Modern-Day Challenges in Electricity Markets: Design, Environmental Impacts, and Adaptive Resilience to Climate Change

Jacqueline Folasade Adelowo

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Department of Economics
Ludwig Maximilian University of Munich

ifo Institute
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Korreferent:	Prof. Sebastian Schwenen, PhD
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Preface

Electricity markets and climate change are closely intertwined. Due to carbon-intensive electricity production, electricity systems have contributed to anthropologic climate change. But high hopes lie on the transformation of electricity systems to reduce greenhouse gas emissions and thereby mitigate climate change. The lever seems large, as electricity is an omnipresent, basic good. Indeed, in 2022, more people worldwide had access to electricity (IEA et al., 2023) than to safely managed drinking water (WHO and UNICEF, 2024). Electricity powers key technology advances like mass production, artificial light, telecommunication, digitization, internet, etc. It is therefore a cornerstone of modern economies, with its global share in total energy use doubling from 10 % in 1973 to 20 % in 2019 (IEA, 2021). Electricity systems, however, are not immune to the impacts of climate change – mainly through increases in extreme weather events, which were responsible for more than 60 % of prolonged electricity outages in the U.S. in recent years (Do et al., 2023). Hence, we need to understand how we can operate electricity markets in a way that electricity prices are fair and affordable, adverse consequences for the environment are minimized, that electricity markets contribute to mitigating climate change, and that resilient supply security is achieved in a world affected by climate change. This gives rise to three major questions. How should electricity markets be designed? How can we steer the environmental externalities of electricity generation? How does climate change, in turn, impact electricity systems and consumers? Insights into these three questions then allow the development of policies to transform modern-day electricity systems as needed. Before looking into these transformations, let me first highlight the characteristics that render electricity markets so special.

Managing electricity markets, especially in times of transformation, is not always straightforward due to the peculiar way of how they work. This is mainly due to electricity being an unconventional good with special properties: It is not storable but the grid is also very sensitive to real-time imbalances of supply and demand. At the same time, real-time demand is rather nonreactive to scarcity (see e.g, Lijesen, 2007) because consumers usually do not receive any real-time price signals. Further, electricity is a basic good both for firms and households, such that the state has a major interest in supply security, to the point that it is a matter of national security. Paradoxically, it is, however, not a very salient good (Hortaçsu et al., 2017), being invisible and historically a cheap product. Interesting to economists, it is probably the most homogeneous real-life good there is. The final products of different production technologies and firms are perfectly substitutable and even physically indistinguishable once fed into the network. There is only one socket for all; it is impossible to physically consume grid electricity from a specific producer or production technology. This creates an interesting distinction between physical electricity systems and economic value chains. Finally, the production and transmission of electricity has traditionally been a very capital-intensive sector, and grids are (regional) natural monopolies.

As promised, let us now undertake a deeper dive into three dimensions of transformation that modern-age electricity markets have faced and are facing.

Market and regulatory design. The combination of special characteristics outlaid above, led to the state being heavily involved in the production, transmission, and delivery of electricity in most countries. This began to change end of the last century. In fact, the economics subfield of industrial organization saw a multi-decade endeavor of rethinking the efficient organization of electricity markets with less state-involvement, and creating geographically integrated markets, such as in the EU (Jamasb and Pollitt, 2005). Like in other network industries, an international trend towards liberalization and privatization of the electricity system materialized. As a sector that was historically characterized by state-owned (partially natural) monopolies, step-by-step in most countries, the value chain was unbundled, vertically integrated organizations were broken up and privatized, market entry was enabled, and new organized markets were introduced along the value chain (see an overview in Newbery, 1997). A whole array of research is dedicated to evaluating the intended and unintended effects of restructuring reforms, and suggesting improvements in market design, pricing mechanisms, and regulatory set-ups. (e.g., Train and Mehrez, 1994; Green, 1996; Newbery and Pollitt, 1997; Joskow, 2000; Borenstein and Bushnell, 2015; Wolak, 2003b).

Tackling climate change. The restructuring phase was quickly joined by another transformative push, driven by the mitigation of climate change via the abatement of greenhouse gas emissions – primarily carbon emissions. The main reasons for the importance of electricity markets for carbon abatement are two-fold. Firstly, electricity systems have traditionally been one of the biggest carbon emitters in most economies. For instance, at the time of the Paris Agreement in 2015, the electricity and heat sector accounted for 32 % of global greenhouse gas emissions (36 % in the U.S., 32 % in the EU-27; Climate Watch, 2024). Hence, decarbonizing electricity markets represents a large-scale potential to abate carbon emissions. Secondly, electricity systems unlock a secondary potential to avoid carbon emissions in other sectors through electrification of the same. If processes, which were previously powered by fossil energy sources, can be powered by electricity instead, this increases the lever of using clean electricity generation to mitigate climate change. A striking example of this is the transport sector's shift to electric vehicles. The field of economics has since worked to figure out how the use of decarbonization technologies can be efficiently incentivized in electricity markets (e.g., Schmalensee, 2012; Holland and Mansur, 2006). Popular instruments include subsidies and remuneration schemes for clean technologies, and carbon pricing (via a tax or a carbon emissions market). A historical pioneer achievement in this regard is the introduction of the EU-ETS (EU Emissions Trading System) in 2005 – the first international cap-and-trade system for carbon emission allowances, and the largest one until today. However, this quickly raised the question of who is burdened by the costs of such policies (Fabra and Reguant, 2014; Reguant, 2019; Simpson and Clifton, 2016). Eventually, decarbonization policies began to manifest in changes of the technology mix in many markets. So economists started to research, how the tried and tested market designs that were developed after the liberalization, can now be adjusted to accommodate new generation technologies, with new cost (recovery) profiles and new generation profiles than conventional electricity generation (Joskow, 2019). Doing so, changes in demand patterns from electrification of e.g. transport, need to be taken into account as well. Finally, the elephant in the room remained as to which mitigation goals are optimal and what the social cost of carbon is (a line of research heavily influenced by the DICE model by Nobel laureate William D. Nordhaus (1992)[1]), to which extent decarbonization efforts are needed to hit set goals,[2] and if economies are on track to achieve them.

Impacts of climate change. As for the aforementioned elephant in the room – despite increasing mitigation efforts, it has become apparent that the world is not on track to achieve the 1.5 °C goal set in the Paris Agreement (2015) (IPCC Synthesis Report, 2023). This means that societies and economies have to prepare for a warming exceeding this goal. Depending on the geographical region, the effects can for instance include a change in temperature, wind, and precipitation patterns, sea-level rise, and extreme weather events (IPCC Synthesis Report, 2023). These changes impact people's way of life, businesses' operating modes, and infrastructure. Consequently, electricity systems, from generation via transmission to final use, are also impacted by this changing environment. Examples are infrastructure damages from extreme weather events, changing wind and solar irradiation potentials, constraints in power plant cooling due to high river temperatures, grid-ignited wildfires, and changes in consumption patterns related to heating and cooling. An illustrative example of addressing one of these issues are the grid operation strategies to proactively prevent wildfire ignition in California – in particular, using sensor equipment to automatically trigger partial shut-offs or putting grid lines

[1] and joined by further models like FUND and PAGE (see an overview of models in Bosetti, 2021).

[2] See also e.g., models like MESSAGE, IMAGE, REMIND (see an overview of models in United Nations Climate Change, 2025).

underground.[3] It ultimately comes down to a public or private decision whether to invest in such costly adaptive resilience measures or to accept disruptions in supply.[4]

* * *

IN THIS DISSERTATION, I explore three challenges of modern electricity markets, each arising from one of the previously outlined transformative phases. In the bigger picture, these challenges build on each other as follows: (1) It is vital to first make sure that electricity markets work efficiently, if (2) policy makers want to implement efficient policies to mitigate the environmental and climate impacts of electricity generation. As, despite mitigation efforts, climate change is already in motion, (3) understanding the mechanisms of adaptive resilience is crucial to reduce vulnerability of households. The resulting essays of this thesis are interconnected through this overarching three-part theme, however they can also be read standalone.

In the *first essay* I introduce new, simpler, and more accurate methods to estimate electricity production costs, enhancing regulators' ability to detect and prevent suspected market power abuse. This enables more efficient markets with welfare gains and rent transfers. In the *second essay* I reveal long-term trade-offs in the simultaneous abatement of carbon emissions and local air pollution from electricity generation. Damages and abatement of both emission types are linked to different generation technologies, whose mix can be carefully balanced via complementary taxation – to achieve a successful energy transition with clean air. Finally, with increased occurrences of extreme weather events due to climate change, the *third essay* investigates the aftermath of a cold-spell. I show that experiencing extreme-weather-induced electricity outages induces households to invest in home electricity back-up systems, but I also reveal notable socio-economic disparities in how strongly and how quickly communities adapt.

The *first chapter* is set in electricity wholesale auction markets, which are known to be prone to market power abuse via strategically inflated bids (e.g., Wolfram, 1998; Wolak, 2003b; Borenstein and Bushnell, 1999), which eventually raises prices for consumers. This chapter deals with the challenge of auction regulators to screen for and detect suspected market power abuse, without knowing firms' production cost. This issue is particularly policy-relevant in markets and market situations with large potential for windfall profits, like renewable-heavy systems or the European gas price crisis (Graf et al., 2021). Together with Moritz Bohland, I analyze existing automated mechanisms to mitigate market power in electricity auction markets and suggest ways to redesign them. In an empirical analysis and simulation on data from the Iberian market, this chapter compares the different design approaches

[3] Warner et al. (2024) undertook a risk-cost analysis of these measures.

[4] See a quantification of this trade-off in Brown and Muehlenbachs (2024).

and their welfare implications. It turns out that there is large, untapped potential to improve the precision of current algorithmic mechanisms with significant welfare transfers from supplier to buyer surplus and overall social welfare gain.

The *second chapter* looks at the climate and also further environmental impacts of electricity generation in Europe – namely damages from local air pollution. While the global costs of carbon emissions (e.g., from DICE-2016R) are very salient, air pollution also imposes significant local health and ecological damages around the emission source (Dedoussi et al., 2020; Markandya and Wilkinson, 2007). Together with Mathias Mier, I numerically model the long-term damages of these two emission types under different scenarios of regulatory intervention. Moreover, I provide a quantitative assessment of the co-benefits and trade-offs of the simultaneous taxation of carbon emissions and local air pollution, when policy priorities exist. For instance, in the U.S., air pollution abatement is more emphasized, whereas in the EU, the focus lies on coordinated carbon pricing. In the former case, moderate carbon taxation can complement a primary policy goal of cleaner air. Meanwhile in the reverse case, if carbon abatement is prioritized, additional air pollution taxation always causes a long-term abatement trade-off. These effects are steered through shifts in the technology mix of electricity generation, with carbon-capture-and-storage (CCS) technologies playing a key role. Although CCS can be carbon-neutral or even carbon-negative, the carbon-capturing process significantly contributes to local air pollution. While this is true today, luckily, it does not have to remain true tomorrow; from a policy perspective, joint taxation could incentivize technological innovations in the carbon-capturing process to mitigate this trade-off.

The *third chapter* studies adaptive resiliency investments of households after wide-spread electricity outages caused by an extreme cold event – a type of extreme weather that is also expected to occur more often due to climate change (Cohen et al., 2018). Recent studies have emphasized that households' past experience of extreme weather events impacts their investment decisions (e.g., Sheldon and Zhan, 2019) and that households are willing to pay for avoided outages (e.g., Brown and Muehlenbachs, 2024). My work combines these two lines of research and sheds light onto which groups are more likely to invest and distinguishes between different grid substitute options. I find that neighborhoods that experienced more outages during the extreme event, later invested at substantially higher rates in both home back-up generators and solar-PV-battery systems. Further investigation of my results reveals that there are, however, socio-economic disparities in adaptive capacity. Responses are both weaker and slower for lower-income, less-educated, and high-minority neighborhoods. This underlines inequities in both the capacity and promptness of households' resilience efforts. In a future impacted by climate change-induced extreme weather events, this leads to systematic imbalances in the vulnerability of households, which should be addressed by policy makers. These results also emphasize the importance and distributional impact of public supply security investments, which are hence over-proportionally relied upon by disadvantaged subpopulations.

* * *

Electricity systems and markets carry the large responsibility to produce and organize the provision of one of the most fundamental resources of modern-day life and economies. Success of this is often measured by invisibility – ideally, firms and households rarely need to consider the complex mechanisms operating in the background or worry about disproportionate cost burdens. At the same time, electricity markets have the potential to mitigate climate change – one of the biggest man-made challenges of humankind – and to weather the impacts of changed climate. In this spirit, I hope to contribute to pinpointing and describing some of the specific challenges that electricity markets face in current times and to exploring possible approaches to address them. These efforts are united by the overarching objective to provide economies with competitively priced electricity, minimize environmental harm, and ensure fair and equitable supply security in the future. My findings conclude that well-designed regulatory interventions can improve social welfare by curbing market power abuse and balancing climate mitigation efforts with local air pollution concerns, as well as they motivate policymakers towards targeted support of vulnerable groups to strengthen their resilience against force-majeure disruptions. These insights contribute to an optimistic outlook – where electricity markets, when properly governed, can serve as a powerful source for both large-scale, affordable energy provision and environmental sustainability.

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1

Redesigning Automated Market Power Mitigation in Electricity Markets

Abstract

Electricity markets are prone to the abuse of market power. Several U.S. markets employ algorithms to monitor and mitigate market power abuse in real-time. The performance of automated mitigation procedures is contingent on precise estimates of firms' marginal production costs. Currently, marginal cost are inferred from the past offers of a plant. We present new estimation approaches and compare them to the currently applied benchmark method. We test the performance of all approaches on auction data from the Iberian power market. The results show that our novel approaches outperform the benchmark approach significantly, reducing the mean (median) absolute estimation error from 11.53 (6.08) €/MWh in the benchmark to 4.03 (2.64) €/MWh for our preferred approach. This approach also performs best in our subsequent simulation of mitigation procedures. Here we find large welfare transfers from supplier to buyer surplus as well as a robust overall welfare gain, stemming from both productive and allocative efficiency gains. Our research contributes to accurate monitoring of market power and improved automated mitigation. Although we focus on power markets, our findings are applicable to monitoring of renewable energy tenders or market power surveillance in rail and air traffic.[1]

Keywords: Regulation; Automated mitigation procedure; Best-response pricing; Market power; Electricity; Mark-up

JEL-Codes: D22; D43; D44; D47; L13; L94

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1.1 Introduction

The liberalization of power markets entailed efficiency gains and cost reductions for electricity producers (e.g. Newbery and Pollitt, 1997; Davis and Wolfram, 2012), but these gains did not necessarily translate into lower market prices (Newbery, 1997). The missing link between cost reductions for producers and reductions in power prices is, at least partially, attributed to market power abuse by electricity generating companies. Market power exertion in liberalized electricity markets is documented for a wide range of markets and periods (e.g. Green and Newbery, 1992; Borenstein et al., 1999; Ciarreta and Espinosa, 2010). Limited storage capacities, inelastic short-run demand, and high market concentration render power markets especially prone to market power exertion. As market power abuse is both inefficient and undesired by policy makers, regulators aim at mitigating undue market power.

Existing mitigation strategies include the implementation of price caps (Wilson, 2000), stringent application of antitrust policies (Green, 1996; Borenstein et al., 1999), fostering of vertical integration (Mansur, 2007; Bushnell et al., 2008), and the implementation of forward contracting obligations for suppliers (Allaz and Vila, 1993; de Frutos and Fabra, 2012). In several U.S. markets, system operators go one step further and monitor and mitigate market power in real-time. To that end, system operators implemented automated mitigation procedures (AMP), i.e. algorithms to screen all supply offers, detect undue market power, and mitigate affected offers. Future electricity systems will depend even more on flexible, quickly dispatchable generators at the margin to balance increasing shares of intermittent renewables (in absence of sufficient storage and short-term demand response) – hence, raising the risk of market power abuse. Graf et al. (2021) point out how this will heighten relevance of AMPs to work properly in increasingly decarbonized systems. A striking example of this is the recent power crisis with high marginal prices from natural gas-fired generation due to the Russian war in Ukraine. This provides powerful firms that own a diverse generation portfolio with the potential to strategically deploy their units to maximize windfall profits.

Our research contributes to improved algorithms for automated mitigation of market power in multi-unit uniform price auctions. In electricity markets, market power is typically measured by the difference between observed offers and underlying marginal cost of power production.[2] Therefore, marginal cost estimates should be as accurate as possible to ensure unbiased measurement of market power (Bushnell et al., 2008) and welfare-improving mitigation thereof. When all cost components of power production are known, engineering based bottom-up calculations deliver precise estimates of marginal cost. However, cost components and power plant characteristics are private information

[2] Going back to the Lerner-Index of the degree of monopoly power as $\frac{price-marginal\ cost}{price}$ as e.g. in Wolak (2003b).

and firms have an incentive to overstate costs. Instead, system operators thus infer marginal cost of power plants from past offers of the respective plant, which leaves room for strategic manipulation by firms (Shawhan et al., 2011). We use this best-practise approach as a benchmark for further analysis and present alternative methods that deliver more accurate marginal cost estimates.

In this paper we test the accuracy of the AMP benchmark approach and alternative methods, which we develop and apply to micro-level bidding data from the Iberian day-ahead electricity market – an unbiased market that is currently not subject to AMPs. First, we calculate marginal cost of power production bottom-up to obtain a measure for "true" marginal cost. To that end, we employ detailed information on power plant characteristics and all relevant cost components. In a second step, we test the benchmark approach based on past offers and compare the outcomes to the true marginal cost we derived in the first step. We then proceed by testing the accuracy of alternative estimation methods and assess their performance as compared to the current benchmark approach. Finally, we carry out a mitigation simulation for all approaches and conduct a welfare analysis.

First, we test a theory-driven approach, which is based on Wolak (2003a, 2007) and accounts for the price reducing effect of a firm's forward obligations. We assume power producing companies to submit profit-maximizing offer curves as a best-response to the offers of competing firms. Under this assumption, we infer marginal cost of power production that justify observed offers. We designate this approach as "Best-response" approach. Additionally, we present two approaches, which methodologically build on the benchmark approach used by system operators but address major flaws of the existing method. In the first of these two approaches, we additionally control for distortions caused by potential start-up and ramping cost. We refer to this approach as the "Start-up" approach. The last estimation method we propose represents an extension to the Start-up cost approach, where we now define clusters of similar power plants and estimate marginal cost for the whole cluster of plants to alleviate strategic manipulation by individual firms. We refer to this method as the "Clustering" approach.

The results of our empirical analysis reveal a low estimation accuracy of the benchmark approach. For the sample of power plants that we analyze, we find a mean (median) absolute deviation of 11.53 (6.08) € /MWh between marginal cost estimates following the benchmark approach and true marginal cost. All suggested alternative approaches deliver more precise estimates. Mean (median) absolute deviations accrue to 10.28 (6.88) € /MWh for the Best-response approach, 7.70 (4.92) € /MWh for the Start-up cost approach, and merely 4.03 (2.64) € /MWh for the Clustering approach. The Clustering approach does not only deliver the most precise estimates, but likewise limits the scope for strategic manipulation of estimates by firms. This is because estimates are based on past bids of a group of plants instead of just one plant. Strategic manipulation of estimates and thus mitigation would hence require a significant extent of coordination among firms. We therefore assess the risk of strategic manipulation as reduced. Applying all approaches to an AMP simulation on the data, we find sizeable overall welfare gains and welfare transfers from supplier to buyer surplus in the magnitude of 20–40 million € . For our preferred Clustering approach we achieve robust 0.83 – 1.01 % welfare gains for the average mitigated hour (roughly a doubling of the benchmark approach), which can be decomposed into 13,060 € productive and 17,800 € allocative efficiency gains per average mitigated hour.

Our findings provide system operators with improved estimation techniques of power plants' marginal cost and with more accurate methods for monitoring and real-time mitigation of market power. Equipped with precise marginal cost estimates, system operators can apply automated mitigation more stringently, and achieve increased market efficiency and reduced costs for consumers. At the same time, improved accuracy benefits producers as the scope for unjust mitigation of offers based on flawed marginal cost estimates is reduced. The main use cases for our approaches are automated procedures for market power mitigation in spot, balancing, and reserve electricity markets. Yet, the approaches can likewise find application in other markets, e.g. for monitoring in renewable energy tenders or price and market power surveillance in rail and air traffic. Additionally, marginal cost estimation approaches which are not contingent on private information facilitate power market research for scholars. The suggested approaches are especially valuable when a bottom-up calculation is infeasible due to limited accessibility of private information on cost components.

Considering the widespread application of AMPs in U.S. power markets and the immediate effect of mitigation procedures on market prices, producer and consumer rents, as well as investment decisions, literature on AMPs is rather scarce and to a large extent of qualitative nature. Twomey et al. (2006) and García and Reitzes (2007) address AMPs in their reviews of market power monitoring and mitigation measures. Helman (2006) and Graf et al. (2021) assess and compare market power monitoring and mitigation procedures in several U.S. markets. Kiesling and Wilson (2007) follow an experimental approach to investigate effects of AMPs on market prices and investments. Shawhan et al. (2011) likewise make use of an experimental setting to test the impacts of AMPs and find that firms can influence marginal cost estimates, and thus mitigation measures, strategically. For the suggested Best-response approach, we additionally draw from the literature on strategic bidding in multi-unit auctions (e.g. Wolfram, 1999; Wolak, 2003a,b, 2007; Hortaçsu and Puller, 2008; Brown and Eckert, 2021) and the literature on the impacts of forward contracts and vertical integration on optimal pricing strategies (e.g. Allaz and Vila, 1993; Wolak, 2007; Bushnell et al., 2008). Graf and Wolak (2020) use best-response functions to measure market power in more complex locational pricing markets.

The remainder is organized as follows. Section 1.2 gives an overview of AMPs in U.S. power markets. In Section 1.3, we outlay and develop the suggested estimation approaches and their empirical implementation. In Section 1.4, we present the market environment in the Iberian electricity market. Section 1.5 provides a description of the employed data. In Section 1.6, we present our results and Section 1.7 concludes.

1.2 Automated market power mitigation in U.S. markets

1.2.1 Overview and procedure

Multiple Independent System Operators (ISO) have implemented automated mechanisms for the mitigation of market power exertion in wholesale auction markets. These ISOs are the California Independent System Operator (CAISO), the Independent System Operator New England (ISO-NE), the New York Independent System Operator (NYISO), the Pennsylvania-New Jersey-Maryland Interconnection (PJM), serving various Eastern states, and the Midcontinent Independent System Operator (MISO), whose network also covers parts of Canada. In short, these mechanisms intervene in the bidding market by reducing suspiciously high bids to a reference price, a so-called reference level. Reference levels are set for each generation unit individually and adjusted for daily input prices. They serve as unit-specific proxies for marginal cost and simulate a competitive bid. The CAISO, ISO-NE, NYISO and MISO use market observations such as historical bids and prices to construct these reference levels. The precise derivation methods are described in a review below. We exclude the PJM, where reference levels are derived by a cost-based method, from our further review, as our goal is to focus on settings where cost information is not available to the market operator. The ISOs are regulated by the U.S. Federal Energy Regulatory Commission (FERC) and publish their full operation tariffs online, which serve as business practices manuals and operating rules. These FERC-approved tariffs allow an extensive understanding of the procedures applied for automated mitigation. The mechanism can be summarized as follows (see Table 1.1 for an overview).

General procedure First comes a *structural test*, which tests if the structural market situation implies potential for market power. If so, secondly, a *conduct test* is carried out, which flags bids that are excessively high. Third, to avoid excess intervention, an *impact test* is carried out, which tests if the flagged bids have a relevant price impact. Only if all tests fail (i.e. test positive), mitigation is triggered, which overrides bids of flagged generation units to their reference levels. Using these, a new supply curve is constructed and the new market clearing price is calculated.

Structural test Is there structural potential for market power? Here ISOs test for (1) the occurrence of local transmission constraints (i.e. the local market cannot be served by alternative suppliers due to the transmission constraint), or (2) the occurrence of pivotal supply (i.e. demand cannot be fully served without the capacity of a specific supplier), or (3) both cumulatively. For the latter two, a pivotal supplier test is carried out after bid submission that either tests individual suppliers or the group of n-largest suppliers for pivotal supply conditions (MISO, 2019; ISO-NE, 2020; NYISO, 2020). In the case of the CAISO, this screening is further specified by a Residual Supply Index (RSI) analysis (CAISO, 2019). The RSI provides a score on the size of the fraction of demand, which can be served without the capacity of a specific supplier.

Conduct test Which bids seemingly exhibit actual exercise of market power? In the case of the CAISO the conduct threshold is met when bids exceed the competitive locational marginal price (LMP, i.e. the nearest local electricity price) (CAISO, 2019). The other ISOs specify a certain percentage (e.g. 200 % or 300 %) or absolute amount (e.g. 100 $/MWh) by which the submitted bid has to exceed the unit's reference level. If the conduct threshold is exceeded, the bid is deemed non-competitive (MISO, 2019; ISO-NE, 2020; NYISO, 2020).

Impact test Is there a relevant consequential price impact? One possibility is to define the impact as significant as soon as a flagged bid sets the LMP or if the bid effectively removes the unit from the economic merit order (CAISO, 2019). Another possibility is to set an impact threshold as a percentage (e.g. 200 %, less for constrained areas) or absolute amount (e.g. 100 $/MWh, less for constrained areas) by which the clearing price would be decreased in a mitigated scenario. This may also be measured by comparing the unit's node's LMP against the node's hub LMP (MISO, 2019; ISO-NE, 2020; NYISO, 2020).

Overriding by reference level Provided the impact threshold for a given hour is exceeded, the automated mitigation takes place by overriding the bids of all units, for which a flagged bid had been submitted in this hour, to the unit's daily reference level. For all analyzed ISOs this practice is applied in day-ahead markets and other spot markets (CAISO, 2019; MISO, 2019; ISO-NE, 2020; NYISO, 2020). Yet, ISOs are heterogeneous in their available methods to calculate reference levels. The applicability ranking of these methods is either at the supplier's choice or set by the ISO. Three general methods are in practice: accepted offer-based, LMP-based, and cost-based calculations. In exceptional cases, reference levels are negotiated.

The first calculation method is based on previously accepted offer bids of the respective unit. It is the default method applied by ISO-NE, MISO and NYISO. In general, the reference level is calculated as the rolling mean or median of accepted offers over the last 90 days during competitive periods, adjusted for changes in fuel prices (MISO, 2019; ISO-NE, 2020; NYISO, 2020).

The second calculation method is based on previous LMPs at the unit's node and is used by all four ISOs. The reference level is calculated as the mean or median of the lowest 25 % (50 % for NYISO) of

LMPs during hours, in which the respective unit was scheduled within the past 90 days. The calculation again includes an adjustment for changes in fuel prices. CAISO additionally distinguishes peak and off-peak hours in the calculation (CAISO, 2019; MISO, 2019; ISO-NE, 2020; NYISO, 2020).

The third calculation method is based on cost estimates and is also applied by all ISOs. This approach considers unit-specific heat rates and fuel cost, unit-specific emissions with respective permit prices, opportunity costs and variable operation and maintenance (O&M) costs. The calculation is done in a consultative approach together with the supplier, who has to provide the required information and documentation of all cost components that cannot be gathered by the ISO (CAISO, 2019; MISO, 2019; ISO-NE, 2020; NYISO, 2020). This approach delivers good estimates of firms' marginal cost, yet requires detailed plant level information on cost structures. Furthermore, regulators are unable to verify the accuracy of data disclosed. Generators naturally have an incentive to overstate their costs, e.g. by understating the heat rate or by overstating the operation and maintenance cost of the power plant.

The last method is based on negotiations and exclusively applied by the CAISO. In this approach suppliers propose an appropriate reference level, which, if not immediately accepted by CAISO, will be further negotiated (CAISO, 2019).

ISOs employ reference levels not only for the incremental (i.e. per MWh) cost components but also for dynamic cost components such as start-up costs. However, the former will be at the focus of this paper.

1.2.2 Calculation of reference levels

Our analysis focuses on the estimation of reference levels, which are crucial for efficient mitigation. As the accepted offer-based method is the default method applied by ISO-NE, MISO and NYISO, we use this method as our benchmark. The accepted offer-based method uses previously accepted bids from competitive periods over the recent 90 days to construct a rolling mean or median as a reference level. The definition of competitive periods is, however, not consistent across analyzed ISOs. For the ISO-NE "competitive" refers to the mere economic scheduling of a unit (ISO-NE, 2020), whereas for the MISO the term is tied to the absence of transmission constraints (MISO, 2019). The NYISO tariff, despite stating the term, does not provide an explicit definition at all (ISO-NE, 2020).

Some ISOs impose additional conditions that narrow down the scope of relevant offers to certain periods or hours within the competitive periods (see Table 1.2). The NYISO takes only hours into account that start from 6am to 9pm and categorically excludes weekend and holiday hours from the calculation (ISO-NE, 2020). This can be interpreted as an on-peak-focused approach. The MISO does not restrict the calculation to certain hours of the day but instead distinguishes between on-peak

Table 1.1: Overview of automated market power mitigation across U.S. markets

Procedures	CAISO	ISO-NE	MISO	NYISO
Application tied to transmission constraint	Yes	No	Yes	No
Test for pivotal supply	Yes + RSI	Yes	Partly	Partly
Conduct threshold	Bids exceeding the competitive LMP	% / $ amount per MWh	% / $ amount per MWh	% / $ amount per MWh
Impact threshold	Bid sets LMP/ moves unit out of economic MO	% / $ amount per MWh	% / $ amount per MWh	% / $ amount per MWh
Basis for reference level	a) Prev. LMP b) Negotiated c) Cost	a) Accepted bids b) Prev. LMP c) Cost	a) Accepted bids b) Prev. LMP c) Cost	a) Accepted bids b) Prev. LMP c) Cost
Types of reference levels	Incremental & dynamic cost components	Incremental & dynamic cost components	Incremental & dynamic cost components	Incremental & dynamic cost components
Relevance for day-ahead	Yes	Yes	Yes	Yes

Summary of the application procedures of automated market power mitigation by different U.S. ISOs. Compiled from CAISO (2019), MISO (2019), ISO-NE (2020), NYISO (2020).

and off-peak hours (MISO, 2019). Last, the ISO-NE does not further narrow down the scope of considered accepted bids apart from its definition of competitive periods (ISO-NE, 2020).

Table 1.2: Conditions for the consideration of previously accepted bids for reference level calculation

Criterion	ISO-NE	MISO	NYISO
Retrospective time frame	90 days	90 days	90 days
Definition of competitive period	Scheduling of the unit in economic merit order	Absence of transmission constraints	None given
Distinction/ exclusion conditions	None given	Distinction of peak and off-peak hours	Only hours starting 6am-9pm; exclusion of weekends + holidays; exclusion of bids below 15 $/MWh

Compiled from MISO (2019), ISO-NE (2020), NYISO (2020).

The detailed calculation approaches for the default accepted offer-based method reveal a lacking consistency in the definition of which categories of hourly bids are most appropriate as a basis for reference level calculation. From the calculation practices no consensus can be found particularly on the handling of peak and off-peak periods in terms of their distinctive use, inclusion or exclusion. In case of the ISO-NE no attempt of distinguishing peak and off-peak hours is even made, which leads to a rudimentary mean or median calculation. The different approaches to accepted offer-based calculation among the ISOs also imply differing calculation results. It is, however, unclear, which ISO's approach yields reference levels that best approximate competitive bids. Moreover, under certain conditions the ISOs may switch to a cost-based calculation for individual bids. The cost-based methodologies are more uniform among all ISOs as compared to the accepted offer-based methodologies. As a consequence, the cost-based calculation can be expected to yield more similar reference level results across the ISOs, when compared to results from accepted offer-based calculations. This inevitably raises the question of how comparable reference levels of the same ISO really are, if, within the same territory, some bids are regulated using cost-based reference levels, whereas others are regulated using accepted offer-based reference levels.

1.2.3 Issues related to current practices

Both the accepted offer-based calculation as well as the cost-based calculation bear risks of Principal-Agent problems arising from hidden information. As the ISOs rely severely on the accepted offer-based method, this has evoked discussions on possible strategic bidding behavior that aims at increasing reference levels. Shawhan et al. (2011) find evidence in an experimental study that, in case of sufficiently high market power, bidders have an incentive to strategically raise their bids during unmitigated periods and thus manipulate the calculation basis for reference levels – so-called reference creep. This issue was not addressed in any of the analyzed ISO tariffs; consequently, there were no measures found in place to detect or account for reference creep. The second problem of hidden information arises in the cost-based reference method, where the ISOs depend on suppliers to truthfully disclose information on cost components, which cannot be obtained otherwise by the ISO. This information includes e.g. unit-specific opportunity costs. Depending on the agent to disclose such private, unobservable information provides opportunity for strategic behavior. Even at the PJM, an ISO that is particularly experienced in working with cost-based reference levels, these information asymmetries are hitherto unaddressed. The PJM's independent market monitor describes the occurrence of resulting strategic behavior of market participants in the submission of cost components and criticizes that true competitive proxies cannot be obtained if suppliers' submissions are not truthful and uniform (Monitoring Analytics, 2019). The complexity of bottom-up cost calculation as well as the information asymmetries of this approach may be a reason why all analyzed ISOs, except for the CAISO, explicitly present the cost-based method as least applicable option to calculate reference levels.

Forcing suppliers to bid at (approximated) short-run marginal cost does effectively limit short-run market power abuse. However, this regulative strategy may still not always be optimal. This is for instance the case for peakers, which rely on scarcity rents, and for opportunity costs, which remain unconsidered (Munoz et al., 2018). For this purpose, in a number of markets, complex bidding has been implemented, which is also the case for the Iberian market used in our simulation study. Complex bids consist of two parts; (1) A simple bid, which should reflect short-run marginal cost of generating electricity, and (2) a complex bid, which contains additional cost components (such as start-up cost) or additional conditions that have to be met (such as a minimum daily revenue e.g. to recover opportunity costs or start-up cost)[3]. Hence, if such a complex bidding system is properly implemented and used, AMPs targeted at the simple bid component do not harm the recovery of complex cost components and scarcity rents. Rather, they contribute to decreasing distortions between simple and complex cost components, while limiting short-run market power abuse.

1.3 Method and empirical strategy

In this section, we present and develop different empirical approaches to calculate reference levels of power plants' short-run marginal cost based on observed simple supply bids. To ensure comparability, all approaches make use of the same data from the Iberian day-ahead market, described in more detail in Section 1.5. First, we present the benchmark procedure as conducted by the NYISO, where we use observations of the preceding 90 days to calculate reference levels. We then proceed by describing the Best-response approach, which builds on Wolak (2003a, 2007) and Hortaçsu and Puller (2008). We present two more approaches, which are bid pattern-driven and represent extensions to the NYISO benchmark method. Here, we address problems, which arise due to start-up cost and reference creep, and increase the precision of estimation. Note that our reference level calculation refers exclusively to short-run marginal cost, i.e. the per MWh component of a bid. Some markets additionally apply separate reference levels to complex bid components, which is, however, not in the scope of this paper.

1.3.1 The NYISO benchmark approach

To assess the relative performance of our proposed calculation approaches we first define a best-practice benchmark. To that end we choose the NYISO method of calculating reference levels of plants' marginal cost. As compared to other ISOs, the NYISO provides relatively more information on the composition of the calculation basis, i.e. the set of historical bids which is employed for the estimation of reference levels. All U.S. system operators in our analysis follow similar procedures, yet approaches differ in details such as the exclusion of bids from the calculation basis (see Table 1.2 for an overview).

We calculate reference levels of plants' marginal cost for a full calendar year (01.04.2017 – 31.03.2018). For each fossil power plant and day within this sample period, we determine a reference level, which should optimally reflect the bottom-up calculated marginal cost for the respective plant and day.[4] As

[3] See Jha and Leslie (2020) for an analysis.

[4] We present a detailed description of our bottom-up calculation of "true" marginal cost in Section 1.5.

calculation basis, we use historical bids of the plant within the last 90 days. In line with the NYISO procedure, we define the reference level as the mean or median (whichever is lower) of bids in the calculation basis. Note that we only use bids within the range of 20 €/MWh to 140 €/MWh, firstly to comply with the NYISO procedure, and secondly to limit the leverage of complementary cost considerations of the firms.[5]

Within the 90 days period that serves as calculation basis, variation in underlying fuel cost and cost for carbon emissions is substantial (see Table 1.4). The precision of reference levels on the one hand benefits from the large calculation basis, but should, on the other hand, not be affected by changes of input prices. System operators account for fuel price changes NYISO (2020), yet do not specify how they proceed exactly.[6] We present our strategy to empirically control for changes in input prices in Appendix A.1.[7] Reference levels are then defined as the rolling mean or median of all adjusted bids in competitive hours of the last 90 days.

1.3.2 Best-response bidding

The second approach is based on Wolak (2003a, 2007), who derives underlying marginal cost directly from observed bids. We use his model of best-response pricing, which assumes according to supply function equilibria (Klemperer and Meyer, 1989) that a profit maximizing firm will submit a set of bids that is ex-post optimal given its residual demand. Assuming profit-maximizing behavior, it is possible to derive a firm's marginal cost C' for observed residual demand RD, observed market clearing prices p and its forward contracted quantity QC.[8] The resulting firm profit function for a single scheduling hour is further dependent on the price received on forward sales PC as well as the uncertain demand shock η and can be expressed as follows:

$$\pi(p) = RD(p, \eta)p - C(RD(p, \eta)) - (p - PC)QC, \tag{1.1}$$

We take the first order derivative with respect to the price and solve for the marginal cost component to receive the following condition:

[5] Companies alienate simple bids to signal that a plant is already running (by bidding at very low prices), or that it would need to start-up (by bidding close to the price cap) (Reguant, 2014).

[6] Adjustments are contingent on detailed price information over time. As fuel prices and emission allowance prices are publicly available, we assume that regulators possess the required information.

[7] This input price adjustment does not only include fuel prices but also emissions allowance cost, following Fabra and Reguant (2014), who show that emission cost are passed through at high rates.

[8] Bohland and Schwenen (2022) use a similar framework to analyze the effect of renewable subsidies on strategic pricing.

$$C'(RD(p^*, \eta)) = p^* - \frac{QC - RD(p^*, \eta)}{RD'(p^*, \eta)} \tag{1.2}$$

All bids are submitted in the expectation that the respective bid could determine the market clearing price, therefore each bid can be regarded as an optimal price p^*. Marginal cost C' are thus derived from observed bid levels p^*, the amount of infra-marginal quantity offered by the firm RD, the slope of the residual demand function faced by the firm RD', and its contracted quantity QC.[9] As we possess information on all supply and demand bids as well as the owning structure of the firms, we can derive the infra-marginal quantity and the residual demand curves. However, residual demand functions are step-wise bid functions in electricity markets and not continuously differentiable. We follow Wolak (2003a) and solve this by applying smoothing parameters for the residual demand curve.[10]

The contracted quantity QC is a crucial element for the bidding strategy of the firm. It incorporates both, forward sales (Wolak, 2007; Holmberg, 2011) as well as resell obligations of vertically integrated retailers (Kühn and Machado, 2004; Mansur, 2007; Bushnell et al., 2008), as the underlying incentives are identical. If the contracted quantity exceeds sales in the market, the firm acts as a net-buyer and aims at lowering the market clearing price by bidding below marginal cost. If market sales exceed the contracted quantity, the firm acts as a net-seller and bids above marginal cost to increase its profits. In case the regulator possesses information on vertical sales and forward contracts, it can directly derive QC and thus the underlying marginal cost C'. Unfortunately, we lack information on firms' forward sales and need an alternative approach for the estimation of QC. We make use of the nature of firm strategies and identify the contracted quantity as the position where the marginal cost curve of a firm intersects its supply function (Hortaçsu and Puller, 2008). The rationale is that if the uncertain residual demand materializes at the exact contract position of the firm, the firm has no incentive to influence the market clearing price and bids equal to marginal cost.[11]

We derive all parameters of equation (1.2) and calculate marginal cost as a function of the observed bid-level, the firm's hourly net-position, and the slope of the residual demand curve at the chosen bid-level. We determine reference levels for all fossil plants in our year of analysis (01.04.2017-31.03.2018). To ensure comparability across methods, we again restrict input bids to the range from 20 € /MWh

[9] Firms owning a larger portfolio can strategically play on this portfolio (and potentially market power), leading to a supply function whose underlying true marginal cost might not be non-decreasing. This implies that the marginal cost derived by the best-response bidding model might calculate a marginal (opportunity) cost at the firm and not the unit level. Using this marginal cost as a unit-specific reference level in mitigation however could incentivize firms to bid truthfully according to non-decreasing actual unit marginal cost to avoid disadvantageous reference levels.

[10] We use the *monpol* function in R, which is part of the *MonoPoly* package and ensures a monotonic fit. We allow for nine degrees of freedom. Note that our findings are not contingent on the exact specification of smoothing parameters.

[11] To retrieve the intersection between the supply curve and the marginal cost curve, we first need to fit a marginal cost curve. We use an isotonic regression that delivers monotonically increasing step-functions and is best-suited to mimic the nature of marginal cost curves.

to 140 € /MWh in competitive hours (from 7am to 11pm). Last, we define daily reference levels for each plant as the mean of all calculated marginal cost estimates for the respective plant and day.

1.3.3 Accounting for start-up cost

In this section we present an extension of the benchmark NYISO method. By following the NYISO approach as presented in Section 1.3.1, we do not structurally incorporate additional cost components such as start-up cost. Yet, the bids in our calculation basis may partly be driven by the presence of start-up cost due to the limited use of complex bids. Reguant (2014) shows that the neglect of start-up cost leads to biased estimates of marginal cost and eventually to flawed mark-ups and measures of market power. Nevertheless, for the sake of simplicity and clarity, we abstain from including start-up cost in the bottom-up calculated marginal cost estimates.[12] We assess the performance of the presented approaches by the deviation between the respective reference levels and the bottom-up estimates of short-run marginal cost. To achieve coherence, we thus need a calculation basis that excludes bids driven by start-up cost.[13]

Empirically, we address this problem by further limiting our calculation basis to those plants which are clearly not affected by start-up cost. Firms submit very low first step bids for plants that are already running to ensure that these plants will be scheduled with certainty (Reguant, 2014). Note that firms are permitted to submit up to 25 discrete steps per power plant. Using the first step to determine whether the plant should be running or not therefore comes at negligible opportunity cost. We make use of this signaling behavior and limit the calculation basis to bids of power plants for which at least one low-priced bid has been submitted within the respective hour.[14] Apart from this constraint, we use the same calculation basis as in our benchmark approach (see Section 1.3.1) and likewise account for changes in input prices.

1.3.4 Clustering

In our final approach, we address several additional shortcomings of the NYISO method, namely the large dispersion of results across power plants, the missing calculation basis for a set of plants,[15] and the potential occurrence of reference creep. We tackle these problems by departing from the calculation

[12] A distinct assessment of start-up cost is difficult as in some cases firms make use of complex bids to express start-up cost, whereas in other cases they incorporate them in simple bids, hence circumventing using a complex bid.

[13] The alternative would be to include start-up cost in the bottom-up estimates of marginal cost and in the reference levels. However, we see no feasible option to determine the extent to which a bid is driven by start-up cost.

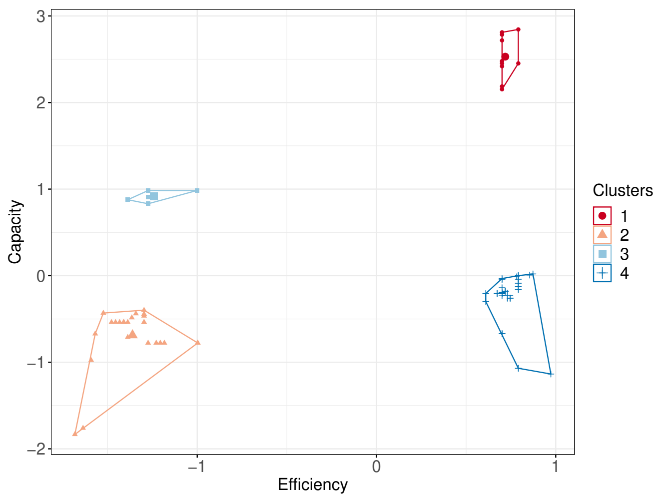
[14] We set the boundary at 30 € /MWh and thus significantly below the expected clearing price within our sample period (mean 51.82 € /MWh, 1st quartile 45 € /MWh) and which is also below bottom-up estimates of marginal cost as seen in Figure 1.3.

[15] This pertains to plants who had been recently inactive in the market, e.g. due to maintenance, or to new generating units entering the market.

of unit-specific reference levels. Instead, we apply a machine learning algorithm (k-means clustering) to cluster the 93 power plants in our sample with respect to their main characteristics relevant for marginal cost, i.e. heat rate (so-called efficiency) and size. As gas-fired plants generally have a higher heat rate than coal plants, this effectively allows also identification of the fuel type. Figure 1.1 depicts the results of the clustering process, showing four clearly distinguishable clusters. Clusters one and four incorporate large (cluster 1) and small (cluster 4) combined-cycle gas turbines (CCGT), whereas clusters two and three show small (cluster 2) and large (cluster 3) coal power plants.

We use these clusters and calculate reference levels analogously to our procedure in Section 1.3.3, yet not for each power plant individually, but at the cluster-level. Thereby we solve the problem of the large dispersion of estimation errors across plants and receive a more concentrated distribution of results. At the same time we limit the influence of outliers, which are usually attributed to a small calculation basis or market power abuse. Furthermore we solve the problem of missing calculation bases. As the calculation basis is now identical for all power plants within a cluster, we obtain reference levels for a larger set of power plants.

Figure 1.1: Clustering of the sample plants with respect to relative efficiency and size



Sample comprises 93 plants. **Clusters 1 and 4** represent efficient CCGT plants with cluster 1 comprising large CCGT plants and cluster 4 smaller CCGT plants. **Clusters 2 and 3** represent inefficient coal power plants, where cluster 2 comprises small coal power plants and cluster 3 large coal power plants. Clustering by efficiency makes additional clustering by fuel-type obsolete because coal and gas power plants are on different ranges of the efficiency spectrum for technological reasons.

For the purpose of AMPs, the main advantage of clustering the plants is the prevention, or at least complication, of reference creep. As long as reference levels for mitigation are merely based on the historical bids of a single power plant, strategically inflating these bids may prove to be beneficial for the firm. The incentives and ability to strategically alter the calculation basis decrease when the regulator shifts to a clustered approach. Firstly, strategic bidding would become more apparent as the clusters comprise plants of similar size and efficiency. Strong deviations from the mean bidding behavior of the plants within the cluster would be conspicuous and could hardly be justified. Secondly, plants within a cluster belong to a set of different firms as long as clusters are sufficiently large. Indeed Brown and Eckert (2022) find sophisticated coordination of firms through numeric pricing patterns of individual bids in the Alberta electricity market. However, using such strategies to jointly perform targeted reference creep across peak and off-peak hours would require even more significant coordination among firms. The Clustering approach thus solves and mitigates several elementary problems of accepted offer-based calculations of reference levels.

