Five essays in energy economics

Numerical and empirical perspectives on the decarbonization of the energy sector

vorgelegt von
M.Sc.
Alexander Roth
ORCID: 0000-0003-0061-7863

an der Fakultät VII – Wirtschaft und Management der
Technischen Universität Berlin
zur Erlangung des akademischen Grades

Doktor der Wirtschaftswissenschaften
- Dr. rer. oec. -

genehmigte Dissertation

Promotionsausschuss:

Vorsitzender:	Prof. Dr. Karsten Neuhoff (TU Berlin)
Gutachter:	Prof. Dr. Christian von Hirschhausen (TU Berlin)
Gutachterin:	Prof. Dr. Claudia Kemfert (Leuphana Universität Lüneburg)
Gutachter:	Dr. Wolf-Peter Schill (DIW Berlin)

Tag der wissenschaftlichen Aussprache: 16. Februar 2024

Berlin 2024

Zusammenfassung

Diese Dissertation behandelt die Herausforderungen der Dekarbonisierung im Energiesektor aus verschiedenen Perspektiven mit unterschiedlichen Methoden. Kapitel 1 liefert Hintergrund und Motivation. Kapitel 2 analysiert die Beziehung zwischen geografischer und zeitlicher Flexibilität im Strommarkt in einem Szenario mit 100% erneuerbaren Energien in zwölf mitteleuropäischen Ländern. Unter Anwendung eines Energiesystemmodells und einer Faktortrennungsmethode werden die Auswirkungen des europäischen Stromverbunds auf die optimale Speicherkapazität untersucht. Es zeigt sich, dass sich der Speicherbedarf durch den Stromverbund um 30% verringert, was in erster Linie auf Unterschiede in den Erzeugungsprofilen der Windenergie zwischen verschiedenen Ländern zurückzuführen ist. In Kapitel 3 wird die Integration des Gebäude- und Wärmesektors in den Stromsektor untersucht, unter besonderer Berücksichtigung der Rolle von Wärmepumpen. Die Auswirkungen auf den Stromsektor in Deutschland von gut sechs Millionen zusätzlichen Wärmepumpen bis 2030 werden untersucht, unter besonderer Berücksichtigung von Wärmespeichern. Die Ergebnisse zeigen, dass zusätzliche Wärmepumpen mithilfe der Photovoltaik zu begrenzten Zusatzkosten eingesetzt werden können. Wärmespeicher spielen dabei eine wichtige Rolle, um den zusätzlichen Bedarf an Stromspeichern und Erzeugungskapazitäten zu verringern. Insgesamt kann mit der Einführung der Wärmepumpen eine erhebliche Reduzierung des Erdgasverbrauchs und der CO_2-Emissionen erreicht werden. In Kapitel 4 wird die gleichzeitige Einführung von Wärmepumpen in mehreren europäischen Ländern untersucht. Es wird sowohl die Korrelation zwischen der Wärmenachfrage und der Residuallast untersucht, als auch die Auswirkungen auf Stromerzeugungskapazitäten. Aufgrund der Korrelation der Wärmenachfrage zwischen den untersuchten Ländern kann der europäische Stromverbund die zusätzlich benötigten Erzeugungskapazitäten der Wärmepumpen nicht wesentlich verringern. Die Ergebnisse dieses Kapitels heben wieder die positiven Eigenschaften von Wärmespeichern hervor und zeigen die Schwankungsbreite der Ergebnisse in Abhängigkeit des verwendeten Wetterjahres. Auch Kapitel 5 analysiert den Wärmesektor, nimmt aber eine empirische Perspektive ein und untersucht verhaltensbedingte Gaseinsparungen in Deutschland im Kontext einer drohenden Gasmangellage im Winter 2022/23. Mithilfe von offenen Daten und kausalem maschinellem Lernen werden signifikante verhaltensbedingte Gaseinsparungen durch Haushalte und Unternehmen quantifiziert, die zur Schließung der Versorgungslücke beitrugen. Das temperaturabhängige Einsparverhalten wird analysiert und die Bedeutung von zeitnah und öffentlich verfügbaren Daten wird unterstrichen, um die Öffentlichkeit und Politik adäquat zu informieren. Kapitel 6 schätzt die externen Effekte von Windkraftanlagen, insbesondere mögliche Gesundheitsauswirkungen. Daten deutscher Haushalte des Sozio-oekonomischen Panels (SOEP) werden mit Informationen zu Windkraftanlagen kombiniert. Mit einem Differenz-in-Differenzen-Ansatz werden die Effekte geschätzt. Hinweise auf negative gesundheitliche Auswirkungen können nicht gefunden werden.

Schlüsselwörter: Energiesystemmodellierung, erneuerbare Energien, Flexibilität, Speicher, Wärmepumpen, Erdgas, Causal Forest, Windkraft, externe Effekte, Gesundheit, Differenz-von-Differenzen-Ansatz

Abstract

This dissertation explores the challenge of decarbonization of the energy sector from different perspectives, applying various methods. Chapter 1 provides background and motivates the thesis. Chapter 2 assesses the relationship between geographical and temporal flexibility in a 100% renewable energy scenario across twelve central European countries. Applying a capacity expansion model and a factor separation method, it disentangles the impact of interconnection on optimal storage capacity. It can be shown that interconnection leads to a reduction of 30% in storage needs, primarily attributed to differences in wind power profiles between countries. Chapter 3 examines the integration of heating into the power sector, particularly the role of heat pumps. The power sector impacts of a substantial rollout of heat pumps in Germany by 2030 are assessed, considering buffer heat storage. The results indicate that even in scenarios with limited wind power expansion, heat pumps, accompanied by solar photovoltaics, can be deployed with limited additional costs. Importantly, heat storage proves effective in reducing the need for electricity storage and other generation capacities, while overall, a substantial reduction in natural gas consumption and CO_2 emissions can be achieved. Chapter 4 expands the analysis to an international setting, studying a simultaneous rollout of heat pumps in several central European countries. Assessing the effects on electricity generation capacities, the chapter also explores the alignment of heating demand with renewable energy scarcities. Because of correlated heat demand between countries, geographical balancing does not substantially reduce the additional needed generation capacities. Confirming the results of the previous chapter, thermal energy storage capacities help reduce the need for additional generation capacities. The chapter also shows that results vary substantially between different weather years. Chapter 5 remains in the field of heating but takes an empirical perspective and studies behavioral gas savings in Germany during the 2022-23 heating season prompted by a potential gas supply shortage. Using open data and causal machine learning, significant behavioral gas savings by German households and businesses are quantified, contributing to closing the supply gap. Temperature-dependent saving dynamics are explored, emphasizing the importance of timely and accessible data for informing the public and policymakers. Continuing with the empirical perspective, Chapter 6 estimates the externalities of energy infrastructures, focusing on the potential health impacts of wind power plants. Data on German households of the Socio-Economic Panel (SOEP) is combined with geolocated data on wind power plants. Applying a staggered difference-in-difference estimation, the analysis finds no evidence of adverse health effects on nearby residents.

Keywords: energy system modeling, renewable energy, flexibility, storage, heat pumps, natural gas, causal forest, wind energy, externalities, health, difference-in-differences

Acknowledgements

First, I am indebted to Wolf-Peter Schill for being an inspiring researcher, co-author, discussion partner, and fabulous research group leader. Wolf's academic guidance helped me to stay on track and fostered my creativity. Similarly, I thank Claudia Kemfert for providing an excellent research atmosphere at DIW's "Energy, Transportation, Environment" department and for being part of my committee. I thank my supervisor, Christian von Hirschhausen, for his continuous support and the freedom he gave me to set my research agenda.

