuns to oil prices and a risk free rate fo return. These additional covariates do not have any predictive power in our estimations, and hence, their inclusion does not have any effect on the results. We provide a comprehensive description of our dataset and various descriptive statistics in Appendix A.3. Throughout the paper, the details of a specification, such as window widths, are listed in the table and figure notes.

Table 1.3 : ACARs by the stages of the proposal

Companies	Events		
	Climate levy proposal	Security reserve proposal	State aid assessment
RWE	0.012	-0.007	-0.102***
	(0.020)	(0.016)	(0.019)
E.ON	0.011	-0.019	-0.072***
	(0.017)	(0.014)	(0.013)

Notes: This table presents the average cumulative abnormal returns of RWE and E.ON from the announcements of each stage of the policy proposal. The event window is the 5 days centered around an announcement. The estimation window is the 90 days just prior to the event window. Hence, the event window observations are excluded in the estimation of normal market performance. Standard errors are in parentheses. Significance levels are indicated as * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

We start by presenting the average effect of announcements for each stage of the proposal. This strategy applies a strict punishment for the presence of irrelevant announcements. Therefore, rejecting the null requires a strong reaction in the relevant announcements. The results are presented in Table 1.3, where each entry refers to the ACAR. For both RWE and E.ON, only the effects of the "challenge to the compensation" stage are significant. That is, investors did not react to the initial climate levy proposal, which was directed at stranding lignite assets by charging an extra fee on carbon emissions, and to the following announcements related to the compensation mechanism, that is, paying plant owners for not operating their units. Only the news that the compensation mechanism might not go through due to violating state aid rules seems to have triggered a significant and negative reaction. These results are consistent with Scenario 3 only. That is, investors do price in the stranded asset risk, but with an expectation of a compensation policy.[29]

Inference based on the average CARs reduces the possibility of incorrect rejection of a true null hypothesis (type I error). However, it increases the possibility of failing to reject a false null hypothesis (type II error), which might be responsible for the insignificant results for the first two stages of the policy development. In Table A.10 in the Appendix, we provide detailed results based on the CARs for each individual announcement in the first two stages. We show that all the announcements in these stages are still insignificant. Therefore, we conclude that there is no reaction in these two stages. Here, we proceed by investigating the significant effect in Stage 3 in detail.

Table 1.4 : CARs by the Announcements for the State aid Assessments

Companies	Announcements		
	(3a)	(3b)	(3c)
RWE	-0.020	-0.135***	-0.150***
	(0.031)	(0.028)	(0.038)
E.ON	0.004	-0.000	-0.220***
	(0.024)	(0.021)	(0.024)

Notes: This table presents the cumulative abnormal returns of RWE and E.ON from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement. The estimation window is the 90 days just prior to the event window. Hence, the event window observations are excluded in the estimation of normal market performance. Standard errors are in parentheses. Significance levels are indicated as $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

[29] EnBW does not own lignite assets. Our results are in line with this fact. We present the corresponding results for EnBW in the following sections, where we use this company as a control unit.

In Table 1.4, we present the test results based on individual CARs due to the announcements in Stage 3. The results indicate that the ACARs in stage 3, presented in Table 1.3, are mainly driven by the CARs during announcements (3b) and (3c): when the media reported on the state aid assessment by Parliament's academic service, and when the EU Commission announced opening the state aid procedure, respectively. Event (3a), the date at which the academic service presented its report to Parliament, seems to have no significant effect on either firm. The insignificant CAR due to this event is in line with our conjecture that this document was not publicly available on that date. Only on the publication dates of the media reports of the assessment do we observe a significant reaction.[30] This pattern is in line with the assumption that investors do not have access to insider information and price in only new information made public via media reports.

The estimated average effect of the announcements related to state aid assessments on RWE is larger, as also illustrated previously in Table 1.3. This result is in line with the fact that RWE is more lignite-intensive (see Section 2). However, in the next section, we show that the ARs of RWE due to event (3b) is partially driven by a strong negative earnings surprise, while E.ON is experiencing a small positive earnings surprise. As a result, the difference in the reactions is smaller. Overall, we do not find a significant difference between the reactions across these two firms.

The results presented above show that investors do care about stranded asset risk, but that they also expect a compensation policy for their economic losses. More specifically, investors in stock markets did not react to the announcement of the climate levy proposal, as they expect that the firms involved would not be financially affected. The underlying reason is that, as their reactions to stages 2 and 3 reveals, they expected that the firms would be compensated for their losses.

It is important that such an interpretation would not be possible by interpreting the reactions to individual events independently, as investors' reactions to policy signals depend on their prior expectations. This is the idea underlying our strategy of tracking investors' reactions in the course of the development of a policy proposal. The significant reaction in Stage 3 shows that there is a surprise element in the third stage. In the absence of confounding events, we can conclude that this surprise was due to the challenge to the compensation policy. In the next section, we show that the results from the third stage are not driven by confounding

[30] The first report on the assessment was published by *Der Spiegel* (event 3b).

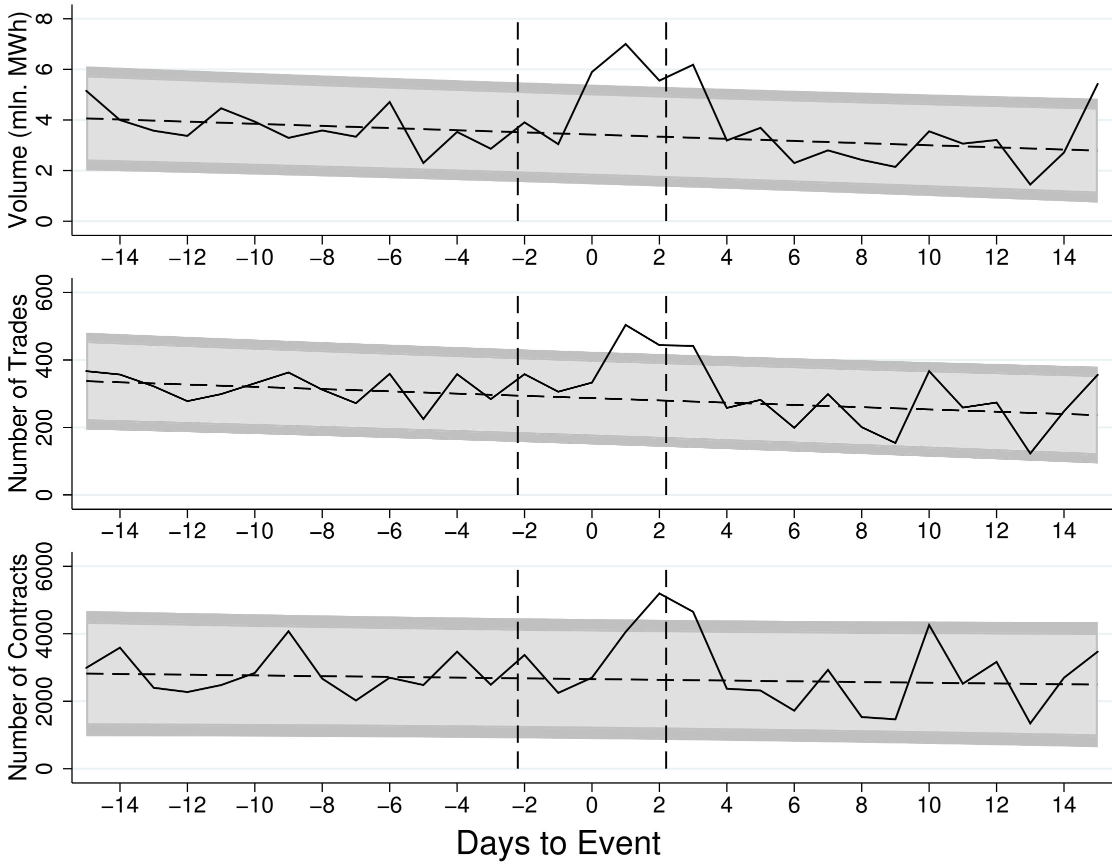
events. Furthermore, this finding explains the underlying reason for our second stage result. Simply, the investors did expect a compensation, and the introduction of a compensation scheme in Stage 2 did not surprise the investors. The result that the investors expect and do care about a compensation scheme explains the absence of reaction to the initial proposal of uncompensated asset stranding in Stage 1. That is, given the findings from Stage 2 and 3, the absence of reaction in the first stage cannot be due to that the investors do not care about a stranded asset risk. In the following, we also provide strong empirical evidence that the initial announcement of the proposal surprised the investors, which also shows that we correctly identified the initial announcement date when new information was released.

To establish surprise for the initial announcement of the proposal, we employ data on future contracts traded at the European Energy Exchange (EEX). Specifically, we use EEX futures data for the German power market. The initial proposal implied the stranding of lignite-related assets and meant that significant baseload capacity would not be available after 2016. Therefore, it had the potential to affect activities on the German power futures market. The affected electricity companies themselves would have needed to buy back their positions for the respective delivery period, as they would not have the required capacity any more. Moreover, it is possible that the proposal introduced a general uncertainty among market participants, causing an increased demand for hedging. Both mechanisms would result in increased trading activity – if the proposal came as a surprise to market participants.

Figure 1.6 illustrates the trading volume, the number of trades, and the number of traded contracts around the first announcement of the climate levy proposal. In all sub-figures, we can clearly see an extraordinary increase in market activity starting on the announcement date which persists for a few days. This means that the initial proposal surprised market participants, and they reacted to the implied capacity reduction. However, the stock market did not react to the implied asset stranding (see Table A.10 in the Appendix for their reaction to the first announcement). Given our sequential event study results, the natural explanation for this pattern of reactions is that stock market investors believed that the capacity reduction would not mean a financial loss for the affected firms because they expected a compensation.

As a result, the two patterns we observe – the simultaneous, different reactions in the stock and futures markets to the first stage, and the pattern of reactions in the stock market – allow us to conclude that the initial climate levy proposal came as a surprise, but did not change the

Figure 1.6 : Power-futures market around the announcement of climate levy



Notes: This figure illustrates the trading volume, the number of traded contracts, and the number of trades for future contracts traded at the EEX around the first announcement of the policy proposal indicated by date 0. The dashed line is the trend estimated by using the non-event days outside the vertical dashed lines. The shaded regions indicate 90% and 95% confidence intervals based on the forecasts from the estimated trend. The results are robust to various configurations of the estimation sample to estimate the trend.

stock market investors' valuation of the firms as they expect compensation.[31] The significant stock market reaction in stage 3 provides evidence that stock market investors do care about stranded asset risk, and that their insignificant reactions to the first and second stages results from having priced in a compensation policy rather than from ignoring the stranded asset risk. These results are in line with the narrative evidence presented in Section 1.2.

[31] We conducted the same analysis for the other announcements. There is a similar, but weaker evidence for an increase in power market activity during the second announcement of the first stage, which implies a delayed reaction to the initial announcement of the proposal. In all the other announcements, there is no extraordinary activity. That is, the power markets did not react to the announcements about the compensation plans (Stage 2 and 3), which is in line with basic intuition.

1.7 Robustness analysis

We present the results from alternative modeling choices in the Appendix. First, in Appendix A.5, we show that our results are robust to using a three-day event window, and employing oil prices and interest rates in the prediction model.[32] Second, we provide extensive specification tests and robustness checks on the assumed error distribution by using both resampling and analytical techniques. These results are presented in Appendix A.6. In the rest of the paper, we present robustness tests on two other dimensions. In Section 1.7.1, we focus on analyzing our model's performance in identifying the event effect. In Section 1.7.2, we investigate whether there are confounding events around the announcement dates that might drive our baseline results.

1.7.1 Placebo tests and model specification

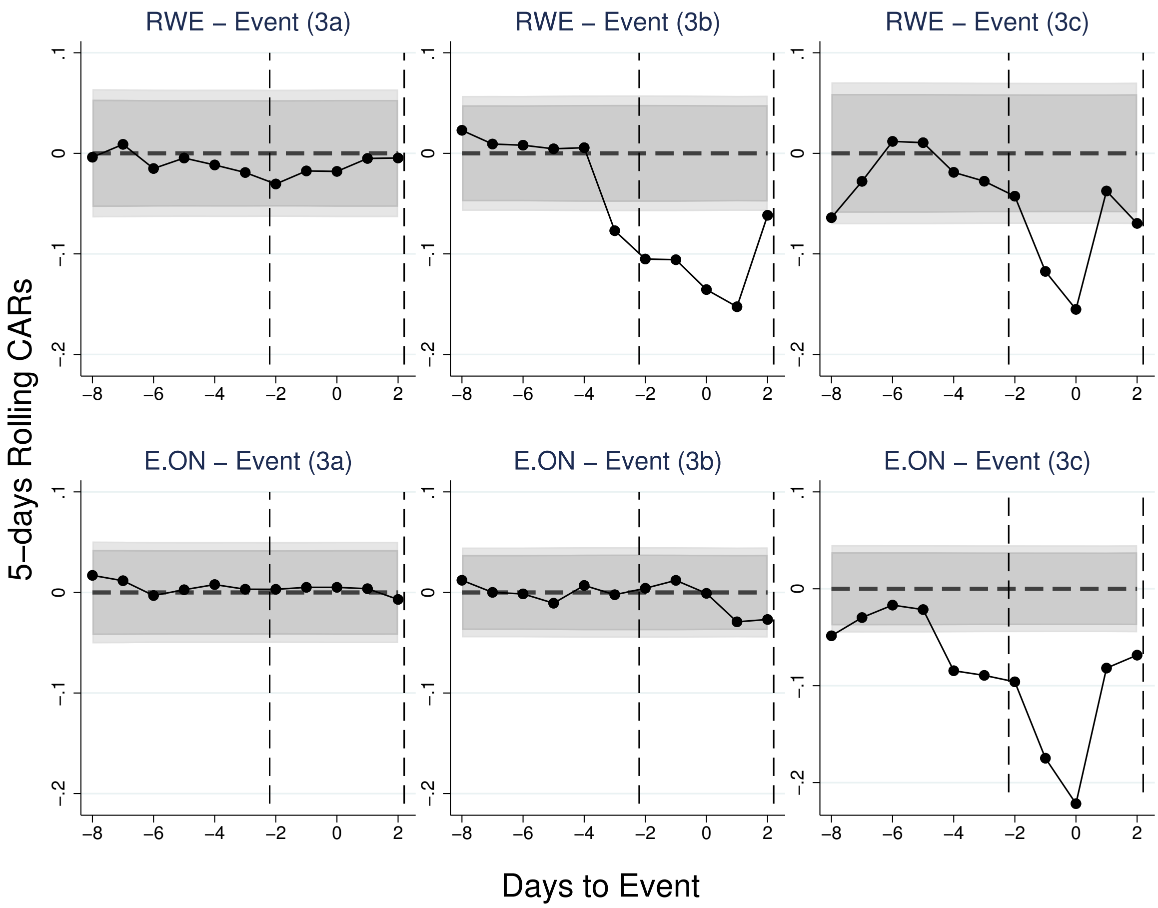
We start by conducting placebo tests by assuming false event windows just prior to our events. This analysis validates our model's performance in predicting the counterfactual returns. Second, we conduct synthetic control estimations to verify that our results are not driven by the endogeneity issue due to the presence of E.ON's and RWE's assets in the DAX30 index.

The results from the placebo tests are presented in Figure 1.7. On each graph, the left panel separated by the dashed line is the pseudo-event window, and the right panel is the event window. Each point on a graph refers to the CAR calculated from the abnormal returns on the five days centered around that date.[33] The estimated CARs for date zero (the event date) correspond to the results presented in Table 1.4. The 90% and 95% confidence intervals for the CARs are illustrated as forecast intervals to ease the readability.

Figure 1.7 shows that the model performs well in predicting the out-of-sample returns in the pseudo window, thus increasing confidence in our model specification. Furthermore, there seems to be no sign of other events in the pseudo windows that bias the estimated CAR around the event day. For the significant events, the CARs are generally stable and insignificant throughout the pseudo window and gradually become negative and significant in the event windows. The gradual change in the CARs and the presence of significant CARs just before the event window is not surprising as we use five-day rolling windows. For example, the

[32] We have verified that our results are robust to using 45, 60, and 120 observations for the estimation sample.
[33] Corresponding estimated abnormal returns are provided in Figure A.13 in the Appendix.

Figure 1.7 : Impact of state aid assessments

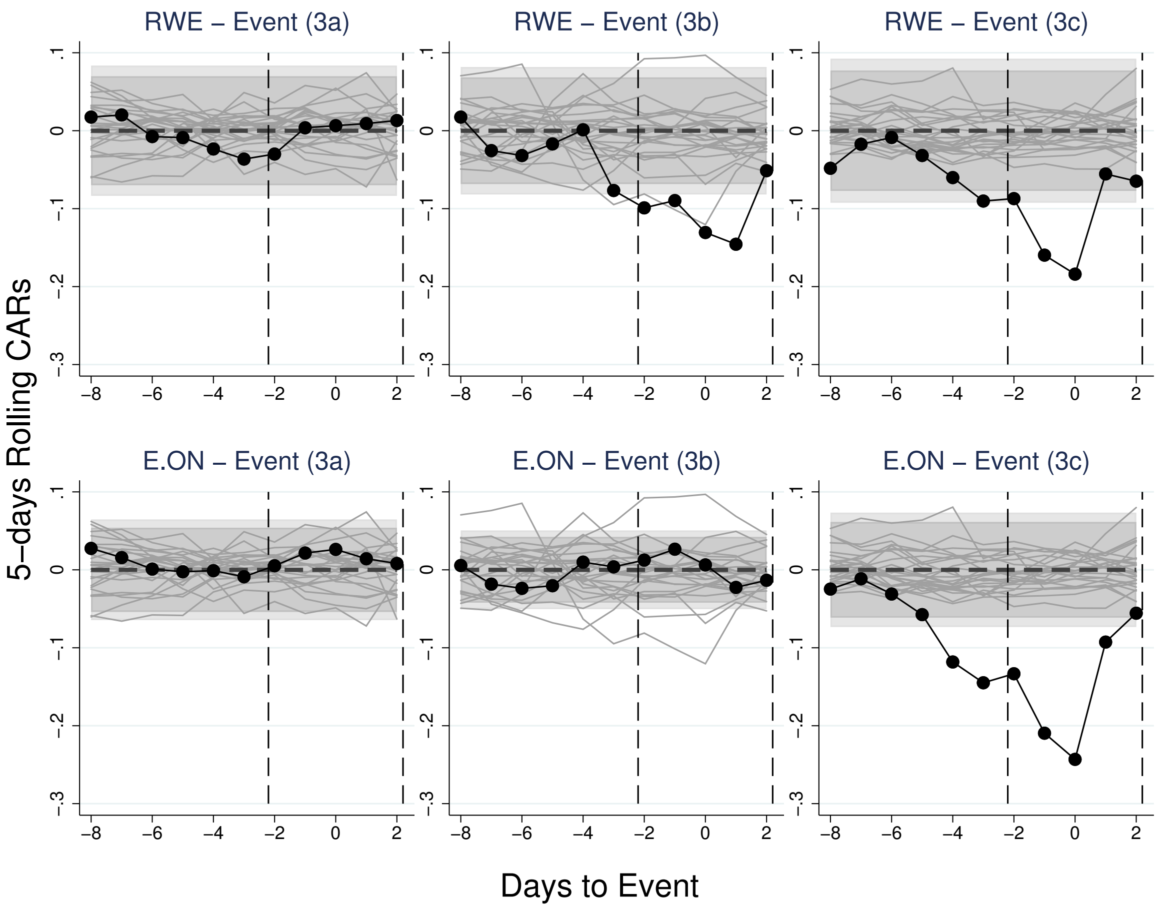


Notes: This figure presents the CARs of E.ON and RWE from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. In the figure, the days prior to the event window are the lacebo announcement days. The estimation window is the 90 days just prior to the pseudo window. Hence, the event window and pseudo window observations are excluded in the estimation of normal market performance. The 90% and 95% confidence intervals are indicated by shaded areas.

calculation of the five-day rolling CAR on date 3, which is in the pseudo window, employs two abnormal returns from the event window. The observed pattern indicates that the event effects seem to be well captured by the five-day event window.

To control for potential biases due to the endogeneity of the DAX30 index, we perform synthetic control estimations. Here, we estimate a synthetic portfolio using DAX30 companies by excluding RWE and E.ON. We base the matching procedure only on the asset returns of these companies. The technical details are provided in Appendix A.4.1. The results are presented in

Figure 1.8 : Synthetic control estimations



Notes: This figure presents the synthetic control estimations of the CARs of E.ON and RWE from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. The days prior to the event window are the placebo announcement days. The estimation window is the 90 days just prior to the pseudo window. Hence, the event window and pseudo window observations are excluded in the estimation of normal market performance. The in-place placebo tests are illustrated with grey lines, and the grey areas are 90% and 95% confidence intervals constructed from the pre-treatment RMSE.

Figure 1.8.[34] While the qualitative results remain the same, the estimated sizes of the CARs are slightly larger. This indicates that the market price index might have been affected by the events subject to our analysis and therefore absorbed some of the event effects. However, the size of this bias is very small and negligible for all the events.

Figure 1.8 further illustrates some inputs to conduct the non-parametric inference strategy suggested by Abadie et al. (2015) for synthetic control estimations. The so-called "in-place placebo" estimations, which are estimations of the event effect on the units in the control

[34] See Figure A.15 in the Appendix for the corresponding abnormal returns.

group (donor pool), are illustrated with grey lines. The shaded areas are 90% and 95% prediction intervals constructed from the pre-treatment root mean squared error (RMSE). It is seen that the predicted CARs of untreated units are generally within the prediction intervals which confirms the predictive power of the model.[35] Second, the CARs for E.ON and RWE during the event window are extraordinarily higher than the CARs of untreated units. These results are in line with our baseline estimations. We present the non-parametric p-values based on the in-place placebo tests in Table A.14 in the Appendix, which are in line with our baseline estimations.

1.7.2 Confounding events

In this section, we control for the presence of confounding events around the announcement dates that might partially or completely drive our baseline results. To detect confounding events, we used a news search engine and conducted a careful review of the news published around the announcement dates of events (3b) and (3c). The search methodology and a summary of all the results are provided in Appendix A.7. Our search resulted in two news items.

The first item is the *nuclear provisioning assessment* announcement and is potentially relevant for both RWE and E.ON. On September 10, the first trading date in the event window of announcement (3c), the media reported the results of a study commissioned by the Ministry of Economy and Energy.[36] This study concluded that the energy companies' provisioning for liabilities in connection with nuclear plant decommissioning and waste disposal was insufficient. Although this study did not imply direct political or financial consequences, one could imagine that investors reacted to it.

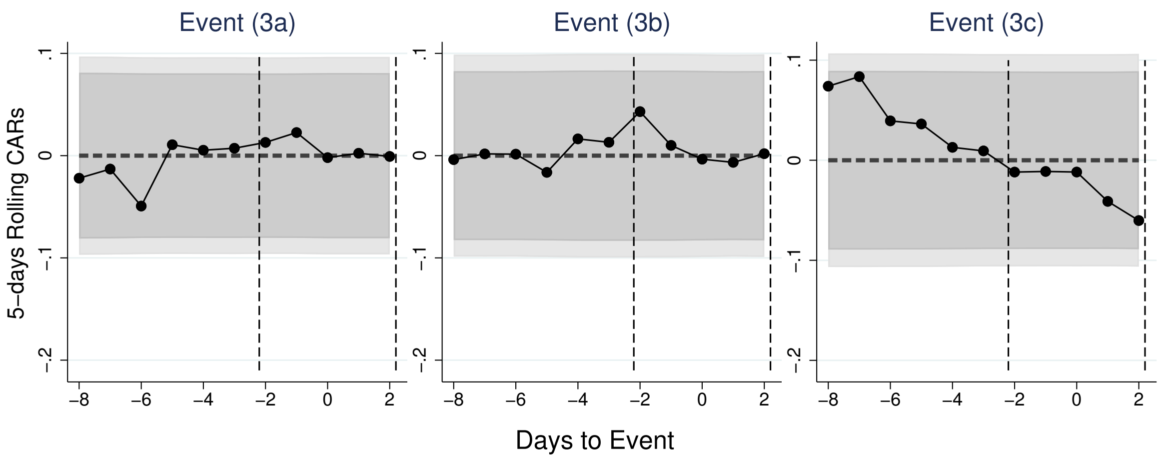
The second item is *earnings announcements*. Both E.ON and RWE published their quarterly earnings announcements just before announcement (3b) – on August 12 and August 13, respectively. Since the announced earnings are company specific, this event has the potential to induce the patterns in the estimated CARs for announcement (3b).

[35] The reason underlying the higher dispersion in the in-place placebo CARs around event (3b) will be clarified in the next subsection.

[36] See http://www.spiegel.de/wirtschaft/unternehmen/atomausstieg-fuer-den-atommuell-fehlen-30-milliarden-euro-a-1052869.html. For an English-language account of the study and its potential implications for the firms' credit ratings, see https://www.moodys.com/research/Moodys-Nuclear-shutdown-costs-stress-German-power-generators--PR_335268.

Controlling for the nuclear provisioning assessment In order to control for the nuclear provisioning assessment, we use EnBW, a company from the same industry but without relevant lignite assets, as the single control unit. This strategy leads to a difference-in-differences estimation of abnormal returns by removing the effects of common industry-wide shocks (see Appendix A.4.2 for technical details). The nuclear provisioning assessment can be classified as an industry-wide shock. First, the assessment does not target a specific company, but all companies with nuclear power plants. Second, the problem of nuclear waste is relevant not only for RWE and E.ON, but also for EnBW, which has substantial shares of nuclear energy in its generation portfolio.[37] On the other hand, the lignite policy proposal is irrelevant for EnBW, since it does not hold any asset targeted by the proposal. Therefore, if the nuclear provisioning assessment had any effect, it should be reflected in EnBW's asset returns. By using EnBW as a control unit, we can eliminate the influence of common systematic shocks in a general manner.

Figure 1.9 : Pseudo tests on EnBW



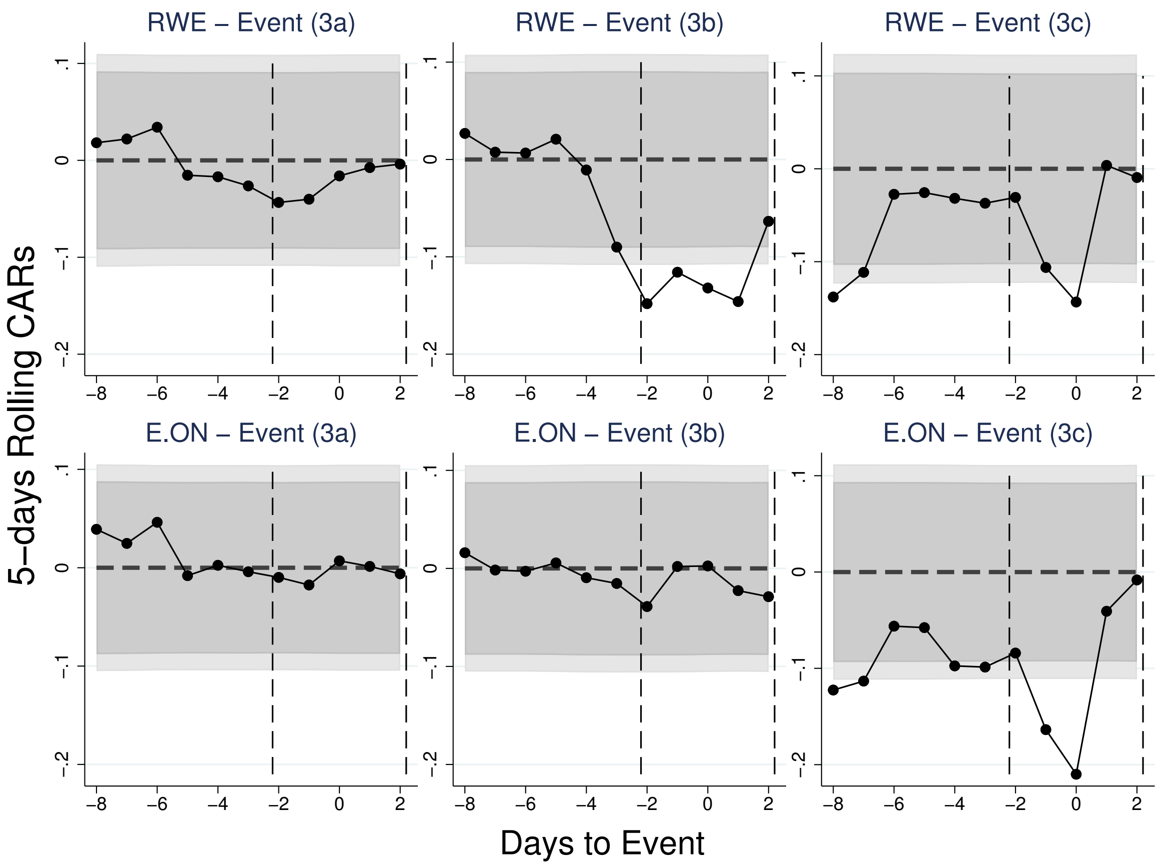
Notes: This figure presents the CARs of EnBW from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. The days prior to the event window are the placebo announcement days. The estimation window is the 90 days just prior to the pseudo window. Hence, the event window and pseudo window observations are excluded in the estimation of normal market performance. The 90% and 95% confidence intervals are indicated by shaded areas.

This approach requires that (i) the events subject to our analysis had no impact on EnBW's asset returns, and (ii) any systematic difference between the affected units and EnBW can be captured by the set of control variables. To assess the validity of EnBW as a control unit, we

[37] According to the firms' annual reports, 23% of EnBW's installed capacity in 2015 was nuclear power plants, compared to 15% for RWE and 28% for E.ON.

investigate the model's performance in predicting EnBW asset returns and check whether there are significant abnormal returns in the event windows. Figure 1.9 presents the results. The CARs stay within the 95% percent confidence intervals both in the pseudo and event windows.[38] This confirms the model's out-of-sample performance in predicting EnBW's returns. Furthermore, these results are generally in line with the assumption that EnBW was not affected by the policy proposals, and reveal that our baseline estimations are not driven by industry-wide shocks such as the nuclear provisioning assessment. If this event had an effect, we would expect to see some reaction in the asset returns of EnBW.

Figure 1.10 : CARs by using EnBW as a control unit



Notes: This figure presents the CARs of E.ON and RWE from each announcement in the third stage of the policy proposal by using EnBW as the control unit. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. In the figure, the days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The 90% and 95% confidence intervals are indicated by shaded areas.

[38] Corresponding estimated abnormal returns are provided in Figure A.13 in the Appendix. See Table A.10 in the Appendix for the CARs for each individual announcement.

The estimation results from using EnBW as the control unit are presented in Figure 1.10.[39] Despite being slightly less precise, these estimations are generally in line with their baseline counterparts in Figure 1.7. The size of the estimated CARs for the event windows is close to those in our baseline estimations, indicating that our results are not driven by some industry-level confounding event such as the report on nuclear waste liabilities (see Table A.16 in the Appendix for details).

Controlling for earnings announcements The second news item in our search for confounding events is an earnings announcement (EA) just before announcement (3b). The surprise content of announced earnings are company specific. Therefore, their influence on the estimation results cannot be eliminated by using a control unit. Our strategy to control for the earnings announcement is to correct the CARs on the date of announcement (3b) for predicted abnormal returns due to the earnings surprise.

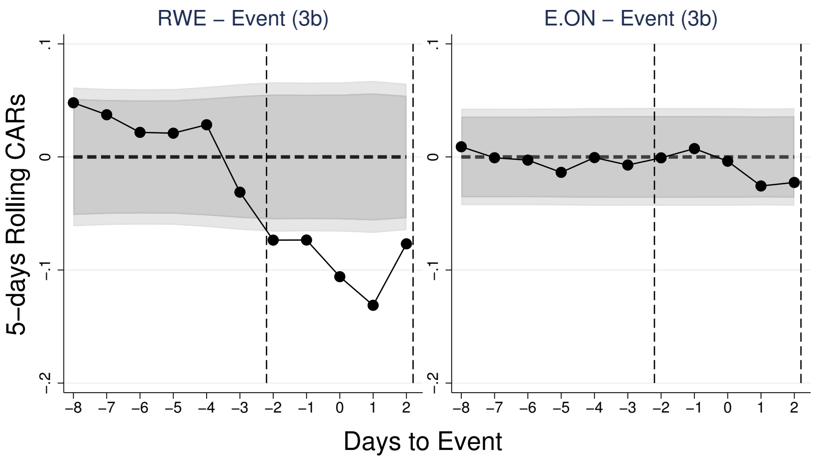
We proxy the expected earnings with the quarterly earnings forecasts reported by the Institutional Brokers Estimate System (I/B/E/S), which is the mean of earnings forecasts by many analysts for a large number of firms. Our measure of surprise is the difference between announced earnings (AE) and mean forecasted earnings (MFE) normalized by the standard deviation of the forecasts, namely, standardized unexpected earnings (SUE) provided by the Thomson Reuters Database.

The technical details of estimating the marginal effect of SUE are provided in Appendix A.4.3. We provide all the details from each step of these estimations in Appendix A.8. To summarize, we start by estimating the five-day CARs for all the earnings announcements in our sample by excluding the two earnings announcements by E.ON and RWE just before event (3b). Next, we estimate the marginal effect of SUE on the predicted CARs. Finally, we extrapolate this result to the excluded earnings announcements of RWE and E.ON around event (3b). Finally, we adjust the CARs due to event (3b) with the predicted effect of the earnings announcements.

We repeat pseudo tests on event (3b) (see Figure 1.7) by taking the predicted effect of the earnings announcement into account. The results are presented in Figure 1.11, where both the rolling CARs and the prediction intervals are corrected for the size of and uncertainty

[39] Other related results are presented in the Appendix: see Figure A.16 for the corresponding abnormal returns. The estimation tables by events and by announcements are provided in Tables A.15 and A.16, respectively.

Figure 1.11 : CARs for announcement (3b) corrected for earnings surprise



Notes: This figure presents the CARs of E.ON and RWE from announcement (3b) corrected for the effect of earnings announcements. The event window is the five days centered around an announcement (date 0), indicated by the dashed lines. The days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The 90% and 95% confidence intervals are indicated by shaded areas.

due to the predicted effect of earnings announcements.[40] With a conservative approach, we apply the correction for all the dates presented in the figure. In Appendix A.8, we provide the corresponding figures illustrating each source of uncertainity separately, and where we assume a five days event window around the date of earnings announcements. In terms of the relative distance to event (3b), the earnings announcement of RWE took place on date -1, while it is date -2 for E.ON. Figure 1.11 shows that the correction does not have an effect on the results for E.ON. However, the results for RWE changes. The corrected CAR is much smaller compared to the baseline estimate. The corrected effect of event (3b) is still significant against the 95% confidence intervals.[41] These results suggest that the reaction to the state aid assessments is mainly due to announcement (3c).

1.8 Discussion

Given our results in the previous section, our most conservative point estimate for the 5-days CARs implies a decrease in the market valuation of firms over 20%, which corresponds to a

[40] The corresponding corrected ARs are presented in Figure A.17 in the Appendix. See Appendix A.8 for the calculations for the confidence interval.
[41] This is not the case with 99% confidence intervals.

4% average abnormal return over the 5 days around the event. Given RWE's considerable market value (see Table A.3 in Appendix A.3), the monetary impact amounts to around 2 billion Euros. These results show that the investors expect substantial costs from an uncompensated policy, such as the climate levy scenario which became more likely after the compensation for the security-reserve plan faced a legal challenge. This result is in line with our theoretical predictions for RWE in Section 1.3, that the profit effect of the climate levy scenario can be as high as 18%.

Note that our theoretical predictions are likely to be upper bounds, as allowing for non-constant marginal costs generally reduces the negative profit effects. Therefore, our empirical results imply a slightly higher market reaction compared to the range of theoretical predictions on the rate of change in RWE's profits. The market value of a firm can be seen as a measure of the capitalized risk-adjusted present value of future profit flows. Therefore, the differences can be due to the uncertainty introduced by these announcements. Note that confirming this difference statistically is not possible due to the level of uncertainty surrounding these predictions.

1.9 Conclusion

We analyze the stock market effects of a German climate policy proposal aimed at stranding fossil assets. We exploit the fact that the proposal underwent three stages. It started as a "climate levy" increasing the CO_2 price for power plants older than 20 years and was subsequently turned into a compensation mechanism paying individual lignite-fired power plants for phasing out. In the third stage, the adoption of the compensation scheme was challenged based on the possibility that it may violate EU state aid rules. We test the effects of news about the different stages of the policy proposal on the German utility companies. We find no significant reactions to the first and second stages, but a significant and negative reaction to the third stage for RWE and E.ON.

Our results suggest that compensation mechanisms are expected and thus priced in the valuation of firms ex-ante. This finding implies that investors do care about stranded asset risk, but because of the expectation of compensation, they do not believe that they will be financially affected – neither by general unburnable carbon risk nor due to specific policy proposals implying the stranding of assets. Only the challenge to the compensation changes their beliefs. Our results imply that the effect of such policy announcements can be substantial. Our most conservative estimates for 5-days CARs imply a loss over 20%.

Stranded asset risk is relevant for the energy sector and beyond. Most fossil energy assets are long-lived; they usually require a large initial investment, but have relatively low operating costs. S. J. Davis and Socolow (2014) show that expected future cumulative emissions from the existing infrastructure of the global power sector have increased dramatically in the last decades. Such long-term investments have the potential to "lock in" carbon-intensive technologies for a long period of time (Erickson et al. 2015).[42] Calculations by IEA (2013) and Pfeiffer et al. (2016) conclude that the "2 degree capital stock" will already be reached in 2017. Investments in fossil capacities after 2017 are inefficient: they lead to "both larger carbon lock-ins and higher short-term emissions that need to be compensated by deeper emissions cuts in the long run" (IPCC 2014a), increasing the cost of climate change mitigation. Moreover, in order to achieve emission cuts in such a scenario, fossil assets need to be stranded. IEA (2013) provides a conservative estimate that the energy industry faces sunk costs of $\$$ 120 billion due to fossil fuel plants being retired early, even if action to achieve the 2°C goal had started in 2012. For a scenario of delaying climate action until 2030 (and using a different methodology), IRENA (2017a) estimates stranded assets of $\$$ 1.9 trillion in electricity generation, and an additional $\$$ 7 trillion in upstream energy infrastructure (mostly oil production). This is approximately equivalent to 3.5$\%$ of global income, and implies a risk not just for the obviously affected energy industry facing sunk costs: international organizations, financial institutions and regulators are increasingly concerned about the "transition risk" of climate policy, especially about a sudden re-pricing of assets.[43]

A sudden devaluation of energy companies will occur only if expectations were not adjusted in accordance with the risk of asset stranding. Sudden changes in the stringency of carbon policies, or expectations in the presence of tipping points can lead to abrupt repricing of fossil fuel assets. Given energy companies' size and interrelation with the rest of the economy, policymakers may regard energy companies as "too big to fail." For this and other political economy reasons,[44] policymakers may opt for compensation policies, and investors may

[42] Also see Unruh and Carrillo-Hermosilla (2006), Seto et al. (2016), and Unruh (2000, 2002).
[43] Cf., e.g., European Systemic Risk Board (2016a), Caldecott et al. (2016), IRENA (2017b), Batten et al. (2016), Banque de France (2015), and Baron and Fischer (2015). Also, see Johnson et al. (2015), Rozenberg et al. (2015), and Iyer et al. (2015) for the estimates of long-term energy- and economic-costs of the 2°C goal.
[44] See Jenkins (2014), Manley et al. (2016), Healy and Barry (2017), and Caldecott et al. (2017) for an overview of political economy constraints on climate policy.

expect them to do so. Compensations, then, are almost a self-fulfilling prophecy: if they are expected, they will be necessary in order to avoid larger shocks.[45] Therefore, understanding the interaction between policy making and investors' expectations is essential for the design of climate policies. Our results suggest that early and credible commitment to climate policies and whether they involve compensation payments or not is crucial. Such clear signals to financial markets can avoid a disruptive and unorderly energy transition and macro shocks, while directing capital towards climate-friendly technologies. We believe that further research in similar contexts can help to generalize these results, or to identify the important factors in the formation of expectations regarding climate related risks.