1.4 Market environment

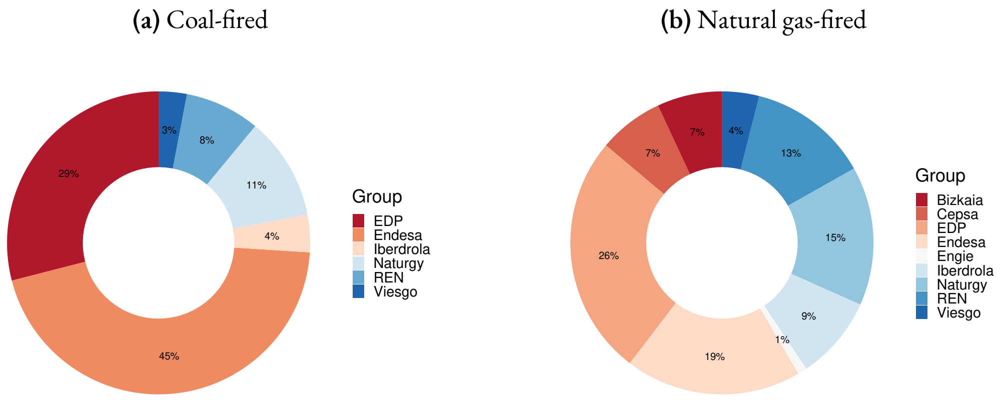
The Iberian electricity market consists of the geographical regions of Spain and Portugal. In 2007 the two countries integrated their electricity markets into one administrative market called Mercado Ibérico de la Electricidad (MIBEL). The peninsular electricity spot market of MIBEL is managed by the nominated electricity market operator called Operador del Mercado Ibérico de Energía – Polo Español (OMIE), which is based in Spain. The organized forward market is managed by the Portuguese equivalent OMIP.

OMIE is responsible for the MIBEL day-ahead and intraday (auction and continuous) energy markets within the spot market management. The OMIE market represents the most important place of electricity exchange within MIBEL, as its markets traded 85 % of the total MIBEL electricity demand in 2017, which mainly makes up our study period. Whenever interconnections between Spain and Portugal are not at capacity limits, OMIE consists of only one pricing zone. This was the case in 94.4 % of the time in 2017. The OMIE market can therefore be regarded as one coupled market consisting of the geographic zones of peninsular Spain and Portugal.

This study concentrates on OMIE's day-ahead market, as it represents the most important trading market accounting for more than 86 % of the total OMIE trading in 2017. In 2017, a total of 247 TWh was traded in the day-ahead market, of which Spanish generation accounted for the large majority of 72 %, whereas Portuguese day-ahead generation accounted for 22 %. On the day-ahead market, agents submit supply (sale) and demand (purchase) bids on electricity transactions for the following day. Buying agents can be direct consumers, retailers, resellers and representative agents; selling agents can be owners of production units, retailers, resellers and representative agents (OMIE, 2015). End consumers can be on real-time pricing plans, although evidence by Fabra et al. (2021) suggests that demand-price elasticity of consumers is negligible for our study's time frame.

The daily scheduling horizon consists of 24 hourly periods, which are all auctioned in a single session. Each bid is comprised of up to 25 blocks for each hourly scheduling period, with decreasing prices for

Figure 1.2: Distribution of fossil power generation across firms



Full unrestricted sample 01.01.2017–31.03.2018.

demand bids and increasing prices for supply bids. The maximum possible bid price was regulated to 180.30 €/MWh in our period of analysis. Demand bids are always simple bids, meaning that they consist only of a price and an amount of power for each block of a scheduling period. Supply bids are tied to a production unit and can be either simple (only price and amount) or complex. Complex bids contain additional conditions that the agent can submit to the market operator and typically cover complementary cost factors such as start-up or ramping cost. OMIE verifies the bids and matches supply to demand bids with the Euphemia matching algorithm that is commonly used in multiple European electricity markets. The algorithm creates two aggregate step-wise curves for demand and supply bids, considering any complex conditions, and finds the corresponding system marginal price as a uniform clearing price (OMIE, 2015). The Iberian bidding market is not subject to any automated mitigation procedures.

The day-ahead market is characterized by the presence of few large players dominating the market. Roughly two thirds of total generation can be accounted to five company groups owning the respective generation units, namely Endesa, Iberdrola, EDP, Naturgy, and Viesgo (Comisión Nacional de los Mercados y la Competencia, 2019). At the same time, these companies are vertically integrated, and likewise act as electricity resellers and retailers. With smaller renewable producers entering the market, the overall market share of the dominant producers shrank after liberalization. This is in line with a relatively low Herfindahl-Hirschmann-Index (HHI) of 883–1,013[16] for our sample period, see Table 1.3. In electricity markets, however, a low HHI of the whole market sheds only limited light onto market power concerns, as substantial market power lies in the hands of the marginal, price-

[16] Lower and upper bounds are given because ca. 14 % of the market share could not be manually assigned to individual groups.

setting producers. These producers are often dispatchable coal and natural gas-fired peaker units,[17] which are at the center of our research. This sub-sample is still in the hands of a few large companies. Only six companies accounted for total production from coal-fired units within our sample period, namely Endesa, Iberdrola, EDP, Naturgy, Viesgo and REN. Production from natural gas-fired CCGTs stemmed from the same companies along with Engie, Cepsa, and Bizkaia. This makes the sub-market for dispatchable coal- and gas-fired generation rather concentrated, as illustrated in Figure 1.2. This is reflected by an elevated HHI for these sub-markets to a highly concentrated level (2,306) for coal plus natural gas-fired generation, and to a moderately concentrated level (1,627) for natural gas-fired generation, only (Table 1.3).

Table 1.3: Conventional concentration statistics

	HHI	Level
HHI_{total}	883–1,013	low
$\text{HHI}_{coal+gas}$	2,306	high
HHI_{gas}	1,627	moderate

We take the level classification from Twomey et al. (2006), where markets with HHIs <1000 are deemed unconcentrated, 1000–1800 moderately concentrated, and >1800 highly concentrated. Note that the HHI is a conventional market concentration measure and due to the particularities of electricity markets, does not give a full picture of market power (see a discussion in Newbery, 2009).

1.5 Data

The centerpiece of our dataset stems from the Iberian market operator OMIE and comprises all supply and demand side bids in the Iberian day-ahead market.[18] Our main analyses cover a whole year from 01.04.2017 to 31.03.2018, while our full data sample covers a slightly larger time frame from 01.01.2017 to 31.03.2018, as we require 3 leading months for our analysis.

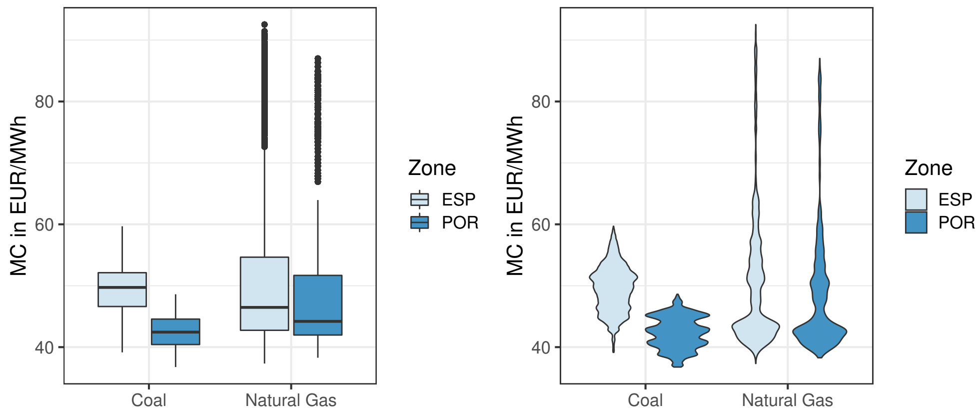
We focus on fossil production from coal and natural gas, where we compare the derived reference levels with bottom-up calculated marginal cost. For fossil generation this calculation is straight forward and delivers precise estimates of the true underlying marginal cost.[19] Our bottom-up engineering estimates of short-run marginal cost include fuel cost, cost for carbon emissions, variable O&M cost as well as all relevant additional taxes and levies. For a detailed overview of the determinants of our calculation, as well as sources of fuel prices and plants' efficiency rates, please see Table A.1. Table A.2 provides the detailed magnitudes of parameters we use for our calculation.

[17] Unlike e.g. must-run nuclear units and renewable units, who are usually at the bottom of the merit order.

[18] Monthly files including all supply and demand curves are provided by OMIE online.

[19] Nuclear generation as must-run generation is usually always bid into the market at low prices and therefore market power issues do not play a relevant role. Renewable generation is also bid into the market at low cost due to marginal cost being virtually zero. We further exclude hydro power as hydro bids represent the dynamic value of water, which is strongly driven by opportunity cost.

Figure 1.3: Distribution of bottom-up engineered marginal cost linked to fossil power plants bids



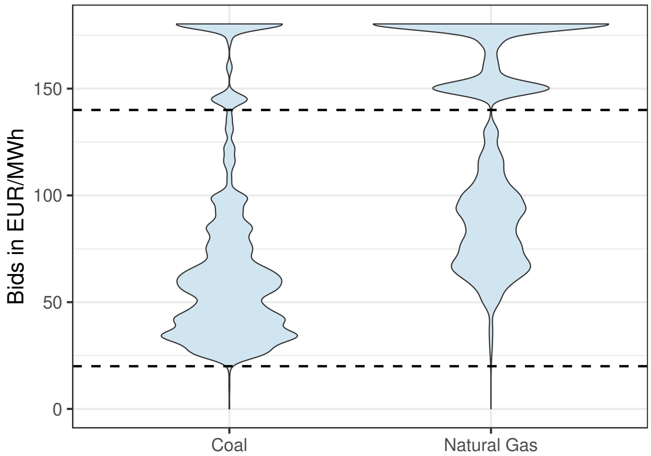
Full unrestricted sample 01.01.2017–31.03.2018.

Figure 1.3 gives an overview of the bottom-up engineered marginal cost across both technologies in Spain and Portugal for all bids in our full sample. Note that taxes and levies in both country jurisdictions structurally differ, attributing to the systematic marginal cost difference between Spanish and Portuguese plants. The initial reason stems from the additional taxation prevalent in Spain. Even though Portugal implemented a clawback mechanism to mitigate the difference in marginal cost via an additional fixed charge, this mechanism lacks the ability to fully compensate the cost gap. At the same time it is apparent that marginal cost of coal power plants are subject to less volatility than marginal cost of CCGT plants, which is attributed to the higher volatility of natural gas prices as compared to hard coal prices.

As part of our analysis is based on firm behavior, we additionally manually assign the parent companies to each power plant, or more precisely, to each bid, to account for ownership structures. This provides us with a dataset that comprises all demand and supply bids within the sample period, enriched by bottom-up engineered marginal cost, information on fuel types, and a variable specifying the owning parent company of the respective plant.

For the benchmark method to calculate reference levels of underlying marginal cost, we mimic the procedure of the NYISO and take it to the Iberian data. We opt for the NYISO procedure as a benchmark because it is the most selective and precise in defining "competitive bids". Analogous to the NYISO procedure, we thus restrict our calculation basis to a certain range of bids deemed competitive according to the NYISO rationale. In the NYISO calculation, all bids lower than 15 $/MWh are excluded. We apply an analogous boundary at 20 € /MWh and furthermore set an upper boundary of 140 € /MWh to exclude miscellaneous bids. This means we exclude all those bids, which we are

Figure 1.4: Price distribution of bids submitted by fossil power plants



Full unrestricted sample 01.01.2017–31.03.2018.

sure not to reflect short-run marginal cost but can rather assumed to be signaling behavior (must-run/ must-not-run). Figure 1.4 displays the observed bid levels of both technology types in our full sample, as well as the cut-offs at 20 € /MWh and 140 €. Even though firms can make use of complex bids to cover cost complementarities such as start-up or ramping cost, firms often circumvent this; instead they simultaneously use simple bids to either ensure that the respective power plant is running (and bid close to zero), or to signal that they not intend to start-up a plant (and bid close to the price cap).[20] This explains bid levels at 0 € /MWh and the density at 180.30 € /MWh as displayed in Figure 1.4. Additionally, we limit the sample to competitive hours (from 7am to 11pm) on weekdays to be consistent with the NYISO procedure.

In Table 1.4, we present the summary statistics of our full unrestricted sample. Note that the dispersion of natural gas prices by far exceeds the dispersion of hard coal prices, further shedding light on the distribution of marginal cost in Figure 1.3.

1.6 Results

In this section we present the results of our empirical analysis. We first present results for the different approaches to reference level calculation. Secondly, we present results of simulating automated market power mitigation with these different reference levels and analyze welfare effects.

[20] In our full sample time frame (01.01.2017–31.03.2018) out of all matched day-ahead supply bids 95 % were simple bids, only 5 % gave complex conditions of an economical type (minimum revenue), and a negligible fraction gave complex conditions of a technical type, only (e.g ramping conditions).

Table 1.4: Summary statistics

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Sd
Coal bid level [€/MWh]	0.00	37.86	47.41	58.09	57.34	180.30	45.60
Coal marginal cost [€/MWh]	36.76	44.71	48.26	47.98	51.43	59.68	4.52
Coal mark-up [€/MWh]	-57.71	-7.91	-0.85	10.11	7.26	143.24	44.70
Coal bid size [MWh]	0.00	37.86	47.41	58.09	57.34	180.30	66.09
Gas bid level [€/MWh]	0.00	51.07	68.77	94.07	151.35	180.30	56.31
Gas marginal cost [€/MWh]	37.33	42.55	46.26	49.94	54.48	92.53	10.24
Gas mark-up [€/MWh]	-91.40	3.12	15.37	44.13	105.96	142.97	56.62
Gas bid size [MWh]	0.00	51.07	68.77	94.07	151.35	180.30	150.91
Clearing price [€/MWh]	2.30	45.00	51.04	51.82	57.98	170.00	13.12
Hard coal price [€/MWh]	8.73	9.48	9.95	10.07	10.69	11.65	0.73
Natural gas price [€/MWh]	15.50	17.50	19.00	21.29	23.20	43.00	5.57
EUA price [€/ton of CO2]	4.39	5.06	5.79	6.63	7.68	13.64	1.99

Full unrestricted sample 01.01.2017–31.03.2018.

1.6.1 Calculating reference levels

As described in detail in Section 1.3, we tested the benchmark approach as well as three alternative approaches to calculate reference levels of marginal cost for an annual sample from 01.04.2017–31.03.2018. We assess the performance of the approaches based on two quality criteria. First, we compare the mean or median absolute error between the derived reference levels and the true marginal cost. The second criterion for the performance of each estimation method is the number of covered plants. The more we restrict the calculation basis within our empirical setting, the lower the number of plants for which we obtain reference levels. To ensure stable operation of an AMP, reference levels should at best be available for all power plants in the market.

In Table 1.5, we present our main findings for reference level calculation.[21] The benchmark NYISO approach performs worst and exhibits the highest mean (median) absolute error across plants of 11.53 (6.08) € /MWh and the largest standard deviation. The Best-response approach delivers smaller mean (and similar median) error terms as well as less dispersed outcomes across plants. Moreover, the maximum error term falls short of what we observe for the benchmark approach.

For the Start-up cost approach, where we exclude bids from the calculation basis that could be driven by complementary cost factors, we receive a low mean (median) error of 7.70 (4.92) € /MWh, which clearly constitutes an improvement over the benchmark method. Yet, the lower error comes at the price of a reduced set of plants due to the restricted calculation basis.

Our last approach overcomes this downside and delivers reference levels for all 93 fossil power plants

[21] In Table A.3 we present a similar table on errors in relative terms (also see Table A.4 for surplus in million € and Table A.5 for mitigated hours by approach).

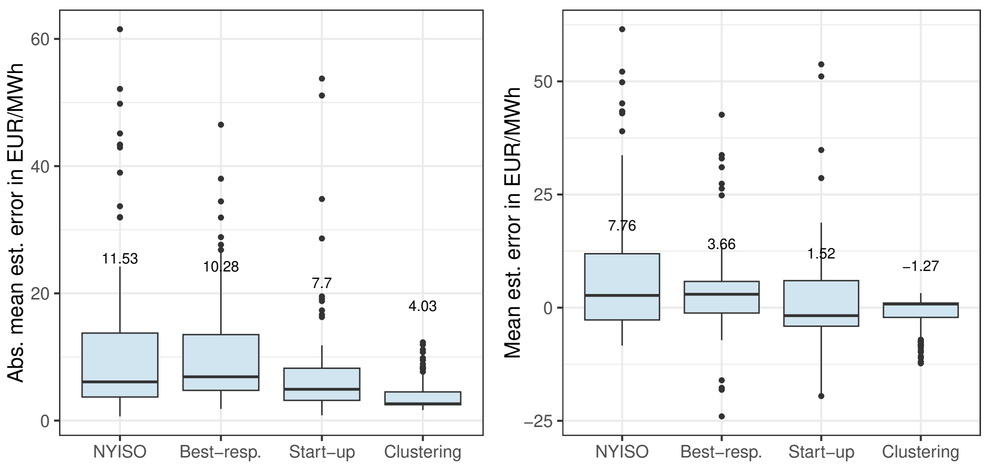
in our sample. The Clustering approach thus covers the broadest set of power plants, which is a crucial aspect for the potential application in AMPs. At the same time, it delivers reference levels that lead to the lowest standard deviation, lowest mean error term of just 4.03 € /MWh, and the lowest median error of 2.64 € /MWh.

Table 1.5: Deviation of reference levels from true marginal cost in absolute terms in € /MWh

	NYISO	Best-resp.	Start-up	Clustering
# Plants covered	92	92	84	93
1st Qu.	3.70	4.74	3.17	2.50
Mean	11.53	10.28	7.70	4.03
Median	6.08	6.88	4.92	2.64
3rd Qu.	13.76	13.51	8.23	4.51
Sd	13.14	8.48	9.09	2.58
Min.	0.66	1.84	0.83	1.65
Max	61.53	46.51	53.76	12.30

Deviation is defined as the absolute difference between derived daily reference levels and the true marginal cost we calculated bottom-up. In total, there are 93 power plants in our sample from 01.04.2017–31.03.2018.

Figure 1.5: Accuracy of marginal cost approximation by reference levels across approaches



Estimation error in absolute (left panel) and relative terms (right panel). Sample period 01.04.2017–31.03.2018.

The box-plots in Figure 1.5 illustrate graphically that all proposed alternatives outperform the method which is currently applied by the NYISO. We deem absolute values of deviations (left panel) from the underlying marginal cost to be generally better suited to assess the performance of an approach than relative deviations. Ultimately, a regulator applying automated mitigation or a researcher, who seeks to receive appropriate estimates of marginal cost, is mainly interested in achieving precise estimation – under or overestimation are both undesired.

Nevertheless, it is relevant whether a method leads to systematic positive or negative bias. To that end, the right panel in Figure 1.5 shows our results in relative terms.[22] Overestimation is especially pronounced in the NYISO and the Best-response approach. In an AMP environment, overestimation may turn out to be costly for consumers as incidents of market power exertion could stay unnoticed due to erroneously high reference levels. Any underestimation, mostly observed in the Start-up and Clustering approach, is usually driven by coal power plants, for which bid levels often fall short of marginal cost. When firms need to meet certain contract obligations, they often price below marginal cost. Since, in our sample, coal power plants are usually situated to the left of CCGT plants within the merit order, coal power plants are more heavily affected by these strategic considerations. If mitigation measures were to be strictly implemented, systematic underestimation of marginal cost would harm producers, as mitigation would enforce bids below true marginal cost. However, this problem is addressed and alleviated in the conduct test by granting a predefined margin by which bids can exceed the reference level without being flagged.

1.6.2 Mitigation simulation and welfare impacts

In order to quantify welfare impacts that a mitigation mechanism (based on the different reference levels) would have on a previously unmitigated market like the Iberian day-ahead, we apply all approaches in a simulation of automated mitigation. We apply the multi-step mitigation procedure outlaid in Section 1.2 to a whole year from 01.04.2017 to 31.03.2018.[23]

Conduct test We submit all bids to a conduct test, which bids fail if they exceed their respective daily reference level by more than a 20 € or 50 % threshold.[24]

Impact test For hours where bids have failed the conduct test, we perform an impact test. This test evaluates if mitigation would lead to a reduction of the clearing price by more than 20 € or 50 %.[25] We calculate the counterfactual mitigated clearing price by constructing a new supply curve ("impact test supply curve"). Bids that have passed the conduct test enter this curve at their original level. Bids that have failed the conduct test enter this curve at their reference levels. We then calculate the impact-clearing price by finding the intersection of the original step-wise demand curve and the step-wise

[22] Table A.3 displays the outcomes in more detail.

[23] As the fossil power generation is quite concentrated in the Iberian market (see HHIs in Table 1.3), we assume that there is a persistent potential for market power and therefore skip the structural test.

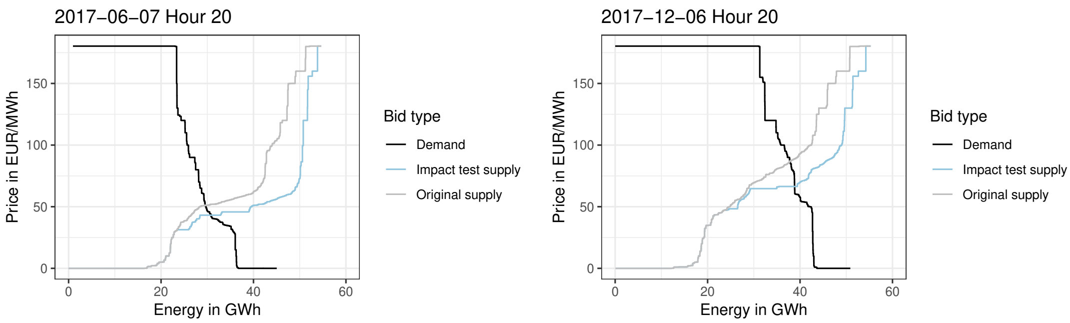
[24] These values follow the thresholds from the NYISO benchmark approach as we want to refrain from using arbitrary values. If AMPs were actually implemented it would of course make sense to consider adapting them to the specific market conditions.

[25] As the Iberian day-ahead market does not have nodal or zonal pricing, we perform the impact test against a collectively mitigated scenario of the whole market.

impact test supply curve as illustrated in Figure 1.6. As a last step, we compare the original clearing price with the impact-clearing price to determine if the above impact thresholds were exceeded.

Figure 1.6: Original and resulting market clearing curves of impact test for two exemplary hours

(a) Unmitigated hour **(b)** Mitigated hour



Both panels display impact tests for the clustering approach for the 20th hour (19:00-20:00) of a Thursday in June (left panel) and December (right panel). The hour in the right panel failed the impact test (in the clustering approach) simulation and was hence mitigated.

Mitigation In hours, in which both tests fail, automated mitigation is triggered and we perform actual bid mitigation of conduct-non-conform bids to their respective reference levels. The new clearing price of these hours is now the clearing price calculated in the impact test. Out of the 8,760 hours in our annual sample, the mitigation incidence varies by approach but within a somewhat reasonable incidence of market interference of 0.4–0.7 %: AMP is most often triggered in the Clustering approach with 57 hours, followed by the Best-response approach with 54, the NYISO approach with 45, and the Start-up cost approach with 32 mitigated hours.

Welfare impacts We start with a surplus decomposition (Table 1.6). For all approaches we find a deadweight-loss-decreasing rise in market efficiency. Total welfare gains are highest for the Clustering approach with 2.24 million €. Irrespective of the mitigation incidence, this approach also exhibits the highest average welfare gain per mitigated hour of 1.01 %. The lowest total and hourly welfare gains are achieved by the NYISO benchmark approach. Importantly, all approaches see large welfare transfers from supplier surplus to buyer surplus in the magnitude of 20–40 million €. For mitigated hours this corresponds to a decrease in supplier surplus of 20–36 % and an increase in buyer surplus of 22–29 %. This provides large potential for consumers to benefit from AMPs in a competitive retail market.

We further carry out a decomposition of observed efficiency gains into productive and allocative efficiency (Table 1.7). The 2.24 million € welfare gains in the Clustering approach can be decomposed roughly equally into observed productive (1,172 thousand €) and allocative (1,063 thousand €) efficiency gains. This corresponds, on average, to 20.56 thousand € and 18.65 thousand € per mitigated hour. While allocative efficiency gains per mitigated hour are roughly in the same magnitude for all approaches, note, that due to the imprecision of reference levels, the other approaches have significantly lower gains in productive efficiency per mitigated hour – lowest for NYISO at 3.20 thousand € (12.92 Best-response, 5.64 Start-up).

Overall, we establish the Clustering approach as our most preferred way of calculating reference levels for AMPs due to superiority in precision, coverage and risk reduction of reference creep, as well as most sizable welfare effects.

Table 1.6: Change in observed surplus due to AMP compared to BAU in million €

	NYISO	Best-response	Start-up	Clustering
# Mitigated hours	45	54	32	57
Buyer surplus change	27.92	29.10	20.90	38.23
Av. buyer surplus change per mitigated hour	25.46 %	21.60 %	29.41 %	26.39 %
Supplier surplus change	-26.98	-27.23	-20.06	-35.99
Av. supplier surplus change per mitigated hour	-48.52 %	-47.23 %	-41.88 %	-46.47 %
Total welfare change	0.95	1.87	0.84	2.24
Av. total welfare change per mitigated hour	0.57 %	0.97 %	0.71 %	1.01 %

Sample period 01.04.2017–31.03.2018.

Table 1.7: Observed productive and and allocative efficiency gains in thousand €

	NYISO	Best-response	Start-up	Clustering
# Mitigated hours	45	54	32	57
Productive efficiency gains	144	698	180	1,172
Av. prod. efficiency gains per mitigated hour	3.20	12.92	5.64	20.56
Allocative efficiency gains	801	1,175	658	1,063
Av. alloc. efficiency gains per mitigated hour	17.80	21.76	20.58	18.65

Sample period 01.04.2017–31.03.2018.

Welfare robustness We have to consider, however, that the reference levels, to which non-competitive coal and gas bids are mitigated, are only a proxy for marginal cost. The true supplier surplus and true welfare impacts, based on true marginal cost, may hence deviate. We therefore check if the welfare impacts are robust to the estimation errors occuring in AMPs. To that end, we calculate the true welfare impacts by applying the same merit order but – for coal and gas bids – instead of taking the (mitigated) bids for welfare calculations, we take our bottom-up engineering estimates of marginal cost. The resulting true losses in supplier surplus are higher across all approaches. The overall impact on true social welfare is slightly lower than the observed one, yet still relevant at 0.83 % for the average mitigated hour in our preferred Clustering approach (Table 1.8). We can therefore conclude that not only observed welfare would increase thanks to precise mitigation, but also true welfare would increase by a similar magnitude. We see similar robustness of the true allocative efficiency gains at 17.8 thousand € per mitigated hour (Table 1.9). Note that our preferred Clustering approach is the only one with true productive efficiency gains. The Best-response approach even exhibits true total welfare losses.

Table 1.8: Change in true surplus due to AMP compared to BAU in million €

	NYISO	Best-response	Start-up	Clustering
# Mitigated hours	45	54	32	57
True supplier surplus change	-27.26	-30.84	-20.59	-36.47
Av. true supplier surplus per mitigated hour	-54.29 %	-58.95 %	-48.81 %	-53.95 %
True total welfare change	0.67	-1.74	0.31	1.76
Av. true total welfare change per mitigated hour	0.42 %	-0.93 %	0.28 %	0.83 %

Sample period 01.04.2017–31.03.2018.

Table 1.9: True productive and and allocative efficiency gains in thousand €

	NYISO	Best-response	Start-up	Clustering
# Mitigated hours	45	54	32	57
True prod. efficiency gains	-25	-1,756	-6	744
Av. true prod. efficiency gains per mitigated hour	-0.56	-32.51	-0.20	13.06
True alloc. efficiency gains	692	16	319	1,014
Av. true alloc. efficiency gains per mitigated hour	15.37	0.29	9.95	17.80

Sample period 01.04.2017–31.03.2018.

1.7 Conclusion

This paper contributes to improved automated mitigation of market power in electricity markets. Automated mitigation procedures (AMPs) find wide application in U.S. power markets and are designed for real-time detection and mitigation of market power abuse. AMPs rely on so-called reference levels, supposed to approximate marginal cost, to evaluate competitiveness of a bid and to mitigate it by overriding. We design alternative approaches to derive reference levels from producers' supply offers. Improved accuracy of marginal cost estimates allows for both, facilitated detection of market power, as well as refined and more targeted mitigation. Refined mitigation protects buyers from excessive redistribution of rents to suppliers, but in a given mitigation setting likewise protects suppliers from excessive and unjust mitigation of competitive offers.

We employ micro-level data from the Iberian day-ahead market to test our suggested approaches to deriving reference levels against a best-practise benchmark. As benchmark approach, we choose the procedure as followed by the New York Independent System Operator (NYISO), where reference levels are inferred from past offers of a power plant. In our application of this benchmark approach, we find deviations of marginal cost estimates from true marginal cost to be substantial, with a mean (median) absolute deviation of 11.53 (6.08) €/MWh. In comparison, the alternative approaches we propose deliver mean (median) absolute deviations ranging between 4.03 (2.64) €/MWh for our novel Clustering approach and 10.28 (6.88) €/MWh for the Best-response approach based on Wolak (2003a, 2007), where we reverse-engineer marginal cost from real-time hourly offers instead of past offers of a plant. For the Clustering approach we depart from the estimation of marginal cost on the unit-level and estimate marginal cost for clusters of similar power plants. This preferred approach of ours does not only yield the most precise and least dispersed estimates, but likewise counteracts reference creep, i.e the strategic manipulation of bids to evade mitigation. System operators should hence consider the adoption of this approach for AMP purposes.

We finally apply all approaches in a simulation setting of AMP. We find a mitigation incidence between 32 (Start-up cost approach) and 57 (Clustering approach) hours out of the annual 8,760 hours, which is associated with notable welfare implications. Welfare gains are largest for our preferred Clustering approach and can be decomposed as follows: In mitigated hours buyer surplus increases by 26 % (38.23 million € in total); supplier surplus decreases by 46–54 %. This large welfare transfer comes with overall observed welfare gains in mitigated hours of 1.01 %, which are robust against measurement error (0.83 %). Accounting for measurement error, these gains can be decomposed into 13,060 € productive and 17,800 € allocative efficiency gains per mitigated hour.

Our findings contribute to potential improvement of policies in electricity markets with market power issues, e.g. related to locational pricing, pivotal supply, and concentrated or integrated market structures. The EU has, for instance, signaled in light of REPowerEU initiatives to reassess locational pricing in the EU and to "ensur[e] an up to date and robust framework to protect against [market power] abuse [...] in periods of high prices and market volatility" (European Commission, Directorate-General for Energy, 2022, p. 11). Any applied frameworks will have to make sure (1) that supply bids are fair and competitive and (2) that underlying fluctuations in input prices are taken into account to not harm the profitability of producers. AMPs are a suitable tool to achieve both. The recent power crisis due to the Russian war in Ukraine is just an extreme example of flexible fossil power generation being the marginal technology and causing high clearing prices with high windfall profits for inframarginal producers. This can potentially be exploited especially by firms who can strategically deploy a technology portfolio. These constellations will continue to occur in decarbonizing electricity systems with increasing shares of cheap, intermittent renewables and limited storage capacities (Graf et al., 2021).

To conclude, we show that current AMPs can be improved considerably by redesigning the estimation of underlying marginal cost of production. This significantly improves market efficiency by means of social welfare increases along with redistribution of excess rents from suppliers to buyers. Moreover, our enhanced approaches facilitate research whenever scholars require cost estimates for empirical analysis in power markets. Our findings are likewise applicable to other use cases and markets, such as monitoring of renewable energy auctions or market power surveillance in air and rail traffic.

2

Complementary Taxation of Carbon Emissions and Local Air Pollution

ABSTRACT

Current decarbonization policies neglect damages from local air pollutants. We analyze the trade-off between complementary taxation of carbon emissions and local air pollution. We quantify results for the European power market until 2050. Taxing only air pollution results in system cost of 6,475 billion € and fosters nuclear deployment. Additional external cost accumulate to 5,890 billion €. Taxing only carbon yields system (external) cost of 8,263 (717) billion € and promotes carbon-capture-and-storage deployment. Taxing both yields (external) cost of 7,697 (1,118) billion €. Moderate carbon taxation can be complementary to a primary policy of air pollution abatement. On the contrary, a primary policy of decarbonization stands in trade-off with air pollution abatement in the long-term.[1]

Keywords: Taxation; External cost; Air pollution; Carbon emission; Externality; Energy system model; Power market model; Decarbonization

JEL-Codes: C61; H21; H23; H43; L94

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2.1 Introduction

Climate change calls for prompt reductions of CO_2 emissions to keep global warming (well) below 2° Celsius (Paris Agreement, 2015), but a focus on CO_2 emissions and climate change neglects local effects from related air pollution and associated damages on human health or loss of biodiversity, respectively. We address this issue by showing how accounting for social cost of air pollution (SCAP) as well as social cost of carbon (SSC) influences power system transformations and the external cost (in the sense of damages) from emissions associated with these systems. In particular, we study how the optimal future European technology mix changes in response to different taxation scenarios, exploiting technology-specific emission profiles and technological substitutability. We further analyze possible co-benefits and trade-offs when jointly abating carbon emissions and local air pollution.

With more than 40%, electricity and related heat generation are the biggest contributors of the 36.3 Gt of energy-related CO_2 emissions.[2] Electricity generation and its role for emitting CO_2 significantly increased over the last decades. It is expected to assume an ever bigger share in the future due to electrification trends (digitization, air conditioning, electric mobility, economic development). Thus, many policies focus on decarbonizing electricity generation. For example, the European Union Emission Trading System (EU ETS) reduced – among other supplementary policies – CO_2 emissions from power generation from 1.191 to 0.914 Gt in the period 2013 to 2021.[3] The European Union even proposes more ambitious targets to achieve carbon neutrality by 2045. However, these measures incur costs where they are taken, while their benefits for climate change mitigation are global. The characteristic of CO_2 emissions as public bad (or reducing them as public good) allows for free riding on abatement efforts by others and thus hampers the binding and enforceable implementation of reduction goals and targets.[4]

Air pollution emissions, in turn, have local impacts and every country should therefore have an own incentive to undertake efforts to internalize those local damages by means of appropriate taxation at the respective marginal damages. Thus, shifting the focus away from sole abatement of CO_2 emissions towards the internalization of air pollution might be a complementary policy to partly resolve the free riding problem – as long as co-benefits of air pollution abatement exist for CO_2 abatement. Each electricity generation technology has a unique profile of carbon and air pollution intensity. An optimized electricity system can therefore be expected to respond to different scenarios of external

[2] See https://www.iea.org/reports/global-energy-review-co2-emissions-in-2021-2.

[3] See https://ec.europa.eu/clima/news-your-voice/news/emissions-trading-greenhouse-gas-emissions-73-2021-compared-2020-2022-04-25_en.

[4] The literature developed and analyzed multiple approaches how to mitigate the problem of free-riding (e.g., Barrett, 1994; Nordhaus, 2015) but those approaches have not been globally implemented so far.

cost internalization through its technology mix. Some climate neutral technologies such as biomass with carbon-capture-and-storage (bio-CCS) reflect internalization trade-offs as they bind CO_2 emissions but are still locally air-polluting. This gives way to interesting questions about how to design a least-cost technology mix with both low carbon and low air pollution emissions, while maintaining system adequacy.

We use the SCC as the climate change-related global marginal damage of one quantity unit of carbon emitted as calculated in the DICE model. We use SCAP as the country-specific external costs on human health, loss of biodiversity, regional crops, and materials of a quantity unit of a type of local air pollutant emitted. We internalize SCC and SCAP via taxes and implement this strategy in the EUREGEN model, a multi-region partial equilibrium model of the European power market that optimizes investments, decommissioning, and dispatch of multiple generation, storage, and transmission technologies until 2050 (Weissbart and Blanford, 2019; Weissbart, 2020). We study how different emission policy schemes interplay with technology-specific emission profiles and technical system adequacy in the cost optimization problem. The European electricity market is particularly interesting to study as it is highly integrated, yet we can exploit its heterogeneity in demand, existing technology mix, renewable resource potentials, and country-specific SCAP. With EUREGEN we employ a detail-rich model of this market with sophisticated representation of national demand (profiles), technology stocks and (intermittent) supply profiles, wind and solar potentials, and transmission. This set-up allows us to introduce technology- and country-specific policy cost of electricity generation, thus changing relative competitiveness of generation technologies and countries as locations for capacity expansion. By combining social cost estimates per quantity unit emitted with technology-specific emission factors, we achieve specific generation taxes. The resulting carbon taxes differ by technology, while the air pollutant taxes differ both by country and technology. We calibrate the DICE model (Nordhaus, 2014) to deliver a global SCC that matches population projections from the World Bank[5] as well as GDP projections from EUREGEN's computable general equilibrium (CGE) model calibration (Siala et al., 2022; Mier et al., 2023). We obtain country-specific SCAP for six air pollutants (NH_3, NMVOC, NO_x, PM_{10}, $PM_{2.5}$, SO_2) from the externE project series (Friedrich and Bickel, 2001; Bickel et al., 2005; Pietrapertosa et al., 2009) and couple these with the respective technology-specific emission factors (EPA, 1995; Cai et al., 2012; EEA, 2019; Juhrich and Becker, 2019).

There exists an array of literature on modeling emissions and resulting damages of electricity generation, among which several papers also consider local air pollutants.[6] A number of studies carry out retrospective damage calculations or simulations. In general, these studies provide insights into dam-

[5] See `https://databank.worldbank.org/source/population-estimates-and-projections`.

[6] This paper is a substantial expansion of Mier et al. (2021) but focuses on the complementary taxation of carbon emissions and local air pollutants only. The effect of diverging private and social discount rates is analyzed in Mier and Adelowo (2022).

age magnitudes but unlike our analysis they do not speak to optimal future electricity mixes and damage abatement potentials. For instance, Shindell (2015) extends the SCC framework to incorporate (local) damages from air pollutants. He finds annual external cost of 330 to 970 billion $ for US electricity generation. This picture is enriched by Holland et al. (2020), who use local and global damages from CO_2 emissions and air pollution. Using an integrated assessment model, they find that annual external cost in the US fell from 245 billion $ in 2010 to 133 billion $ in 2017. These studies give reason that damages might also be substantial in Europe and that there may be potential for abatement. Nam et al. (2010) do indeed find fundamental welfare losses (2%) from air pollution for Europe using a computable general equilibrium (CGE) analysis for 18 European countries. This study however does not provide insights into joint abatement, possible trade-offs as well technological insights. This is complemented by a strand of empirical literature retrospectively quantifying emission and pollution impacts from changes in the electricity mix. Millstein et al. (2017) quantify avoided CO_2 and air pollution emissions via substitution effects of renewable energy generation in the US. Jarvis et al. (2022) find extensive external cost from air pollution caused by substitution effects from the nuclear phase-out in Germany. However, these studies do not allow for insights from optimization trade-offs in the medium to long term, which we analyze in our work. Finally, a number of studies use power models to analyze how internalization affects carbon emissions and/or air pollution as well as co-benefits. These studies differ from our work in limited representation of relevant pollutants, damage quantification, or technological detail. For instance, taking a global perspective Klaassen and Riahi (2007) apply MESSAGE-MACRO to internalize air pollution damages but unlike in our analysis they refrain from internalizing climate damages (from CO_2 emissions). They also use SCAP estimates from the externE project series (that are similar but less recent than ours). However, two of our core technologies, bio-CCS and gas-CCS, are not part of their technology set, hence lacking important levers in the technology-emission-mix. Barteczko-Hibbert et al. (2014) integrate life cycle assessment and electricity generation, taking into account climate impacts and a wide set of environmental aspects (ozone layer, acidification etc.). Their results indicate that internalizing climate damages also benefits other environmental aspects. The study however has a significant focus on greenhouse gases and the particular interplay with local damages from air pollution is not analyzed in detail. Furthermore, the analysis is limited to the UK, such that any technological substitution effects are limited and cannot be further encouraged by transmission interconnection. Burtraw et al. (2014) look at the introduction of CO_2 emissions regulation in the US in addition to existing air pollution regulation under different policy scenarios by using a power market model. Their analysis focuses on quantifying (consumer) surplus depending on the policy instrument used. The study however only covers SO_2 and thus lacks other key pollutants. Driscoll et al. (2015) find co-benefits for human health from improvements in air quality following from CO_2 emissions regulation scenarios by using US power market models. However, they do not quantify health benefits in monetary terms and do not take into account external cost beyond human health (as we do). Their scenarios differ by options to reduce CO_2 emissions and only one of their scenarios uses SCC in the sense of carbon taxation. Moreover, Driscoll et al. (2015) only allow for carbon-capture-and-storage (CCS) in coal-fired plants. We allow for this technology as well but identify CCS on the basis of biomass (bio-CCS) and natural gas-fired power plants (gas-CCS) as key technologies to manage the trade-offs between damages from CO_2 emissions and local air pollutants.[7]

Our contribution delivers insights into how the long term technology and emission mix of the European power system varies under different internalization strategies or taxation choices (no taxation, sole air pollutant taxation, sole CO_2 taxation, joint CO_2 and air pollutant taxation), respectively. We test robustness of results by varying assumptions about SCC, SCAP, technological progress of wind power, air pollutant emission factors, electricity demand, inflexibilities of power plants, and technology cost. Sole CO_2 taxation internalizes accumulated external cost of carbon (ECC) of 281 billion € in the 30 years from 2021 to 2050. Accumulated external cost of air pollution (ECAP) of 435 billion € are not internalized (joint sum of 717 billion €). The relation of ECC and ECAP turns around when looking at net present values (194 billion € ECC vs. 92 billion € ECAP) because CO_2 emissions are initially high and eventually become even negative in the long-run, while being accompanied by considerably higher air pollution. Those late air pollutant emission damages, however, are heavily discounted so that the net present values are below the ones from CO_2 emissions. When only taxing air pollution, 5,547 (1,340) billion € of (net present value) ECC remain uninternalized and ECAP are reduced to 343 (92) billion €. Our results show that sole CO_2 taxation yields tremendously lower external cost compared to taxing solely air pollution, underlining that the abatement of carbon emissions should dominate the policy making.

Jointly abating the two yields accumulated ECC (ECAP) of 923 (195) billion €. In net present value terms, we obtain cost of 307 (53) billion €, respectively. Thus, the efficient combination of CO_2 emissions and air pollution yields higher ECC but lower ECAP; adding air pollution taxation to existing carbon taxation thus inherits a trade-off with abating damages from CO_2, whereas adding carbon taxation to existing air pollution taxation comes with a substantial co-benefit. Moreover, system cost from generating electricity (not considering any external cost) are structurally lower when taxing carbon and air pollutants jointly (7,697 billion €) compared to sole CO_2 taxation (8,263 billion €). In fact, deep decarbonization and even negative CO_2 emissions from electricity generation (using bio-CCS) come at extraordinary system cost. Thus, the benefit of adding air pollution taxation does not lie in abating the occurrence of external cost but allowing less costly electricity generation technologies due to balanced abatement.

[7] In fact, coal-CCS is absent in our optimized equilibrium because capture rates are worse and cost are considerably higher than for gas-CCS.

We further determine trade-offs and co-benefits of taxation choices when iteratively adding increasing tax levels for one emission type (e.g., air pollution) to a full Pigouvian tax for the other emission type (e.g., CO_2). In particular, adding air pollution taxation to existing carbon taxation always comes with a trade-off because accumulated ECC increase substantially. Adding CO_2 taxation to already existing air pollution taxation in turn comes with some co-benefits as long as the carbon tax level is not above the efficient one, i.e., the Pigouvian tax level. Increasing the carbon tax above the efficient level in turn increases air pollution and related damages. Such non-linear effects stem from the substantial differences in emission profiles of electricity generation technologies. In particular, high CO_2 taxes lead to a technology switch from gas-CCS to bio-CCS, whereas low or no air pollution taxes substitute nuclear by bio-CCS. High air pollution taxes in turn reverse this shift away from nuclear at the cost of CCS technologies. Finally, low CO_2 taxes foster the usage of conventional gas technologies. Policy makers can use those findings to shape policies according to their preferential policy goals. When the main goal is to primarily reduce CO_2 emissions and related ECC, additional air pollution taxation creates abatement trade-offs. When the primary goal is to reduce air pollution and associated ECAP, moderate additional carbon taxation can further contribute to this.

Section 2.2 introduces the modeling strategy. Section 2.3 presents the calibration by focusing on emissions and external cost. Section 2.4 presents results. Section 2.5 discusses, summarizes, and extends most important results from the previous section. Section 2.6 tests for robustness of (extended) results. Section 2.7 concludes.

2.2 Modeling strategy

Notation Suppose there are generation technologies i, storage technologies j, and transmission technologies k. r indicates regions and rr is an alias of r. We use subscripts i, j, k, r, rr for technologies as well as regions and parentheses (h, v, t) for time indices – h is the hour, v the year of installation (vintage), and t the current year (period) – to denote parameters (small letters) and variables (capital letters).

$IQ\left(v\right)$ are investments from vintage v that translate into currently (in period t) active capacities $Q\left(v,t\right)$ (both in GW). Capacity investments are costly, $c^{IQ} > 0$ (in €/GW), as it is holding capacity, $c^{Q} > 0$ (in €/GW and year), so that endogenous decommissioning might be optimal, i.e., $Q\left(v,t\right) \leq IQ\left(v\right)$. For storage technologies, charge and discharge capacity (e.g., pumps and turbines) are assumed to be the same. We assume that cost of holding capacity apply only for joint charge and discharge capacity but not for the storage size. For transmission technologies, we refer to net transfer capacities (NTC) and distinguish between export and import lines to reflect current political situation of constraining capacities in one of the respective directions.

Y_i is generation, Y_j^+ is storage charge, Y_j^- is storage discharge, and $Y_{k,r,rr}$ is the bilateral trade flow from region r to rr (all in GWh). Generation is costly, $c_i^Y(v,t) > 0$ (in €/GWh), but we assume no further variable cost for storage operations and transmission (only losses for charge, discharge, hourly discharge, and for transmission). $\eta \in (0,1]$ denotes efficiencies. In particular, η_i is the burning efficiency of generation technologies. Finally, the overall target is to meet electricity demand d but it could to optimal to allow for lost load L (both in GWh) at cost $c^L > 0$ (in €/GWh).