I am truly grateful to the DIW and its Graduate Center (GC) for providing an environment in which young researchers have the freedom to develop, and I am thankful for all the GC-related activities and for the institutional and financial support. Financial support by various research grants, mentioned in the respective chapters, is gratefully acknowledged.

My co-authors and colleagues of the research group "Transformation of the Energy Economy", Carlos Gaete-Morales, Adeline Guéret, Dana Kirchem, Martin Kittel, and Felix Schmidt, were an indispensable part of my research journey and the reason I returned to the office daily. Thanks for all the great work together, the good discussions, and nice lunch breaks! I am also very grateful to my co-authors Christian Krekel and Johannes Rode, with whom I shared a great research project and who taught me much about empirical research.

Special thanks to Johannes Seebauer, Mara Barschkett, Laura Pagenhardt, Adrián Santonja di Fonzo, and Laura Schmitz for the great moments shared inside the DIW and many more outside. Moreover, I would like to thank all other fellow GC students for filling the doctoral program with life, especially during the challenging first year.

Finally, I want to thank my whole family, especially my parents. Because of their continuous support and inspiration, I was able to start and follow my academic path.

Last but certainly not least, I thank my wonderful wife Chiara! You endured not only my long working hours but traveled for me through half of Europe and supported me and my moods in every moment possible. Thank you so much!

Rechtliche Erklärung

Hiermit versichere ich, dass ich die vorliegende Dissertation selbstständig und ohne unzulässige Hilfsmittel verfasst habe. Die verwendeten Quellen sind vollständig im Literaturverzeichnis angegeben. Die Arbeit wurde noch keiner Prüfungsbehörde in gleicher oder ähnlicher Form vorgelegt.

Alexander Roth
Berlin, 4. März 2024

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List of Abbreviations and Acronyms

CH_4 methane

CO_2 carbon dioxide

ASHP air-sourced heat pump

COP coefficient of performance

ERAA European Resource Adequacy Assessment

GHG greenhouse gas

GW Gigawatt

GW Megawatt

kWh Kilowatt hour

MWh Megawatt hour

NTC net-transfer capacity

p2g2p power-to-gas-to-power

PV photovoltaics

RES renewable energy sources

TWh Terawatt hour

US United States

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Introduction

1.1 Motivation

"Human activities, principally through emissions of greenhouse gases, have unequivocally caused global warming [...]" states the latest *AR6 Synthesis Report: Climate Change 2023* of the Intergovernmental Panel on Climate Change (IPCC, 2023, p.42). By now, there is robust scientific evidence that human-caused global warming constitutes an enormous risk for planetary health and human life. Already in 2007, the "Stern Review" (Stern, 2007) concluded that avoiding global warming through abatement of greenhouse gas (GHG) emissions is economically far cheaper than the follow-up costs of global warming. As the central driver for the increase in global mean temperature lies in the emission of GHGs, primarily carbon dioxide (CO_2) and methane (CH_4), the reduction of these emissions is the centerpiece of global climate policies.

The energy sector, specifically the generation of electricity and heat, plays a significant role in two dimensions. Not only is it one of the sectors with the highest emissions, responsible for 23% of global GHG emissions in 2019 (IPCC, 2023), but it will gain a central role in the decarbonization due to the electrification of the economy. The IEA foresees that "[...] electrification emerges as a crucial economy-wide tool for reducing emissions" (IEA, 2021, p.14) as renewable electricity will be used in sectors, such as industry, transport, and heating, that are currently still overwhelmingly dependent on fossil fuels. Therefore, the energy sector has a crucial role in reducing its own emissions and enabling the decarbonization of other sectors and, hence, the entire economy (Clarke et al., 2022).

As the energy sector is one of the areas with the largest share of GHG emissions, special focus must be placed on this sector. In particular, the power sector will grow and play a central role in the future energy system, supplying other sectors with energy. In many regions of the world, especially in Europe, wind and solar photovoltaics (PV) will provide the largest part of the electricity supply. Their dependency on wind and sunshine patterns makes them inherently variable, creating unique challenges to balance the supply and demand of electricity in every moment of time. Consequently, the electricity sector has to become much more "flexible" adjusting on short notice either supply or demand to balance the grid. Accordingly, one of the central techno-economic challenges of the energy sector, specifically the power sector, is to provide sufficient "flexibility". Some definitions of flexibility, such as the "ability of conventional generators to vary output and respond the variability and uncertainty of the net load" (Denholm and Hand, 2011, p.1818), focus mainly on supply. Yet, it seems more adequate to follow a broader definition of flexibility, such as "flexibility is the capability to balance rapid changes in renewable generation and forecast errors within a power system" (Bertsch et al., 2012, p.1).

Various flexibility options exist, but sorting them into demand- and supply-side is inadequate because options such as storage and grid expansion cannot be easily classified in such categories. It appears to be more useful to sort options into "Power-to-Power" (e.g., demand side management such as shifting of load and classical electricity storage), "X-to-Power" (e.g., flexible operation of dispatchable generators), "Power-to-X" (e.g., "sector coupling" options such (flexible) loads of other sectors such as heat and mobility), and finally transmission and distribution grid optimizations and expansions (Kondziella and Bruckner, 2016; Schill, 2020). However, options can also be categorized according to other criteria, such as temporal dimensions (Lund et al., 2015), as well as technical and economic potentials (Kondziella and Bruckner, 2016). Heider et al. (2021) provides an overview of the different classification schemes found in the literature.

Two of these options, (short- and long-duration) electricity (grid) storage and interconnection between countries, are regarded as essential for the functioning of a future decarbonized power sector. Electricity storage provides flexibility on a temporal dimension, shifting excess renewable energy generation to hours of scarcity, with different time horizons depending on the storage technology. Interconnection provides flexibility on a geographic dimension, shifting excess or scarcity between regions by cross-border electricity trades. Through various analyses, the literature has implicitly established a negative relationship between the size of the geographical area and the need for electricity storage (Bussar et al., 2014; Child et al., 2019). That coincides with the intuitive idea that in an interconnected European grid, countries can supply their neighbors with excess energy if in need instead of using previously stored energy. However, how interconnection and electricity storage interact and why exactly the former is reducing the latter have not been properly understood. Chapter 2 sheds light on that topic.

Previously separated sectors, such as heating and transportation, will be connected to the electricity sector. This is understood as "sector coupling" and will add, on the one hand, flexibility. If these new consumers, heat pumps, for instance, were operated system-friendly, they could integrate excess electricity generation of renewable energies that would have been curtailed otherwise, thereby decreasing overall system costs. On the other hand, sector coupling generates new demand for electricity as new consumers, such as heat pumps and electric vehicles, will be connected to the grid. Consequently, sector coupling not only requires new generation capacities to generate the additional electricity but could even lead to increased electricity demand in already high-demand hours (peak load), therefore demanding additional flexibility options. The building sector, in particular the heating of buildings, makes, therefore, an interesting and relevant application of studying flexibility options. Heating (only encompassing space and water heating of buildings, not industrial heat) is traditionally provided by fossil fuels, mainly oil and natural gas, in most European countries. In 2019, more than 12% of total GHG emissions in the EU were emitted to heat buildings (Ritchie, Rosado, and Roser, 2023), which does not even include the emissions of the power sector to generate electricity used for heating and district heating. Among several technical solutions to decarbonize heating (Bloess, Schill, and Zerrahn, 2018), the heat pump is considered to be one of the most promising technical solutions due to its efficiency and ability to use (renewable) electricity directly (IEA, 2022). Heat pumps "harvest" heat from different sources, such as ambient air or the ground, bring it to a useful temperature level, and transfer it to the needed place, such as to a heating system of a building. As they consume electricity, they could add a substantial load to the electricity system in cold winter months, requiring additional flexibility options. Therefore, attached thermal energy storage, in combination with system-friendly operation, could help to reduce peak loads and reduce system costs. In a country such as Germany, in which almost three-quarters of all housing units still use gas- or oil-based heating systems, it would be particularly relevant to estimate how much additional electricity generation capacity would be needed to power a heat pump fleet of six million units, as planned by the current government for 2030. In addition, the importance of thermal heat storage, the implied emissions, and natural gas savings are relevant to asses. Chapter 3 touches upon these topics.