[45] Batten et al. (2016) use a similar argument referring to the potential time inconsistency of government policies in the context of stranded assets. They do not consider compensations, however, but only distinguish between a "low carbon equilibrium" and a "high carbon equilibrium."

2 Institutional Investors, Climate Policy Risk, and Directed Innovation

2.1 Introduction

The tightening of climate policies may cause technologies related to fossil fuel use to lose value compared to "green" technologies. (Future) climate policy then entails a "technological risk" for firms whose business model relies on fossil-based knowledge. This risk translates into a risk for investors. According to a recent survey, 75% of institutional investors – i.e. organizations that invest on behalf of their members or clients – consider technological risk to be a financial risk already today or within the next five years (Krueger et al. 2020). With large and increasing shares of worldwide equity under management, institutional investors will have an important role to play in the transition to a green economy. Due to their size, they can use voting power and direct conversations with management to affect firm-level outcomes. Building on evidence that institutional investors have an impact on firm-level innovation (Aghion et al. 2013) as well as environmental, social and governance (ESG) scores (Dyck et al. 2019; Dimson et al. 2015) and CO_2 emissions (Azar et al. 2020), this paper aims to find out whether institutional investors mitigate technological risk by influencing the direction of innovation in firms.

Institutional investors are playing an increasingly large role in financial markets, holding on average 40% of the equity of the firms in this paper's sample. More importantly still, a large number of institutional investors have voiced concern about climate risk. Typically, climate risk is understood as an aggregate of two types of risk: *physical risk* from climate change itself (see, e.g., Dietz et al. 2016), and *transition risk* (sometimes also called *regulatory risk*) due to stricter climate policies affecting asset values (McGlade and Ekins 2015; Battiston et al. 2017; Batten et al. 2016). Institutional investors are reported to be particularly concerned about transition risk, and many institutional investors have signed initiatives such as the "United Nations Principles for Responsible Investment" (UN PRI) or "Climate Action 100+", committing to (climate) responsible investment. This paper focuses on a particular case of transition risk: the risk that technologies related to fossil fuel use lose value due to climate policies. Car manufacturers, for instance, will meet climate policy goals less by reducing own emissions, but by changing the type of technology they sell.

The financial sector has traditionally not been equipped for dealing with uncertainties due to climate change or climate policy: models for risk management in portfolios are based on past, quantifiable risks and are not designed to reflect future uncertainties (Battiston et al. 2019; Silver 2016).[1] Using data for 2015, Battiston et al. (2017) have shown how institutional investors are still exposed to firms and sectors which face a high transition risk. They also demonstrate how the financial system, due to second-round effects from indirect holdings adding to the first-round effects, would get under stress in case of a strict climate policy scenario. This appears to reflect a very limited success of initiatives for sustainable investment.

However, institutional investors can choose different strategies to act (climate) responsibly, of which portfolio adjustment plays a minor role. In a survey among international institutional investors on climate risk, 84% of respondents reported that they had taken climate-related engagement actions in the last five years – compared to 29% attempting to reduce carbon footprints through portfolio shifts (Krueger et al. 2020). Engagement can take various forms: the most visible channel is proxy voting in shareholder meetings. Analysts have noted that institutional investors are increasingly voting in favor of climate-related shareholder proposals, although there is quite some heterogeneity between them (Berridge and Nurjadin 2020). However, less visible channels also play a role: engagement can take place "via letters, emails, telephone conversations, and direct conversations with senior management" (Dimson et al. 2015). The actual influence of institutional investors can work via different mechanisms. They can use public pressure, threaten to divest, vote against proposals in shareholder meetings, or vote against re-election of managers. In a more positive sense, they can also back managers who initiate changes which only pay back later. With success measured by changes implemented after the engagement activities, such activities in the field of ESG themes have been shown to be effective and to create positive stock market reactions (Dimson et al. 2015; Dyck et al. 2019; Nguyen et al. 2020).

The relationship between the investor and the firm is that between a principal and an agent. In equity markets, agency problems between managers and shareholders have traditionally been

[1] Risk and uncertainties in the context of climate change damages as well as climate policy are discussed in the literature on climate and energy economics, see e.g. Crost and Traeger (2014), Rudik (2020), Sinn (2008), Fried et al. (2020), Wesseler and Zhao (2019), Pommeret and Schubert (2018), Barradale (2014), Yang et al. (2008), Torani et al. (2016), and IEA (2007).

a concern due to the disperson of ownership. The increasing number and size of institutional investors have changed this relationship (Bebchuk et al. 2017). In the case of climate transition risk, it is not a priori clear whether the principal or the agent should have a stronger incentive to become active. Essentially, it can be seen as a question of the time horizon (and the ability to deal with uncertainty) of managers vs. investors. The available literature suggests that managers of listed firms tend to be driven by short-term performance goals; institutional owners can back them with a long-term commitment, allowing to take risks in the short term for a more profitable future (Dimson et al. 2015; Aghion et al. 2013; Bushee 1998). This is relevant in the context of R&D and technological change.

This paper uses firm-level panel data to test for the influence of institutional ownership on the direction of innovation. The main data source is the Orbis database. It includes yearly information on the shares of each owner in total market capitalization and distinguishes between different investor types. This allows to calculate the share of total institutional ownership per firm and year, or shares of different investor types. For instance, signatories of the UN PRI or investors with a long time horizon (e.g. pension funds) would be expected to have a larger interest in future climate risks than the average institutional investor. Further firm-year specific control variables are also sourced from Orbis, as well as other data suppliers.

Data on patents comes from the Orbis Intellectual Property (Orbis IP) database and can be directly linked to firms. This paper classifies patents into *green* and *fossil* categories, based on their technological classification codes, applying a modified classification based on Dechezleprêtre et al. (2017). It then separately looks at the influence of institutional ownership on green and fossil patenting to draw conclusions on investors' preferences regarding the direction of innovation. Patents are a useful measure when discussing the (potentially) long-term horizon of institutional investors: they are the result of lengthy R&D efforts which bear fruit in the future. When successful, they grant the exclusive right to use an invention (in the jurisdiction of the patent office). Information on patents is publicly available. In particular, typical investor newsfeeds include information on patent applications and grants.[2] Moreover, institutional ownership has been shown to increase patenting activities (Aghion et al. 2013).

[2] Kogan et al. (2017) have recently used the attention of financial markets to patent grant events to derive a measure for patent values.

Studying green and fossil patents as an outcome variable of owners' engagement offers the advantage of being more clearly about climate issues than aggregate ESG scores.[3] Moreover, patents are rarely discussed in the broader media. This makes them an ideal measure to study institutional investors' motives beyond reputational issues, which are often the underlying concern behind ESG "risks". At the same time, the use of patents allows for more middle ground than approaches that divide firms into "clean" and "dirty" ones. Based on their innovation activities, companies can be *green* and *fossil* at the same time; they can also gradually shift their activities over time. This kind of gradual pattern fits with those institutional investors that use engagement rather than divestment.

To account for the count property of patent data and the path dependency of innovation, I use a dynamic count data model in the spirit of Aghion et al. (2016), where patenting depends on previous knowledge, knowledge spillovers, and R&D efforts. The share of institutional ownership is added as an additional explanatory variable. The model includes firm fixed effects using the pre-sample mean method (Blundell et al. 1999). To control for patent quality, I focus on patents filed at one of the main patenting offices (EU, US, Japan) which are ultimately granted. To account for potential bias through endogenous selection of investors, I apply a control function approach. A firm's institutional ownership share is instrumented by the inclusion of the firm in a large stock index.

Tracking more than 1,200 firms worldwide over the years 2009-2018, I find no evidence for investors' engagement for directed innovation. Overall, the number of patent applications increases with more institutional ownership. However, when looking at patents classified as green or fossil, no effect can be detected. This is true for more disaggregate measures of innovation (such as green/fossil transport and energy, respectively) and for more disaggregate types of investors (e.g. signatories of the UN PRI or pension funds). There is a positive association between climate-related opportunities mentioned in investor conference calls and subsequent green patenting; it is difficult, however, to ascertain that this effect is causal. If institutional investors try to influence firms to become less susceptible to climate risk, then these efforts are not (yet) detectable in the innovation activities of firms.

[3] Berg et al. (2019) show how the different methodologies of measuring and combining different issues in ESG scores by different providers leads to very heterogeneous scores within the same firm, giving rise to "aggregate confusion".

Related literature This paper contributes to the literature on institutional investors and environmental concerns. Dyck et al. (2019) and Gibson and Krueger (2017) find that institutional investors improve firms' environmental and social performance; they do not look at climate policy risk specifically, though. Azar et al. (2020) show that firms tend to reduce their carbon emissions when the ownership share of the "Big Three" index funds (BlackRock, Vanguard, State Street) increases, consistent with data on these firms' engagement activities. Krueger et al. (2020) report survey results showing that institutional investors are concerned with climate risk, in particular regulatory risk; and that one of their preferred modes of action is engagement. Sautner et al. (2020b) use transcripts of investor conference calls to develop a measure for firm-level exposure to climate risk, thus making use of statements by managers as well as investors' concerns. The paper at hand tests whether these stated concerns and actions yield results in the technological sphere, using innovation activities as revealed engagement outcomes. In this context, the paper draws on previous work on institutional investors and innovation (Aghion et al. 2013; Borochin et al. 2020; Jiang and Yuan 2018; Rong et al. 2017; Bushee 1998). It is also related to the literature on ownership structure and financing innovation (Bernstein 2015; Chemmanur et al. 2014; Atanassov 2013; Lerner et al. 2011; Kerr and Nanda 2015; Hall and Lerner 2010; Munari et al. 2010).[4]

It also connects with the literature on environmental policy and green innovation. Theoretical work on climate policy and green innovation is mostly concerned with positive spillovers from green innovation, path dependencies, and their interaction with climate policies (Acemoglu et al. 2012; Fried 2018; Bretschger and Schaefer 2017; Di Maria and Smulders 2017; Lambertini et al. 2017). Empirical studies confirm the relevance of knowledge spillovers in the context of clean technologies (Dechezleprêtre et al. 2017; Verdolini and Bosetti 2017; Verdolini and Galeotti 2011; Lanzi et al. 2011) and for overall innovation (Peri 2005), with heterogeneity between sectors. Although path dependencies and spillovers are not the main focus of this paper, these considerations have inspired the path-dependency model used in this paper's empirical estimations. In the empirical literature on policy impacts, several studies find a positive effect of climate policies on green innovation (Kiso 2019; Calel and Dechezleprêtre 2016; Aghion et al. 2016; Nesta et al. 2014). This paper is methodologically closely related to

[4] There is also a literature on "overlapping ownership" (also *cross-ownership* or *common ownership*), referring to the fact that the same institutional investors tend to own shares in all or most of an industry's competitors. Overlapping ownership may affect competition (Vives 2020; He and Huang 2017; Borochin et al. 2020), also via R&D spillovers (López and Vives 2019). This effect, or the generally established link between innovation and competition (Aghion et al. 2005; Dasgupta and Stiglitz 1980), is not the focus of this paper.

Aghion et al. (2016). It is the first to link the direction of innovation to institutional investors' engagement activities.

The paper further contributes to the field of climate transition risk and financial markets. Central banks and other financial institutions have voiced concerns that these risks may not be adequately priced in yet in financial markets. Following an unexpected tightening of policies or sudden changes in expectations, the re-pricing might occur suddenly and with implications for financial stability (van der Ploeg and Rezai 2020; Monasterolo 2020; Batten et al. 2016; European Systemic Risk Board 2016b). There is some empirical evidence that stock market investors are aware of these risks and price them in when they receive new information about regulation (Sen and von Schickfus 2020; Carattini and Sen 2019; Griffin et al. 2015; Ramiah et al. 2013). Especially the election of Donald Trump and the conclusion of the Paris Agreement have been used as events which changed policy expectations (Kruse, Mohnen, and Sato 2020; Monasterolo and de Angelis 2020; Ramelli et al. 2019; Mukanjari and T. Sterner 2018).

However, the mentioned event studies focus on immediate stock market reactions, excluding the engagement channel; moreover, firms are mostly selected as being "fossil" or not, leaving no ground for gradual change within firms. A notable exception is Kruse, Mohnen, Pope, et al. (2020), who use data on firms' green revenues and find that firms providing more environmental goods and services have, on average, a higher market valuation (measured by Tobin's q). Other strands of literature look at regulatory risk and the pricing of bank loans and corporate bonds (Seltzer et al. 2020; Delis et al. 2019), and at the exposure of interconnected financial markets to climate risk (Battiston et al. 2017). This paper is the first to examine technological transition risk, and to focus on institutional investors.

The remainder of the paper is organized as follows: Section 2.2 provides some background on patents and patent data characteristics. The methodological approach is presented in section 2.3, and section 2.4 describes the data sources and the construction of the dataset. Section 2.5 presents and discusses the results. Section 2.6 concludes.

2.2 Patents: background and classification

This section describes relevant patent data characteristics and how to classify patents by technology. Section 2.4 gives details on the data sources and provides summary statistics.

Patents protect intellectual property rights: Individuals and firms apply for patenting in order to receive the exclusive right to use their invention. An example of a patent (its first page) can be found in Figure B.1 in Appendix B.1. Patent applications are examined by patent office examiners, whose task is to ensure that only novel innovations are protected. Patents are often applied for at several patent offices to ensure protection in the relevant markets. All patent applications with the same content at different offices are referred to as one "patent family". Patents also cite other patents, i.e. previous knowledge; they are themselves cited by other patents (forward citations).

Applications, examinations and generating citations all takes time. Table 2.1 shows the development of numbers for different patent measures in this paper's sample over time. Due to the nature of the patenting process, the number of patent applications in the data appears to decrease in recent years (see the column "Patents"): the closer we are to today, the fewer patent applications have actually been published and are available in the data - although it is very likely that applications have been filed.[5]

Table 2.1 : Mean number of patents, family size and citations over time

Year	Patents	Family size	Citations
2010	109.68	399.60	281.11
2011	109.02	389.46	273.82
2012	119.81	413.71	273.22
2013	116.61	390.00	197.16
2014	106.75	345.31	148.77
2015	107.25	320.00	124.30
2016	75.05	205.93	77.61
2017	51.10	120.74	28.39
2018	24.28	49.24	4.45
Average	89.93	287.35	150.85

Notes: Numbers are shown for patents (all technology types) applied for in the given year. Patent numbers are based on a sample of publicly listed firms which filed at least one patent classified as green or fossil in the sample period. Due to the lagged structure of the estimation, the sample period for patents is 2010-2018.

Like previous work on green innovation, this paper exploits the fact that examiners classify patents by technological field. There are two main classification schemes: The International Patent Classification (IPC) and the Cooperative Patent Classification (CPC). The latter is the result of efforts of the European Patent Office (EPO) and the US Patent Office (USPTO) to harmonize their systems. Each patent is usually assigned several technology classes. Within

[5] Table B.5 shows the development of the counts over time separately for patents classified as green and fossil.

the CPC, a special Y category has been introduced to mark climate-friendly innovations. This is helpful, but not sufficient, to identify in particular fossil-based patents.

To classify patents as *green* and *fossil*, I use a slightly modified version of the classification by Dechezleprêtre et al. (2017) into clean and dirty patents.[6] Examples for fossil transport categories are F02F, *Cylinders, pistons, or casing for combustion engines; arrangements of sealings in combustion engines*, or F02N, *Starting of combustion engines*. Green transport includes, for instance, B60K 1, *Arrangement or mounting of electrical propulsion units*, or B60L 8, *Electric propulsion with power supply from force of nature, e.g. sun, wind*. For energy, corresponding categories would be Y02E 10 (*Energy generation through renewable energy sources*) and F23 (*Combustion apparatus; combustion processes*).

In reality, it is sometimes hard to identify climate-friendly innovation. For instance, there are inventions that make the use of fossil fuels more efficient and reduce emissions (Lanzi et al. 2011). Following Dechezleprêtre et al. (2017), I introduce a third category (in robustness checks): *grey* patents. Most of these technologies make combustion (in engines or power plants) more efficient, and they are thus a subset of the fossil technologies. In the case of energy, the *grey* category also includes the production of fuels of non-fossil origin, e.g. biofuels. However, all of these technologies have only limited potential to address technological risk, which is mainly about the phase-out of fossil-based technologies. Improving existing technologies at the margin may be successful in the short and medium run, but does not help on the way to new, carbon-free systems. An overview of the classifications for transport and energy-related patents can be found in Tables B.1 and B.2 in Appendix B.1.

The literature agrees that plain patent counts are a very imprecise measure, since patent quality (or value) is highly skewed (see Aghion et al. 2013, for example). It is therefore important to account for patent quality. As a first step, I filter patents based on the offices where they were filed. Only patents applied for at the US, EU, or Japanese patent office are considered. In a second step, patents were filtered to only include granted patents.

In robustness checks, family size and citations are used instead of patent counts. Family size measures the number of patent offices where the patent has been applied for: it is a measure

[6] I am using the term *fossil* instead of *dirty* due to the focus on climate change and climate risk: CO_2, the result of burning fossil fuels, is not a pollutant, but a greenhouse gas. Climate risk affects fossil-based technologies, but does not affect all "dirty" technologies with any environmental externalities. In the same vein, not all technologies replacing fossil fuels are automatically "clean" (biomass-fired power plants, for instance, do contribute to air pollution). The term *green* is therefore used to describe technologies which replace fossil-based technologies.

for the importance the inventor attaches herself to the patent. If the inventor considers the invention to be of high value, she will opt to protect (and use) it in many jurisdictions. Protection at several offices incurs direct and administrative costs, so we can assume that it is a conscious decision of the inventing firm to increase a patent's family size. Citations, on the other hand, are a measure for the relevance that others attach to the patent: if the invention is cited by other patents, it is sufficiently novel and relevant to spur further innovation. Citations can be regarded as a measure for the scientific value of a patent; family size is closer to the commercial value of the patent.

The censoring issue discussed above is also relevant for the choice of patent measure. As Table 2.1 shows, the downward trend over time is particularly pronounced for citation counts. This is not surprising: citations accumulate over time, and patents applied for in 2018 did not have much time to collect citations. It is generally possible to take care of this issue by using year fixed effects. With count data, however, the amount of zeroes can become quite large towards the end of the sample, impeding estimations. Family size also decreases faster over time than plain patent counts - the process of applying for protection at different patent offices takes time as well, and this lag may differ between technologies and sectors. For this reason, the standard patent measure used in this paper is the patent count. Family size and citations are included as a robustness check.

2.3 Empirical approach

2.3.1 Path dependency model

The question of this paper is: do institutional investors influence green and/or fossil patenting, and if yes, in a different way? I therefore test for the impact of the ownership share of institutional investors on green and fossil patenting. The idea for the econometric specification is inspired by the dynamic path-dependency model by Aghion et al. (2016). In such a model, the amount of patenting depends on the firm's own stock of patents; on innovation spillovers from other firms in the country; and on R&D investments. Since most of the path-dependent explanatory variables can be derived for green and fossil patent classifications, the model can be used to separately assess the impact of institutional ownership on green and fossil patenting. In the following, the subscripts G and F are used to refer to green and fossil patents, respectively. For the exposition, green patents are used as the default example for the dependent variable.[7]

Following the literature standard, a Poisson specification is used to account for the count nature of the dependent variable. The model including institutional ownership reads

$$\begin{aligned} PAT_{G,it} = \exp(&\alpha_G + \beta_{G,IO} IO_{it-1} + \beta_{G,1} \ln K_{G,it-1} + \beta_{G,2} \ln K_{F,it-1} \\ &+ \beta_{G,3} \ln SPILL_{G,it-1} + \beta_{G,4} \ln SPILL_{F,it-1} \\ &+ \beta_{G,5} R\&D_{it-1} + \tau_{G,t} + \eta_{G,i} + \epsilon_{G,it}), \end{aligned} \tag{2.1}$$

where

- $PAT_{G,it}$ is the count of green patents applied for by firm i in year t;
- IO_{it} is the percentage of institutional ownership in firm i in year $t-1$;
- $K_{G,it-1}$ is the firm's pre-period green patent stock;
- $K_{F,it-1}$ is the firm's pre-period fossil patent stock;
- $SPILL_{G,it-1}$ are country-level green spillovers to firm i in period $t-1$;
- $SPILL_{F,it-1}$ are country-level fossil spillovers to firm i in period $t-1$;
- $R\&D_{it-1}$ are R&D expenditures of firm i in year $t-1$;
- $\tau_{G,t}$ is a year fixed effect;
- $\eta_{G,i}$ is a firm fixed effect; and
- $\epsilon_{G,it}$ is an error term.

Institutional ownership is a continuous variable reflecting the relative quantity of institutional ownership compared to other owners. The literature on institutional owners suggests that this quantity makes a qualitative difference: (Many) large investors have more (joint) influence in proxy votes, conference calls, etc.

[7] Further categories are possible, such as green transport patents, grey patents, or total patents; these are introduced later in the text.

Essentially, the idea of Equation 2.1 is to single out the influence of institutional ownership while controlling for already existing knowledge stocks (due to own patenting and spillovers) and the inherent path dependency. Previous own knowledge on green technologies, $K_{G,it-1}$ can explain further innovative activities in this direction. $SPILL_{G,it-1}$ are country-level green innovation spillovers, based on the assumption that an environment of domestic firms with knowledge on green technologies is conducive to each firm's innovation in this direction. Following Aghion et al. (2016), previous knowledge on fossil technologies and fossil spillovers are also included ($K_{F,it-1}$, $SPILL_{F,it-1}$). This specification is derived from the observation that many firms with a track record in fossil innovation become active in green innovation: the technologies are used to serve similar markets, e.g. in the car industry. The construction of knowledge stocks and spillovers is discussed in detail in section 2.4.

However, patents of course are not generated simply out of previously existing patents. Research and Development is a further obvious part of the firm's production function of patents (see also Hall et al. 2005). The inclusion of R&D is particularly useful in the context of this paper's research question. R&D expenditure controls for the overall R&D efforts, so any change in green or fossil patents we observe can be more clearly interpreted as a directional change, as opposed to a pure increase.[8] In addition, investors may observe R&D efforts and select into firms with higher R&D expenditures, expecting larger innovation output; this would cause an omitted variable bias and an overestimation of investors' influence.

In robustness checks, two more control variables are used: Tobin's q and firm-specific climate exposure (see section 2.3.5 for details). One might think of other firm-specific variables that are associated with innovation, like financing constraints or firm size. Including measures for tangibility, leverage, operating revenue, capital-labor ratio, or profits did not significantly alter the outcome, so the corresponding results are not included in this paper.

[8] Contrary to e.g. Aghion et al. (2013) and Hall et al. (2005), this paper uses yearly R&D spendings instead of R&D stocks. There are two main reasons for this choice. First, the specification in equation 2.1 already accounts for knowledge stocks, measured by patents. The additional value of the R&D variable (which does not appear in the, otherwise very similar, specification of Aghion et al. 2016) lies in capturing additional innovation efforts which are on top of, and separate from, existing knowledge stocks. The second reason is a data concern. Many firms in the sample have incomplete R&D time series, making the construction of R&D stocks difficult and error-prone. Sticking with yearly expenditures - and excluding missing firm-years from the analysis - is thus the safer variant. Test regressions (not shown) were run using R&D stocks, without significantly affecting results.

2.3.2 Firm fixed effects

Equations 2.1 and 2.3 include firm-level fixed effects: Unobserved heterogeneity between firms needs to be controlled for. In Poisson estimations, the standard approach is to use the conditional fixed effects estimator proposed by Hausman et al. (1984). Put simply, it conditions on the sample average of the observable variables. The conditional fixed effects estimator requires strict exogeneity of the explanatory variables. This assumption is violated in a dynamic panel data model such as Equation 2.1, which exhibits serial correlation between innovation stock measures.

Therefore, an alternative approach to modelling firm fixed effects is used: the pre-sample mean estimator proposed by Blundell et al. (1999) (BGVR), which has been used in the environmental context e.g. in Nesta et al. (2014). The idea is to condition on the pre-sample mean of the dependent variable to proxy out the fixed effect. This approach is particularly well suited to patent data, because patent data is typically available in pre-sample years. Blundell et al. (2002) show that this estimator leads to some bias, but increasing the number of pre-sample periods (and, to a lesser extent, the number of in-sample periods and the number of observation units) improves performance. The pre-sample mean enters the estimation in logged form.

For the research question at hand, the choice of pre-sample periods means dealing with a trade-off: more pre-sample information is generally desirable, but green technologies are a relatively "young" phenomenon. Pre-sample averages of green patenting going back a long time may not be useful to reflect current firm characteristics regarding green innovation.[9] In this analysis, the pre-sample average for the years 1995-2008 is used. This is a reasonable amount of years and at the same time, years with measurable patenting activity in both green and fossil areas are covered.[10]

2.3.3 Selection issues and control function

One concern when estimating Equation 2.1 is the selection of investors into firms. The coefficient on institutional ownership share may be biased if investors select into firms with

[9] Aghion et al. (2016), who have a sample covering the years 1986 to 2005, argue against the use of the BGVR method for this reason: green patenting in the early 1980s was not a good indicator for green patenting in the early 2000s.
[10] In a robustness check (not shown), the average for the years 2000-2008 was used, since the data show higher green patenting activity after 2000. The estimation results are virtually the same.

more expected green (or more fossil) innovation. Most investors use a combination of strategies to deal with climate risk; so it is possible that some investors select the most promising green-innovation firms, others try to encourage green innovation, and others do both.

I therefore use a source of exogenous variation in institutional ownership: The inclusion of a firm in a large stock index. It has been widely used as an instrument for institutional ownership (Aghion et al. 2013; Crane et al. 2016; Appel et al. 2016). The idea is that many institutional investors either directly track such indices, or their managers are benchmarked against them. Therefore the instrument is expected to be correlated with institutional ownership. For it to fulfill the exclusion restriction, I need to rule out a relationship between pre-period index membership on this year's (green / fossil / total) patenting, controlling for observables. It is therefore helpful to understand the selection of index members.

Index membership is decided on by Index Committees; none of their criteria explicitly mention innovation. One of the main criteria for inclusion in a large stock index is market capitalization. Also, firms need to fulfil basic eligibility criteria to be added to an index, such as certain thresholds for free-float market capitalization and earnings in the quarters prior to index admission. There may be a concern that a firm's market value increases in expectation of future patenting, and this leads to admission to the index. All estimations control for R&D expenditures and thus for the observable part of innovation activities that may result in patents. I also show in Table B.12 that Tobin's q, a measure for above-fundamental market valuation, is not a significant predictor of innovation. In the first-stage regressions, the coefficient of Tobin's q is insignificant as well, implying that this measure of market valuation does not affect institutional ownership, controlling for other observables. It has also been shown that markets price in most of the value of patents at a later stage: when a patent is granted (Kogan et al. 2017).[11]

Moreover, Index Committees do not simply decide based on fixed criteria. For instance, it is the explicit goal of the S&P 500 Index to be representative of the US economy in terms of sector coverage. Also, if a current index member does not fulfil the eligibility criteria any more, this does not automatically lead to exclusion. Index managers are interested in a stable

[11] Considering the eligibility criteria, the relationship between high free-float (with, e.g., low family or management ownership) and innovation is not a priori clear, and the evidence on family or management ownership and innovation is mixed (Munari et al. 2010; Schmid et al. 2014; Beyer et al. 2012; Ortega-Argilés et al. 2005). Looking at earnings, it is difficult to think of a reason why higher earnings would be followed by patent filings, given that the required R&D expenditures reduce earnings.

composition of the index. This discretion provides another source of variation that is not related to other firm variables.

I define the instrument $indexmember_{it}$ as a dummy equal to one if a firm was a member of the S&P 500, the STOXX Europe 600 and/or the S&P Global 1200 index in year t. These indices cover a wide range of countries, while still being exclusive enough to have explanatory power. Given the nonlinear model, the instrument enters the estimation in a control function approach (Wooldridge 2010). In the first stage (OLS), institutional ownership is regressed on the instrument and all control variables of the second stage. The residuals from this estimation - i.e., the part of institutional investors' ownership that cannot be explained by the instrument - are then included as a control variable in the second-stage regression. As a result, the coefficient on IO_{it} reflects the effect of the part of institutional ownership that is due to the index membership of the firm.

2.3.4 Heterogeneity of sectors and institutional owners

The measurement of green and fossil patents is noisy. Some of the noise can be addressed by differentiating between sectors. The transport and the energy sector are quite different, and it is well possible that innovation and patents play a different role in the two sectors. For capital-heavy energy firms, their fossil fuel reserves or power generating infrastructure are important assets which are directly affected by climate policy, whereas intangible assets such as patents are likely to play a smaller role. In the transport industry, by contrast, knowledge and innovation are relatively more important.

In separate regressions, Equation 2.1 is modified accordingly to reflect green/fossil transport and energy patents separately. The estimated equation for green transport patents, denoted by GT, thus reads

$$
\begin{aligned}
PAT_{GT,it} = \exp(&\alpha_G T + \beta_{GT,IO} IO_{it-1} + \beta_{GT,1} \ln K_{GT,it-1} + \beta_{GT,2} \ln K_{FT,it-1} \\
&+ \beta_{GT,3} \ln SPILL_{GT,it-1} + \beta_{GT,4} \ln SPILL_{FT,it-1} \\
&+ \beta_{GT,3} R\&D_{it-1} + \tau_{GT,t} + \eta_{GT,i} + \epsilon_{GT,it}).
\end{aligned} \tag{2.2}
$$

Models for fossil transport and green/fossil energy patents can be derived analogously.

Similarly, there is noise in the measurement of institutional ownership: there are many different types of institutional investors, and they may have quite different investment/ engagement strategies, time horizons, or environmental concerns. One way to deal with the noise is to look at these different types specifically. The literature on institutional owners' engagement suggests some time-invariant types which are expected to have long-term investment strategies (Hsu and Liang 2017; Borochin et al. 2020). Insurance companies and pension funds are prime examples. Government ownership is also typically long-term and stable; state-owned enterprises have been shown to perform better environmentally. Moreover, domestic investors (sharing the portfolio firm's headquarter country) may have better opportunities to engage.

In the context of sustainable finance, it is also possible to exploit a time-varying investor type, namely signatories of the UN Principles for Responsible Investment (UN PRI) initiative (see also Dyck et al. 2019). Principle 2, for instance, reads: "We will be active owners and incorporate ESG issues into our ownership policies and practices."[12] The UN PRI sees itself as "the world's leading proponent of responsible investment". The initiative was launched in 2006 and currently has more than 3,000 signatories. With their membership, investors declare their willingness to implement the six principles.

In the literature on institutional investors, the role of engagement has been very prominently discussed in the context of the big passive index funds. Instead of actively managing funds, these hold relatively fixed positions as they are mirroring certain stock indices. This means they cannot easily sell their positions, and some argue that this limits their shareholder power. On the other hand, they have an incentive to use engagement, since this is the only way they can manage risk. A growing literature shows how the big indexers use their voting power in director (re-)elections and other governance choices (Fichtner et al. 2017; Appel et al. 2016), support activists (Appel et al. 2018), and have an influence on firms' emission reductions. In this light, direct engagement activities with management seem to be a successful strategy even, or particularly, for big "passive" investors. Therefore, the "Big Three" index fund investment companies (BlackRock, Vanguard, and State Street) are defined as another investor type.

To account for investor type heterogeneity, the variable IO from Equation 2.1 can be replaced by specific sub-groups of institutional owners: government (GOV), insurance and pension

[12] Stated on the PRI website, see `https://www.unpri.org/pri`.

funds (INP), domestic owners (DOM), signatories of the UN Principles for Responsible Investment (UN PRI) initiative (PRI), and "Big Three" investment companies ($BIG3$).[13]

2.3.5 Informational value of nonsignificant results

As will be shown in detail in section 2.5 on Results, I do not find a statistically significant effect of institutional ownership on green or fossil innovation. I therefore conducted some additional estimations, which are not robustness checks in the typical sense. The usual robustness checks aim to rule out a type I error, i.e., falsely rejecting the null hypothesis. The additional estimations presented here are rather attempts to rule out a type II error: failure to reject the null despite an actually existing relationship. Abadie (2020) argues that insignificant estimates can be highly informative: it is interesting to learn that a previously expected relationship does not exist. The question is whether insignificant estimates are meaningful, i.e. can be interpreted as "no effect". Type II errors are most likely to result from data quality or research design issues. The two specifications presented in the following aim to answer the question whether research design or data quality are a concern.[14]

Institutional ownership and total innovation A first check concerns the overall setup of the model, and the sufficiency of data variation in the institutional ownership variable. The relationship between institutional ownership and patenting is an established result (Aghion et al. 2013). If the data and model used here cannot confirm this result, the research design and / or the measurement of the institutional ownership would need to be re-examined. Equation 2.3 tests whether institutional ownership affects total innovation (denoted by A):

$$\begin{aligned} PAT_{A,it} = &\exp(\alpha_G + \beta_{A,IO} IO_{it-1} + \beta_{A,1} \ln K_{A,it-1} + \beta_{A,2} \ln SPILL_{A,it-1} \\ &+ \beta_{A,3} R\&D_{it-1} + \tau_{A,t} + \eta_{A,i} + \epsilon_{A,it}). \end{aligned} \tag{2.3}$$

In this case, previous own knowledge and spillovers in terms of all technologies are included as explanatory variables. In a robustness check, Tobin's q is also included. Tobin's q is defined as $(marketcapitalization + totaldebt)/totalassets$ and is therefore a measure of the market's future expectations deviating from current fundamentals. As argued in Aghion et al. (2013),

[13] Further investor type definitions are possible (see section B.2), but are less likely to be relevant in a climate context, and their results are not shown in the paper.
[14] In addition, section 2.5.1 provides results for some specification alterations that also partly address this question. Section 2.6 provides a general discussion of the plausibility of the results.

the market valuation of firms may be an omitted variable in a regression involving institutional ownership and innovation. It is correlated with the number of patents and could be correlated with institutional ownership, since institutional owners are more likely to invest in firms with high market valuation.

Firm-specific climate concerns: "climate exposure" The second approach addresses the question whether there is sufficient statistical power in the dependent variable(s), i.e. in the counts of green and fossil patents; it also addresses the question whether the degree to which firms are affected by climate issues play a role in explaining innovation. The degree to which firms are affected by, or concerned about, climate issues varies between firms and over time. Previous research has shown that firms facing higher fuel taxes tend to patent more in green technologies, and less in fossil technologies (Aghion et al. 2016). It is logical to test whether the panel used in this paper can confirm the relationship between firm-level climate policy impacts and the direction of innovation.

In the context of the research question on institutional ownership and risk from future climate policies, a newly developed measure is particularly useful: "climate exposure", an indicator derived from conference calls between managers and investors. This indicator, developed by Sautner et al. (2020b), measures the relative frequency with which climate-related issues are mentioned in these conference calls.

As climate-related issues can be quite broad and diverse, four different sets of bigrams (expressions) are used: one for broadly defined climate change aspects ("climate change exposure" or "exposure to a climate change-related shock"), and three for more specific topics. These are physical, regulatory, and opportunity shocks, relating to physical climate change-induced events (such as heatwaves or sea-level rise), regulatory changes (such as CO_2 pricing), and opportunities (capturing opportunities related to climate change issues, mostly green technologies). Since physical shocks are unlikely to influence green or fossil patenting (the patent classifications do not include technologies for adaptation to climate change), the measures used in this paper are "climate change exposure", "regulatory exposure", and "opportunity exposure". Table 2.2 shows the top 10 bigrams contributing to general climate exposure, regulatory exposure, and opportunity exposure, respectively.

To interpret the exposure measures, it is helpful to think of them as "firm-level exposure to a particular shock", where the shock can be positive or negative. For opportunity shocks, on

Table 2.2 : Top 10 bigrams contributing to climate exposure measures

Climate exposure	**Regulatory exposure**	**Opportunity exposure**
renewable energy	greenhouse gas	renewable energy
electric vehicle	reduce emission	electric vehicle
clean energy	carbon emission	clean energy
new energy	carbon dioxide	new energy
wind power	gas emission	wind power
wind energy	air pollution	wind energy
energy efficient	reduce carbon	solar energy
climate change	energy regulatory	plug hybrid
greenhouse gas	carbon tax	heat power
solar energy	carbon price	renewable resource

Notes: These bigrams are the "top 10" since they enter the respective measures with the largest weights. Source: Own representation based on Sautner et al. (2020b).

could think of clean technology subsidies or R%D incentive schemes. However, the "shocks" can also originate from within the firm, if it initiated or completed green technology development. Conference calls are held in conjunction with firms' quarterly earnings reports, and investors tend to be interested in the firm's future outlook. The exposure indicators therefore most likely include current climate policy impacts as well as expectations for future impacts. At the same time, they tell us something about the awareness of this among managers and investors.[15] Being firm- and year-specific, they go beyond a general notion of "transition risk" due to multilateral climate agreements; they are more likely to capture (expectations of) implemented policies.

To incorporate these measures of impacts, expectations and awareness, Equation 2.1 is adjusted to read

$$\begin{aligned} PAT_{G,it} = \exp(&\alpha_G + \beta_{G,IO} IO_{it-1} + \beta_{G,1} \ln K_{G,it-1} + \beta_{G,2} \ln K_{F,it-1} \\ &+ \beta_{G,3} \ln SPILL_{G,it-1} + \beta_{G,4} \ln SPILL_{F,it-1} \\ &+ \beta_{G,5} R\&D_{it-1} + \beta_{G,6} CCExp_{E,it-1} + \tau_{G,t} + \eta_{G,i} + \epsilon_{G,it}), \end{aligned} \tag{2.4}$$

where $CCExp_{E,it-1}$ is firm i's climate exposure in year $t-1$, and E stands for the type of exposure: overall, regulatory, or opportunity. Note that the share of institutional ownership in the firm is still included in the regression. $CCExp$ is a measure that combines firm-specific

[15] Unfortunately, the available data does not distinguish whether issues are mentioned by managers or investors.

exposure to climate-related shocks with the intensity of their discussion between management and investors.

If no effect of climate exposure on green or fossil innovation can be detected, this would be an indication that there is not enough meaningful variation in the dependent variable. The coefficient on $CCExp$ is also an interesting outcome in itself: it shows whether a more forward-looking firm-level climate indicator, reflecting awareness at manager and investor level, can explain firm-level innovation.[16]

2.4 Data

The main sample consists of $1,261$ publicly listed firms over 10 years (2009-2018), with an average of 90 patents per firm per year. Table 2.3 provides summary statistics for the main variables. Typical for patent data, all patent counts are highly skewed, with the maximum far away from the mean. The same is true for R%D expenditures. The institutional owner share of 40.6% on average is comparable to data reported in the literature (Dyck et al. 2019; Bebchuk et al. 2017).

Table 2.3 : Summary statistics

	Mean	Standard deviation	Minimum	Maximum
All patents	89.93	316.17	0	7,975
Fossil patents	3.08	20.22	0	708
Green patents	2.47	16.93	0	794
Patent stock	633.6	1,960.3	0	36,324.3
Fossil patent stock	20.4	118.3	0	4,404.1
Green patent stock	16.3	99.9	0	3,845.9
Spillover	259,268.6	218,863.6	0	584,411.2
Fossil spillover	9,183.1	9,491.4	0	24,151.9
Green spillover	7,577.0	8,560.5	0	21,157.4
R & D exp., in thousand USD	1,117,383	$6.96 \cdot 10^6$	0	$6.43 \cdot 10^{12}$
IO share, in percent	40.64	27.10	0	100

Climate-relevant – i.e. fossil or green – patents account for about 6% of total patents. Note that the sample is restricted to firms which have filed at least one climate-relevant patent in the sample period. Green and fossil patents are quite similar in terms of patent counts,

[16] More details on the construction of the climate exposure variable can be found in Appendix B.3.

patent stocks and spillovers, with green innovation always slightly below fossil. Table B.4 in Appendix B.4 shows the respective averages for family size and citations.