Objective The standard objective is to minimize the net present value of overall system cost ($\delta(t)$ is the discount factor) from investments (**IQ** is the vector of investment decisions for all generation, storage, transmission technologies), holding capacity (**Q** the vector of capacity decisions), and dispatch (**Y** is the vector of dispatch decisions) over all regions and time periods:

$$
\begin{aligned}
\min_{\mathbf{IQ},\mathbf{Q},\mathbf{Y}} \sum_{t,r} \delta(t) \Bigg[& c_r^L(t) \sum_h L_r(h,t) + \\
& \sum_i \left(\sum_{v=t} c_{ir}^{IQ}(v)\, IQ_{ir}(v)\, \Gamma_i(v,t) + \sum_{v\leq t} c_{ir}^{Q}(v,t)\, Q_{ir}(v,t) + \sum_{v\leq t} c_{ir}^{Y}(v,t) \sum_h Y_{ir}(h,v,t) \right) + \\
& \sum_j \left(\sum_{v=t} c_{jr}^{IQ}(v)\, IQ_{jr}(v)\, \Gamma_j(v,t) + \sum_{v\leq t} c_{jr}^{Q}(v,t)\, Q_{jr}(v,t) \right) + \\
& \sum_{k,rr} \left(\sum_{v=t} c_{k,r,rr}^{IQ}(v)\, IQ_{k,r,rr}(v)\, \Gamma_k(v,t) + \sum_{v\leq t} c_{k,r,rr}^{Q}(v,t)\, Q_{k,r,rr}(v,t) \right) \Bigg],
\end{aligned} \tag{2.1}
$$

where $\Gamma(v,t)$ is the fraction of investment cost that should be considered within the planning horizon (from t until t^{end}). In particular, $\Gamma(v,t) = 1$ when the depreciation time of an investment is completely within the planning horizon and $\Gamma(v,t) < 1$ when the depreciation time of an investment spans above the planning horizon (depreciates longer than t^{end}). This endeffect is calculated on the basis of private discount rates and the time exceeding the planning horizon.

The first line of (2.1) after the square bracket reflects cost of lost load: $c_r^L(t)$ is the respective value of lost load, and $\sum_h L_r(h,t)$ is total lost load in region r in period t. The second line reflects cost of generation technologies i: c_{ir}^{IQ} are unit investment cost (e.g., in €/MW) with $IQ_{ir}(v)$ being capacity addings (e.g., in MW), $c_{ir}^{Q}(v,t)$ are fixed cost in period t from capacity installed in period v (e.g., in €/MW*a) with $Q_{ir}(v,t)$ being installed capacity from vintage v (e.g., in MW). Finally, $c_{ir}^{Y}(v,t)$ are dispatch cost in period t from capacity installed in period v (e.g., in €/MWh) with $Y_{ir}(h,v,t)$ being generation from capacity $Q_{ir}(v,t)$ (e.g., in MWh). The third line reflects cost of storage technologies j:

$c^{IQ}_{jr}(v)$ are per unit investment cost (e.g., in €/MW including reservoir size in MWh as a fixed relation to MW) with storage capacity addings $IQ_{jr}(v)$. There are no dispatch cost of storage in the objective function because the cost of electricity provision is already included in the generation cost; storage losses are part of the storage balance and demand-equals-supply constraints. However, there are fixed cost c^{Q}_{jr} (e.g., in €/MW*a) of storage capacity $Q_{jr}(v,t)$ (e.g., in MW). The fourth line reflects cost of transmission technologies k: r, rr describes transmission between region r and rr. $c^{IQ}_{k,r,rr}(v)$ are per unit investment cost (e.g., in €/MW) with $IQ_{k,r,rr}(v)$ being transmission capacity addings (e.g., in MW). Again, there are no variable cost of transmission but rather transmission losses of costly generated electricity. However, $c^{Q}_{k,r,rr}(v,t)$ are fixed cost (e.g., in €/MW*a) of transmission capacity $Q_{k,r,rr}(v,t)$ (e.g, in MW). All transmission cost are specific to the respective region pair r, rr, that is, the distances between two regions' centroids represent necessary line lengths and drive cost.

Internalization of external cost We suppose that a social planner internalizes external cost from carbon emissions and air pollution by setting tax rates according to the respective marginal damages. We can thus directly include those marginal damages – SCC and SCAP – into our objective function via generation cost. Denote by $scc\,(t)$ the SCC and by $scap_{r,ap}\,(t)$ the SCAP (both in €/ton) with ap being different air pollutants. SCC and SCAP change over time. Moreover, SCAP are region-specific, whereas SCC refer to a global value. Carbon emission factors $\xi^{car}\,(v)$, air pollution emission factors $\xi^{air}_{i,ap}\,(v)$ (both in ton/GWh thermal), and power plant efficiencies $\eta_i\,(v)$ depend on the vintage, that is, older vintages have lower efficiencies and higher emission factors leading to higher emissions. In particular, $\sum_{v\le t}\sum_h \frac{1}{\eta_i(v)} Y_{ir}\,(h,v,t)$ is total fuel used per technology in period t (in GWh thermal) with $p_{ir}\,(t)$ beeing the time-varying fuel price in region r for technology i. Multiplying this total fuel used with the respective emission factors yields CO_2 emissions and local air pollution (in ton). We can now derive the generation cost as

$$c^{Y}_{ir}\,(v,t) \quad = \quad c^{var}_{ir}\,(v) + \left[p_{ir}\,(t) + scc\,(t)\,\xi^{car}_{i}\,(v) + \sum_{ap} scap_{r,ap}\,(t)\,\xi^{air}_{i,ap}\,(v)\right] \sum_{v\le t}\sum_{h} \frac{1}{\eta_i\,(v)} \tag{2.2}$$

Variable cost c^{var} are independent of efficiencies. Cost from fuel, damages from CO_2, and damages from air pollution, in turn, depend on those efficiencies, while the latter two are also subject to their respective emission factors.

Optimization constraints The minimization problem is subject to multiple constraints that we abstain from showing here but Appendix B.1 contains the full set of demand, generation, storage, and transmission constraints of the optimization problem.

2.3 Calibration

2.3.1 Setup

We *quantify* the trade-offs and potential benefits of internalizing external cost of CO_2 and air pollutant emissions with EUREGEN (Weissbart and Blanford, 2019; Weissbart, 2020). EUREGEN is a multi-region partial equilibrium model of the European power market that intertemporally (i.e., assumes perfect foresight) minimizes either private or social cost from 2015 (base year) to 2050 (end year).[8] We work with an adjusted 2015 calibration to account for real-world developments until 2020. In particular, we assume that taxation choices in periods 2015 and 2020 reflect real-world policies, i.e., until 2020 CO_2 prices follow from the EU ETS and there is no air pollution tax in place.[9] From 2021 onwards, we change policies to either not taxing at all, taxing only air pollution, taxing only CO_2 emissions, or taxing both. In our base specification the taxes are Pigouvian taxes at the level of SCC or SCAP, respectively.

The CGE model PACE delivers annual electricity demand and major fuel prices (oil, coal, and natural gas).[10] CO_2 emissions follow from emission factors and EUREGEN applies either a carbon price or a quantity target (e.g., Weissbart, 2020; Mier and Weissbart, 2020; Azarova and Mier, 2021). We extend the EUREGEN model by emission factors for different air pollutants (Section 2.3.3). We refrain from using carbon prices resulting from the CGE calibration or quantity targets as imposed for instance by the EU ETS and instead apply optimal carbon or air pollution taxes that follow from SCAP (Section 2.3.4) and SCC (Section 2.3.5) from 2021 onwards.[11]

EUREGEN can switch between implementations of different discount and interest rates, investor types, and spatial resolutions (Mier and Azarova, 2021). We opt for a discount rate of 7%.[12] Furthermore, we apply the *normal* investor that carries cost of investments within the period of investment and uses endeffects if the investment's depreciation extends beyond the model horizon (and thus neglects the role of different interest rates). Moreover, we apply the maximum spatial resolution of 28 countries (EU27 less the island states of Cyprus and Malta, including Norway, Switzerland,

[8] Private cost comprise of the sum of overall system cost (from investments, holding and decommissioning of capacity, and dispatch of multiple generation, storage, and transmission technologies) and taxes. Social cost comprise of the sum of overall system cost and external cost (ECC plus ECAP).

[9] Except for 2015, all periods reflects 5 years, i.e., 2020 considers the years 2016 to 2020, ..., and 2050 the year 2046 to 2050.

[10] Appendix B.2.1 contains detailed values. Mier et al. (2023) describes the origin of the calibration in detail and how the CGE model PACE is used to quantify input parameters under different qualitative scenarios for further usage in power market models. Note that electricity demand and major fuel prices are exogenous input parameters power market models. This means that the CGE model and the respective power market model are not in the same equilibrium with respect to demand for fossil fuels, which would require feeding this fossil fuel demand from the power market model back into the CGE model. See Siala et al. (2022) for an application of the very same calibration.

[11] Optimality refers to full internalization of the external cost (i.e, the Pigouvian tax level).

[12] This is in line for example with Zwick and Mahon (2017); Newell and Pizer (2004).

and United Kingdom) and an hour choice algorithm to reduce the temporal resolution of the year for numerical feasibility.[13]

2.3.2 Considered technologies

Our generation technologies burn either biomass, coal, lignite, natural gas, and uranium or use wind, solar, geothermal, and hydro power to generate electricity. We further consider steam turbines, gas turbines, combined-cycle gas turbines, and engines. In particular, we consider steam turbines "burning" biomass (*bioenergy*), steam turbines "burning" biomass with carbon-capture and storage (*bio-CCS*), steam turbines "burning" *coal*, *coal-CCS*, steam turbines "burning" *lignite*, and steam turbines "burning "natural gas (*gas-ST*).[14] We further consider open-cycle gas turbines burning natural gas (*gas-OCGT*), combined-cycle gas turbines burning natural gas (*gas-CCGT*), the same with carbon-capture and storage (*gas-CCS*), and gas turbines or engines, respectively, using oil and other non-biomass non-natural gas fuels (*oil*). We restrict the annual level of burnable biomass to 2,045 thermal TWh (half of the total available sustainable biomass potential) but have no further limits for other fuels. Moreover, we do not account for combined-heat-and-power (CHP) plants due to the considerable transformation in the heating sector that is driven by decarbonization efforts and demands for not burning fossil fuels anymore. Such transformations make most existing CHP plants obsolete. Moreover, heating electrification is considered by the CGE calibration.

We further consider steam turbines using uranium (*nuclear*) and *geothermal* power plants. Out of the group of intermittent technologies, we model run-in-the-river power plants (*hydro*), *wind onshore*, *wind offshore*, and *solar PV* by means of hourly-varying availability. Regarding wind onshore and wind offshore we assume that the existing fleet has hub heights of 80m, while we consider hub heights of 100m for future vintages. Hydro cannot be expanded beyond the existing level. Nuclear, lignite, and coal expansion is restricted to countries that already use those technologies. Wind and solar expansion is constrained by resource potential quality classes (high, mid, and low). Appendix B.2.2 summarizes efficiencies, emission factors, and investment cost of those technologies. We further model three storage technologies (pump hydro, batteries, and power-to-gas), where expansion of pump hydro is again restricted to existing capacities. Transmission technologies are represented by AC lines as well as DC cables.[15]

[13] The hour choice algorithm selects and weights hours that present the extremes of load, wind onshore, wind offshore, solar, and hydro generation. We obtain 280 hours and finally scale timeseries to match annual demand and full-load hours of all intermittent technologies.

[14] In fact, steam turbines only use the steam generated from burning the respective fuel and do not burn it directly.

[15] DC cables mainly apply to connect countries that are divided by water.

2.3.3 Emissions from electricity generation

CO_2 emissions are the major source of pollution from electricity generation. We additionally focus on ammonia NH_3, non-methane volatile organic compounds NMVOC, nitrogen oxides NO_x, particulate matter PM_{10} as well as the finer $PM_{2.5}$, and sulfur dioxide SO_2 (or SO_x expressed in SO_2 equivalents). Due to the existing wide-spread application of air pollution abatement technologies, we abstain from using raw air pollution emission factors that do not assume any type of emission control.[16] Instead, we aim for fleet average emission factors for existing plant vintages, which are calculated via annual statistics of actual total emissions *after* abatement and total fuel consumption. The literature provides lower and upper bounds as well as medium range emission factors (EPA, 1995; Cai et al., 2012; EEA, 2019; Juhrich and Becker, 2019).

Table 2.1: 2020 emission factors (in ton/GWh electric)

	NO_x	SO_2	$PM_{2.5}$	PM_{10}	NH_3	NMVOC	All AP	CO_2
Bio-CCS	1.719	0.243	0.629	0.716	0.086	0.164	3.557	-855
Bioenergy	1.376	0.194	0.503	0.573	0.023	0.132	2.801	
Gas-CCGT, Gas-ST		0.001	0.005	0.005		0.001	0.201	341
Gas-CCS		0.001	0.007	0.007		0.002	0.253	41
Gas-OCGT		0.001	0.008	0.008		0.002	0.287	484
Coal	0.582	0.509	0.027	0.062	0.002	0.008	1.190	763
Coal-CCS	0.728	0.509	0.034	0.077	0.009	0.010	1.367	91
Lignite	0.545	0.686	0.024	0.059	0.002	0.011	1.327	838
Oil		0.825	0.225	0.294		0.027	2.031	910

Appendix B.2.3 contains the full set of emission intensities (in g/GJ). We combine those with technology- and vintage-specific plant efficiencies (Table B.3 in Appendix B.2.2) to arrive at a sophisticated representation of actual emission factors (in ton/GWh electric). For CCS technologies, we further consider increased NH_3 emissions occurring during the capture process (Heo et al., 2015) and reflect overall slightly increased emissions for NO_x, NMVOC, and PM due to increased fuel consumption via decreased efficiencies of CCS plants compared to their non-CCS counterparts.

We choose medium emission factors for existing vintages, reflecting commonly used emission control technology. Where applicable, we include linear improvements in average abatement efficiency for future vintages, so that 2050 vintages across all regions achieve abatement efficiencies of today's most modern plants. Table 2.1 summarizes emission factors of different technologies for 2020 vintages. Observe that CO_2 emission factors are by far the highest. Among the air pollutants NO_x, PM_{10}, and $PM_{2.5}$ are most emitted. Gas technologies do not emit relevant amounts of NH_3, and sulfur-content of natural gas is almost negligible. In general, technologies burning natural gas are the cleanest, whereas biomass technologies are the most emission intensive.[17]

[16] Emission control technologies include, e.g., low NO_x burner technologies, selective and non-selective catalytic reduction, electrostatic precipitation, fabric filters, and flue gas desulfurization processes (so-called scrubber systems). See EEA (2019) for an overview of the occurrence and abatement of the respective pollutants.

[17] Biomass emission factors are quite dispersed in range. This reflects the availability of different abatement techniques

2.3.4 Social cost of air pollution

Air pollution leads to higher mortality, discomfort, and productivity loss (e.g., Markandya and Wilkinson, 2007; Dedoussi and Barrett, 2014; Dedoussi et al., 2020). Value of life concepts (e.g., Viscusi and Aldy, 2003) such as disability adjusted life years (e.g., Murray, 1994; Anand and Hanson, 1997; Murray et al., 2012) monetize those damages. The externE project series calculates those damages by employing life cycle assessment (e.g., Klöpffer, 1997), the impact pathway approach (e.g., Douthwaite et al., 2003), diffusion patterns of air pollutants, as well as meteorological, geological, demographic, and health data.

We apply results from the NEEDS project (e.g., Bickel et al., 2005; Pietrapertosa et al., 2009), which is part of the externE project series (e.g., Friedrich and Bickel, 2001; Söderholm and Sundqvist, 2003), that provides SCAP (in current 2000-€) for six air pollutants (NH_3, NMVOC, NO_x, PM_{10}, $PM_{2.5}$, SO_2) for five categories of external costs (human health, loss of biodiversity, regional crops, materials, and international damages) at the national level in the 28 countries under investigation, taking into account e.g. differences in population density.[18] We take the estimates for high release heights (as suggested in the user manual for electricity generation) that are calculated for meteorological conditions of 2010. NEEDS authors suggest increasing the SCAP by a rate according to GDP growth. GDP of the 28 countries under consideration grew by 25.84% between 2000 and 2015. We apply the same increase to translate the values from current 2000-€ to current 2015-€.[19] Growth rates for 2020 onwards are based on country-level projections from our CGE calibration.[20]

Table 2.2 shows average SCAP (in current €/ton), weighted by 2020 country annual electricity demand, for the six air pollutants and the damage categories. The category *International* accumulates the impact of those air pollutants outside of the 28 countries under consideration and is uppermost relevant for NMVOC (33% of NMVOC damages). Observe that (regional) human health impacts dominate with shares of 57% (for NMVOC) to almost 100% (for PM_{10}). Moreover, NH_3 and $PM_{2.5}$ are the most damaging air pollutants, followed by NO_x and SO_2.[21]

Keep in mind that the damage estimates increase with GDP growth. Moreover, those estimates are highly heterogeneous across countries. For example, NO_x damage is highest in Switzerland (20,071

in combination with the variation in emission intensity from using heterogeneous fuels or fuel compositions (wood, crops and agricultural residues, waste).

[18] See `https://cordis.europa.eu/project/id/502687/de` for details. The project page, https://needs-project.org, is no longer available. Data and further documents can be now accessed via the project page of the University of Stuttgart, `https://www.ier.uni-stuttgart.de/forschung/modelle/ecosense/`.

[19] We increase SCAP by 1.2584 to reflect GDP growth and then divide again by 1.3334. In fact, 2000-€ SCAP have the same absolute value as do 2015-€ SCAP.

[20] See Table B.7 in Appendix B.2.4 for GDP projections.

[21] The SCAP values grow with GDP per capita (per country) so that 2050 values would be around 60% higher than 2020 values.

Table 2.2: 2020 SCAP (€/ton) by impact category and air pollutant

	NO_x	SO_2	$PM_{2.5}$	PM_{10}	NH_3	NMVOC
Human health	8,516	10,490	24,538	1,081	17,561	1,100
Loss of biodiversity	1,672	612			6,197	-136
Regional crops	382	-118			-302	337
Materials	124	463				
International	234	498	282	4	5	640
Total global cost	10,928	11,945	24,820	1,084	23,461	1,940

The presented values follow from weighting country-specific values with 2020 country-specific annual demand. The depicted values are measured in current €. Country level data is available in Appendix B.2.5. The international damage is the same for each country and we thus refrain from presenting it in Appendix B.2.5.

€/ton) but very low in Finland (1,905) and Portugal (916). The estimates refer to current meteorological and air pollution conditions that might change in the future. In particular, pollution levels might change regionally, which might impact the marginal damage. However, for a country's damage estimates the total level of air pollution is less relevant than population density, quality of the health system, and meteorological conditions. For parsimony, we thus assume that SCAP levels remain independent of the realized pollution mix, that is, the marginal damages from air pollution are assumed to be constant.[22]

2.3.5 Social cost of carbon

We apply a slightly adjusted version of DICE-2016R-091216a to calculate SCC (in current €/ton).[23] DICE maximizes the net present value of utility (from consumption) and thus the SCC is calculated according to the fraction of the marginal of the emission equation (in utility units per ton) and the consumption equation (in utility units per $). Utility units are in present values, so that the division of present value utility (per ton) by present value utility (per $) leaves SCC in current $/ton. We can thus use the calculated SCC directly again in another discounting framework that uses current values to minimize the net present value of cost via discounting. Table 2.3 presents calibration (GDP, population) and selected output (SCC, CO_2 emissions, and temperature increase). We calculate SCC of 206 $/ton in 2050.

[22] The authors are not aware of any literature providing credible evidence to assume otherwise.

[23] We transform the 2015 world GDP of 105.5 trillion 2010-US$ to 86.1 trillion 2015–US$ and total factor productivity by 0.8254 to obtain real-world 2020 CO_2 emission of 39.6 Gt. Moreover, we adjust population growth and total factor productivity from 2020 to 2050 to obtain population projections from the World Bank and GDP projections from the CGE model used to calibrate EUREGEN (see DICE calibration in Table 2.3). We further reduce the DICE default pure rate of time preference from 1.5% to 0.04% (Drupp et al., 2018). Original GAMS code is available at `http://www.econ.yale.edu/~nordhaus/homepage/homepage/DICE2016R-091916ap.gms`. The adjusted version is available upon request from the corresponding author.

Table 2.3: DICE calibration and output

		2020	2030	2040	2050
Calibration	Gross world GDP (trillion 2015-$)	101	134	175	224
	World population (billion)	7.75	8.50	9.14	9.68
Output	SCC ($/ton)	94	123	160	206
	CO_2 emissions (Gt)	39.60	31.03	29.05	25.26
	Atmosphere temperature increase (°C)	1.02	1.36	1.68	1.99
Conversion in €	SCC (€/ton)	86	112	145	187

We apply an exchange rate of 1.1 to convert US-$ into €, i.e., 1 € is worth 1.1 US-$ in 2015.

Keep in mind that we assume SCAP levels not to change with local air pollution levels (see Section 2.3.4). For carbon emissions, on the contrary, there is evidence that the marginal damage changes considerably with the realized emission level. Observe that in the DICE output global CO_2 emissions drop from 39.6 in 2020 to 25.26 Gt in 2050 in response to an optimal carbon policy. The associated temperature increase is 1.99°C in 2050.[24] Such an optimal policy seems quite consistent with European decarbonization goals that eventually fully decarbonize European electricity generation. If, under less stringent policy, European electricity generation were not fully decarbonized or experienced increasing emissions even, then global carbon emissions would increase directly (by European electricity generation emissions) and indirectly (because other sectors and regions would likely experience a similar emissions trend). In response, the SCC would rise considerably. However, such a scenario is inconsistent with current policy targets. For parsimony, we therefore refrain from using multiple DICE calibrations to calculate SCC for other emission trajectories that accommodate increasing electricity emissions in Europe, that is, we assume that the marginal damages from CO_2 are constant.

2.3.6 Comparison of carbon and air pollution taxes

Setting carbon or air pollutant taxes equal to their respective marginal damages (SCC and SCAP) and calculating the respective tax rate per technology by employing efficiencies and emission factors yields results in Table 2.4. The first block shows carbon taxes and the second one shows air pollution taxes for each of the relevant technologies. We present taxes for 2025, 2030, 2040, and 2050. Remember that carbon and air pollution taxes in 2015 and 2020 are assumed to reflect real-world conditions with carbon taxes of 7.75 €/ton (in 2015) and 15 €/ton (in 2020), while there is no air pollution tax in place. Periods 2035 and 2045 are not shown for the sake of parsimony. The chosen unit (€/MWh electric) makes tax rates directly comparable across technologies and between carbon and air pollution taxes.

[24] The maximum temperature increase is in fact 3.36°C.

Table 2.4: Technology-specific carbon and air pollution taxes (in €/MWh electric)

	Carbon tax				Air pollution tax			
	2025	2030	2040	2050	2025	2030	2040	2050
Bioenergy					31.92	32.53	34.08	36.52
Bio-CCS	-80.13	-89.66	-112.09	-139.34	41.32	42.16	44.24	47.49
Gas-CCGT, Gas-ST	32.30	36.29	47.19	60.94	2.33	2.41	2.69	3.06
Gas-CCS	4.01	4.58	5.95	7.68	2.92	3.02	3.37	3.84
Gas-OCGT	44.30	49.53	63.02	81.38	3.20	3.29	3.59	4.09
Coal	69.68	77.71	101.06	130.49	12.61	12.55	13.11	13.78
Coal-CCS	8.93	10.20	13.26	17.12	14.53	14.48	15.20	16.09
Lignite*	81.88	93.50	121.59	157.01	16.43	17.51	20.11	23.47
Oil*	88.89	101.50	131.99	170.44	25.44	27.09	31.01	36.18

Values refer to state-of-the-art capacities from the respective vintage. *Lignite and oil values refer to 2015 vintages in the respective period because we do not observe any lignite and oil expansion in our results.

Remember that bioenergy is carbon-neutral and thus not subject to carbon taxes. Bio-CCS delivers negative carbon emissions so that the carbon tax is negative, i.e., a subsidy that grows from 80.13 to 139.34 €/ton from 2025 to 2050. The air pollution tax in turn is positive but grows only slightly from 41.32 to 47.49 €/ton due to two reasons. First, the SCAP grow with GDP by 60% from 2015 to 2050, while SCC more than double. Second, technological improvements with regard to efficiencies and emission factors reduce the underlying damage and thus have dampening effects on the optimal air pollution tax. However, air pollution taxes cannot fully cover the benefits from the carbon subsidy for bio-CCS, which is highly negative (and even higher than the average electricity price, around 70 €/MWh). Among the other technologies, coal, lignite, and oil have by far the highest carbon tax and also air pollution tax rates are high. Gas, in turn, has considerably lower carbon tax rates and air pollution rates are even lowest among technologies, making gas technologies a viable option in the optimized technology mix. However, gas-CCS combines the best of the two worlds with quite low carbon taxes and only marginally higher air pollution taxes than the corresponding comparable conventional gas technology. Coal-CCS in turn seems to be by far less competitive than gas-CCS due to considerably higher air pollution taxes.

2.4 Results

We now analyze the generation and emission mix when a social planner decides for no taxation, only taxing either air pollution or CO_2, and jointly taxing air pollution and CO_2 (Section 2.4.1). We test sensitivities of our results with regard to SCC and SCAP (Section 2.4.2). Finally, we summarize technology substitution patterns for those diverging tax choices as well as SCC and SCAP levels (Section 2.4.3).

2.4.1 Taxation choice

Figure 2.1 visualizes taxation choice results. The stacked bars in the upper panel depict annual generation by technology (in TWh). The stacked bars in the lower panel show annual emissions by air pollutant (in Mt) and the gray diamonds depict annual CO_2 emissions (in Gt). 2015 serves as calibration year. Different model specifications are grouped for periods 2025, 2030, 2040, and 2050.[25] Assuming no air pollution taxes and CO_2 prices of 7.75 €/ton (2015 EU ETS average) in our *calibration year* 2015, the technology mix is dominated by nuclear (836 TWh, 25.8%), conventional gas (720 TWh, 22.2%), and coal (538 TWh, 16.6%). Hydro (418 TWh, 12.9%), wind (306 TWh, 9.4%), lignite (245 TWh, 7.6%), and solar (109 TWh, 3.4%) contribute relevant shares (above 2%). CO_2 emissions are at 1.06 Gt and air pollution at 1.54 Mt, stemming mainly from NO_x and SO_2. PM and NMVOC are the remaining air pollutants and NH_3 amounts are negligible due to the absence of CCS technologies.

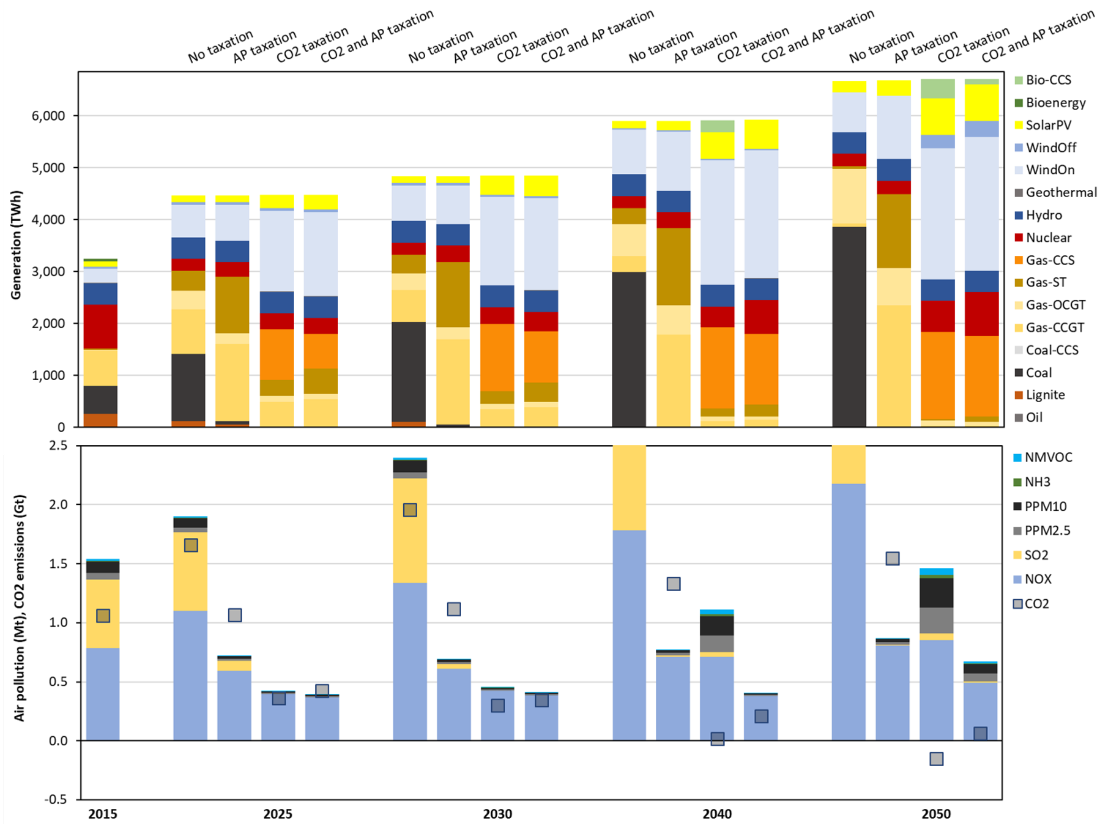
From 2025 onwards, taxation choices across specifications differ. *No taxation* (first column of each grouping) encourages the short-run deployment of conventional gas technologies (from 720 TWh in 2015 to 1,225 TWh in 2025 to 1,171 TWh in 2050) at the cost of nuclear (from 836 TWh to 351 TWh to 235 TWh), and promotes massive deployment of coal in the short-run as well as long-run (from 538 to 1,286 to 3,862 TWh, generation shares of 16.6%, 28.8%, and 57.9%). However, also wind generation more than doubles from 306 TWh (2015, 9.4%) to 763 TWh (2050, 11.4%). Solar PV shares remain constant (3.4%, generation increases from 109 to 227 TWh). CO_2 emissions increase already in 2025 to 1.66 Gt and continue to grow to 3.21 Gt in 2050. Also related air pollution increases from 1.9 Mt in 2025 to 3.81 Mt in 2050.[26] The composition of the air pollution mix does not change much over time, NO_x and SO_2 emissions from burning coal thus remain the dominant air pollutants.

The generation mix completely changes when imposing *AP taxation* (second column). Coal is almost absent already in 2025 (small shares remain active until 2045). In turn, conventional gas technologies start dominating in 2025 with a generation share of 62.2% (22.2% in 2015) that increases to 67.2% in 2050. Nuclear generation drops from 2015 to 2025 (285 TWh) as well but then remains almost constant until 2050 (261 TWh). Wind generation quadruples and solar generation triples from 2015 to 2050. However, the 2050 generation shares of wind and solar are still low at 18.3% and 4.4%. The reliance on technologies burning natural gas is reflected in the air pollution mix. Total air pollutant emissions drop to 0.72 Mt in 2025 already, whereas CO_2 emissions see almost no change. Also the air pollution composition changes away from high SO_2 and substantial PM emissions to a completely

[25] EUREGEN optimizes in five-year steps. For parsimony, we refrain from presenting 2020, 2035, and 2045 outcomes.

[26] Observe that the bars and squares for no taxation leave the scale of the lower panel in 2040 already.

Figure 2.1: Generation (upper panel) and emission (lower panel) mix for different taxation choices



NO_x dominated system (82.22%). After 2025, both CO_2 and air pollutant emissions then slightly increase, but the increase of CO_2 is more pronounced (to 1.55 Gt in 2050). The composition further changes so that SO_2 is almost absent and NO_x is more or less the only (air) pollution source (93.15%).

The substitution of coal by conventional gas technologies is the dominant change when adding air pollution taxation to a policy regime of no taxation. Adding instead only *CO_2 taxation* (third column) or exchanging air pollution by CO_2 taxes, respectively, yields a substantially more diverse substitution pattern. There is no one single dominating technology anymore. Instead, gas-CCS (21.8%) and wind (35.9%) overtake the major generation part in 2025. This dynamic even intensifies over time. Gas-CCS generation grows to 1,674 TWh (share of 25%) and wind generation to 2,775 TWh (41.4%) in 2050. Additionally, nuclear generation rises from 302 TWh in 2025 to 604 TWh in 2050 (shares of 6.8% or 9%, respectively). Conventional gas contribution is only 2.4%. Solar PV (714 TWh, 10.7% in 2050) and bio-CCS (362 TWh, 5.4%) are the remaining relevant technologies. Turning to the emission mix, observe that CO_2 and air pollution emissions immediately drop to 0.36 Gt or 0.42

Mt, respectively, in 2025. The air pollution level remains low until bio-CCS is introduced to the technology mix in 2040. We can now observe substantial amounts of SO_2, PM, NMVOC, and also NH_3, all stemming mainly from burning biomass. The CO_2 in turn is captured, so that the European power system is carbon neutral already in 2040. The spread in the development between air pollutant and CO_2 emissions grows with bio-CCS usage until 2050, so that final air pollution is at 1.46 Mt, whereas CO_2 emissions are at -0.15 Gt.

The joint taxation of CO_2 and air pollution (*CO_2 and AP taxation*, fourth column) shows similar patterns as sole CO_2 taxation in 2025 and 2030. The gas-CCS share is slightly lower, while conventional gas and wind generation is slightly higher. Those small differences yield slightly higher CO_2 and slightly lower air pollutant emissions. However, the composition of air pollutants remains the same. Major differences start in 2040 again, when sole CO_2 taxation starts deploying bio-CCS, while additional air pollution taxation discourages bio-CCS in the optimized system. However, the CO_2 price increases further from 145 to 187 €/ton until 2050, making small amounts of bio-CCS (103 TWh, 1.5%) competitive in the generation mix. CO_2 emissions drop from 0.18 to 0.06 Gt, whereas air pollution increases from 0.44 to 0.67 Mt. Air pollution composition is comparable to sole taxation of CO_2. The lower bio-CCS and gas-CCS generation is substituted by substantially higher nuclear generation (12.6% compared to 9% in 2050) and more wind deployment (42.9% vs. 41.4%).

Different taxation choices for CO_2 and air pollutants impose vastly different optimal technology and emission mixes. The taxation of air pollutants fosters conventional gas technologies. Those technologies burn natural gas, which comes at substantially lower SO_2 and PM emissions. Carbon taxation in turn encourages the deployment of intermittent renewable energies such as wind and solar and, additionally, the deployment of CCS technologies that capture carbon and permanently store it. As a result, gas-CCS is almost carbon-neutral and bio-CCS is even carbon-negative. There is little need for nuclear when only taxing CO_2 because other emission types do not matter. Adding air pollution taxation to already existing CO_2 taxation in turn incentivizes nuclear deployment because the dispatchable carbon-neutral (gas-CCS) or carbon-negative (bio-CCS) technologies still come with substantial air pollution (and at the related cost). However, also wind power is fostered by air pollution taxation.

2.4.2 Uncertainty of SCAP and SCC

Despite careful calibration, some uncertainty remains regarding SCAP and SCC. We address this uncertainty by additionally modifying SCAP and SCC levels to 25%, 50%, 200%, 400%, and 800% of the default level. We use the joint taxation specification *CO_2 and AP taxation* as a benchmark for this task, where we modify either SCAP (Figure B.2) or SCC (Figure B.1) to alternative levels, while the other one stays at the 100% default level.

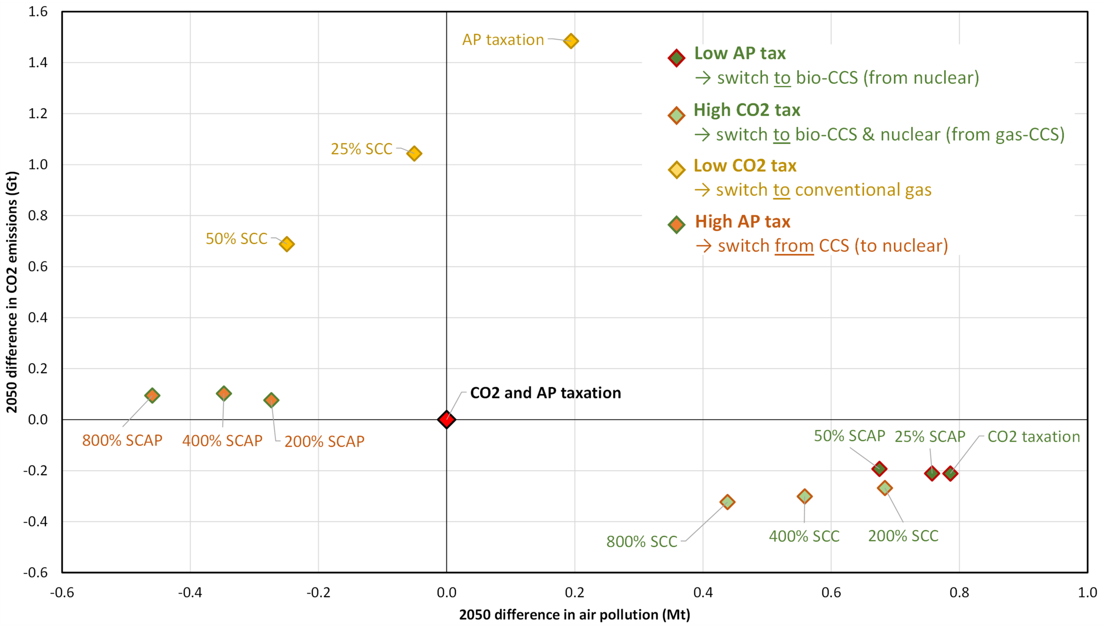
SCAP. Bio-CCS embodies an emission trade-off, as it is severely locally air polluting but tremendously reduces CO_2 emissions. As a result, cheap air pollution at 25% SCAP encourages full usage of the biomass potential in terms of bio-CCS in 2050. The 50% SCAP scenario exploits almost the total biomass potential in 2050 (but 2040 and 2045 deployment is substantially lower). 200% SCAP ends up with negligible bio-CCS generation in 2050 (0.2%). Higher SCAP levels prevent bio-CCS altogether. Gas-CCS contributes 24.2% (23.4%, 20.9%, 17%, 9.1%) and nuclear 9.4% (10.4%, 15%, 17.7%, 27%) for 25% (50%, 200%, 400%, 800%) SCAP. Wind (41.6% for 25% SCAP, 44% for 800% SCAP) and solar (10.6% for 25% SCAP, 8.1% for 800% SCAP) are less affected by changing SCAP. Lower SCAP thus foster CCS technologies, yield more air pollution but lowest CO_2 emissions. Higher SCAP in turn foster nuclear and wind, leading to a lower air pollution but higher CO_2 emissions.

SCC. 25% and 50% SCC are insufficient to induce competitiveness of CCS technologies. Instead, conventional gas technologies substitute for bio-CCS, gas-CCS, substantial parts of nuclear (for 25% and 50% SCC), and considerable wind generation (only 30.2% in 2050 for 25% SCC). Not relying on CCS technologies leaves 25% and 50% SCC with a substantially lower air pollution burden but tremendously higher CO_2 emissions (1.11 Gt for 25% SCC and 0.75 Gt for 50% SCC in 2050). 200% SCC uses almost the entire biomass potential for CCS from 2030 onwards. 400% and 800% SCC use almost the entire potential already from 2025 onwards. This biomass usage makes the European power system carbon-negative from 2025 onwards when doubling the underlying SCC. Associated air pollution in turn skyrockets to 2015 levels with substantially higher shares of PM, NMVOC, and NH_3 (SO_2 share is smaller due to the absence of oil, lignite, and coal). Increasing SCC above 200% does not change much in the overall CO_2 emission level because biomass usage is limited. Instead, there is a substantial shift from gas-CCS to nuclear to avoid even the small remaining CO_2 emissions associated with gas-CCS. As a consequence, also air pollution decreases again for very high SCC values. Wind (42.2% for 50% SCC and 42% for 800% SCC) and solar shares (10.7% for 25% SCC and 8.1% for 800% SCC) are impacted considerably less.

2.4.3 Substitution patterns

From the previous results it is apparent that technology switch patterns are of high relevance when accounting for local air pollution. We thus analyze general behavioral patterns and trends of technology deployment in this subsection. This allows us to synthesize technological substitution effects in relation to system profiles of CO_2 emissions and air pollution. In particular, we group specifications into policy clusters and analyze for each cluster which technologies systematically gain and lose most in the final 2050 mix compared to our benchmark *CO_2 and AP taxation* (at 100% SCAP and SCC levels). We exploit the fact that the (relative) taxation intensity of CO_2 vs. air pollution varies across all our specifications. This is achieved by different taxation choices, varying SCAP and SCC. We can therefore sort specifications into clusters of high air pollution taxes, low air pollution taxes, high CO_2 taxes, and low CO_2 taxes. Figure 2.2 depicts all clustered specifications in a scatter plot. The y-axis measures 2050 CO_2 emissions and the x-axis measures 2050 air pollution emissions, each in absolute differences to the benchmark.[27] The color scheme indicates cluster membership and emphasizes the technologies that are at the center of the cluster's technology switch.

Figure 2.2: 2050 emissions in relation to benchmark and clustered by technology switch



CO_2 and air pollutant emissions are displayed in absolute difference to the benchmark of joint *CO_2 and AP taxation* at 100% SCC and SCAP.

Clusters *Low AP tax* and *High CO_2 tax* both exhibit a distinct switch towards bio-CCS. For *Low AP tax*, the switch takes place away from emission-neutral nuclear, whereas for *High CO_2 tax* the substitution happens away from gas-CCS to fully avoid this technology's residual CO_2 emissions. However, observe that the resulting CO_2 and air pollution profiles of the systems are very similar for both clusters despite very different taxation regimes. *High AP tax* is marked by specifications that shift away from air polluting CCS technologies (bio-CCS and gas-CCS) towards emission-neutral nuclear. This substitution pattern under aggressive air pollution taxation is associated with a nearly horizontal movement along the x-axis, and thus hardly impacts CO_2 intensity of the system. *Low CO_2 tax* is characterized by an extensive shift from various technologies to conventional gas. Such a regime of cheap CO_2 emissions does not only increase CO_2 emissions but also increasingly enhances local air

[27] Note that social damages from CO_2 are proportional to the CO_2 intensity of the system. This is not the case for air pollution, as we depict the total aggregate of all air pollutants for complexity reasons here. Across specifications, the composition of total air pollution might change between more or less harmful compositions.

pollution when burning natural gas.

It is interesting to note that excessive taxing of either of the emission types, i.e., clusters *High CO_2 tax* and *High AP tax*, is also at the expensive of the solar PV generation share. The intuition behind this implies that both clusters switch away from dispatchable gas-CCS generation, whose low but nevertheless existing emissions are heavily taxed. This leaves the system at a lack of a flexible (low-emission) technology to balance intermittent renewable generation. For cluster *High CO_2 tax*, bio-CCS as a dispatchable carbon-negative technology is expanded. However, the biomass limits constrain usage to compensate large-scale fluctuating renewable supply. As a result, the model in both clusters slightly cuts down on intermittent solar PV and relies more on emission-neutral nuclear.

2.5 Discussion

Our results indicate that joint taxation schemes bear important abatement and cost dynamics. We thus discuss accumulated values as well as co-benefits of complementary taxation in the remainder of this section.

2.5.1 Cost dynamics

Table 2.5 contains system cost, external cost, taxes, social cost, and private cost for our four main specifications in accumulated terms (in billion €). System cost comprise all costs from generating, storing, and transmitting electricity, including investment, fixed, and dispatch cost. System cost also include cost of lost load (under the assumption of a certain value of lost load (VOLL)). External cost are comprised of the external cost of carbon (ECC) and the external cost of air pollution (ECAP). The taxes follow from the respective (optimal) taxation choices. Social cost are comprised of system and external cost; and private cost are system cost plus taxes.[28] Brackets show the net present value (subject to discounting).

Observe that system cost are lowest for no taxation and, as a general pattern, grow due to abatement cost when internalizing ECC and/or ECAP, respectively. However, some interesting cost dynamics can be observed when comparing the taxation regimes. For instance, moving from no taxation to sole air pollution taxation only leads to a slight increase in system cost while the external cost halve. From a social planner perspective, air pollution internalization is thus a low hanging fruit, in particular, because it also reduces ECC (from 10,636 to 5,547 billion €). System cost are highest for sole carbon taxation because deep decarbonization and negative emissions from using bio-CCS are expensive. Jointly taxing both carbon and air pollution allows for more flexibility in allocating abatement

[28] Note that we do not account for the social benefit of reinvesting tax revenues when comparing social and private cost. However, tax revenue is actually a supplementary benefit from social planners perspective.

Table 2.5: Accumulated/average values and electricity price range from period 2025 to 2050

	No	AP	CO_2	CO_2 & AP
System cost (billion €)	5,937 (1,888)	6,475 (1,939)	8,263 (2,622)	7,697 (2,522)
External cost (billion €)	12,057 (2,795)	5,890 (1,432)	717 (286)	1,118 (364)
ECC (billion €)	10,636 (2,449)	5,547 (1,340)	281 (194)	923 (311)
ECAP (billion €)	1,420 (346)	343 (92)	435 (92)	195 (53)
Taxes (billion €)	0 (0)	343 (92)	281 (194)	1,118 (364)
Social cost (billion €)	17,994 (4,684)	12,365 (3,370)	8,980 (2,908)	8,815 (2,885)
Private cost (billion €)	5,937 (1,888)	6,819 (2,030)	8,544 (2,816)	8,815 (2,885)
CO_2 (Gt)	73.1	38.8	3.3	7.4
CO_2 (ton/GWh)	468.07	248.29	21.25	47.36
AP (Mt)	87.9	23.1	27.0	13.7
AP (ton/MWh)	562.69	148.00	172.94	87.39
System cost (€/MWh)	38.00	41.45	52.89	49.27
External cost (€/MWh)	77.18	37.70	4.59	7.16
ECC (€/MWh)	68.08	35.50	1.80	5.91
ECAP (€/MWh)	9.09	2.20	2.79	1.25
Taxes (€/MWh)	0.00	2.20	1.80	7.16
Social cost (€/MWh)	115.18	79.15	57.48	56.43
Private cost (€/MWh)	38.00	43.65	54.69	56.43
Electricity price (€/MWh; max, year)	51.44–47.04 (51.44, 2025)	53.78–52.03 (53.78, 2025)	78.39–77.84 (79.91, 2035)	80.41–79.03 (81.07, 2045)

All values except those for electricity price refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Parentheses show net present values. Average cost values (in /MWh) calculate from the respective accumulated value divided by demand. The last column presents ranges of electricity prices with the first value referring to period 2025 and the second one to 2050 (parentheses show the maximum electricity price with the respective year). Social cost are the sum of system and external cost. Private cost are the sum of system cost and taxes.

efforts and therefore leads to lower system cost. External cost rise but also taxes are four times the amount compared to taxing carbon only (1,1182 (364) compared to 281 (194) billion €).