When discussing questions of the power sector, the European market should always be considered, especially when assessing the widespread use of heat pumps. As heat pumps are inherently dependent on temperatures, hence weather patterns, it is essential to understand how heat demand patterns span beyond borders and whether they overlap with renewable energy scarcities. That is needed to properly estimate the additional electricity generation capacity needs and comprehend how different flexibility options, specifically thermal energy storage and interconnection, influence required generation capacities. Chapter 4 addresses these topics.

While the aforementioned topics were viewed primarily from a techno-economic and system perspective — "what would be the most efficient solution for the entire system?" — all these challenges can also be regarded from a societal or political perspective. In Germany, but also in other countries, year-long discussions about the expansion of electricity grids (Weise, 2022) and recently about heat pumps (Amelang, 2023; Mathiesen, 2023) have shown that — seemingly — technical topics can become inherently societal and even political. However, it is clear that the upcoming years will be marked by profound societal and economic changes to enable the transition to a net-zero economy and adapt to the changes of global warming. Thus, studying and understanding the individuals' and companies' behavior of adaption and reaction is important. The Russian invasion of Ukraine in 2022 and the subsequent energy price crisis in Europe triggered major aggregated changes. In that environment, despite difficulties in identifying individual factors, it is relevant to explain aggregate behavior with adequate methods. Chapter 5 sheds light on the consumer reaction towards higher prices, political communications, and other factors and estimates the aggregated natural gas savings.

Another aspect of societal challenges is adaption. In the context of climate change, it is crucial to understand the adaptation mechanisms of humans to a changing environment (e.g., coping with higher temperatures), as well as the adaptation to policies that either fight or adapt to climate change. For instance, in the field of energy, the transition to a decarbonized energy system requires the installation of new infrastructures on a large scale in new locations. It is important to measure the impact of installing, for instance, photovoltaic panels, wind power plants, battery systems, electrolysis, and power lines. Analysis could be undertaken regarding life satisfaction (Zerrahn, 2017), political convictions (Comin and Rode, 2023), and health. Understanding the impact of the infrastructure is crucial, as local resistance has become a prevalent phenomenon in many countries ("nimbyism"). If people believe that new infrastructure affects their health negatively, that belief might translate to political discontent and resistance. Hence, it is essential to quantify the impact of infrastructure on health to avoid harming people and to ensure public approval of the sustainable transition. Wind power plays a crucial role here for two reasons. Firstly, it has a strong visual and aesthetic impact on the landscape, and secondly, it is considered one of the central pillars of a decarbonized energy system in Germany, Europe, and many countries worldwide (IEA, 2021). Therefore, it is especially important to understand the health impacts of wind power plants. Chapter 6 gives some answers to that question.

As highlighted in that section, this dissertation sheds light on techno-economic and societal challenges in the energy sector. The topics marked above provide a flavor of the width and complexity of the subject, which any single thesis will naturally never be able to address adequately. Nevertheless, the wide range of topics could also motivate the wide use of methods. Within quantitative economics, one could differentiate between “ex-ante” and “ex-post” methods. “Ex-ante” methods, often theoretical and numerical models, are used to think about interrelationships and aim to look ahead by simulating and exploring counterfactual scenarios. On the contrary, “ex-post” methods, typically empirical research, try to understand, identify, and quantify relationships based on data. Numerical models are one of the principal methods of research in the field of energy. Very broadly, they can be sorted into “top-down” and “bottom-up” models (Herbst et al., 2012). With the big picture in mind, top-down modeling aims to explain the relationship between aggregated variables, such as supply and demand and wants to quantify, for instance, the aggregate consequences of certain policies. In contrast, bottom-up modeling takes a more granular approach, including more technological details. They aim to represent the supply and demand of the energy sector, featuring various technologies and hence can answer more specific questions regarding the energy sector. Within bottom-up modeling, an often-used modeling approach is linear (cost) optimization models due to their ability to solve even complex problems in a reasonable time. The analyses in Chapter 2 to 4 apply such a type of model to find a cost-minimal solution given various technical and policy constraints. While being detailed on one side, many linear optimization models are very simplistic with respect to economic questions, assuming perfect markets, neglecting uncertainties, and not considering individual agents.

One challenge in numerical modeling is to properly attribute changes in outcomes to changes in assumptions and parameters due to the complexity of models. Often, it is difficult to understand how model results come about or can be interpreted. With the help of factor separation methods (Stein and Alpert, 1993) and counterfactual model runs, model outcomes can be attributed to input changes. Chapter 2 applies such a method that had been previously used mainly in climate science to energy system modeling.

In empirical economics, two major trends have emerged in recent years. One revolves around causal inference, specifically focusing on achieving “proper” identification of a causal effect instead of only measuring mere correlations. The “Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel” in 2021 was awarded to a group of economists partly “for their methodological contributions to the analysis of causal relationships” (The Royal Swedish Academy of Sciences, 2021). One of the fundamental ideas of causal inference is to formulate a problem in social science as an experiment with “treatment” and “control” groups. While in pharmaceutical tests, these groups can be perfectly created, true experiments in social science are rarely possible. Hence, it is important to uncover “quasi-experimental” settings in which similar groups were affected differently, which in turn allows for an identification of a treatment effect. One of the most widely used approaches in econometrics in that context is the “difference-in-differences”. Comparing averages between groups over time, typically before and after a treatment, such as a policy, allows for estimating the treatment effect and the causal effect of that policy. In recent years, however, this method has been criticized for rendering unreliable results if applied in settings of staggered treatments (Goodman-Bacon, 2021). Numerous new robust estimators have been developed, such as by Sun and Abraham (2021), as applied in the analysis in Chapter 6.

The second major trend affecting empirical research in economics involves integrating machine learning methods. Traditionally, machine learning methods were mainly used in prediction due to their ability to process high dimensional data more efficiently and reliably than traditional econometric methods. Recently, machine learning techniques have been increasingly integrated into econometric methods. Among the wide array of machine learning methods, random forests are one of the most common methods for the classification of data and regression tasks. As an extension of random forests, causal forests can be used to estimate heterogeneous treatment effects, combining insights from causal inference and machine learning. In Chapter 5, that method has been applied to estimate natural gas savings effects.