The main data source for patents, firms and ownership is Orbis and Orbis Intellectual Property, offered by Bureau van Dijk (BvD). Orbis provides information on more than 300 million companies worldwide, with the data including standardized financials, ownership links, and more.

Ownership data Data on ownership is recorded in the Orbis Historical Database. It provides links between firms and their shareholders, listing the respective ownership shares. The ownership data is collected from various sources, leading to over-reporting in the dataset. Extensive manual checks were done to rule out duplicates. In case a duplicate was identified, preference was given to the most recent reporting, to the most comprehensive (and thus consistent) data sources,[17] or to the parent company in case of holding reportings.

The ownership data allows to distinguish between different investor types based on their NACE codes and BvD classifications. Details on the mapping can be found in section B.2 in Appendix B.2. In addition, the headquarter country of each investor is recorded in the dataset, allowing to identify domestic investors.

Information on the investors' signature dates in the United Nations Principles for Responsible Investment initiative is from the PRI's website.[18] The PRI signatories are only available by name. They were matched to the investor dataset using a fuzzy matching approach as a first step; this was augmented with a manual check of the matches. In some cases, it is difficult to find out from an investor's PRI reporting which parts of the company can be counted as PRI signatories. The matches were checked with the greatest care possible, but some mismatches can not be ruled out.

Summary statistics for the different owner types can be found in Table B.6 in Appendix B.4. The average share of governments and Big Three investors is lowest; the ownership share of domestic owners is the highest of all types used (27.7% on average, more than half of total

[17] The most prevalent data source, and therefore most consistent across firms and years, is Factset. Factset is an independent data provider collecting data on large investors' holdings, based on filings with national stock exchange supervision authorities. The most well-known are the so-called "13F" filings, which are mandatory for investors in US-listed firms when their share crosses a certain threshold. Unfortunately, the sample could not be restricted to Factset alone, since in many cases important investors appeared under different sources in different years in the same firm.

[18] `https://www.unpri.org/signatories/signatory-directory`

institutional ownership, and with a maximum value of 100%). In the shares of governments as well as insurance and pension fund companies, the variation is somewhat larger than for the other groups.

Patent data Orbis Intellectual Property is the result of a matching between PATSTAT (a worldwide patent database run by the European Patent Office) and Orbis. Linked to company IDs, it provides rich information on each patent, including its classification, date of publication, and application offices. The dataset in this paper consists of all patents which were filed at the European Patent Office (EPO), the US Patent and Trademark Office (USPTO), the Japanese Patent Office (JPO), or the World Intellectual Property Organization (WIPO) in the relevant period; which were ultimately granted; and which can be linked to a listed firm (either through direct or indirect ownership, currently or formerly).

The database offers information of the applicant firm(s), current direct owner(s), and current indirect owner(s) of the patents. The patents were thus assigned to firms based on the original applicant (or several original applicants), if this original applicant is a listed firm. If the original applicant is not listed, but the current indirect owner is (and if there has been no ownership change), then the patent is assigned to the indirect owner. Since the database does not easily allow to track indirect ownership of firms over time, cases with changes in ownership are not assigned an indirect owner. Changes in ownership are determined by a) using the label "with ownership change" from Orbis, and b) by ensuring that the data lists the applicant also as the direct owner.

The estimations use patent applications (a flow) as the dependent variable, but patent stocks as explanatory variables. In line with the literature, these patent stocks are calculated using the perpetual inventory method. Firm i's green patent stock in year t, $K_{G,it}$, is equal to the discounted flow of green patents in the previous years:

$$K_{G,it} = PAT_{G,it} + (1-\rho)K_{G,it-1}, \tag{2.5}$$

and symmetrically for fossil ($K_{F,it}$) or all patents ($K_{A,it}$), respectively. A discount rate of $\rho = 0.15$ is used, which is in the medium range of depreciation rates for intellectual capital used in the literature.[19]

[19] For example, Aghion et al. (2016) use 20%; Peri (2005) uses 10%, Hall et al. (2005) and Cockburn and Griliches (1988) use 15%.

Spillovers are accounted for in a relatively straightforward way. A firm's green spillover at time t is equal to the sum of green patents applied for in the firm's country c at time t, minus the firm's own green patent applications in that year:

$$SPILL_{G,it} = \sum_{j \in c} PAT_{G,jt} - PAT_{G,it}. \tag{2.6}$$

In all expressions involving the log of a number of patents (i.e. $\ln K$, $\ln SPILL$, as well as the pre-sample mean), I follow the literature standard of replacing zeroes by an arbitrary small constant and including dummies for the number of patents being zero (Aghion et al. 2016; Blundell et al. 1999).

Firm data Firm-level data on R&D expenditures and Tobin's q is from the Orbis Historical Database. BvD firm-level data is mainly sourced from companies' mandatory filings. For companies with subsidiaries, sometimes both unconsolidated and consolidated (including subsidiaries) reporting is available. Whenever a company appears as an indirect patent applicant (or as both direct and indirect), and both filing versions are available, then the consolidated reporting version is used. In further regressions, more firm-level characteristics were used as control variables (such as operating revenue, capital-labor ratio), but as they did not alter the results, the respective regressions are not shown in the paper.

Firm-level data is augmented by other sources: Thomson Reuters Datastream was used to extract time series of index constituents of the STOXX Europe 600 and S&P Global 1200 indices. The time series of the S&P 500 is from Wharton Research Data Services (WRDS).

In addition, the Sautner et al. (2020a) data was merged to the firms to cover firm-level climate exposure and its recognition with managers and investors. Since all firms in the sample are publicly listed, ISINs (International Securities Identification Numbers) of their traded shares could be used to match the firms. The climate change exposure data is limited in terms of firm coverage and in terms of time series coverage per firm, reducing the sample size of the dataset to roughly half of the original dataset. Summary statistics for the reduced sample can be found in Table B.7 in Appendix B.4. Firms in the climate exposure sample have filed more patents (in all categories), have higher R&D expenditures, and a higher institutional owner share than the average of the full sample.

2.5 Results

2.5.1 Institutional owners and climate-relevant innovation

Table 2.4 show the main results for Equation 2.1, separately for green and fossil patents. For each estimation, the first stage of the control function approach is shown in an extra column. As can be seen from columns 2 and 4, the *indexmember* instrument is positive and significant: Institutional investors own about 2.3 percentage points more stocks in members of large stock indices than we would expect from other observables.

Table 2.4 : Green and fossil patents

	(1)	(2)	(3)	(4)
Model	Poisson	OLS (first stage)	Poisson	OLS (first stage)
Dep. var.	Green patents	L.IO share	Fossil patents	L.IO share
L.IO share	0.0227		0.0103	
	(0.0561)		(0.0387)	
L.Own stock green	1.464***	-1.341***	0.0224	-2.550***
	(0.104)	(0.493)	(0.107)	(0.268)
L.Own stock fossil	0.134**	-1.076***	1.321***	-2.556***
	(0.0617)	(0.264)	(0.122)	(0.524)
L.Green spillover	0.544	-20.05***	0.212	-20.01***
	(1.141)	(0.788)	(0.783)	(0.781)
L.Fossil spillover	-0.515	20.24***	-0.223	20.15***
	(1.147)	(0.791)	(0.787)	(0.783)
L.R and D exp.	0.0131	3.962***	0.0943	4.012***
	(0.238)	(0.170)	(0.171)	(0.171)
L.Index member		2.286***		2.291***
		(0.705)		(0.705)
Observations	8621		8621	

Notes: Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

After controlling for their endogeneity, the influence of institutional investors on both green and fossil patenting is positive, but statistically indistinguishable from zero. Based on the aggregate measures of green and fossil patents as well as institutional ownership used here, I cannot say that there is any causal relationship between institutional ownership and green or fossil patenting.

The results do, however, qualitatively confirm the findings from Aghion et al. (2016) on path dependency: A higher fossil (green) patent stock significantly increases the probability of filing another fossil (green) patent. The data also confirm another result, namely that a firm's fossil knowledge stock is also associated with more green patenting, whereas the green knowledge stock does not affect fossil patent applications. Overall, the path dependency model seems to fit the data quite well. The very simple spillover measure applied in this estimation is not significant though, neither for green nor for fossil patenting.

Accounting for sector heterogeneity As mentioned in section 2.3.4, the aggregate measures on green and fossil patenting may hide some important differences between the energy and the transport sector. Most likely, (green) innovations play a larger role in the transport sector than in the capital-heavy energy sector. Moreover, product market competition likely differs between these sectors, with implications for the innovation process and ownership.[20] Table 2.5 therefore shows results for green and fossil patents in the transport (columns 1 and 2) and energy sector (columns 3 and 4) separately. In all cases, the coefficient on institutional ownership is small or even negative, and the null hypothesis of it being zero cannot be rejected.

Again, the general path dependency model performs well: Both green and fossil transport knowledge stocks influence green transport patenting positively, while green transport knowledge is not associated with an increase in fossil transport patenting – this is in line with the results in Aghion et al. (2016), which are in fact focused on the transport sector. In the case of energy-related patents, the same pattern can be observed with very similar coefficients. This suggests that the specification in Equation 2.2 works well for both sectors.

Accounting for investor heterogeneity The insignificant influence of institutional owners on the direction of innovation may also be due to the underlying heterogeneity of investors, as mentioned in section 2.3.4.[21] Not all institutional owners invest with a long time horizon, not all of them have voiced an interest in climate change issues, and not all of them are prone to engage. The results for the effect of different types of investors on green innovation can be found in Table 2.6. This table only shows the coefficient for investor type ownership; the full tables for green as well as fossil innovation can be found in Appendix B.5 (Tables B.10 and B.11).

[20] For the relevance of competition in the context of (green) innovation and ownership, see e.g. Aghion et al. (2005), Atanassov (2013), Borochin et al. (2020), Lambertini et al. (2017), and Nesta et al. (2014).
[21] For summary statistics for the respective owner types, please refer to Table B.6.

Table 2.5 : Patents split into transport and energy sectors

Sector	Transport		Energy	
	(1)	(2)	(3)	(4)
Dep. var.	Green patents	Fossil patents	Green patents	Fossil patents
L.IO share	0.0104	-0.116	-0.0462	0.0352
	(0.0599)	(0.106)	(0.0448)	(0.0229)
L.Own stock gr. tr.	1.656***	-0.198		
	(0.188)	(0.379)		
L.Own stock fo. tr.	0.169***	1.952***		
	(0.0457)	(0.224)		
L.Green tr. spillover	0.308	-1.776		
	(1.016)	(1.839)		
L.Fossil tr. spillover	-0.251	1.567		
	(0.940)	(1.710)		
L.Own stock gr. en.			1.561***	0.0978
			(0.122)	(0.0687)
L.Own stock fo. en.			0.193*	1.416***
			(0.109)	(0.0889)
L.Green en. spillover			-0.648	0.541
			(0.715)	(0.356)
L.Fossil en. spillover			0.645	-0.550
			(0.721)	(0.357)
L.R and D exp.	0.0497	0.584	0.331	-0.0237
	(0.238)	(0.434)	(0.212)	(0.110)
Observations	8622	8622	8622	8622

Notes: All columns: Poisson control function estimation (first stage not shown). Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. First stage of control function not shown. Significance levels are indicated as $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

For governments, PRI signatories, and insurers and pension funds, one might expect a particular interest in long-term investments and a preference for low transition risk. The results for the three groups can be seen in columns 1-3. The coefficient on government ownership and PRI signatory ownership is large and positive (a one percentage point increase in PRI signatory ownership is associated with 3 percent more green patents in the following year), but insignificant. For insurance and pension fund companies, no significant influence on the direction of innovation of their portfolio companies can be detected either; the coefficient even turns negative. This result may be due to the necessary aggregation of this investor type (see section B.2 for details).

Domestic investors (column 4) are not necessarily more interested in climate issues, but may have better capacities to engage in firms close to them. However, this ability is not reflected

Table 2.6 : Special investor types and green patenting

	(1)	(2)	(3)	(4)	(5)
L.Gov. share	0.0342				
	(0.0882)				
L.PRI sig. share		0.0343			
		(0.0796)			
L.Ins.& pens. fd. share			-0.121		
			(0.298)		
L.Domestic owner share				-0.0210	
				(0.0505)	
L.Big 3 share					0.0257
					(0.0610)
Observations	8622	8622	8622	8622	8622

Notes: Dependent variable: Green patents. All columns: Poisson control function estimation (first stage not shown). Robust standard errors in parentheses. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Further regressors not shown. Significance levels are indicated as $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

in the results, where the coefficient on domestic investors is insignificant and even negative. Column 5 reports results with the share of the “Big Three” index fund managers (BlackRock, Vanguard, and State Street) as the dependent variable. All of them have voiced concern about climate risk.[22] Given their limited ability to influence their risk via selection, the engagement channel might be particularly important for them. Although the Big Three have been shown to contribute to emission reductions of firms (Azar et al. 2020), the insignificant coefficient suggests that their engagement activities do not yet address technological risk in a measurable way.

In summary, the findings for all of these investor types are the same as for the aggregate: no statistically significant effect of a larger ownership share of any particular investor type on green or fossil patenting can be detected.

Some further specification alterations Tables B.8 and B.9 in Appendix B.5 show results for some basic changes in the specification.

One could argue that institutional investors have a particular interest to direct innovation towards *high-quality* green patenting. Despite focusing on patents which are ultimately

[22] In fact, they are all PRI signatories, implying some overlap between the Big Three type and the PRI signatory type.

granted, patent counts may not capture patent quality sufficiently. As described in section 2.2, family size could be a useful measure in the context of this analysis: it captures the firm's expected commercial value of the patent, and it suffers less from sample censoring than citations. Columns 1 and 2 of Table B.8 show the impact of institutional ownership on the family size of green and fossil patents, respectively. The coefficients decrease in size and remain insignificant. Owners' concern with innovative quality does not seem to be the main issue.

Another concern could be that the dichotomy of *green* and *fossil* technologies does not fully capture climate-relevant innovation. There is also the interim case of *grey* patents, which make fossil technologies more efficient and thus reduce emissions. It is possible that investors value the (potentially) low cost and low risk character of these types of incremental innovations. As column 3 in Table B.8 shows, this hypothesis is not supported by the data.

One of the main arguments why institutional owners can exert influence on firms is that their large stakes imply more concentrated ownership. It might therefore only be the largest owners that drive successful engagement. In columns 1 and 2 of Table B.9, the share of institutional ownership is replaced by the share of the five largest owners. The coefficient is negative in both cases, and insignificant.

It is also possible that the influence of institutional investors takes longer to materialize than one year.[23] Columns 3 and 4 of Table B.9 therefore show results for a two-year lag of institutional ownership, IO_{it-2}. The coefficient on green patenting gets larger compared to the baseline, and the coefficient on fossil patenting gets smaller, indicating that there might be some truth in this argument; however, the coefficients are still insignificant.

2.5.2 Institutional owners and total innovation

From the results presented so far, the interim conclusion is that there is no evidence of institutional owners influencing the direction of innovation in firms. However, this lack of significant effects on climate-related patenting might be due to specification or data issues that have nothing to do with the green and fossil patents themselves. Can the data and model identify any effect of institutional ownership on innovation? To answer this question, equation 2.3 is estimated, covering all patents.

[23] Atanassov (2013), for instance, uses a time lag of two years.

The main results from these regressions (omitting all explanatory variables except institutional ownership from the table[24]) are presented in Table 2.7. In this case, institutional ownership has a positive and significant effect on total innovation: A ten percentage point increase in institutional ownership leads to 11.4% more patent filings. At the mean, this would mean a shift from 40.6 to 50.6% in institutional ownership resulting in an increase from 89.9 to 100.2 patents. Despite a different model equation, this result is quite close to the findings in Aghion et al. (2013), where the Poisson specification delivers coefficients between 0.007 and 0.010. It is surprisingly robust over a wide range of specifications. Column 1 shows the baseline Poisson control function regression of equation 2.3, which is comparable to the estimations in Tables 2.4 and 2.5. Column 2 introduces two-way clustering of standard errors at the 4-digit NACE code and country level.

In column 3, an additional control variable is introduced: Tobin's q, a measure of the market's future expectations deviating from current fundamentals. It could bias the results, since it might be correlated with patents as well as institutional ownership. However, controlling for Tobin's q hardly changes the coefficient on institutional ownership; as shown in Table B.12, the coefficient on Tobin's q is also insignificant.

In columns 4 and 5, robustness with respect to the choice of patent count measure is tested. Column 4 uses family-weighted patents in all patent variables, and column 5 uses citations. The citation-based regression is the only one without a significant effect of institutional ownership. As explained in section 2.2, citations suffer particularly from sample attrition due to the time line of the patenting and citation process. Also, the number of citations can be zero, which leads to an excessive amount of zeroes especially towards the end of the sample (whereas the family size of each patent is always at least 1, the patent itself). Finally, column 6 changes the estimation model from Poisson to negative binomial, which is sometimes recommended in case of overdispersion of the data.[25] The coefficient on institutional ownership gets smaller, but is still significant.

From Table 2.7, we can conclude that a connection between institutional ownership and innovation can be established with the given data and model. Looking at the combined results on carbon-relevant and total patenting, investors appear to encourage overall innovation,

[24] The complete results are available in Appendix B.5, Table B.12.
[25] Note that the GMM-based ivpoisson estimator implemented in Stata works for any exponential model with multiplicative error and is robust to overdispersion. The negative binomial estimator, on the other hand, is less robust to misspecification.

Table 2.7 : Institutional investors and total patents

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Neg. bin.
Dep. var.	Patents	Patents	Patents	Family size	Citations	Patents
L.IO share	0.0114***	0.0114**	0.0110*	0.0129**	-0.0258	0.00671**
	(0.00348)	(0.00481)	(0.00603)	(0.00624)	(0.0177)	(0.00310)
Clustered SEs	no	yes	yes	yes	yes	yes
Add. control	no	no	yes	no	no	no
Observations	8622	8622	8040	8622	8622	8622

Notes: All estimations use a control function approach (first stage not shown). "Add. control" refers to the inclusion of Tobin's q as an additional control variable. Robust standard errors in parentheses. In the Poisson control function estimations starting in column 2, standard errors are two-way clustered at the 4-digit NACE code and country level. In the negative binomial control function estimation, standard errors are clustered at the 4-digit NACE code level. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include further controls, year fixed effects, and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

while not exerting any influence on climate-relevant innovation. However, the estimates on total patenting may simply be more precise because of higher counts of total patents in the data. As can be seen in the summary statistics in Table 2.3, climate-relevant patents account for only about 6% of the patents in the sample (which, notably, is a sample of companies which have filed at least one green or fossil patent during the sample period).

2.5.3 Climate exposure and climate-relevant innovation

This section presents results for testing Equation 2.4, including climate exposure as an explanatory variable. This specification is a check for statistical power in the dependent variable, looking for any measurable influence between patents and a variable that is not directly innovation-related. It also helps to find out whether firm-specific concerns with climate issues explain green or fossil patenting.

As described in detail in section 2.3.5, the Sautner et al. (2020a) dataset measures different types of "climate exposure" at firm level based on transcripts of firms' quarterly earnings conference calls with investors. The data reflect both managers' and investors' awareness of these issues. "Climate exposure" can be understood as "exposure to a climate-related shock" specific to the firm. The general "climate exposure" variable can refer to any climate-related shock. The Sautner et al. (2020a) dataset also offers more specific indicators, which are of interest here: "Regulatory exposure" reflects the discussion of climate policies affecting the firm; "opportunity exposure" reflects the discussion of opportunities the firm faces in conjunction with climate issues. Sautner et al. (2020b) show that both of these measures are correlated with other available indicators for climate regulation at country or firm level. Aghion et al. (2016) find a clear relationship between policy-driven fuel prices and a redirection of innovation away from dirty and into clean technologies. We would expect regulatory exposure to have a similar effect.

Table 2.8 : Climate exposure and carbon-relevant patenting

Dep. var.	(1) Green patents	(2) Green patents	(3) Green patents	(4) Fossil patents	(5) Fossil patents	(6) Fossil patents
L.IO share	-0.00790	-0.000916	-0.0126	0.00964	0.00749	0.00927
	(0.0266)	(0.0268)	(0.0274)	(0.0220)	(0.0234)	(0.0228)
L.CC Exposure	0.0617**			-0.0188		
	(0.0301)			(0.0203)		
L.CC Regulatory Exp.		-0.0893			-0.00158	
		(0.454)			(0.156)	
L.CC Opportunity Exp.			0.134***			-0.0249
			(0.0471)			(0.0346)
L.Own stock fossil	0.0638	0.0640	0.0652	1.364***	1.337***	1.346***
	(0.0645)	(0.0524)	(0.0683)	(0.117)	(0.113)	(0.120)
L.Own stock green	1.443***	1.498***	1.424***	0.0256	0.00423	0.0235
	(0.106)	(0.114)	(0.111)	(0.117)	(0.132)	(0.125)
L.Green spillover	-0.147	-0.0359	-0.190	0.0631	0.0502	0.0679
	(0.288)	(0.293)	(0.297)	(0.219)	(0.236)	(0.227)
L.Fossil spillover	0.183	0.0384	0.246	-0.0656	-0.0439	-0.0683
	(0.354)	(0.362)	(0.365)	(0.284)	(0.306)	(0.296)
L.R and D exp.	0.165***	0.110***	0.175***	0.118***	0.132***	0.125***
	(0.0348)	(0.0314)	(0.0389)	(0.0456)	(0.0452)	(0.0467)
Observations	3972	3972	3972	3972	3972	3972

Notes: All estimations: Poisson control function estimation (first stage not shown). Robust standard errors in parentheses, two-way clustered at the 4-digit NACE code and country level. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table 2.8 shows the effects of different measures of climate change exposure on green (columns 1-3) and fossil (columns 4-6) patenting.[26] Overall climate change exposure is significantly positively associated with green patenting. Exposure to regulatory shocks, however, does not have any significant impact on green or fossil patenting. Regulatory exposure as measured by Sautner et al. (2020a) differs from policy exposure as measured by fuel prices (Aghion

[26] The inclusion of the climate change exposure measures significantly reduces sample size. For the sake of completeness, Table B.13 reproduces the baseline results (comparable to Table 2.4) for the reduced sample. Table B.7 reports summary statistics for the reduced sample.

et al. 2016) in one key aspect: Fuel prices are measures of existing climate policies. They are observable, and firms can easily build expectations regarding future fuel prices (at least the tax component of it) based on past fuel prices. This is what might make lagged fuel prices a good predictor of green patenting.[27] The regulatory climate change exposure measure probably reflects more long-term expectations voiced by investors. In line with the insignificant results on institutional owner shares, it seems that the concerns about expected regulation do not (yet) translate into a change in the direction of innovation within firms.[28]

Exposure to opportunity shocks, on the other hand, is significantly positively associated with green patenting. According to these results, a one standard deviation increase in climate opportunity exposure leads to a staggering 25% increase in green patents (0.134*1.887). As shown in Table 2.2, the top bigrams for opportunity and overall exposure are very similar, indicating that the frequency of opportunity-related keywords is driving the results for overall climate change exposure.

Given the way in which the "climate change opportunity" measure is constructed, it is difficult to interpret the effect as causal. The question is what "exposure to opportunity shocks" actually means. Only very few of the underlying bigrams relate to opportunity-creating policies, which would reflect an exogenous opportunity shock. Looking at the bigrams, it is possible that investors are making management aware of green opportunities in a more general sense, and push for more innovation. It is, however, also likely that managers mention particular green R&D successes in earnings conference calls – resulting in high "climate change opportunity" measures –, which are followed by green patent applications in the next year. Therefore, the results from table 2.8 suggest that "climate change opportunity exposure" is a good predictor of green patenting activity, but not necessarily reflecting a causal relationship.

Nevertheless, the clear results on climate change opportunity exposure (with the expected sign) indicate that the patent data exhibit sufficient variation over time to detect effects of firm-specific characteristics related to climate risk and institutional ownership. This is an indication that the nonsignificant results can be interpreted as "no effect". In this light, it is interesting that fossil patenting is not affected by any climate-related exposure. There is no

[27] The fact that tax-driven fuel price changes can lead to larger fuel demand changes is an established result in the literature on environmental and energy economics, see e.g. Li et al. (2014) and L. W. Davis and Kilian (2011). It is usually attributed to the predictability of the tax component.

[28] Regressions using the second lag of regulatory exposure yield insignificant coefficients as well. Results are available upon request.

evidence that green technologies crowd out fossil ones, or that technological risk is addressed by actively moving out of fossil technologies.

2.6 Conclusion

The tightening of climate policies entails transition risk not only for fossil fuel producers and emitters, but also for innovators in related technologies: their knowledge is at risk of losing value due to climate policy. This translates into a risk for investors of the affected technology firms. This paper explores whether institutional investors have recognized this risk, and whether their engagement directs firms' innovation into green technologies.

The analysis draws on the growing literature on the role of institutional investors in equity markets.
and funds can influence the behavior of firms (Appel et al. 2016, 2018; Dimson et al. 2015) and have been shown to encourage innovation (Aghion et al. 2013; Bushee 1998). The underlying idea is that many institutional investors have a more long-term perspective than “myopic” managers who are incentivized by short-term performance goals.

In this paper, I construct a worldwide firm-level panel on patents and institutional ownership. A classification of patents into *green* and *fossil* technology categories is applied to measure firm-specific technological knowledge and innovation. I then estimate a dynamic patent count data model building on Aghion et al. (2016), where patenting depends on previous knowledge, spillovers, R&D efforts, and the share of institutional ownership. The endogeneity of institutional ownership is addressed by a control function approach.

I find robust evidence for the positive influence of institutional ownership on overall patenting activity. However, there is no evidence for any effect on fossil or green technologies, not even for investors with long-term perspective or signatories of the UN Principles for Responsible Investment (UN PRI). The results also hold when looking specifically at the transport sector, where technological knowledge likely plays a larger role. These results are in contrast to previous studies which show a positive relationship between climate policy and green innovation (Aghion et al. 2016), and between institutional ownership and environmental outcomes (Dyck et al. 2019; Dimson et al. 2015; Azar et al. 2020). Institutional investors seem to perceive and address technological risk differently from overall environmental or transition risks.

To find out whether climate-relevant patenting can be explained by firm-specific climate-related risks, I use a newly developed dataset on firm-level climate exposure (Sautner et al. 2020a). It is based on firms' conference calls with investors and measures the relative frequency at which climate-related terms are mentioned. I find a significant positive relationship between "climate opportunity exposure" and subsequent green variation. I cannot ascertain that this is a causal effect of an exogenous opportunity shock, e.g., green technology support schemes. What the indicator rather seems to reflect is that managers talk about green innovation activity that is filed as a patent in the following year.

The results on climate exposure can be used to address another issue. If the insignificant effects I find for institutional ownership just result from a dataset with insufficient variation, they do not have any informational value. The climate exposure results show that there is sufficient statistical power in the data to detect a relationship between green patents and a variable that is not directly related to innovation. The insignificant effect of institutional ownership on green and fossil innovation can therefore likely be interpreted as a zero effect.

It is remarkable that neither institutional ownership, nor firm-specific regulatory or opportunity shocks have any effect on fossil patenting. Moving out of fossil technology development does not (yet) seem an answer to (expected) policies. Possibly, the use of fossil technologies still generates too much income today to be given up in favor of more future-oriented technologies; neither investors nor regulation appear to generate sufficient pressure to draw managers away from their "cash cows". For the large, publicly listed firms which constitute my sample, such a turnaround may be particularly difficult.[29]

One reason for the missing influence of institutional ownership on fossil as well as green technologies could be related to reputational concerns, or the lack thereof. "ESG risks" are often reputation risks: a firm may be affected by negative headlines in case of oil spills or worker protests, for example. Innovation is less visible. It is possible that investors' main concern is about reputational risk, and they are therefore less interested in the direction of innovation.

[29] In the management literature, we can find the idea that established companies focus more on incremental improvements, whereas small start-ups create "disruptive innovation" (Christensen et al. 2015). As most green innovations can still be regarded as more "novel" (Dechezleprêtre et al. 2017), a typical strategy for an incumbent firm would be to continue with their traditional business areas, and to acquire new-technology startups. In future research, it would be interesting to see whether an increase in indirect green knowledge acquisition can be observed in the data, and whether institutional investors support this.

Policy uncertainty has been shown to reduce innovation (Bhattacharya et al. 2017) and could be another explanation for the absence of an effect of institutional ownership on climate-relevant patenting. With climate policy uncertainty, investors' strategy might be to support innovation in other fields rather than betting on green or fossil technologies. An important next step in this line of research would be to examine events that reduce policy uncertainty and the resulting market valuation of green and fossil patenting.

This also points to a related issue: the timing of this analysis. Event studies have shown that the conclusion of the Paris Agreement changed investors' expectations regarding climate policy stringency (Ramelli et al. 2019; Kruse, Mohnen, and Sato 2020). Despite early actions such as the launch of the UN PRI in 2006, investors may have only started to recognize and address transition risk more recently. It is possible that too few years have passed since Paris to detect an effect of institutional ownership on the direction of innovation – but repeating the analysis in a couple of years may provide a different picture.

3 Economic Effects of Regional Energy System Transformations: An Application to the Bavarian Oberland Region

3.1 Introduction

The lack of ambitious responses to climate change from the international community and from national governments motivates subnational entities to set their own goals and formulate their own plans towards the reductions of greenhouse gas emissions in their jurisdictions. From an economics perspective, national unilateral efforts (not to mention subnational unilateralism) are by no means the first best response to a global problem. Yet, it is laudable that civil society comes together and becomes active when they hold the view that they can do more. This is the case of three districts in the Bavarian Oberland Region, who set themselves the target to generate as much electricity and heat from renewable sources as they consume by the year 2035. Since 2014, a research consortium has accompanied the region in identifying its potential for renewables generation, the degree of acceptability of the different technologies. Based on this, possible scenarios were formulated for how the transformation path might look like from now until 2035, and the economic effects were quantified.

As it is often the case in the policy debate, there is a strong interest from local decision makers in the economic effects of the transition to an energy system based on renewable energies. Thus, the purpose of this study is to analyze the effects of the different energy transition paths on regional value added and on employment, divided into three qualification levels: low-skilled, medium-skilled, and high-skilled employment. This endeavor poses four main challenges, whose solutions constitute our contributions to the literature. Our first and most important contribution lies in taking into account the scarcity of factors of production and of financial resources needed to undertake the investments, giving rise to crowding out effects. Related to that, our second contribution involves an extension of Fisher and Marshall (2011) and Benz et al. (2014) aiming at satisfying the needs of a regional and energy economic analysis. Third, we base the analysis on an input-output (IO) table where the energy sector is disaggregated to better account for the specificities of each generation technology and its interconnections with the rest of the economy. Our fourth contribution consists in taking into account the fact that the three districts are not economically isolated but interact with each other and with other regions.

We find that the three districts on the Oberland region benefit from investments towards the regional energy transition, both in terms of additional value added and employment. Yet, the positive development comes at the expense of value added and employment in the rest of the country. Moreover, our analysis shows that medium-skilled employment increases most across all scenarios. In the light of the current shortage of medium-skilled labor in Germany (Stippler et al. 2019), this finding represents an alarm signal that calls for integrating labor market considerations into climate policy strategies.

Previous work on the economic impacts of (renewable) energy policy can be summarized in three main strands: input-output analysis; ex-post econometric studies, focusing on specific regions or policies; and more complex models or meta-studies. A number of often policy-commissioned reports use standard input-output analysis, evaluating the additional demand for products in other sectors due to the construction (and sometimes operation) of renewable energy facilities (Bickel et al. 2009; Böhmer et al. 2015; Breitschopf et al. 2015; Hirschl et al. 2015; Höher et al. 2015; Lehr et al. 2015, 2011; Lutz et al. 2014; O'Sullivan et al. 2014; Ulrich and Lehr 2014). Their contribution lies in the construction of a demand vector specific to the installation (or operation) of different renewable energy technologies. These studies suffer from three limitations: first, they often focus on the construction of renewable energy plants, therefore concentrating on a one-off effect and neglecting the phase of operations, in particular their structural effect changing the interlinkages and production structure in the economy. Second, they disregard scarcity aspects: in these models, the demand created due to renewables expansion is always additional and does not come at the expense of other economic activities. Third, these studies do not take cross-country interlinkages into account, ignoring the dimension of internationally traded intermediate and final goods. The same is true for scholarly articles using an input-output approach, such as Allan et al. (2007) or Lehr et al. (2008). Heindl and Voigt (2012) represent an exception with respect to the consideration of crowding out effects, yet the interlinkages between countries and regions are not accounted for in this study.

The second strand of literature concerned with the economic effects of renewables expansion is econometric. For example, in an ex-post econometric exercise controlling for economic structure and other socio-economic variables, Brown et al. (2012) confirm the positive economic and employment effects of wind power expansions found in input-output studies. However, such econometric studies also mostly focus on one-off effects induced by policies (i.e., the effects of constructing or installing power equipment). In a recent analysis, Buchheim et al. (2020) show that the employment effects of increased solar energy installations depend on the tightness of the labor market, the effects being larger when unemployment is high. The authors conclude that crowding out is the most plausible explanation for small job effects. This finding in an ex-post study further motivates our consideration of crowding out effects in a forward-looking method.

More complex models such as CGE, PANTA RHEI or E3ME can take crowding-out effects as well as international economic linkages into account (see, e.g., IRENA (2016b), the chapter on net effects in Lehr et al. (2011), or the special issue of the *Energy Journal* on "Hybrid Modeling of Energy-Environment Policies"). However, these models rely on a number of assumptions made "in the background" and are not replicable without access to the computational model. They are also usually not available at the regional level. Meta-studies have combined results on job gains in renewable industries and job losses in conventional energy to estimate trade-offs (e.g., Meyer and Sommer 2014; Wei et al. 2010). The results of their spreadsheet models are useful, but not replicable as they rely on the availability of previous studies.

Our approach consists in an IO analysis which we extend in several dimensions. The advantage of IO analysis over other methods that are commonly used to estimate the economic effects of sectoral developments, like the analysis of value-added chains, lies in the ability to consider indirect besides direct effects on other sectors. That means that if a sector faces an increased demand for its goods, expanding production does not only increase demand for its direct inputs, but also for the intermediate inputs used to produce these inputs and so on. This can only be considered up to a limited extent in an analysis of the value-added chain, as done in Hirschl et al. (2010, 2015). Thus, to be able to use an IO approach, we construct IO tables for the three districts in the Bavarian Oberland following the method proposed by Többen and Kronenberg (2015), based on the German IO table. It allows us to model trade between the districts as well as with the rest of the country and the rest of the world, which is important considering that the districts are open economies that interact with other regions. Thus, the additional demand generated by investments (in renewable energies) is not satisfied exclusively by the local economy but also by sectors outside of their borders. Ignoring this would lead to a overestimation of the economic effects derived from the investments.

One of the extensions of the traditional IO analysis, which also allows us to rule out further sources of overestimation of the economic effects, is considering scarcity of financial resources and production factors. We distinguish between investments by private households and investments by institutional investors. Moreover, we differentiate between the investment and the operation phase. In the case of private households, investments (in renewables, renovations and storage capacity) and the corresponding expenditures during the operation phase crowd out consumption in the same amount.[1] Similarly, investments by institutional investors crowd out alternative investments. This distinction allows us to take into consideration the different structure of these two final demand components (consumption by private households and investments by private organizations) and, thus, to explicitly consider the increasingly important role of private households as investors in the electricity and heating sectors.

For the operations phase, we take into account that the investments increase the capital stock of the concerned sectors. Assuming full employment of the factors of production and fixed factor input coefficients, the increased capital attracts labor from other sectors, reducing their production. For the analysis of the economic effects in the operations phase we further develop the approaches of Fisher and Marshall (2011) and Benz et al. (2014) to make them applicable in a context when small regions (which in our case are the three German districts) are embedded in a system with much larger regions such as the rest of the country and the rest of the world.

An important characteristic of our analysis is that it is made prior to the investments, allowing to take measures targeted at attenuating possible negative developments. For instance, the identification of sectors that might be negatively affected makes it possible to support them in the appropriate manner before or during the transition. Moreover, identifying the sectors where labor requirements might increase most strongly allows a proactive approach to prevent and solve shortage problems.

The contributions of this paper do not only refer to the three districts in the Bavarian Oberland region. On the contrary, they can be applied to other regions, either at the same or other levels of regional sub-division, and also to other research and policy questions. Thus, the methodology, which was further developed to satisfy the needs of a regional analysis, is by no means exclusive to investments in the energy sector or to the Oberland region. Following the

[1] This can be seen as a simple representation of a policy instrument financed by a surcharge on the electricity price for all consumers, as in the German Renewable Energy Law (EEG).

method described in Section 3.2.2, we can construct IO tables for other subnational regions. The method described in Section 3.2.3 can be applied to analyze the economic effects of all types of investments.

In the following sections, we first outline our approach to produce the multi-regional IO table, to disaggregate the energy sector, and to assess the effects of the energy transition. Section 3.3 describes the data sources and Section 3.4 presents the effects on value added and employment. Finally, Section 3.5 concludes.

3.2 Methodology

For the analysis of the effects of the energy transition we want to consider the impact on the whole regional economy, taking into account the direct and indirect effects. Thus we rely on input-output analysis for the assessment. This confronts us with three methodological challenges. First, since subnational tables are not available in Germany, we are required to produce IO tables for each of the districts and link them to each other and to the tables for the rest of Germany and the rest of the world. This requires estimating trade between the three districts of analysis but also of each of the districts with the other two regions. Second, the energy sector of the multi-regional IO table needs to be disaggregated in such a way that the different renewable energy technologies and conventional technologies are considered as individual sectors. This disaggregation is necessary to account for the different input structures and, therefore, for the specific interconnections of each technology with the rest of the economy. The third challenge is concerned with the calculation of the economic effects. In this respect, we extend the traditional IO analysis to consider scarcities of financial resources and production factors and, therefore, to account for the fact that investments in renewables energies crowd out other investments and production in other sectors. In the following, we describe how we address each of these challenges.