Let us now take a closer look into the trade-off dynamics between carbon and air pollution taxation. Table 2.5 also presents accumulated CO_2 emissions (in Gt) and air pollution (in Mt). It is intuitive that accumulated CO_2 and air pollutant emissions are by far the highest for no taxation. Observe that CO_2 emissions co-drop when taxing air pollution. ECC decrease by more than 5,000 billion €, while ECAP are reduced by around 1,000 billion € only. When taxing only CO_2 emissions, external cost are considerably lower, as are accumulated CO_2 emissions (3.3 Gt). At the same time, accumulated air pollution is only slightly higher than when solely taxing air pollution (27 vs. 23.1 Mt). However, net present value ECAP remain the same because the time profile of air pollutant emissions differs considerably between the two policy regimes. Air pollution taxation reduces air pollution in later periods. In contrast, CO_2 taxation has quite an extensive abatement effect (i.e., reducing air pollution) in the mid-term, whereas it substantially increases air pollution in the long-run (due to bio-CCS usage).

We observe a similar effect for ECC when adding air pollution taxation to existing CO_2 taxes. Here, ECC increase by 642 billion €, but net present value ECC only by 115 billion €. Again, differences in emissions and associated external cost manifest mainly in the long-run due to the deployment of bio-CCS.

Finally, let us turn to average cost per MWh and electricity price ranges in Table 2.5. The average cost per MWh values follow from dividing accumulated cost by accumulated demand. Electricity prices are given as range from period 2025 (first value) to 2050 (last value) with the maximum price and the respective year in brackets below. As expected, electricity prices are lowest for no taxation. Air pollution taxation increases them only by 5% (in 2025) to 10% (in 2050). CO_2 taxes raise prices by no more than 50% than in the no taxation case and by almost 50% compared to taxing air pollution only. Combining air pollution and carbon taxes finally result in highest prices. The average cost values allow us to view electricity prices in the context of cost compositions. In particular, in terms of cost components, private cost are most comparable to prices.[29] Observe that average external cost exceed prices in the no taxation regime. In contrast, under joint CO_2 and AP taxation, where external cost are fully internalized by taxes, the tax share makes up only a small portion of prices and private cost. This implies that they are mainly driven by abatement cost.

2.5.2 Co-benefits of complementary taxation

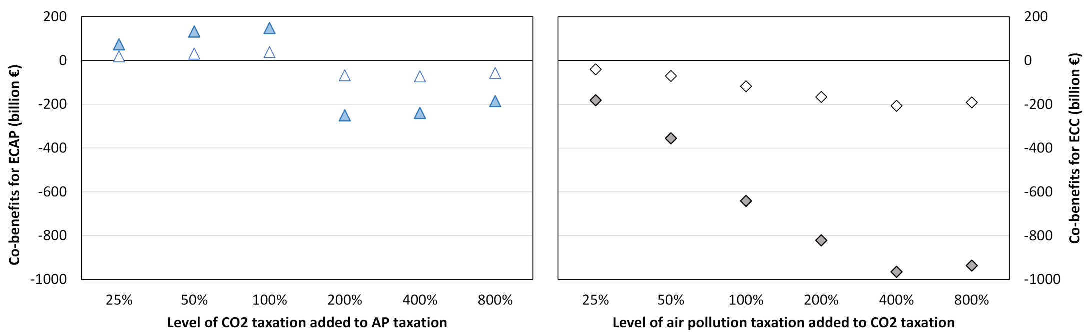
The intuition that joint taxation schemes significantly reduce external cost is not generally true because the model takes into account associated abatement cost when minimizing the net present value of system cost. However, the composition of external cost (ECAP vs. ECC) fundamentally changes. Such findings open up discussions about co-benefits of complementary taxation. Moreover, in practice it may not be necessary, feasible, or intended to heavily tax both emission types and nor may "the more the better" lead to efficient returns from taxation. With the goal of understanding how long of a way co-abatement effects go, we analyze the co-benefits of CO_2 and air pollution taxation on the respective other emission type. For instance, if taxing air pollution as a measure to internalize local damages also has positive benefits for ongoing CO_2 emission abatement, this would be a useful instrument to complement existing policies of carbon pricing.

Starting with sole CO_2 taxation (at 100% SCC level) as benchmark, we iteratively add increasing levels of air pollution taxation (as done implicitly by 25% to 800% SCAP, see Section 2.4.2). The co-benefits

[29] Observe that average private cost do not fully explain prices, e.g., system cost divided by demand are 38 €/MWh in the no taxation scenario. Meanwhile, electricity prices range closer to 50 €/MWh. This difference can be explained by the fact that electricity prices are calculated from the shadow prices of the demand-equals-supply constraints, i.e., the electricity price reflects the cost of adding a marginal unit of demand to the system. The price is thus driven by the marginal technologies and are not an average above all technologies. Consequently, electricity price ranges are strictly above average private cost per demand unit.

are the amount of (non-discounted, unless stated otherwise) CO_2 emission damages (expressed at the 100% SCC level) that are additionally avoided compared to the benchmark. For example, sole CO_2 taxation leads to ECC of 281 billion € (see Table 2.5). When air pollution taxation is added as a complementary instrument at 25% SCAP level, this leaves a system with 182 billion € higher ECC. The co-benefit of added air pollution taxation on ECC would then be −182 billion €. Increasing air pollution taxation to 50% SCAP level yields an even more negative co-benefit of −356 billion €. We continue this exercise until arriving at 800% SCAP (co-benefit is −937 billion €) and repeat it vice versa for sole air pollution taxation and added levels of CO_2 taxation. Figure 2.3 presents results. Appendix B.2.6 contains the full set of results. The left panel shows the dynamics of adding CO_2 taxation to existing air pollution taxation. The co-benefit (filled blue triangles) is thus expressed in avoided ECAP. Hollow triangles show the net present value of co-benefits. The right panel presents the outcome of adding air pollution taxation to existing CO_2 taxation. The co-benefit (filled gray diamonds) is measured in avoided ECC. Hollow diamonds show the net present value of co-benefits.

Figure 2.3: Co-benefits of complementary taxation as accumulated external cost avoided



The left panel shows AP taxation with diverging levels of CO_2 taxation. The right panel shows CO_2 taxation with diverging levels of AP taxation. Co-benefits are expressed in reduction of ECC or ECAP (evaluated at 100% SCC or SCAP levels), respectively. Filled markers represent non-discounted values; hollow markers represent net present values.

Coming from existing air pollution taxation (left panel), adding mild to moderate carbon pricing has increasingly positive co-abatement effects on local air pollution. Such taxation schemes discourage the deployment of technologies that exhibit residual emissions of both types (e.g., conventional gas, gas-CCS). Co-benefits grow from 74 billion € at 25% to a peak of 148 billion € at 100% CO_2 taxation. Co-benefits are however strongly non-linear so that beyond 100% CO_2 taxation, the co-benefits actually turn into abatement trade-offs. In fact, co-benefits drop to −250 billion € for 200% and then slightly improve to −185 billion € for 800%. Aggressive CO_2 taxation leads to a technology mix that accepts increased air pollution damages for extensive abatement of carbon emissions, e.g., via bio-CCS usage towards the end of the model horizon. Hence, in case the primary policy goal is abatement of local air pollution, the abatement benefits can be even increased by low to moderate carbon pricing as a complementary policy.

Coming from a taxation scheme that fully internalizes CO_2 emission damages already (right panel), CO_2 emissions cannot be further decreased through complementary air pollution taxation. For all our specifications with additive air pollution taxation, co-abatement effects on CO_2 are negative (overall effect on social damage abatement may still be positive). Yet again, co-benefit effects are non-linear, such that they are slightly negative for mild air pollution taxation (−182 billion € at 25% air pollution taxation) and floor at −966 to −937 billion € for high to very high levels of air pollution taxation. Note that these numbers are aggregate co-benefits covering the long term optimization horizon. It is important to keep in mind that timing of co-benefit effects matters strongly here for two reasons. (1) The negative co-benefits of CO_2 are strongly driven by bio-CCS usage in later periods, which can turn positive mid term co-benefits into negative co-benefits in the cumulative long-term. (2) As the negative co-benefits driven by bio-CCS occur in later periods, they are heavily discounted in the optimization process. This causes an increasing gap between net present value co-benefits and non-discounted co-benefits for excessive air pollution taxation. This divergence should be taken into account when assessing actual generational (i.e. non-discounted) damages of different policy regimes.

2.6 Robustness

Uncertainties regarding SCAP and SCC are addressed in Subsection 2.4.2 already. We assess remaining calibration uncertainties and modeling inaccuracies by running sensitivity analyses with respect to wind power improvements (technology boost), air pollution emission factors, a lower electricity demand projection, and the inflexibility of nuclear power plants in adjusting production freely (nuclear minimum dispatch). Moreover, we conduct an uncertainty analysis with respect to technology cost, where we provide the 95% confidence intervals for results. None of these robustness checks stand in contradiction to the results described in the two prior sections. Appendix B.2.7 contains more detailed descriptions and the full set of results of our robustness checks.

For parsimony, we will focus on the most relevant outcomes here, which are presented in Table 2.6. For each taxation scenario, we provide results for our default calibration and add results from the sensitivity runs in terms of technology generation shares (of wind, solar, nuclear, and CCS) and average cost measures (system cost, ECC, and ECAP). Observe from Table 2.6 that general patterns still hold across the taxation scenarios. That is, within a taxation scenario, generation shares and cost remain in the same magnitudes in the sensitivity runs as in the default calibration. This pattern consistency underlines confidence in our baseline results presented in prior sections. In the following, we provide more detail on the robustness checks, referencing the respective results (1–21 in Table 2.6).

Table 2.6: Selected sensitivity results

No.	Sensitivity	Wind	Solar	Nuclear	CCS	System cost	ECC (€/MWh)	ECAP
No taxation		14.9%	3.0%	4.5%	0.0%	38.00	68.08	9.09
1	Nuclear minimum dispatch	14.9%	3.0%	4.5%	0.0%	38.00	68.08	9.09
2	Low demand growth	17.0%	3.2%	5.8%	0.0%	37.27	59.59	8.10
3	CI (95%) lower bound	14.9%	2.9%	4.4%	0.0%	37.95	66.94	8.92
4	CI (95%) upper bound	15.8%	3.1%	4.4%	0.0%	38.07	67.86	9.04
AP taxation		19.4%	3.5%	5.7%	0.0%	41.45	35.50	2.20
5	Nuclear minimum dispatch	19.4%	3.5%	5.7%	0.0%	41.45	35.51	2.20
6	Low demand growth	23.0%	3.6%	6.9%	0.0%	39.76	31.30	2.03
7	Low AP emission factor	19.0%	3.4%	5.6%	0.0%	41.41	36.42	1.88
8	High AP emission factors	20.0%	3.7%	6.0%	0.0%	41.44	34.37	3.14
9	CI (95%) lower bound	18.9%	3.4%	5.7%	0.0%	41.38	35.35	2.19
10	CI (95%) upper bound	19.7%	3.7%	5.7%	0.0%	41.52	35.79	2.21
CO_2 taxation		42.2%	9.4%	7.8%	31.1%	52.89	1.80	2.79
11	Nuclear minimum dispatch	41.9%	9.4%	8.1%	31.2%	52.97	1.76	2.80
12	Low demand growth	44.2%	9.0%	7.5%	26.9%	50.15	1.10	2.85
13	CI (95%) lower bound	41.5%	9.3%	7.7%	30.4%	52.58	1.84	2.74
14	CI (95%) upper bound	42.2%	9.6%	8.6%	31.4%	52.89	2.13	2.81
CO_2 and AP taxation		43.9%	9.9%	11.0%	23.7%	49.27	5.91	1.25
15	Nuclear minimum dispatch	43.5%	9.9%	11.2%	23.9%	49.32	5.90	1.25
16	Low demand growth	46.6%	9.7%	8.7%	21.3%	46.31	5.75	1.17
17	Low AP emission factor	43.7%	10.0%	10.1%	24.8%	49.51	5.73	1.09
18	High AP emission factors	44.3%	10.1%	12.2%	20.0%	48.30	6.95	1.66
19	Technology boost	52.4%	8.8%	5.4%	22.2%	45.98	6.07	1.16
20	CI (95%) lower bound	43.3%	9.7%	10.4%	23.2%	49.06	5.81	1.24
21	CI (95%) upper bound	44.1%	10.0%	11.7%	24.4%	49.38	6.13	1.28

All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). %-values calculate from generation divided by demand. Average cost values in the last three columns calculate from the respective aggregate cost divided by demand.

2.6.1 Technology boost

We generally observe stable 2050 wind deployment around 40–45% of the electricity mix across taxation choices.[30] This consistency in deployment suggests that the economically viable potential of wind does not differ much across the underlying specifications under the given technological assumptions. We test for this effect by introducing a technology boost in 2040—i.e., full-load hours (FLH) of wind onshore and offshore increase (see Appendix B.2.7 for details)—and apply joint CO_2 and air pollution taxation (19 in Table 2.6). As expected, a technology boost would raise the economically viable wind potential, such that wind generation shares increase. This happens especially at the cost of nuclear,

[30] A small number of our many specifications does not follow this pattern: No taxation (11.4%), sole air pollution taxation with low (17.3%), mid (18.3%), and high emission factor assumptions (18.2%) as well as deciding to internalize only 25% of the SCC (30.2%) yield indeed substantially lower wind deployment rates. However, those options are also furthest away from realistic policy options in Europe, where substantial carbon pricing plays a key role.

hinting that wind and nuclear are deployed by the model as emission-free technological substitutes. Figure B.3 and Appendix B.2.7 contain visualizations and supplementary results.

2.6.2 Air pollution emission factors

Air pollution emission factors additionally depend for instance on the firing/furnace technology and a broad but diverse set of available abatement technologies.[31] For air pollution emission factors, we thus additionally develop a low and a high emission factor scenario. The low scenario starts at same values as our benchmark but assumes more optimistic technological progress of pollution abatement than the benchmark. The high scenario in turn is less optimistic than our default scenario. We apply those scenarios on sole air pollution taxation as well as joint taxation. The impact of changing air pollution emission factors on average ECAP (in €/MWh) is straightforward; lower emission factors decrease average ECAP per MWh (7 and 17 in Table 2.6) and higher emission factors increase it (8, 18). In contrast, the impact on average ECC depends on the taxation scenario and the subsequent abatement co-benefits and trade-offs, which supports our findings in Section 2.5.2. Increasing air pollution emission factors (and thus increasing average ECAP) requires more air pollution abatement efforts in the sole AP taxation scenario, which inhibits co-abatement of carbon emissions. As a consequence, average ECC decrease (8). However, in the joint taxation scenario an abatement trade-off arises around bio-CCS (18). Increased air pollution emissions are traded-off against negative carbon emissions, leading to a rise in average ECC. The mirrored effects can be observed for lower air pollution emission factors and their impact on ECC (7, 17). System cost are hardly affected at all by changes in air pollution emission factors. This emphasizes our earlier finding that air pollution abatement seems to be a low-hanging fruit. Figure B.3 and Appendix B.2.7 contain supplementary results.

2.6.3 Electricity demand

In our default calibration we assume that electricity demand increases from around 3,000 TWh to 6,203 TWh until 2050. This increase considers deep electrification of sectors (in particular, industry, heating, and transport) and stems from the CGE model PACE that is used to calibrate the power market model EUREGEN (Siala et al., 2022; Mier et al., 2023).[32] ENTSO-E and ENTSOG (2022) projects only a growth to 4,000 TWh in electricity demand until 2050. ENERDATA projects that electricity demand in Europe increases to 4,645 TWh in 2050. However, their generation is at 6,300

[31] See EEA (2019) for an overview. Carbon emission factors are not modified as they mainly depend on the plant efficiency and fuel used, which are both explicitly modeled.

[32] Electricity demand growth is endogenous in the CGE model and substitution effects between electricity and fossil fuels are accounted for. Moreover, the increase in each country depends on the underlying industrial and economic structure. For example, Austria sees quite an extreme increase (almost tripling), whereas electricity demand in Norway increases only by 55%; mainly because many sectors in Norway are already electrified (e.g., heating).

TWh in the same scenario, which leaves the careful reader puzzled.[33] Most probably, the difference is caused by European hydrogen production, which is not accounted for as electricity consumption in their methodology. Schmitt (2022) claims that electricity demand increases to 5,500 TWh until 2050. Agora (2020) forecasts a doubling of German electricity consumption until 2050. Compared to ENTSO-E and ENTSOG (2022) projections, Germany would already make up half of the entire European increase. Studies substantially differ in their underlying assumptions of economic growth and energy efficiency development.[34] Moreover, uncertainty about future amounts of hydrogen production within Europe (and the associated electrification intensities by countries) leads to considerable differences in demand forecasts across studies.[35]

Considering the high uncertainty about future electricity demand in Europe, we test robustness of our results by assuming a more moderate electricity demand increase than in our default calibration. We decrease 2050 European electricity by a third, that is to 4,135 instead of 6,203 TWh. We adjust growth rates such that the growth pattern over time stays similar to our default calibration. We also maintain relative growth patterns across countries.[36] The main effect of reduced demand is consistent with our previous finding of an economically viable potential of wind generation. Given this wind potential, the remaining gap to demand is smaller in the low demand scenario, which leads to relatively higher wind generation shares across all taxation scenarios (2, 6, 12, and 16 in Table 2.6). Furthermore, average cost measures decrease as wind generation is both cheap and non-polluting. The entire set of outcomes is shown in Appendix B.2.7. Sensitivities between the two extremes are fairly linear. For parsimony, we thus refrain from discussing and/or showing them here or in the Appendix.

2.6.4 Inflexibility of power plants

The used model version of EUREGEN ignores some technological characteristics of conventional power plants that might change results. In particular, EUREGEN is in principle able to account for minimum dispatch of power plants, ramping constraints (by means of the possible speed to ramp generation up or down within capacity limits) and ramping cost (higher dispatch cost due to ramping as approximated mark-up), start-up constraints (allowing to switch nuclear power plants off with minimum down times), and start-up cost (from the number of starts). Modeling start-up constraints

[33] All numbers refer to the EnerBlue scenario, demand: `https://eneroutlook.enerdata.net/forecast-world-electricity-consumption.html`, generation: `https://eneroutlook.enerdata.net/total-electricity-generation-projections.html`.

[34] Mier and Weissbart (2020) show that energy efficiency does not play a sizable role for electricity consumption because potential is limited and costly.

[35] For example, if hydrogen can be imported at low prices, many industries would not need to fully electrify. For reference, full electrification of the German chemistry industry would for instance require around 500 TWh per year—Germany's electricity demand of today. See `https://www.energate-messenger.de/news/232361/strombedarf-der-chemieindustrie-waechst-immens`.

[36] That is, Austria still grows more than Norway.

(and cost) considerably increases complexity of the optimization program because it requires to formulate the model as a mixed-integer program (MIP) with binary variables defining whether the power plant is online or offline, respectively. Ramping constraints do not add much complexity but are less suitable when working with representative hours (as we do).[37] Those conditions constrain mainly nuclear power plants, to some extent also lignite power plants, and slightly even coal power plants (older plants more so than newer ones). Gas power plants are almost unaffected. Observe that coal only plays a vital role in the no taxation regime, which is the most unlikely scenario. Moreover, wind and solar deployment is very limited under such a taxation choice so that all the mentioned technological constraints are negligible. However, nuclear plays a considerable role in the schemes containing CO_2 taxation and is also most affected technology-wise. We thus decide to test sensitivity for minimum dispatch of nuclear power.[38]

Intuitively, modeling the inflexibility of nuclear power pushes slightly more nuclear power into the system at the cost of wind power (i.e., relative market value of nuclear over wind increases). Another intuitive result is that the inflexibility of nuclear increases the market value of other options to balance intermittent supply such as CCS power plants, which, in turn, decreases the value of wind, and in turn increases the one of nuclear (1, 5, 11, and 15 in Table 2.6). Average system cost exhibit a slight increase but overall cost effects are of negligible magnitude.

2.6.5 Technology cost

Projections of investment cost (see Table B.5 in Appendix B.2.2) are subject to uncertainty. We identified four decisive technology clusters in the prior sections: wind (onshore, offshore), solar, nuclear, and CCS (bio-CCS, gas-CCS). We concentrate our following analysis on the technologies included in these four clusters, and assess how technology cost uncertainty affects our results. In particular, we assume that true technology cost in 2050 are normally distributed around the 2050 cost assumptions from our default calibration. We conduct a Monte Carlo analysis, where we modify investment cost independently for each cluster by a random index that is normally distributed around mean 1 with a standard deviation of 0.1.[39] In particular, we adjust 2050 cost by this random index and linearly

[37] We work with 280 representative hours as outcome of an extensive selection and weighting algorithm, and scale solar, hydro, wind, and load time series to re-construct full-load hours of the respective technologies and annual demand.

[38] We assume that nuclear power plants can reduce production to 45% of installed capacity. If the robustness check with minimum dispatch showed fundamental changes in technology investment and dispatch, we would test ramping constraints (and cost) as well. For start-up constraints and cost, in turn, the hourly resolution would require fundamental changes (from 280 to less than 50 to solve the model within reasonable time frames), which would distort our original results and also some dynamics (for example, of storage) might get lost using only very few representative hours. Moreover, from experience, we know that smaller numbers of representative hours increase the value of intermittent sources such as wind and solar, which might be suitable for some comparative static analysis of model changes but finally would yield highly distorted (external) cost calculations.

[39] We acknowledge that, in principle, cost developments might be correlated. As a side effect, this characterization of cost uncertainties reduces the number of necessary runs from 1,600 (4 clusters times 4 taxation choices times 100 runs)

interpolate between 2015 and 2050, while the 2015 value is assumed to be 1.

We draw a value from the distributions for each technology cluster and then run the model with the resulting technology cost combination and repeat this procedure 100 times per taxation scenario. Our Monte Carlo analysis is thus an analysis where uncertainties realize independently but simultaneously for all clusters. In a second step, we take results from the 100 Monte Carlo runs per taxation choice and estimate the 95% confidence intervals for several accumulated model outputs. We consider 100 runs as minimum to estimate useful density distributions of results to determine high-quality 95% confidence intervals later. A full set of results is provided in Appendix B.2.7, selected results are presented in Table 2.6 (3, 4, 9, 10, 13, 14, 20, and 21). Observe that the 95% confidence intervals are very tight for all taxation scenarios. The vast majority of our results from our default calibration lies well within the interval bounds. Some exemptions lying slightly outside are still in the same magnitude, such that they do not discourage confidence in our default calibrations.

2.7 Conclusion

We derive emissions factors of six local air pollutants (NH_3, NMVOC, NO_x, PM_{10}, $PM_{2.5}$, and SO_2) for multiple electricity generation technologies (e.g., bio-CCS, coal, gas-CCGT, gas-CCS) depending on fuel used (e.g., biomass, coal, natural gas) and underlying technological characteristics as well as the year of installation to reflect potential air pollution of the current and future power plant fleet in Europe (Cai et al., 2012; EPA, 1995; EEA, 2019; Juhrich and Becker, 2019). We then use country-specific estimates of the social cost of air pollution (SCAP) from the externE project series that are tailored to electricity generation technologies (Friedrich and Bickel, 2001; Pietrapertosa et al., 2009). We further derive social cost of carbon (SCC) from an own calibration of DICE-2016R-091216a (Nordhaus, 2014). We implement technology-specific air pollution emission factors and pollution taxes (equal to the respective SCAP and SCC) in EUREGEN (Weissbart and Blanford, 2019) to quantify the impact of accounting for air pollution for the European power market until 2050.[40] In particular, we match SCAP and SCC estimates with EUREGEN's CGE calibration by accounting for country-specific GDP growth and the underlying population projections from the World Bank. We then analyze different internalization strategies of external cost by either deciding for no taxation, only taxing air pollution or CO_2, respectively, or jointly taxing both emission types. We additionally test for sensitivities of SCC and SCAP levels to gain insight into technological substitution patterns when deciding to tax

to 400, and thus the computation time from more than 100 days to less than a month (for each standard deviation). We account for this by working with technology clusters. Moreover, we undertake the very same procedure for a standard deviation of 0.2. Results can be assessed in the supplementary material.

[40] EUREGEN is a multi-region partial equilibrium model of the European power market that optimizes investments, decommissioning, and dispatch of multiple generation, storage, and transmission technologies under the objective of minimizing the sum of system cost and tax burden (firm perspective).

air pollution and/or CO_2 emissions. We calculate the external cost occurring from different taxation choices and determine whether or not adding CO_2 (or air pollution) taxation to already existing air pollution (CO_2) taxation comes with co-benefits (or trade-offs) by means of reduced (increased) damages from air pollution (CO_2). Finally, we test and find robustness of results with respect to technological progress of wind power, air pollution emission factors, electricity demand growth, inflexibility of power plants, and technology cost. Our key findings are fourfold.

First, we determine the technology and emission mix occurring under different taxation choices. No taxation encourages coal deployment. Air pollution taxation fosters the usage of conventional gas technologies and comes with significant reductions in air pollution, whereas carbon emissions increase. CO_2 taxation yields considerable amounts of nuclear as well as gas-CCS and employs air polluting bio-CCS up to the biomass limit. Consequently, air pollution increases considerably when introducing bio-CCS but overall carbon emissions in fact drop to negative levels in the long-run. Binary decisions to tax either air pollution or carbon thus come with completely diverging emission profiles, mainly due to the employment of bio-CCS (and secondarily also due to gas-CCS). The technology and emission mix when jointly taxing air pollution and CO_2 is dominated by carbon taxes. However, additional air pollution taxation halves the total air pollution by reducing usage of CCS technologies, whereas nuclear generation is substantially higher.

Second, we test sensitivity of results by changing the underlying SCC and SCAP levels and thus the respective taxation levels. We use those results to systematically assess technological substitutions patterns. The results of this task underline that high air pollution taxes foster nuclear at the cost of bio-CCS and gas-CCS. Low air pollution taxes in turn substitute nuclear by bio-CCS only. High CO_2 taxes foster nuclear at the expense of gas-CCS because gas-CCS still emits residual amounts of CO_2. Moreover, bio-CCS is fostered, too, as long as the biomass limit is not reached already. Low CO_2 taxes in turn foster conventional gas technologies.

Third, we scrutinize accumulated system and external cost, emissions, as well as electricity prices from 2021 to 2050 under different taxation choices. No taxation comes with lowest electricity prices (47 €/MWh in 2050) but external cost accumulate to 12,057 billion €, which amounts to more than 400 billion €/a and is close to the 2022 annual government budget of Germany—the biggest country within the European power market. Sole air pollution taxation more than halves those damages, while electricity prices increase only by 10% in the long-run. Interestingly, air pollution taxation co-reduces the burden of external cost of carbon from 10,636 to 5,547 billion €. CO_2 taxation actually yields lowest overall damages (281 billion € from CO_2 and 435 billion € from air pollution). Here, air pollution (damage) is only around 16% (92 billion €) higher. Electricity prices increase tremendously by around 26 €/MWh (+48%). Those results show some complementarity in the abatement of CO_2

and air pollutant emissions. However, the socially optimal policy regime is joint taxation of both emission types. Such a policy regime in fact increases the overall external cost from 716 to 1,118 billion € but comes at similar electricity prices (compared to sole CO_2 taxation). However, the objective is not to minimize external cost but the net present value of either private or social cost, which includes abatement cost as well. In particular, the net present value of external cost increases only from 286 to 364 billion €. Notably, discounting plays a fundamental role when assessing damages from CO_2 and air pollution because different taxation choices impose a completely different time profile of emissions.

Fourth, we determine co-benefits from different taxation regimes. In particular, we do not observe large power systems that jointly internalize damages from CO_2 and air pollution. For example, the United States mainly focus on air pollution regimes, thereby neglecting damage mitigation from CO_2. Europe, in turn, predominantly focuses on CO_2 abatement. However, the internalization of local damages from air pollution should be undertaken by each country on their own initiative because free-riding does not matter. This might lead to situations where additional air pollution (in Europe) possibly also reduces (global) damages from CO_2. In turn, one argument to employ carbon pricing in the United States might be that there is also an associated benefit in terms of reduced air pollution. We quantify those scenarios and find that there is indeed a co-benefit when CO_2 taxation is added to existing air pollution taxation as long as the level of CO_2 taxation is not above the efficient one. However, adding air pollutant taxes to existing carbon taxes always comes with negative co-benefits for CO_2 abatement.

Our paper shows that the interpretation of modeling results and their consideration by policy makers requires careful review of the assumptions about taxes, underlying technological characteristics, and prioritization of policy goals. Our findings inform about impacts of different taxation choices and levels on resulting emissions, associated damages and technology switch patterns. Our results also emphasize how sensitive the optimal system reacts to different versions of complementary taxation schemes. Interestingly, nuclear plays a key role because wind and solar deployment at competitive spots is naturally limited and thus nuclear is the only remaining (competitive and expandable) emission-neutral technology. As a consequence, accounting for air pollutant damages shifts the focus back towards nuclear in the choice set of policy makers. In addition, bio-CCS is the dominant technology driving air pollutant damages but reducing those of CO_2 emissions. This trade-off challenges the role of bio-CCS as panacea to achieve a deep decarbonization. Our findings also inform about policies that do not appropriately internalize CO_2 or air pollutant damages, respectively, and underline that the focus on decarbonization should leave space also for co-internalization of air pollutant damages. This is particularly important once CCS technologies become competitive. We also deliver insights into how much potential is borne in complementary taxation schemes to yield co-benefits for an existing primary abatement goal. Those co-abatement effects need to be carefully handled by policy makers as they are non-linear. To summarize, we advise policy makers to use mild carbon pricing as additional tool to reduce air pollution but not to use air pollution taxes as a tool to reduce carbon emissions. However, from a holistic system perspective it is best to jointly internalize both emission types. This joint taxation also means that ambitions to decarbonize economies must be reviewed in the sense that one of the most powerful carbon-negative technologies, biomass in combination with carbon-capture and storage, is problematic regarding its air pollution impact.

Our analysis comes with some limitations. We use a European power market model to quantify results. Consequently, quantification of external cost is only valid for Europe which is quite densely populated and thus carries quite high damages from air pollutants. However, technology cost are similar across the globe and the determined substitution effects and the emissions trade-offs of CCS technologies are generally applicable. Moreover, wind and solar potential in time and space is limited under current electricity demand projections. Other world regions without that scarcity might overcome the entire air pollutant relevance by avoiding CCS technologies. Additionally, we assume that nuclear cost decline over time and, thus, see endogenous expansion of nuclear in our model, in particular when air pollution is taxed. Such expansion depends on cost estimates that do not completely reflect all real world cost. At least in Europe, given the history of European nuclear, the declining cost assumption is disputable, too. Moreover, the quite prominent role of nuclear is fostered by the fact that we do not account (for short- and long-term) radiation damages from using nuclear. Considering external cost of nuclear generation could therefore be a useful topic for future work.[41] However, reduced nuclear capacities come with higher reliance on CCS technologies, which in turn makes the role of air pollutant damages and their appropriate taxation even more severe. One limitation is caused the model resolution being limited to the national level for numerical complexity reasons. This prohibits modeling air pollution taxes at a more granular regional level. However, there is also evidence from Fowlie and Muller (2019) that under uncertainty differentiated air pollution taxation may not be welfare-increasing. Similarly, we assume that marginal damages from carbon and local air pollutants are constant across taxation choices. This is clearly a simplifying assumption that is necessary for air pollutant damages (because there are no appropriate calibrations providing other than constant values) and even credible for carbon if European decarbonization of electricity generation is supposed to be in line with global decarbonization goals. Finally, we apply the very same discount rate to evaluate damages from carbon and air pollutant emissions. There are at least some arguments supporting higher discount rates on air pollutant damages than on the social cost of carbon, because the damages of local air pollution are immediate and not as long-lasting and intergenerational as those from emitting CO_2.

[41] Jarvis et al. (2022) conclude that the cost of unlikely yet possible nuclear accidents as well as nuclear waste disposal are uncertain but can arguably matter to a risk-averse policy maker.

3

Extreme Weather Events, Blackouts, and Household Adaptation

Abstract

Extreme weather events are becoming more frequent with climate change, yet cold stress events remain understudied. I use the 2021 Texas freeze to examine household adaptation to extreme weather-induced blackouts, focusing on (1) adaptation uptake, (2) socio-economic disparities in adaptive capacity, and (3) salience spillovers. Using an event study design, I analyze the time-varying effects of a one-off dosage treatment, defined as blackout exposure. I leverage novel data on installation permits for home generators and rooftop-solar-battery systems as adaptation measures. Results show a significant, robust response peaking in the second calendar quarter post-treatment, where a 10 percentage point increase in outages leads to 16.4 (8) additional quarterly permits per 10,000 households for generators (solar-battery systems). Google search data suggests the 2021 freeze was widely associated with climate change for the first time, possibly explaining the adaptation response absent in earlier events. Notably, in addition to finding weaker responses for lower-income, less-educated, and high-minority neighborhoods, I also identify a one-quarter time delay in their response, highlighting disparities in both adaptive capacity and promptness. Salience spillovers further reinforce adaptation, which can be explained both by social connectedness and geographic proximity. My findings underscore the need for public outage resiliency investments and regulation to decrease unequal future exposure and policies that address inequities in climate resilience.[1]

Keywords: Extreme weather; Adaptation; Outage; Climate change; Event study; Dosage treatment

JEL-Codes: D12; Q54; L94

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3.1 Introduction

Climate change is already in motion and the world is on track to exceed the 1.5°C target from the Paris Agreement (2015), as reports from the current IPCC assessment cycle have emphasized (IPCC, 2022; IPCC Synthesis Report, 2023). While mitigation strategies for carbon abatement remain important, it will, however, also become relevant to understand and optimally use adaptation potentials to dampen the impacts of climate change. With climate change, adverse weather events and extreme temperatures become more frequent (IPCC Synthesis Report, 2023) – and go beyond heat and drought-related events. Natural scientists forecast breakouts of the polar vortex to happen more frequently, causing extreme cold waves in North America and Europe (Cohen et al., 2018) – hitting also historically mild regions further south. Extreme weather events are known to cause substantial damages and experiencing natural disasters has an impact on households' investment choices, such as home ownership (Sheldon and Zhan, 2019). Most prolonged outages in the U.S. are caused by extreme weather (Do et al., 2023) and Rubin and Rogers (2019) reveal that many studies find preparedness to play a key role in household resilience against major blackouts. Understanding households' investments (or lack thereof) in adaptation and resilience is therefore vital, if policymakers want to incentivize appropriate adaptation under equity considerations.

In this study, I analyze the aftermath of the Texas freeze in February of 2021. This cold wave brought extreme negative °Celsius temperatures in a state that is used to mild winters. This caused severe outages for multiple days, leaving millions of Texans without electricity during already challenging weather conditions.[2]

Hence, I use the Texas case study to analyze adaptation behavior at the ZIP code level in the City of Austin after this extreme weather event in order to understand (1) if and to what extent households took up adaptive resiliency measures, (2) if there are socio-economic disparities in adaptive capacity, (3) if there are salience spillovers to adaptation behavior. In an event study design, I analyze the causal treatment effect of an absorbing one-off dosage treatment on adaptation investments, allowing for varying treatment effects over time. The treatment is defined as exposure to the outages during the freeze event. As a measure of adaptation I use a novel type of granular data collected on mandatory installation permits for home electricity stand-by generators and rooftop-solar-battery systems. These permits are required for any permanent building and electrical construction works to building structures and granted by the city or county. My identification strategy relies on an unanticipated treatment event with parallel pre-trends, and on variation in treatment dosage via the outages. The causal identification is supported by the assumption that the blackout treatment was as good as random, as

[2] See a report by the University of Texas at Austin (2021) on the timeline of events.

it is uncorrelated with relevant observables. The treatment intensity (dosage) is a continuous variable in terms of hours and customers blacked-out per ZIP code over the course of the outage event. This allows a rich analysis of dosage effects instead of simple binary treatments.

My findings show a significant, prolonged treatment response, which peaks in the second calendar quarter post-treatment, where a 10 percentage point increase in electricity service disruption leads to 16.4 (8) additional quarterly permits per 10,000 households for generators (solar-battery systems). Sample splits by socio-economic characteristics show policy-relevant heterogeneity in treatment responses. Notably, besides finding weaker responses for lower-income, less university-educated, and high-minority neighborhoods, I also show a consistent one-quarter time delay in their response, informing on disparities in both adaptive capacity and promptness. Salience spillovers further reinforce adaptation, which can be explained both by social connectedness and geographic proximity.

The case of the Texas freeze with its subsequent blackouts is especially interesting to study for three reasons. First, it is known that cold-stress causes damages and seems to induce adaptation behavior (Yu et al., 2019). However, the literature on unanticipated cold-stress events is scarce, even though multiple regions are seeing unusual cold events (Europe cold snap 2018, Texas freeze 2021, Spanish snowstorm 2021), which can be associated with climate change (Cohen et al., 2018). Second, I study a case, where the baseline level of cold-stress adaptation can be assumed to be very low, such that the treatment effect can be cleanly measured. Despite two prior cold-stress events in 1989 and 2011, the permits for electricity generators in my sample had been consistently low prior to the 2021 event, while adequate public investments were missing, too. Google searches around the 2011 event did not show a systematic association with climate change and historical permit data also does not show an obvious investment response after this event, which speaks to the unpreparedness of households. In contrast, Google searches during the 2021 event indicate a systematic association with climate change and coincide with significant treatment effects found in this study. This suggests that the recent response is likely motivated by adaptive resilience. Third, the adaptation interventions of cold-stress and related blackouts have large policy relevance. For instance, household interventions against blackouts from cold-stress (e.g., generators) also lead to benefits in the common case of heat-stress-related blackouts, which are also amplified by climate change. Further, interventions against weather-related blackouts are highly relevant for energy policy and low-carbon transitions. For instance, investments in fossil-fuel-based home electricity generators can be regarded as maladaptation from a climate policy perspective, while investments in rooftop-solar-battery systems can be viewed as clean adaptation.

My research complements increasing efforts in the literature to study the potentials, instruments, and issues of households' investments in outage resilience and adaptation to climate change. There is evidence for adaptation via mortality associated with temperature extremes (Barreca et al., 2016), where rural households exhibit less adaptive investments than urban households (Yu et al., 2019). This indicates the relevance of equity aspects of adaptation but provides no further differentiation of disparities. Noll et al. (2021) provide evidence on how household characteristics influence household adaptation efforts but are constrained to survey data. Furthermore, households' previous experience of natural disasters also influences their housing investments (Sheldon and Zhan, 2019), and survey-based salience of climate change and risk perception (Demski et al., 2016). This aligns with a study on hurricanes, where Beatty et al. (2019) find systematic differences in ex-post disaster response regarding bottled water, batteries, and flashlights as emergency supplies.

My work is most similar to very recently published studies that used blackouts and solar-PV-battery installations in California to analyze the value of lost load (VOLL) (Brown and Muehlenbachs, 2024), the technological complementarity of solar PV and storage (Bollinger et al., 2023), and the welfare effects of these private substitutes for grid reliability via a calibrated theory model (Brehm et al., 2024). All of these studies focus only on California, which is known for wildfire-related outages, and do not take into account investments in home electricity generators in the empirical analysis.[3] Hence, the VOLL from Brown and Muehlenbachs (2024) and investments in private grid substitutes in Brehm et al. (2024) can be expected to be lower bound estimates, as important alternatives to PV with storage, namely generators, are not considered.

To the best of my knowledge, this study is the first to look at causal adaptive responses to electricity infrastructure disruptions during cold-stress events, using data from a state other than California, and working with actual archive data for stand-by electricity generators. Combining this with data on PV with storage from the same data source, I am the first, to my knowledge, to estimate causal responses for both types of investment alternatives, and providing an opportunity to compare them. I further present a novel argument that responses are of adaptive nature not only with regards to grid independency but also to climate change being a significant risk factor for outages. This is supported by Google search data associating the extreme weather event with climate change. My findings contribute to filling the literature gap on private adaptive resilience responses to cold-stress related disruptions of critical infrastructure services, in light of dirty and clean intervention measures and socio-economic inequities in adaptive capacity.

The remainder of this paper is organized as follows. Section 3.2 describes the treatment event and provides some context, Section 3.3 introduces the data, Section 3.4 develops the empirical strategy, Section 3.5 presents results, Section 3.6 discusses them, and Section 3.7 concludes.

[3] Brehm et al. (2024) present survey data on the general stock of generators as motivating empirical facts. However, their causal estimation of treatment responses is based only on battery storage.

3.2 The treatment event and background

Weather In February 2021, Texas was hit by an unusual, largely unanticipated cold wave that caused two-digit negative °C temperature in a region that usually experiences mild winters (e.g., in Austin in February the average maximum temperature is +19°C and average minimum temperature is +7°C).[4] The responsible winter storm lasted from February 13 to February 20 and its severity was largely unanticipated by both the Electric Reliability Council of Texas (ERCOT) and the public. The University of Texas at Austin (2021) report summarizes that by end of January, the expert community on meteorology did indeed forecast a polar vortex event. However, weather models had issues predicting the extent and severity of the temperature impacts at the regional level. As a consequence, the weather model employed by ERCOT underestimated the temperature drop even shortly before its arrival. Due to temperature being an important predictor of electricity demand, ERCOT's demand projections were also underestimated for the freeze event (University of Texas at Austin, 2021).

Electricity generation failures Despite some irregular previous cold wave events, e.g., in 1989 and 2011, the Texas power system was significantly impacted by the winter storm of 2021. In particular, already on February 13, first major generation capacity began to fail and by February 14, first supply shortages began to occur and cause grid instability. At the peak, about 40 % of the ERCOT generation capacity (thermal and renewable capacity being both affected) was out, mainly directly due to not being able to operate under the weather conditions, due to fuel or equipment issues or due to being taken off-grid to avoid damages at the generation unit from low grid frequencies (ERCOT, 2021). The situation in Texas is special, as the power system is largely independent and hardly connected to any neighboring power systems, which could have dampened the impact of regional generation outages through cross-border transmission. In response to the severe supply shortage, ERCOT set electricity prices to the system price cap of $ 9,000 per MWh for multiple days, which particularly harmed a minority of customers on real-time pricing plans (University of Texas at Austin, 2021).

Electricity outages The combination of generation failures, high demand, and lack of grid interconnection with other states, led to severe outages over the course of multiple days from February 15 to February 18 (University of Texas at Austin, 2021), marking the outage treatment event period. Starting on February 15, ERCOT had to order load shedding, i.e. controlled partial blackouts, so-called brownouts[5], to avoid a complete grid collapse. The procedure was as follows. ERCOT gave ad-hoc load shedding quotas for the next 15 minutes to the transmission network[6] operators, who

[4] See https://weather-and-climate.com.

[5] For simplicity, here and in the following, I use the terms outages and blackouts synonymously.

[6] high-voltage, long-range grid

then had to fulfill these quotas by in return giving quotas to their distribution network[7] operators. It was the responsibility of the distribution network operators to finally decide ad-hoc, which circuits to cut-off in real-time in their area of operation. The majority of service disruption occurred in this partially controlled but unsystematic manual manner and was complemented by automatic load shedding. This refers to circuits being automatically cut-off by installed grid switches, when local grid frequencies deviate beyond a certain threshold (University of Texas at Austin, 2021). Combined, this led to quite some variation in outage patterns and fluctuations in the hourly share of blacked-out customers across ZIP codes over the event window (Figure C.1). Overall, it was, hence, for customers not possible to anticipate the timing, duration, and location of outages.

Precedence Texas had experienced two similar, major cold events with subsequent blackouts in 1989 and in 2011. There are some notable similarities and differences between the three events: In terms of temperature lows, the cold spell in 1989 was comparable to the 2021 event, but lasted only for three days. The week long cold spell in 2011 was similarly long as in 2021 but milder. Looking at the extent of generation failures, both preceding events fall short of the 40 % generation failure in 2021 (FERC and NERC, 2011). Controlled outages in 1989 lasted for up to 10 hours at maximum (differing by region) and for about 8 hours in 2011. While the market structure in 1989 consisted of vertically integrated utilities without a joint market, the 2011 market structure was roughly the same as in 2021. System price caps were reached for multiple hours in 2011, which were at the time set at $ 3,000 per MWh (University of Texas at Austin, 2021). In summary, both events preceding the 2021 freeze fall slightly behind in terms of outages and economic impacts, however, both constitute major preceding electricity supply disruptions. Some policy intervention efforts were undertaken after 2011, relating to weatherization of generation units and emergency planning, but they were largely unsuccessful or not properly put into action (University of Texas at Austin, 2021).

3.3 Data

3.3.1 Electricity outages data

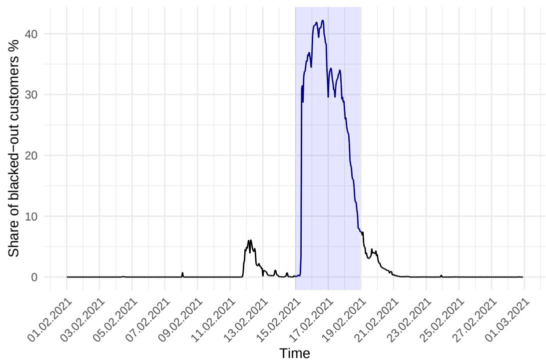
The relevant time frame for the blackout event is February of 2021, in particular, the main event time being the outages in the Texan power grid from February 15 to February 18. Data for outages is collected and published by electricity providers and tracked and aggregated by the data service provider Bluefire Studios LLC (2023) on PowerOutage.US. I acquired historical outage data on the event month of February 2021 from this source at the hourly level for the state of Texas. In particular, the data contains the hourly number of tracked customers and customers with interrupted service per tracked location. Even if not the whole population is observed, this allows to keep track of how large

[7] lower-voltage, shorter-range grid

the share of observed population is and to control for possible data quality issues here. The granularity level of tracked locations depends on the tracking level of electricity providers, such that the most granular location can be at the county, city, or ZIP code level. Generally, the more densely populated an area, the more granular the tracking level. As I need sufficient variation in outages, I constrain the data to locations tracked at the ZIP code level. The resulting data set is ZIP code-based panel data, not household panel data, meaning that the total number of blacked-out customers is tracked without being able to trace household-specific durations of outages.