Table 1.1: Overview and summary of the chapters

	Chapter 2	Chapter 3	Chapter 4	Chapter 5	Chapter 6
Title	Geographical balancing of wind power decreases storage needs in a 100% renewable European power sector	Flexible heat pumps: must-have or nice to have in a power sector with renewables?	Power sector impacts of a simultaneous European heat pump rollout	Not only a mild winter: German consumers change their behavior to save natural gas	Do Wind Turbines Have Adverse Health Impacts?
General topics	Temporal and spatial flexibility in the power sector	Electrification of heat, power sector effects, and temporal flexibility	Electrification of heat, power sector effects, temporal, and spatial flexibility	Natural gas demand and savings in Germany	Externalities of energy infrastructures
Research question	Why does geographical balancing reduce storage needs, and what are its causes?	What are the generation capacity effects of six million additional heat pumps in Germany, and what are the impacts of thermal energy storage?	What are the generation capacity effects of a simultaneous heat pump rollout in several European countries, and how is it impacted by different flexibility options?	How much natural gas did German consumers save in the winter 2022?	What are the health effects of wind power plants on people living in proximity?
Main finding	Heterogeneous wind power profiles are mostly responsible for reducing storage needs through geographical balancing.	The heat pump expansion can be managed with additional solar PV capacities and moderate costs, while even small thermal energy storage reduce firm capacity needs.	Geographical balancing has a limited effect on capacities, while small thermal energy storage have a large effect.	German consumers saved substantial amounts of natural gas in 2022.	No evidence for physical or mental effects of wind turbines are found.
Approach	Numerical modeling	Numerical modeling	Numerical modeling	Empirical analysis	Empirical analysis
Method	Linear optimization; factor separation	Linear optimization	Linear optimization	Causal forest	Staggered difference-in-difference estimation
Geographic scope	12 European countries	Germany (and ten other countries as dispatch only)	Nine European countries	Germany	Germany

1.2 Outline

This dissertation consists of six chapters. While Chapter 1 aims to introduce the reader to the topics and provides an outline, the Chapters 2–6 shed light on distinct topics. Each of these chapters is based on an original research article, starting with three chapters applying numerical modeling to questions of flexibility and heating in the power sector. The topic of heating is followed up in Chapter 5, now approached from an empirical perspective, whereas Chapter 6 concludes this dissertation using causal inference applied to the topic of infrastructure externalities. Table 1.1 and Figure 1.1 provide a tabular and graphical overview of this dissertation. Table 1.2 lists the papers on which the following chapters are based on, my contributions, and the publication status.

Providing flexibility is one of the principal challenges for a changing power sector that becomes not only more fluctuating due to the integration of renewable energies but also more important due to the integration of other sectors. **Chapter 2: Geographical balancing of wind power decreases storage needs in a 100% renewable European power sector** assesses how geographical balancing enabled by interconnection and electricity storage can provide such flexibility. In a 100% renewable energy scenario of twelve central European countries, it is investigated how geographical balancing between countries reduces the need for electricity storage. A principal contribution is to separate and quantify the different factors at play. By applying a capacity expansion model and a factorization method borrowed from climate science, the effect of interconnection on optimal storage capacities through distinct factors is disentangled. The following explaining factors are considered: differences in countries' solar PV and wind power availability patterns, load profiles, as well as hydropower and bioenergy capacity portfolios. The results show that interconnection reduces storage needs by around 30% compared to a scenario without interconnection. Differences in wind power profiles between countries can explain around 80% of that effect. The analysis in that chapter relies on ten weather years, increasing the robustness of the results. This chapter not only sheds light on the interplay between different flexibility options but also successfully applies methods from different fields.

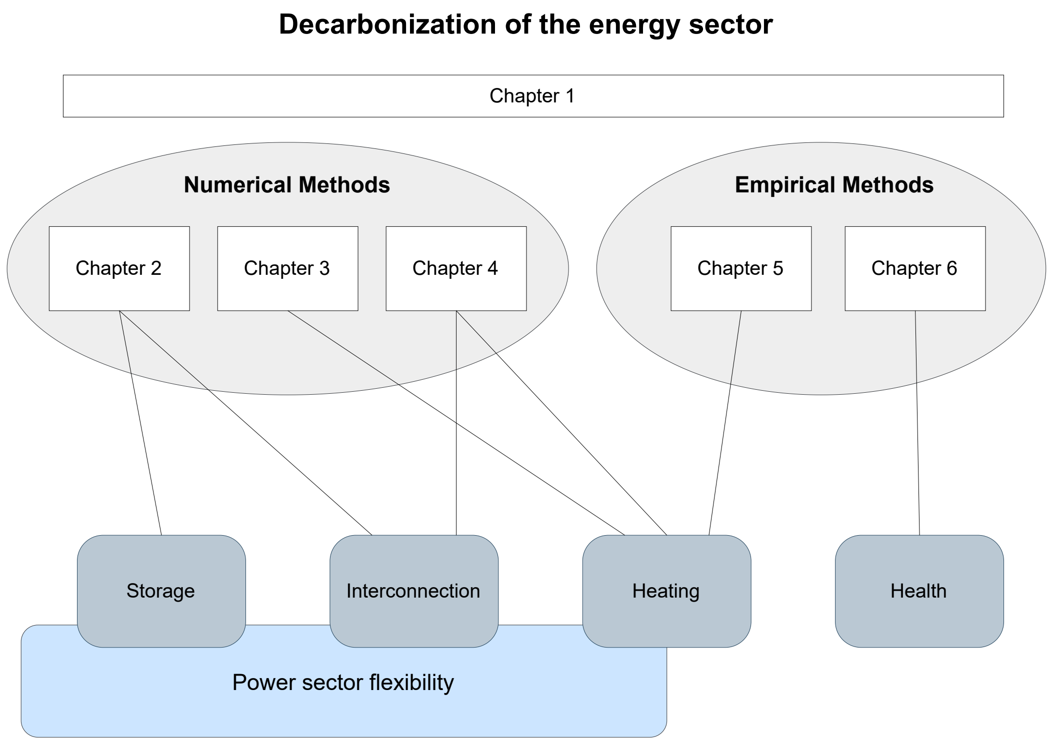


Figure 1.1: Graphical overview of the chapters

Sector coupling will increase the importance of the power sector. One of the coupled sectors will be heating, in which heat pumps will play a crucial role in decarbonizing heating by using renewable electricity. However, a transition to heat pumps implies increased electricity demand, especially in cold winter months. In **Chapter 3: Flexible heat pumps: must-have or nice to have in a power sector with renewables?**, the power sector impacts of a massive expansion of decentralized heat pumps in Germany in 2030 are assessed, combined with buffer heat storage of different sizes. Assuming that the additional electricity used by heat pumps has to be fully covered by renewable energies in a yearly balance, the required additional investments in renewable energy sources (RES) are estimated. If wind power expansion potentials are limited, the rollout of heat pumps can also be accompanied by solar PV with little additional costs, using the European interconnection. The need for additional firm capacity and electricity storage generally remains limited, even in the case of temporally inflexible heat pumps. Already relatively small heat storage capacities of two to six hours can substantially reduce the need for short- and long-duration electricity storage, other generation capacities, and power sector costs. With respect to reducing energy use and emissions, it is shown that 5.8 million additional heat pumps in Germany save around 120 Terawatt hour (TWh) of natural gas and 24 million tonnes of CO_2 emissions per year.

The results presented in Chapter 3 quantify the challenges of adding a substantial amount of heat pumps to the German power sector. However, one important dimension of flexibility, the interconnection between countries, is not fully developed in the analysis of that chapter. For a better understanding of the associated challenges, **Chapter 4: Power sector impacts of a simultaneous European heat pump rollout** expands the analysis to an international setting. In that chapter, a simultaneous rollout of heat pumps in several central European countries with an hourly-resolved capacity expansion model of the power sector is studied. Not only are the effects on generated capacities assessed but also how hours and periods of elevated heating demand coincide with hours and periods of renewable energy scarcities. For a 2030 scenario, results show that if 25% of the total heat demand of buildings would be supplied by heat pumps, the additional electricity would be covered best with additional wind power generation capacities. In addition, the important role of small thermal energy storage is highlighted to reduce the need for additional firm generation capacity. One important finding is that due to the co-occurrence of heat demand, the interconnection between countries does not substantially reduce the additional generation capacities needed for heat pump deployment. Importantly, the analysis presented in that chapter is based on six different weather years, showing the strong heterogeneity of results between them and cautioning against relying on results coming from a single year.