3.2.1 Disaggregation of the energy sector

We start by disaggregating the energy sector in both source IO tables: the tables for Germany and the rest of the world from the World Input-Output Database (WIOD) (Timmer et al. 2015) and the German input-output table (GIOT) from the German statistical office. Thus, for instance, the sector “Electricity, steam and hot water, production and distribution services thereof” from the GIOT is disaggregated into nine subsectors.[2] These consists of different renewable and conventional technologies, transmission and distribution of electricity.[3] For disaggregation, we use the information contained in the IO table for Germany from EXIOBASE 2 (Wood et al. 2015), where the energy sector is disaggregated.[4]

Table 3.1 : Disaggregation of the intersectoral transactions of the energy sector

						Electricity					
						Coal	Solar	Distribution			
			Sector 1	…	Sector j	Sector h	…	Sector H	…	Sector J	**Total intermediate Use**
		Sector 1	z_{11}	…	z_{1j}	z_{1h}	…	z_{1H}	…	z_{1J}	$z_{1.}$
		⋮	⋮	⋮	⋮	⋮		⋮	⋮	⋮	
		Sector i	z_{i1}	⋮	z_{ij}	z_{ih}		z_{iH}	⋮	⋮	
Electricity	Coal	Sector e	z_{e1}	…	z_{ej}	z_{eh}	…	z_{eH}	…	z_{eJ}	$\mathbf{z_{e.}}$
	Solar	⋮	⋮		⋱	⋮	⋱	⋮	⋱	⋮	⋮
	Distribution	Sector E	z_{E1}	…	z_{Ej}	z_{Eh}	…	z_{EH}	…	z_{EJ}	$\mathbf{z_{E.}}$
		⋮	⋮	⋮	⋮	⋮		⋮	⋮	⋮	
		Sector I	z_{II}	…	…	z_{Ih}	…	z_{IH}	…	z_{IJ}	
Total inputs			$z_{.1}$			$\mathbf{z_{.h}}$	…	$\mathbf{z_{.H}}$			

To arrive at a matrix like in Table 3.1, we need to calculate the elements in the shaded areas, where z_{ih} represents the input from the non-electricity sector i required in the electricity subsector h, and z_{ej} represents the input from the electricity subsector e required in sector j. Thus, to calculate z_{ih} we scale the input from i required in the (only) electricity sector from

[2] For simplicity, in the following we will refer to the "Electricity, steam and hot water, production and distribution services thereof" sector as the electricity sector, although it also includes activities different to electricity generation.
[3] For a complete list of the energy sectors see Table C.1 in Appendix C.1 (Sectors 10-18).
[4] Note that we first need to aggregate the sectors in the EXIOBASE table and in the GIOT to be consistent with our final sector aggregation, described in Table C.1.

the GIOT, z_{ih}^{GIOT}:

$$z_{ih} = z_{ih}^{GIOT} \frac{z_{ih}^{Exio}}{\sum_h z_{ih}^{Exio}} \qquad \forall \quad i \neq e, \tag{3.1}$$

where $\sum_h z_{ih}^{Exio}$ is the sum of interindustry sales of sector i to all electricity sectors. The superscripts $GIOT$ and $Exio$ indicate that the variables are obtained from the German IO table from the German statistical office and from the German EXIOBASE table, respectively. Accordingly, we calculate z_{ej} as

$$z_{ej} = z_{ej}^{GIOT} \frac{z_{ej}^{Exio}}{\sum_e z_{ej}^{Exio}} \qquad \forall \quad j \neq h. \tag{3.2}$$

To calculate the entries of the intersectoral transactions between the energy subsectors (i.e., in the darker area in Table 3.1) we need to proceed slightly differently:

$$z_{eh} = z_{eh}^{GIOT} \frac{z_{eh}^{Exio}}{\sum_e \sum_h z_{eh}^{Exio}}, \tag{3.3}$$

where z_{eh} is the input from the electricity subsector e required in the electricity subsector h.

The remaining components of the IO table for the electricity subsectors, that is, value added, output, imports of similar final goods, the different components of final demand (consumption of private households, consumption of private organizations, consumption of state organizations, investment and changes in stocks, exports), as well as total final demand are calculated in a similar manner. For instance, for value added, w_e, we scale w_h^{GIOT} by multiplying it with the share of w_h^{Exio} in total value added of all electricity subsectors, $\sum_h w_h^{Exio}$.

3.2.2 Construction of the multi-regional IO table

The goal of the process described in this section is creating a multi-regional IO table consisting of the IO tables of Miesbach (MB), Bad Tölz-Wolfratshausen (BW), and Weilheim-Schongau (WS) (together, the Oberland region[5]), the rest of Germany and the rest of the world. Their "internal" IO tables are on the main diagonal of the multi-regional matrix; the intermediates traded interregionally are in the off-diagonal parts.

[5] To be precise, the district Garmisch-Partenkirchen is also part of the administrative Oberland region, but did not take part in the INOLA research project. For simplicity, we use the terms "Oberland region" and "INOLA region" interchangeably.

The construction of the multi-regional matrix follows four major steps. First, we construct regional IO tables by adjusting the German coefficients with regional output figures and scaling numbers for final goods use. In a second step we employ the modified "cross-hauling adjusted regionalization method" (CHARM) approach developed by Többen and Kronenberg (2015) to estimate each district's sectoral trade flows with the rest of Germany and with the rest of the world. Applying a simple gravity approach in a third step, we model the multi-regional trade flows: sectoral trade flows between the districts and between each district and non-Oberland Germany. Finally, using the "proportionality assumption", we create the multi-regional IO (MRIO) matrix by combining the data on sectoral trade flows and input coefficients. So, the first and the last step are concerned with input-output tables. There we assume that the production technology in the districts is equal to Germany's production technology. The inner two steps are about estimating inner-country trade flows.

Note that the regions we are interested in (the Oberland region) do *not* sum up to the national level. We index our districts by b, m, and w and denote the national totals by n. From the perspective of each district r, the rest of the country is denoted by q, such that, e.g., output is $x_{i,r} + x_{i,q} = x_{i,n}$. Similarly, if we look at all three districts together and the respective rest of the country, this is denoted by roc (the rest of the country, or "non-Oberland region"). The set G comprises these sub-regions and the rest: $g = b, m, w, roc$.

Construction of regional IO tables

Gross value added We start with regional data on gross value added, as this measure is the closest proxy to output that is available from administrative sources. Since regional value added data is only available at a highly aggregated sectoral level, we disaggregate the data using employment figures.[6] First, we compute preliminary figures for disaggregated value added, $w^p_{i,r}$, by multiplying with the labor shares of the disaggregated sectors:

$$w^p_{i,r} = w_{a,r} \cdot \frac{L_{i,r}}{L_{a,r}} \cdot \frac{w_{i,n}/L_{i,n}}{w_{a,n}/L_{a,n}}, \tag{3.4}$$

where the subscript a stands for the aggregated sector containing sector i. The third term on the right hand side (RHS) captures the national productivity differences. It is used as a correction factor to account for potential differences in labor productivity across subsectors.

[6] Table C.2 provides an overview of the highly aggregated sector level and the comprised sectors.

In a second step, we scale the preliminary values so they match the totals of the aggregated sectors:

$$w_{i,r} = w^p_{i,r} \cdot \frac{w_{a,r}}{\sum_{i \in a} w^p_{i,r}}. \tag{3.5}$$

Regional output of non-energy sectors From the sectoral values on regional w, we compute output by scaling national sectoral output using regional to national w shares:

$$x_{i,r} = x_{i,n} \cdot \frac{w_{i,r}}{w_{i,n}}, \tag{3.6}$$

where x denotes output of intermediate and final goods.

The output values of the rest of the country can be calculated as a residual:

$$x^{roc}_i = x_{i,n} - \sum_r x_{i,r}. \tag{3.7}$$

Regional output of the energy sectors To take advantage of the fact that we have detailed information on the energy sectors in the region, we proceed differently when regionalizing these sectors. For each of the electricity and heat generation sectors we scale German output down to the district level by multiplying it with the ratio of generation (in GWh) in the district, $g_{i,r}$ to generation in Germany, $g_{i,n}$ per sector:

$$x_{i,r} = x_{i,n} \cdot \frac{g_{i,r}}{g_{i,n}}. \tag{3.8}$$

The scaling factor for regionalization of the "Transmission of electricity" and "Distribution and trade of electricity" sectors is based on the length of the transmission or the distribution network located in the region and in the whole of Germany.

Regional input-output matrix For the (technical) regional IO matrix capturing the use of intermediates, we multiply the input-output coefficients of the German IO table ($c_{ij,n}$) with the regional output values, assuming identical production technology at the national and regional level:

$$z_{ij,r} = x_{j,r} \cdot c_{ij,n}, \tag{3.9}$$

where $z_{ij,r}$ denotes the input from sector i required in region r's sector j.

Note that each of the regional matrices constructed in this way is "technical" in the sense that it doesn't distinguish between sources of intermediates. It simply states that in a region r and sector j, a certain amount of inputs from other sectors i is needed to produce this region's sectoral output. It does not make a statement on where these inputs come from. The technical regional input-output matrix derived here is used later on to construct the interregional and intraregional IO matrices.

Regional domestic final use Final goods use per sector and use item is only available at the national level.[7] We therefore need to scale it using Bavarian data on total final goods use, and regional data on disposable income in the case of household consumption.

For private household consumption, we start from the national sectoral value and scale it by Bavarian consumption shares, as well as regional disposable income in comparison to Bavaria:

$$d_{i,r}^{ph} = d_{i,n}^{ph} \cdot \frac{d_{by}^{p}}{d_{n}^{p}} \cdot \frac{di_r}{di_{by}}, \tag{3.10}$$

with d_{ph} denoting consumption (final demand) of private households, d_p denoting total private consumption, di denoting disposable income, and by denoting Bavaria.

For investment and consumption by private and state organizations, we again scale by Bavarian shares following Heindl and Voigt (2012) and then use regional GDP to scale to regional level:

$$d_{i,r}^{k} = d_{i,n}^{k} \cdot \frac{d_{by}^{k}}{d_{n}^{k}} \cdot \frac{GDP_r}{GDP_{by}} \qquad \forall \qquad k \neq cs. \tag{3.11}$$

[7] For simplicity we refer to the different final use items of the IO table as follows:
"Final consumption expenditure by households"= private household consumption;
"Final consumption expenditure by non-profit organizations serving households"= consumption of private organizations;
"Final consumption expenditure by government"= consumption of state organizations;
"Gross fixed capital formation"= investments;
"Changes in inventories and valuables"= changes in stocks.

The index $k = cpo, cso, inv, cs$ denotes consumption of private organizations, consumption of state organizations, investments, and changes in stocks. We scale down changes in stocks using the regional GDP share only.

Regional (domestic) total use By summing up intermediate use and domestic final use (by private households, denoted by ph, and organizations, denoted by k) we can derive total regional domestic use $d^t_{i,r}$:

$$d^t_{i,r} = z_{i\cdot,r} + d^{ph}_{i,r} + \sum_k d^k_{i,r} = z_{i\cdot,r} + d_{i,r}. \tag{3.12}$$

Rest of country The values for intermediate use, domestic final use, value added and output for the rest of the country are calculated as residuals, subtracting the values for the three districts from the national figures.

Estimation of interregional trade: modified CHARM

As noted by Kronenberg (2009), trade of regions with the rest of the country and the rest of the world is characterized by surplus imports and exports (trade balance) as well as substantial amounts of cross-hauling, which is the simultaneous imports and exports of goods or services of the same sector. The more heterogeneous the products within a sector are, the more cross-hauling takes place (Kronenberg 2009).

The adjusted CHARM as suggested by Többen and Kronenberg (2015) allows to estimate trade flows between each region and the rest of the country ("biregional trade"), as well as between each region and abroad, while taking into account cross hauling. An important assumption made in Kronenberg's CHARM and of the modified CHARM is that product heterogeneity in the region is the same as in the country, which is based on the argument that heterogeneity is a characteristic of the commodity and not of the geographical location (Kronenberg 2009). This assumption is criticized by Jackson (2014) who emphasizes that the product mix within an aggregate commodity might well be a function of the geographical location, since the region might not produce all commodity sub-types while the country does.

The consequences of this assumption will depend on three aspects: First, the level of aggregation in the commodities classification; second, the unique character of different commodities;

and third, the economic size of the subnational regions. Since our regions are rather small and we have a high level of aggregation, there are potentially consequences for regionalization in our framework. However, the lack of administrative data on trade between the districts and with the rest of the country and the world makes it impossible to quantify the consequences. Thus, we have to keep in mind that the estimates for the interregional transactions might be inaccurate.

Estimating regional foreign trade As a first step, we estimate each region's foreign trade. The basic assumptions are that foreign imports are proportional to domestic demand, and foreign exports are proportional to domestic output. Then regional foreign exports (denoted by $e^f_{i,r}$) and imports (denoted by $m^f_{i,r}$) can be approximated as

$$m^f_{i,r} = m_{i,n} \frac{z_{i\cdot,r} + d_{i,r}}{z_{i\cdot,n} + d_{i,n}}, \tag{3.13}$$

$$e^f_{i,r} = e_{i,n} \frac{x_{i,r}}{x_{i,n}}. \tag{3.14}$$

We use foreign trade data from the German IO table and scale it with regional demand or supply figures, respectively. Foreign imports and exports for the rest of the country roc are calculated as a residual.

Estimating total interregional trade The second step is concerned with estimating trade within the country, between regions. The adjusted CHARM formula only works for a bi-regional setting. Therefore, we calculate cross-hauling between each of the districts and, from its perspective, the rest of the country, as suggested by Többen and Kronenberg (2015). These biregional values are what we refer to as "interregional".

The adjusted CHARM defines the cross-hauling potential as the minimum of output and domestic use. The intuition behind this is that the highest possible amount of cross-hauling occurs if the region with relatively small output figures exports all its output, and imports the same amount of goods. The (maximum) cross-hauling potential, q_i is then twice the amount of the region's output.

Correspondingly, the method defines the cross-hauling potential at national level to be constrained as $\max q_{i,n} = 2\min(x_i; z_{i\cdot} + d_i)$.[8] Then the national product heterogeneity measure is calculated as

$$h_{i,n} = \frac{q_{i,n}}{2\min(x_{i,n}; z_{i\cdot,n} + d_{i,n})}. \tag{3.15}$$

Following the above reasoning and in order to ensure accounting balances between the two regions, the adjusted CHARM sets upper limits for the cross-hauling potential. Denoting the cross-hauling in interregional trade between regions r and q by q_i, their maximum CH potential can be written as

$$\max(\frac{q_i}{2}) = \min(x_{i,r} - e^f_{i,r}; z_{i\cdot,r} + d_{i,r} - m^f_{i,r}; x_{i,q} - e^f_{i,q}; z_{i\cdot,q} + d_{i,q} - m^f_{i,q}). \tag{3.16}$$

Assuming that $h_{i,n} = h_{i,r}$, biregional cross-hauling can be estimated as the national heterogeneity parameter (which is the share of national cross-hauling in national cross-hauling potential) times the regional cross-hauling potential:

$$q_i = 2h_{i,r}\min(x_{i,r} - e^f_{i,r}; z_{i\cdot,r} + d_{i,r} - m^f_{i,r}; x_{i,q} - e^f_{i,q}). \tag{3.17}$$

In a further step we calculate interregional gross trade flows, which are interregional gross exports and imports and are defined bilaterally: t_{rq} is the trade flow from region r to region q. To calculate them, we need to combine our estimate of cross-hauling with the commodity balance. The commodity balance, b, is usually defined as the difference between regional supply and demand (resulting in a value for net regional imports or exports), and in the subnational case it needs to be corrected for foreign imports and exports:

$$b_{i,r} = -b_{i,q} = (x_{i,r} - e^f_{i,r}) - (z_{i\cdot,r} + d_{i,r} - m^f_{i,r}). \tag{3.18}$$

[8] Note that, since there is a large quantity of variables and parameters to be estimated in the regionalization of the IO table and calculation of the economic effects, some letters are used twice: once to denote a variable and once to denote an index. While this is not optimal, please note that there is no implicit relation between the index and the variable, although they are denoted by the same letter.

Then, the gross trade flows between the two sub-regions are given by[9]

$$t_{i,rq} = \frac{q_i + |b_{i,r}| + b_{i,r}}{2}, \tag{3.19}$$

$$t_{i,qr} = \frac{q_i + |b_{i,q}| + b_{i,q}}{2}. \tag{3.20}$$

Estimation of multi-regional trade: gravity

As we have more than two regions in our setting, we need to distribute the interregional (or biregional) trade flows calculated above among the several regions. We apply a simple gravity framework for this: we assume that trade between sub-regions is proportional to their economic size and their distance from each other. Moreover, we estimate the trade share ts of one region with another as the quotient of estimated trade flows between regions r and s and the estimated trade flows of region r with all other regions:

$$ts^1_{rs} = \frac{\ln(GDP_r GDP_s) - \ln(dist_{rs})}{\sum_{u \neq r}(\ln(GDP_r GDP_u) - \ln(dist_{ru}))}. \tag{3.21}$$

The denominator is similar to the "multilateral resistance" term in gravity trade models.[10] Here, u is an index over all districts other than r - so it refers to the rest of the country from r's perspective. It is similar to the index q as in the notation for the modified CHARM formula further above, but in the trade share calculations we actually use data on each of the 380 other German districts individually. Therefore, we use another index here to avoid confusion.

Note that we could also have a denominator based on region s's multilateral trade. Essentially, we can follow two approaches, which result in different trade shares. The first is to use r's trade share for estimating all of r's exports, which means that each region s's imports from r are scaled by r's multilateral resistance. The second approach is to use s's trade share for estimating all of s's imports, which means that r's exports to s are scaled by s's multilateral resistance.

[9] Note that we need to divide cross hauling by 2 because we are interested in one-directional flows from r to q, whereas cross-hauling gives the sum of simultaneous imports and exports.

[10] The specification in (3.21) implies trade elasticities of one with respect to GDP and distance.

Approach 2 reads:

$$ts_{rs}^2 = \frac{\ln(GDP_r GDP_s) - \ln(dist_{rs})}{\sum_{u \neq s}(\ln(GDP_s GDP_u) - \ln(dist_{su}))}. \tag{3.22}$$

Combining the multi-regional trade share with interregional trade flows gives the multi-regional trade flows (shown here according to approach 1):

$$t_{i,rs}^1 = t_{i,rq} \cdot ts_{rs}^1. \tag{3.23}$$

Trade between each district and the non-INOLA region is calculated as a residual. So, for instance for district b

$$t_{b,roc} = t_{bq} - t_{bm} - t_{bw}, \tag{3.24}$$

where q denotes the rest of the country from the perspective of the exporting district, and m and w denote the other two Oberland districts.

Since both approaches for the calculation of the districts' trade flows lead to different estimates, we chose to combine the two approaches. To guarantee that the calculation for the rest of the country in (3.24) does not deliver negative values, we always use the smaller of the two:

$$t_{i,rs} = \min(t_{i,rs}^1; t_{i,rs}^2). \tag{3.25}$$

Construction of the multi-regional IO matrix

Imported intermediates: proportionality assumption To construct the MRIO matrix from the technical IO matrix and the multi-regional trade flows, we use the proportionality assumption also used by Benz et al. (2014) among others. According to this assumptions "an industry uses an import of a particular product in proportion to its total use of that product" (OECD 2002, p. 12). For example, if the motor vehicles industry in region A uses steel in production and 10% of all steel is imported from a particular region B, then 10% of the steel used by the motor vehicles industry in region A is imported from region B.

So the intermediate inputs used by region r's sector i from region s's sector j read as

$$z_{ij,sr} = z_{ij,r} \frac{t_{j,sr}}{d^t_{j,r}}, \tag{3.26}$$

where $d^t_{j,r}$ denotes total use of product j in region r. In a similar manner, we calculate the intermediate inputs used by region r's sector i from sector j of the rest of the world (ROW), using the foreign imports $m^f_{i,r}$ calculated above and the proportionality assumption, and denote them $z^{row}_{ij,r}$.

Intersectoral transactions within each district We then calculate the within-district IO matrix as the residual of the "technical" matrix calculated above, and all imported intermediates from the other districts, the rest of the country and the rest of the world

$$z_{ij,rr} = z_{ij,r} - \sum_{s \neq r} z_{ij,s} - z_{ij,rowr}. \tag{3.27}$$

Linking the regional and German tables to the rest of the world Having the MRIO table for the districts and the rest of the country, we proceed to link it to the rest of the world. We aggregate the individual countries of the WIOD table (except Germany) to form the ROW region and the sectors to match the sectors of the IO tables for the districts. Aggregated WIOD tables are taken as the base table. We then disaggregate the intersectoral transaction within Germany from the WIOD table, $z^{WIOD}_{ij,n}$ using origin-destination shares that can be calculated from the MRIO table generated using the methodology described above:

$$z_{ij,rs} = z^{WIOD}_{ij,n} \frac{z^{GIOT}_{ij,rs}}{\sum_r \sum_s z^{GIOT}_{ij}}, \tag{3.28}$$

where the superscript $GIOT$ denotes the variables that were calculated above using the German IO table from the German statistical office. The intersectoral transactions between German sectors and ROW's sectors are regionalized in proportion to output, that is: $z_{ij,rrow} = z^{WIOD}_{ij,nrow} \frac{x^{GIOT}_{i,r}}{x^{GIOT}_{i,n}}$.

Factors of production

Starting from the production factor figures for Germany, we scale down the respective factor to the district level using the sectoral factor coefficients for Germany and sectoral output for the districts. For instance, we compute K_{ir}, the capital stock in region r's sector i, as

$$K_{ir} = K_{in} \frac{x_{i,r}}{x_{i,n}}, \tag{3.29}$$

where K_{in} denotes the sectoral capital stock for the whole of Germany. The factors of production for the rest of the world are calculated in a similar way.

3.2.3 Economic effects: extended IO analysis

Being placed in an IO framework, we implicitly assume a Leontief production function with fixed input coefficients and constant returns to scale. Furthermore, although the period of analysis is relatively long (from 2015 to 2035), we also need to make the assumption that the input coefficients and factors coefficients will stay the same throughout the period of analysis, that is, the production technology of the economy will remain unchanged. This assumption becomes more realistic for other possible applications with shorter periods of analysis.

For the assessment, we consider both the one-off effects of the investment (or construction) phase as well as the effects of the operations phase. Importantly, we take into account scarcity of financial resources and of the factors of production, thus in the investment and in the operation phase crowding out of other activities occurs. Specifically, investments in the energy transition crowd out other investments by companies or consumption by private households. Here we assume that financial resources do not only come from the region where investments take place but also from other regions. The rationale behind this assumption is that investments in the energy transition are typically financed by national climate policy instruments that redistribute funds from the whole of the country to the actual investment location.[11] Similarly, in the operations phase factors of production that could be employed otherwise, are used in the operation and maintenance of renewables, reducing their activity (and therefore output) in other sectors.

[11] An example for such a redistribution mechanism is the German EEG which finances the investments via a surcharge on the electricity price paid by all consumers (with some exceptions). In the case where policies are financed by the national public budget, redistribution occurs through the tax system.

The next subsections describe our methodology. First, we introduce the general method to compute the amount of output necessary to meet the additional investment demand generated by the energy transition. We then present the method to consider scarcities in the investment phase and the operation phase. Finally, we show how we calculate the effects on value added and employment, starting from the additional output figures.

Additional output

The starting point of our analysis are the future investments in renewable energies for electricity and heat generation, energy efficiency measures and electricity storage appliances.[12] We denote these by $\mathbf{f}$, which is a $N \times 1$ column vector, where N is the total number of sectors per region. The vector $\mathbf{f}$ describes how total demand for investment goods is composed of investment goods from other specific sectors, thus it breaks down the overall investment in region r into the components needed from each sector i. Note that this vector does not provide information on the geographical origin of the components yet, thus we use the intra-sectoral transactions in intermediates from the MRIO table as a proxy to distribute the sectoral investment demand among the regions and obtain the additional investment demand:

$$\Delta \mathbf{d}^{\mathbf{inv}} = \mathbf{U}\mathbf{f}. \tag{3.30}$$

where d^{inv} is an $NR \times 1$ column vector, and R is the total number of regions. $\mathbf{U}$ is a $NR \times NR$ matrix whose elements, $u_{ij,rs}$, describe the share of $z_{ij,rs}$ (i.e., of inputs from region r's sector i used in regions s's sector j), in the intrasectoral transactions:

$$u_{ij,rs} = \frac{z_{ij,rs}}{\sum_{r=1}^{R} \sum_{s=1}^{R} z_{ij,rs}} \qquad \forall \quad i = 1, \ldots, N \quad \text{and} \quad j = i. \tag{3.31}$$

[12] For simplicity, in the following the expression *investment in renewables* will also mean energy efficiency measures and the deployment of storage capacity.

Following classical IO analysis, the amount of output of final goods and intermediates, $\mathbf{\Delta x}$, that is necessary to satisfy the additional investment demand can be computed as follows:

$$\mathbf{\Delta x} = (\mathbf{I} - \mathbf{L})^{-1}\mathbf{\Delta d^{inv}}, \tag{3.32}$$

where $\mathbf{I}$ is the unity matrix and $\mathbf{L}$ is the matrix of fixed input coefficients, which shows the direct use of intermediates per unit of output. Leontief's inverse, $(\mathbf{I} - \mathbf{L})^{\mathbf{-1}}$, is the matrix to which the infinite series of powers of $\mathbf{L}$ converges. Accordingly, it accounts for the fact that, besides the directly used intermediates, output production also uses indirectly the intermediates used for production of the direct intermediates and so on. Thus, Leontief's inverse indicates the level of output needed to satisfy a unit vector of final demand after infinite rounds of this process.

To this point we have not considered any scarcity effects and have assumed that additional resources and factors of production are readily available and enter the system in an unlimited manner. However, it is more reasonable to assume that investments in renewables crowd out other types of demand, e.g., alternative investment or consumption by private households. Moreover, factors of production are not unlimited in stock and waiting to be employed. To consider scarcity effects we follow two different approaches depending on the actors undertaking the investment: private households or institutional investors. Moreover, we distinguish between the investment phase and the operation phase.

Considering scarcity in the investment phase Crowding out in the investment phase for both types of investors follows a similar principle: investments in renewables crowds out an alternative average investment (alternative average consumption) in the same amount as the total investment in renewables. Thus, the calculation of additional output, net of crowding out reads:

$$\mathbf{\Delta x^{inv,net}} = (\mathbf{I} - \mathbf{L})^{-1}(\mathbf{\Delta d^{inv,ii}} + \mathbf{\Delta d^{inv,ph}} - \mathbf{\Delta d^{invco}} - \mathbf{\Delta d^{phco}}), \tag{3.33}$$

where $\mathbf{\Delta d^{inv,ii}}$ and $\mathbf{\Delta d^{inv,ph}}$ denote the additional investment demand generated by institutional investors and by private households, respectively. $\mathbf{\Delta d^{invco}}$ is a vector of crowded out investment demand and $\mathbf{\Delta d^{phco}}$ is a vector of crowd out consumption by private households.

The elements of $\mathbf{\Delta d^{invco}}$ are defined as

$$\Delta d_{i,r}^{invco} = \frac{d_{i,r}^{inv}}{\sum_{i,r} d_{i,r}^{inv}} \sum_{i,r} \Delta d_{i,r}^{inv,ii}. \tag{3.34}$$

The fraction on the right hand side of (3.34) describes the proportional distribution of an average investment among sectors and regions.[13] In other words, it describes how many cents out of each Euro invested in any of the regions appear as investment demand in a specific regional sector. The last term on the right hand side is the sum of the investments. $\mathbf{\Delta d^{phco}}$ is similarly defined, yet in this case an average consumption vector is multiplied with the additional investment demand generated by private households.

Considering scarcity in the operation phase To consider crowding out in the operations phase, we apply and modify the approach introduced by Fisher and Marshall (2011) to an energy economic analysis, and extend it to suit the requirements of an analysis of small regions embedded in an international IO table.

Before turning to the formal representation, consider first the intuition behind our approach, which is based on Rybczynski effects (Rybczynski 1955) well-known in the trade literature (see Feenstra 2004). By investing in renewables, the capital stock of each renewables sector increases by the amount of the respective investment. Assuming that there are no changes in technology, the capital stock increase attracts into the renewables sectors the amount of labor that is necessary to use the new capital stock in the production process. Assuming scarcity in the factors of production, which is a sensible assumption considering the current situation on the German labor market, labor is necessarily attracted from other sectors of the same or of other regions. Thus, output in these sectors decreases. This is, of course, a simplified representation of the whole process, since actually the adjustment consists of infinite rounds of intermediate input sectors.

Formally, we assume the Leontief production function to be transregional as in Benz et al. (2014). That means that production of final goods in one region potentially uses factor inputs from all other regions by using intermediates from the other regions. The production function

[13] Recall that $d_{i,r}^{inv}$ is investment demand and is readily available for the IO tables.

is then given by

$$y_{ir} = min\left\{\frac{v_{ir11}}{a_{ir11}}, \dots, \frac{v_{irfs}}{a_{irfs}}, \dots, \frac{v_{irFS}}{a_{irFS}}\right\} \quad \forall \quad i = 1, \dots, N \quad \text{and} \quad r = 1, \dots, R, \tag{3.35}$$

where y_{ir} is final goods output in sector i of region r. v_{irfs} is the amount of region s's factor f used in region r's sector i, and a_{irfs} the input coefficient that determines the amount of factor input f from region s which is required to produce one unit of output in sector i of region r. The number of factors is denoted by F.

Assuming full employment, scarcity and a positive remuneration of all production factors implies that the employment of region r's factor f in all regions in all sectors equals the endowment of region r with factor f

$$v_{rf} = \sum_{s=1}^{S}\sum_{i=1}^{N} a_{irfs}y_{ir} \quad \forall \quad f = 1, \dots, F \quad \text{and} \quad r = 1, \dots, R. \tag{3.36}$$

Writing (3.36) in matrix notation leads to

$$\mathbf{v} = \mathbf{A}'\mathbf{y}, \tag{3.37}$$

where information on each region's factor endowment is contained in $\mathbf{v}$, which is a column vector of length FR. Furthermore, the column vector $\mathbf{y}$ of length NR contains each region's final goods output in each sector. $\mathbf{A}$ is a matrix of dimension $NR \times FR$ containing the *direct* and *indirect* factor requirements expressed as factor input coefficients.

$\mathbf{A}$ is not readily available from the data. Fisher and Marshall (2011) show that it can be obtained by multiplying the matrix of direct factor inputs, $\mathbf{B}$, with the Leontief inverse:

$$\mathbf{A}' = \mathbf{B}'(\mathbf{I} - \mathbf{Z})^{-1}, \tag{3.38}$$

where $\mathbf{B}$ is the matrix of *direct* factor inputs. It contains information on the factors of production directly employed to produce one unit of domestic total (intermediate and final goods) output, $\mathbf{x}$. Denoting low, medium and high-skilled labor as L, M and H, respectively, and capital as K, and assuming mobile factors of production, that is, that factors of production of each region and each sector can be directly employed across sectors and regions, $\mathbf{B}_m$ reads

$$\mathbf{B}_m = \begin{bmatrix} L_{11} & M_{11} & H_{11} & K_{11} \\ \vdots & \vdots & \vdots & \vdots \\ L_{ir} & M_{ir} & H_{ir} & K_{ir} \\ \vdots & \vdots & \vdots & \vdots \\ L_{NR} & M_{NR} & H_{NR} & K_{NR} \end{bmatrix}, \tag{3.39}$$

and its dimensions are $NR \times F$. However, we assume the factors of production to be partly mobile, that is, mobile within Germany and between sectors in Germany but not to be directly employed in the rest of the world.[14] Thus, there are two types of each factor, one for Germany and one for ROW, which means that $\mathbf{B}_{pm}$ is of dimensions $NR \times G$, where $G = 2F$ and the subscript pm stands for partly mobile. Assuming the rest of the world is the last region in the multi-regional matrix and letting $(R-1)$ denote the penultimate region, $\mathbf{B}_{pm}$ reads

$$\mathbf{B}_{pm} = \begin{bmatrix} L_{11} & 0 & M_{11} & 0 & H_{11} & 0 & K_{11} & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ L_{N(R-1)} & 0 & M_{N(R-1)} & 0 & H_{N(R-1)} & 0 & K_{N(R-1)} & 0 \\ 0 & L_{1R} & 0 & M_{1R} & 0 & H_{1R} & 0 & K_{1R} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & L_{NR} & 0 & M_{NR} & 0 & H_{NR} & 0 & K_{NR} \end{bmatrix}. \tag{3.40}$$

Fisher and Marshall (2011) further show that, although $\mathbf{A}$ is not invertible because the number of factors F and the number of sector-region combinations IR are not equal, the full employment condition in (3.37) can be solved for $\mathbf{y}$ with the Moore-Penrose Pseudo inverse of $\mathbf{A}$ denoted by $\mathbf{A}^{+}$. Thus, it follows

$$\mathbf{y} = \mathbf{A}'^{+}\mathbf{v} + (\mathbf{I} - \mathbf{A}'^{+}\mathbf{A}')\mathbf{z}, \tag{3.41}$$

where $\mathbf{z}$ is an arbitrary vector.

Taking the derivative with respect to factor endowment leads to the result that $\mathbf{A}'^{+}$ indicates the output response in each region in each sector to a unit increase in each production factor.

[14] This is a strict assumption, yet, in general, any mobility assumption would be possible. While we considered several different specifications, this specific assumption is the simplest setting that allows to cover our policy questions.

However, the approach of taking the derivative with respect to factor endowment at this stage is not appropriate in a context where the regions are so different in their size and the sectors in the different regions are assumed to have the same technology.[15] The reason is that in the process of reallocating factors so as to maximize output, there is no further information available than the production technology. Since we assume the production technology to be the same in the rest of Germany and the three districts, the same absolute amount of factors is assigned to a specific sector in all regions, leading to very implausible values for the regionalized sectors.[16] In this context, $\mathbf{z}$ becomes relevant. As it is not further specified in Fisher and Marshall (2011), and we cannot solve for it analytically, we develop an algorithm to approximate its elements.

The routine starts by assigning an initial value to each element of $\mathbf{z}$ and calculate the predicted $\hat{\mathbf{y}}$ using (3.41). Since we know the actual $\mathbf{y}$, we calculate $\hat{y}_{ir}$'s relative deviation from y_{ir}. The algorithm's goal is to find a vector $\hat{\mathbf{z}}$ that minimizes the maximum relative deviations. Note that minimizing the absolute deviations as in a least squares estimation technique would give more importance to the deviations in the ROW region since the deviations in absolute terms in the three districts are extremely small in comparison to the ROW. However, we are particularly interested in the districts, so we minimize the relative deviations.

Specifically, after assigning an starting value of one to each element of $\mathbf{z}$, and initially defining a prediction, $\hat{y}_{ir}$, to be an outlier if it is 4 times larger (or $1/4$ times smaller) than the actual y_{ir},[17] we proceed as follows:

1. Calculate $\hat{\mathbf{y}}$ using (3.41) and inserting the current values for $\hat{\mathbf{z}}$
2. Identify outlier sectors
3. Adjust the values of the $\hat{\mathbf{z}}$ vector for the outlier sectors according to $\Delta \hat{z}_{ir} = f(\hat{y}_{ir} - y_{ir})$[18]
4. Adjust the threshold for the definition of outliers by 1%

[15] As outlined in Section 3.2.2, lacking detailed administrative data at the regional level we need to make the "same technology assumption" to be able to produce IO tables and estimates of the production for the districts.
[16] Indeed, even if the production technology of sector i differs for the regions, the differences would not be substantial. Since $\mathbf{A}'^{+}$ does not contain information on the size of the sector, very similar amounts of factors of production would be assigned to sector i in all regions.
[17] The initial definition of an outlier sector can be chosen arbitrarily, but it should be in a range that only few outlier sectors exist.
[18] To ensure convergence it proved preferable to use only one percent of the total difference for the adjustment, thus: $f(\hat{y_{ir}} - y_{ir}) = 0.01 \cdot (\hat{y_{ir}} - y_{ir})$

5. Repeat steps 1 to 4 until there are no more improvements in the relative deviations within a chosen limit of iterations (1 million in our case).

We can then insert the estimated $\hat{\mathbf{z}}$ in (3.41). We extend the right term of the right hand side by $\mathbf{v}^{+}\mathbf{v} = 1$ to obtain

$$\mathbf{y} = (\mathbf{A}'^{+} + (\mathbf{I} - \mathbf{A}'^{+}\mathbf{A}')\hat{\mathbf{z}}\mathbf{v}^{+})\mathbf{v}. \tag{3.42}$$

This last transformation allows us to determine how sectoral final goods output, $\mathbf{y}$, reacts to changes in the factors of production. We define the outer parentheses on the right hand side of (3.42) as

$$\mathbf{\Lambda} = \mathbf{A}'^{+} + (\mathbf{I} - \mathbf{A}'^{+}\mathbf{A}')\hat{\mathbf{z}}\mathbf{v}^{+}, \tag{3.43}$$

where $\mathbf{\Lambda}$ is a matrix whose columns indicate the response in final goods output in each sector in each region to a unit increase in each factor of production. We extract the columns of $\mathbf{\Lambda}$ to have eight single column vectors, one for each factor of production. So, for instance, the vector containing the effect of a unit increase in the capital stock in Germany on output is denoted as $\lambda^{\mathbf{KG}}$.

Having all the elements to compute the change in output of intermediate and final goods, we can now outline the procedure. First, we calculate the initial change in output without considering scarcities as follows:

$$\mathbf{\Delta x^{op,p}} = (\mathbf{I} - \mathbf{L})^{-1}\mathbf{\Delta d^{K}}, \tag{3.44}$$

where $\mathbf{\Delta d^{K}}$ is a vector of the changes in final demand, whose elements are calculated by multiplying ΔK_{ir} and the fraction of final demand per capital stock, $\frac{d_{ir}}{K_{ir}}$. Furthermore, we assume that ΔK_{ir} is equal to the investment in each type of renewables.

The preliminary changes in $\mathbf{x}$ require changes in the employment of production factors. We denote these preliminary changes $\Delta K_{ir}^{op,p}$, $\Delta L_{ir}^{op,p}$, $\Delta M_{ir}^{op,p}$, $\Delta H_{ir}^{op,p}$ and compute them as follows:

$$\Delta H_{ir}^{op,p} = \Delta x_{ir}^{op,p}\frac{H_{ir}}{x_{ir}}, \tag{3.45}$$

where $\frac{H_{ir}}{x_{ir}}$ is the factor coefficient, defined as the ratio of high-skilled labor per unit of output. Accordingly, we can calculate the changes in value added, as well as low and medium-skilled labor by inserting the appropriate factor coefficient. Aggregating the effects across sectors at the level of the regions where production factors are mobile, that is, within Germany and within ROW, we get the preliminary changes in high-skilled labor $H^{G,op,p}$.

To compute the net effects on $\mathbf{x}$, we subtract the effects generated by the scarcity of factors of production. However, we first need to translate the scarcity effects to express them in terms of intermediates and final goods output, $\mathbf{x}$, since they were computed in terms of final goods output, $\mathbf{y}$. Sticking to the example of high-skilled labor in Germany, we compute:

$$g_{ir}^{HG} = \lambda_{ir}^{HG} \frac{x_{ir}}{y_{ir}}. \tag{3.46}$$

Now, we can proceed as follows to calculate the net effect on $\mathbf{x}$ in the operations phase:

$$\Delta x_{ir}^{op,net} = \Delta x_{ir}^{op,p} - g_{ir}^{LG} L^{G,op,p} - g_{ir}^{MG} M^{G,op,p} - g_{ir}^{HG} H^{G,op,p} - g_{ir}^{KG} K^{G,op,p}. \tag{3.47}$$

The total effect on output from the investment and the operations phase is then:

$$\Delta x_{ir}^{net} = \Delta x_{ir}^{inv,net} + \Delta x_{ir}^{op,net}. \tag{3.48}$$

Value added and employment effects

To evaluate the effects of investments in renewables on regional value added, low, medium and high-skilled employment we can now use the total changes in output from (3.48) and the factor coefficients as in the following example for high-skilled employment:

$$\Delta H_{ir} = \Delta x_{ir}^{net} \frac{H_{ir}}{x_{ir}}, \tag{3.49}$$

We can derive aggregate effects for the regions, by summing across the sectors in each region:

$$\Delta H_r = \sum_{i=1}^{N} \Delta H_{ir}. \tag{3.50}$$

Similarly, we can aggregate the effects to present results for the single sectors, across regions:

$$\Delta H_i = \sum_{r=1}^{R} \Delta H_{ir}, \tag{3.51}$$

or aggregate to consider only the three districts.

3.3 Data

3.3.1 Input-output table

The IO tables on which the analysis is based are the German IO table of inland production and imports for the year 2014 and the 2014 World IO Table from WIOD (Timmer et al. 2015). For disaggregation of the energy sector we use Exiobase 2 (Wood et al. 2015), which is, to our knowledge, the only table where the energy sector is disaggregated into several electricity production technologies, electricity transmission, electricity distribution, heat production, and gas distribution.

3.3.2 Regional data

From the Regional Accounts database of the federal and regional statistical offices we obtain data for the districts' GDP, aggregated gross value added data and disposable income of private households for the districts. GDP, government consumption, gross investments in equipment and buildings and private consumption for Germany and Bavaria are also obtained from this database. Employment statistics by sector both for Germany and the districts come from the federal employment statistics office.

Electricity and heat consumption, as well as data on electricity generation in the three districts was obtained from Reinhardt et al. (2017). Updated information was generously provided by the authors. Data on the length of electricity transmission lines in the districts were obtained from the Bavarian State Ministry of Economics and Energy (StMWi 2018). Data on electricity and heat generation by energy source in Germany comes from IEA (2017).