Figure 3.1 provides insights into the extent of outages aggregated for the City of Austin. On the vertical axis customers with interrupted service are plotted in the aggregate for all Austin ZIP codes as a percentage share of total tracked customers. The event period from February 15 to February 18 is highlighted in blue.

Figure 3.1: Share of hourly outages in percent for the City of Austin



Event period Feb 15 - Feb 18 2021 marked in blue.

As the ZIP code-based treatment variation is lost in the aggregate plot in Figure 3.1, Table 3.1 presents the summary statistics for the ZIP code-specific outage shares for the whole event period.

Table 3.1: Summary statistics of the ZIP code-specific outage share over the course of Feb 15 - Feb 18, 2021

Min.	1st Qu.	Median	Mean	3rd Qu.	Max	N=
0.000	7.412	24.760	22.450	32.830	66.730	44

3.3.2 Permit data

I use novel data on grid electricity substitutes. In particular, I have collected rich permit data from city archive records for the City of Austin, Texas (2023). Specifically, I use permits for stand-by generators, rooftop solar PV, and battery storage installations. I concentrate on Austin for my study as both the outages data and permit data exhibit high quality. All permits track the exact street address, permit type, exact application and issue dates of the permit, the permit status, and some even state an expected dollar amount for the whole work planned for the project. The permit data is available not only for years 2021 and 2022 following the blackout event but also dates back multiple decades. This provides a rich basis to analyze pre-trends. The request or even the granting of an installation permit is not a guarantee that the respective household will actually have a generator installed. Instead, the permit data only records an intent and permission to take up this adaptation intervention. However, given that households have to invest time, effort, and a permit fee to go through the permitting process, which is often even done by an already contracted electric installation company, it is highly likely that the work has already been planned and commissioned and that some type of binding agreement already exists between the household and a contractor. It can therefore be assumed that the permits constitute a credible commitment and hence a good proxy for the installation of this adaptation measure. It should be noted that permits are mandatory for permanently installed electrical modifications such as stand-by generators, rooftop solar PV, and battery storage in this case – but not for portable generators. The latter are hence not covered by the permit data but also do not represent a reliable substitute for grid electricity due to low power and lack of weatherization compared to stand-by generators. A comparison of both generator types and battery systems for rooftop solar PV, including their potential to bridge prolonged outages, is provided in Table C.1. On a general note, the permit application itself is a complex bureaucratic process. It involves identifying the appropriate permit type(s) among many, checking for any permit exemptions, investigating if the application should be submitted by the homeowner or a contractor, and gathering all necessary information to fill the respective web application forms. The process may also involve appointments with service units from the City of Austin Permitting and Development Center to receive support on the permitting process.

3.3.3 Socio-economic data

In order to control for socio-economic and socio-demographic characteristics of the population in the empirical setting, I employ U.S. Census Bureau (2021) data from the American Community Survey (ACS) at the ZIP code level. This pertains most importantly to population size but also includes data on income, race, education, dwelling characteristics like owner-occupancy versus renter occupancy, etc.

3.4 Empirical strategy

I develop my empirical design tailored to the characteristics of the study setting as follows.

Treatment is simultaneous, one-time, absorbing, with no/few never-treated units I use the last pre-treatment period as the omitted category,[8] which is supported by the following identifying assumptions; (a) I assume that there are no relevant determinants of the outcome that are correlated with time, as the pre-trend of generator permits is virtually flat at 0 and therefore a credible counterfactual (Miller, 2023). This is further supported by the lack of anticipation of the event (along the lines of Borusyak et al., 2023); (b) I assume that there are no confounders that change abruptly with treatment. Exploiting such a discontinuity introduces some regression discontinuity design in time (RDiT) properties to my study. However, as Hausman and Rapson (2018) point out, RDiT designs do not handle time-varying effects well, which typically leads to bias in the treatment effect estimates. This brings me to the next point.

Treatment effects likely fade over time This is due to salience fading over time and due to long-run saturation effects (intuitively, once a household has acquired a generator, they will be saturated over the medium-term). In order to allow for time-varying treatment effects, I finally decide to use an event study set-up with time period dummies.

Treatment is continuous (non-binary) Units receive treatment in different intensities, i.e., there is continuous variation in treatment dosage. This presents an opportunity for richer insights from dosage response effects. For identification, I further use the supporting assumption that the blackout treatment dosage is as good as random due to the ad-hoc nature and institutional set-up of the rolling brown-outs (see Section 3.2).

3.4.1 Threats to identification

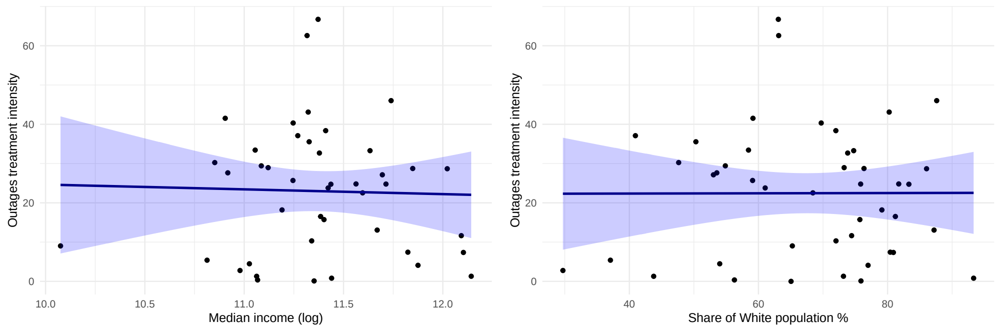
Sample selection bias My sample is restricted by the availability of outage (i.e. the treatment) data at the ZIP code level. This data is collected from electricity retail providers and aggregated by a third party – however, not all electricity retailers are covered. It would be a concern if the outage treatments were systematically correlated with the participation in outage statistics. This, however, is not possible as it was up to the distribution system operators (DSO) to take final decisions on load shedding, not electricity retail companies, and DSOs further do not share the same business operation areas as retailers. For instance, the same retail company may be active in multiple DSO areas and multiple retail companies can operate in the same DSO area.

Treatment selection bias When analyzing dosage treatment effects, the most relevant threat to identification is possible endogeneity with regard to the treatment intensity. Two arguments, one

[8] Neither never-treated unit as in a DiD design, nor not-yet-treated units as in staggered adoption designs can be used as a control group.

anecdotal and one empirical, support the assumption that the outages were as good as random. (1) The institutional set-up. Remember that the rolling blackouts were decided upon by DSOs, who received load shed quotas from the transmission system operators, who in turn received quotas from ERCOT (University of Texas at Austin, 2021). This means that the decision process of the DSOs was significantly constrained due to the multi-layered quota cascade and the very short-term decision-making. (2) Descriptive empirics. The biggest concern would be if the treatment intensity were somewhat correlated with relevant predictors for permit applications. I therefore run regressions of the treatment intensity on logged median income and the share of White population (two major inequality indicators and likely determinants of permit applications) and find no correlation (see Figure 3.2).

Figure 3.2: Tests for selection into treatment (intensity)



Regression of outage treatment intensity on logged median income (left panel) and on the share of White population (right panel) for Austin ZIP codes (without controls) with 95 % confidence bands.

Parallel trends assumption and lack of anticipation Intuitively, the parallel trends assumption is likely to hold due to the seemingly random nature of treatment discussed previously. Due to the random treatment and the short-term forecast of the weather phenomenon, it is also unlikely that households could anticipate treatment. Both of these intuitions are supported by the raw time series data for permit applications. Even if aggregated for the whole City of Austin, in the 10 years prior to treatment, the monthly total generator permit applications are between 0 and 10. For most months the number is below 5. For reference, in this time frame the number of inhabitants in Austin ranged between 800,000 and 1,000,000. A placebo test for the parallel trends assumption and lack of anticipation is incorporated into the regression design and outlaid in Section 3.4.2.

Average dosage response effects As part of the most recent DiD and event study literature, Callaway et al. (2024) have pointed out some issues when measuring dosage treatment effects in TWFE event studies. Some of their concerns relating to selection bias and variation in treatment timing are alleviated in my study, as treatment seems as good as random and is simultaneous. Further, Callaway et al. (2024) emphasize that the measured dosage treatment effect is mainly driven by the treatment effect around the average dosage, i.e. in my case the effect of a percentage point dosage increase around the average dose. This has two implications; (1) any non-linear dosage response effects are lost, and (2) high weight on the dosage response makes the interpretation of the results more difficult, if the treatment dosage is not normally distributed around the average dose or if the distribution has fat tails. Due to the small sample size, it is unlikely that the outage intensity is normally distributed. In fact, a density plot (Figure C.2) reveals high weight especially to the left tail of the distribution and slight bimodality. However, there is still substantial weight of the distribution around the mean, rendering the dosage effect still informative, while being cautious about the above-named limitations.

3.4.2 Baseline model for the adoption of generators

I start out with an event study fixed-effects design with continuous treatment:

$$Gen_{it} = \alpha + \sum_{k \leq -2} \beta_k Out_i * I_{pre}\{k = t\} + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + \delta_i + \varepsilon_{it} \qquad (3.1)$$

where indices i and t represent the ZIP code area and time period in quarters (treatment in $t = 0$), Out is the treatment intensity, I_{pre} and I_{post} are indicator functions for the pre- and post-treatment time period dummies, δ are unit fixed effects.[9] The omitted category for the treatment effect is the last period before treatment, $t = -1$. Further, Out is a continuous treatment intensity in percentage share of blacked-out customer×hours in the event period and the main variable of interest. Customer×hours is a measure jointly capturing the number of hours, in which a ZIP code experienced outages (extensive margin) and the number of households affected in each hour (intensive margin). I provide more detail on how this variable is constructed in Appendix C.1. Finally, Gen is the continuous outcome variable, measuring the generator permit applications per 10,000 households.[10]

As stated in my previous assumptions, the treatment is unanticipated and exhibits parallel pre-trends such that all pre-treatment coefficients (β_k) should be zero. In essence, I could therefore also reduce equation (3.1) to

$$Gen_{it} = \alpha + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + \delta_i + \varepsilon_{it} \qquad \forall\, (t \geq -1) \qquad (3.2)$$

where $t - 1$ remains the omitted category. However, I can exploit equation (3.1) with the pre-period

[9] I opt to not use time fixed effects, as the pre-treatment data shows generator permit applications quite stable throughout, i.e. being very robust to time-varying external factors (e.g., macroeconomic environment). Furthermore, I aim to capture time-varying treatment effects. These would otherwise be absorbed by time fixed effects, as there is no variation in treatment timing (see Borusyak et al., 2023, for a related discussion).

[10] Note that I have aggregated the analysis at the quarterly level due to noisiness of the monthly data.

treatment dummies included as a placebo test for parallel trends and lack of anticipation (as discussed in de Chaisemartin and D'Haultfœuille, 2023). Given that the results are robust to the placebo test, I can proceed by using the simplified model in equation (3.2).

To shed light on linearity of treatment effects, I also estimate a model where the continuous treatment variable is categorized into tertile bins:

$$Gen_{it} = \alpha + \sum_{k \geq 0} \gamma_k Tertile_i * I_{post}\{k = t\} + \delta_i + \varepsilon_{it} \qquad \forall\, (t \geq -1) \tag{3.3}$$

3.4.3 Adoption of rooftop solar PV with storage

The permit application data likewise contains data for PV with storage. This presents an opportunity to use this as a second outcome measure, as both options can be set-up in a way to provide back-up power during a multi-day outage. One could argue that generators, however, leave households vulnerable to fuel shortages (and price spikes), which can be expected to occur during such extreme events. PV with storage, meanwhile, also serves an additional benefit beyond outage resilience thanks to possible usage throughout the year – not just during outages. In addition, considering decarbonization and air pollution abatement efforts of current policies, generators may be seen as a maladaptation intervention compared to clean and regularly employable rooftop-solar-battery systems.

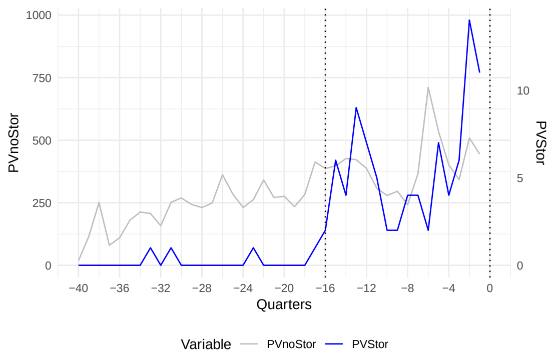
I hence run a similar specification, where I change the outcome variable to permits mentioning PV in combination with storage capacity (*PVStor*). This covers both new installations of combined solar-battery-systems as well as retrofits of already existing PV installations through the addition or expansion of battery capacity.

I also add a control variable for permits for PV-only systems, i.e. without any mention of storage, to control for general PV adoption trends, incentive policies, and investment incentives from electricity price signals. By measuring the net effect between PV-only and PV-battery investments, I capture the grid independence incentive because PV-only installations are not a viable grid electricity substitute for two reasons. Without a battery, PV can only provide electricity during sunny hours – which, even for sunny weather, leaves evening and night-time hours uncovered. Second, in Austin, electricity generated from PV installations is usually fed back into the grid, for which the household is remunerated, while the household gets charged for the gross electricity consumed. In this case, the household physically consumes grid electricity even in hours in which the PV installation generates more electricity than the household consumes. Hence, such a PV-only installation would not grant grid independence in the case of an outage. Only combined systems with batteries provide an option for actual self-sufficiency, which is the effect I aim to capture. Figure 3.3 graphically illustrates how, since the arrival of battery adoption in the Austin market (around quarter -16), permits for combined PV-storage systems follow similar trends as permits for PV-only. This is further supported by a simple OLS estimation, ZIP-code-wise regressing *PVStor* on *PVnoStor* for quarters -16 to -1 (Table C.2). I hence add permits for PV-only systems as a control *PVnoStor* and obtain

$$PVStor_{it} = \alpha + \sum_{k \leq -2} \beta_k Out_i * I_{pre}\{k = t\} + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + PVnoStor_{it} + \delta_i + \varepsilon_{it} \quad (3.4)$$

I refrain from adding additional controls or fixed effects, as *PVnoStor* and *PVStor* are driven by essentially the same conditions (high electricity prices, PV incentive policies, etc.).

Figure 3.3: Parallel trends of permits for PV with and without storage



Permits for PV-only systems on the left axis. Permits for combined PV-storage on the right axis. Since the start of battery adoption in the Austin PV market (around quarter -16), both exhibit similar overall trends in the 4 years preceding the event.

3.4.4 Model extensions

In order to understand the dynamics behind treatment effects and possible disparities, I develop two additional sets of analyses with regard to socio-economic heterogeneity in treatment effects and salience spillovers.

Socio-economic heterogeneity

Even if socio-economic characteristics seem to have not played a relevant role in treatment assignment, they may have an impact of the adaptive capacity of households. This would have distributional implications on the resilience and future disaster preparedness of households and can lead to systematic differences in vulnerability during future events. I therefore test for heterogeneous treatment effects with regard to socio-economic aspects. I extend the baseline models for generators and PV with storage by adding a dummy for the ZIP code being above the sample median for a socio-economic characteristic. This is essentially performing a sample split by a socio-economic characteristic. This approach does not provide any causal inference and some of these characteristics are likely correlated. However, it does provide valuable insights into systematic differences in treatment effects based on policy-relevant characteristics, while keeping statistical power with a relatively small sample size. For the example of generators, the regression equation becomes:

$$Gen_{it} = \alpha + \sum_{k \leq -2} (\beta_k + \vartheta_k D_i) * Out_i * I_{pre}\{k = t\} + \sum_{k \geq 0} (\gamma_k + \zeta_k D_i) * Out_i * I_{post}\{k = t\} + \delta_i + \varepsilon_{it} \quad (3.5)$$

where D is a dummy variable for a socio-economic characteristic, such as income, the share of White population, education attainment, etc. It is equal to 1 for ZIP codes above the sample median and 0 otherwise. The main treatment effect coefficients γ (and the placebo coefficients β), now represent the treatment effect for the bottom half of the sample split, while ζ is the additional effect for the top half (and their placebo coefficient ϑ). Consequently, the total treatment effect for the top half is given by the sum of γ and ζ.

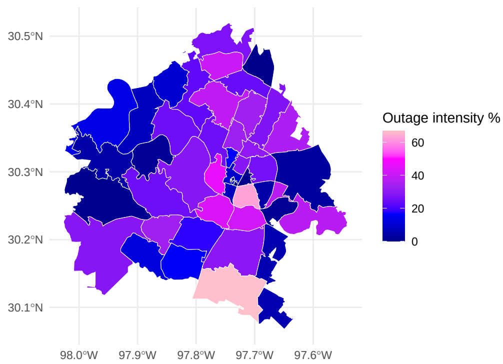
Treatment effect spillovers

Since salience is a relevant factor for household adaptive responses, there is a possibility that this mechanism is intensified by how affected the social environment of a household was by treatment. Measuring spillovers is particularly relevant in contexts with variation in treatment without systematic clustering. Section 3.4.1 has already laid out the absence of systematic clustering of outages by income and the share of White population of neighborhoods. Mapping out the outage intensity across ZIP codes in Figure 3.4 shows that also spatial clustering is limited. Often, spillovers are measured via the geographical proximity of two households. However, the social interactions through which experiences are shared, play a major role in how spillovers happen. I therefore use the social connectedness index at the ZIP code level (Humanitarian Data Exchange, 2021), as introduced by Bailey et al. (2020), to measure spillovers between two ZIP codes.

The social connectedness index (SCI) measures the number of friend connections on Facebook between two geographical areas, weighted by the product of total Facebook users in each of the two areas, scaled to range from 0 to 1,000,000 (equation 3.6). Conceptually, the SCI therefore measures the likelihood that two given users from the two areas are friends on Facebook.[11] Hence, the SCI

[11] Hence, the index is robust to different levels of social media penetration.

Figure 3.4: Spatial variation of treatment intensity



proxies how socially intertwined two regions are.[12]

$$SCI_{nm} = \frac{connections_{nm}}{users_n * users_m} \tag{3.6}$$

Figure 3.5a shows that the within-sample pairs in my data are not particularly sampled in terms of the relationship of distance and SCI (except for all being in Austin), compared to pairs with out-of-sample ZIP codes. It also illustrates that while, generally, the SCI and distance are inversely correlated, there are some outliers where the SCI is higher or lower than would be predicted by distance (holds both for within and out-of-sample pairs) – i.e. SCI is a spillover measure that can only imperfectly be proxied by distance, especially for very low distances.

I adjust my empirical model to consider the treatment intensity of all other ZIP codes in the same city, weighted by the SCI with ZIP code i and interact it with a dummy indicating whether $t > 0$, i.e. simply whether after the treatment period. To avoid collinearity with the ZIP code FE, instead of estimating a fixed effects model, I perform a simple OLS estimation with a vector **X** of socio-economic and dwelling controls:

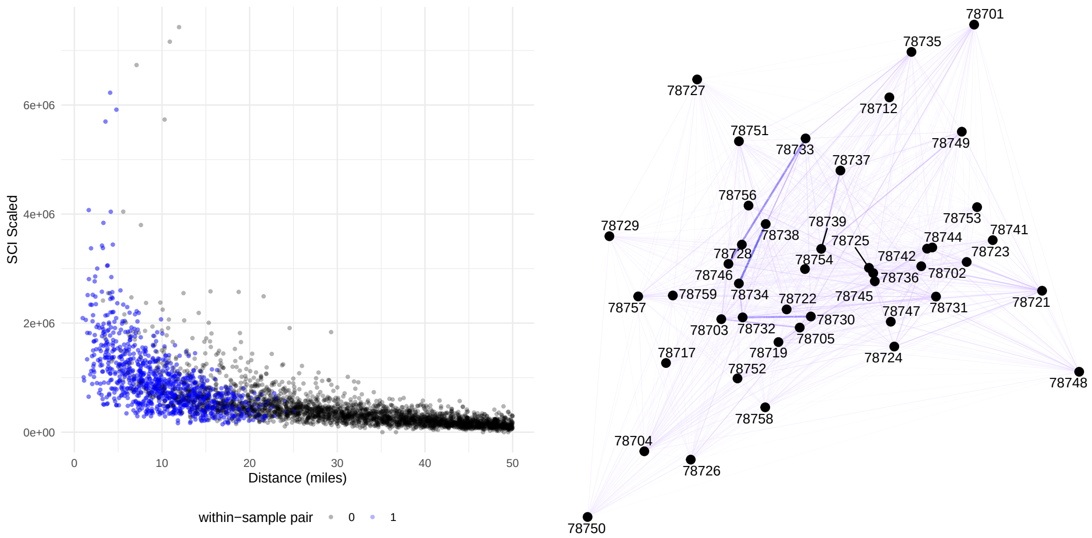
$$Gen_{it} = \alpha + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + \eta \sum_{j \neq i} SCI_{ij} * Out_j * Post_t + \mathbf{X_i} + \varepsilon_{it} \quad \forall\, (t \geq -1) \tag{3.7}$$

For comparison, I run the same specification with inverted log distance as the spillover weighting:

[12] The SCI is calculated based on October 2021 data and is not available as a time series. However, studies suggest that social networks change little over time (Bailey et al., 2021; Kuchler et al., 2022).

Figure 3.5: Social connectedness across Austin

(a) Social connectedness and geographical distance **(b)** Social connectedness network



Left panel: Scatterplot of Austin ZIP codes and their distance and social connectedness to other ZIP codes up to 50 miles distance. Blue scatter points mark pairs where both ZIP codes are within this study's sample.
Right panel: Network graph of social connections between within-sample ZIP codes. Darker and thicker connections represent higher social connectedness.

$$Gen_{it} = \alpha + \sum_{k \geq 0} \gamma_t Out_i * I_{post}\{k = t\} + \eta \sum_{j \neq i} \frac{1}{log(Distance_{ij})} * Out_j * Post_t + X_i + \varepsilon_{it} \quad \forall \, (t \geq -1) \tag{3.8}$$

3.5 Results

3.5.1 Treatment effect for generators

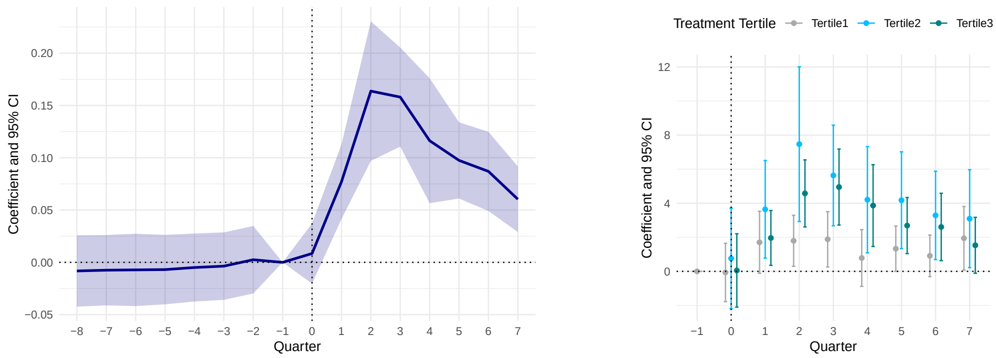
Continuous treatment intensity I begin my estimating the baseline model for generators from equation (3.1). Here and in all following reported results, I use HC1 cluster-robust standard errors and adjust significance thresholds for a t-distribution, both to account for small numbers of clusters.[13] As expected, pre-treatment effect coefficients are not statistically different from zero. This confirms the parallel trends assumption and provides justification to simplify the model for further analyses without the placebo coefficients (see also Table 3.2). The results of the event study are graph-

[13] All results are, however, very robust to using conventional p-values, for which sets of results are reported in Table C.7 and Figure C.6 to Figure C.9.

ically reported in Figure 3.6a. It can be observed that in the treatment period itself ($t = 0$) treatment shows no statistical effect yet. This is not surprising, as t is measured in calendar quarters, such that the treatment event falls in the middle of the $t = 0$ period. Figure 3.6a also graphically illustrates the importance of allowing for time-varying effects, as the treatment ramps up to full effect by quarters 2-3 and then begins to fade out. An intuitive mechanism behind this would be a lag in households' investment response (e.g., due to other ad-hoc disaster issues, time-consuming collection of information, decision processes, and bureaucratic procedures) but also salience of the experienced treatment fading out over time and possibly saturation. As the outcome variable is measured in permit applications per 10,000 households, the interpretation of the coefficient is as follows. An increase in one percentage point[14] of disrupted supply service[15] led to 0.077 additional generator permit applications per 10,000 households in quarter 1, 0.164 in quarter 2, etc. Or in more intuitive magnitudes, an increase of 10 percentage points in service disruptions led to 16.4 additional generator permit applications per 10,000 households at the peak in quarter 2 after treatment. For comparison, in the 10 years prior to the event, the median (mean) number of quarterly permit applications for generators per 10,000 households was around 3.5 (4.3) in Austin. Although the effect is likely not linear, a treatment effect of 16.4 additional permits for a 10 percentage point increase of outages, when average outages were recorded at 22.4 %, speaks to the order of response magnitude. Even around two years later, in quarter 7 after treatment, generator permit applications per 10,000 households still remain higher by 6 applications.

Figure 3.6: Treatment effect coefficients for generator-related permits

(a) Continuous treatment **(b)** Tertile treatment



The period preceding the treatment period is omitted ($t = -1$).

[14] around the average dosage and not ruling out non-linear dosage effects. See the discussion in Callaway et al. (2024).
[15] Perfect service equals 0 % outage intensity.

Table 3.2: Treatment effect coefficients for generator-related permits with continuous treatment

	Dependent variable:	
	Gen_per10kHH	
	Continuous/FE	Continuous/FE
	(1)	(2)
Out:'T-8'	−0.008	
	(0.017)	
Out:'T-7'	−0.007	
	(0.017)	
Out:'T-6'	−0.007	
	(0.017)	
Out:'T-5'	−0.007	
	(0.016)	
Out:'T-4'	−0.005	
	(0.016)	
Out:'T-3'	−0.004	
	(0.016)	
Out:'T-2'	0.003	
	(0.016)	
Out:T0	0.008	0.008
	(0.014)	(0.027)
Out:T1	0.077***	0.077***
	(0.018)	(0.022)
Out:T2	0.164***	0.164***
	(0.033)	(0.032)
Out:T3	0.158***	0.158***
	(0.023)	(0.026)
Out:T4	0.116***	0.116***
	(0.030)	(0.030)
Out:T5	0.097***	0.097***
	(0.018)	(0.022)
Out:T6	0.087***	0.087***
	(0.019)	(0.026)
Out:T7	0.060***	0.060***
	(0.016)	(0.022)
FE	ZIP	ZIP
clust-rob. SE	ZIP	ZIP
Observations	688	387
R^2	0.521	0.702
Adjusted R^2	0.477	0.657
Residual Std. Error	2.760 (df = 630)	2.804 (df = 336)
F Statistic	12.002*** (df = 57; 630)	15.819*** (df = 50; 336)

Note: Based on t-distribution: *p<0.1; **p<0.05; ***p<0.01

Treatment intensity tertiles I now move to a decomposition by treatment intensities, where I assign units to tertiles of treatment intensity. *Tertile*1 is assigned to the ZIP codes that were in the lowest tertile of treatment intensity, *Tertile*3 to the ones in the highest. Since I can exploit the fact that up to treatment, the outcome variable was virtually constant, the treatment effect of *Tertile*1 also provides an idea of the magnitude of the salience effect, as this group was hardly treated. The results are plotted in Figure 3.6b.[16] For *Tertile*1 the point estimates of the treatment effect show a distinct discontinuity between pre-treatment and the treatment period versus post-treatment periods. This effect, which is likely to a high degree driven by salience, is only small but quite persistent. However, the effect is only statistically significant at the 5 % level in quarters 2 and 3.

In contrast, treatment effect coefficients of *Tertile*2 and *Tertile*3 are much stronger and significant at the 5 % or 1 % level from quarter 1 on, which are intuitive results. However, it is surprising that in all periods, despite being not statistically different from each other, point estimates for *Tertile*2 exceed the ones of *Tertile*3, particularly in early periods. This suggests that the treatment effects are not at all linear in dosage. Concretely, the treatment effect of *Tertile*2 peaks at 7.47 additional generator permit applications per 10,000 households in quarter 2, while for *Tertile*3 the peak is achieved one period later, in quarter 3, at only 4.95 additional permit applications. This general pattern is also confirmed by a robustness check dividing treatment groups by quartiles (Figure C.3). These results may seem unintuitive at first sight but a possible mechanism is the following. Neighborhoods that experienced the most outages, have likely experienced not just minor inconvenience and discomfort, but more severe structural damages and disruptions caused by the outages (e.g., burst pipes due to electric heating failure) and may have even temporarily relocated.[17] Hence, heavily affected households may have prioritized time, effort, and income investment in repairing these damages and returning to daily routines, over investing in long-term resilience measures – which would explain both the weaker and slower response. More generally, the results suggest that for investments in generators, it matters whether to have been substantially hit by outages or not – but experience of very extreme outages does not translate to even stronger investment responses.

Overall, the magnitude of treatment effects may not seem immense in absolute numbers at first sight. However, compared to the median 3.5 quarterly permits per 10,000 households in Austin in the 10 years preceding the event, the treatment effects are indeed substantial. It should also be considered

[16] Regression table in Table C.3.

[17] The City of Austin, Texas (2025) reports, e.g., 381 public water pipeline damages, 200 housing complexes without water access due to damages in private plumbing infrastructure, 1,500 emergency water shut-offs, 164 hours with negative °C temperatures in Austin and Travis County. In a survey by Jones et al. (2024), Texans were most likely to report difficulties in food/ grocery supply, loss of internet service, loss of electricity service, and loss of access to drinkable and running water; 18 % of Texans who lost power at home, sought shelter elsewhere.

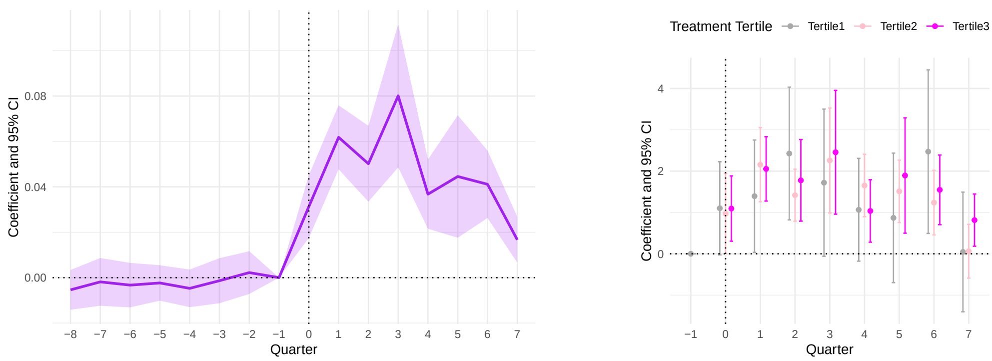
that for the stock of generators in a population, the treatment effects need to be accumulated over time. For instance, for the ZIP codes in *Tertile*2 on average this led to a cumulative additional 31.5 generator permit applications per 10,000 households[18] in the 2 years after treatment. Generally, it can be assumed that the found estimates are a lower bound of generator-related investment responses to the outage event, as my data does not cover lower-cost portable generators. It should be noted, however, that portable generators are unweatherized and less powerful. They are, hence, usually not suited for powering entire homes during extreme weather conditions. With my estimates I therefore capture the type of generators that represent viable grid electricity substitutes.

3.5.2 Treatment effect for rooftop solar PV with storage

Continuous treatment intensity Analogous to the analysis of generator permit applications, the placebo coefficients before treatment also confirm the parallel trends assumption for PV with storage permit applications (Figure 3.7a), allowing me to concentrate on the post-treatment period coefficients in subsequent analyses. The event study for PV with storage shows a similar pattern as for generators, with statistically significant treatment effects building up until about quarter 3 and then starting to fade out again. The magnitude of effects, however, is smaller. At the peak in quarter 3, a 10 percentage point increase in electricity supply disruption led to 8 additional permit applications for (retrofits of) rooftop PV with storage per 10,000 households.

Figure 3.7: Treatment effect coefficients for PV with storage-related permits

(a) Continuous treatment **(b)** Tertile treatment



The period preceding the treatment period is omitted ($t = -1$).

Treatment intensity tertiles The analysis by treatment intensity tertiles is presented in Figure 3.7b. *Tertile*2 and *Tertile*3 exhibit significant treatment effects in virtually all post-treatment

[18] counting only significant effect coefficients.

periods. However, a linear treatment effect that is systematically lowest for *Tertile*1 and highest for *Tertile*3, cannot be confirmed. A possible intuition behind this could be that PV with storage seems a reasonable measure to all treatment groups, as it can be employed throughout the year and not only as a back-up option – i.e. treatment intensity possibly mattering relatively less here than in the generator analysis to justify investment.

3.5.3 Socio-economic disparities in adaptive capacity

I now turn to the heterogeneity analysis of adaptive capacity by socio-economic characteristics of neighborhoods. Figure 3.8 plots the treatment effects for generators (Figure 3.8a) and PV with storage (Figure 3.8b) for repeated sample splits of the ZIP codes based on 7 socio-economic and dwelling characteristics; namely median household income, the share of White population, the share of Black population, the share of population aged 25 years or older holding a Bachelor or higher degree, the share of population aged 65 years or older, the share of owner-occupied (as opposed to renter-occupied) housing, and the share of single-unit buildings. Each plot shows the main effect for the bottom half of the sample split and the total effect for the top half of the sample split (main effect + interaction effect).[19]

For generators, population characteristics seem to be more relevant to reinforced treatment responses than dwelling characteristics. Neighborhoods with higher income, higher share of White population, higher education, and older population exhibit stronger responses to increased treatment intensity, while neighborhoods with higher shares of Black population exhibit weaker treatment responses. The most striking heterogeneity is found for income, racial composition, and high education attainment of ZIP codes – characteristics, which can be correlated. Possible mechanisms driving this could be higher financial means for investments, better understanding of the recurrence risk and the bureaucratic procedures for permit applications, and systemic privileges. It is interesting that ZIP codes with a high share of population of retirement age show a reinforced response to treatment intensity. A possible reason could be that elderly people are more vulnerable to outages, e.g., due to lower mobility exacerbated by loss of indoor lighting, fewer social contacts providing community support, higher dependence on electric household or medical appliances, or decreased tolerance of low room temperatures during loss of heating. Regarding dwelling characteristics, it could be expected that owning your home and living in an independent 1-unit building could increase your ability and liberty to install a generator. Notably, I find no evidence that these dwelling characteristics are associated with a statistically significant increase of the treatment response. One notable, heterogeneous pattern in the timing of treatment responses can be observed across all sample splits. Not only do the ZIP codes in the bottom half of the sample split (top half for the share of Black population) react more weakly to

[19] The same set of plots showing only the interaction effects is presented in Figure C.5.

treatment, but they also consistently react more slowly. Note how the above-median sub-samples all peak in quarter 2, while all the below-median sub-samples peak in quarter 3 (inversely for the share of Black population). This underlines the advantages of estimating time-varying effects. This observation would be consistent with the earlier suggestion that adaptive capacity is constrained in magnitude and also promptness, due to hurdles like financial constraints and completing bureaucratic procedures – exacerbated by systemic under-privileges.

The results for PV with storage are less clear-cut. Point estimates for the interaction effects are generally positive (negative for the share of Black population), this suggests that disparities exist also in the treatment response for PV with storage. However, magnitudes are smaller and in most cases the interaction effects are not statistically different from zero. Nonetheless, this could be routed in the overall very small numbers of permit applications for PV with storage per ZIP code and quarter, possibly leading to noisy estimates.

3.5.4 Salience spillovers

Table C.6 reports the results from the analysis of salience spillovers based on distance (column 1) and based on social connectedness (column 2). Both spillover measures exhibit a highly significant coefficient for the interaction with a post-treatment dummy. This highlights the important role that salience plays in adaptive responses, where salience can be increased through interaction with affected population groups. While coefficient sizes cannot be compared between the two measures because they are in different units, the coefficient and standard errors suggest that social connectedness explains salience spillovers even slightly better than geographic proximity.

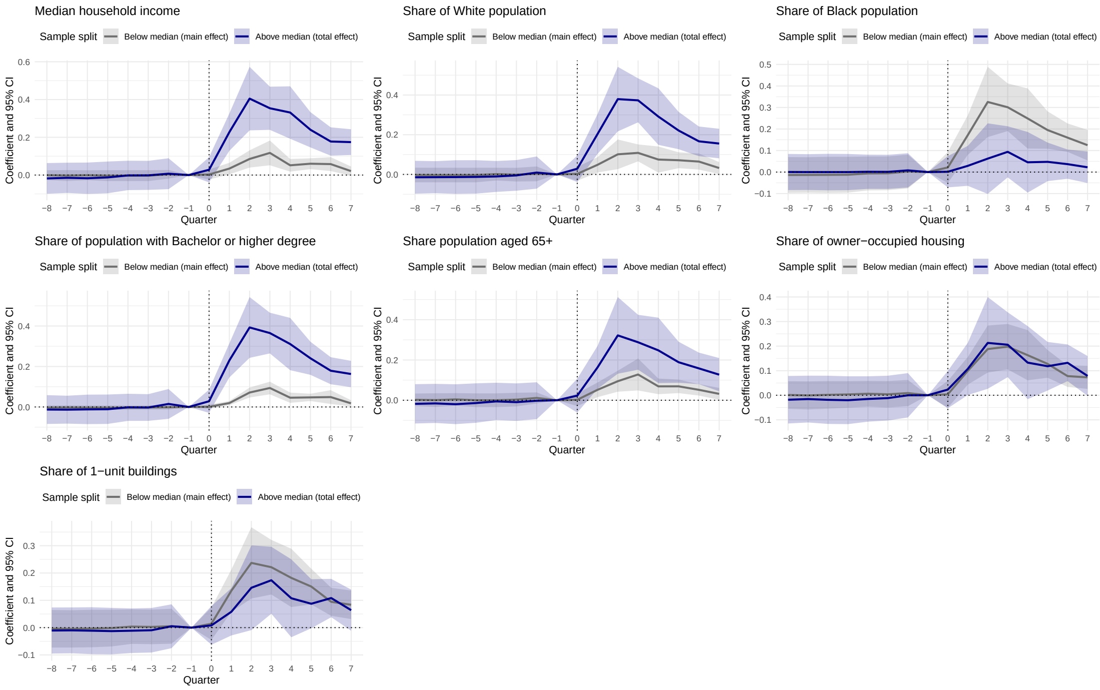
3.6 Discussion and policy implications

Concerning the adaptive nature of investments, a descriptive analysis of Google search data suggests, that the 2021 response may indeed have been also a climate change adaptation-related behavior. While both during the similar event in 2011 and in 2021, searches for blackout-related keywords saw a spike, the search patterns for the reasons and climate context of the cold spell look very different between the two events (Figure 3.9). It seems that the 2011 event left Texans mainly puzzled about how an unusual snowstorm occurs in times of global warming (upper panel), as other climate change-related keywords saw virtually no response. Notably, also no striking response in terms of generator permits was recorded (Figure 3.10). In contrast, following the 2021 event (lower panel of Figure 3.9), Texans seemed to understand the weather event as a polar vortex breakout and its possible relationship with climate change (and thus risk of recurrence) after being hit the second time in 10 years. Note how, after the 2021 event, searches now also spike for the more sophisticated weather phenomena and more

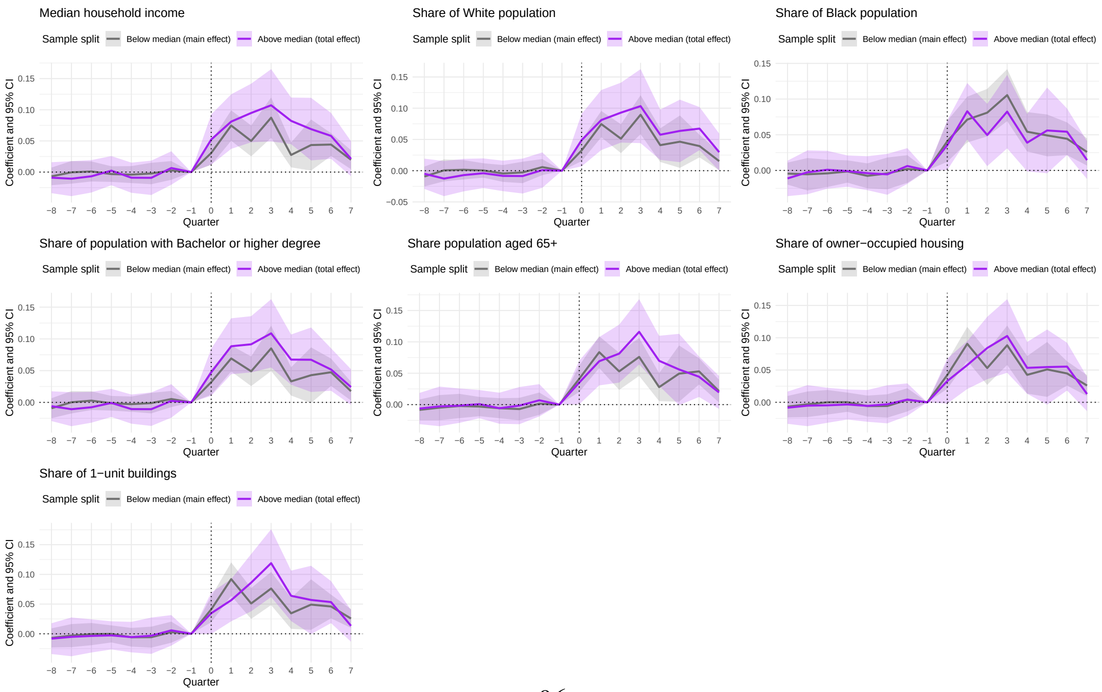
Figure 3.8: Heterogenous treatment effects by socio-economic characteristics

The period preceding the treatment period is omitted ($t = -1$).
Above median (total effect) is plotted as the sum of the main effect point estimate and the interaction effect.

(a) Generator-related permits

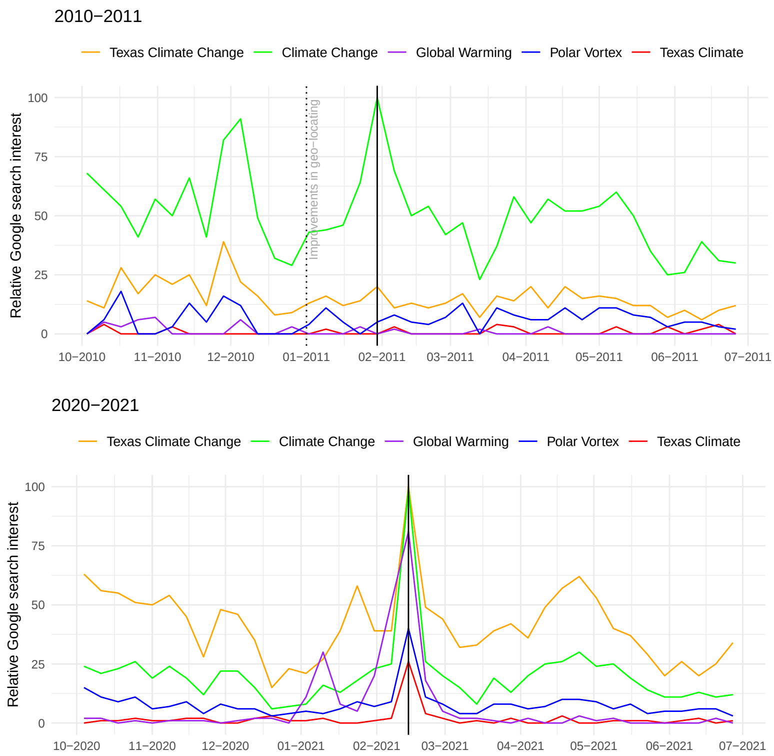


(b) PV with storage-related permits



differentiated climate-related keywords. This suggests that the very clear response after the 2021 event that I find econometrically and that is also visible from the time series in Figure 3.10, may also be an adaptive resilience response to the impacts of climate change-related extreme weather. This intuition is in line with survey results in Jones et al. (2024), who find that 69 % of Texans expect that due to climate change, Texas will more negatively impacted by extreme weather events than 30 years ago.

Figure 3.9: Relative Google search interest in Texas for multiple keywords



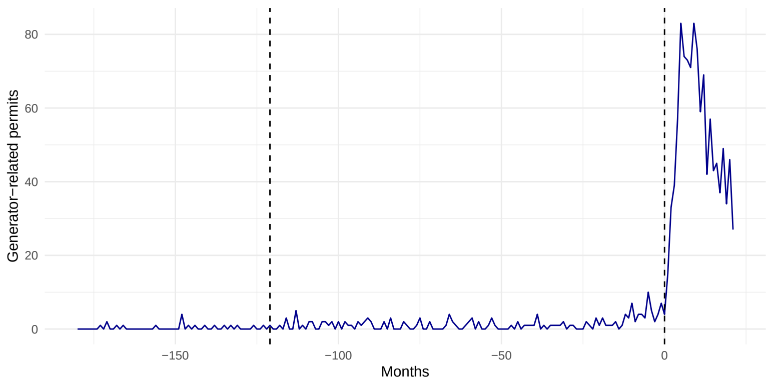
Google (2023) Search interests are aggregated at the weekly level. Most popular search interest among a keyword comparison of a given time period is normalized to 100. The black vertical line in each plot marks the freeze event week.

My results also complement suggestions and findings of recent literature on similar dynamics.

To recap, the two interventions in this study, generators and PV with storage, each embody distinct advantages and disadvantages.[20] Generators have lower upfront cost and can run as long as fuel is available (e.g., through emergency tanks). It is possible to pre-stock fuel in larger amounts, however, once it runs out, households are exposed to possible fuel shortages and price spikes during prolonged disaster events. Running a generator always causes marginal (fuel) cost, such that they are an inferior substitute when cheaper grid electricity is available. In contrast, PV installations with storage have

[20] See also the complementary comparison in Table C.1.