The topic of heating can be assessed not only from the modeling but also from an empirical perspective. The year 2022 gave, unfortunately, enough reason for an improved understanding of the heating system. By the start of the 2022-23 heating season, Germany and many other European countries faced a potential gas supply shortage in the wake of Russia's invasion of Ukraine. In search of a response, authorities called on residential and commercial sectors to save natural gas. Exploiting winter 2022-23 as a "natural experiment", **Chapter 5: Not only a mild winter: German consumers change their behavior to save natural gas** sheds light on the magnitude of behavioral gas savings using open data and a causal forest, a machine learning method. Despite being exposed to incomplete price signals, significant behavioral gas savings by German households and businesses are found, contributing to closing the supply gap. Temperature-dependent saving dynamics are uncovered, and the potential roles of different drivers of this change are discussed. Finally, the pivotal role of a timely and continuous provision of openly accessible data and analysis to inform the general public and policymakers is highlighted in that chapter.

Continuing on assessing societal aspects through an empirical perspective, **Chapter 6: Do Wind Turbines Have Adverse Health Impacts?** delves into the topic of externalities of energy infrastructures. As mentioned in Chapters 1-3, wind power is considered key in transitioning towards a net-zero economy. However, there are concerns about adverse health impacts on nearby residents. Based on precise geographical coordinates, the analysis in that chapter links a representative longitudinal household panel to all wind turbines in Germany and exploits their staggered rollout over two decades for identification to estimate a causal effect. No evidence of negative effects on general, mental, or physical health in the 12-Item Short Form Survey (SF-12), nor on self-assessed health or doctor visits are found. Also, no evidence for effects on suicides, an extreme measure of negative mental health outcomes, at the county level are detected.

Table 1.2: Chapter origins and own contribution

Chapter	Pre-publications & Own Contribution
2	**Geographical balancing of wind power decreases storage needs in a 100% renewable European power sector**
	A. Roth and W.-P. Schill (2023a). "Geographical Balancing of Wind Power Decreases Storage Needs in a 100% Renewable European Power Sector". *iScience* 26.7. DOI: 10.1016/j.isci.2023.107074
	Joint work with Wolf-Peter Schill. AR and WS jointly conceptualized the research, analyzed the data, and wrote the paper. AR curated the data, developed the methodology, and ran the numerical model. WS initiated the research.
3	**Flexible heat pumps: must-have or nice to have in a power sector with renewables?**
	A. Roth, D. Kirchem, et al. (2023). "Flexible Heat Pumps: Must-Have or Nice to Have in a Power Sector with Renewables?" *arXiv preprint* arXiv:2307.12918 [econ.GN]. DOI: 10.48550/arXiv.2307.12918, revise & resubmit by *Communications Earth & Environment*.
	Joint work with Dana Kirchem, Carlos Gaete-Morales, and Wolf-Peter Schill. AR curated the data (with CG, DK), developed the methodology (with CG, DK, WS), ran the numerical model (with DK), analyzed the data (with DK, WS), and drafted the manuscript (with DK). WS initiated and conceptualized the research.
4	**Power sector impacts of a simultaneous European heat pump rollout**
	A. Roth (2023). "Power Sector Impacts of a Simultaneous European Heat Pump Rollout". *arXiv preprint* arXiv:2312.06589 [econ.GN]. DOI: 10.48550/arXiv.2312.06589
	Single-author original research article.
5	**Not only a mild winter: German consumers change their behavior to save natural gas**
	A. Roth and F. Schmidt (2023). "Not Only a Mild Winter: German Consumers Change Their Behavior to Save Natural Gas". *Joule*, S2542435123001733. DOI: 10.1016/j.joule.2023.05.001
	Joint work with Felix Schmidt. AR and FS jointly conceptualized the research, curated the data, developed the methodology, analyzed the data, and wrote the manuscript. FS did the empirical analysis. AR initiated the research.
6	**Do Wind Turbines Have Adverse Health Impacts?**
	C. Krekel, J. Rode, and A. Roth (2023). "Do Wind Turbines Have Adverse Health Impacts?" *DIW Discussion Papers* 2054. DOI: http://hdl.handle.net/10419/279485
	Joint work with Christian Krekel and Johannes Rode. AR, CK, JR jointly conceptualized the research and analyzed the results. AR curated the data and did the empirical analysis. CK and JR wrote the manuscript. AR edited and reviewed the manuscript. CK and JR initiated the research.

1.3 Conclusion

This dissertation aims to provide a multifaceted view of the challenges of decarbonizing energy, with a focus on the crucial role of the electricity sector in achieving this goal. The importance of the electricity sector lies not only in reducing emissions but also in facilitating the decarbonization of other sectors, as discussed in Chapters 2 to 4. While the results of Chapter 2 show the importance of geographical balancing in reducing storage, the insights of Chapter 4 highlight that interconnection does not add much flexibility to balance the electricity demand of heat pumps. Small thermal energy storage appears to be more effective, as highlighted in Chapter 3 and 4. Further research should concentrate on the interaction of different flexibility options. Extending an analysis, such as the one of Chapter 2, to more countries and including other flexibility options could generate vital insights into the functioning of a future power sector. Geographical aspects, such as including several countries or regions, and temporal aspects, including various weather years, are central to a comprehensive understanding.

The research presented in Chapter 3 and 4 invites integrating heating even more into power sector models to gain an improved understanding of the interactions between conventional load and heating. Given the growing importance of heating in the power sector, it is also paramount to think more precisely about consumer behavior and how to represent that adequately in power sector models. Many aspects of modeling demand, such as consumer behavior and industrial production, appear to be very relevant for the future due to the increasing importance of demand in providing flexibility (Pfenninger, Hawkes, and Keirstead, 2014; Fodstad et al., 2022). With growing importance due to sector coupling, power sector models are and will have to be enhanced by other sectors and energy carriers (Fodstad et al., 2022). Future research will have to assess further integration of different models and sectors: might top-down models become more “bottom-up”, while top-down models become more “bottom-up”? The integration of different model types or even the creation of “hybrid” models will remain a challenge (Herbst et al., 2012).

In the wake of the European energy crisis in 2022, aggregate natural gas consumption became a topic of general interest, and the results shown in Chapter 5 suggest that considerable savings were achieved in Germany. A promising research avenue would be to further disentangle the aggregate savings. It would be relevant to quantify how much of the savings can be attributed to price changes, political communication, beliefs, or other factors. Also, it would be highly interesting to uncover group-specific savings patterns to estimate whether households or small businesses were the principal drivers for the savings. Furthermore, the nature of savings, whether they were driven by changes in behavior, investments into efficiency, or reduction of output, is of high interest. Analyzing some of these effects would be timely and relevant for policymakers. Similar analyses for other European countries could shed light on differences between countries in Europe. Finally, it seems promising to further apply machine learning methods in the field of energy, complementing and even enhancing numerical modeling.

The importance of wind power plants, especially to facilitate the deployment of additional heat pumps, has been highlighted throughout this dissertation. The results presented in Chapter 6 shed light on the health effects of wind turbines on people living in their proximity, with no effect being detected. However, the current analysis is also restricted by sparse data. With better and more granular data, e.g., administrative health data and more detailed geographic data, even more precise effects could be estimated. For instance, one could assess possible effects on people living in very close proximity. As infrastructure is likely to have very diverse impacts, estimating heterogeneous treatment effects seems very relevant. Importantly, further empirical research has to assess the nature of resistance against the infrastructure needed for a sustainable transition. Questions of fairness and procedural justice in newly built projects and the equitable distribution should be addressed. If empirical research could estimate how local resistance against infrastructure is formed, future energy modeling applications could include these estimates to better define the upper bounds of certain technologies or to calculate trade-offs. Combining empirical and modeling methods could lead to valuable insights.