3.3.3 Factors of production

The three categories of labor input (low-, medium-and high-skilled) for Germany and the ROW are also from Exiobase 2 (Wood et al. 2015). Data for capital stocks for Germany had to be derived from various sources. For standard NACE 2-digit sectors, capital stocks are available from Eurostat (2016a) (total non-financial fixed assets, gross at replacement costs). For the energy subsectors, capital stocks were disaggregated manually. The general approach was to calculate the capital stock in each subsector from existing data on installed capacity and the current costs of building such capacity, such as to approximate replacement costs. In a second step, the results were scaled to the total capital stock of the energy sector available from Eurostat (2016a). Details on the data sources can be found in Appendix C.2.

3.3.4 Future renewables deployment and investments

Future deployment of renewables for electricity and heat generation, energy efficiency measures and electricity storage in each of the three districts were obtained from the simulations done in the framework of the project by two Geography Departments of LMU Munich. Thus, the deployment figures constitute an exogenous input in the present study. The simulations are based on the natural potential for renewable energy generation in the region, the available land use restrictions (e.g., due to conservation areas), the preferences of the population regarding technology types and installations' size, and the profitability of the measures, besides the usually considered factors like interest rates and energy prices.

The scenarios are constructed along two dimensions: one describing the overall economic and social setting, and another outlining possible deployment paths. The first dimension considers, on the one hand, a business-as-usual (BAU) scenario and, on the other hand, a scenario with a trend towards a more sustainable economy and society (GREEN). The deployment paths differentiate between focusing primarily on small scale installations or on large scale installations of renewable energies. Combining both dimensions leads to four scenarios: BAU SMALL, BAU LARGE, GREEN SMALL, and GREEN LARGE.[19] From the simulations we obtain the annual average sum of renovation expenditures per district and information on the capacity (in kWp) installed per technology type and year from 2015 to 2035. In our analysis, we consider the average installed capacity per year.

[19] For more information on the simulations see Danner et al. (2019). Table C.3 in Appendix C.3 provides an overview of the scenarios. For a more detailed information of the scenario construction process, see Musch and Streit (2017).

Table 3.2 depicts the comprehensive set of technologies and measures we consider in the analysis. It also shows that companies and other institutional investors invest in almost all type of technologies and measures except in heat pumps. Investments by private households take place in rooftop solar PV, solar thermal installations and heat pumps, on the generation side, and in district heating networks, renovations and batteries, on the energy infrastructure side.

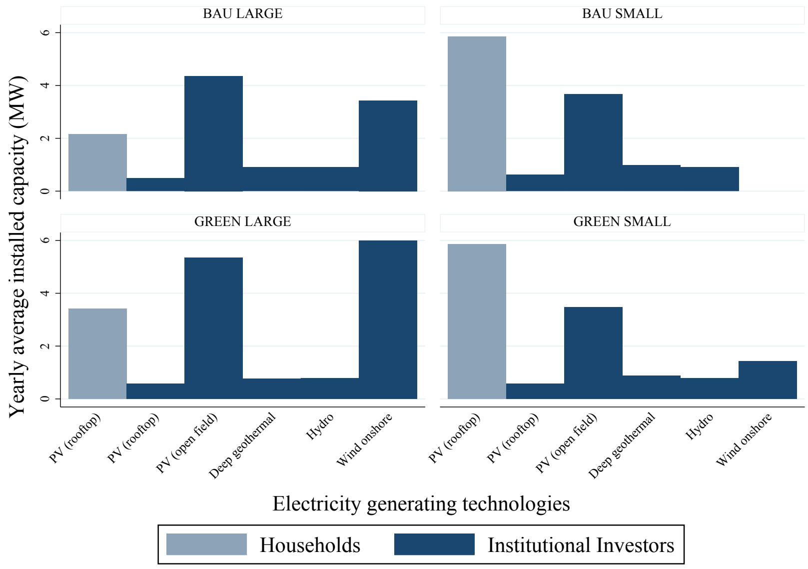
Table 3.2 : Technologies, measures and type of investor

Technology	Companies	Private households
PV (rooftop)	x	x
PV (open field)	x	
Solar thermal	x	x
Biomass	x	
Wind onshore	x	
Hydro	x	
Deep geothermal	x	
Geothermal heat pumps		x
District heating network	x	x
Renovations	x	x
Batteries	x	x
Power-to-Gas	x	
Gravity storage	x	

The investment and operating costs for most power and heat generating technologies, as well as their distribution among sectors was obtained from Hirschl et al. (2010). The information for deep geothermal is from Hirschl et al. (2015). The renovations costs as well as their distribution among sectors is obtained from Hinz (2015), Loga et al. (2015) and IWU (2018). For each scenario we combine this information with the installed capacity by year, technology, investor type and district, which results in several cost vectors. We subsequently sum up over technologies to arrive at a vector by investor type, district and scenario. These vectors are the basis of the methodology outlined in Section 3.2.3.

In the following, we describe the deployment figures obtained from Danner et al. (2019). Figure 3.1 shows the average installed capacity for electricity generating technologies, classified by technology, type of investor and scenario. From the figure, it becomes clear that the largest differences in the yearly installed capacity arise from concentrating the efforts on small scale installations (scenarios BAU SMALL and GREEN SMALL) or focusing on large scale installations (scenarios BAU LARGE and GREEN LARGE). So, for instance, in the GREEN SMALL scenario the

Figure 3.1 : Installed capacity by scenario, yearly average



average installed capacity of rooftop solar by households is, with 6 MW, twice as large than in the GREEN LARGE scenario. The contrary and with even more pronounced differences, occurs for wind installations, where the average installed capacity in the GREEN LARGE is 6 MW versus 1.2 under the GREEN SMALL scenario. Figure C.1 in the Appendix shows a similar pattern for heat generating technologies.

Expressing these figures in relation to the number of inhabitants allows a comparison to current deployment in the whole of Bavaria. We see that for the GREEN LARGE scenario, the yearly PV and wind installations are equivalent to 25.7 kW per 1,000 inhabitants and 18.5 kW per 1,000 inhabitants, respectively. The newly installed capacity in kW per 1,000 inhabitants in Bavaria for the year 2017 (2018) was 50.9 (31.3) for PV and 24.2 (17) for wind (Agentur für Erneuerbare Energien 2019). Thus, putting the regional deployment figures into context shows that, although the regional energy transition in the Bavarian Oberland requires an important deployment of renewable technologies, it does not require an unrealistic development. Yet, it is important to mention that these deployment scenarios would not achieve a complete coverage of the energy demand by renewables by 2035, but would bring the coverage rate in electricity from 38% in 2015 to 51-62% in 2035. For heating, the coverage rate would increase from 26% in 2015 to 62-66% in 2035. Although the natural and technical potential would allow the region to meet its target by 2035, in the deployment simulations an annual technology specific “administrative installation cap” was set. The main rationale behind this cap was to account for the observed limited capacity of the public administration when it comes to granting the necessary licenses for the installation of renewable energies.

3.4 Results

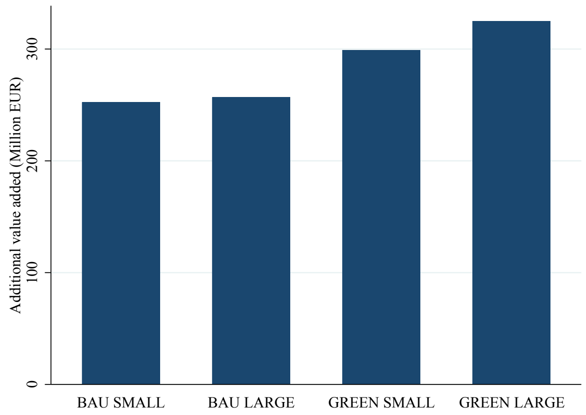
In this section we present the results obtained by applying the methodology outlined in Section 3.2 to investigate the economic effects of a future energy transition in the Bavarian Oberland region. We start by presenting aggregated effects for the whole region and then dig deeper and show value added and employment effects for the individual districts and for individual sectors.

3.4.1 Effects on value added

Investments in renewables generate an aggregated regional value added ranging from 252 to 325 Million EUR, depending on the scenario, as shown in Figure 3.2. Considering that the value added in 2014 amounted to 9.5 Billion EUR, the presented figures translate to an increase in value added of between 2.6% and 3.4%. In Figure 3.3 we see that all three districts benefit to a similar extent from RES investments in absolute terms. The overall effects for the whole of Germany (that is, including the Oberland region) are also positive, yet the rest of the country suffers from the crowding out of alternative investments and consumption, and from the Oberland region attracting factors of production which are then missing for production in the rest of Germany. The reason for the overall effects for Germany to be positive is that we allow for financial resources to be attracted from the rest of the world when considering crowding out effects in the investment phase. This approach leads to a lower investment crowding out in Germany than if we had restricted financial resources in the investment phase to come only from Germany.

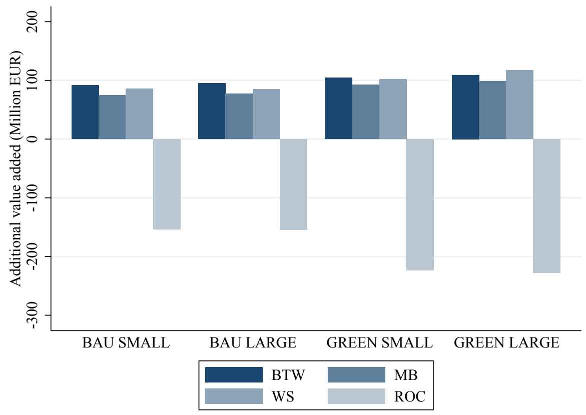
Looking at the sectoral effects in Figure 3.4, which shows exemplarily the results for the GREEN LARGE scenario, it is not surprising that the winners from the energy transition in the Oberland region are the sectors that are more closely related to the installation and operation of renewables as well as to renovations to increase the energy efficiency of buildings. Capturing about 30% of the additional value added, the *Construction* sector benefits the most across all scenarios, as can also be seen for the remaining scenarios depicted in Figures C.5 to C.7 in the Appendix. *Wholesale and repairs*, *Electricity from solar* and *Electricity nec; steam and hot*

Figure 3.2 : Aggregated effects on value added, by scenario



Notes: The bars show the aggregate value added figure for the three districts in the Oberland region.

Figure 3.3 : Effects on value added, by scenario and region

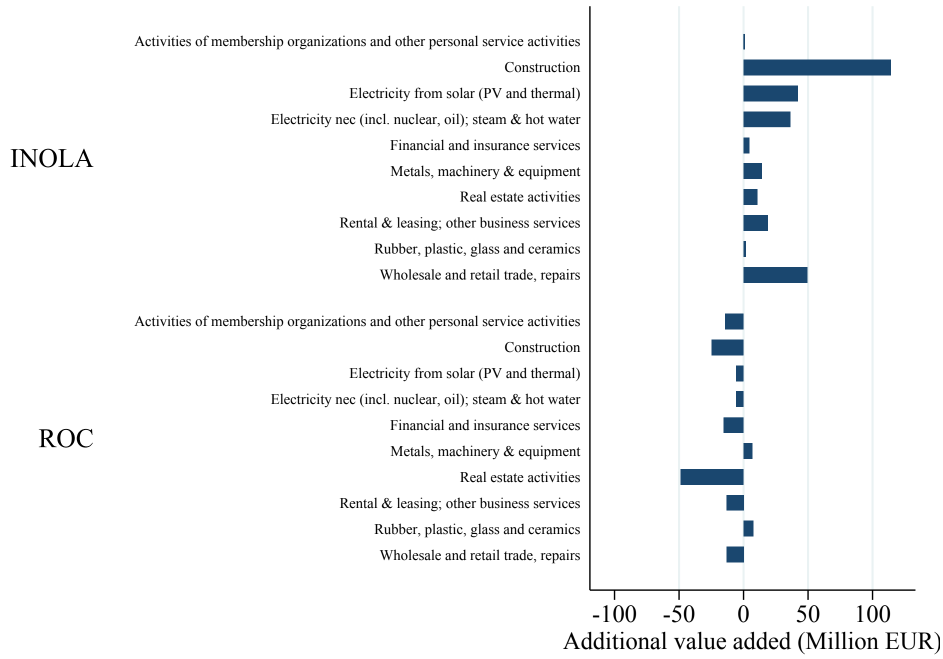


water are also among the sectors that benefit most across all scenarios.[20] Although we cannot verify the subsectors' share in the increase or decrease in a sector's value added, it can be argued that *steam and hot water* are the subsectors contributing most to the increase in value added in the *Electricity nec; steam and hot water* sector. Within the Oberland region there are no proper losers from the energy transition. The sector with the most negative change in value added is *Human health and social work activities* with a decrease of 0.5 Million EUR. To a certain extent, this can be explained by our assumption that factors of production are fully mobile within Germany, granting the Oberland region access to a large pool of factors. The consequence of the assumption is that sectors in the Oberland region increase their

[20] nec: not elsewhere classified.

production at the expenses of sectors in the rest of the country and not at the expenses of other sectors within the region.

Figure 3.4 : Effects on value added for selected sectors, GREEN LARGE scenario



Notes: For a better visualization some sector descriptions have been shortened. See Appendix C.1 for the full sector descriptions.

The careful reader might be missing conventional electricity sectors among the losers of the energy transition. In fact, in the rest of the country value added in the sectors *Electricity from coal* and *Electricity from gas* decreases, yet, only by about 5 Million Euro, corresponding to a decrease of approximately 0.02% of these sectors' value added in 2014. The almost insignificant loss for these two sectors is more reassuring than worrying, given the small size of the Oberland region compared to the rest of Germany. Since there are no coal power plants in the Oberland region, there is no *Electricity from coal* sector in any of the districts and, therefore, no value added losses.

3.4.2 Effects on employment

The employment effects of the energy transition in the Oberland region are shown in Figure 3.5. Most of the increase occurs in medium-skilled employment, making up about 66% of the

Figure 3.5 : Aggregated effects on categories of employment in the Oberland region, by scenario

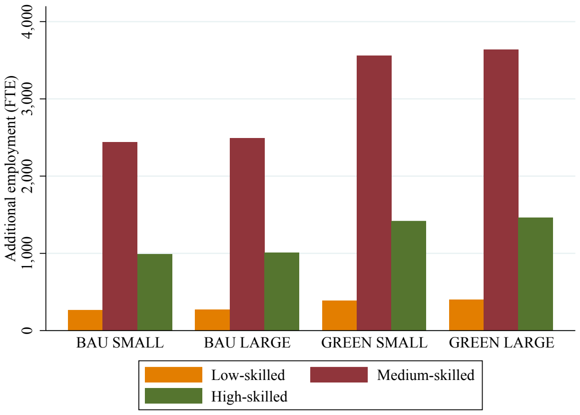
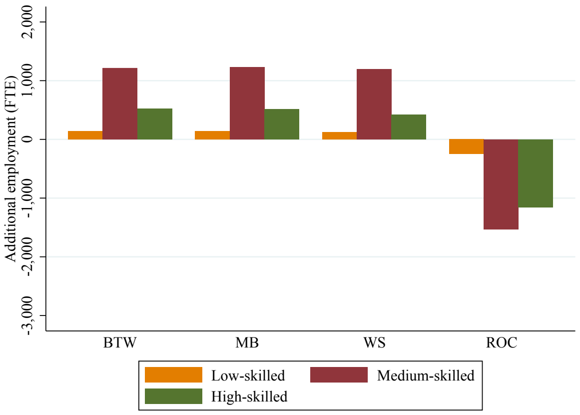


Figure 3.6 : Effects on employment by category and region, GREEN LARGE scenario

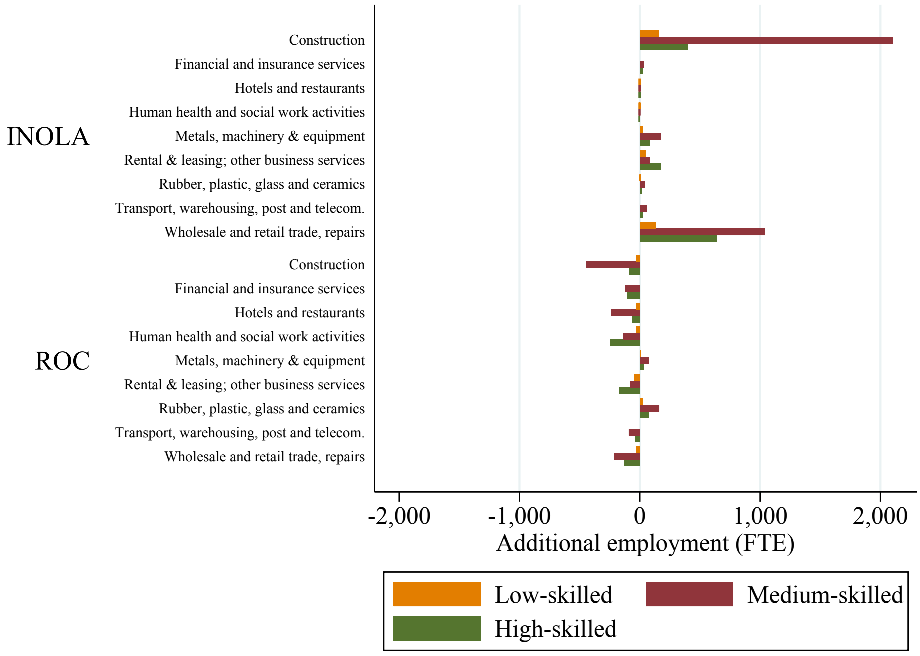


additional full time equivalent (FTE) jobs.[21] Under the GREEN LARGE scenario, for instance, the considered investments in renewables create 3,640 medium-skilled jobs in the region, while the increase in high-skilled and low-skilled jobs is close to 1,460 and 400, respectively.[22] In relative terms the increase in medium-skilled employments lies between 3% and 4.5% with respect to the year 2014. For low-skilled and high-skilled employment, the percentage increase is 2-2.9% vs. 1.6-2.4%, respectively. This implies that, in contrast to the absolute changes, the relative increase in low-skilled employment is larger than in high-skilled employment.

[21] Considering that in 2014 medium-skilled labor accounted for 52% of employment across all categories, this result implies that the increase in medium-skilled labor is more than proportional to the pre-energy transition shares.

[22] Note that, technically, we should rather refer to a reallocation of jobs instead of job creation, since we assume labor to be scarce. However, interpreting the results as job creation in the region is not wrong per se, but we need to keep in mind that this requires that jobs are “destroyed” somewhere else.

Figure 3.7 : Aggregated effects on employment by category, selected sectors and aggregated region, GREEN LARGE scenario



Notes: For a better visualization some sector descriptions have been shortened. See Appendix C.1 for the full sector descriptions.

Looking at the regional distribution of the employment effects, we see that it follows a pattern similar to the effects on value added (see Figure 3.6 and Figures C.2 to C.4 in Appendix C.4). The negative effects for the rest of the country in all three categories show that most of the employment effects occurring in the Oberland region are job reallocations from the rest of the country and, therefore, cannot be referred to as job creation. Note, however, that in light of the findings of Buchheim et al. (2020), the employment results under the mobile labor assumption can to some extent be understood as results for slack labor markets: when we interpret labor from the rest of the country as coming from an unemployment pool. It has to be noted though that in our model, these employees contributed to production in the rest of the country before the “shock”, so it is not an accurate respresentation of unemployment.

Breaking down the employment effects in the GREEN LARGE scenario by sector delivers the results in Figure 3.7.[23] Considering the results presented so far, it is not surprising that for medium-skilled labor the *Construction* sector exhibits the largest positive effects for the

[23] A sector breakdown for the other scenarios can be found in Figures C.8-C.10.

Oberland region and the largest negative effects for the rest of the country. *Electricity from solar* and *Electricity nec; steam and hot water* are among the sectors that benefit most in terms of value added, yet, due to their low labor intensity, the employment effects in these sectors are rather low.

3.5 Conclusions

In this investigation of the economic effects of an intended energy transition in the Bavarian Oberland region we contribute to the literature in several ways. First, we disaggregate the energy sector in the IO table to be able to consider the specificities of each technology's interlinkages with the rest of the economy. Second, we contribute to the literature on the economic effects of regional investments, in a broader sense, and more specifically, on the effects of regional investments towards a transformation of the energy system. The key contribution to this literature is the consideration of scarcities, which generate crowding out effects both in the investment and in the operation phase. A third contribution consists in expanding the approach developed by Fisher and Marshall (2011) Benz et al. (2014) to apply it to an energy-related question and to improve its performance in a subnational context.

We show that following investments in a sector embedded in a framework where full employment and scarcity of financial resources is realistically assumed, value added and employment in this and other sectors increase, but this comes at the expenses of other sectors and other regions. We further show that assuming full mobility of factors of production within Germany, gives the sectors in the Oberland region access to a very large pool of workers and capital, that is, that of the rest of the country. Thus, the negative effects on other sectors are almost fully "exported" to the region(s) where the investments do not take place. In our case the decline in value added and employment occurs almost exclusively in sectors of the rest of the country and not in our region of study. Moreover, we find that although employment in the Oberland region increases in all three categories (low, medium and high-skilled), the increase in medium-skilled employment is stronger than for the other two categories.

Thus, from the analysis of the employment effects of the intended energy transition in the Bavarian Oberland region we can also draw conclusions for the whole of Germany and for other countries with similar conditions. Irrespective of whether the energy transition occurs at the regional or the national level, our results show that fundamentally restructuring the energy system, as it is necessary to reduce greenhouse gas emissions in a serious manner, requires an intensified employment of medium-skilled labor. Thus, considering that already today Germany suffers from medium-skilled shortages, this can turn into a bottleneck for the transformation of the energy system. We could expect market forces to fix the shortages by increasing incentives (i.e., wages) in the demanded professions. Yet, the working of market forces could take time, which is not available when talking about mitigating climate change. The other, better option is to be proactive and increase the awareness for the importance of these professions and their attractiveness as part of climate and energy policy interventions.

It is important to take into account that our analysis of the economic effects of a regional energy transition is placed in a context where investments in renewable energies remain constant outside of the Oberland region. If, on the contrary, other regions pursue a similar goal or the energy transition at the national level is intensified, scarcities in the factors of production would inhibit the achievement of the goals and therefore limit the positive effects on the regional economy. Hence, further questions that arise in this context concern the consequences of a far-reaching regionalization of the energy transition goal, that is, when many regions intend to totally cover energy consumption by renewable energy generation. In particular, an interesting question would be whether this regionalization could give rise to a systems competition between the regions, seeking to attract capital (and labor) for the respective energy transitions.

Possible extensions of the methodology could consider alternatives to our assumption of full mobility of factors of production within Germany. On the one hand, the full mobility assumption is a plausible assumption, specially for the production factor capital. On the other hand, although in theory it is possible that workers move freely, there might also be frictions binding workers to a specific region. A further development of our methodology could deal with restricting mobility partially, so that it is possible to attract workers form other regions, but to a limited extent. One possibility in this respect is to include neighboring districts in the analysis to allow mobility within that larger region, but not with the rest of Germany. Finally, modelling unemployment specific to sectors, regions and skill levels can be a useful addition in light of the findings of Buchheim et al. (2020) and the current economic crisis.

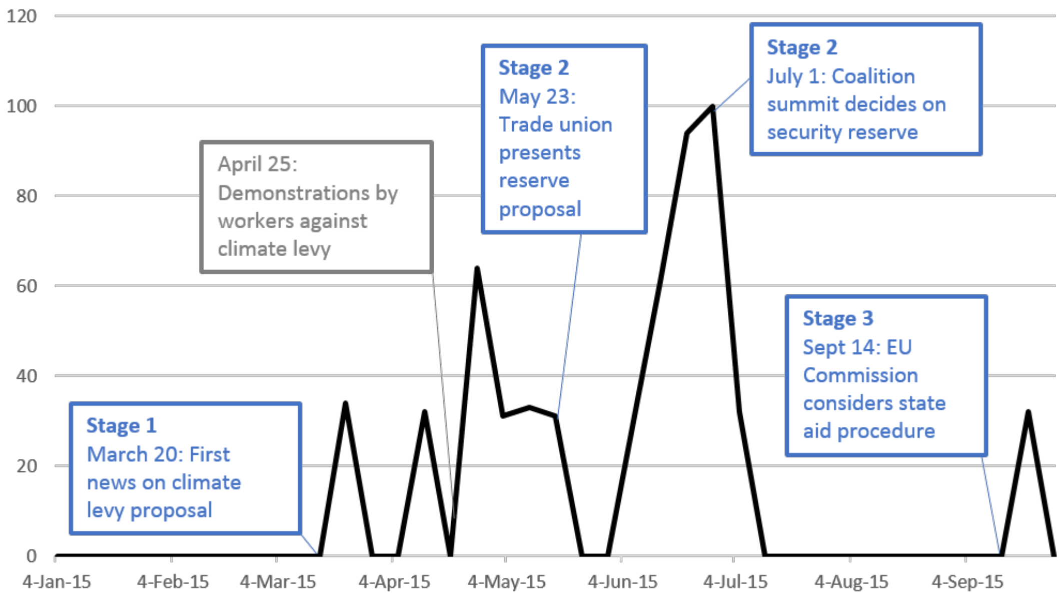
Appendices

A Appendix to Chapter 1

A.1 Google trends statistics

Figure A.1 shows the google trends statistics for the term “Klimabeitrag” (climate levy) between January and September 2015. Google trends report relative frequencies of searches (not absolute search numbers) in weekly intervals. We highlight some of the announcement dates we identified. We also included information on demonstrations against the climate levy as this helps explain some spikes in searches.[1]

Figure A.1 : Google trends statistics for the term “Klimabeitrag” in Germany



We restricted our search to the term “Klimabeitrag” because this is the only term related to the proposal development with a unique meaning. For example, the official term “security reserve” was often replaced by other terms such as “capacity reserve”, “lignite compromise” or “climate reserve” in the media, making it difficult to follow the trends in the public interest.

[1] For the demonstrations against (and also for) the climate levy proposal, see e.g. https://www.tagesspiegel.de/wirtschaft/streit-um-zukunft-der-kohle-tausende-demonstrieren-gegen-und-fuer-die-braunkohle/11689424.html.

A.2 Details on the theoretical analysis

In this section, we provide further details about the theoretical analysis in Section 1.3.

A.2.1 Electricity market data

We obtain data on total load, renewable generation, and day ahead prices at the EEX for German power market at hourly resolution from Open Energy Modeling Initiative (OEMI 2019). We calculate the residual load as total load minus renewable electricity generation. Table A.1 presents a set of summary statistics for our main variables based on the raw 2015 electricity market data for Germany. Figure A.2 illustrates the distribution of hourly electricity demand and prices, where we only exclude negative prices. In our analysis, we truncate the prices at the upper and lower 2nd percentiles which drops negative prices as well.

Table A.1 : Summary statistics for data on the electricity market

	N	Mean	Median	St. Dev.	Min.	Max.
Total load (GW)	8760	59.46	59.03	10.56	36.15	79.89
Renewable generation (GW)	8760	12.83	11.26	8.54	0.34	42.47
Residual load (GW)	8760	46.63	46.48	11.75	9.39	78.50
Price (Euro/MWh)	8759	31.63	30.54	12.66	-79.94	99.77

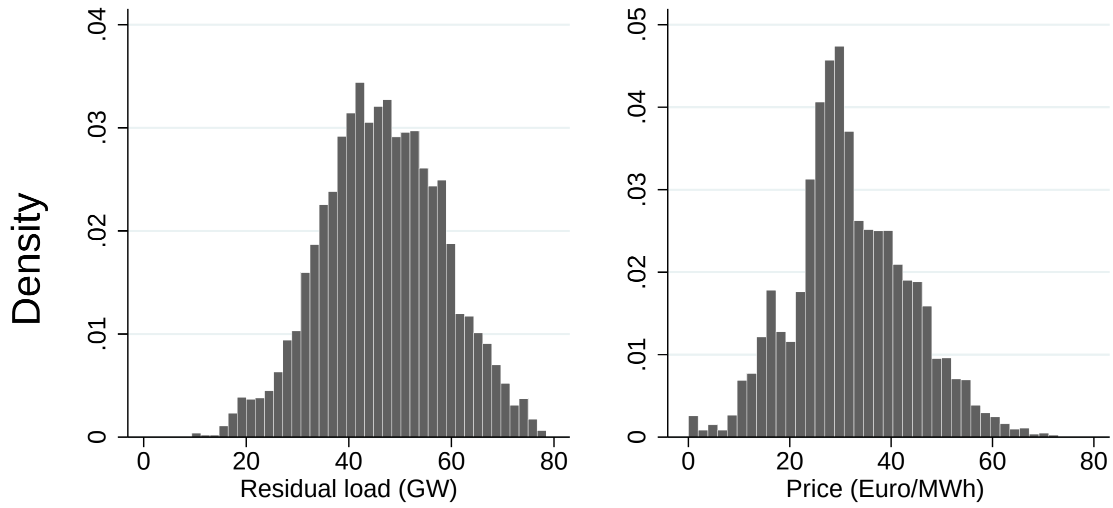
Notes: This table presents a set of summary statistics for our main variables based on the raw 2015 electricity market data for Germany.

A.2.2 Capacity utilization

In order to conduct our scenario analysis, we have to rank alternative technologies based on their marginal costs. Our ranking is based on the IEA's cost projections. We depict the implication of this strategy in Figure A.3, which shows the technological capacity ranges once more, but together with the merit order curve and the residual load distribution. In order to verify this strategy, we also illustrate the distribution of hourly average power generation by technology in Figure A.4.[2] Comparing these two figures verifies the imposed merit order of technologies as follows: The distribution for nuclear is left-tailed, and the mass is close to its full capacity. This evidence confirms that the nuclear capacity is rarely a marginal technology, but often the infra-marginal technology. The picture for the gas capacity is just the opposite, verifying that it is the marginal technology only at the high load instants.

[2] We obtain these data from ENTSOE Transparency Data Platform.

Figure A.2 : Electricity prices and residual load in Germany in 2015



Notes: This figure illustrates the density of hourly residual load over 2015 and the day ahead prices in the EEX market. The residual load is given by total load minus generated electricity from renewables.

One can verify the merit order of other technologies with the same reasoning: when the distribution is more left skewed and the capacity utilization is higher, then this technology must have priority in serving to the market. The distribution for the lignite is less left-skewed compared to that of nuclear, and it works at the full capacity less often. Finally, the power generation from hard coal has a quite symmetric distribution which is in line with its merit order rank and its location at the center of the residual load distribution. Hence, this evidence confirms that the marginal technology is generally hard coal.

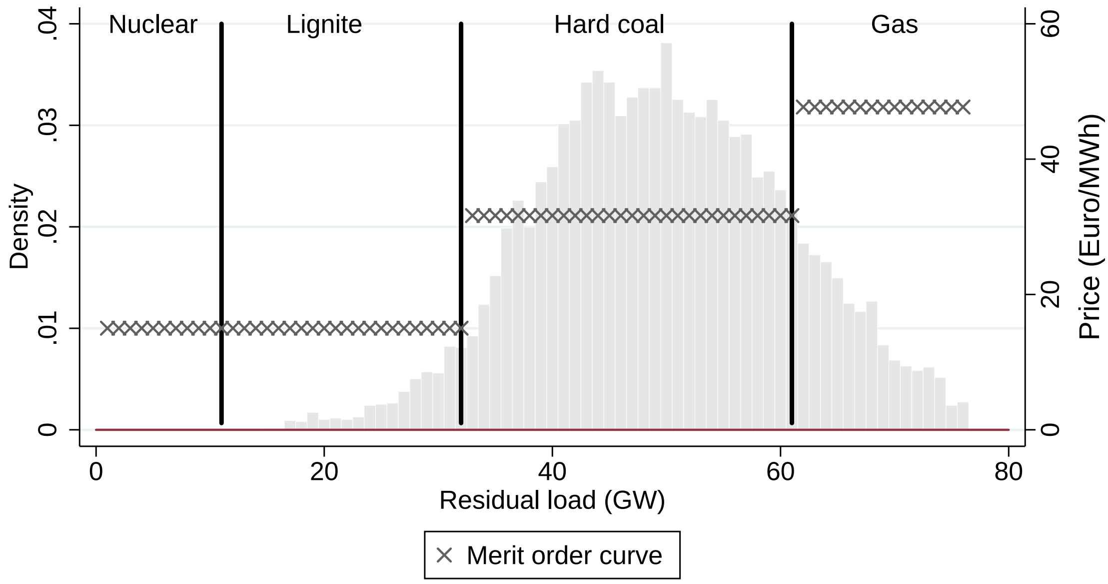
A.2.3 Capacities affected by the policies

Table A.2 presents the list of units to be transferred into the security reserve. This list includes five units of RWE. There are two more firms operating with lignite: Vattenfall GmbH and Mibrag GmbH. However, they are not publicly listed companies, hence not relevant for the event study analysis.

A.2.4 Non-constant marginal costs

In order to illustrate the overall profit effect of using a non-constant supply curve, we provide a naive estimate for the merit order curve. In Figure A.5, we display our linear predictions per

Figure A.3 : Density of residual load and the merit order



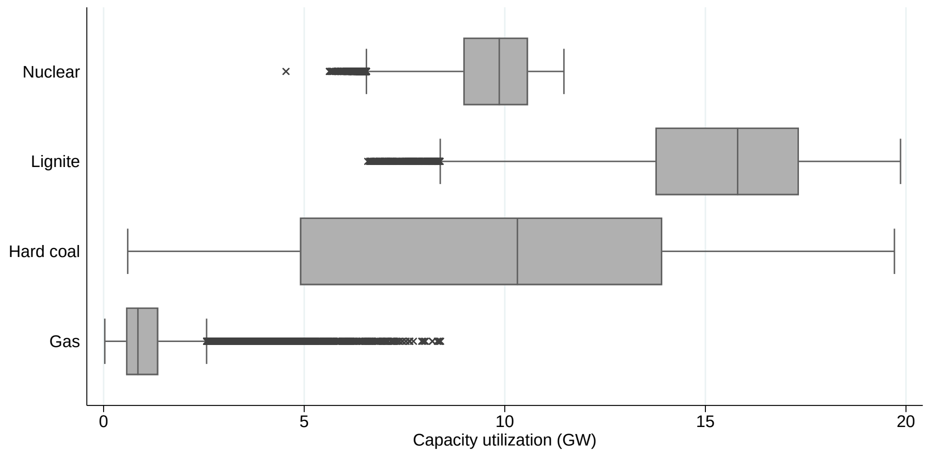
Notes: This figure illustrates the density of daily residual load in 2015 by technology and the merit order curve used in our scenario analyses. The residual load is given by total load minus generated electricity from renewables.

technology, where we estimate the supply curve separately for each capacity range determined by the merit order of different technologies. It is seen that the technology-specific fit is very close to the fitted line to the full sample. In the rest of the section, we use these technology-specific linear estimations.

Figure A.6 shows the effect of the climate levy on the supply curve, where the technological capacities are illustrated for the baseline situation prior to the arrival of the policy shock. We assume that the policies affect the lignite capacities with the highest marginal cost of electricity production. The supply curve of the hard coal capacity shifts to left, and the affected lignite capacity is relocated just to the left of the gas capacity. Hence, the location of the gas capacity does not change in this scenario. Note that this is not the case in the security reserve scenario, where we simply remove the affected lignite capacity from the supply schedule. We do not present the same figure for the security reserve scenario for brevity. However, we illustrate the price and profit effects for both scenarios in the following analyses.

The predicted changes in prices are illustrated in Figure A.7 for both the climate levy and the security reserve scenarios. This figure highlights several important points. First, there is no shift in the supply curve for the nuclear and unaffected lignite capacities. Therefore, the

Figure A.4 : Distribution of power generation by technology

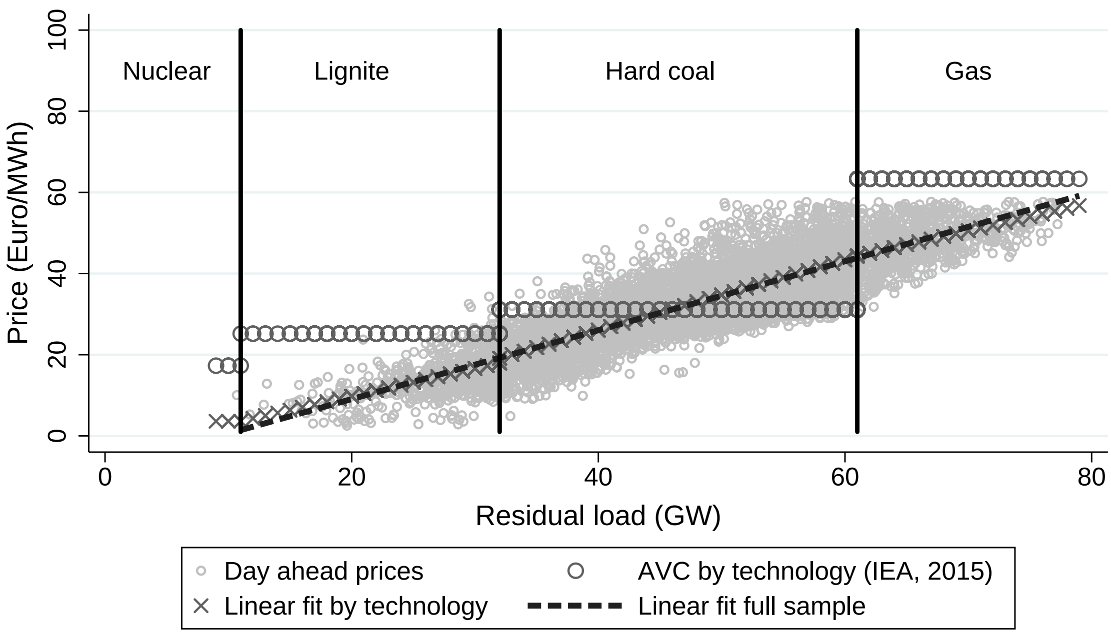


Notes: This figure illustrates the distribution of average daily power generation in 2015 by technology. The boxes illustrate the quartiles. Capped lines indicate adjacent values (1.5 times the interquartile range away from the upper and lower quartiles). Outliers are marked with cross.

prices do not change. Second, the location of the gas capacity changes in the security reserve scenario, but not in the climate levy scenario. As a result, the prices at the high-load instants do not change due to the climate levy. Third, the price increase is constant in residual load for the capacity ranges where there is only a shift in the supply curve. However, the price changes can be increasing or decreasing in residual load depending on the change in the slope of the supply curve. Since we assumed linearity, the slope of the supply curve changes only at the capacity ranges where the production technology changes.