Figure 3.10: Generator-related permits (time series)



Dashed lines mark the 2011 and 2021 freeze events. Cumulative number for the City of Austin.

higher upfront cost and bureaucratic hurdles (e.g., tax incentives, feed-in remuneration). The duration of emergency supply via the battery depends on its initial charging level and the size of the battery. When sun is absent (likely the case during a winter storm), no re-charge is possible. But once installed, they can be used year-round and generate electricity bill savings. Now, I find a stronger treatment effect for generators than for PV with storage. Abstracting from local policy incentives for PV (with or without storage), Texas is a state with excellent sun conditions for rooftop solar PV. Given that I still find generators a much more widely chosen intervention measure, my results suggest that studies considering only PV with storage as grid substitutes, substantially underestimate both the value of lost load (Brown and Muehlenbachs, 2024)[21] and the welfare implications of grid independency investments (Brehm et al., 2024, who also leave social damages from carbon and air pollutant emissions from generators unconsidered). All of these considerations are even reinforced when considering that I only observe stand-by generators and not portable generators. Despite portable generators being only an imperfect substitute for grid electricity due to lower power, they represent a much lower-barrier investment both in terms of financial and bureaucratic barriers. Ongoing work by Harris (2023) on portable generators suggests that they likely saw a rise in sales, too. Brehm et al. (2024) point out that private investments in grid substitutes decrease the level of efficient public investments in grid reliability. In this context, it is important to consider that if many households invest in generators because PV with storage is less accessible to them (financially, bureaucratically), this leaves them unequally exposed to fuel shortages, fuel price spikes, and air pollution from generator emissions (Lin and Kassem, 2025). This has important distributional implications for optimal public grid reliability investments and disaster damage exposure.

[21] The authors acknowledge this by presenting their VOLL estimate as a lower-bound estimate for this precise reason. My study results strongly support this rationale.

My finding of socio-economic disparities in the adaptive capacity and promptness of response also has relevant implications for support policies. First, I obtain the same average timing of response peaks as Brehm et al. (2024), despite using different data, a different geographical location, and a different type of extreme event causing the outages. This suggests, that the timing of responses is consistent across different settings. However, I find that behind these aggregate effects, more weakly reacting neighborhoods also react more slowly than average. This should be addressed in post-disaster aid policies. They are often tied to a specific time window after the event, which should be long enough to also accommodate delayed responses of disadvantaged households. Policies could also be designed to specifically facilitate more prompt responses for disadvantaged households, e.g., lowering financing barriers and providing support in facing procedural barriers. In addition to that, even if I do not find significant evidence for disparities regarding dwelling characteristics, policymakers should address the fact that some households do not have any adaptive capacity due to their housing situation. For instance, landlords may not allow permanent modifications such as generator or PV-battery installations, and multi-unit housing restricts individual installation decisions.

My work comes with some limitations. Firstly, the data sample size is relatively small and restricted to ZIP codes in Austin. This is due to the fact Austin exhibited both good data quality and historical time span of the city archive data on permits, as well as good data quality and granularity of the outage data. This combination was not given for other major cities. Secondly, I can only exploit one single, large-scale outage event caused by cold-stress. Such events are rare and my outage data was constrained to February 2021. With a larger data sample and longer time span of outage data, e.g., more refined econometric estimations would be possible without losing statistical power, and effects of repeated treatment could be analyzed.

3.7 Conclusion

Climate change is associated with an increase of extreme weather events (IPCC Synthesis Report, 2023). While heat stress and drought-related weather anomalies receive much attention, cold-stress events, whose frequency is also associated with climate change (Cohen et al., 2018), are also causing recurring service disruptions of critical infrastructure. A lack of public investments in adaptive resiliency measures can leave households exposed and may induce private responses. I analyze household investment responses in Austin after experiencing prolonged outages during an extreme cold-stress event in Texas in 2021. In particular, I collect and analyze novel data on permit applications for electricity home generators and rooftop-solar-PV installations with storage. Using event study methods with time-varying treatment effects and a continuous treatment dosage, I find that at the peak, an increase of 10 percentage points in grid electricity service disruption during the treatment event, led to 16.4 (8) additional quarterly permit applications for generators (solar-PV-battery systems) per 10,000 households. For comparison, the very stable baseline level of generator permit applications in Austin was at a median of around 3.5 quarterly permits per 10,000 households in the preceding 10 years, while mean treatment dosage was recorded at 22.45 %. Accounting for salience spillovers shows significant treatment spillovers both based on geographic proximity and social connectedness of neighborhoods.

These response results are particularly interesting from a climate change adaptation angle. Based on Google search data, during a similar prior event in 2011, the public did not make a systematic association of the cold wave with climate change and historical time series data shows that clear responses in investments in generators were absent. In the 2021 event instead, Google search data reveals a systematic association with climate change, coinciding with my finding of significant investment responses after this event. Time-varying effects show that the response builds up after the treatment event, peaks in the second quarter after treatment, and then begins to fade out. A subsequent heterogeneity analysis via sample splits based on socio-economic characteristics shows, that ZIP codes with lower median income, higher minority shares, lower share of university education, and lower share of retirement-age population exhibit not only a weaker but also consistently slower response to treatment (peaking in quarter 3 instead of 2). This muted magnitude and delay of response could both be a consequence of e.g., financial constraints, hurdles to completing bureaucratic procedures, or systemic under-privileges. These systematic differences illustrate the heterogeneity of households' adaptive capacity both in terms of magnitude and promptness – leaving underprivileged households more vulnerable and less prepared for recurring extreme weather events.

In summary, my findings show that cold-stress events can induce adaptive resilience responses in households through the channel of major electricity disruptions and that both fossil and renewable resilience interventions are sought out, but the former dominate. This provides an opportunity for policymakers to incentivize renewable intervention options, given that a household chooses to invest. Policymakers should at the same time consider that households have heterogeneous adaptive capacity based on socio-economic characteristics. Policies should be designed to prevent households with less adaptive capacity from systematic vulnerability during recurring extreme weather events, as long as public, exposure-decreasing resiliency investments are missing.

A
Supplementary Materials to Chapter 1

A.1 Supplementary information

Fuel price adjustment The approach for the adjustment of fuel prices is best explained by an example: We want to derive a reference level of marginal cost r for power plant x at a certain day t. This means that for an exemplary bid b within the calculation basis B, submitted at time $t-20$ for power plant x, we can derive a hypothetical efficiency rate ε^* that would justify the observed bid level b under the assumption of competitive bidding. Subsequently we use this efficiency rate ε^*, as well as current input prices at time t to calculate an adjusted bid b' which becomes part of the adjusted calculation basis B'. Equation (A.1) shows the first step, where we equate the past bid b on the LHS with the marginal cost calculation on the RHS.

$$b(x)_{(t-20)} = \frac{Fuelprice_{(t-20)} + CO2price_{(t-20)} * CO2intensity}{\varepsilon^*} + O\&M + Taxes\&Levies \quad \text{(A.1)}$$

We solve equation (A.1) for ε^*, which captures the level of competitiveness of bid b in $t-20$. We then employ this hypothetical efficiency rate ε^* to calculate b' at time t, i.e. the adjusted bid that reflects both, the level of competitiveness of bid b in $t-20$, as well as fuel and emission prices at time t.

$$b'(x)_{(t)} = \frac{Fuelprice_{(t)} + CO2price_{(t)} * CO2intensity}{\varepsilon^*} + O\&M + Taxes\&Levies \quad \text{(A.2)}$$

We apply this procedure to each bid in B and end up with the adjusted calculation basis B' that incorporates the competitiveness of bids, net of changes in input prices. From this calculation basis, we then derive the reference level r.

A.2 Tables

Table A.1: Overview of variable cost input data for coal and gas-fired generation

Data type	Content	Scope	Source
Plant efficiencies	Plant-specific efficiency figures where possible; or else average efficiencies acc. to year of commissioning	All coal/ gas-fired plants bid into the day-ahead in 2017	Global Energy Observatory
Coal prices	Daily spot prices for imported coal + RSI	2017	Bloomberg MFE1 COMB
Natural gas prices	Daily spot prices for gas prices in the Iberian gas market	2017	MIBGAS Data 2017, product GDAES_D+1
EUA prices	Daily spot prices for EU-ETS allowances (EUAs)	2017	Bloomberg EEXX03EA
National environ-mental taxes	1) Taxes on use/ disposal of input resources 2) Energy generation tax (all technologies)	Power plants on Spanish territory; Rate levels of 2017	Ley 15/2012 Título I, Título III; Comisión Nacional de Energía (2013)
Clawback rate	Charge to compensate for unequal tax burdens	Power plants on Portuguese territory; Rate levels of 2017	Decreto-Lei n.º 74/2013 Artigo 1.º; EDP (2018)
Variable O&M costs	Median variable O&M costs per MWh	Coal and gas-fired plants, dataset of 2015	IEA and NEA (2015)

Table A.2: Overview of magnitudes of parameters applied in the marginal cost estimation

Data type	Value	Source
Clawback charge Portugal	6.50 € /MWh until 16.11.2017 4.75 € /MWh as of 17.11.2017	Decreto-Lei n.º 74/2013 Artigo 1.º; EDP (2018)
Energy generation tax Spain	7 % of revenue	Ley 15/2012 Título I
Fossil fuel consumption tax Spain	0.65 € /GJ	Ley 15/2012 Título III
Variable O&M cost coal	2.52 € /MWh	IEA and NEA (2015)
Variable O&M cost gas	3.18 € /MWh	IEA and NEA (2015)
Net calorific value hard coal (averaged for Spain's main import origins Russia, Colombia, Indonesia)	7.333 MWh/t	United Nations (2015)

Table A.3: Deviation of reference levels from true marginal cost in relative terms in € /MWh

	NYISO	Best-resp.	Start-up	Clustering
# Plants covered	92	92	84	93
1st Qu.	-2.71	-1.19	-4.09	-2.15
Mean	7.76	3.66	1.52	-1.27
Median	2.71	2.96	-1.77	0.80
3rd Qu.	11.92	5.79	5.97	1.02
SD	15.33	10.26	11.34	4.16
Min.	-8.39	-24.02	-19.53	-12.30
Max	61.53	42.63	53.76	3.22

Positive values signify that the respective approach delivers higher values than the bottom-up calculation. Deviation is defined as the difference between derived daily reference levels and the true marginal cost we calculated bottom-up. In total, there are 93 power plants in our sample from 01.04.2017–31.03.2018.

Table A.4: Surplus in million €

	BAU	NYISO	Best-response	Start-up	Clustering
# Mitigated hours	0	45	54	32	57
Buyer surplus	26,803	26,830	26,832	26,823	26,841
Supplier surplus	10,216	10,189	10,188	10,196	10,180
Total welfare	37,018	37,019	37,020	37,019	37,020
True supplier surplus	8,426	8,399	8,396	8,406	8,390
True total welfare	35,229	35,230	35,227	35,229	35,231

Sample period 01.04.2017–31.03.2018.

Table A.5: Mitigated hours by approach

Datetime	NYISO	Best-response	Start-up	Clustering	Total
2017/04/30 07:00:00	1	0	0	1	2
2017/04/30 10:00:00	1	0	0	1	2
2017/04/30 11:00:00	1	0	0	1	2
2017/04/30 12:00:00	1	0	0	1	2
2017/04/30 13:00:00	1	0	1	1	3
2017/04/30 14:00:00	1	0	1	1	3
2017/04/30 15:00:00	1	0	1	1	3
2017/04/30 16:00:00	1	0	1	1	3
2017/04/30 17:00:00	1	0	1	1	3
2017/04/30 18:00:00	1	0	1	1	3
2017/11/03 08:00:00	1	1	1	1	4
2017/11/20 07:00:00	0	0	0	1	1
2017/11/20 18:00:00	0	0	0	1	1
2017/11/23 19:00:00	0	0	0	1	1
2017/11/30 05:00:00	1	1	1	1	4
2017/12/01 02:00:00	0	1	1	0	2
2017/12/01 05:00:00	0	1	1	0	2
2017/12/02 02:00:00	1	1	1	1	4
2017/12/03 07:00:00	0	1	1	1	3
2017/12/05 18:00:00	0	0	0	1	1
2017/12/05 19:00:00	0	0	0	1	1
2017/12/06 19:00:00	0	0	0	1	1
2017/12/09 02:00:00	0	0	1	0	1
2017/12/09 18:00:00	0	0	0	1	1
2017/12/09 19:00:00	0	0	0	1	1
2017/12/10 02:00:00	1	1	1	1	4
2017/12/12 02:00:00	1	1	1	1	4
2017/12/12 06:00:00	1	0	1	1	3
2017/12/13 06:00:00	1	0	1	1	3
2017/12/14 02:00:00	1	1	1	1	4
2017/12/14 06:00:00	1	1	1	1	4
2017/12/15 06:00:00	1	1	1	1	4
2017/12/16 02:00:00	1	1	1	1	4
2017/12/17 20:00:00	0	0	0	1	1
2017/12/18 01:00:00	1	1	0	1	3
2017/12/20 02:00:00	1	1	1	1	4
2017/12/20 05:00:00	1	1	1	1	4
2017/12/21 02:00:00	1	1	1	1	4
2017/12/21 05:00:00	1	1	1	1	4
2017/12/22 02:00:00	1	1	1	1	4
2017/12/22 05:00:00	1	1	1	1	4
2017/12/23 02:00:00	1	1	1	1	4
2017/12/24 02:00:00	1	1	1	1	4
2017/12/30 06:00:00	0	0	0	1	1
2018/01/01 01:00:00	1	1	0	1	3

Continued on next page

Datetime	NYISO	Best-response	Start-up	Clustering	Total
2018/01/01 02:00:00	1	1	1	1	4
2018/01/01 03:00:00	0	1	0	0	1
2018/01/01 04:00:00	0	1	0	0	1
2018/01/01 05:00:00	0	1	0	0	1
2018/01/01 06:00:00	0	1	0	0	1
2018/01/01 07:00:00	0	1	0	0	1
2018/01/01 08:00:00	0	1	0	0	1
2018/01/01 09:00:00	0	1	0	0	1
2018/01/01 10:00:00	0	1	0	0	1
2018/01/01 11:00:00	0	1	0	0	1
2018/01/01 12:00:00	0	1	0	0	1
2018/01/01 13:00:00	0	1	0	0	1
2018/01/01 14:00:00	0	1	0	0	1
2018/01/01 15:00:00	0	1	0	0	1
2018/01/01 16:00:00	0	1	0	0	1
2018/01/03 00:00:00	1	0	1	1	3
2018/01/03 02:00:00	1	0	0	1	2
2018/01/03 03:00:00	1	0	0	1	2
2018/01/03 04:00:00	1	0	0	1	2
2018/01/03 05:00:00	1	0	0	1	2
2018/01/03 06:00:00	1	0	0	1	2
2018/01/04 01:00:00	0	1	0	1	2
2018/01/04 02:00:00	1	1	0	1	3
2018/01/04 03:00:00	1	1	0	1	3
2018/01/04 04:00:00	1	1	0	1	3
2018/01/04 05:00:00	1	1	0	1	3
2018/01/05 01:00:00	1	0	0	1	2
2018/01/06 00:00:00	0	1	0	0	1
2018/01/07 01:00:00	1	1	0	1	3
2018/01/07 02:00:00	1	0	1	1	3
2018/03/18 03:00:00	0	1	0	0	1
2018/03/18 04:00:00	0	1	0	0	1
2018/03/18 05:00:00	0	1	0	0	1
2018/03/18 06:00:00	0	1	0	0	1
2018/03/18 07:00:00	0	1	0	0	1
2018/03/18 08:00:00	0	1	0	0	1
2018/03/18 14:00:00	0	1	0	0	1
2018/03/18 15:00:00	0	1	0	0	1
2018/03/18 16:00:00	0	1	0	0	1
2018/03/18 17:00:00	0	1	0	0	1

A value of 1 corresponds to a failed impact test and thus mitigation. The first column shows the hour starting at the indicated time, e.g., the entry 15:00:00 corresponds to the hour 15:00–16:00, which is hour 16 of a day.

B
Supplementary Materials to Chapter 2

B.1 Supplementary information

Optimization constraints

Demand constraints Equation (B.1) ensures to meet an exogenous given demand $d_r(h,t)$, which can be reduced by allowing for lost load $L_r(h,t)$ (*demand-equals-supply constraint*). The difference of demand and lost load is final consumption. Total supply from generation $\sum_{i,v} Y_{ir}(h,v,t)$, storage operations (discharge including discharge losses $\eta^{-}_{jr}(v)$ less charge, second line), and transmission operations (imports including import losses $\eta_{k,rr,r}$ less exports including export losses $\eta_{k,r,rr}$, third line; $\mu_{k,r,rr}$ describes the mapping of regions that are eligible for transmission exchange) must be higher than consumption by distribution grid losses $\eta^{loss}_r(t)$.

Equation (B.2) ensures that there is sufficient back-up capacity in every region to meet demand and refrains from accounting for the possibility of lost load (*resource adequacy constraint*). We work with capacity credits α that indicate the secured amount of capacity for each technology. Storage charge and exports does not play any role here due to the fact that those operations hamper to meet the adequacy target.

$$\begin{aligned}
\frac{d_r(h,t)-L_r(h,t)}{\eta^{loss}_r(t)} &= \sum_{i,v} Y_{ir}(h,v,t) \\
&+\sum_{j,v\leq t}\left(Y^{-}_{jr}(h,v,t)\,\eta^{-}_{jr}(v)-Y^{+}_{jr}(h,v,t)\right) \\
+\sum_{\mu_{k,rr,r}} Y_{k,rr,r}(h,t)\,\eta_{k,rr,r} &- \sum_{\mu_{k,r-rr}}\frac{Y_{k,r,rr}(h,t)}{\eta_{k,r,rr}} \quad \forall \quad (h,r,t)\,, \qquad \text{(B.1)}
\end{aligned}$$

$$\begin{aligned}
\frac{d_r(h,t)}{\eta^{loss}_r(t)} &= \sum_{i,v}\alpha_i Q_{ir}(h,v,t) \\
&+\sum_{j,v\leq t}\alpha_j Q^{-}_{jr}(h,v,t)\,\eta^{-}_{jr}(v) \\
&+\sum_{\mu_{k,rr,r}}\alpha_k Q_{k,rr,r}(h,t)\,\eta_{k,rr,r} \quad \forall \quad (h,t)\,. \qquad \text{(B.2)}
\end{aligned}$$

Generation constraints Equation (B.3) restricts generation by available capacity (*capacity constraint*). $\beta_{irnw(i),r}(h,v) \in [0,1]$ is hourly availability of the subset of intermittent renewables *irnw* (i) (solar PV, wind onshore, wind offshore, hydro), $\gamma_{\text{not}\,irnw,r}(h,v) \in [0,1]$ is hourly availability for all other technologies (bioenergy, bio-CCS, gas-OCGT, gas-CCGT, gas-ST, gas-CCS, coal, coal-

CCS, lignite, oil, nuclear, and geothermal) following from monthly generation patterns and reliability assumptions. We further have $\beta_{\text{not}irnw(i)} = \gamma_{irnw(i)} = 1$.

Equations (B.4) and (B.5) describe the movement of capacity over time (*capacity stock constraints*). Equation (B.4) describes the movement of existing capacities $q_{ir}^{base}(v)$ that is still active at t^{base} (the beginning of the planning horizon). Equation (B.5) describes the movement of added capacity. $\Lambda_i(v,t) \in [0,1]$ is a lifetime parameter that describes the respective active share of capacity. Endogenous decommissioning is permitted from $t^{base}+1$ onward. We relinquish to show the respective constraints that avoid early decommissioning of existing capacities in t^{base} already. Existing or added capacity, respectively, is capable of reaching the end of the specified lifetime. Additionally, 50\% might be still active 5 years later, and 30% even 10 years later. We further specify $\Lambda\left(t^{base}\right), \Lambda\left(t^{base}+1\right) = 1$ for existing capacities to avoid distortions from enforced decommissioning in early periods although those existing capacities are still active in reality. We then apply the 50% or 30% metric with one period lag.

Equation (B.6) enforces monotonic decommissioning of capacity (*monotonicity constraint*), that is, ensures that already decommissioned capacity cannot be build up again. Equation (B.7) enforces that overall capacity does not exceed a certain limit $q_{ir}^{lim}(t)$ (*capacity limit constraint*). Equation (B.8) enforces investments that are already planned or under construction but not commissioned yet $iq_{ir}(v)^{pipe}$ (*pipeline constraint*). This constraint is particular important in $t^{base}+1 = 2020$ for wind and solar investments but also in later periods when it is about ongoing nuclear projects. We work with an adapted 2015 calibration that already contains lots of investments until the end of 2020 that are enforced in the model by this pipeline constraint. Equation (B.9) restricts expansion of intermittent renewable energies according to their resource potential by quality class (*resource potential constraint*). In particular, we consider three classes (high, mid, low) of wind onshore, wind offshore, and solar PV potential. $\mu_{irnw(i)}(class)$ is the mapping of the respective intermittent technology to its class. $q_{ir}^{lim}(class)$ is then the upper limit of the respective quality class (GW). Equation (B.10) restricts annual usage of biomass (*biomass constraint*). $bio(i)$ is the subset of technologies using biomass, $\sum_{bio(i)} \sum_{h,v\leq t} \frac{1}{\eta_{ir}(v)} Y_{ir}(h,v,t)$ is used biomass, and $bio_r^{lim}(t)$ the annual limit per region (both in GWh thermal). Equation (B.11) restrict overall storage of carbon in the ground (*stored carbon constraint*). $ccs(i)$ is the subset of carbon-capture-and-storage (CCS) technologies, $\varepsilon_{ir}^{CCS}$the capture rate (ton/GWh electric), and sc_r^{lim} is the region-specific potential of storing carbon in the ground (ton).

$$Y_{ir}(h,v,t) \leq \beta_{ir}(h,v)\,\gamma_{ir}(h,v)\,Q_{ir}(v,t) \quad \forall \quad (i,r,h,v \leq t,t)\,, \tag{B.3}$$

$$Q_{ir}(v,t) \leq q_{ir}^{base}(v)\,\Lambda_i(v,t) \quad \forall \quad \left(i,r,v \leq t^{base},t\right), \tag{B.4}$$

$$Q_{ir}(v,t) \leq IQ_{ir}(v)\,\Lambda_i(v,t) \quad \forall \quad \left(i,r,t^{base} < v \leq t,t\right), \tag{B.5}$$

$$Q_{ir}(v,t) \geq Q_{ir}(v,t+1) \quad \forall \quad \left(i,r,v \leq t,t < t^{end}\right), \tag{B.6}$$

$$\sum_{v \leq t} Q_{ir}(v) \leq q_{ir}^{lim}(t) \quad \forall \quad (i,r,t)\,, \tag{B.7}$$

$$IQ_{ir}(v) \geq iq_{ir}^{pipe}(v) \quad \forall \quad \left(i,r,t^{base} < v\right), \tag{B.8}$$

$$\sum_{\mu_{irnw(i)}(class)} \sum_{v \leq t} Q_{ir}(v,t) \leq q_{ir}^{lim}(class) \quad \forall \quad \left(\mu_{irnw(i)}(class),r,t\right), \tag{B.9}$$

$$\sum_{bio(i)} \sum_{h,v \leq t} \frac{Y_{ir}(h,v,t)}{\eta_{ir}(v)} \leq bio_r^{lim}(t) \quad \forall \quad (r,t)\,, \tag{B.10}$$

$$\sum_{ccs(i)} \sum_{h,v,t} \varepsilon_{ir}^{CCS}(v)\,Y_{ir}(h,v,t) \leq sc_r^{lim} \quad \forall \quad (r)\,. \tag{B.11}$$

Storage constraints Equation (B.12) restricts storage charge by storage capacity (*charge constraint).* Equation (B.13) restricts storage discharge by storage capacity (*discharge constraint*). Equation (B.14) restricts the storage balance by storage size (*size constraint*). For parsimony, we assume a fixed relation between charge and discharge capacity to the storage size with $hours_{jr}(v)$ being a constant parameter (in hours) for each technology-region pair. Equation (B.15) describes the movement of stored energy over time (*balance constraint*), including hourly storage losses $\eta_{jr}^{h}(v)$ and charge losses $\eta_{jr}^{+}(v)$ (discharge losses $\eta_{jr}^{-}(v)$ enter the demand-equals-supply constraint (B.1)). Equations (B.16) and (B.17) are the *capacity stock constraints*, Equation (B.18) is the *monotonicity constraint*, Equation (B.19) the *capacity limit constraint*, and Equation (B.20) the *pipeline constraint*. Those five constraints mirror equations (B.4) to (B.8) from the set of generation constraints.

$$Y_{jr}^{+}(h,v,t) \leq Q_{jr}(v,t) \quad \forall \quad (j,r,h,v \leq t,t)\,, \tag{B.12}$$

$$Y_{jr}^{-}(h,v,t) \leq Q_{jr}(v,t) \quad \forall \quad (j,r,h,v \leq t,t)\,, \tag{B.13}$$

$$B_{jr}(h,v,t) \leq Q_{jr}(v,t) \cdot hours_{jr}(v) \quad \forall \quad (j,r,h,v \leq t,t)\,, \tag{B.14}$$

$$\begin{aligned} B_{jr}(h,v,t) &= B_{jr}(h-1,v,t)\,\eta_{jr}^{h}(v) \\ &+ Y_{jr}^{+}(h,v,t)\,\eta_{jr}^{+}(v) - Y_{jr}^{-}(h,v,t) \quad \forall \quad (j,r,h,v \leq t,t)\,, \end{aligned} \tag{B.15}$$

$$Q_{jr}(v,t) \leq q_{jr}^{base}(v)\,\Lambda_j(v,t) \quad \forall \quad \left(j,r,v \leq t^{base},t\right), \tag{B.16}$$

$$Q_{jr}(v,t) \leq IQ_{jr}(v)\,\Lambda_j(v,t) \quad \forall \quad \left(j,r,t^{base} < v \leq t,t\right), \tag{B.17}$$

$$Q_{jr}(v,t) \geq Q_{jr}(v,t+1) \quad \forall \quad \left(j,r,v \leq t,t < t^{end}\right), \tag{B.18}$$

$$\sum_{v \leq t} IQ_{jr}(v) \leq q_{jr}^{lim}(t) \quad \forall \quad (j,r,t)\,, \tag{B.19}$$

$$IQ_{jr}(v) \geq iq_{jr}^{pipe}(v) \quad \forall \quad (j,r,v)\,. \tag{B.20}$$

Transmission constraints Equation (B.21) restricts transmission between eligible region pairs to the overall amount (over all vintages) of transmission capacity (*trade constraint*). Equations (B.22) and (B.23) are the *capacity stock constraints*, Equation (B.24) is the *monotonicity constraints*, Equation (B.25) is the *limit constraint*, and Equation (B.26) is the *pipeline constraint*. Those five constraints mirror equations (B.4) to (B.8) from the set of generation constraints. $q_{k,r,rr}^{lim}$ is the upper limit of possible transmission expansion and grows over time to account for the political will to increase interchange in Europe but still limits expansion to a socially acceptable level. $iq_{k,r,rr}^{pipe}$ reflects plans of transmission system operators to reach a 25% interconnectivity target and contains already planned projects.

$$Y_{k,r,rr}(h,t) \leq \sum_{v \leq t} Q_{k,r,rr}(v,t) \quad \forall \quad \left(\mu_{k,r,rr},h,t\right), \tag{B.21}$$

$$Q_{k,r,rr}(v,t) \leq q_{k,r,rr}^{base}(v)\,\Lambda_k(v,t) \quad \forall \quad \left(\mu_{k,r,rr},v \leq t^{base},t\right), \tag{B.22}$$

$$Q_{k,r,rr}(v,t) \leq IQ_{k,r,rr}(v)\,\Lambda_k(v,t) \quad \forall \quad \left(\mu_{k,r,rr},t^{base} < v \leq t,t\right), \tag{B.23}$$

$$Q_{k,r,rr}(v,t) \geq Q_{k,r,rr}(v,t+1) \quad \forall \quad \left(\mu_{k,r,rr},v \leq t,t < t^{end}\right), \tag{B.24}$$

$$\sum_{rr,v \leq t} IQ_{k,r,rr}(v) \leq q_{k,r,rr}^{lim}(t) \quad \forall \quad \left(\mu_{k,r,rr},t\right), \tag{B.25}$$

$$IQ_{k,r,rr}(v) \geq iq_{k,r,rr}^{pipe}(v) \quad \forall \quad \left(\mu_{k,r,rr},v\right). \tag{B.26}$$

B.2 Tables

B.2.1 Electricity demand and fuel prices from the CGE calibration

Table B.1: Annual electricity demand (TWh)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	63	64	78	91	137	147	156	163
Belgium	83	82	96	107	131	157	181	196
Bulgaria	30	30	35	36	37	39	41	43
Croatia	16	16	17	18	18	20	23	25
Czech Republic	59	63	116	121	125	133	141	149
Denmark	32	32	37	35	39	47	52	56
Estonia	7	8	9	11	12	12	13	14
Finland	80	73	83	79	80	82	87	91
France	448	450	759	768	813	868	926	986
Germany	528	534	832	843	843	874	910	950
Greece	52	53	58	54	58	63	68	71
Hungary	38	37	44	53	67	71	75	81
Ireland	26	26	31	32	39	42	45	49
Italy	297	319	421	562	597	644	689	735
Latvia	6	7	8	9	10	12	12	13
Lithuania	10	12	18	18	17	18	19	20
Luxembourg	6	6	7	8	11	14	15	17
Netherlands	109	113	148	186	189	199	210	226
Norway	119	124	131	126	158	168	179	190
Poland	139	143	164	179	229	267	280	293
Portugal	47	52	61	62	66	70	73	76
Romania	47	47	54	58	60	67	74	80
Slovak Republic	25	27	34	39	48	56	58	60
Slovenia	13	13	15	17	19	22	23	24
Spain	239	247	313	367	494	523	543	568
Sweden	128	133	159	161	232	248	265	282
Switzerland	58	61	67	71	117	128	139	151
United Kingdom	311	317	358	389	435	489	533	595

Table B.2: Exemplary fuel prices for Germany (€/MWh thermal)

	2015	2020	2025	2030	2035	2040	2045	2050
Bioenergy	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00
Coal	8.35	8.22	8.09	7.94	7.79	7.68	7.58	7.49
Lignite	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00
Gas	20.65	20.34	20.01	19.63	19.27	18.99	18.74	18.53
Oil	40.26	40.84	41.18	41.58	42.14	42.74	43.51	44.34
Uranium	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33

Bioenergy, lignite, and uranium prices are the same for each country. Coal, gas, and oil prices slightly differ reflecting results from the CGE calibration. However, differences are not decisive with regard to overall competitiveness of technologies in certain regions.

B.2.2 Technology parameters

Table B.3: Efficiencies of generation technologies

	2015	2020	2025	2030	2035	2040	2045	2050
Bioenergy	0.20	0.20	0.21	0.21	0.21	0.22	0.22	0.23
Bio-CCS	0.16	0.16	0.17	0.17	0.17	0.18	0.18	0.18
Gas-CCGT, Gas-ST	0.59	0.60	0.61	0.62	0.62	0.62	0.62	0.62
Gas-CCS	0.47	0.48	0.49	0.50	0.50	0.50	0.50	0.50
Gas-OCGT	0.42	0.44	0.45	0.46	0.46	0.47	0.47	0.47
Coal	0.45	0.47	0.48	0.49	0.49	0.49	0.49	0.49
Coal-CCS	0.36	0.37	0.38	0.39	0.39	0.39	0.39	0.39
Lignite*	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
Oil*	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
Geothermal	0.09	0.11	0.11	0.12	0.13	0.13	0.14	0.14
Nuclear	0.59	0.60	0.61	0.62	0.62	0.62	0.62	0.62

Efficiency estimates are mainly from JRC (2014). See Siala et al. (2022); Mier et al. (2023) for more details. Values refer to state-of-the-art capacities from the respective vintage.
*Lignite and oil values refer to 2015 vintages in the respective period because we do not observe any lignite and oil expansion in our results.

Table B.4: Carbon emission factors (ton/GWh electric) of generation technologies

	2015	2020	2025	2030	2035	2040	2045	2050
Bio-CCS	-855	-855	-805	-805	-805	-760	-760	-760
Gas-CCGT, Gas-ST	347	341	335	330	330	330	330	330
Gas-CCS	42	41	40	39	39	39	39	39
Gas-OCGT	507	484	473	463	463	453	453	453
Coal	797	763	747	732	732	732	732	732
Coal-CCS	94	91	89	86	86	86	86	86
Lignite*	838	838	838	838	838	838	838	838
Oil*	910	910	910	910	910	910	910	910

Emission factor estimates are mainly from JRC (2014). See Siala et al. (2022); Mier et al. (2023) for more details. Values refer to state-of-the-art capacities from the respective vintage.
*Lignite and oil values refer to 2015 vintages in the respective period because we do not observe any lignite and oil expansion in our results. Bioenergy, geothermal, and nuclear are emission neutral.

Table B.5: Investment cost (€/kW) of generation technologies

	2015	2020	2025	2030	2035	2040	2045	2050
Bioenergy	4,322	4,236	4,149	4,149	4,106	4,063	4,063	4,020
Bio-CCS	6,322	6,236	6,149	6,149	6,106	6,063	6,063	6,020
Gas-CCGT, Gas-ST	850	850	850	850	850	850	850	850
Gas-CCS	1,495	1,495	1,495	1,495	1,495	1,495	1,495	1,495
Gas-OCGT	437	437	437	437	437	437	437	437
Coal	1,500	1,500	1,440	1,410	1,395	1,380	1,380	1,365
Coal-CCS	3,415	3,415	3,278	3,210	3,176	3,142	3,142	3,108
Lignite*	1,640	1,640	1,640	1,640	1,640	1,640	1,640	1,640
Oil*	822	822	822	822	822	822	822	822
Geothermal	12,364	11,993	11,622	11,498	11,251	11,127	11,004	11,004
Nuclear**	7,600	7,006	6,346	6,082	5,818	5,488	5,488	5,356
Solar	1,300	1,027	936	858	819	780	741	715
Wind offshore	3,600	3,024	2,700	2,520	2,376	2,268	2,160	2,088
Wind onshore	1,520	1,397	1,368	1,339	1,325	1,310	1,310	1,296

Cost estimates are mainly from JRC (2014). See Siala et al. (2022); Mier et al. (2023) for more details. Values refer to state-of-the-art capacities from the respective vintage.

*Lignite and oil values refer to 2015 vintages in the respective period because we do not observe any lignite and oil expansion in our results.

** JRC (2014) provides estimates for nuclear power ranging from 4,000–6,000 €/kW in 2013 to 3,350–5,000 in 2050 for Generation III Light Water Reactor, i.e., cost are expected to fall. Social cost of nuclear are often neglected in energy system analysis as it is decommissioning cost and cost of storing nuclear waste. Given cost estimates of around 6,000 €/kW for installing nuclear facilities, estimates are around 1,000 €/kW for decommissioning them. However, the timing of those cost at the very end of the respective life times impedes their appropriate consideration. In fact, a discount rate of 7% leads to the consideration of only 100 €/kW decommissioning cost. Moreover, experiences from Germany show that decommissioning cost are substantially higher in Europe. We thus opt for an approach, where firms need to pay a decommissioning premium of 1,000 €/kW into a decommissioning fund at time of construction, so that 2020 investment cost are at 7,000 (instead of 6,000) €/kW.

B.2.3 Air pollution emission profiles

Table B.6: Air pollution emission intensities (g/GJ thermal)

	2015	2020	2025	2030	2035	2040	2045	2050
NH_3								
Bio-CCS	3.84	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Bioenergy	1.28	1.28	1.28	1.28	1.28	1.28	1.28	1.28
Coal	0.30	0.29	0.28	0.27	0.26	0.25	0.24	0.23
Coal-CCS	0.90	0.87	0.84	0.81	0.78	0.75	0.72	0.69
Gas-CCGT, Gas-OCGT, Gas-ST, Oil	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gas-CCS	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Lignite	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
NMVOC								
Bio-CCS, Bioenergy	7.31	7.31	7.31	7.31	7.31	7.31	7.31	7.31
Coal, Coal-CCS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24
Lignite	1.40	1.35	1.31	1.26	1.21	1.17	1.12	1.07
Oil	2.30	2.30	2.30	2.30	2.30	2.30	2.30	2.30
NO_x								
Bio-CCS, Bioenergy	76.42	73.77	71.13	68.48	65.84	63.19	60.55	57.90
Coal, Coal-CCS	72.50	71.23	69.96	68.69	67.43	66.16	64.89	63.62
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	31.01	30.62	30.24	29.85	29.46	29.07	28.69	28.30
Lignite	72.50	71.64	70.78	69.92	69.07	68.21	67.35	66.49
Oil	56.60	54.57	52.54	50.51	48.49	46.46	44.43	42.40
PM_{10}								
Bio-CCS, Bioenergy	31.81	31.81	31.81	31.81	31.81	31.81	31.81	31.81
Coal, Coal-CCS	7.70	6.85	6.00	5.15	4.30	3.45	2.60	1.75
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Lignite	7.90	6.85	5.80	4.75	3.71	2.66	1.61	0.56
Oil	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20
$PM_{2.5}$								
Bio-CCS, Bioenergy	27.94	27.94	27.94	27.94	27.94	27.94	27.94	27.94
Coal, Coal-CCS	3.40	3.14	2.87	2.61	2.35	2.09	1.82	1.56
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Lignite	3.20	2.81	2.43	2.04	1.65	1.26	0.88	0.49
Oil	19.30	19.30	19.30	19.30	19.30	19.30	19.30	19.30
SO_2								
Bio-CCS, Bioenergy	10.80	10.24	9.68	9.12	8.57	8.01	7.45	6.89
Coal	63.45	59.74	56.03	52.32	48.60	44.89	41.18	37.47
Coal-CCS	50.76	47.79	44.82	41.85	38.88	35.91	32.95	29.98
Gas-CCGT, Gas-OCGT, Gas-ST	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Gas-CCS	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Lignite	91.20	81.44	71.68	61.92	52.16	42.40	32.64	22.88
Oil	70.70	68.69	66.67	64.66	62.64	60.63	58.61	56.60

Emission intensities are displayed for each vintages and thus include technological progress of abatement measures that differ for each air pollutant. The literature provides lower and upper bounds as well as medium range emission factors (EPA, 1995; Cai et al., 2012; EEA, 2019; Juhrich and Becker, 2019). The displayed ones show medium range emission factors.

B.2.4 GDP and population projections

Table B.7: GDP projections (billion 2015-€)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	436	474	511	546	589	636	683	728
Belgium	528	566	606	654	719	797	877	960
Bulgaria	56	62	67	71	75	79	83	86
Croatia	57	62	65	69	75	82	88	94
Czech Republic	204	223	238	258	277	297	317	338
Denmark	346	388	429	463	499	542	590	643
Estonia	26	29	31	33	35	38	40	41
Finland	271	287	303	323	350	382	413	445
France	2,841	3,066	3,270	3,488	3,763	4,094	4,435	4,820
Germany	3,850	4,091	4,328	4,490	4,640	4,855	5,097	5,334
Greece	234	241	246	256	275	295	306	316
Hungary	137	148	165	180	194	207	217	231
Ireland	250	282	306	333	363	393	420	455
Italy	2,132	2,273	2,409	2,556	2,733	2,939	3,144	3,385
Latvia	31	35	39	42	44	47	50	52
Lithuania	47	54	57	58	59	63	67	71
Luxembourg	65	74	84	95	108	123	138	154
Netherlands	876	938	987	1,028	1,083	1,153	1,230	1,317
Norway	507	555	601	654	715	785	861	936
Poland	542	622	698	769	826	881	919	947
Portugal	228	245	266	281	296	309	319	330
Romania	198	222	243	261	278	297	317	338
Slovak Republic	99	114	128	144	156	164	169	173
Slovenia	49	53	58	62	65	70	74	78
Spain	1,376	1,510	1,652	1,793	1,936	2,061	2,141	2,264
Sweden	570	630	697	765	847	937	1,033	1,131
Switzerland	700	776	859	950	1,055	1,172	1,300	1,430
United Kingdom	2,984	3,188	3,366	3,611	3,948	4,354	4,780	5,215
World	78,242	90,573	104,038	119,466	136,834	155,959	175,894	196,762

Table B.8: Population projections (million)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	8.64	8.92	8.98	9.04	9.07	9.06	9.01	8.93
Belgium	11.27	11.54	11.70	11.83	11.93	12.01	12.06	12.09
Bulgaria	7.18	6.92	6.66	6.38	6.10	5.84	5.59	5.36
Croatia	4.20	4.04	3.93	3.82	3.70	3.56	3.43	3.30
Czech Republic	11	11	11	11	11	11	11	11
Denmark	5.68	5.83	5.94	6.03	6.10	6.17	6.21	6.25
Estonia	1.32	1.33	1.30	1.27	1.24	1.21	1.18	1.15
Finland	5.48	5.53	5.56	5.55	5.52	5.50	5.48	5.45
France	66.55	67.20	68.01	68.54	68.87	69.09	69.18	69.09
Germany	81.69	83.15	82.55	82.22	81.72	80.93	79.80	78.53
Greece	10.82	10.66	10.38	10.15	9.93	9.71	9.48	9.20
Hungary	9.84	9.74	9.58	9.40	9.18	8.94	8.73	8.52
Ireland	4.70	4.98	5.14	5.27	5.38	5.50	5.60	5.68
Italy	60.73	60.18	59.51	58.59	57.64	56.62	55.29	53.59
Latvia	1.98	1.89	1.81	1.73	1.66	1.60	1.55	1.50
Lithuania	2.90	2.76	2.64	2.54	2.44	2.35	2.26	2.18
Luxembourg	0.57	0.63	0.66	0.69	0.72	0.74	0.76	0.78
Netherlands	16.94	17.38	17.55	17.65	17.67	17.61	17.48	17.29
Norway	5.19	5.39	5.62	5.83	6.03	6.21	6.37	6.52
Poland	37.99	37.91	37.57	36.95	36.09	35.09	34.12	33.19
Portugal	10.36	10.25	10.11	9.95	9.77	9.57	9.34	9.08
Romania	19.82	19.25	18.82	18.35	17.84	17.31	16.82	16.30
Slovak Republic	5.42	5.46	5.44	5.39	5.30	5.19	5.07	4.96
Slovenia	2.06	2.09	2.08	2.06	2.03	2.00	1.97	1.93
Spain	46.44	47.13	46.87	46.46	45.93	45.30	44.51	43.49
Sweden	9.80	10.34	10.61	10.83	11.01	11.19	11.38	11.55
Switzerland	8.28	8.63	8.90	9.13	9.32	9.47	9.59	9.68
United Kingdom	65.12	67.16	68.44	69.54	70.48	71.36	72.13	72.74
World	7,339	7,754	8,140	8,501	8,836	9,145	9,426	9,676

B.2.5 Social cost of air pollution

Table B.9: 2020 weighted average of SCAP (€/ton) by impact category and air pollutant (1)

	Average	AT	BE	BG	CH	CZ	DE	DK	EE	EL
Human health										
NH_3	16,543	19,650	36,698	9,475	14,214	28,161	21,930	11,964	8,563	7,149
NMVOC	1,039	1,702	2,633	-87	1,301	980	1,394	957	273	259
NO_x	8,003	11,803	9,576	7,235	20,071	9,885	11,574	5,131	1,903	2,553
PM_{10}	1,019	789	2,441	634	549	939	1,493	591	241	500
$PM_{2.5}$	23,105	24,759	33,185	15,381	26,800	27,356	36,745	11,805	7,360	11,544
SO_2	9,844	11,300	13,504	7,551	16,003	11,381	13,067	6,214	5,397	7,207
Loss of biodiversity										
NH_3	5,790	6,483	3,342	1,382	14,710	8,897	10,510	2,297	5,585	1,118
NMVOC	-129	-80	-60	-14	-177	-146	-356	-82	-50	-17
NO_x	1,570	1,276	1,100	229	2,567	2,413	2,435	1,426	941	325
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	583	402	480	32	424	731	944	630	349	69
Regional crops										
NH_3	-281	-97	-133	-125	-207	-211	-106	-149	-11	-318
NMVOC	319	119	432	35	254	228	470	334	51	51
NO_x	356	324	1	214	784	390	629	212	55	149
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	-112	-73	-111	4	-214	-100	-195	-127	-26	-5
Materials										
NH_3	0	0	0	0	0	0	0	0	0	0
NMVOC	0	0	0	0	0	0	0	0	0	0
NO_x	116	141	78	82	120	203	156	121	52	88
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	435	355	461	178	387	850	733	425	165	142

SCAP data comes from the NEEDS Project (`https://cordis.europa.eu/project/id/502687/de`). The project page, https://needs-project.org, is no longer available. Data and further documents can be now accessed via the project page of the University of Stuttgart, `https://www.ier.uni-stuttgart.de/forschung/modelle/ecosense/`.

Table B.10: 2020 weighted average of SCAP (€/ton) by impact category and air pollutant (2)

	ES	HU	FI	FR	HR	HU	IE	IT	LT	LU
Human health										
NH_3	6,024	22,941	5,302	14,423	19,968	22,941	3,028	16,842	7,296	29,975
NMVOC	546	810	294	1,178	992	810	859	857	547	2,554
NO_x	3,034	11,998	1,905	10,928	9,590	11,998	4,149	8,406	5,868	11,334
PM_{10}	489	1,119	74	1,040	819	1,119	384	1,073	366	1,355
$PM_{2.5}$	11,273	27,537	4,921	27,382	23,825	27,537	9,386	22,115	10,308	32,757
SO_2	7,391	10,882	3,742	10,548	11,005	10,882	7,651	10,455	6,809	14,702
Loss of biodiversity										
NH_3	2,705	5,335	3,090	5,224	7,844	5,335	635	9,755	3,905	11,331
NMVOC	-43	-82	-55	-95	-100	-82	-34	-130	-49	-136
NO_x	851	1,822	1,266	1,570	2,167	1,822	668	1,894	940	2,541
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	197	475	641	950	562	475	251	265	241	996
Regional crops										
NH_3	-451	-280	-4	-529	-336	-280	-279	-447	-19	-285
NMVOC	139	144	50	376	234	144	206	327	59	564
NO_x	438	659	59	389	1,121	659	438	590	171	891
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	-80	-34	-31	-162	-108	-34	-112	-62	-75	-261
Materials										
NH_3	0	0	0	0	0	0	0	0	0	0
NMVOC	0	0	0	0	0	0	0	0	0	0
NO_x	31	298	36	126	120	298	53	93	124	175
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	69	817	144	420	387	817	118	188	324	755

SCAP data comes from the NEEDS Project (https://cordis.europa.eu/project/id/502687/de). The project page, https://needs-project.org, is no longer available. Data and further documents can be now accessed via the project page of the University of Stuttgart, https://www.ier.uni-stuttgart.de/forschung/modelle/ecosense/.