2

Geographical balancing of wind power decreases storage needs in a 100% renewable European power sector

This chapter is based on A. Roth and W.-P. Schill (2023a). "Geographical Balancing of Wind Power Decreases Storage Needs in a 100% Renewable European Power Sector". *iScience* 26.7. DOI: 10.1016/j.isci.2023.107074

2.1 Introduction[1]

The massive expansion of RES is a major strategy to mitigate GHG emissions (IPCC, 2022). Thus, many countries have ambitious targets for increasing renewable shares in their power sectors (REN21, 2022). For example, the G7 countries aim for “achieving a fully or predominantly decarbonized power sector by 2035” (G7, 2022). As the potentials for firm renewable generation technologies such as geothermal and bioenergy are limited in most countries, much of the projected growth needs to come from variable RES, e.g., wind power and solar PV (Child et al., 2019). As these depend on weather conditions and daily and seasonal cycles, their electricity generation potential is variable (López Prol and Schill, 2021). Increasing their share in the electricity supply thus requires additional flexibility of the power system to deal with their variability (Kondziella and Bruckner, 2016). Geographical balancing, i.e. transmission of electricity between different regions and countries, is a particularly relevant flexibility option (Schlachtberger et al., 2017). This allows for balancing renewable variability over larger areas, using differences in load and generation patterns. Aside from such spatial flexibility, various temporal flexibility options can be used to manage the variability of wind and solar PV, particularly different types of electricity storage (Schill, 2020). Both geographical and temporal balancing can help to integrate surplus renewable generation and to meet residual load that could not be supplied by variable renewable sources at a particular location.

From a techno-economic perspective, geographical balancing, using the electricity grid, and temporal balancing, using electricity storage, are substitutes for one another to a certain degree. Therefore, the need for storage capacities in a specific region decreases if electricity can be exchanged with neighboring areas that have partly uncorrelated weather and demand patterns. In an application to twelve central European countries, we investigate the interactions between geographical and temporal balancing, enabled by electricity storage, in a future 100% renewable energy scenario. We do not aim to estimate the optimal amount of interconnection to be built; instead, we are interested in identifying and quantifying the drivers of why interconnection with neighboring countries mitigates electricity storage requirements. In terms of storage, we differentiate between “short-duration” storage, parameterized as lithium-ion batteries, and “long-duration” storage, parameterized as power-to-gas-to-power storage. We analyze the effects on both storage types separately. First, we measure the substitution effect between interconnection and storage by comparing the optimal storage capacities of two stylized least-cost power sector scenarios: in one, electricity interconnection between countries is allowed; in the other, it is not. Then, we define several factors that can explain the reduced need for storage capacities in an interconnected electricity sector compared to one without interconnection. Finally, we quantify the magnitude of the different factors.

[1]Two anonymous reviewers, the members of the research group *Transformation of the Energy Economy* at DIW Berlin and participants of the *PhD Strommarkttreffen 2021*, the *Enerday 2021*, *IAEE Online Conference 2021*, the *DIW GC Workshop 2021*, the *FSR Summer School 2021*, and the *YEEES 2022 Copenhagen* are thanked for very helpful comments and feedback. Financial support from the German Federal Ministry of Economic Affairs and Climate Action (BMWK) via the project MODEZEEN (FKZ 03EI1019D) is gratefully acknowledged.

We focus on five different factors to explain the storage-reducing effect of geographical balancing: differences between countries in hourly capacity factors of (1) wind and (2) solar PV, which are a function of spatially heterogeneous weather patterns and daily and seasonal cycles; (3) hourly time series of the electric load; and the availability of specific technologies such as (4) hydropower and (5) bioenergy that differ due to geographic or historical factors. A capacity factor determines how much electricity a power plant can produce in a given hour compared to its installed capacity. E.g., a capacity factor of 50% in a given hour means that a wind power plant with a power rating of 10 Megawatt (GW) produces 5 Megawatt hour (MWh) in that hour.

To determine the importance of each factor for storage capacity, we employ a factor separation method (Stein and Alpert, 1993; Lunt et al., 2021), which attributes model outcomes to different model inputs. This can be achieved by systematically varying only specific model inputs and comparing the outcomes of selected model runs. At the core of the analysis lies a comparison between an interconnected central European energy system with interconnection capacities foreseen by regulators (ENTSO-E, 2018a) and a counterfactual system without any interconnection. The difference in optimal storage deployed by the model can be explained with the factor separation method.

To generate these model outcomes, we use an open-source model of the European electricity system that minimizes total system costs given an hourly exogenous electricity demand in each county. The model determines endogenously optimal investment and hourly usage of different generation and storage technologies for each country to meet the energy demand as well as other policy-related constraints, such as minimum-renewable requirements. Thus, market clearing is achieved every hour. The solution of a cost-minimizing model represents a long-run equilibrium in which, under idealized assumptions, all generators and storage assets exactly cover their fixed and variable costs with their revenues. The model comprises twelve central European countries that are connected in a “net transfer capacity model” with fixed interconnection capacities. For increased robustness, our analysis considers ten weather years from a 30-years period.

Several studies have estimated electricity storage needs in Europe in scenarios with high shares of renewables. Literature reviews identify a positive, linear relationship between renewable electricity shares and optimal electricity storage deployment (Cebulla et al., 2018; Blanco and Faaij, 2018). Focusing on single countries, such as Germany, various analyses find that storage needs depend on the model scope, e.g., on the number of sector coupling technologies included and on how detailed these are modeled, as well as on the availability of other flexibility options (Weitemeyer et al., 2015; Babrowski, Jochem, and Fichtner, 2016; Scholz, H. C. Gils, and R. C. Pietzcker, 2017; Schill and Zerrahn, 2018). Other studies investigate how much storage is needed in the wider European power sector. While results again depend on model and technology assumptions, studies covering several European countries imply relatively lower storage needs than analyses focusing on a single country only (Bussar et al., 2014; Després et al., 2017; Child et al., 2019; Moser, H.-C. Gils, and Pivaro, 2020). Other analyses investigate the need for electricity storage in the U.S. (Safaei and W. Keith, 2015; De Sisternes, Jenkins, and Botterud, 2016; Phadke et al., 2020). For instance, long-duration storage requirements in Texas increase with growing penetration of variable RES (Johnson et al., 2021). Related studies derive similar findings and also conclude that interconnection decreases storage needs, focusing on other parts of the U.S. (Ziegler et al., 2019) or the whole of the United States (Tong et al., 2020; Dowling et al., 2020; P. R. Brown and Botterud, 2021; Bloom et al., 2022). Similarly, geographical balancing and electricity storage are identified as partial substitutes in a model analysis of the North-East Asian region (Bogdanov and Breyer, 2016). This substitution is considered to be particularly relevant for long-duration storage technologies (Jenkins and Sepulveda, 2021). Various papers have analyzed wind and/or solar PV variability and its impacts on the future energy system, partly focusing on extreme energy drought events (Collins et al., 2018; Raynaud et al., 2018; Cannon et al., 2015; Ohlendorf and Schill, 2020; Weber et al., 2019). Yet, none of these studies focus primarily on quantifying the effect of interconnection on storage needs or on systematically isolating individual drivers of this effect.