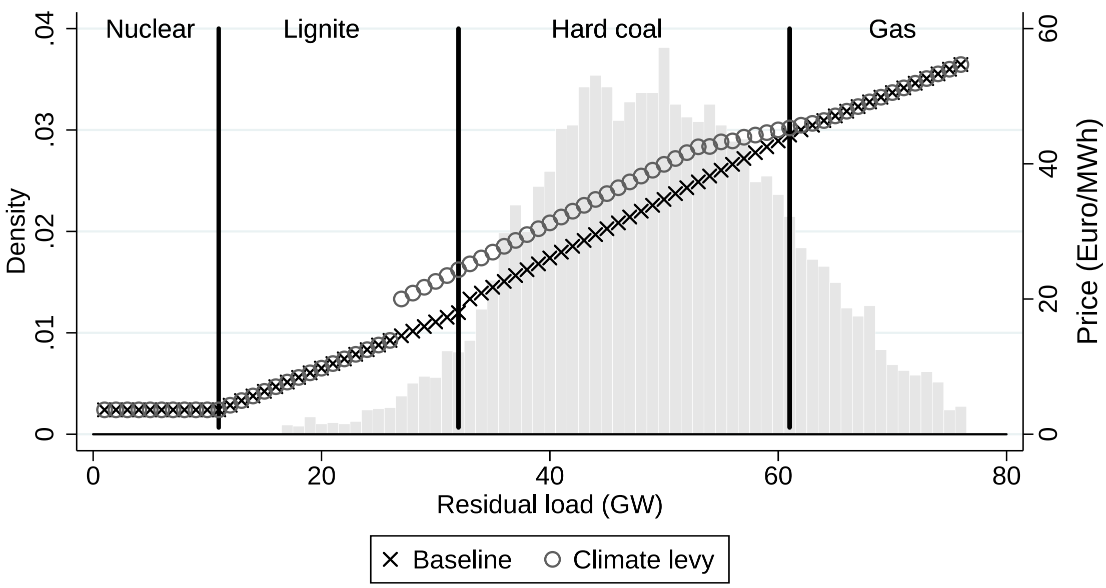
Figure A.8 presents the profit effects by using the estimated technology-specific linear merit order curve. The results are as follows: First, there is no change in the profits when the marginal technology is nuclear, as there is no change in prices. Second, there is a minor and negative profit effect at the hours when the unaffected lignite capacity is the marginal technology, although there is no price change at those hours. The reason is that the policy scenarios change the RWE's share in the unaffected lignite capacity. Third, there is a strong jump in prices at the load instants where the lignite capacity is replaced with hard coal capacity. This jump results in extra profits from the infra-marginal nuclear and unaffected lignite capacity. The profit effects are increasing in residual load within this capacity range, because the hard coal replacing lignite capacity has a steeper supply curve. Fourth, at the average load instant where the hard coal capacity is operating, the increase in price leads to positive profit effects for the infra-marginal nuclear and unaffected lignite capacity. On the other hand, the hard

Figure A.5 : Technology-specific linear fits



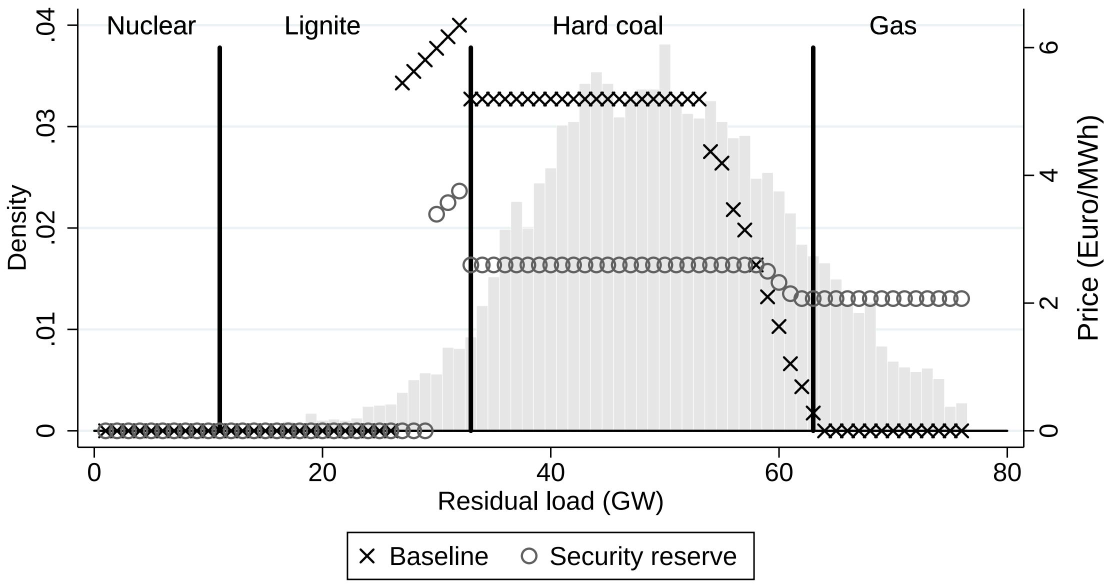
Notes: This figure illustrates the price and residual load observations, the linear fits per technology, the linear fit to the full sample, and the IEA's cost projections. The prices are day-ahead prices in the EEX market in 2015. The residual load is given by total load minus electricity generation from renewables.

Figure A.6 : Climate levy and the supply curve



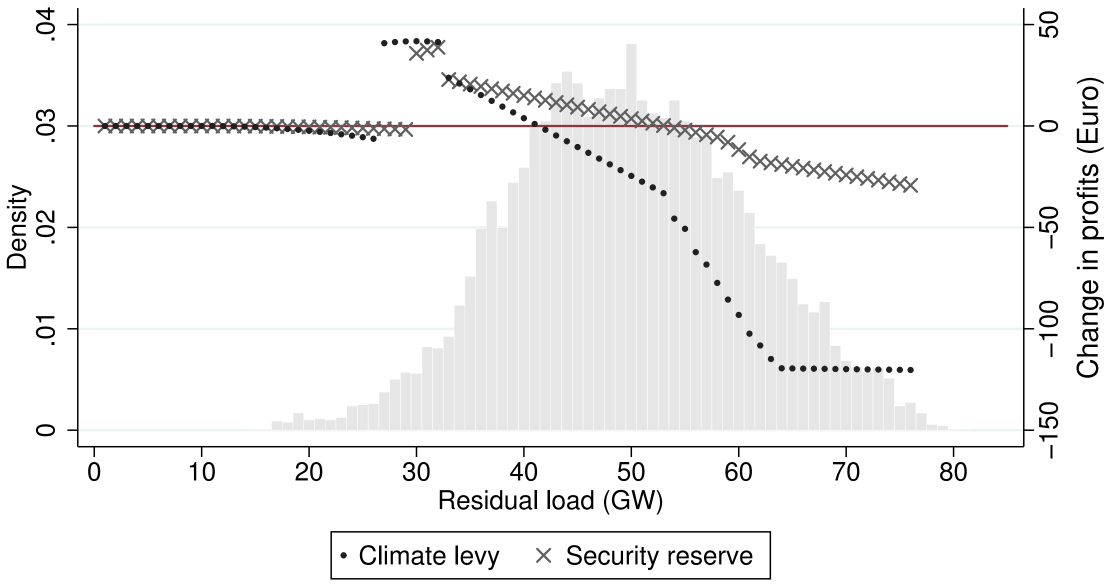
Notes: This figure illustrates the changes in the supply curve for the climate levy scenario. The residual load is given by total load minus generated electricity from renewables.

Figure A.7 : Changes in prices



Notes: This figure illustrates the predicted changes in prices for the climate levy and the security reserve scenarios. The residual load is given by total load minus generated electricity from renewables.

Figure A.8 : Changes in profits



Notes: This figure illustrates the predicted changes in profits at each load instant for the climate levy and the security reserve scenarios. The residual load is given by total load minus generated electricity from renewables.

Table A.2 : Phase-out schedule

Operator	Name of unit	Nameplate capacity	Mothballing	Decommissioning
Mibrag	Buschhaus	352 MW	Oct 1, 2016	Sep 30, 2020
RWE	Frimmersdorf P	284 MW	Oct 1, 2017	Sep 30, 2021
	Frimmersdorf Q	278 MW	Oct 1, 2017	Sep 30, 2021
	Niederaußem E	295 MW	Oct 1, 2018	Sep 30, 2022
	Niederaußem F	299 MW	Oct 1, 2018	Sep 30, 2022
	Neurath C	292 MW	Oct 1, 2019	Sep 30, 2023
Vattenfall	Jänschwalde F	465 MW	Oct 1, 2018	Sep 30, 2022
	Jänschwalde E	465 MW	Oct 1, 2019	Sep 30, 2023

Source: State Aid Decision Text (SA.42536), Closure of German Lignite Plants: Letter to the Member State. Available at `http://ec.europa.eu/competition/state_aid/cases/261321/261321_1762503_157_2.pdf`.

coal capacity operating at the average load is now producing with higher marginal costs, which exerts a negative pressure on the profits. The net effect is generally positive to the left of the average load and generally negative to the right. The reason is that, the share of capacity operating with higher marginal cost is higher to the right of the average load instant. Therefore, the profit effects become gradually negative at higher load instants.

We calculate the overall profit effects as the average of the profit changes weighted with the residual load densities. Overall, we find that the climate levy causes 11$\%$ profit loss on average. For the security reserve scenario, even without any compensation, our results indicate that there is no change in profits on average (0.06$\%$ increase). This result shows that allowing for non-constant marginal costs tends to reduce the negative profit effects compared to our baseline assumption of constant marginal cost.

We conclude this section with some final remarks. The predicted price changes in this section are quite high. Around the average load, the climate levy leads to a more than 5 Euros increase in the equilibrium price, and the security reserve scenario causes an increase around 2.5 Euros. As a result the market equilibrium occurs at a higher price, which has a strong positive profit effect on each capacity unit operating at an average load instant, in particular for infra-marginal nuclear and unaffected lignite capacities. These predictions for price changes are much higher than those in Oei et al. (2015), where the predicted price increase is minor. The explanation might be that our naive estimate of the slope can be upward biased for several reasons. One problem might be the linearity assumption. Note that the estimated technology-specific lines form a quite smooth merit order curve. This result may be at odds with its common illustration with discrete jumps due to the presence of different production technologies in the supply schedule. In addition, one might expect its slope to be lower at lower load instants and higher at higher load instants. However, we have verified our estimations by conducting nonparametric robustness checks. A more likely problem is the simultaneity bias in the estimations of reduced-form supply or demand functions. Identifying the supply curve from data on equilibrium outcomes requires the demand to be fully inelastic. This might be an extreme assumption at the hourly resolution, as consumers might have a certain degree of flexibility in shifting their activity to different hours in a day (Mier and Weissbart 2019).

A.3 Data and descriptive statistics

Our dataset is mainly from Thomson Reuters Datastream. The market return is based on the DAX, a performance index consisting of the 30 major German companies trading on the Frankfurt stock exchange. The continuously compounded returns are first differences of the logarithm of prices. The descriptive statistics for the stock prices and market value of the three utility firms, and the returns to DAX30 index are provided in Table A.3. Figure A.9 illustrates the distribution of the returns for all three companies. The right panel excludes outliers to ease comparison around the center of the distribution.

In Appendix A.5, we provide robustness tests by using oil prices and interest rates. Their inclusion does not have any effect on the results. We use the crude oil spot price of Brent, FOB, and the German three-month government bond benchmark rate as the risk-free rate of return. The summary statistics for these additional variables are provided in Table A.3 along with our main variables. The level of and the variation in the interest rates are very low throughout 2015. The returns to oil prices is characterized by many outliers. As a result these variables do not add much to the explanatory power of the market model.

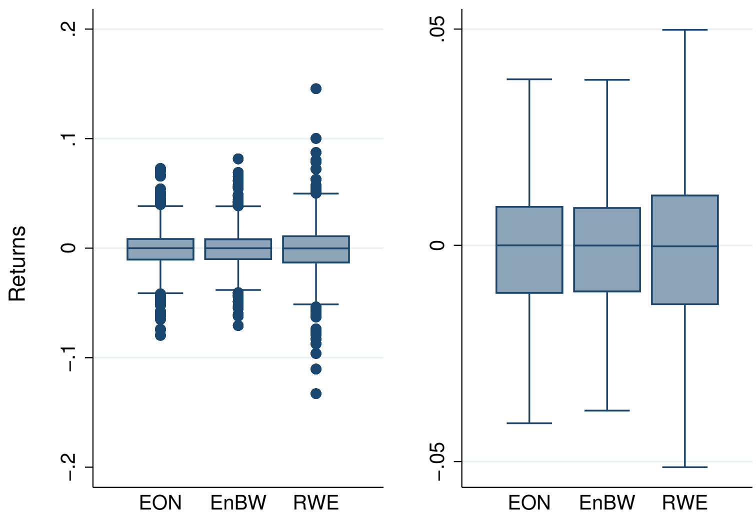
In using EnBW as a control unit, one concern might be that the results for EnBW are driven by a company-specific characteristic that makes its assets immune to any type of shock. In this case, using EnBW as a control unit would not eliminate the influence of a potential industry-wide shock. In Figure A.9 it is clear that the distributions of returns are more or less the same both at the tails and at the center. Therefore, it is not likely that the results for EnBW are driven by a company-specific characteristic. Hence, using EnBW as a control unit seems a sensible strategy.

Table A.3 : Descriptive statistics

	Units	Mean	Median	St. Dev.	Min.	Max.	Obs.
Stock price - RWE	€	18.392	19.789	5.330	9.219	25.684	261
Stock price - E.ON	€	10.253	10.853	1.957	6.331	12.889	261
Stock price - EnBW	€	24.120	24.800	1.660	19.866	26.759	261
Market value - RWE	bln. €	10.589	11.393	3.069	5.308	14.787	261
Market value - E.ON	bln. €	23.388	24.758	4.464	14.441	29.403	261
Market value - EnBW	bln. €	6.672	6.860	0.459	5.495	7.402	261
Risk free rate	%	-0.001	-0.001	0.000	-0.002	-0.000	261
Returns to DAX30 price index	%	0.035	0.063	1.460	-4.816	4.852	261
Returns to oil price	%	-0.188	0.000	2.346	-12.452	15.537	261

Notes: All values are based on 2015 data. Market value is equal to daily stock price times number of outstanding shares.

Figure A.9 : Distribution of the returns



Notes: This figure illustrates the distribution of the returns for all three companies. The dots indicate outliers. The right panel excludes outliers.

A.4 Details on estimation strategies

Our baseline estimation strategy is a short-run event study analysis. However, we use several specifications and identification strategies. To lay out our assumptions about the identification of an event effect and to facilitate comparison among alternative estimators and specifications, this section adopts a regression-based exposition of the short-run event study approach, while we also explain how it is related to the classical exposition in the main text.[3]

Consider the following specification to assess the impact of a single event at date T on the returns of a single asset i:

$$r_{it} = X_{it}\beta_i + \sum_{d=-h}^{+h} \gamma_i^d D_t^d + \epsilon_{it}, \tag{A.1}$$

Almost all the elements of this specification has been introduced in the main text: r_{it} is the continuously compounded return of the asset at the trading date t, X_{it} is the vector of covariates predicting the normal performance, and h is the half-width of the event window. We ignore the pseudo window for brevity. The potential effect of the event on the returns is captured by the set of event day dummies, $D_t^d = 1\{\tau = d\}$, where $d = -h, -h+1, .., h$ and the relative time index τ measures the distance to the event. Since the coefficient vectors, β_i and γ_i^d, and the error term, ϵ_{it}, are asset specific, Equation (A.1) is asset specific.

In this specification, as the event day dummies capture the whole variation in the event window, the event window observations are not relevant for the estimation of normal returns.[4] As a result, this specification is equivalent to the approach described in the main text: the event related abnormal return is given by $\gamma_i^d = r_{i,T+d} - \mathsf{E}[r_{i,T+d}|X_{i,T+d}]$, and its estimate is the prediction error, given by $\hat{\gamma}_i^d = r_{i,T+d} - \hat{r}_{i,T+d}$. The null hypothesis that the event does

[3] The short run event study methodology was introduced by Fama et al. (1969). See MacKinlay (1997) for a detailed description. The regression-based exposition is an alternative that is widely used in the literature. See, for example, Binder (1985a,b).

[4] Equation (A.1) excludes the event window observation in the estimation of expected returns as explained earlier. The pseudo window can be introduced as follows:

$$r_{it} = X_{it}\beta_i + \sum_{d=-k^u}^{-h-1} \gamma_i^d D_t^d + \sum_{d=-h}^{h} \gamma_i^d D_t^d + \epsilon_{it}, \tag{A.2}$$

where the chosen relative distance to the announcement date is k^u such that $k^u > h$. The abnormal returns between $T - k^u$ and $T - h$ are expected to be insignificant, and can be used to conduct pseudo tests.

not have an effect over the event window is formulated as:

$$H_0\colon \sum_{d=-h}^{h} \gamma_i^d = 0.$$

To account for many announcements, the second term of Equation (A.1) can be extended to all announcements. This is the approach described in Binder (1985a). The event day dummies are modified as $D_t^d = 1\{d = \tau \text{ for all } j\}$, where T_j denotes the date of announcement j. For example, $D^{-1} = 1$ when $\tau = t - T_j = -1$, which is the case for all dates one day prior to any announcement date. The average abnormal return (AAR) can be estimated by using Equation (A.1), but with redefined event day dummies.

$$r_{it} = X_{it}\beta_i + \sum_{d=-h}^{h} \gamma_i^d D_t^d + \epsilon_{it}. \tag{A.3}$$

In this case, each event day dummy captures the AAR across announcements for a day in the event window. Therefore, testing H_0 amounts to testing the significance of the average of cumulative abnormal returns (ACAR) over the events. To utilize variation across firms, one can simply impose $\gamma_i^d = \gamma^d$ and/or $\beta_i = \beta$.

In all our estimations, we allow the parameter vector β to be not only firm but also announcement specific. That is, in order to predict the counterfactual returns for each announcement, we employ a different sample around each announcement, and estimate β separately. This is equivalent to using Equations (A.1) or (A.2) to estimate the CARs and calculating the ACAR subsequently, as described in the main text. This approach can be represented by a regression model as follows:

$$r_{ijt} = X_{ijt}\beta_{ij} + \sum_{d=-h}^{h} \gamma_i^d D_t^d + \epsilon_{ijt}, \tag{A.4}$$

where j is the announcement index.[5]

In a single asset - single event case, there is only one observation for each date in the event window, hence the estimated abnormal returns are simply prediction errors. This is the case for

[5] Note the unusual indexation of the observations in this specification. Normally, the asset return, covariates, and error term should be uniquely defined by i and t. Indeed, if the normal market performance is estimated from a common sample of firm i's returns for all announcements, one can drop the j index. However, we allow the market structure to differ around announcements. In this case, the effective time index is τ, which is uniquely identified by j and t. Similarly, each i and j combination can be considered as a separate cross-sectional unit.

Equation (A.1) as it represents a separate regression for each firm and announcement. When there are repeated observations for the event, in the form of many announcements or assets, and if the specification includes common event day dummies across announcements or assets as in Equations (A.3) and (A.4), then the estimation utilizes some of the variation in the event window in the calculation of expected returns. In the following discussion, we use common event day dummies for the sake of clarity and brevity. However, this is not our approach in practice: we implement all our abnormal returns estimations as described in the main text by excluding the event windows, and apply aggregation over assets or announcement expost. The equivalent regression-based approach would be to define separate dummies for each event day observation identified by (i, j, t). However, if the estimation windows are much larger than the event windows, then both approaches lead to similar results. In our case, the differences are ignorable.

A.4.1 Endogeneity of the market price index

Given the limited number of observations for the event effect, applying a synthetic control approach (Abadie and Gardeazabal 2003) is an obvious, yet rarely pursued strategy in short-run event studies. Its main requirement is to have sufficient observations in the pre-event sample to form a control unit. Extrapolating the outcome variable of the control unit to the event period and comparing it with the observed outcome of the affected units is the same idea underlying both the short-run event study approach and the synthetic control approach.

Note that Equation (A.1) can be reformulated as a synthetic control estimation where $X_{it}\hat{\beta}_i$ can be considered the predicted outcome of the control unit. Then, the event effect is tested on the difference between the observed outcome at the event date, r_{iT}, and the extrapolated control outcome to the event date, $X_{iT}\hat{\beta}_{i|T-h-1}$. Indeed, the usual control variable in X_{it}, the market index, is already a weighted average of asset prices in a given market. The problem is that the event-affected units might participate in this portfolio, and the weights do not aim to produce a proper counterfactual control unit for the affected company, rather to reflect the average market conditions. The synthetic control approach allows to choose assets to form a counterfactual portfolio and to estimate their weights.

Let $i = 1$ be the company that is hypothesized to be affected by the event. A synthetic control is a weighted average of the units in the so-called donor pool of I units unaffected by the event. Each choice of the vector of weights $W = (w_2, ..., w_{I+1})$ such that $0 \leq w_i \leq 1$ and

$w_2 + \cdots + w_{I+1} = 1$ refers to a particular synthetic control. This choice is based on the pre-event characteristics $Z_{i,t<T-k} = \bar{Z}_{it}$. Potentially, one can include the outcome variable as a potential characteristic. That is, we have $\bar{Z}_{it} = [\bar{r}_{it}, \bar{X}_{it}]$. Indeed, Abadie et al. (2010) argue that matching on pre-event values of outcome variables mitigates the concerns related to unobserved factors in $\bar{Z}_{it}$. Weights can be chosen with the following criteria

$$w_i^* = \arg\min_{w_i} \sum_i v \left(\bar{Z}_1 - \bar{Z}_{i\in I}\right)^2 \text{ st. } 0 \leq w_i \leq 1,\ w_2 + ... + w_{I+1} = 1, \tag{A.5}$$

where v is a vector of variable-specific weights. For example, in Equation (1), the parameter vector β can be considered a special form of v. The synthetic control estimation of abnormal returns is then given by

$$\gamma_{1t}^d = r_{1t} - \sum_{i\in I} w_i^* r_{it}, \text{ for } t \in [T-h, T+h].$$

We calculate the cumulative abnormal returns as the sum of abnormal returns. In estimating a synthetic portfolio, we use DAX30 companies by excluding RWE and E.ON. We base the matching procedure only on the asset returns of these companies.

A.4.2 Controlling for industry-wide shocks

We use EnBW as the control unit, a company in the same industry but without any relevant lignite asset. This gives a difference-in-differences estimate of the abnormal returns by removing biases from industry-wide shocks. To see this formally, let $i = 1$ denote the company that is hypothesized to be affected by the event, and $i = 2$ denote the control unit. Let the dummy variable $C_i = 1\{i = 1\}$ indicate the treatment group. We have the following specification:

$$r_{it} = X_{it}\beta_i + \sum_{d=-h}^{h} \delta^d D_t^d + \sum_{d=-h}^{h} \gamma^d D_t^d C_i + \epsilon_{it}. \tag{A.6}$$

Note that the asset specific intercepts are already included in the parameter vector β to control for differences between the two cross-sectional units over the estimation window. The second term captures the shocks that affect both units. Then $\hat{\gamma}^d$ is the estimated average event effect on firm 1 on an event window day d.

A.4.3 Other specifications

Intensity of the event. In some applications, there is a continuous variable measuring the intensity of the potential event. For example, in one of our robustness analyses, we investigate the effect of a confounding event: in this case, an earnings announcement. In this analysis, the surprise in the earnings announcement is a continuous variable and if the announcement has any effect, it is expected to be correlated with the magnitude of the surprise. Having repeated observations for the event effect allows estimating the marginal abnormal returns due to the surprise.

Denote the intensity of the surprise with s_{ij}. Then, Equation (A.4) can be modified as follows:

$$r_{ijt} = X_{ijt}\beta_{ij} + \sum_{d=-h}^{h} \gamma_i^d D_t^d s_{ij} + \epsilon_{ijt}. \tag{A.7}$$

Here γ_i^d is the marginal effect of the surprise. The abnormal return of firm i due to announcement j is calculated as $\gamma_i^d s_{ij}$.

Estimation window with repeated observations for the event effect. As explained earlier, the specification in Equation (A.1) does not employ any information from the event window to estimate the expected returns. This strategy can control for potential feedbacks from the event to the normal market performance. However, this is not the case for Equations (A.4) and (A.7), because the event dummies are assumed to be homogeneous across announcements (or firms) and do not partial out the whole variation in the event window. Hence, one has to include a dummy for each observational unit in the event window.

We take care of the feedback from the events to the normal market performance by estimating the normal market performance separately from the pre-event observations. The return on a day in the event window is predicted by $\hat{r}_{i,T+d} = \mathrm{E}[r_{i,T+d}|X_{i,T+d}] = X_{ij,T+d}\hat{\beta}_{ij|T-h-1}$, where the estimated parameter vector is conditioned on the available information prior to the event window. The abnormal return is then given by:

$$\gamma_{ij}^d = r_{i,T+d} - X_{ij,T+d}\hat{\beta}_{ij|T-h-1}. \tag{A.8}$$

As a result, the prediction of the expected returns does not employ any information from the event window. In this case, the intensity of the event effect is estimated in a second-stage regression by regressing the estimated CARs on the surprise (see MacKinlay 1997). In all our applications, we exclude the event window observations in estimating the normal market performance.

A.5 Robustness checks on the choices for baseline specification

In this section, we present the results from alternative choices for the event window and covariate set. In Table A.4, we present the results from assuming three-days event windows instead of five days. These estimations correspond to our baseline estimations leading to Table 1.3 where we assume five-days event windows. As the ACARs in Table A.4 are based on three days ARs, the size of the coefficients is smaller compared to their baseline counterparts also by construction. It is seen that assuming a three-days event window does not alter the significance levels. We are therefore confident that our baseline specification of five days does well in capturing the full event effects. In Appendix A.9, we present the corresponding results from announcement specific estimations in Table A.11 which corresponds to the announcement-specific baseline estimations in Table A.10.

Table A.4 : ACARs by the stages of the proposal: three-days event window

Companies	Stages of the proposal		
	Climate levy proposal	Security reserve proposal	State aid assessment
RWE	0.007	0.003	-0.063***
	(0.016)	(0.012)	(0.015)
E.ON	0.009	-0.009	-0.034***
	(0.013)	(0.010)	(0.011)

Notes: This table illustrates the average cumulative abnormal returns of E.ON and RWE from the announcements of each stage of the policy proposal. The event window is the three days centered around an announcement. The event window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the event window. Standard errors are in parentheses. Significance levels are indicated as $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

In the main text, we do not find any significant market reaction to Event (1a). However, we provide empirical evidence that it was still surprising. In order to verify that the insignificance of CARs from Event (1a) is not driven by our event-window specification, we present the abnormal returns around this event in Figure A.14. It is clear that any meaningful combination of these abnormal returns cannot lead to significant CARs.

Some of our event dates are very close. This is not a problem for the events in Stages 1 and 2, as there are no abnormal patterns in the returns around these dates. However, the estimation window of Event (3c) includes the event window of Event (3b). Therefore, the significant abnormal returns due to Event (3b) might have consequences on the estimated normal market performance of Event (3c). In order to address such concerns, we provide robustness chekcs by estimating the normal market performance by using the 60 days window which ends at 30 trading days before the event window. The results are presented in Table A.12 in the Appendix for further tables and figures. It is seen that our results for Event (3c) are not driven by this concern. As a further specification test on the choice of estimation windows, Table A.12 presents this robustness check for all the other events as well. The results are similar to our baseline results.

Table A.5 : ACARs by the stages of the proposal: extended covariate set

Companies	Stages of the proposal		
	Climate levy proposal	Security reserve proposal	State aid assessment
RWE	0.009	-0.008	-0.102***
	(0.020)	(0.016)	(0.019)
E.ON	0.011	-0.019	-0.073***
	(0.017)	(0.014)	(0.013)

Notes: This table presents the average cumulative abnormal returns of E.ON and RWE from the announcements of each stage of the policy proposal. The event window is the five days centered around an announcement. The event window observations are excluded in the estimation of normal market performance. Normal market performance is predicted by a constant, returns to DAX30 index, returns to oil prices, and a risk free rate of return. The estimation window is the 90 days just prior to the event window. Standard errors are in parentheses. Significance levels are indicated as * $p < 0.10$, **, *** $p < 0.01$.

In Table A.5, we provide results from extendeding our covariate set by including interest rates and (returns to) oil prices. We control for oil prices following Keller (2010) and Griffin et al. (2015) in order to take into account specificities of energy stocks. We use the crude oil spot price of Brent, FOB. To control for the opportunity costs of investment on a given date, we include the risk-free rate of return, namely, the German three-month government bond benchmark rate. The results in Table A.5 are similar to our baseline results. The reson is that these additional covariates do not add much to the predictive power of the market model in our application. In the Appendix for further tables and figures (Appendix A.9), we present the corresponding results from announcement specific estimations in Table A.13.

A.6 Robustness checks on the baseline distributional assumption

In this section, we provide specification tests and robustness checks on the assumption of NID disturbances. The first panel of Table A.6 presents the results from the estimation of normal market performance. For brevity, we focus on the announcements in stage 3. The second panel presents the p-values from various specification tests on the residuals. The Durbin test is for serial correlation where the null hypothesis is there is no serial correlation up to fifth order. The null is rejected if any lags of the residuals is significant in an auxiliary regression of the residuals on its lags. The null for the LM (Engle's Lagrange multiplier) tests is that there is no p^{th} order autoregressive conditional heteroscedasticity (ARCH(p)) in the residuals. The third panel presents the alternative estimates for the standard errors: (i) robust standard errors for arbitrary forms of heteroscedasticity, (ii) standard errors based on pair-bootstraping, and (iii) Newey-West standard errors taking into account up to fifth order autocorrelations.

According to the results from the Durbin tests and the LM tests for ARCH(p) effects, there is no sign for serial correlation or heteroscedaticity. This result is further confirmed by the results in the third panel. The alternative estimates of standard errors are very close to our baseline estimates. There is only one exception to this general result, where the Durbin test rejects the null in the fifth column. However, the baseline and the Newey-West standard errors are still very close to each other, suggesting that the influence of significant lag order is minor.

Figure A.10 illustrates the prediction intervals based on bootstrapping. Here, the contribution of sampling uncertainty is calculated based on pair-bootstrapped standard errors. As mentioned in the main text, this type of uncertainty is typically small which is the case in our application too. Therefore, the estimation method for sampling uncertainty have almost no influence on the width of the prediction intervals. In Figure A.10, we assume IID errors in estimating the error uncertainty by resampling OLS-residuals with replacement (1000 repetitions) which is robust to departures from normality assumption. The width of these confidence intervals are close to their baseline counterparts. Table A.7 presents the bootstrapped standard errors calculated from the empirical distribution of resampled OLS residuals. Again, the results are very close to their baseline counterparts.

Table A.6 : Specification tests and alternative estimates of standard errors

	RWE-(3a)	RWE-(3b)	RWE-(3c)	E.ON-(3a)	E.ON-(3b)	E.ON-(3c)
DAX30 Market Return	0.669	0.699	0.864	0.710	0.701	0.784
	(0.104)	(0.090)	(0.106)	(0.080)	(0.070)	(0.066)
Durbin test	0.683	0.255	0.521	0.506	0.063	0.355
LM test - order 1	0.997	0.626	0.716	0.391	0.717	0.421
LM test - order 3	0.875	0.824	0.908	0.484	0.796	0.797
LM test - order 5	0.929	0.911	0.976	0.320	0.797	0.903
Robust s.e.	0.087	0.076	0.106	0.075	0.065	0.090
Bootstrap s.e.	0.090	0.080	0.108	0.078	0.067	0.090
Newey-West s.e.	0.091	0.083	0.099	0.075	0.064	0.074

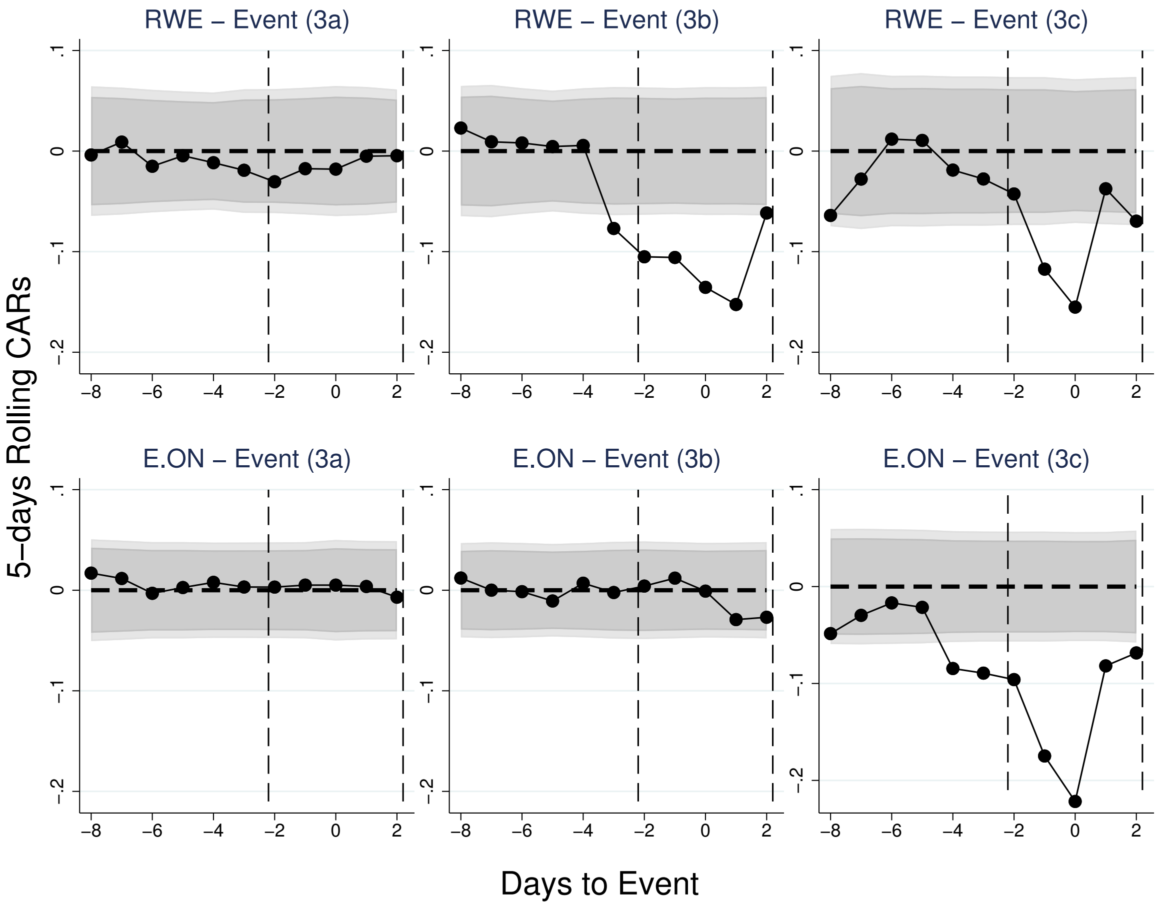
Notes: The first panel presents the results from the OLS estimation of normal market performance. The second panel presents the p-values from various specification tests on the residuals. The Durbin test is for serial correlation where the null hypothesis is there is no serial correlation up to p^{th} order. The null for the LM (Engle's Lagrange multiplier) tests is there is no p^{th} order autoregressive conditional heteroscedasticity (ARCH(p)) in the residuals. The third panel presents the alternative estimates for the standard errors. Bootstrap standard errors are based on 1000 replications. The estimation of Newey-West standard errors include all the lags of the residuals up to fifth order.

Table A.7 : CARs and bootstrapped standard errors

Companies	Announcements		
	(3a)	(3b)	(3c)
RWE	-0.020	-0.135***	-0.150***
	(0.033)	(0.032)	(0.036)
E.ON	0.004	-0.000	-0.220***
	(0.025)	(0.024)	(0.028)

Notes: This table presents the cumulative abnormal returns of RWE and E.ON from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement. The estimation window is the 90 days just prior to the event window. Hence, the event window observations are excluded in the estimation of normal market performance. Bootstrapped standard errors are in parentheses. Significance levels are indicated as $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Figure A.10 : CARs and bootstrap prediction intervals



Notes: This figure presents the CARs of RWE and E.ON from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. In the figure, the days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The 90% and 95% bootstrap confidence intervals are indicated by shaded areas.

A.7 Confounding events investigation

This section presents details on the search for potential confounding events around announcements (3b) and (3c). We conducted a search for English- and German-language news in LexisNexis for the five-day window (working days) around each of these announcements, filtering by company name (RWE or E.ON, respectively). We restricted the search to business news in newswires and press releases to avoid a large number of news items appearing multiple times. Still, we were faced with a large number of very diverse news items in the event window for each firm.

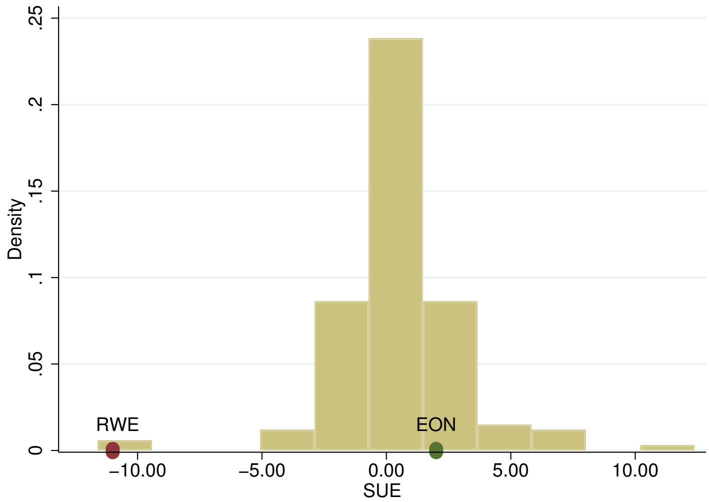
We therefore manually categorized the news items according to their content and counted the number of news items on a specific topic in the given event window. We then assessed, based on content and press coverage, whether the news topics could be relevant drivers for the stock performance we observe in our event window. When we identified a potential company-specific confounding event for announcement (2b), we performed robustness analyses (see Section 1.7.2 for robustness checks on earnings announcements). For announcement (3c), we are more concerned with news that affects both RWE and E.ON, and thus performed robustness analyses for the case of a potential industry confounding event. Here we identified the nuclear provisioning issue as outlined in Section 1.7.2. LexisNexis provides a good overview of important issues around the event dates, but it was essential to complement this with own research on the events identified as potentially confounding. For instance, we found that the German business newspaper *Handelsblatt* was the first to report on the nuclear provisioning report on September 11; however, the first news items in LexisNexis mentioning this in the context of RWE appear on September 15.

In Appendix A.9, Tables A.17, A.18, A.19, and A.20 present the main news topics and numbers of news items on these topics for each company and each event window.

A.8 Estimation of earnings surprise

Effects of earnings announcements. We start by investigating the information content of quarterly earnings announcements for the market valuation of RWE and E.ON. If there is any investor reaction to earnings announcements, it should be due to the departure of announced earnings from investors' prior expectations, namely, the surprise in the information release.

Figure A.11 : Distribution of SUE



Notes: This figure illustrates the distribution of SUEs in our sample.

We proxy the expected earnings with the quarterly earnings forecasts reported by the Institutional Brokers Estimate System (I/B/E/S). It is the average of earnings forecasts by many analysts for a large number of firms. Our measure of surprise is the difference between announced earnings (AE) and mean forecasted earnings (MFE) normalized by the standard deviation of the forecasts. This measure is called the standardized unexpected earnings (SUE), which is provided by the Thomson Reuters Database. We employ the dataset on quarterly earnings announcements of DAX30 companies in 2015 and 2016. Figure A.11 illustrates the distribution of SUEs in our sample. The SUEs for RWE and E.ON within the event (3b) window are indicated by dots. While the SUE is small and positive for E.ON, it is negative and large for RWE. This pattern has the potential to explain our findings for event (3b).