Table B.11: 2020 weighted average of SCAP (€/ton) by impact category and air pollutant (3)

	LV	NL	NO	PL	PT	RO	SE	SI	SK	UK
Human health										
NH_3	8,096	28,196	4,273	16,194	4,958	11,039	10,224	22,073	25,327	21,596
NMVOC	497	2,038	461	758	521	489	482	1,399	653	1,093
NO_x	3,995	8,678	3,585	6,510	916	8,508	3,693	9,935	10,156	4,807
PM_{10}	348	2,388	191	1,012	328	917	170	843	928	1,136
$PM_{2.5}$	8,838	36,246	6,012	24,798	7,080	18,976	6,421	23,387	23,614	20,252
SO_2	5,891	12,927	2,093	10,981	4,831	9,108	4,833	12,333	10,576	8,858
Loss of biodiversity										
NH_3	5,220	5,929	1,399	6,486	1,737	3,963	2,403	13,424	9,157	1,042
NMVOC	-59	-107	-74	-90	-17	-36	-68	-150	-99	-53
NO_x	994	1,760	825	1,781	270	675	1,638	2,965	1,656	1,020
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	249	1,223	463	-54	86	101	967	748	524	377
Regional crops										
NH_3	-14	-279	-36	-160	-361	-192	-33	-321	-216	-406
NMVOC	67	645	146	192	91	75	111	262	156	521
NO_x	60	-263	360	236	102	326	191	922	644	-30
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	-39	-200	-47	-13	-42	-9	-74	-189	-47	-102
Materials										
NH_3	0	0	0	0	0	0	0	0	0	0
NMVOC	0	0	0	0	0	0	0	0	0	0
NO_x	78	137	120	220	19	222	53	215	273	70
PM_{10}	0	0	0	0	0	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	216	827	387	880	49	644	186	576	813	320

SCAP data comes from the NEEDS Project (`https://cordis.europa.eu/project/id/502687/de`). The project page, https://needs-project.org, is no longer available. Data and further documents can be now accessed via the project page of the University of Stuttgart, `https://www.ier.uni-stuttgart.de/forschung/modelle/ecosense/`.

Table B.12: Adding AP taxation to existing CO_2 taxation

	0%	25%	50%	100%	200%	400%	800%
Accumulated cost (billion €)							
System cost	8,263	8,097	7,936	7,697	7,516	7,372	7,391
	(2,622)	(2,584)	(2,558)	(2,520)	(2,482)	(2,464)	(2,531)
External cost	717	827	925	1,118	1,262	1,374	1,308
	(286)	(312)	(330)	(364)	(405)	(437)	(412)
ECC	281	463	637	923	1,103	1,247	1,219
	(194)	(234)	(264)	(311)	(360)	(401)	(385)
ECAP	435	364	288	195	158	127	89
	(92)	(78)	(66)	(53)	(45)	(36)	(27)
Taxes	281	554	781	1,118	1,420	1,756	1,930
	(194)	(253)	(297)	(364)	(450)	(546)	(604)
Social cost	8,980	8,924	8,860	8,815	8,778	8,746	8,698
	(2,908)	(2,895)	(2,888)	(2,884)	(2,887)	(2,901)	(2,944)
Private cost	8,544	8,651	8,717	8,815	8,937	9,128	9,321
	(2,816)	(2,837)	(2,855)	(2,884)	(2,932)	(3,010)	(3,135)
Accumulated and average emissions							
CO2 (Gt)	3.3	4.6	5.7	7.4	8.7	9.8	9.5
CO2 (ton/GWh)	21.25	29.32	36.34	47.36	55.70	62.55	60.74
AP (Mt)	27.0	22.7	18.9	13.7	11.2	9.5	7.3
AP (ton/MWh)	172.94	145.60	121.07	87.39	71.43	60.77	46.44
Average cost (€/MWh)							
System cost	52.89	51.83	50.80	49.27	48.11	47.19	47.31
External cost	4.59	5.30	5.92	7.16	8.08	8.80	8.37
ECC	1.80	2.97	4.08	5.91	7.06	7.98	7.80
ECAP	2.79	2.33	1.84	1.25	1.01	0.81	0.57
Taxes	1.80	3.55	5.00	7.16	9.09	11.24	12.35
Social cost	57.48	57.12	56.72	56.43	56.19	55.98	55.68
Private cost	54.69	55.38	55.80	56.43	57.21	58.43	59.66

All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand. Note that the underlying objective is to minimize the sum of system cost and taxes (in net present value terms) because taxes are cost for firms.

Table B.13: Adding CO_2 taxation to existing AP taxation

	0%	25%	50%	100%	200%	400%	800%
Accumulated cost (billion €)							
System cost	6,475	6,353	6,411	7,697	9,075	9,288	9,495
	(1,939)	(1,973)	(2,059)	(2,520)	(3,073)	(3,246)	(3,436)
External cost	5,890	4,641	3,586	1,118	-149	-366	-528
	(1,432)	(1,161)	(944)	(364)	(-11)	(-77)	(-123)
ECC	5,547	4,372	3,375	923	-742	-948	-1,056
	(1,340)	(1,089)	(884)	(311)	(-170)	(-241)	(-271)
ECAP	343	269	211	195	594	582	528
	(92)	(72)	(59)	(53)	(159)	(164)	(149)
Taxes	343	1,362	1,898	1,118	-891	-3,210	-7,922
	(92)	(344)	(502)	(364)	(-181)	(-800)	(-2,023)
Social cost	12,365	10,994	9,997	8,815	8,926	8,922	8,967
	(3,370)	(3,135)	(3,003)	(2,884)	(3,062)	(3,169)	(3,313)
Private cost	6,819	7,715	8,310	8,815	8,184	6,078	1,573
	(2,030)	(2,318)	(2,561)	(2,884)	(2,892)	(2,446)	(1,413)
Accumulated and average emissions							
CO2 (Gt)	38.8	31.0	24.4	7.4	-5.1	-6.8	-7.6
CO2 (ton/GWh)	248.29	198.16	155.99	47.36	-32.73	-43.28	-48.42
AP (Mt)	23.1	17.8	14.0	13.7	41.9	41.0	37.4
AP (ton/MWh)	148.00	113.87	89.53	87.39	268.31	262.32	239.44
Average cost (€/MWh)							
System cost	41.45	40.66	41.04	49.27	58.09	59.45	60.78
External cost	37.70	29.71	22.95	7.16	-0.95	-2.34	-3.38
ECC	35.50	27.98	21.60	5.91	-4.75	-6.07	-6.76
ECAP	2.20	1.72	1.35	1.25	3.80	3.73	3.38
Taxes	2.20	8.72	12.15	7.16	-5.70	-20.55	-50.71
Social cost	79.15	70.37	63.99	56.43	57.14	57.11	57.40
Private cost	43.65	49.38	53.19	56.43	52.39	38.90	10.07

All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand. Note that the underlying objective is to minimize the sum of system cost and taxes (in net present value terms) because taxes are cost for firms. Total cost contain the social planner perspective.

B.2.7 Robustness

Technology boost

Table B.14 shows the total theoretical potential by wind resource class as well as corresponding average (potential-weighted) full-load hours (FLH) for wind onshore (see Table B.15 for country-specific potentials). Wind offshore is less relevant in the technology mix. We thus refrain from showing it here (see Tables B.16 and B.17 for details). Observe that total wind onshore potential in the *high* resource class is 585 GW. The potential above 3,000 FLH is just 275 GW. The technology boost increases this potential to 946 GW, whereas FLH increase by 23% in the *high* class and by 49% in the *mid* class.

Table B.14: Potential and full-load hours of wind onshore by resource class (low, mid, high) without and with technology boost

Resource class	low	mid	high
Total potential (GW)	585	1,756	585
Potential (GW) $\geq$ 3000 FLH without boost	0	0	275
Potential (GW) $\geq$ 3000 FLH with boost	50	487	409
Average FLH without boost	1,089	1,725	2,898
Average FLH with boost	1,776	2,578	3,558
Difference in FLH	63.08%	49.49%	22.78%

Table B.15: Potential (GW) of wind technologies by country and resource class (low, mid, high)

	Wind offshore			Wind onshore		
	low	mid	high	low	mid	high
Austria				10	30	10
Belgium	1	2	1	3	9	3
Bulgaria	12	36	12	14	43	14
Croatia	19	57	19	7	22	7
Czech Republic				10	29	10
Denmark	36	108	36	5	16	5
Estonia	13	38	13	5	16	5
Finland	27	82	27	40	119	40
France	119	358	119	71	214	71
Germany	19	58	19	43	128	43
Greece	167	502	167	17	50	17
Hungary				12	36	12
Ireland	148	444	148	9	28	9
Italy	178	535	178	37	111	37
Latvia	10	30	10	8	24	8
Lithuania	2	7	2	8	25	8
Luxembourg				0	1	0
Netherlands	22	67	22	4	12	4
Norway	321	963	321	35	106	35
Poland	10	31	10	40	119	40
Portugal	110	329	110	12	36	12
Romania	10	31	10	31	92	31
Slovak Republic				6	18	6
Slovenia	0	0	0	2	7	2
Spain	195	585	195	67	201	67
Sweden	53	159	53	53	158	53
Switzerland				5	14	5
United Kingdom	252	756	252	31	92	31
Sum	1,724	5,178	1,724	585	1,756	585

Table B.16: Full-load hours of wind technologies by resource class (low, mid, high) without technology boost

	Wind offshore			Wind onshore		
	low	mid	high	low	mid	high
Austria				558	1,675	2,814
Belgium	2,758	2,763	3,255	2,197	2,292	2,930
Bulgaria	594	1,203	1,523	479	1,337	2,555
Croatia	462	1,107	915	284	619	2,288
Czech Republic				1,894	2,326	2,812
Denmark	2,800	3,312	4,106	1,376	2,764	2,992
Estonia	2,248	2,160	3,420	1,299	1,836	2,903
Finland	1,151	2,033	2,683	742	940	3,462
France	1,671	2,735	3,414	1,462	2,003	2,889
Germany	2,617	3,190	3,267	1,757	2,105	2,403
Greece	610	1,440	2,133	259	718	2,201
Hungary				637	848	2,686
Ireland	2,061	3,557	4,046	2,131	2,682	3,324
Italy	664	979	956	255	970	1,849
Latvia	1,809	2,833	3,375	648	2,265	2,704
Lithuania	1,885	2,708	1,881	485	1,580	2,317
Luxembourg				1,862	2,087	2,254
Netherlands	2,959	3,116	3,728	1,929	2,135	2,513
Norway	1,114	2,218	2,070	664	2,317	3,303
Poland	2,196	2,751	3,149	1,883	2,032	3,406
Portugal	1,368	1,632	2,211	620	1,619	2,821
Romania	1,112	1,336	1,667	512	1,010	2,518
Slovak Republic				679	1,620	2,834
Slovenia	685	685	457	331	894	1,722
Spain	752	1,084	1,574	1,602	2,328	3,295
Sweden	709	1,391	3,003	325	947	3,258
Switzerland				1,499	1,793	2,501
United Kingdom	2,912	3,150	4,148	1,901	2,700	3,019
Average	1,450	2,135	2,601	1,089	1,725	2,898

Table B.17: Full-load hours of wind technologies by resource class (low, mid, high) with technology boost

	Wind offshore			Wind onshore		
	low	mid	high	low	mid	high
Austria				831	2,719	3,753
Belgium	2,964	2,970	3,489	3,269	3,247	3,616
Bulgaria	881	1,333	1,685	732	2,120	3,242
Croatia	893	923	996	472	966	2,975
Czech Republic				2,722	3,178	3,834
Denmark	3,037	3,567	4,353	1,876	4,083	4,443
Estonia	2,459	2,978	3,654	1,888	2,573	4,328
Finland	1,190	1,695	2,901	1,419	1,776	3,886
France	1,833	2,964	3,638	3,053	3,003	3,708
Germany	2,836	2,573	3,661	2,893	2,977	3,003
Greece	773	1,270	2,318	456	1,060	2,896
Hungary				965	1,271	3,575
Ireland	2,217	3,980	4,214	2,797	3,737	3,895
Italy	735	1,058	1,886	394	1,498	2,401
Latvia	1,970	3,065	3,607	1,012	3,550	3,664
Lithuania	2,044	2,891	3,205	766	2,644	3,216
Luxembourg				2,523	2,660	2,903
Netherlands	3,175	3,338	3,956	2,843	3,251	3,331
Norway	1,244	1,843	2,167	940	3,271	3,835
Poland	2,110	2,973	3,390	2,873	3,263	4,314
Portugal	1,237	1,970	2,413	968	2,847	3,646
Romania	1,240	1,583	1,844	832	1,752	2,881
Slovak Republic				1,010	2,209	3,652
Slovenia	761	761	507	515	1,509	2,417
Spain	832	1,511	2,499	2,578	3,031	3,928
Sweden	796	1,796	3,200	550	1,770	3,704
Switzerland				2,141	2,520	2,838
United Kingdom	3,127	3,375	4,324	2,387	3,642	3,615
Average	1,577	2,230	2,937	1,776	2,578	3,558

Technology boost and air pollution emission factors

See visualization in Figure B.3.

Table B.18: Sensitivity to air pollution emission factors and the technology boost (full results)

	AP taxation			CO_2 and AP taxation			Techn.
	low	mid	high	low	mid	high	boost
Accumulated generation (TWh)							
Wind	29,698	30,376	31,291	68,244	68,530	69,174	81,851
Solar	5,285	5,498	5,813	15,664	15,468	15,759	13,808
Nuclear	8,762	8,908	9,300	15,811	17,109	19,100	8,453
CCS	0	0	0	38,805	37,087	31,230	34,609
Accumulated demand (TWh) = 156,224							
Accumulated cost (billion €)							
System cost	6,469	6,475	6,474	7,734	7,697	7,546	7,184
	(1,938)	(1,939)	(1,949)	(2,522)	(2,520)	(2,484)	(2,408)
External cost	5,983	5,890	5,859	1,065	1,118	1,345	1,129
	(1,442)	(1,432)	(1,418)	(353)	(364)	(428)	(369)
ECC	5,690	5,547	5,370	895	923	1,086	948
	(1,361)	(1,340)	(1,287)	(307)	(311)	(354)	(316)
ECAP	293	343	490	170	195	259	180
	(81)	(92)	(131)	(47)	(53)	(75)	(53)
Taxes	293	343	490	1,065	1,118	1,345	1,129
	(81)	(92)	(131)	(353)	(364)	(428)	(369)
Social cost	12,452	12,365	12,334	8,799	8,815	8,890	8,313
	(3,380)	(3,370)	(3,367)	(2,875)	(2,884)	(2,912)	(2,777)
Private cost	6,762	6,819	6,964	8,799	8,815	8,890	8,313
	(2,018)	(2,030)	(2,080)	(2,875)	(2,884)	(2,912)	(2,777)
Accumulated and average emissions							
CO_2 (Gt)	39.6	38.8	37.4	7.2	7.4	8.6	7.6
CO_2 (ton/GWh)	253.69	248.29	239.71	46.30	47.36	54.73	48.37
AP (Mt)	20.1	23.1	33.7	11.8	13.7	17.7	12.1
AP (ton/MWh)	128.53	148.00	215.79	75.59	87.39	113.58	77.66
Average cost (€/MWh)							
System cost	41.41	41.45	41.44	49.51	49.27	48.30	45.98
External cost	38.30	37.70	37.51	6.82	7.16	8.61	7.23
ECC	36.42	35.50	34.37	5.73	5.91	6.95	6.07
ECAP	1.88	2.20	3.14	1.09	1.25	1.66	1.16
Taxes	1.88	2.20	3.14	6.82	7.16	8.61	7.23
Social cost	79.70	79.15	78.95	56.32	56.43	56.91	53.21
Private cost	43.28	43.65	44.58	56.32	56.43	56.91	53.21

Low, mid, and high in brackets present the respective air pollution emission factor scenarios. The mid scenario is used for all prior specifications. The low scenario starts at very same 2015 emission factors as the mid scenario but assumed technological progress is higher, so that emission factor decrease more. The high scenario starts at higher 2015 emission factors (less optimistic assumptions about current fleet) and technological progress is less optimistic as well (compared to the mid scenario). The technology boost indeed uses joint CO_2 and air pollution taxation with emission factors from the mid scenario. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand.

Table B.19: Sensitivity to electricity demand (full results)

	NO	AP	CO2	CO2 and AP
Demand 2050 (TWh)	4,135–6,203	4,135–6,203	4,135–6,203	4,135–6,203
Accumulated generation (TWh)	129,930–168,131	129,981–168,248	130,452–168,690	130,523–168,764
Wind	20,541–23,284	27,728–30,376	53,266–65,988	56,144–68,530
Solar	3,840–4,683	4,316–5,498	10,801–14,733	11,693–15,468
Nuclear	7,043–6,971	8,338–8,908	9,097–12,204	10,433–17,109
CCS	0	0	32,484–48,630	25,694–37,087
Sum	31,423–34,938	40,381–44,782	105,648–141,555	103,964–138,195
Accumulated demand (TWh)	120,573–156,224	120,573–156,224	120,573–156,224	120,573–156,224
Accumulated cost (billion €)				
System cost	4,493–5,937	4,794–6,475	6,047–8,263	5,584–7,697
	(1,506–1,888)	(1,531–1,939)	(2,026–2,622)	(1,947–2,520)
External cost	8,162–12,057	4,018–5,890	477–717	835–1,118
	(2,047–2,795)	(1,070–1,432)	(229–286)	(288–364)
ECC	7,185–10,636	3,774–5,547	133–281	694–923
	(1,790–2,449)	(998–1,340)	(156–194)	(246–311)
ECAP	977–1,420	244–343	344–435	141–195
	(257–346)	(72–92)	(73–92)	(42–53)
Taxes	0–0	244–343	133–281	835–1,118
	(0–0)	(72–92)	(156–194)	(288–364)
Social cost	12,656–17,994	8,812–12,365	6,524–8,980	6,419–8,815
	(3,553–4,684)	(2,601–3,370)	(2,254–2,908)	(2,235–2,884)
Private cost	4,493 5,937	5,039 6,819	6,180 8,544	6,419 8,815
	(1,506–1,888)	(1,603–2,030)	(2,181–2,816)	(2,235–2,884)
Accumulated and average emissions				
CO_2 (Gt)	50.85–73.12	27.31–38.79	2.27–3.32	5.69–7.40
CO_2 (ton/GWh)	421.78–468.07	226.49–248.29	18.82–21.25	47.19–47.36
AP (Mt)	60.90–87.91	16.71–23.12	21.28–27.02	9.81–13.65
AP (ton/GWh)	505.09–562.69	138.57–148.00	176.47–172.94	81.34–87.39
Average cost (€/MWh)				
System cost	37.27–38.00	39.76–41.45	50.15–52.89	46.31–49.27
External cost	67.70–77.18	33.33–37.70	3.96–4.59	6.93–7.16
ECC	59.59–68.08	31.30–35.50	1.10–1.80	5.75–5.91
ECAP	8.10–9.09	2.03–2.20	2.85–2.79	1.17–1.25
Taxes	0.00–0.00	2.03–2.20	1.10–1.80	6.93–7.16
Social cost	104.96–115.18	73.09–79.15	54.11–57.48	53.24–56.43
Private cost	37.27–38.00	41.79–43.65	51.26–54.69	53.24–56.43

First row shows 2050 exogenous demand assumption. The first value always refers to 2050 demand of 4,135 TWh and the second one is the default assumption of 6,203 TWh. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand.

Table B.20: Sensitivity to nuclear minimum dispatch (full results)

	NO	NO*	AP	AP*	CO2	CO2*	CO2 & AP	CO2 & AP*
Accumulated generation (TWh)								
Wind	23,284	23,280	30,376	30,342	65,988	65,417	68,530	67,949
Solar	4,683	4,672	5,498	5,499	14,733	14,669	15,468	15,432
Nuclear	6,971	6,979	8,908	8,925	12,204	12,668	17,109	17,551
CCS	0	0	0	0	48,630	48,780	37,087	37,308
Sum	34,938	34,931	44,782	44,767	141,555	141,534	138,195	138,239
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	5,937	6,475	6,476	8,263	8,275	7,697	7,705
	(1,888)	(1,888)	(1,939)	(1,939)	(2,622)	(2,625)	(2,520)	(2,522)
External cost	12,057	12,056	5,890	5,891	717	713	1,118	1,118
	(2,795)	(2,795)	(1,432)	(1,432)	(286)	(285)	(364)	(364)
ECC	10,636	10,636	5,547	5,547	281	275	923	922
	(2,449)	(2,449)	(1,340)	(1,340)	(194)	(192)	(311)	(311)
ECAP	1,420	1,420	343	343	435	438	195	196
	(346)	(346)	(92)	(92)	(92)	(93)	(53)	(53)
Taxes	0	0	343	343	281	275	1,118	1,118
	(0)	(0)	(92)	(92)	(194)	(192)	(364)	(364)
Social cost	17,994	17,993	12,365	12,366	8,980	8,988	8,815	8,823
	(4,684)	(4,684)	(3,370)	(3,371)	(2,908)	(2,910)	(2,884)	(2,885)
Private cost	5,937	5,937	6,819	6,819	8,544	8,550	8,815	8,823
	(1,888)	(1,888)	(2,030)	(2,030)	(2,816)	(2,817)	(2,884)	(2,885)
Accumulated and average emissions								
CO_2 (Gt)	73.1	73.1	38.8	38.8	3.3	3.3	7.4	7.4
CO_2 (ton/GWh)	468.07	468.04	248.29	248.33	21.25	20.99	47.36	47.32
AP (Mt)	87.9	87.9	23.1	23.1	27.0	27.2	13.7	13.7
AP (ton/MWh)	562.69	562.59	148.00	148.03	172.94	174.30	87.39	87.66
Average cost (€/MWh)								
System cost	38.00	38.00	41.45	41.45	52.89	52.97	49.27	49.32
External cost	77.18	77.17	37.70	37.71	4.59	4.57	7.16	7.16
ECC	68.08	68.08	35.50	35.51	1.80	1.76	5.91	5.90
ECAP	9.09	9.09	2.20	2.20	2.79	2.80	1.25	1.25
Taxes	0.00	0.00	2.20	2.20	1.80	1.76	7.16	7.16
Social cost	115.18	115.18	79.15	79.16	57.48	57.53	56.43	56.48
Private cost	38.00	38.00	43.65	43.65	54.69	54.73	56.43	56.48

The columns with * show outcomes applying nuclear minimum dispatch. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand.

Table B.21: Technology cost uncertainty analysis for CO_2 and AP taxation, $\sigma = 0.1$ (full results)

	Joint	Min	Max	Med	Mea	SD	CI (95%)	
Accumulated generation (TWh)								
Wind	68,530	60,164	76,060	68,553	68,313	3,041	67,710–68,917	Yes
Solar	15,468	11,905	18,387	15,459	15,404	1,364	15,133–15,674	Yes
Nuclear	17,109	8,591	31,083	17,214	17,253	4,803	16,299–18,206	Yes
CCS	37,087	27,858	48,734	36,512	37,122	4,666	36,196–38,048	Yes
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	7,399	7,971	7,676	7,689	126	7,664–7,715	Yes
	(2,520)	(2,438)	(2,582)	(2,518)	(2,516)	(30)	(2,510–2,522)	(Yes)
External cost	1,118	800	1,409	1,133	1,129	113	1,106–1,151	Yes
	(364)	(285)	(431)	(364)	(365)	(29)	(359–371)	(Yes)
ECC	923	563	1,211	937	932	124	908–957	Yes
	(311)	(226)	(378)	(313)	(312)	(31)	(306–318)	(Yes)
ECAP	195	158	242	194	196	17	193–200	Yes
	(53)	(46)	(61)	(52)	(53)	(3)	(52–54)	(Yes)
Taxes	1,118	800	1,409	1,133	1,129	113	1,106–1,151	Yes
	(364)	(285)	(431)	(364)	(365)	(29)	(359–371)	(Yes)
Social cost	7,055	8,199	9,380	8,808	8,818	102	8,798–8,838	Yes
	(2,884)	(2,724)	(3,013)	(2,882)	(2,881)	(24)	(2,876–2,886)	(Yes)
Private cost	7,055	8,199	9,380	8,808	8,818	102	8,798–8,838	Yes
	(2,884)	(2,724)	(3,013)	(2,882)	(2,881)	(24)	(2,876–2,886)	(Yes)
Accumulated and average emissions								
CO_2 (Gt)	7.40	4.91	9.37	7.48	7.45	0.87	7.28 – 7.62	Yes
CO_2 (ton/GWh)	47.36	31.45	60.01	47.87	47.69	5.57	46.59–48.80	Yes
AP (Mt)	13.65	11.01	17.20	13.43	13.66	1.28	13.40–13.91	Yes
AP (ton/MWh)	52.75	46.21	60.72	52.50	52.97	3.02	52.37–53.57	Yes
Average cost (€/MWh)								
System cost	49.27	47.36	51.03	49.13	49.22	0.81	49.06–49.38	Yes
External cost	7.16	5.12	9.02	7.25	7.22	0.73	7.08–7.37	Yes
ECC	5.91	3.60	7.75	6.00	5.97	0.80	5.81–6.13	Yes
ECAP	1.25	1.01	1.55	1.24	1.26	0.11	1.24–1.28	Yes
Taxes	7.16	5.12	9.02	7.25	7.22	0.73	7.08–7.37	Yes
Social cost	56.43	52.48	60.04	56.38	56.45	0.65	56.32–56.57	Yes
Private cost	56.43	52.48	60.04	56.38	56.45	0.65	56.32–56.57	Yes

First column shows the outcome under default parameter assumptions for joint (CO_2 and AP) taxation. The remaining columns shows the minimum (Min), maximum (Max), median (Med), mean (Mea), standard deviation (SD), and the 95% confidence interval (CI (95%)) from the 100 random draws. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand, which is constant across all specifications within the uncertainty analysis. The last column indicates whether or not the outcome from default assumptions lies within the 95% confidence interval.

Table B.22: Technology cost uncertainty analysis for CO_2 taxation, $\sigma = 0.1$ (full results)

	CO_2	Min	Max	Med	Mea	SD	CI (95%)	
Accumulated generation (TWh)								
Wind	65,988	56,820	73,370	65,590	65,384	3,100	64,769–65,999	Yes
Solar	14,733	11,030	17,745	15,023	14,797	1,389	14,521–15,072	Yes
Nuclear	12,204	8,639	26,170	12,204	12,773	3,627	12,053–13,493	Yes
CCS	48,630	38,643	57,169	48,297	48,232	4,108	47,417–49,047	Yes
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	7,957	8,480	8,233	8,238	124	8,214–8,263	Yes
	(2,622)	(2,545)	(2,671)	(2,614)	(2,614)	(28)	(2,609–2,620)	(No)
External cost	717	529	987	735	743	93	724–761	No
	(286)	(232)	(350)	(288)	(291)	(25)	(286–296)	(No)
ECC	281	34	576	297	310	113	287–332	No
	(194)	(124)	(264)	(196)	(199)	(29)	(193–205)	(Yes)
ECAP	435	372	496	433	433	26	428–438	Yes
	(92)	(79)	(107)	(92)	(92)	(6)	(91–93)	(Yes)
Taxes	281	34	576	297	310	113	287–332	No
	(194)	(124)	(264)	(196)	(199)	(29)	(193–205)	(Yes)
Social cost	6,654	8,486	9,467	8,968	8,981	109	8,959–9,003	Yes
	(2,908)	(2,777)	(3,021)	(2,902)	(2,905)	(24)	(2,901–2,910)	(Yes)
Private cost	6,218	7,991	9,056	8,530	8,548	103	8,527–8,568	Yes
	(2,816)	(2,670)	(2,934)	(2,810)	(2,814)	(24)	(2,809–2,818)	(Yes)
Accumulated and average emissions								
CO_2 (Gt)	3.32	1.46	5.39	3.42	3.51	0.83	3.34 – 3.67	No
CO_2 (ton/GWh)	21.25	9.34	34.48	21.90	22.45	5.28	21.40–23.50	No
AP (Mt)	27.02	22.85	31.09	26.85	26.73	1.83	26.37–27.09	Yes
AP (ton/MWh)	92.31	79.50	107.28	91.63	91.85	5.50	90.76–92.94	Yes
Average cost (€/MWh)								
System cost	52.89	50.93	54.28	52.70	52.73	0.79	52.58–52.89	Yes
External cost	4.59	3.39	6.32	4.70	4.75	0.59	4.64–4.87	No
ECC	1.80	0.21	3.69	1.90	1.98	0.73	1.84–2.13	No
ECAP	2.79	2.38	3.17	2.77	2.77	0.17	2.74–2.81	Yes
Taxes	1.80	0.21	3.69	1.90	1.98	0.73	1.84–2.13	No
Social cost	57.48	54.32	60.60	57.40	57.49	0.70	57.35–57.63	Yes
Private cost	54.69	51.15	57.97	54.60	54.72	0.66	54.59–54.85	Yes

First column shows the outcome under default parameter assumptions for joint (CO_2 and AP) taxation. The remaining columns shows the minimum (Min), maximum (Max), median (Med), mean (Mea), standard deviation (SD), and the 95% confidence interval (CI (95%)) from the 100 random draws. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand, which is constant across all specifications within the uncertainty analysis. The last column indicates whether or not the outcome from default assumptions lies within the 95% confidence interval.

Table B.23: Technology cost uncertainty analysis for AP taxation, $\sigma = 0.1$ (full results)

	AP	Min	Max	Med	Mea	SD	CI (95%)	
Accumulated generation (TWh)								
Wind	30,376	18,449	38,517	30,128	30,140	3,269	29,492–30,789	Yes
Solar	5,498	2,804	9,251	5,497	5,577	1,102	5,358–5,795	Yes
Nuclear	8,908	8,795	8,964	8,906	8,906	34	8,899–8,913	Yes
CCS	0							
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	6,332	6,623	6,478	6,475	53	6,465–6,486	Yes
	(1,939)	(1,922)	(1,948)	(1,938)	(1,938)	(6)	(1,937–1,939)	(Yes)
External cost	5,890	5,478	6,509	5,900	5,901	180	5,865–5,937	Yes
	(1,432)	(1,364)	(1,530)	(1,433)	(1,433)	(29)	(1,428–1,439)	(Yes)
ECC	5,547	5,155	6,136	5,556	5,557	171	5,523–5,591	Yes
	(1,340)	(1,276)	(1,434)	(1,341)	(1,342)	(28)	(1,336–1,347)	(Yes)
ECAP	343	323	373	344	344	9	342–345	Yes
	(92)	(88)	(96)	(92)	(92)	(1)	(91–92)	(Yes)
Taxes	343	323	373	344	344	9	342–345	Yes
	(92)	(88)	(96)	(92)	(92)	(1)	(91–92)	(Yes)
Social cost	11,827	11,810	13,131	12,378	12,376	233	12,330–12,422	Yes
	(3,370)	(3,286)	(3,478)	(3,371)	(3,372)	(34)	(3,365–3,378)	(Yes)
Private cost	6,280	6,655	6,996	6,821	6,819	62	6,807–6,831	Yes
	(2,030)	(2,010)	(2,045)	(2,030)	(2,030)	(7)	(2,028–2,031)	(Yes)
Accumulated and average emissions								
CO_2 (Gt)	38.79	36.40	42.37	38.84	38.86	1.04	38.65 – 39.06	Yes
CO_2 (ton/GWh)	248.29	232.97	271.22	248.62	248.73	6.69	247.40–250.05	Yes
AP (Mt)	23.12	21.81	25.21	23.14	23.16	0.58	23.04–23.27	Yes
AP (ton/MWh)	91.54	88.02	96.32	91.52	91.55	1.44	91.26–91.84	Yes
Average cost (€/MWh)								
System cost	41.45	40.53	42.39	41.46	41.45	0.34	41.38–41.52	Yes
External cost	37.70	35.07	41.66	37.77	37.77	1.15	37.54–38.00	Yes
ECC	35.50	33.00	39.27	35.57	35.57	1.10	35.35–35.79	Yes
ECAP	2.20	2.06	2.39	2.20	2.20	0.06	2.19–2.21	Yes
Taxes	2.20	2.06	2.39	2.20	2.20	0.06	2.19–2.21	Yes
Social cost	79.15	75.60	84.05	79.23	79.22	1.49	78.92–79.52	Yes
Private cost	43.65	42.60	44.78	43.66	43.65	0.40	43.57–43.73	Yes

First column shows the outcome under default parameter assumptions for joint (CO_2 and AP) taxation. The remaining columns shows the minimum (Min), maximum (Max), median (Med), mean (Mea), standard deviation (SD), and the 95% confidence interval (CI (95%)) from the 100 random draws. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand, which is constant across all specifications within the uncertainty analysis. The last column indicates whether or not the outcome from default assumptions lies within the 95% confidence interval.

Table B.24: Technology cost uncertainty analysis for no taxation, $\sigma = 0.1$ (full results)

	No	Min	Max	Med	Mea	SD	CI (95%)	
Accumulated generation (TWh)								
Wind	23,284	14,812	33,346	23,050	23,951	3,529	23,251–24,651	Yes
Solar	4,683	3,726	6,632	4,697	4,710	570	4,597–4,823	Yes
Nuclear	6,971	6,058	7,086	6,976	6,905	196	6,866–6,944	No
CCS	0							
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	5,825	6,060	5,944	5,938	45	5,929–5,947	Yes
	(1,888)	(1,868)	(1,922)	(1,890)	(1,891)	(11)	(1,889–1,893)	(No)
External cost	12,057	10,841	12,832	12,086	11,933	407	11,852–12,014	No
	(2,795)	(2,585)	(2,941)	(2,803)	(2,777)	(71)	(2,763–2,791)	(No)
ECC	10,636	9,572	11,340	10,663	10,530	361	10,458–10,602	No
	(2,449)	(2,267)	(2,581)	(2,456)	(2,434)	(63)	(2,421–2,446)	(No)
ECAP	1,420	1,269	1,491	1,425	1,403	46	1,394–1,412	No
	(346)	(318)	(360)	(346)	(343)	(9)	(341–345)	(No)
Taxes	0							
	(0)							
Social cost	17,994	16,665	18,892	18,030	17,871	451	17,782–17,961	No
	(4,684)	(4,454)	(4,863)	(4,694)	(4,668)	(81)	(4,652–4,684)	(No)
Private cost	5,937	5,825	6,060	5,944	5,938	45	5,929–5,947	Yes
	(1,888)	(1,868)	(1,922)	(1,890)	(1,891)	(11)	(1,889–1,893)	(No)
Accumulated and average emissions								
CO_2 (Gt)	73.12	66.50	77.63	73.31	72.49	2.25	72.04 – 72.94	No
CO_2 (ton/GWh)	468.07	425.66	496.91	469.23	464.02	14.41	461.16–466.88	No
AP (Mt)	87.91	79.09	93.12	88.09	86.98	2.83	86.42–87.54	No
AP (ton/MWh)	345.94	318.16	360.42	346.48	343.12	8.52	341.43–344.81	No
Average cost (€/MWh)								
System cost	38.00	37.28	38.79	38.05	38.01	0.29	37.95–38.07	Yes
External cost	77.18	69.39	82.14	77.36	76.38	2.61	75.87–76.90	No
ECC	68.08	61.27	72.59	68.26	67.40	2.31	66.94–67.86	No
ECAP	9.09	8.12	9.55	9.12	8.98	0.30	8.92–9.04	No
Taxes	0.00							
Social cost	115.18	106.68	120.93	115.41	114.39	2.89	113.82–114.97	No
Private cost	38.00	37.28	38.79	38.05	38.01	0.29	37.95–38.07	Yes

First column shows the outcome under default parameter assumptions for joint (CO_2 and AP) taxation. The remaining columns shows the minimum (Min), maximum (Max), median (Med), mean (Mea), standard deviation (SD), and the 95% confidence interval (CI (95%)) from the 100 random draws. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand, which is constant across all specifications within the uncertainty analysis. The last column indicates whether or not the outcome from default assumptions lies within the 95% confidence interval.

Table B.25: Technology cost uncertainty analysis for CO_2 and AP taxation, $\sigma = 0.2$ (full results)

	Joint	Min	Max	Med	Mea	SD	CI (95%)	
Accumulated generation (TWh)								
Wind	68,530	52,333	79,811	67,734	67,911	5,649	66,790–69,032	Yes
Solar	15,468	6,862	20,118	15,003	14,863	2,549	14,357–15,368	No
Nuclear	17,109	8,524	39,022	18,224	18,639	7,732	17,104–20,173	Yes
CCS	37,087	7,229	52,736	37,485	36,443	9,255	34,607–38,279	Yes
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	6,794	8,189	7,690	7,663	271	7,609–7,717	Yes
	(2,520)	(2,275)	(2,638)	(2,514)	(2,505)	(65)	(2,493–2,518)	(No)
External cost	1,118	742	1,693	1,104	1,130	216	1,088–1,173	Yes
	(364)	(274)	(506)	(360)	(365)	(54)	(355–376)	(Yes)
ECC	923	498	1,534	924	933	236	886–980	Yes
	(311)	(213)	(461)	(309)	(313)	(58)	(301–324)	(Yes)
ECAP	195	116	275	195	198	32	191–204	Yes
	(53)	(37)	(65)	(53)	(53)	(6)	(52–54)	(Yes)
Taxes	1,118	742	1,693	1,104	1,130	216	1,088–1,173	Yes
	(364)	(274)	(506)	(360)	(365)	(54)	(355–376)	(Yes)
Social cost	7,055	7,536	9,882	8,794	8,793	218	8,750–8,837	Yes
	(2,884)	(2,549)	(3,144)	(2,874)	(2,871)	(50)	(2,861–2,881)	(No)
Private cost	7,055	7,536	9,882	8,794	8,793	218	8,750–8,837	Yes
	(2,884)	(2,549)	(3,144)	(2,874)	(2,871)	(50)	(2,861–2,881)	(No)
Accumulated and average emissions								
CO_2 (Gt)	7.40	2.00	11.69	7.38	7.46	1.65	7.13 – 7.78	Yes
CO_2 (ton/GWh)	47.36	28.77	74.80	47.23	47.73	10.57	45.64–49.83	Yes
AP (Mt)	13.65	7.76	19.05	13.88	13.70	2.45	13.21–14.19	Yes
AP (ton/MWh)	52.75	37.20	65.30	52.77	52.97	5.73	51.84–54.11	Yes
Average cost (€/MWh)								
System cost	49.27	43.49	52.42	49.23	49.05	1.73	48.71–49.39	Yes
External cost	7.16	4.75	10.83	7.07	7.24	1.38	6.96–7.51	Yes
ECC	5.91	3.19	9.82	5.91	5.97	1.51	5.67–6.27	Yes
ECAP	1.25	0.74	1.76	1.25	1.26	0.21	1.22–1.31	Yes
Taxes	7.16	4.75	10.83	7.07	7.24	1.38	6.96–7.51	Yes
Social cost	56.43	48.24	63.25	56.29	56.29	1.40	56.01–56.56	Yes
Private cost	56.43	48.24	63.25	56.29	56.29	1.40	56.01–56.56	Yes

First column shows the outcome under default parameter assumptions for joint (CO_2 and AP) taxation. The remaining columns shows the minimum (Min), maximum (Max), median (Med), mean (Mea), standard deviation (SD), and the 95% confidence interval (CI (95%)) from the 100 random draws. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand, which is constant across all specifications within the uncertainty analysis. The last column indicates whether or not the outcome from default assumptions lies within the 95% confidence interval.

Table B.26: Technology cost uncertainty analysis for CO_2 taxation, $\sigma = 0.2$ (full results)

	CO_2	Min	Max	Med	Mea	SD	CI (95%)	
Accumulated generation (TWh)								
Wind	65,988	49,715	76,846	65,171	65,144	5,803	63,992–66,295	Yes
Solar	14,733	6,419	19,193	14,431	14,230	2,518	13,731–14,730	No
Nuclear	12,204	8,463	34,304	12,883	14,829	6,263	13,586–16,071	No
CCS	48,630	14,971	60,300	48,313	46,576	8,603	44,869–48,283	No
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	6,933	8,741	8,207	8,172	297	8,113–8,231	No
	(2,622)	(2,322)	(2,731)	(2,610)	(2,599)	(67)	(2,585–2,612)	(No)
External cost	717	438	1,456	711	765	206	724–806	No
	(286)	(215)	(446)	(284)	(295)	(50)	(285–305)	(Yes)
ECC	281	-36	1,237	285	345	261	293–397	No
	(194)	(109)	(386)	(195)	(205)	(61)	(193–217)	(Yes)
ECAP	435	137	511	442	420	63	407–432	No
	(92)	(43)	(110)	(94)	(90)	(12)	(87–92)	(No)
Taxes	281	-36	1,237	285	345	261	293–397	No
	(194)	(109)	(386)	(195)	(205)	(61)	(193–217)	(Yes)
Social cost	6,654	7,371	10,197	8,919	8,937	226	8,892–8,982	Yes
	(2,908)	(2,537)	(3,177)	(2,894)	(2,894)	(51)	(2,883–2,904)	(No)
Private cost	6,218	6,898	9,978	8,492	8,517	206	8,477–8,558	Yes
	(2,816)	(2,431)	(3,118)	(2,804)	(2,804)	(49)	(2,794–2,814)	(No)
Accumulated and average emissions								
CO_2 (Gt)	3.32	0.99	9.59	3.34	3.73	1.82	3.37 – 4.09	No
CO_2 (ton/GWh)	21.25	6.33	61.36	21.36	23.86	11.65	21.54–26.17	No
AP (Mt)	27.02	8.74	31.85	27.43	25.94	4.14	25.12–26.76	No
AP (ton/MWh)	92.31	42.88	109.66	93.65	89.62	12.34	87.18–92.07	No
Average cost (€/MWh)								
System cost	52.89	44.38	55.95	52.53	52.31	1.90	51.93–52.69	No
External cost	4.59	2.80	9.32	4.55	4.90	1.32	4.63–5.16	No
ECC	1.80	-0.23	7.92	1.82	2.21	1.67	1.88–2.54	No
ECAP	2.79	0.88	3.27	2.83	2.69	0.40	2.61–2.77	No
Taxes	1.80	-0.23	7.92	1.82	2.21	1.67	1.88–2.54	No
Social cost	57.48	47.18	65.27	57.09	57.21	1.45	56.92–57.49	Yes
Private cost	54.69	44.15	63.87	54.36	54.52	1.32	54.26–54.78	Yes

First column shows the outcome under default parameter assumptions for joint (CO_2 and AP) taxation. The remaining columns shows the minimum (Min), maximum (Max), median (Med), mean (Mea), standard deviation (SD), and the 95% confidence interval (CI (95%)) from the 100 random draws. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand, which is constant across all specifications within the uncertainty analysis. The last column indicates whether or not the outcome from default assumptions lies within the 95% confidence interval.

Table B.27: Technology cost uncertainty analysis for AP taxation, σ = 0.2 (full results)

	AP	Min	Max	Med	Mea	SD	CI (95%)	
Accumulated generation (TWh)								
Wind	30,376	11,381	44,801	30,485	30,079	7,078	28,675–31,483	Yes
Solar	5,498	1,805	13,265	5,513	5,595	2,034	5,192–5,999	Yes
Nuclear	8,908	8,448	8,960	8,895	8,864	97	8,845–8,884	No
CCS	0							
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	6,189	6,793	6,472	6,469	119	6,445–6,492	Yes
	(1,939)	(1,892)	(1,995)	(1,936)	(1,936)	(16)	(1,933–1,939)	(Yes)
External cost	5,890	5,120	6,920	5,886	5,910	390	5,833–5,987	Yes
	(1,432)	(1,311)	(1,621)	(1,431)	(1,436)	(64)	(1,423–1,449)	(Yes)
ECC	5,547	4,816	6,528	5,544	5,566	370	5,493–5,640	Yes
	(1,340)	(1,226)	(1,520)	(1,340)	(1,344)	(61)	(1,332–1,356)	(Yes)
ECAP	343	305	392	342	344	19	340–348	Yes
	(92)	(85)	(101)	(91)	(92)	(3)	(91–92)	(Yes)
Taxes	343	305	392	342	344	19	340–348	Yes
	(92)	(85)	(101)	(91)	(92)	(3)	(91–92)	(Yes)
Social cost	11,827	11,309	13,712	12,358	12,379	508	12,278–12,479	Yes
	(3,370)	(3,203)	(3,615)	(3,367)	(3,372)	(78)	(3,356–3,388)	(Yes)
Private cost	6,280	6,494	7,185	6,814	6,813	138	6,785–6,840	Yes
	(2,030)	(1,977)	(2,096)	(2,027)	(2,028)	(19)	(2,024–2,031)	(Yes)
Accumulated and average emissions								
CO_2 (Gt)	38.79	34.39	45.04	38.79	38.93	2.27	38.48 – 39.38	Yes
CO_2 (ton/GWh)	248.29	220.11	288.28	248.27	249.18	14.53	246.30–252.07	Yes
AP (Mt)	23.12	20.69	26.65	23.12	23.21	1.27	22.96–23.46	Yes
AP (ton/MWh)	91.54	85.37	100.88	91.32	91.64	3.25	91.00–92.28	Yes
Average cost (€/MWh)								
System cost	41.45	39.62	43.48	41.43	41.41	0.76	41.26–41.56	Yes
External cost	37.70	32.78	44.29	37.68	37.83	2.50	37.33–38.33	Yes
ECC	35.50	30.83	41.78	35.49	35.63	2.37	35.16–36.10	Yes
ECAP	2.20	1.95	2.51	2.19	2.20	0.12	2.18–2.23	Yes
Taxes	2.20	1.95	2.51	2.19	2.20	0.12	2.18–2.23	Yes
Social cost	79.15	72.39	87.77	79.10	79.24	3.25	78.59–79.88	Yes
Private cost	43.65	41.57	45.99	43.62	43.61	0.88	43.43–43.78	Yes

First column shows the outcome under default parameter assumptions for joint (CO_2 and AP) taxation. The remaining columns shows the minimum (Min), maximum (Max), median (Med), mean (Mea), standard deviation (SD), and the 95% confidence interval (CI (95%)) from the 100 random draws. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand, which is constant across all specifications within the uncertainty analysis. The last column indicates whether or not the outcome from default assumptions lies within the 95% confidence interval.