Hence, we contribute to the literature by illustrating how spatial flexibility influences the need for temporal flexibility in an application to twelve central European countries. Our principal contribution is to quantify how different factors contribute to the reduction in storage capacity caused by geographical balancing. To identify the importance of these different factors, we use an adapted "factor separation" method (Stein and Alpert, 1993; Lunt et al., 2021). As there is so far no established method to attribute outcomes of power market models to changing model inputs, we propose a modified procedure that builds on counterfactual scenarios and factor separation, which could also be used in other energy modeling applications. We are the first to employ factor separation in the context of energy modeling, using it to quantify the importance of which factors drive down storage needs in an interconnected central European energy system.

2.2 Methods

2.2.1 Factorisation method

Factorization (also known as "factor separation") is used to quantify the importance of different variables concerning their changes in a system. In complex systems, where more than one variable is altered simultaneously, it can be used to identify the importance of these variables for the changes in outcomes. Therefore, it can be used to analyze the results of numerical simulations (Lunt et al., 2021).

There are several factorization methods, and our analysis builds on the factorization method by "Stein and Alpert" (Stein and Alpert, 1993) and its extension, the "shared-interactions factorization" (Lunt et al., 2021). The basic principle of factorization relies on comparing the results of various counterfactual scenarios to separate the influence of different factors on a specific outcome variable. For a broader introduction to factor separation, we refer to the Supplemental Information (A.3) and to a recent paper (Lunt et al., 2021) providing an excellent introduction and overview.

To decompose the changes in storage needs, we define six factors that will impact the need for storage. Each factor can take two different states, which, to ease explanations, we call A and B. Table 2.1 provides an overview of all factors and their possible states.

Factor	State A	State B
(1) Interconnection	not allowed	allowed
(2) Wind	harmonized	not harmonized
(3) Solar PV	harmonized	not harmonized
(4) Load	harmonized	not harmonized
(5) Hydropower	harmonized	not harmonized
(6) Bioenergy	harmonized	not harmonized

Table 2.1: Factors and states

To determine the magnitude of the different factors, we compare model outcomes of different scenario runs. We compare a default "real-world" setting to a counterfactual setting. In the counterfactual setting, corresponding to state A, all factors are *harmonized* which means that their respective cross-country variation is eliminated. In contrast, in the state B *not harmonized*, all countries exhibit their own solar PV capacity factors. The same logic generally applies to the other factors as well. A more detailed definition and explanation of the factors is provided in the next section 2.2.2.

In contrast to other applications of factor separations, we are not interested in the *entire* effect of each factor on storage needs. To identify which factors are most important in influencing storage needs through interconnection, we focus instead on the "interaction terms" between interconnection (1) and the other factors (2)-(6).

To identify the influence of the factors, we run several counterfactual scenarios. The notation to define the different factors is as follows. Whenever a factor is in state B, hence *allowed* or *not harmonized*, a subscript with the respective number is added. If the factor is in state A, no subscript 1-6 is added. The scenario in which all factors are in state A is called f_0, hence all factors are *harmonized*, and no interconnection is allowed. In this scenario, all modeled countries are very similar, i.e., they have the same capacity factors, load patterns, and equal relative installed hydropower and bioenergy capacities. The scenario f_1 is nearly identical, with the expectation that interconnection is allowed as it is indicated by subscript 1, pointing to the factor interconnection. Following that logic, scenario f_2 resembles f_0, except that factor (2), i.e., wind, is not harmonized. Following that structure, we can define and name all relevant scenarios. For instance, f_{12} denotes the scenario in which interconnection is allowed, and wind capacity factors are not harmonized, yet all the other factors are in their state A, hence *harmonized*.

Of all possible scenarios, two are of special interest:

- f_{123456}: This scenario can be regarded as our "default" scenario with no capacity factors or power plant portfolios being harmonized and interconnection between countries allowed.
- f_{23456}: This scenario equals the previous one, with the only difference that interconnection between countries is not allowed. Thus, all countries operate as electric islands.

We aim to explain the difference in optimal storage energy and power installed between these two scenarios f_{123456} and f_{23456}, and to attribute the difference to the various factors (2)-(6). To quantify the importance of the different factors, we calculate the size of interaction factors between factor *interconnection (1)* and the other factors (2)-(6).

The size of the individual factors can be defined as differences between scenario runs. These are denoted $\hat{f}_1$, $\hat{f}_2$, ..., $\hat{f}_{12}$, ..., etc. $\hat{f}_1$ is the sole effect of factor (1) by comparing the scenarios f_0 and f_1:

$$\hat{f}_1 = f_1 - f_0. \tag{2.1}$$

As described above, we rely on the interaction effects of factors for our attribution. The definition of interaction effects is more complicated and requires the results of several scenarios. For instance, the combined effect of the factors (1), (2), and (3), denoted $\hat{f}_{123}$, is defined as:

$$\hat{f}_{123} = f_{123} - (f_{12} + f_{13} + f_{23}) + (f_1 + f_2 + f_3) - f_0 \tag{2.2}$$

Put in words, $\hat{f}_{123}$ measures *only* the *combined* influence of the factors interconnection (1), wind (2), and solar PV (3) on storage need, hence the interaction effect. The (direct) effects of the factors (such as $\hat{f}_1$) are not comprised.

To quantify the importance of different factors of interconnection on storage, we first define the "difference of interest" (INT), which we define as:

$$INT = f_{123456} - f_{23456}. \tag{2.3}$$

Then, we quantify which factors explain most of this difference. INT can be written as the sum of all interaction factors between the different factors (2)-(6) and the interconnection factor (1). Hence, every element of that sum has to comprise at least factor (1). It can be shown that the difference INT is the sum of all the interaction factors where interconnection is involved, therefore

$$\begin{aligned} \text{INT} =& \hat{f}_1 + \hat{f}_{12} + \hat{f}_{13} + \cdots + \hat{f}_{16} + \hat{f}_{123} + \cdots + \hat{f}_{156} \\ &+ \hat{f}_{1234} + \cdots + \hat{f}_{1456} + \hat{f}_{12345} + \cdots + \hat{f}_{13456} + \hat{f}_{123456}. \end{aligned} \tag{2.4}$$

To calculate the contribution of one of the factors on the difference of interest, INT, we collect all interaction effects between the factor interconnection (1) and the respective other factor. For instance, to quantify the contribution of the factor wind (2), we sum up all interaction effects that include the factors interconnection (1) and wind (2). The principal interaction effect $\hat{f}_{12}$ is part of it, but, e.g., also the interaction effects between interconnection, wind, and solar PV: $\hat{f}_{123}$. To avoid double-counting, we have to distribute these shared interaction effects between - in this case - the factors wind and solar PV. There are different ways to distribute these effects. We use the "shared-interactions factorization" (Lunt et al., 2021) that distributes the interaction effects equally between the different factors. Hence, the total interaction effect between the factors interconnection and wind can be defined as follows:

$$\hat{f}_{12}^{total} = \hat{f}_{12} + \frac{1}{2}\hat{f}_{123} + \frac{1}{2}\hat{f}_{124} + ... + \frac{1}{3}\hat{f}_{1234} + ... + \frac{1}{5}\hat{f}_{123456} \tag{2.5}$$

Similarly, we define the interactions between interconnection and solar PV as $\hat{f}_{13}^{total}$, between interaction and load as $\hat{f}_{14}^{total}$, between interaction and hydropower as $\hat{f}_{15}^{total}$, and between interaction and bioenergy as $\hat{f}_{16}^{total}$.