The technical details of estimating the marginal effect of SUE are provided in Appendix A.4.3. In words, we start by estimating the five-day CARs for all the earnings announcements in our sample by excluding the two earnings announcements by E.ON and RWE just before event (3b). Next, we estimate the marginal effect of SUE on the predicted CARs. The results are presented in the first column of Table A.8. In the first regression, the effect of SUE on the five-day CARs are insignificant. However, this does not mean that the earnings announcement has no effect. In the following columns, we estimate the marginal effect of SUE on the individual ARs in the event window. Evidently, the only significant impact occurs on the event day. The size of the estimated effects on the days before and after announcement dates is very small. Therefore,

Table A.8 : Marginal effect of earnings surprise

	5-Days CAR	ARs				
Relative distance		(-2)	(-1)	(0)	(1)	(2)
SUE	0.003	0.000	0.000	0.003^{***}	-0.000	0.000
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	120	120	120	120	120	120

Notes: This table presents the estimated marginal effect of SUE on the predicted CARs. Standard errors are in parentheses. Significance levels are indicated as $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table A.9 : Predicted CARs and ARs due to earnings surprise

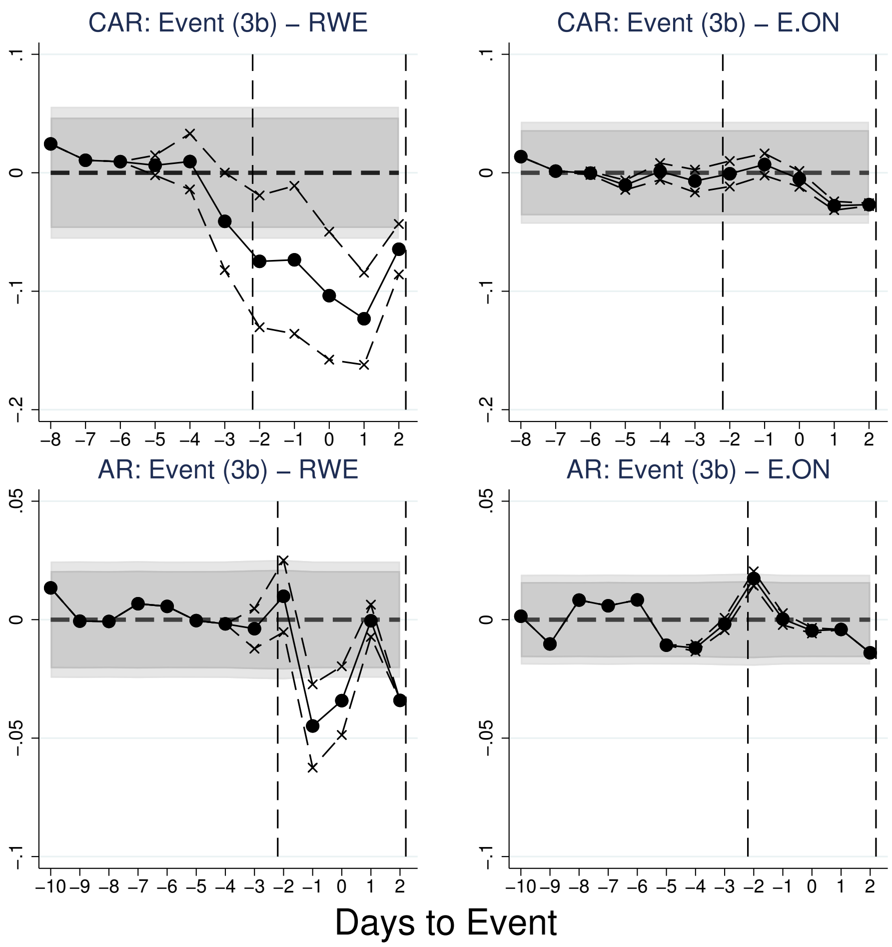
Panel A: Predicted 5-day CARs due to earnings surprise					
Company	Date		Predicted CARs by SUE	95% Confidence Interval	
E.ON	8/12/2015		0.005	-0.000	0.011
RWE	8/13/2015		-0.032	-0.065	0.002
Panel B: Predicted ARs due to earnings surprise					
Company	Date	Relative distance	Predicted AR by SUE	95% Confidence interval	
E.ON	18/10/2015	-2	0.000	-0.001	0.002
	8/11/2015	-1	0.000	-0.002	0.003
	8/12/2015	0	0.006	0.002	0.009
	8/13/2015	1	-0.001	-0.003	0.002
	8/14/2015	2	0.000	-0.001	0.002
RWE	8/11/2015	-2	-0.001	-0.009	0.008
	8/12/2015	-1	-0.003	-0.018	0.013
	8/13/2015	0	-0.032	-0.050	-0.014
	8/14/2015	1	0.006	-0.009	0.020
	8/15/2015	2	-0.002	-0.009	0.005

Notes: This table presents the predicted CARs and ARs due to the earnings announcements of E.ON and RWE just before event (3b) .

the size of the estimated effects on the five-day CARs and the estimated effect on the ARs on the event date are virtually the same.

In the next step, we employ these results to predict the CARs and ARs due to the earnings announcements of E.ON and RWE just before event (3b). The results are presented in Table A.9. Panel A shows the CARs predicted by the SUEs, and Panel B shows the predicted ARs for each day of the event window. Reflecting the results in Table A.8, the predicted CARs due to SUEs are positive and small for E.ON, while they are negative and large for RWE. Panel B shows that the impact of the earnings announcement occurs only on the event day, and the 95% confidence intervals support the estimated sign of the impacts. Other than on the event day, the size of the announcement effect is negligible and insignificant.

Figure A.12 : Effect of announcement (3b) corrected for earnings surprise



Notes: This figure presents the ARs and CARs of E.ON and RWE from announcement (3b) corrected for the earnings announcements. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. The days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The 90% and 95% confidence intervals for the (uncorrected CARs) are presented as forecast intervals (shaded areas). The 90% confidence interval of predicted effect of earnings announcement is illustrated around the corrected CARs.

Correcting for the effect of earnings announcements. The rolling CARs and the ARs, corrected for the size of the predicted earnings announcement effect, are presented in Figure A.12. This figure differs from the one presented in the main text in two ways. First, this figure illustrates the two sources of uncertainity, rather than the aggregated one presented in the main text. Second, the correction assumes a five-day event window for the earnings announcement. For example, the correction for RWE includes the dates between -3 and 1, as the earnings announcement of RWE is on date -1. This is also a conservative approach given that our results reveal that the effect of the earnings announcements is taking place on the announcement date only. The figure also illustrates the 90% confidence interval of the predicted earnings announcement effect constructed around the corrected CARs and ARs. The effect of the correction on CARs extends beyond the correction window due to the aggregation of ARs across days.

Figure A.12 confirms the results presented in the main text and illustrates its details. An informal and conservative inference strategy is to compare the 90% confidence intervals. It is conservative, because a formal comparison requires calculating the standard error of the difference of these two random effects as in the main text. In our case, assuming that these two peredictions are uncorrelated is reasonable due to the way that these effects are predicted by using different samples. In this case, the standard error of the difference is equal to the square-root of the sum of variances. The standard error of the net effect is always smaller than the sum of the standard errors of the two predictions. Hence, the formal confidence interval, presented in the main text, is smaller than the sum of the confidence intervals of these two effects. However, Figure A.12 is useful to illustrate the confidence intervals separately for expositional clarity. It is seen that the confidence intervals of the corrected CAR on the event day (day 0) and the predicted returns do not overlap. Figure A.12 do not present the 95% confidence interval for the corrected CAR, which do overlap slightly. As a result, the corrected effect of event (3b) is still significant at reasonable levels, but much smaller than the baseline estimate.

A.9 Additional tables and figures

Table A.10 : CARs by announcement: baseline specification

Stages	Announcements	Companies		
		RWE	E.ON	EnBW
Climate levy proposal	1a	0.033	0.040	-0.004
		(0.034)	(0.029)	(0.039)
	1b	0.004	-0.011	-0.014
		(0.035)	(0.029)	(0.039)
	1c	-0.002	0.005	0.007
		(0.035)	(0.028)	(0.042)
Security reserve	2a	-0.004	-0.029	0.014
		(0.033)	(0.027)	(0.044)
	2b	-0.033	-0.028	0.017
		(0.032)	(0.027)	(0.043)
	2c	-0.002	-0.013	-0.007
		(0.030)	(0.028)	(0.048)
	2d	0.012	-0.007	0.011
		(0.030)	(0.027)	(0.049)
State aid assessment	3a	-0.020	0.004	-0.001
		(0.031)	(0.024)	(0.050)
	3b	-0.135***	0.000	-0.004
		(0.028)	(0.021)	(0.050)
	3c	-0.150***	-0.220***	-0.017
		(0.038)	(0.024)	(0.050)

Notes: This table presents the cumulative abnormal returns of all companies due to each announcement. The event window is the five days centered around an announcement. The estimation window is the 90 days just prior to the event window. Hence, the event window observations are excluded in the estimation of normal market performance. Standard errors are in parentheses. Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11 : CARs by announcement: three-day event window

Stages	Announcements	Companies		
		RWE	E.ON	EnBW
Climate levy proposal	1a	0.000	0.012	0.020
		(0.027)	(0.023)	(0.031)
	1b	0.025	0.006	0.005
		(0.027)	(0.023)	(0.030)
	1c	-0.003	0.010	0.014
		(0.027)	(0.021)	(0.032)
Security reserve proposal	2a	-0.006	-0.026	0.024
		(0.026)	(0.021)	(0.033)
	2b	-0.013	0.003	-0.002
		(0.025)	(0.021)	(0.034)
	2c	0.003	-0.019	-0.026
		(0.023)	(0.021)	(0.037)
	2d	0.027	0.006	-0.002
		(0.022)	(0.020)	(0.038)
State aid assessment	3a	-0.004	0.000	0.015
		(0.024)	(0.018)	(0.039)
	3b	-0.108***	-0.010	-0.006
		(0.021)	(0.017)	(0.039)
	3c	-0.076***	-0.092***	-0.016
		(0.029)	(0.021)	(0.038)

Notes: This table presents the cumulative abnormal returns of all companies due to each announcement. The event window is the three days centered around an announcement. The event window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the event window. Standard errors are in parentheses. Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12 : CARs by announcement: robustness to estimation window

Stages	Announcements	Companies		
		RWE	E.ON	EnBW
Climate levy proposal	1a	0.036	0.041	-0.002
		(0.035)	(0.028)	(0.040)
	1b	0.010	-0.008	-0.014
		(0.034)	(0.028)	(0.042)
	1c	0.000	0.009	0.005
		(0.038)	(0.029)	(0.034)
Security reserve proposal	2a	-0.009	-0.026	0.015
		(0.036)	(0.029)	(0.034)
	2b	-0.038	-0.025	0.018
		(0.034)	(0.030)	(0.040)
	2c	-0.003	-0.013	0.002
		(0.033)	(0.030)	(0.046)
	2d	0.009	-0.016	0.004
		(0.033)	(0.028)	(0.044)
State aid assessments	3a	-0.018	-0.002	-0.013
		(0.030)	(0.025)	(0.048)
	3b	-0.133***	0.001	-0.004
		(0.026)	(0.023)	(0.057)
	3c	-0.162***	-0.225***	-0.014
		(0.029)	(0.022)	(0.047)

Notes: This table presents the cumulative abnormal returns of all companies due to each announcement. The event window is the five days centered around an announcement. The event window observations are excluded in the estimation of normal market performance. The estimation window is the 60 days window ending at 30 days prior to the event window. Standard errors are in parentheses. Significance levels are indicated as $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table A.13 : CARs by announcement: extended covariate set

Stages	Announcements	Companies		
		RWE	E.ON	EnBW
Climate levy proposal	1a	0.032	0.046	0.010
		(0.035)	(0.029)	(0.040)
	1b	0.002	-0.013	-0.009
		(0.035)	(0.030)	(0.040)
	1c	-0.008	0.000	0.010
		(0.035)	(0.028)	(0.043)
Security reserve proposal	2a	-0.006	-0.029	0.015
		(0.033)	(0.027)	(0.044)
	2b	-0.035	-0.028	0.016
		(0.032)	(0.027)	(0.044)
	2c	-0.003	-0.013	-0.008
		(0.030)	(0.028)	(0.049)
	2d	0.012	-0.007	0.010
		(0.030)	(0.027)	(0.050)
State aid assessment	3a	-0.020	0.004	-0.005
		(0.031)	(0.024)	(0.051)
	3b	-0.135***	0.001	-0.006
		(0.028)	(0.021)	(0.051)
	3c	-0.152***	-0.222***	-0.016
		(0.038)	(0.024)	(0.051)

Notes: This table presents the cumulative abnormal returns of all companies due to each announcement. The event window is the five days centered around an announcement. Normal market performance is predicted by a constant, returns to DAX30 price index, returns to oil prices, and a risk-free rate of return. The estimation window is the 90 days just prior to the event window. Hence, the event window observations are excluded in the estimation of normal market performance. Standard errors are in parentheses. Significance levels are indicated as $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table A.14 : Synthetic control: CARs and non-parametric p-values

Companies	Announcements		
	(3a)	(3b)	(3b)
RWE	-0.006	-0.130	-0.184
	(0.808)	(0.038)	(0.000)
E.ON	0.017	0.006	-0.243
	(0.885)	(0.231)	(0.000)

Notes: This table presents the synthetic-control estimates of the cumulative abnormal returns of RWE and E.ON from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement. The estimation window is the 90 days just prior to the pseudo window. Hence, the event window observations are excluded in the estimation of normal market performance. Non-parametric p-values, following Abadie et al. 2015, are in parentheses. The p-values are the fraction of the units in the control group (donor pool) for which the estimated effects are at least as large as the estimated effect for the treated unit. If the pre-treatment match quality is distorted by some control units, the p-values can be conservative. In this case, one can normalize the estimated effects with pre-treatment RMSE reflecting the match quality. We do not apply this normalization. Pre-tretament RMSEs are illustrated in the main text.

Table A.15 : ACARs by the stages of the proposal: EnBW as the control unit

Companies	Stages of the proposal		
	Climate levy proposal	Security reserve proposal	State aid assessment
RWE	0.016	-0.016	-0.094***
	(0.031)	(0.027)	(0.033)
E.ON	0.015	-0.028	-0.065**
	(0.028)	(0.026)	(0.031)

Notes: This table presents the average cumulative abnormal returns of RWE and E.ON for each stage of the proposal by using EnBW as a control unit. The event window is the five days centered around an announcement. The estimation window is the 90 days just prior to the event window. Hence, the event window observations are excluded in the estimation of normal market performance. Standard errors are in parentheses. Significance levels are indicated as $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table A.16 : CARs by announcement: EnBW as the control unit

Stages	Announcements	Companies	
		RWE	E.ON
Climate levy proposal	1a	0.037	0.044
		(0.053)	(0.049)
	1b	0.018	0.003
		(0.054)	(0.049)
	1c	-0.008	-0.002
		(0.055)	(0.049)
Security reserve proposal	2a	-0.018	-0.043
		(0.054)	(0.050)
	2b	-0.050	-0.046
		(0.053)	(0.050)
	2c	0.004	-0.006
		(0.056)	(0.055)
	2d	0.001	-0.019
		(0.054)	(0.054)
State aid assessment	3a	-0.019	0.005
		(0.055)	(0.054)
	3b	-0.131***	0.004
		(0.055)	(0.053)
	3c	-0.133**	-0.203***
		(0.061)	(0.055)

Notes: This table presents the cumulative abnormal returns of RWE and E.ON due to each announcement by using EnBW as a control unit. The event window is the five days centered around an announcement. The estimation window is the 90 days just prior to the event window. Hence, the event window observations are excluded in the estimation of normal market performance. Standard errors are in parentheses. Significance levels are indicated as $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table A.17 : Type and number of company-related news around event (3b), RWE

Topic	Wed 12/08	Thu 13/08	Fri 14/08	Mon 17/08	Tue 18/08
Earnings announcements (EA), financials	1	9		1	
Background on EA, company strategy	2	6			
Voting rights announcements		4			
Investments of company		2		5	3
Personnel appointments					2
Other					2

Source: Own summary based on LexisNexis, German- and English-language newswires and press releases, filtered by date and company name. “Other” includes local activities such as Czech gas management and local protests.

Table A.18 : Type and number of company-related news around event (3b), E.ON

Topic	Wed 12/08	Thu 13/08	Fri 14/08	Mon 17/08	Tue 18/08
Earnings announcements (EA), financials	7				
EA and background, company strategy	16	6			
E.ON Russia financials	7	15		1	
E.ON UK financials	1	1	2	1	1
Voting rights announcements	5				
Investments of company	5		2		
Other	2			4	2

Source: Own summary based on LexisNexis, German- and English-language newswires and press releases, filtered by date and company name. “Other” includes local activities such as the opening of a plant, school visits, public relation activities related to a wind farm, etc., or the mentioning of E.ON in news about other firms. News items from Saturday and Sunday are assigned to the following Monday.

Table A.19 : Type and number of company-related news around event (3c), RWE

Topic	Thu 10/09	Fri 11/09	Mon 14/09	Tue 15/09	Wed 16/09
Tendering and contracting	6		4		
Issues with power plant permissions	4	1	1	2	
Personnel issues	1	4			
Background on past stock performance		4	1		
Pending lawsuits		6	4		
Local operations & PR		6		1	
General industry news (gas supply)			**4**	**2**	
Nuclear provisioning Germany				**1**	**7**
Other		1	1	3	2

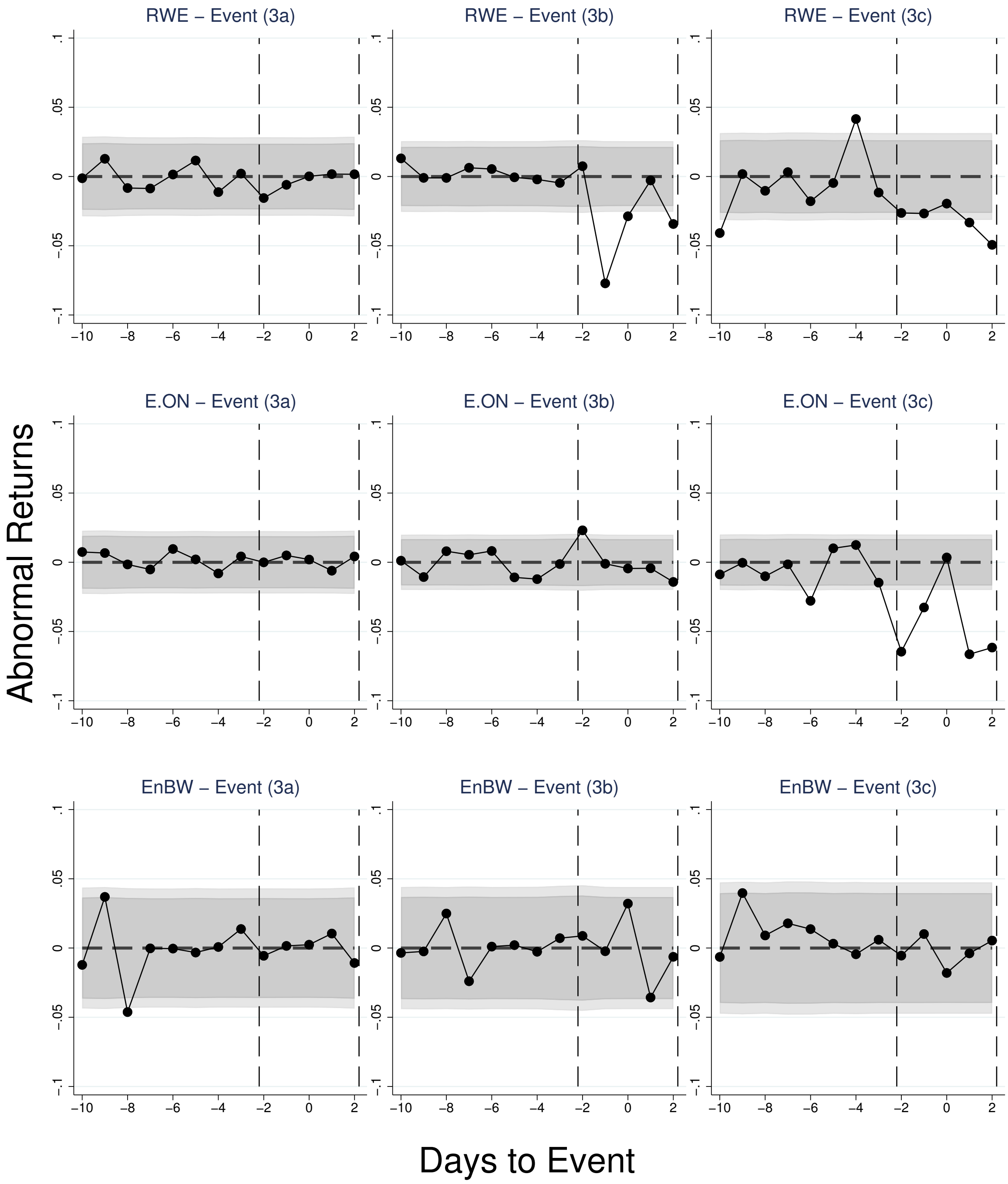
Notes: Industry-wide news in bold.
Source: Own summary based on LexisNexis, German- and English-language newswires and press releases, filtered by date and company name. News items from Saturday are assigned to the following Monday. "Pending lawsuits" relates to a gas procurement conflict where RWE may need to pay a penalty, for part of which the company already booked provisions. "Issues with power plant permissions" involve wind farm projects (new proposal after rejection) and a coal-fired power plant (court ruling that permit is upheld). "General industry news on gas supply" is a report on Iran as a potential new gas supplier for Europe. While this news is relevant industry-wide, we would expect it to have a positive impact on returns, if any.

Table A.20 : Type and number of company-related news around event (3c), E.ON

Topic	Thu 10/09	Fri 11/09	Mon 14/09	Tue 15/09	Wed 16/09
Tendering and contracting		2			
Obligatory notifications on stocks and securities	3				
Nord-Stream pipeline	16	4	3		
E.ON's record low & background info on restructuring	10				
Stock market update mentioning E.ON	2	1	3		
Local customer relations and projects		2	6	3	2
General industry news (gas supply)			**1**	**3**	**1**
Nuclear provisioning Germany		**1**		**3**	
Other	1	1	2	1	

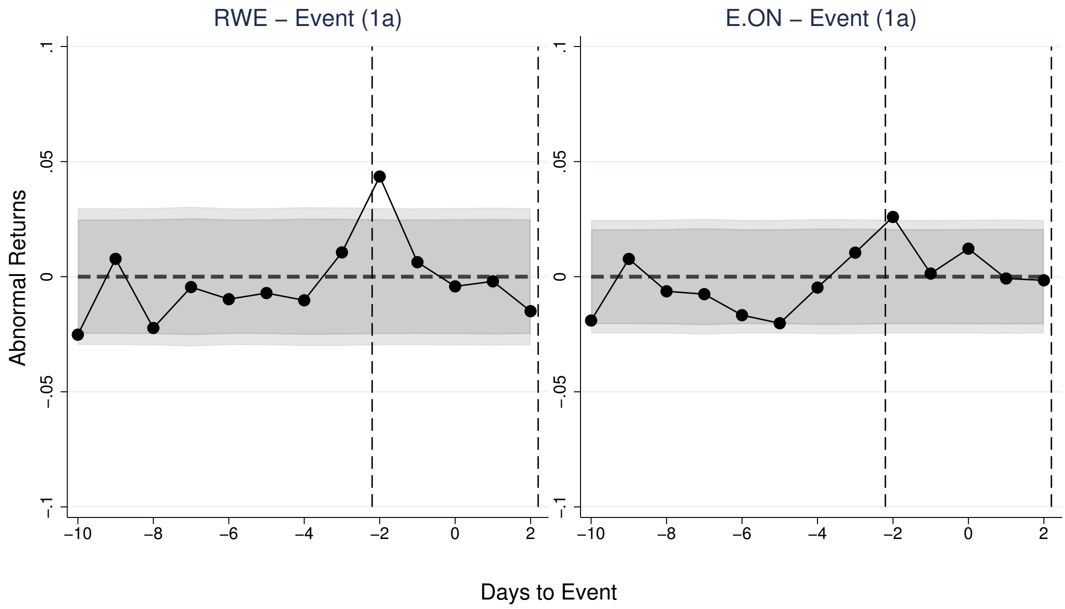
Notes: Industry-wide news in bold.
Source: Own summary based on LexisNexis, German- and English-language newswires and press releases, filtered by date and company name. News items from Saturday are assigned to the following Monday. "Nord-Stream pipeline" refers to business news over the shareholders' agreement on the pipeline, as well as political concerns voiced by Slovakia and Ukraine (calling the project "anti-European"). "E.ON's record low" on stock markets was recorded on September 10 and is why E.ON appeared in several general stock market updates. In background information, it was attributed to an unexpected announcement related to E.ON's company reorganization: In splitting the company into "clean" E.ON and "dirty" Uniper, E.ON would keep its nuclear business and the related liabilities. This decision is also relevant for the subsequent reaction of E.ON's shares to the nuclear provisioning assessment. "General industry news on gas supply" is a report on Iran as a potential new gas supplier for Europe. While this news is relevant industry wide, we would expect it to have a positive impact on returns, if any.

Figure A.13 : Abnormal returns in the placebo tests



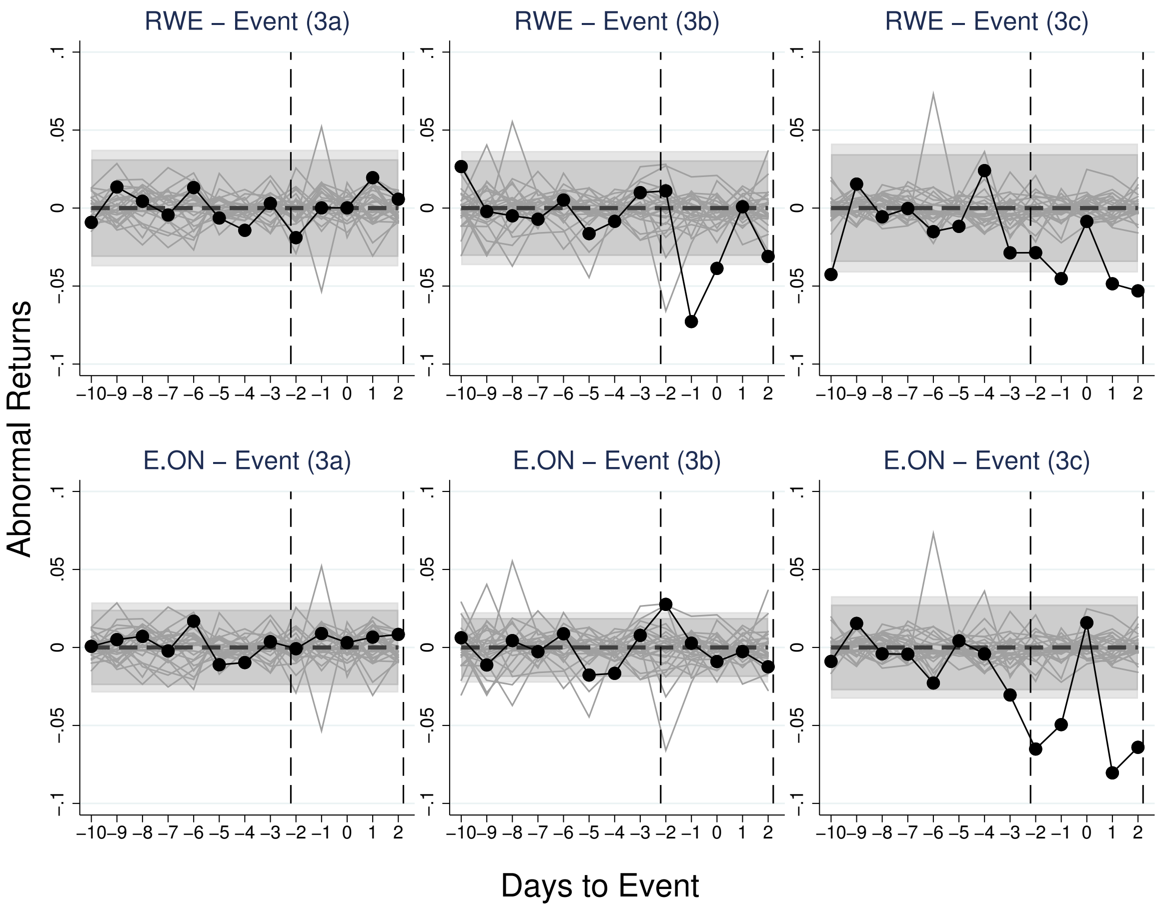
Notes: This figure presents the ARs of RWE, E.ON and EnBW from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. In the figure, the days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The 90% and 95% confidence intervals are indicated by shaded areas.

Figure A.14 : Abnormal returns around event (1a)



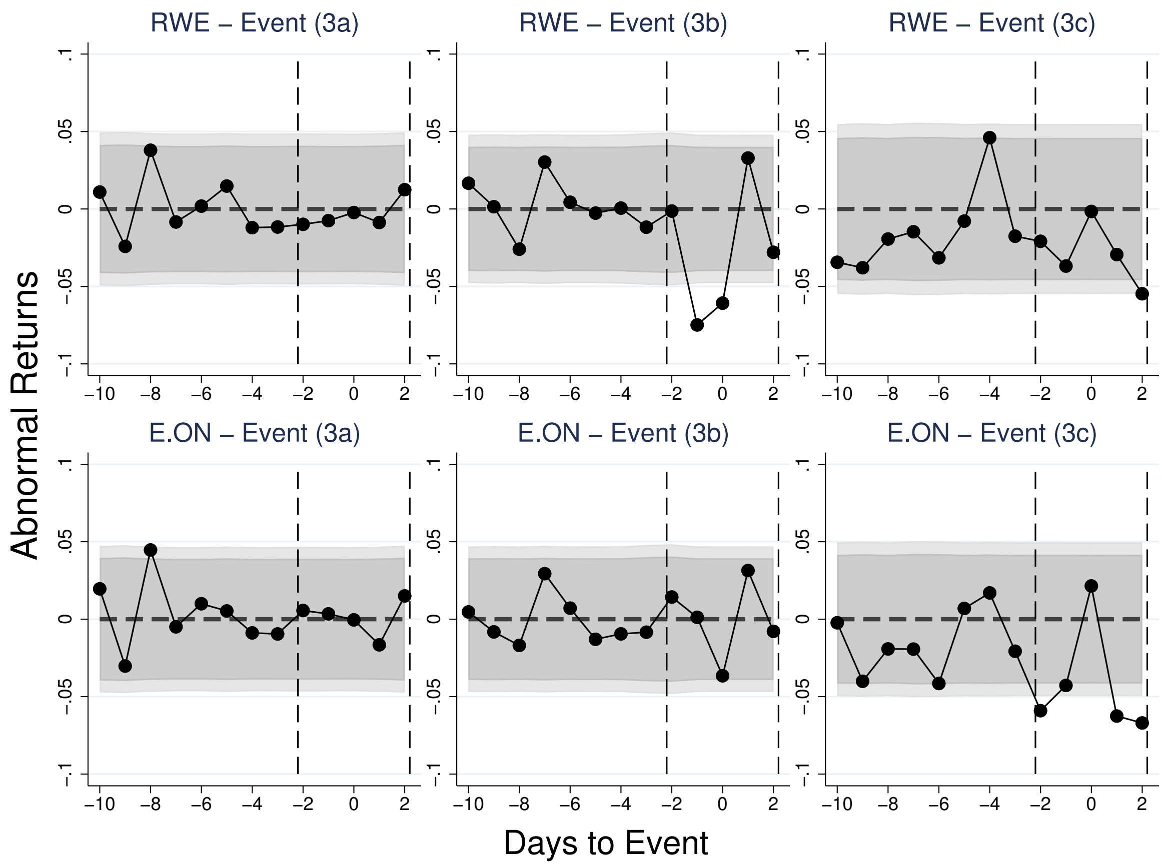
Notes: This figure presents the ARs of RWE and E.ON around Event (1a). The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. In the figure, the days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The 90% and 95% confidence intervals are indicated by shaded areas.

Figure A.15 : Abnormal returns from the synthetic control estimations



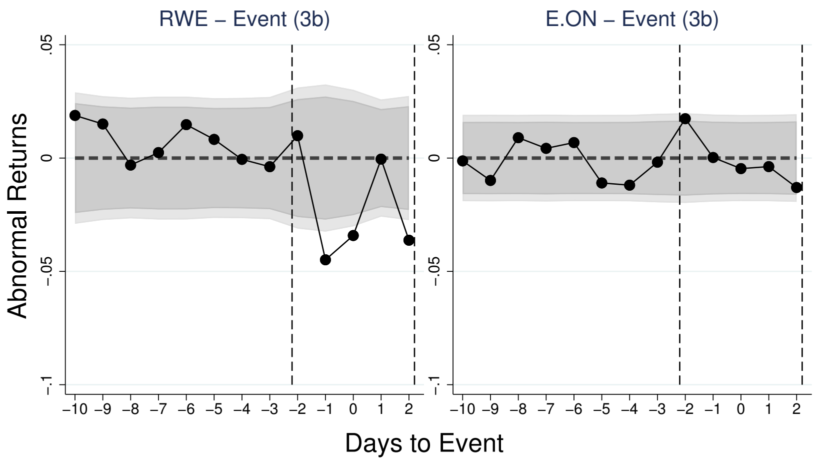
Notes: This figure presents the synthetic control estimates for ARs of E.ON and RWE from each announcement in the third stage of the policy proposal. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. In the figure, the days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The in-place placebo tests are illustrated with grey lines, and the grey areas are 90% and 95% confidence intervals constructed from the pre-treatment RMSE.

Figure A.16 : Abnormal returns: EnBW as the control unit



Notes: This figure presents the estimates for ARs of E.ON and RWE from each announcement in the third stage of the policy proposal by using EnBW as the control unit. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. In the figure, the days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The 90% and 95% confidence intervals are indicated by shaded areas.

Figure A.17 : ARs for announcement (3b) corrected for earnings Surprise



Notes: This figure presents the ARs of E.ON and RWE from announcement (3b) corrected for the effect of earnings announcements. The event window is the five days centered around an announcement (date 0) indicated with the dashed lines. The days prior to the event window are the placebo announcement days. The event window and pseudo window observations are excluded in the estimation of normal market performance. The estimation window is the 90 days just prior to the pseudo window. The 90% and 95% confidence intervals are indicated by shaded areas.

B Appendix to Chapter 2

B.1 Patent example and patent classification codes

Figure B.1 : Patent example

US010018145B2

(12) **United States Patent**
Hussain

(10) **Patent No.: US 10,018,145 B2**
(45) **Date of Patent: Jul. 10, 2018**

(54) **SYSTEM AND METHOD FOR IN-CYLINDER THERMAL ENERGY RECOVERY AND CONTROLLING CYLINDER TEMPERATURE**

(71) Applicant: **Ford Global Technologies, LLC**, Dearborn, MI (US)

(72) Inventor: **Quazi Ehtesham Hussain**, Holland, OH (US)

(73) Assignee: **Ford Global Technologies, LLC**, Dearborn, MI (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 158 days.

(21) Appl. No.: **15/013,786**

(22) Filed: **Feb. 2, 2016**

(65) **Prior Publication Data**

US 2017/0218878 A1 Aug. 3, 2017

(51) **Int. Cl.**

F02F 1/10	(2006.01)
F02B 7/00	(2006.01)
F01K 23/06	(2006.01)
F02F 1/40	(2006.01)
F01N 5/02	(2006.01)
F02B 37/00	(2006.01)
F02G 5/02	(2006.01)
F02G 5/04	(2006.01)

(52) **U.S. Cl.**
CPC ***F02F 1/10*** (2013.01); ***F01K 23/065*** (2013.01); ***F01N 5/02*** (2013.01); ***F02B 37/00*** (2013.01); ***F02F 1/40*** (2013.01); ***F02G 5/02*** (2013.01); ***F02G 5/04*** (2013.01); *F02G 2262/00* (2013.01); *Y02T 10/166* (2013.01)

(58) **Field of Classification Search**
CPC F02F 1/10; F02F 1/40; F02B 37/00; F02G 5/02; F02G 5/04; F02G 2262/00; F01K 23/065; F01N 5/02; Y02T 10/166
USPC 60/605.1, 605.2, 614, 616, 618
See application file for complete search history.

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(74) *Attorney, Agent, or Firm* — Julia Voutyras; McCoy Russell LLP

(57) **ABSTRACT**

Methods and systems are provided for an in-cylinder thermal energy recovery device that utilizes the Rankine Cycle to recover energy from exhaust gasses that may be used to produce additional work in the vehicle. In one example, a method may include outfitting the head area of each cylinder of an engine with a tube array comprising one or more tubes passing through the combustion chamber of the corresponding cylinder. Each tube array may receive an injection of working fluid that is based, in part, on the temperature of the tube array's corresponding cylinder, which may then be utilized to recover heat energy.

20 Claims, 4 Drawing Sheets

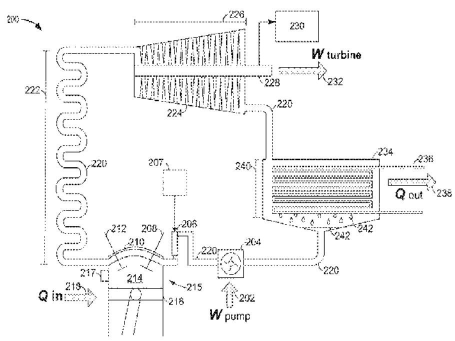


Table B.1 : Patent classification codes: transport

GREEN	
B60K 1	Arrangement or mounting of electrical propulsion units
B60K 6	Arrangement or mounting of hybrid propulsion systems comprising electric motors and internal combustion
B60K 16	Arrangements in connection with power supply of propulsion units in vehicles from force of nature, e.g. sun or wind
B60L 3	Electric devices on electrically-propelled vehicles
B60L 7	Dynamic electric regenerative braking
B60L 8	Electric propulsion with power supply from force of nature, e.g. sun, wind
B60L 9	Electric propulsion with power supply external to vehicle
B60L 11*	Electric propulsion with power supplied within the vehicle
B60L 13	Electric propulsion for monorail vehicles, suspension vehicles or rack railways; Magnetic suspension or levitation for vehicles
B60M	Power supply lines, or devices along rails, for electrically-propelled vehicles
B60L 15	Methods, circuits, or devices for controlling the traction-motor speed of electrically-propelled vehicles
B60R 16	Electric or fluid circuits specially adapted for vehicles and not otherwise provided for
B60S 5/06	Supplying batteries to, or removing batteries from, vehicles
B60W 10**	Conjoint control of vehicles sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle B60L0011)
B60W 20**	Control systems specially adapted for hybrid vehicles
H01 M8	Fuel cells
GREY***	
F02M 39, F02M 71	Fuel injection apparatus
F02M 3/02-05	Idling devices for carburettors preventing flow of idling fuel
F02M 23	Apparatus for adding secondary air to fuel-air mixture
F02M 25	Engine-pertinent apparatus for adding non-fuel substances or small quantities of secondary fuel to combustion-air, main fuel, or fuel-air mixture
F02D 41	Electric control of supply of combustion mixture or its constituents
F02B 47/06	Methods of operating engines involving adding non-fuel substances or anti-knock agents to combustion air, fuel, or fuel-air mixtures of engines, the substances including non-airborne oxygen
FOSSIL	
F02B*	Internal-combustion piston engines; combustion engines in general
F02D**	Controlling combustion engines
F02F	Cylinders, pistons, or casing for combustion engines; arrangements of sealings in combustion engines
F02M	Supplying combustion engines with combustiles mixtures or constituents thereof
F02N	Starting of combustion engines
F02P	Ignition (other than compression ignition) for internal-combustion engines

* : A patent with code B60L 11 is not considered clean when it is also classified as F02B (e.g., a diesel locomotive).
** : Patents with code B60W 10 and B60W 20 are not considered as clean when they are also classified as F02D.
*** : Note that codes classified as grey are a subset of codes classified as fossil in the transport case.
Source: Adapted from Dechezleprêtre et al. (2017), using information from the International Patent Classification. In this table, all codes are from the International Patent Classification (IPC).

Table B.2 : Patent classification codes: energy

	GREEN
Y02E 10	Energy generation through renewable energy sources
Y02E 30	Energy generation of nuclear origin
E02B 8/08	Tide or wave power plants
F03B 13/10-26	Submerged units incorporating electric generators or motors characterized by using wave or tide energy
F03D	Wind motors
F03G 4	Devices for producing mechanical power from geothermal energy
F03G 6	Devices for producing mechanical power from solar energy
F03G 7/05	Ocean thermal energy conversion
F24J 2	Use of solar heat
F24J 3	Other production or use of heat, not derived from combustion
F24S	Solar heat collectors; solar heat systems
F24T	Geothermal collectors; geothermal systems
F26B 3/28	Drying solid materials or objects by processes involving the application of heat by radiation, e.g. from the sun
	GREY
Y02 E20	Combustion technologies with mitigation potential
Y02 E50	Technologies for the production of fuel of non-fossil origin
	FOSSIL
C10 G1	Production of liquid hydrocarbon mixtures from oil-shale, oil-sand, or non-melting solid carbonaceous or similar materials, e.g. wood, coal
C10 L1	Fuel
C10 J	Production of fuel gases by carburetting air or other gases
F01 K	Steam engine plants; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles
F02 C	Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants
F22	Steam generation
F23	Combustion apparatus; combustion processes
F27	Furnaces; kilns; ovens; retorts

Source: Adapted from Dechezleprêtre et al. (2017), using information from the International Patent Classification and Cooperative Patent Classification.
In this table, the patent classes starting with Y are from the Cooperative Patent Classification (CPC), all other codes are from the International Patent Classification (IPC).