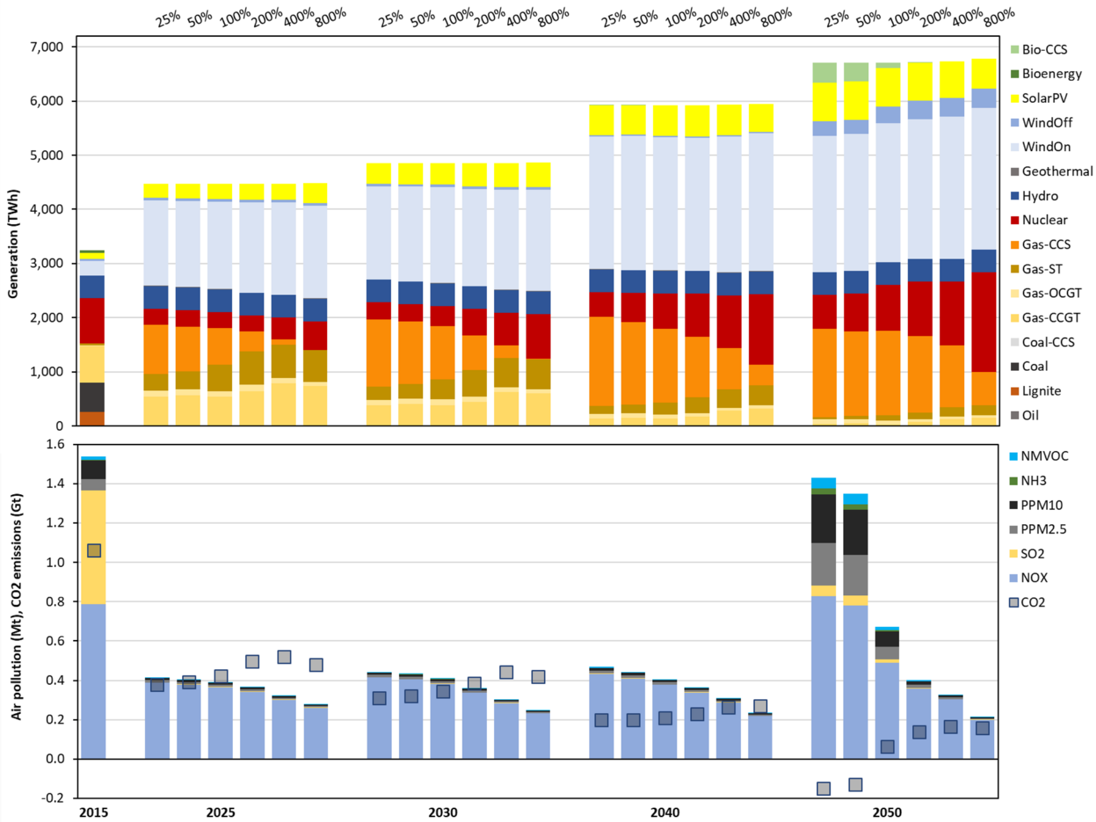
Table B.28: Technology cost uncertainty analysis for no taxation, $\sigma = 0.2$ (full results)

	No	Min	Max	Med	Mea	SD	CI (95%)	
Accumulated generation (TWh)								
Wind	23,284	9,901	38,099	23,520	24,743	6,571	23,439–26,047	No
Solar	4,683	2,903	9,813	4,661	4,795	1,098	4,577–5,013	Yes
Nuclear	6,971	5,173	7,334	6,945	6,718	481	6,622–6,813	No
CCS	0							
Accumulated demand (TWh) = 156,224								
Accumulated cost (billion €)								
System cost	5,937	5,726	6,139	5,935	5,931	89	5,914–5,949	Yes
	(1,888)	(1,840)	(1,944)	(1,889)	(1,890)	(21)	(1,886–1,894)	(Yes)
External cost	12,057	10,215	13,475	11,985	11,799	759	11,648–11,950	No
	(2,795)	(2,475)	(3,047)	(2,784)	(2,755)	(133)	(2,728–2,781)	(No)
ECC	10,636	9,027	11,926	10,570	10,417	674	10,283–10,550	No
	(2,449)	(2,172)	(2,677)	(2,440)	(2,415)	(117)	(2,392–2,438)	(No)
ECAP	1,420	1,188	1,550	1,412	1,383	86	1,365–1,400	No
	(346)	(303)	(370)	(345)	(339)	(16)	(336–343)	(No)
Taxes	0							
	(0)							
Social cost	17,994	15,941	19,615	17,919	17,730	847	17,562–17,898	No
	(4,684)	(4,315)	(4,991)	(4,673)	(4,645)	(153)	(4,614–4,675)	(No)
Private cost	5,937	5,726	6,139	5,935	5,931	89	5,914–5,949	Yes
	(1,888)	(1,840)	(1,944)	(1,889)	(1,890)	(21)	(1,886–1,894)	(Yes)
Accumulated and average emissions								
CO_2 (Gt)	73.12	63.10	81.24	72.74	71.80	4.21	70.96 – 72.63	No
CO_2 (ton/GWh)	468.07	403.90	520.03	465.59	459.57	26.95	454.22–464.91	No
AP (Mt)	87.91	74.42	97.46	87.33	85.93	5.34	84.87–86.99	No
AP (ton/MWh)	345.94	302.62	370.06	344.53	339.49	16.00	336.31–342.66	No
Average cost (€/MWh)								
System cost	38.00	36.65	39.30	37.99	37.97	0.57	37.85–38.08	Yes
External cost	77.18	65.39	86.26	76.71	75.53	4.86	74.56–76.49	No
ECC	68.08	57.78	76.34	67.66	66.68	4.31	65.82–67.53	No
ECAP	9.09	7.61	9.92	9.04	8.85	0.55	8.74–8.96	No
Taxes	0.00							
Social cost	115.18	102.04	125.56	114.70	113.49	5.42	112.42–114.57	No
Private cost	38.00	36.65	39.30	37.99	37.97	0.57	37.85–38.08	Yes

First column shows the outcome under default parameter assumptions for joint (CO_2 and AP) taxation. The remaining columns shows the minimum (Min), maximum (Max), median (Med), mean (Mea), standard deviation (SD), and the 95% confidence interval (CI (95%)) from the 100 random draws. All values refer to accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). Values in parentheses show the net present value. Average cost values calculate from the respective accumulated value divided by demand, which is constant across all specifications within the uncertainty analysis. The last column indicates whether or not the outcome from default assumptions lies within the 95% confidence interval.

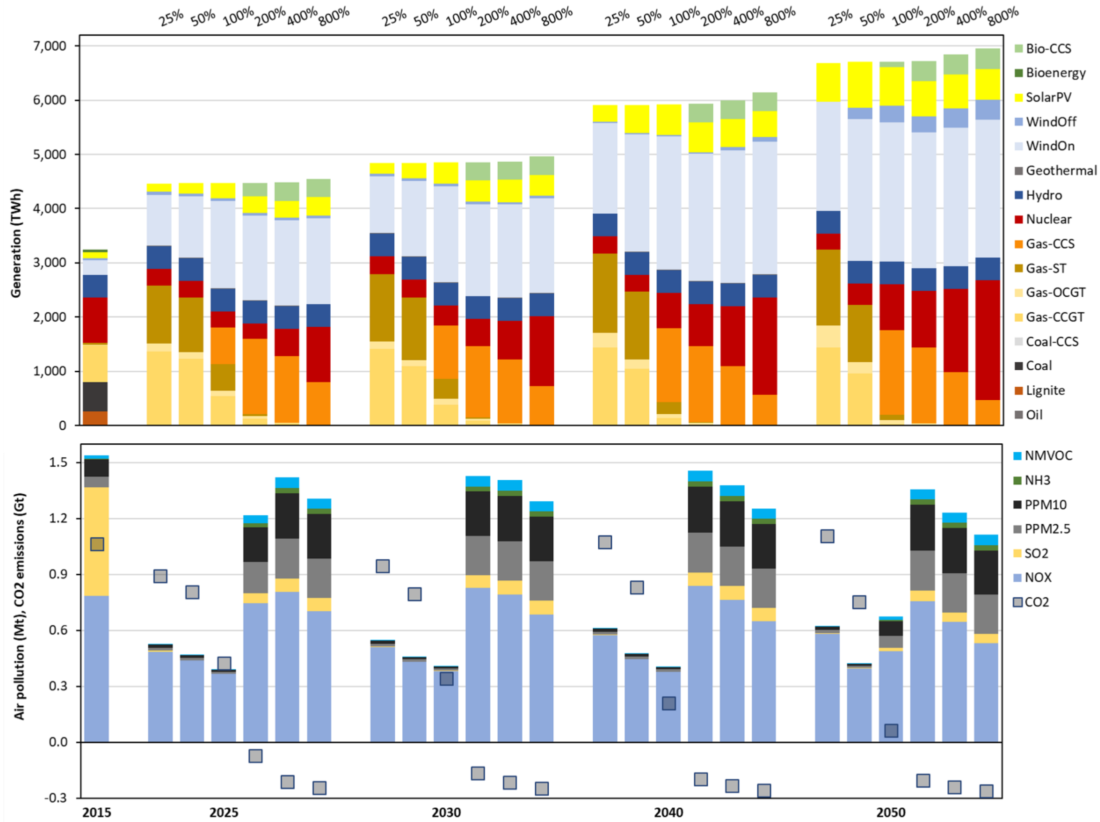
B.3 Figures

Figure B.1: Generation (upper panel) and emission (lower panel) mix for varying SCAP



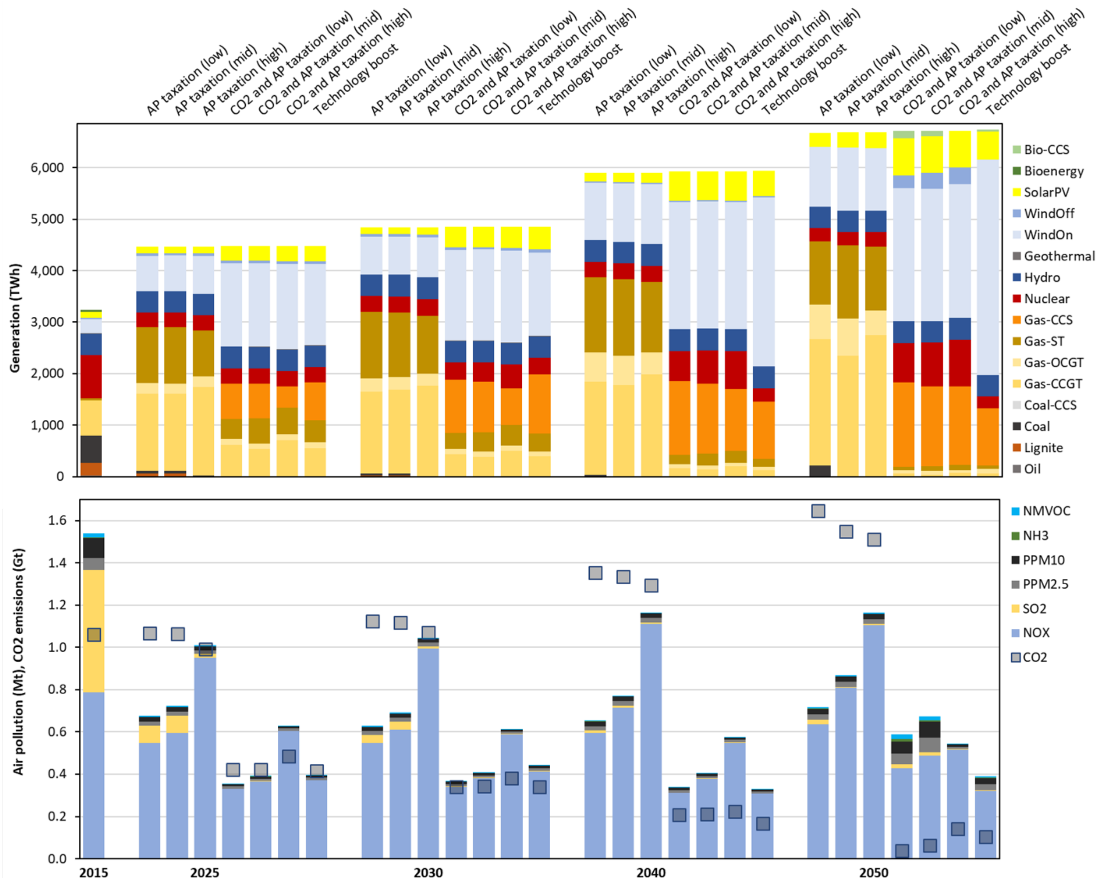
The percentage values reflect a change in SCAP and the respective air pollution taxes from 2025 onward. The SCC and respective carbon tax remains unchanged.

Figure B.2: Generation (upper panel) and emission (lower panel) mix for varying SCC



The percentage values reflect a change in SCC and the respective carbon tax from 2025 onward. The SCAP and respective air pollution taxes remain unchanged.

Figure B.3: Generation (upper panel) and emission (lower panel) mix for air pollution emission factor sensitivity and the technology boost



Low, mid, and high in brackets present the respective air pollution emission factor scenarios. The mid scenario is used for all prior specifications. The low scenario starts at very same 2015 emission factors as the mid scenario but assumed technological progress is higher, so that emission factor decrease more. The high scenario starts at higher 2015 emission factors (less optimistic assumptions about current fleet) and technological progress is less optimistic as well (compared to the mid scenario). The technology boost indeed uses joint CO_2 and air pollution taxation with emission factors from the mid scenario.

C
Supplementary Materials to Chapter 3

C.1 Supplementary information

The treatment variable I calculate the treatment intensity *OUT* as percentage share of blacked-out customer×hours, i.e. as the sum of affected customers[1] over over all hours relative to the sum of tracked customers over all hours[2]:

$$OUT_i = \frac{\sum_h CUST_{i,h}}{\sum_h TRACKED_{i,h}} * 100 \tag{C.1}$$

where *CUST* is the number of customers blacked-out per each hour h of the event period in each ZIP code area i and *TRACKED* is the number of customers tracked per hour and ZIP code. This allows to capture different outage patterns like widespread short outages as well as long lasting concentrated outages. Let for instance the event period be a 24-hour day affecting two ZIP codes A and B, with each 100 customers. For simplicity let us assume that in each hour all of the 100 customers are tracked in both A and B. Let A experience a short but widespread blackout, where over the course of the 24-hour event period 25 customers in total are affected in hour 9, and 23 customers in total were affected in hour 10. In all other hours the number of affected customers is 0. For ZIP code area A OUT_A would therefore record $\frac{(25+23)}{100\times 24} \times 100 = 2\%$ blacked-out customer×hours. Meanwhile, let ZIP code area B experience 2 affected customers for all 24 event hours. OUT_B would therefore also record 2% blacked-out customer-hours.

[1] Remember that this is ZIP code time series data, not household panel data, meaning that I do not know which exact customers are affected from one hour to the next.

[2] Note that the number of tracked customers varies over time.

C.2 Tables

Table C.1: Comparison of potential grid substitutes

	Portable generator	Stand-by generator	Battery for rooftop solar PV
Installation permit required	No	Yes	Yes
Weatherization	No	Yes	Yes
Transfer switch	Optional, manual	Integrated, automatic	Integrated
Professional installation	Optional	Required	Required
Usual power/ energy output	<8-10 kW	8-24+ kW	10-20 kWh (stackable)
Multi-day emergency coverage	Selected appliances*	Entire home*	Up to entire home**
Usual price range	<1,500 USD	2,000-15,000+ USD	15,000+ USD

* Based on 7-12 kW power for emergency use of essential appliances (e.g. from `https://www.hinen.com`, `https://www.electricgeneratorsdirect.com`, `https://diallplumbing.com`)
** Stacked set-up can power a home for multiple days based on average daily electricity consumption of 39 kWh of a Texan household (EIA, 2025). Daily consumption during emergency use can be lower.
Prices are before incentives and tax credits. Information, product characteristics, and price ranges are available from generator production companies, solar PV installation companies, and energy marketplace and information platforms. E.g. `https://www.duromaxpower.com`, `https://www.generac.com`, `https://www.sunenergyguide.com`, `https://www.canarymedia.com`, `https://www.energysage.com`. Generators are usually available to buy at (online) retailers and specialized electricity equipment resellers.

Table C.2: Regressing PV with storage-related permits on PV-related permits without storage

	Dependent variable:
	PVStor
PVnoStor	0.006***
	(0.002)
clust-rob. SE	ZIP
Observations	688
R^2	0.015
Adjusted R^2	0.013
Residual Std. Error	0.525 (df = 686)
F Statistic	10.334*** (df = 1; 686)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table C.3: Treatment effect coefficients for generator-related permits with tertile treatment

	Dependent variable:
	Gen_per10kHH By tertile/FE
Tertile1:T0	−0.065
	(0.847)
Tertile2:T0	0.759
	(1.463)
Tertile3:T0	0.052
	(1.066)
Tertile1:T1	1.706*
	(0.902)
Tertile2:T1	3.642**
	(1.419)
Tertile3:T1	1.961**
	(0.797)
Tertile1:T2	1.794**
	(0.742)
Tertile2:T2	7.470***
	(2.250)
Tertile3:T2	4.576***
	(0.976)
Tertile1:T3	1.882**
	(0.805)
Tertile2:T3	5.632***
	(1.463)
Tertile3:T3	4.950***
	(1.106)
Tertile1:T4	0.783
	(0.825)
Tertile2:T4	4.207***
	(1.545)
Tertile3:T4	3.863***

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	Dependent variable:
	Gen_per10kHH
	By tertile/FE
	(1.190)
Tertile1:T5	1.330*
	(0.660)
Tertile2:T5	4.176***
	(1.408)
Tertile3:T5	2.689***
	(0.815)
Tertile1:T6	0.912
	(0.605)
Tertile2:T6	3.287**
	(1.285)
Tertile3:T6	2.607**
	(0.980)
Tertile1:T7	1.944**
	(0.925)
Tertile2:T7	3.093**
	(1.424)
Tertile3:T7	1.531*
	(0.813)
FE	ZIP
clust-rob. SE	ZIP
Observations	387
R^2	0.717
Adjusted R^2	0.658
Residual Std. Error	2.800 (df = 320)
F Statistic	12.275*** (df = 66; 320)
Note: Based on t-distribution:	*p<0.1; **p<0.05; ***p<0.01

Table C.4: Treatment effect coefficients for PV with storage-related permits with continuous treatment

	Dependent variable:
	PVStor_per10kHH Continuous/FE
PVnoStor_per10kHH	0.005 (0.012)
Out:T0	0.033*** (0.008)
Out:T1	0.063*** (0.008)
Out:T2	0.051*** (0.009)
Out:T3	0.080*** (0.016)
Out:T4	0.039*** (0.008)
Out:T5	0.045*** (0.013)
Out:T6	0.041*** (0.008)
Out:T7	0.018** (0.007)
FE	ZIP
clust-rob. SE	ZIP
Observations	387
R^2	0.416
Adjusted R^2	0.327
Residual Std. Error	1.712 (df = 335)
F Statistic	4.683*** (df = 51; 335)
Note: Based on t-distribution:	*p<0.1; **p<0.05; ***p<0.01

Table C.5: Treatment effect coefficients for PV with storage-related permits with tertile treatment

	Dependent variable:
	PVStor_per10kHH By tertile/FE
PVnoStor_per10kHH	−0.001
	(0.013)
Tertile1:T0	1.101*
	(0.559)
Tertile2:T0	0.973**
	(0.482)
Tertile3:T0	1.094***
	(0.392)
Tertile1:T1	1.393**
	(0.674)
Tertile2:T1	2.155***
	(0.444)
Tertile3:T1	2.054***
	(0.386)
Tertile1:T2	2.426***
	(0.796)
Tertile2:T2	1.417***
	(0.312)
Tertile3:T2	1.777***
	(0.490)
Tertile1:T3	1.720*
	(0.883)
Tertile2:T3	2.259***
	(0.629)
Tertile3:T3	2.456***
	(0.742)
Tertile1:T4	1.065*
	(0.616)
Tertile2:T4	1.652***

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	Dependent variable:
	PVStor_per10kHH
	By tertile/FE
	(0.375)
Tertile3:T4	1.036***
	(0.375)
Tertile1:T5	0.869
	(0.777)
Tertile2:T5	1.511***
	(0.374)
Tertile3:T5	1.894***
	(0.692)
Tertile1:T6	2.472**
	(0.981)
Tertile2:T6	1.237***
	(0.387)
Tertile3:T6	1.547***
	(0.417)
Tertile1:T7	0.044
	(0.717)
Tertile2:T7	0.061
	(0.322)
Tertile3:T7	0.814**
	(0.313)
FE	ZIP
clust-rob. SE	ZIP
Observations	387
R^2	0.462
Adjusted R^2	0.349
Residual Std. Error	1.684 (df = 319)
F Statistic	4.085*** (df = 67; 319)
Note: Based on t-distribution:	*p<0.1; **p<0.05; ***p<0.01

Table C.6: Treatment and spillover effect coefficients for generator-related permits with continuous treatment

	Dependent variable:	
	Gen_per10kHH	
	Continuous/OLS	Continuous/OLS
	(1)	(2)
Out:T0	0.017	0.032**
	(0.015)	(0.015)
Out:T1	0.043**	0.036**
	(0.018)	(0.018)
Out:T2	0.130***	0.123***
	(0.031)	(0.030)
Out:T3	0.124***	0.117***
	(0.025)	(0.025)
Out:T4	0.083***	0.075**
	(0.031)	(0.030)
Out:T5	0.064***	0.056***
	(0.019)	(0.019)
Out:T6	0.053**	0.046*
	(0.024)	(0.024)
Out:T7	0.027*	0.019
	(0.016)	(0.016)
Spill_dist_scaled:Post	0.033***	
	(0.011)	
Spill_SCI_scaled:Post		0.024***
		(0.005)
FE	-	-
clust-rob. SE	ZIP	ZIP
Spillovers	Distance	SCI
Observations	387	387
R^2	0.425	0.443
Adjusted R^2	0.402	0.420
Residual Std. Error (df = 371)	3.707	3.648
F Statistic (df = 15; 371)	18.270***	19.650***
Note: Based on t-distribution		*p<0.1; **p<0.05; ***p<0.01

Table C.7: Treatment and spillover effect coefficients for generator-related permits with continuous treatment (conventional p-values)

	Dependent variable:	
	Gen_per10kHH	
	Continuous/OLS	Continuous/OLS
	(1)	(2)
Out:T0	0.017	0.032**
	(0.015)	(0.015)
Out:T1	0.043**	0.036**
	(0.018)	(0.018)
Out:T2	0.130***	0.123***
	(0.031)	(0.030)
Out:T3	0.124***	0.117***
	(0.025)	(0.025)
Out:T4	0.083***	0.075**
	(0.031)	(0.030)
Out:T5	0.064***	0.056***
	(0.019)	(0.019)
Out:T6	0.053**	0.046*
	(0.024)	(0.024)
Out:T7	0.027*	0.019
	(0.016)	(0.016)
Spill_dist_scaled:Post	0.033***	
	(0.011)	
Spill_SCI_scaled:Post		0.024***
		(0.005)
FE	-	-
clust-rob. SE	ZIP	ZIP
Spillovers	Distance	SCI
Observations	387	387
R^2	0.425	0.443
Adjusted R^2	0.402	0.420
Residual Std. Error (df = 371)	3.707	3.648
F Statistic (df = 15; 371)	18.270***	19.650***
Note:		*p<0.1; **p<0.05; ***p<0.01

C.3 Figures

Figure C.1: Hourly outage intensity by ZIP code from Feb 15 to Feb 18

Based on data from Bluefire Studios LLC (2023).

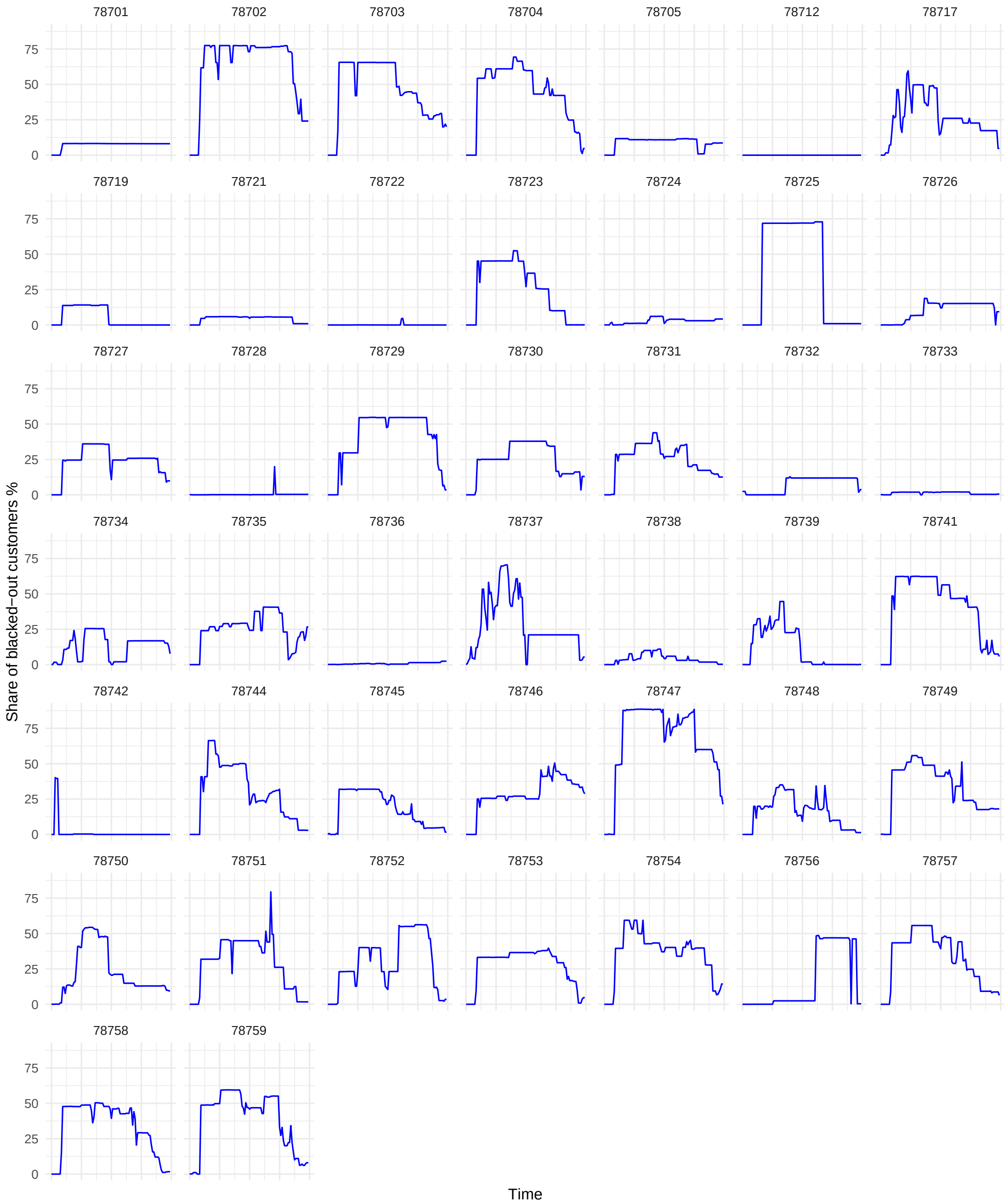


Figure C.2: Density plot of outage intensity across the ZIP code sample

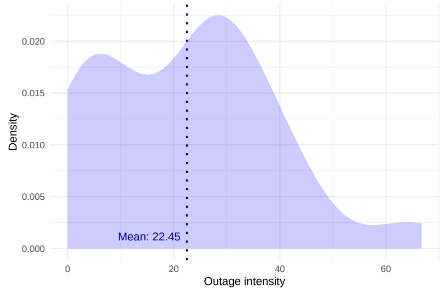
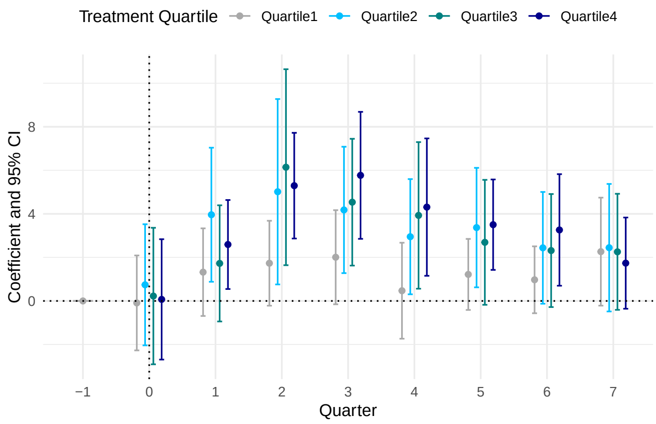
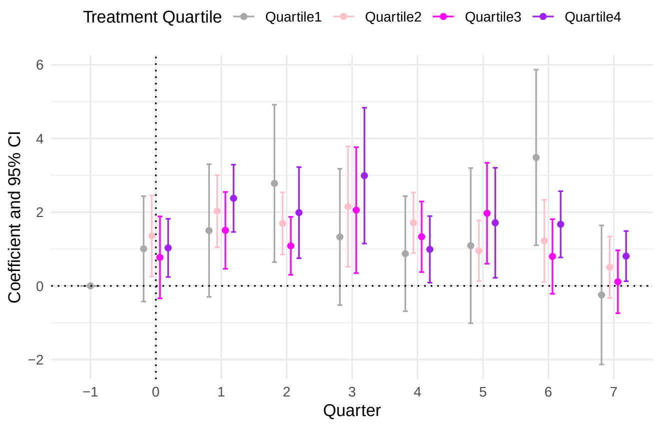


Figure C.3: Treatment effect coefficients for generator-related permits with quartile treatment



The period preceding the treatment period is omitted ($t = -1$).

Figure C.4: Treatment effect coefficients for PV with storage-related permits with quartile treatment

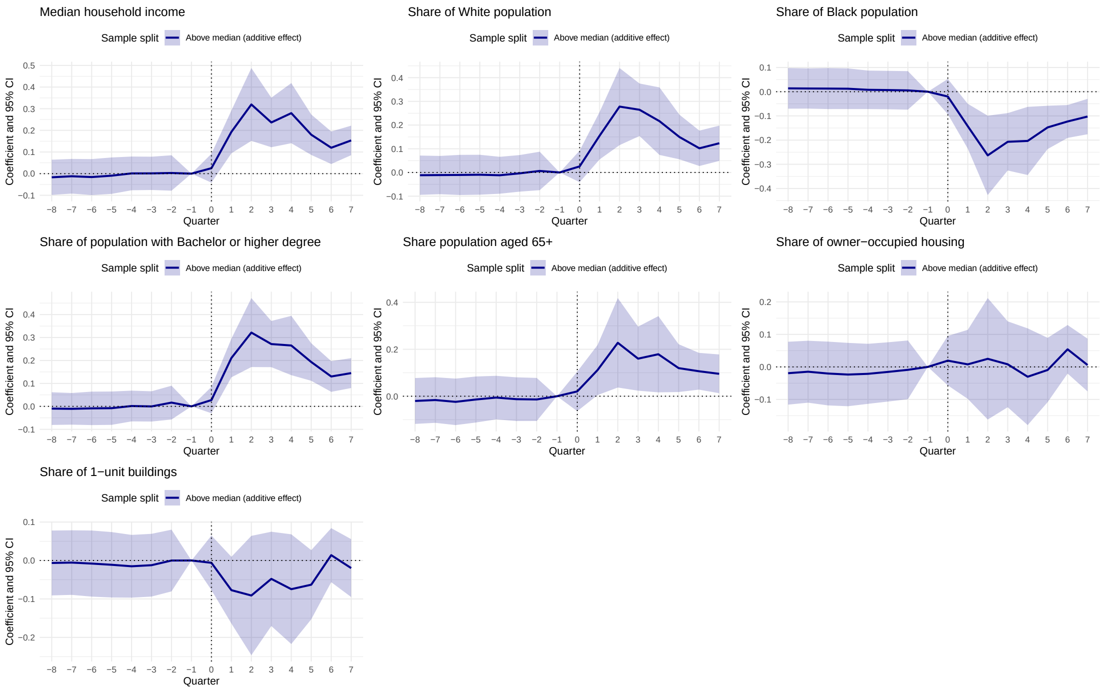


The period preceding the treatment period is omitted ($t = -1$).

Figure C.5: Heterogeneous treatment effects by socio-economic characteristics (interaction effects)

Notes: The period preceding the treatment period is omitted ($t = -1$). *Above median (additive effect)* is the interaction effect.

(a) Generator-related permits



(b) PV with storage-related permits

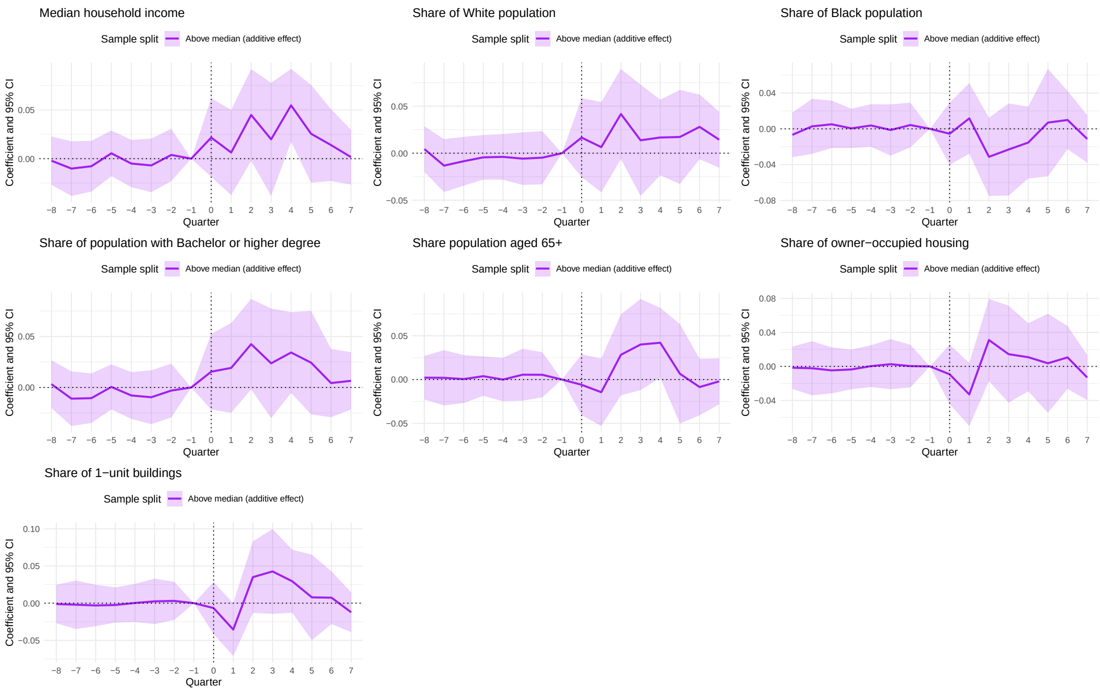
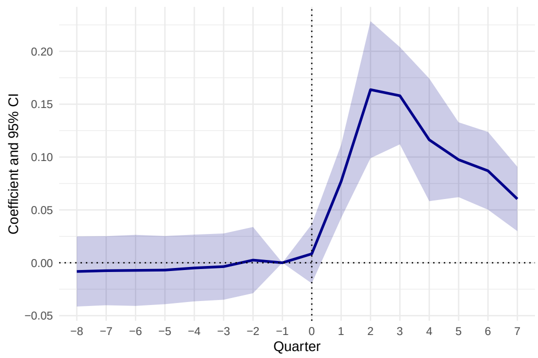
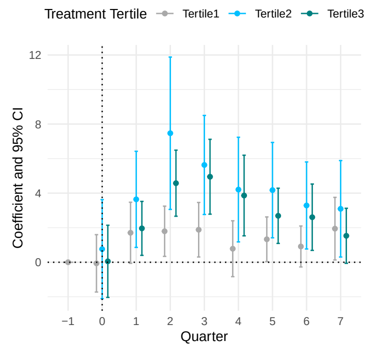


Figure C.6: Treatment effect coefficients for generator-related permits (conventional p-values)

(a) Continuous treatment



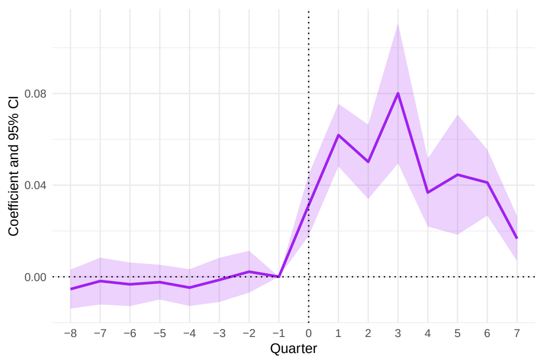
(b) Tertile treatment



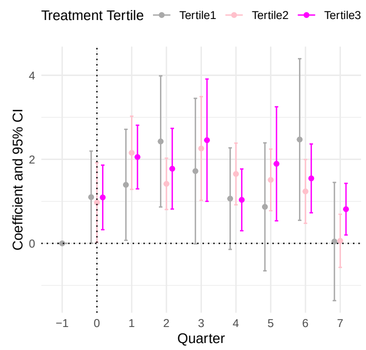
The period preceding the treatment period is omitted ($t = -1$).

Figure C.7: Treatment effect coefficients for PV with storage-related permits (conventional p-values)

(a) Continuous treatment



(b) Tertile treatment

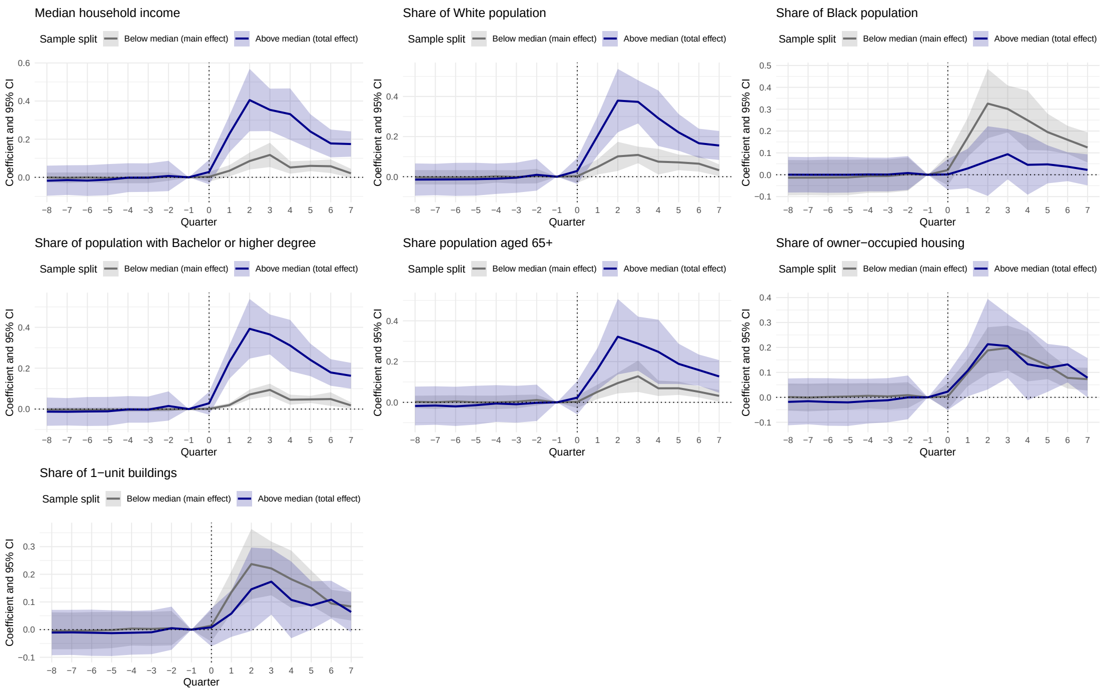


The period preceding the treatment period is omitted ($t = -1$).

Figure C.8: Heterogeneous treatment effects by socio-economic characteristics (conventional p-values)

The period preceding the treatment period is omitted ($t = -1$).
Above median (total effect) is plotted as the sum of the main effect point estimate and the interaction effect.

(a) Generator-related permits



(b) PV with storage-related permits

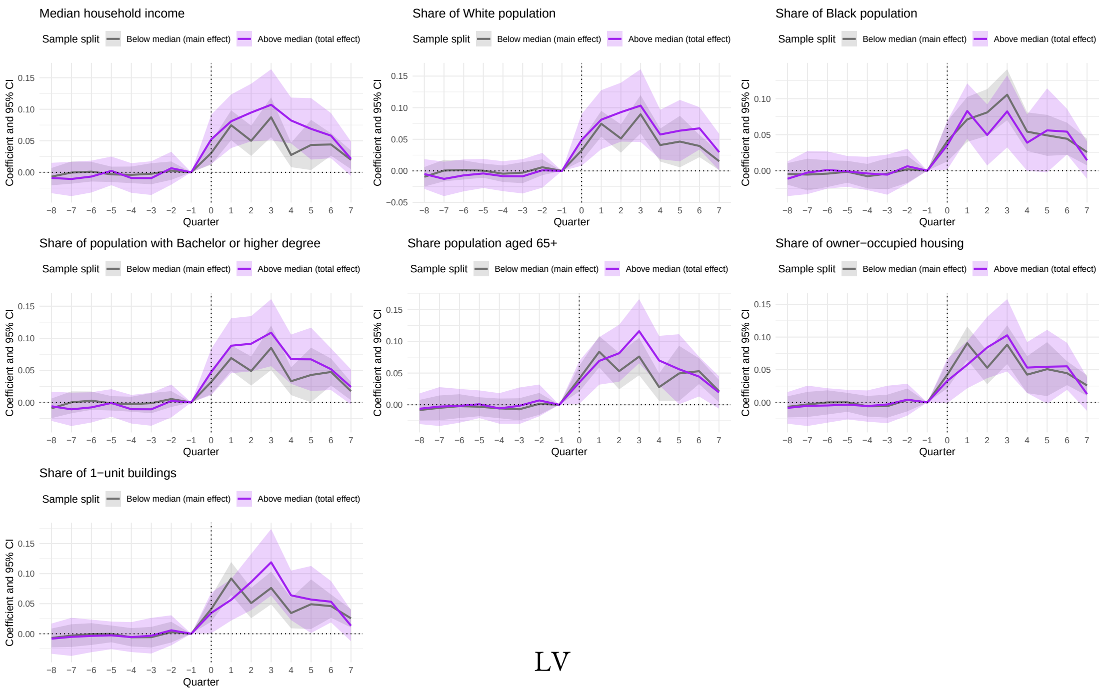
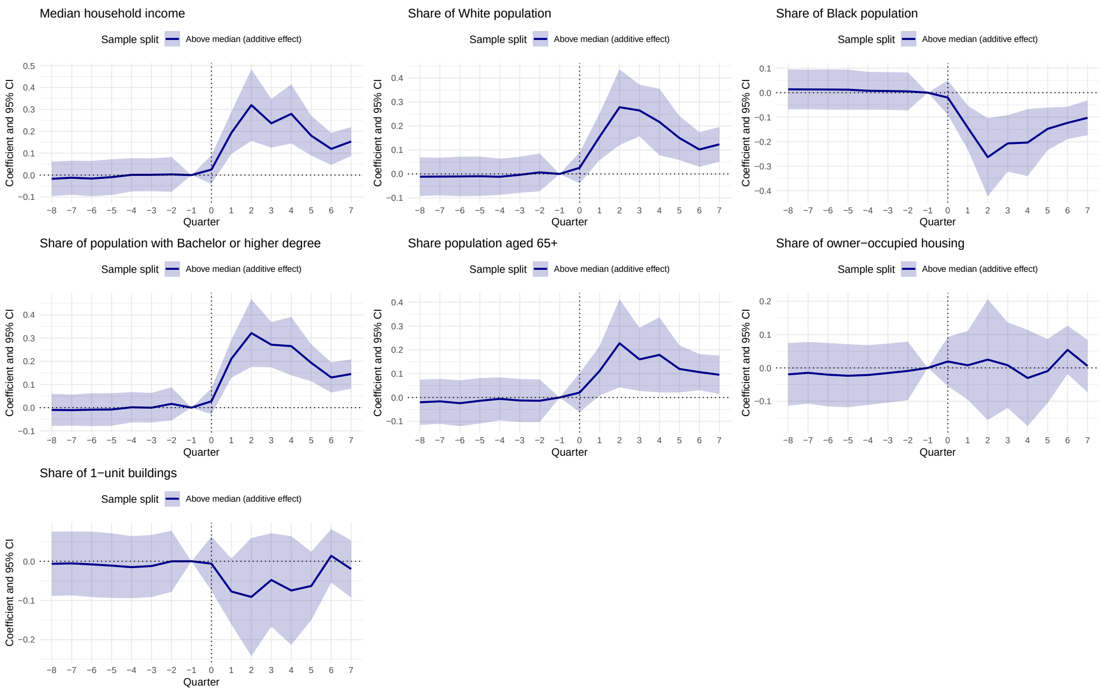


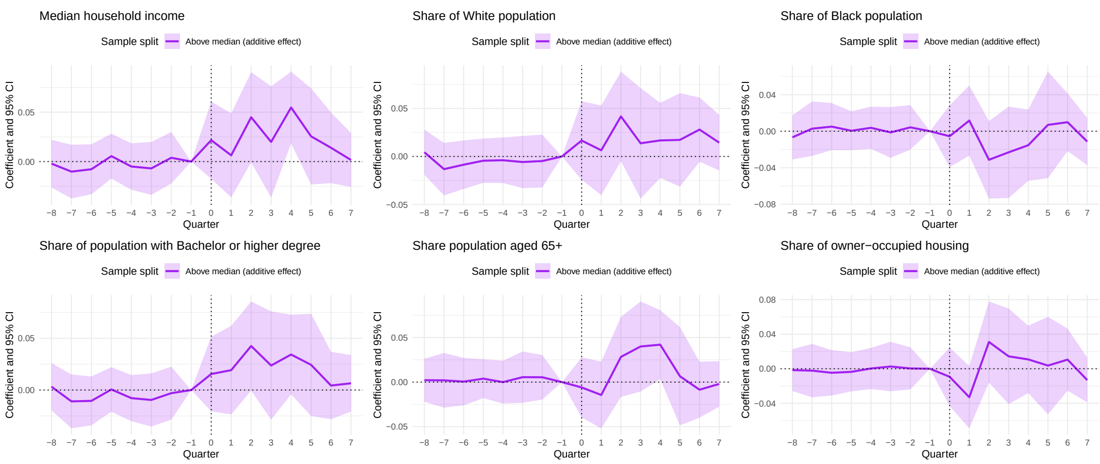
Figure C.9: Heterogeneous treatment effects by socio-economic characteristics (interaction effects) (conventional p-values)

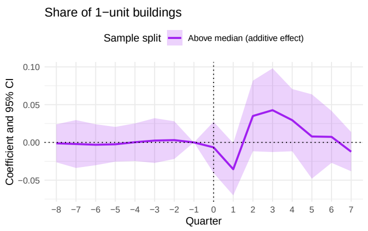
Notes: The period preceding the treatment period is omitted ($t = -1$).
Above median (additive effect) is the interaction effect.

(a) Generator-related permits



(b) PV with storage-related permits





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