B.2 Mapping of investor types

Table B.3 provides an overview of the mapping of shareholder types. The shareholders are identified by their own BvD ID (if available). In order to classify them into different shareholder types, both their NACE code and the “entity type” asigned by BvD are used. Each of the classifications have their own advantages and disadvantages. NACE codes generally allow for a good distinction between private financial services institutions, such as banks, investment funds, or insurance and pension funds. However, outside of the financial services classification, NACE codes become less useful: many foundations, private funds or even cooperative banks are classified as “Activities of membership organizations”. The shareholder types provided by BvD, on the other hand, identify these institutions more clearly. Moreover, they are generally useful to distinguish between individuals and institutional investors, and to differentiate between government investors and private ones. Within private investment organizations, the attribution of types in the BvD classification seems somewhat arbitrary (e.g. pension funds are sometimes coded as “insurance companies”, and BlackRock is labelled “Bank”). Therefore, the financial sector classification follows, and slightly adapts, the approach from Battiston et al. (2017):

- The Orbis classification is used in case of “Government” and “Foundation”.
- In all other cases, the NACE classification is used, if it is available and if it is equal to some financial services-related sector (for the mapping, see Table B.3).
- If no NACE code is available or if it is not related to financial services, the Orbis classification is used (for the mapping, see Table B.3).
- Investors which do not belong to the institutional ownership category are dropped from the analysis:
  - In case the Orbis classification lists them as “Industrial Company”, “self-owned”, or “One or more known individuals or families”, observations are excluded.
  - In case the Orbis classification lists them as “Other unnamed private shareholders” or “Other unnamed shareholders”, they are excluded if there is no NACE code available (these often appear to be unclassified funds or investment vehicles).

Table B.3 : Mapping of shareholder types

Type	NACE Rev. 2 4-digit codes	BvD Entity types
Bank	6410-6419	Bank
Insurance and Pension funds	6510-6539, 6620-6629	Insurance company; Mutual & Pension Fund/ Nominee/ Trust/ Trustee
Investment fund	6420-6439, 6491, 6612, 6630-6639	Hedge fund; Private equity
Other Credit Institutions	6492, 6499	Venture Capital
(Other) Financial Services	6611, 6619, 6400	Financial Company
Government		Government
Foundation		Foundation

Notes: For types in normal font, the NACE code was given precedence; only if it was missing or equal to none of the listed codes, the BvD classification was used.
For types in italics, the BvD classification was used regardless of the NACE classification code.

Firms are assigned dummies whenever a Global Ultimate Owner for them is reported who controls more than 50% or more than 25%, respectively, and if this Global Ultimate Owner is different from the firm itself. Another dummy indicates that a firm is self-owned.

B.3 Background on climate exposure variable

Publicly listed firms are required to report their quarterly earnings; in conjunction with these reportings, firm managers hold conference calls with investors and analysts. Sautner et al. (2020b) have developed a method – and corresponding dataset – to measure firm-specific climate change exposure by the use of transcripts of these conference calls. The conference calls are considered to play an important role in reducing information asymmetry between managers and investors, and have been described as “more or less routine” (Hollander et al. 2010) for already quite a while. Transcripts of the conference calls are available from financial data providers such as Thomson Reuters.

Importantly, a conference call consists of two parts: a presentation by management is followed by a question-and-answer round. In the first part, managers can choose what information to disclose; in the second part, call participants can ask questions also about issues which were not disclosed previously. Therefore, conference calls provide an important source of information beyond voluntary disclosure such as in sustainability reports.

The conference calls can cover virtually any topic of relevance to the firm at the time. With the help of the transcripts and machine learning algorithms, certain words or expressions can be identified and assigned to a topic of interest. Sautner et al. (2020b) develop and use a set of signal word combinations (termed "bigrams") related to climate change and climate policy to derive a measure of "climate change exposure" at firm-year level.

Similar methods have been used to identify risks and opportunities that firms face in various dimensions, such as political risk (Hassan et al. 2019), uncertainty about Brexit (Hassan et al. 2020b), or even Covid-19 (Hassan et al. 2020a). In this literature, the term "exposure" is used to describe "the proportion of the conversation during the conference call that is centered on a particular topic" (Sautner et al. 2020b).[1]

B.4 Further summary statistics

Table B.4 : Average patent numbers per firm and year

	Green	Fossil	All patents
Raw patent count	2.47	3.08	89.93
Family-size-weighted patent count	8.85	10.97	287.35
Average family size per patent	3.58	3.56	3.20
Citation-weighted patent count	1.25	1.50	150.85
Average citations per patent	0.51	0.49	1.68

Notes: The table shows averages over all sample years. Due to the lagged structure of the estimation, the sample period for patents is 2010-2018. Note that in this paper's definition, family size is at least equal to 1 (each patent is applied for at least once in one country). Citations, on the other hand, can be zero.

[1] This use of the term exposure differs from how the term "risk exposure" is defined in the asset pricing literature, see Hassan et al. (2019) for a discussion.

Table B.5 : Mean number of fossil, green and all patents, family size and citations over time

Year	Green patent count	Green patent family size	Green patent citations	Fossil patent count	Fossil patent family size	Fossil patent citations	All patents count	All patents family size	All patents citations
2010	3.58	14.84	2.04	3.49	13.99	2.23	109.68	399.60	281.11
2011	3.90	14.92	2.38	3.80	15.13	2.96	109.02	389.46	273.82
2012	4.07	15.33	2.27	4.02	15.04	2.90	119.81	413.71	273.22
2013	3.12	10.95	1.92	4.08	15.76	2.26	116.61	390.00	197.16
2014	2.65	9.45	1.48	4.01	13.62	1.74	106.75	345.31	148.77
2015	2.45	7.81	0.79	3.94	12.84	1.14	107.25	320.00	124.30
2016	1.67	5.14	0.48	2.67	8.47	0.52	75.05	205.93	77.61
2017	0.97	2.83	0.22	1.53	4.33	0.15	51.10	120.74	28.39
2018	0.35	0.84	0.03	0.51	1.17	0.03	24.28	49.24	4.45
Average	2.47	8.85	1.25	3.08	10.97	1.50	89.93	287.35	150.85

Notes: Numbers are shown for patents applied for in the given year. Patent numbers are based on a sample of publicly listed firms which filed at least one patent classified as green or fossil in the sample period. Due to the lagged structure of the estimation, the sample period for patents is 2010-2019.

Table B.6 : Summary statistics for different investor types

	Mean	Standard deviation	Minimum	Maximum
Gov. share	3.07	5.97	0	89.08
PRI sig. share	8.83	8.90	0	52.26
Ins. and PF share	6.45	7.18	0	81.35
Domestic share	27.73	24.99	0	100.00
Big 3 share	5.97	6.48	0	30.25
Observations	8.622			

Table B.7 : Summary statistics for climate change exposure sample

	Mean	Standard deviation	Minimum	Maximum
CC Exposure	1.988	3.353	0	37.648
CC Regulatory Exp.	0.098	0.448	0	11.111
CC Opportunity Exp.	0.898	1.887	0	26.037
All patents	125.64	411.11	0	7,975
Fossil patents	3.91	24.45	0	708
Green patents	3.16	23.10	0	794
Patent stock	844.7	2471.1	0	36324.3
Fossil patent stock	25.6	156.9	0	4404.1
Green patent stock	20.2	137.0	0	3,845.9
Spillover	179,300.7	151,570.5	0	584,380.8
Fossil spillover	4,625.5	5,829.4	0	24,151.9
Green spillover	3,094.1	5,161.2	0	21,157.4
R & D expenditures, in thousand USD	2,307,401	$1.03 \cdot 10^{11}$	0	$6.43 \cdot 10^{12}$
IO share, in percent	56.21	24.57	0	100

Notes: CC Exposure is "Climate Change Exposure", CC Regulatory Exp. is "Climate Change Regulatory Exposure", and CC Opportunity Exp. is "Climate Change Opportunity Exposure" as constructed in Sautner et al. (2020a); all climate exposure variables are scaled by the factor 1000 compared to the Sautner et al. (2020a) dataset.

B.5 Further estimation results

Table B.8 : Family size and grey patents

	(1)	(2)	(3)
Dep. var.	Green family size	Fossil family size	Grey patents
L.IO share	0.000346	-0.00364	-0.00489
	(0.0391)	(0.0276)	(0.140)
L.Own stock fossil, FS	0.105***	0.887***	
	(0.0385)	(0.0858)	
L.Own stock green, FS	1.034***	0.0332	
	(0.0838)	(0.0672)	
L.Green spillover, FS	0.0104	-0.0205	
	(0.598)	(0.417)	
L.Fossil spillover, FS	-0.0304	0.00764	
	(0.598)	(0.414)	
L.R and D exp.	0.128	0.165	0.330
	(0.166)	(0.123)	(0.602)
L.Own stock fossil			0.378
			(0.246)
L.Own stock green			-0.271
			(0.329)
L.Own stock grey			1.896***
			(0.231)
L.Green spillover			-0.153
			(2.935)
L.Fossil spillover			-0.730
			(2.328)
L.Grey spillover			0.810
			(0.756)
Observations	8622	8622	8622

Notes: All columns: Poisson control function estimations (first stage not shown). Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table B.9 : Ownership concentration and two-year lag

Dep. var.	(1) Green patents	(2) Fossil patents	(3) Green patents	(4) Fossil patents
L.Top 5 share	-0.0629	-0.0282		
	(0.148)	(0.102)		
L2.IO share			0.0673	-0.00383
			(0.0705)	(0.0414)
L.Own stock fossil	0.101*	1.283***	0.170**	1.295***
	(0.0536)	(0.0780)	(0.0768)	(0.124)
L.Own stock green	1.435***	0.00734	1.575***	-0.00861
	(0.0715)	(0.0502)	(0.154)	(0.128)
L.Green spillover	0.0742	-0.00195	1.488	-0.126
	(0.0834)	(0.0749)	(1.502)	(0.867)
L.Fossil spillover	-0.0590	-0.0150	-1.463	0.119
	(0.0813)	(0.0742)	(1.503)	(0.867)
L.R and D exp.	0.0763	0.123**	-0.170	0.162
	(0.0825)	(0.0624)	(0.309)	(0.189)
Observations	8622	8622	7345	7345

Notes: All columns: Poisson control function estimations (first stage not shown). Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10 : Special investor types and green patenting, full table

	(1)	(2)	(3)	(4)	(5)
L.Gov. share	0.0342				
	(0.0882)				
L.PRI sig. share		0.0343			
		(0.0796)			
L.Ins.& pens. fd. share			-0.121		
			(0.298)		
L.Domestic owner share				-0.0210	
				(0.0505)	
L.Big 3 share					0.0257
					(0.0610)
L.Own stock green	1.431***	1.452***	1.445***	1.421***	1.444***
	(0.0720)	(0.0851)	(0.0908)	(0.0769)	(0.0775)
L.Own stock fossil	0.110**	0.113***	0.0909	0.0850	0.111**
	(0.0437)	(0.0425)	(0.0793)	(0.0851)	(0.0435)
L.Green spillover	0.0777	0.259	-0.270	-0.251	0.182
	(0.0805)	(0.416)	(0.877)	(0.807)	(0.246)
L.Fossil spillover	-0.0294	-0.235	0.320	0.322	-0.160
	(0.0954)	(0.434)	(0.923)	(0.902)	(0.268)
L.R and D exp.	0.0997***	0.0712	0.161	0.176	0.0755
	(0.0356)	(0.0937)	(0.119)	(0.162)	(0.0874)
Observations	8622	8622	8622	8622	8622

Notes: Dependent variable: Green patents. All columns: Poisson control function estimations (first stage not shown). Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table B.11 : Special investor types and fossil patenting

	(1)	(2)	(3)	(4)	(5)
L.Government share	0.0171				
	(0.0629)				
L.PRI sig. share		0.0135			
		(0.0539)			
L.Ins.& pens. fd. share			-0.0858		
			(0.186)		
L.Domestic owner share				-0.0101	
				(0.0362)	
L.Big 3 share					0.0120
					(0.0412)
L.Own stock green	-0.00700	0.00880	0.00566	-0.0218	0.00789
	(0.0340)	(0.0608)	(0.0374)	(0.0710)	(0.0528)
L.Own stock fossil	1.289***	1.289***	1.249***	1.278***	1.289***
	(0.0742)	(0.0700)	(0.124)	(0.0904)	(0.0699)
L.Green spillover	0.00426	0.0720	-0.249	-0.156	0.0513
	(0.0729)	(0.280)	(0.552)	(0.582)	(0.167)
L.Fossil spillover	-0.00563	-0.0854	0.250	0.164	-0.0662
	(0.0853)	(0.293)	(0.579)	(0.646)	(0.184)
L.R and D exp.	0.134***	0.123*	0.170**	0.170	0.122*
	(0.0296)	(0.0699)	(0.0721)	(0.113)	(0.0653)
Observations	8622	8622	8622	8622	8622

Notes: Dependent variable: Fossil patents. All columns: Poisson control function estimations (first stage not shown). Robust standard errors in parentheses. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.12 : Institutional investors and totel patents, full table

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Neg. bin.
Dep. var.	Patents	Patents	Patents	Family size	Citations	Patents
L.IO share	0.0114^{***}	0.0114^{**}	0.0110^{*}	0.0129^{**}	-0.0258	0.00671^{**}
	(0.00348)	(0.00481)	(0.00603)	(0.00624)	(0.0177)	(0.00310)
L.Own patent stock	1.274^{***}	1.274^{***}	1.270^{***}			1.483^{***}
	(0.0374)	(0.0313)	(0.0370)			(0.0340)
L.Own patent stock, FS				1.109^{***}		
				(0.0540)		
L.Own patent stock, cit.					1.318^{***}	
					(0.0758)	
L.Total spillover	-0.0174^{*}	-0.0174	-0.0154			-0.0167
	(0.00902)	(0.0161)	(0.0172)			(0.0104)
L.Total spillover, FS				-0.00957		
				(0.0224)		
L.Total spillover, cit.					0.0989	
					(0.0633)	
L.Tobin's Q			0.0257			
			(0.0276)			
L.R and D exp.	0.0132	0.0132	0.0179	0.0447	0.128^{**}	0.0358
	(0.0277)	(0.0374)	(0.0436)	(0.0467)	(0.0610)	(0.0228)
Clustered SEs	no	yes	yes	yes	yes	yes
Add. control	no	no	yes	no	no	no
Observations	8622	8622	8040	8622	8622	8622

Notes: All estimations use a control function approach (first stage not shown). "Add. control" refers to the inclusion of Tobin's q as an additional control variable. Robust standard errors in parentheses. In the Poisson control function estimations starting in column 2, standard errors are two-way clustered at the 4-digit NACE code and country level. In the negative binomial control function estimation, standard errors are clustered at the 4-digit NACE code level. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects, and firm fixed effects using the BGVR method. Significance levels are indicated as $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table B.13 : Baseline results with climate exposure sample

	(1) Green patents	(2) Fossil patents
L.IO share	-0.00157	0.00760
	(0.0272)	(0.0236)
L.Own stock fossil	0.0609	1.335**
	(0.0567)	(0.120)
L.Own stock green	1.496**	0.00494
	(0.114)	(0.134)
L.Green spillover	-0.0467	0.0551
	(0.293)	(0.237)
L.Fossil spillover	0.0525	-0.0488
	(0.363)	(0.309)
L.R and D exp.	0.114**	0.133**
	(0.0399)	(0.0469)
Observations	3972	3972

Notes: All columns: Poisson control function estimation (first stage not shown). Robust standard errors in parentheses, two-way clustered at the 4-digit NACE code and country level. Estimation period is 2009-2018. All regressions include year fixed effects, and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Appendix to Chapter 3

C.1 Sectors

Table C.1 : Sector description and numbers

Sector number	Sector description
1	Agriculture, forestry and fishing
2	Mining and quarrying
3	Food, beverages, textiles, leather
4	Wood, paper, publishing, broadcasting, arts, entertainment, recreation
5	Coke and refined petroleum products
6	Chemicals and pharmaceuticals
7	Rubber, plastic and glass products and ceramics
8	Metals & metal products, machinery & equipment, and other products
9	Water supply, sewerage, waste management and remediation
10	Electricity from coal
11	Electricity from gas
12	Electricity from hydro
13	Electricity from wind
14	Electricity from biomass and waste
15	Electricity from solar (PV and thermal)
16	Electricity nec (incl. nuclear, oil); steam & hot water
17	Transmission of electricity
18	Distribution and trade of electricity
19	Manufacture of gas; distribution of gaseous fuels through mains
20	Construction
21	Wholesale and retail trade, repairs, including motor vehicles
22	Hotels and restaurants
23	Transport, warehousing, post and telecommunications
24	Financial and insurance services
25	Real estate activities
26	Rental & leasing; other business services
27	Computer programming and information service
28	Scientific research & development
29	Public administration & defense, social security
30	Education
31	Human health and social work activities
32	Activities of membership organizations and other personal service activities

Table C.2 : Available regional gross value added values

Aggregated sector	Corresponding CPA classifications	Sector description
A	1-3	Agriculture, forestry and fishing
B-E	5-39	Industry excluding construction
C	10-33	Manufacturing
B, D, E	5-9, 35-39	Industry excluding construction and manufacturing. B: Mining and quarrying; D: Electricity, gas, steam and air conditioning supply; E: Water supply; sewerage, waste management and remediation activities
F	41-43	Construction
G-J	45-63	G: Trade, repair of motor vehicles; H: Transportation and storage; I: accommodation and food services; J: Information and communication
K-N	64-82	K: Financial and insurance activities; L: real estate activities; M: Professional, scientific and technical activities; N: Administrative and support service activities
O-T	84-98	O: Public administration and defense, social security; P: Education; Q: Health and social work; R: Arts, entertainment and recreation; S: Other service activities; T: Activities of households as employers

C.2 Details on disaggregation of capital stocks

For the electricity-producing technologies, data on installed capacity are from ENTSO-E (2017b) and (for renewables) IRENA (2016a). Data on installation costs were combined (and sometimes averaged) from various sources (Nitsch et al. 2012; AEE 2012; Breyer et al. 2013; Dumont and Keuneke 2011; Blesl et al. 2012; Kost et al. 2013; Hirschl et al. 2015; Hobohm and Mellahn 2010; Peter et al. 2013; Photovoltaik-Guide 2017; Sachverständigenrat für Umweltfragen 2011; Pahle et al. 2012; Bickel et al. 2012).

Data on the length of electricity transmission lines were obtained from ENTSO-E (2017a). Information from ACER (2015) and ICF Consulting (2003) was combined to derive installation costs per kilometer. For electricity distribution, data on the length of distribution networks come from Vaillancourt (2012), and data on the investment costs are from Deutsche Energie-Agentur (2012).

In the heat sector, Eurostat (2016b) provides information on the amount (energy content) of derived heat available for final consumption. The data on investment cost per heat demand came from Grözinger et al. (2013). Finally, data on gas distribution networks was obtained from Eurogas (2008), while the cost per km is an estimate based on press reports on costs of the German distribution network at different pressure levels, scaled by the shares of these pressure levels.

C.3 Scenarios

Table C.3 : Scenario description

Green scenario	Business as usual scenario
Low price path for fossil energy sources on the global market	High price path for fossil energy sources on the global market
Return to the historical interest rate level in Germany	Moderate recovery of interest rates in Germany
Strong increase of the Gross Domestic Product in Germany	Moderate increase of the Gross Domestic Product in Germany
Increasing globalisation, increasing trade relations with a global paradigm shift on sustainability	Increasing globalisation, increasing trade relations without common environmental and energy targets
Higher population (weak decrease), higher migration balance	Higher population (weak decrease), higher migration balance
Societal value orientation: trend towards a sustainable materialism	Societal value orientation: trend towards differentiation
Trend towards a decentralised energy production and storage	Trend towards a mixed structure in energy production and storage
Preference for technology-specific economic instruments for the energy sector (e.g., EEG)	Preference for technology-specific economic instruments for the energy sector (e.g., EEG)
Higher policy stability for the energy sector	Constant level of policy stability for the energy sector
Redistribution of the EU Common Agricultural Policy funds: More funding for environmental protection in agriculture	Continuation of the EU Common Agricultural Policy
Intensified environmental and resource protection in Germany	Constant level of activity in environmental policy in Germany
Comparatively low global greenhouse gas concentration (temperature increase 2046-2065 probably between $0.4°$C and $1.6°$C)	Medium level of global greenhouse gas concentration (temperature increase 2046-2065 probably between $0.9°$C and $2°$C)

Source: Musch and Streit (2017)

C.4 Additional figures

Figure C.1 : Installed capacity for heat generation by scenario, yearly average

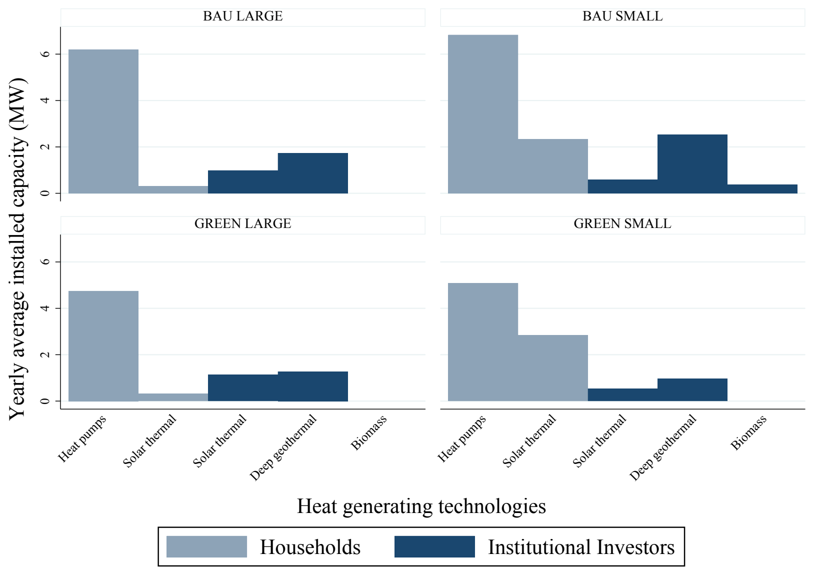


Figure C.2 : Effects on employment by category and region, BAU SMALL scenario

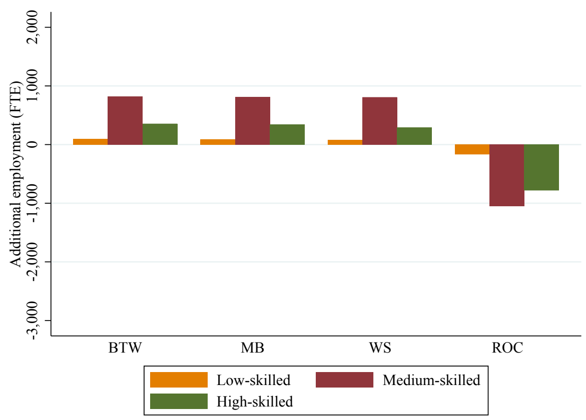


Figure C.3 : Effects on employment by category and region, BAU LARGE scenario

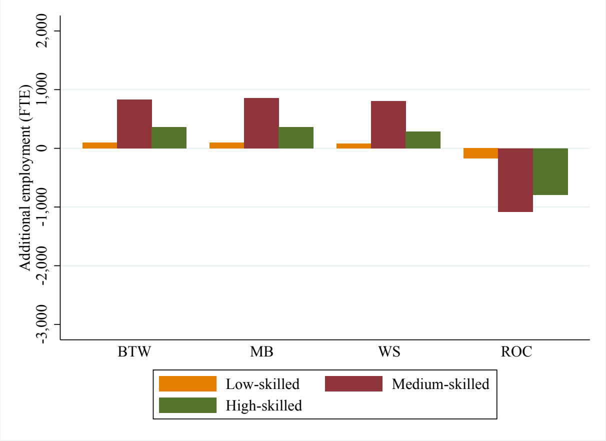


Figure C.4 : Effects on employment by category and region, GREEN SMALL scenario

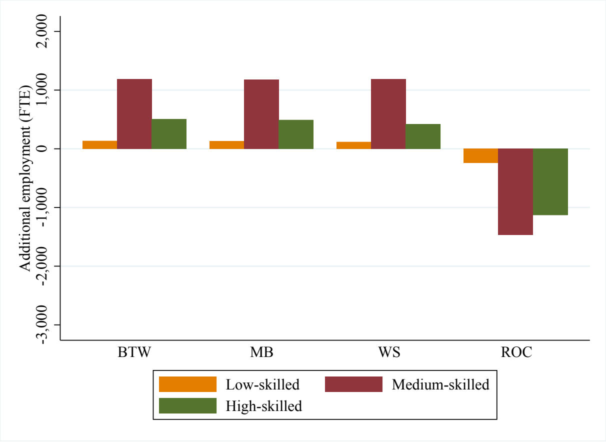
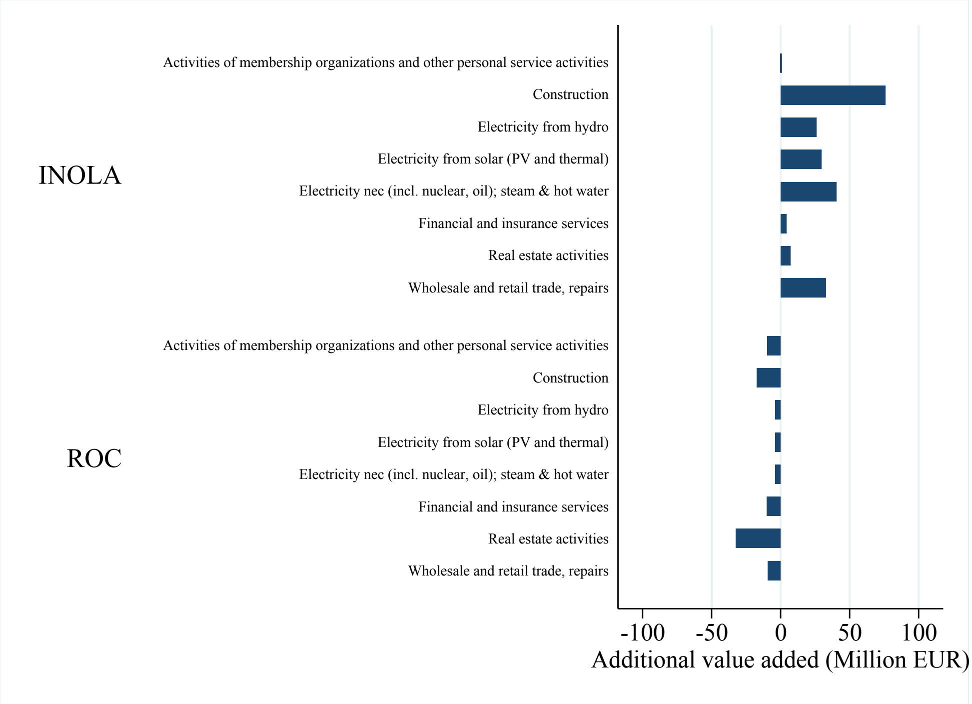
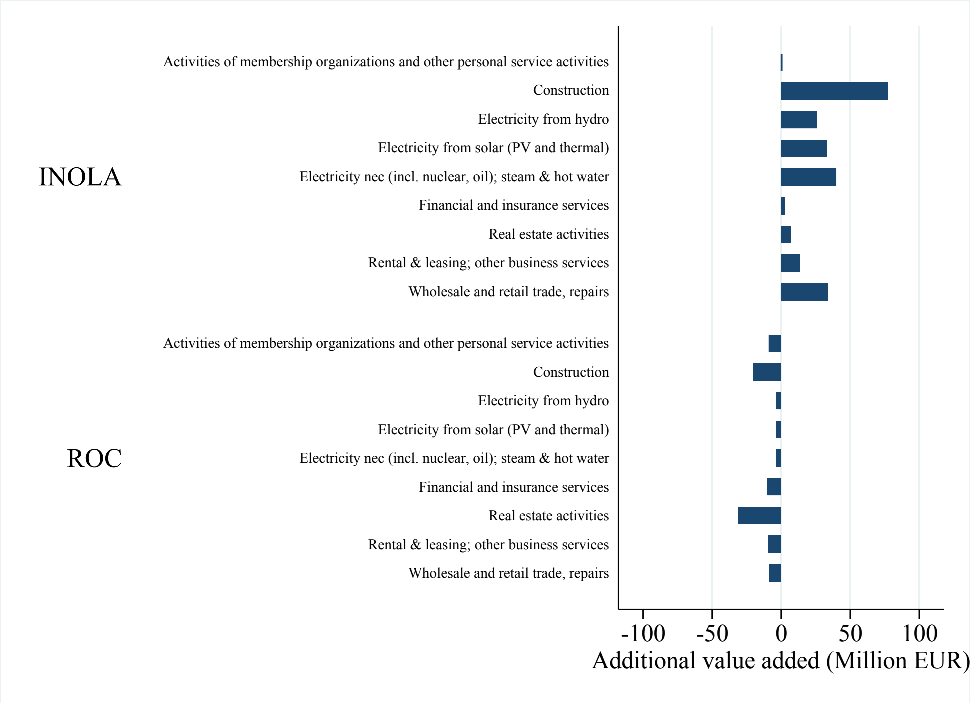


Figure C.5 : Effects on value added for selected sectors, BAU SMALL scenario



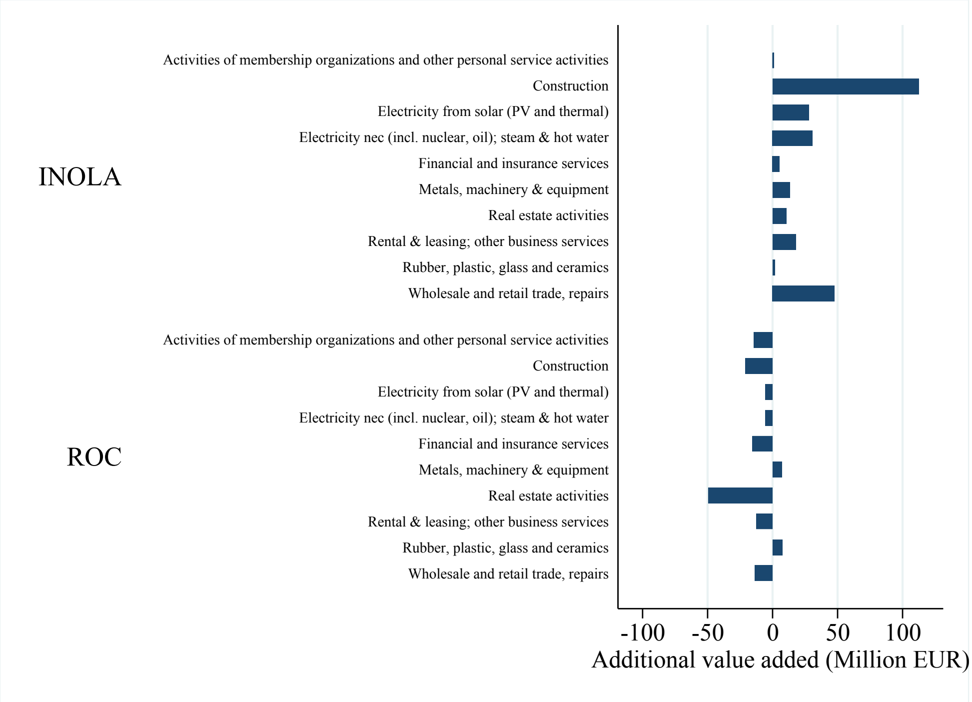
Notes: For a better visualization some sector descriptions have been shortened. See Appendix C.1 for the full sector descriptions.

Figure C.6 : Effects on value added for selected sectors, BAU LARGE scenario



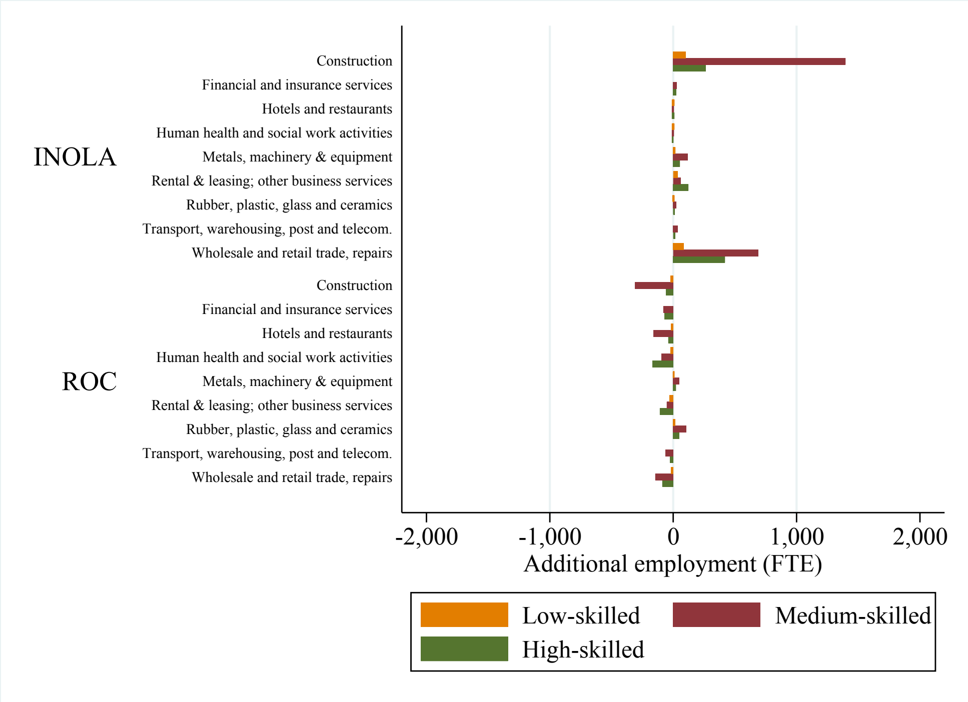
Notes: For a better visualization some sector descriptions have been shortened. See Appendix C.1 for the full sector descriptions.

Figure C.7 : Effects on value added for selected sectors, GREEN SMALL scenario



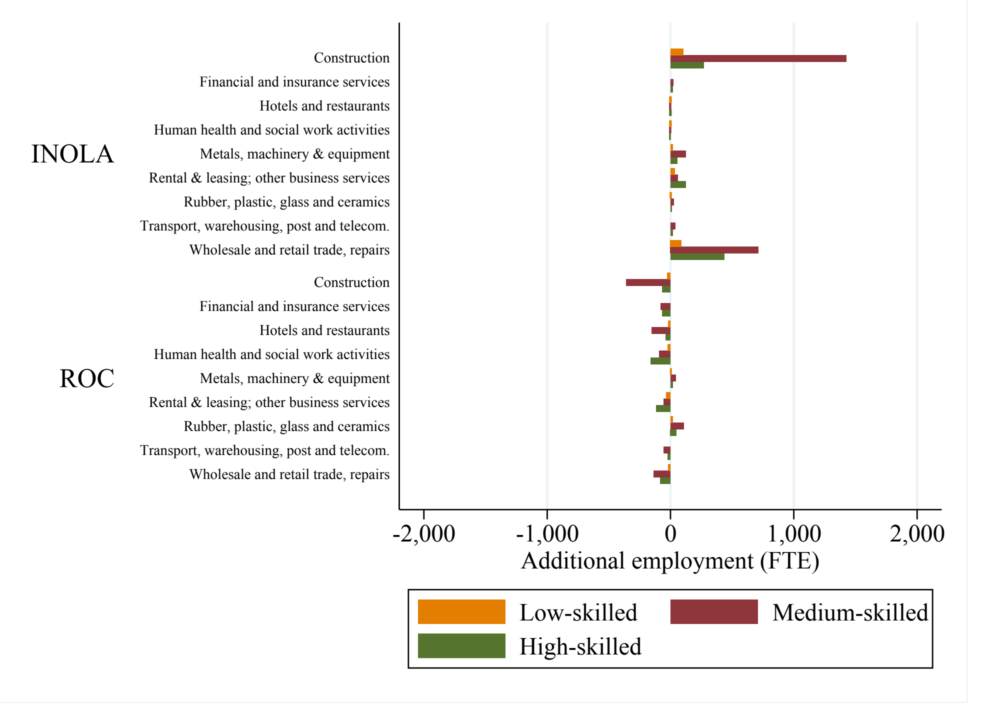
Notes: For a better visualization some sector descriptions have been shortened. See Appendix C.1 for the full sector descriptions.

Figure C.8 : Aggregated effects on employment by category, selected sectors and aggregated region, BAU SMALL scenario



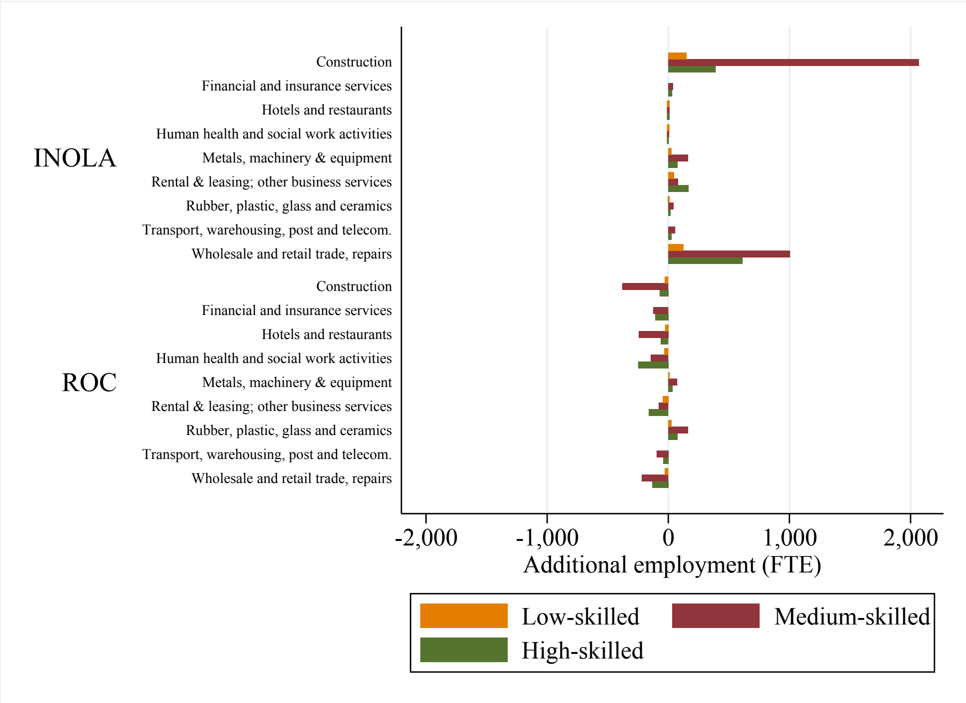
Notes: For a better visualization some sector descriptions have been shortened. See Appendix C.1 for the full sector descriptions.

Figure C.9 : Aggregated effects on employment by category, selected sectors and aggregated region, BAU LARGE scenario



Notes: For a better visualization some sector descriptions have been shortened. See Appendix C.1 for the full sector descriptions.

Figure C.10 : Aggregated effects on employment by category, selected sectors and aggregated region, GREEN SMALL scenario



Notes: For a better visualization some sector descriptions have been shortened. See Appendix C.1 for the full sector descriptions.

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