All these interaction terms $\hat{f}_{1i}^{total}$ add up to our difference of interest:

$$\text{INT} = \hat{f}_{12}^{total} + \hat{f}_{13}^{total} + \hat{f}_{14}^{total} + \hat{f}_{15}^{total} + \hat{f}_{16}^{total}. \tag{2.6}$$

To determine the contribution of each factor (wind, solar PV, load, etc.) to the change in optimal storage capacities facilitated through interconnection, we calculate their share s. For instance, for the factor wind, this share reads as

$$s_{wind} = \hat{f}_{12}^{total} / INT. \tag{2.7}$$

As we have defined six factors, we need to run $2^6 = 64$ scenarios for a complete factorization of one weather year. As we perform our analysis for ten different weather years, we run 640 different scenarios (see Table A.5 for an illustrative overview).

2.2.2 Definition of factors

The basic principle to quantify how different factors impact optimal storage through interconnection is the use of counterfactual scenarios, in which the state of these factors is varied. For all our factors, we define two states in which they can exist. For most of the factors, these states are *not harmonized* and *harmonized*, in which, in the latter, all countries are made equal to eliminate the variation between countries. By "making equal", we refer to a counterfactual scenario in which differences between countries, such as different renewable energy availability time series or hydropower availabilities, are eliminated.

We define five factors we consider to be most relevant. The two factors "wind" and "solar PV", covering most of the energy supply, are associated with the variable capacity factors of these technologies. Another factor is "load" which covers energy demand. The two factors "hydropower" and "bioenergy" relate to different inherited power plant portfolios in different countries. Finally, the factor "interconnection" is defined only to make the analysis operational, not to explain reduced storage needs.

Wind The factor that captures the impact of wind patterns is operationalized with the help of capacity factors and takes two different states: *not harmonized* or *harmonized*. In the state *not harmonized*, every country has its own capacity factor time series, as provided by the database used (De Felice, 2020) (more information in Section A.1) given the specific weather year. On the contrary, in the state *harmonized*, capacity factors are equal in all countries using the capacity factors of our reference country Germany. Hence, the entire variation between countries in wind power capacity factors is taken away.

On top of that, we also have to account for geographic differences in offshore wind power, which cannot be deployed in all countries because of differences in access to the sea. In contrast to onshore wind power and solar PV which could be, in principle, deployed everywhere, offshore wind power, like hydropower, cannot. In the state *harmonized*, not only do the capacity factors have to be the same across all countries, but also all countries have to operate "as if they are the reference country" (Germany in our case). Therefore, in the state *harmonized*, all countries exhibit the same share of offshore wind power plants. That share is defined as installed capacity divided by the total yearly load. We use the total yearly load as the denominator as it is not related to the power plant fleet but is still country-specific. If we used the share of installed power plant capacity, the model would have the incentive to change the total power plant fleet, which we have to avoid. This share is determined based on a scenario run of our reference country, Germany, in isolation.

Using this approach implies, given the share is larger than zero, that countries without sea access, e.g., Austria or Switzerland, have offshore wind power plants in the state *harmonized*. Although this is clearly not realistic, this harmonization step - including the application of the share - is necessary to take away all the cross-country variation of capacity factors, and also geographic differences such as access to the sea. In the state *harmonized*, all countries act as if they were the reference country in isolation.

Solar PV The factor *solar PV*, like wind power, takes two states. The state *not harmonized* corresponds to the default with solar PV capacity factors as provided by our data source. In the *harmonized* case, solar PV capacity factors are equal in all countries using those of our reference country. Hence, all variation between countries in solar PV capacity factors is taken away.

Load The definition of the factor "load" is similar to factors "wind power" and "solar PV". In the state *harmonized*, all countries have the same load time series as our reference country, yet scaled to their original total yearly demand. Therefore, in the state *harmonized*, all countries have the same load profile (same as the reference country Germany) but on country-specific levels.

Hydropower In addition to differences in wind, solar PV, and load patterns, we also aim to quantify how much of the storage capacity reduction can be attributed to specifics of the existing power plant portfolios because of legacy capacities and limited expansion potentials. Hydropower, comprising reservoirs, pumped-hydro, and run-of-river, can be considered to be exogenous. Some countries happen to have them, while others do not. Also, their installed generation capacities are considered to be exogenous.

In the state *harmonized*, all countries have the same share of installed power plant capacities of the respective technologies. We treat all countries as if they had a power plant portfolio like the reference country in isolation. In the case of hydropower, we also assume the German hydro times series for the other countries. These shares are determined based on a scenario run of our reference country, Germany, in isolation. We calculate the relative weight of the exogenous technologies as a share of installed capacity over the total yearly load. In the state *harmonized*, this share is applied to all countries. For a detailed explanation regarding the shares, we refer to paragraph *Wind* above.

Bioenergy The definition of the factor *bioenergy* closely follows the one of hydropower described above. In the state *harmonized*, all countries have the same share of installed bioenergy power plant capacities. We consider all countries as if they had a power plant portfolio in isolation like the reference country.

Interconnection The factor interconnection is needed to make the factor separation operational. Like the other factors, it has only two states. In contrast to the other factors, they are called *not allowed* and *allowed* and determine whether electricity flows between countries is possible. In the state *allowed*, interconnection is allowed and the interconnection capacities between countries are fixed, as given in Table A.4. If interconnection is *not allowed*, electricity flows between countries are not possible.

2.2.3 Model

To obtain the model results needed for the factor separation, we use the open-source capacity expansion model DIETER (Zerrahn and Schill, 2017; Gaete-Morales, 2021), which has previously been used for detailed long-term electricity sector planning analyses (Schill and Zerrahn, 2018; Say, Schill, and John, 2020; Stöckl, Schill, and Zerrahn, 2021; H. C. Gils, Gardian, Kittel, Schill, Murmann, et al., 2022; van Ouwerkerk et al., 2022) and for more stylized illustrations (Schill, 2020; Kittel and Schill, 2022; H. C. Gils, Gardian, Kittel, Schill, Zerrahn, et al., 2022). It minimizes total power sector costs for one year, considering all 8760 consecutive hours. DIETER focuses on the temporal flexibility of renewable integration. It assumes unconstrained electricity flows within countries. In this application, the model comprises 12 central European countries: Austria, Belgium, Czechia, Denmark, France, Germany, Italy, Netherlands, Poland, Portugal, Spain, and Switzerland (Figure A.1). In scenarios in which electricity exchange between countries is allowed, countries are connected with a transport model based on Net Transfer Capacity (NTC). These are fixed according to an ENTSO-E scenario (Table A.4); an expansion or reduction of these cross-border interconnection capacities is not possible. The model does not consider transmission or distribution bottlenecks within a country.

Endogenous model variables of interest are the installed capacity of on- and offshore wind power and solar PV and the installed capacity of short- and long-duration storage, differentiated by storage energy, as well as charging and discharging power. Further model outputs are hourly patterns of electricity generation and curtailment (of renewables), the charging and discharging patterns of storage, and the power exchange between countries.

Exogenous model inputs include techno-economic parameters such as investment and variable costs, the time series of capacity factors of wind and solar PV, and electricity demand. Electricity demand is assumed to be price-inelastic. To ensure the relevance of our results, we impose certain bounds on the investments of some generation technologies. In particular, we consider the installed storage energy and power capacities of different types of hydropower plants (run-of-river, reservoir, pumped-hydro) and the installed generation capacity of bioenergy to be exogenous, without any possibility of additional investments. Accordingly, there is no need to additionally cap the yearly electricity generation of bioenergy. Only a subset of countries can install offshore wind power. In Section A.1, we provide more details on assumptions and the input data.

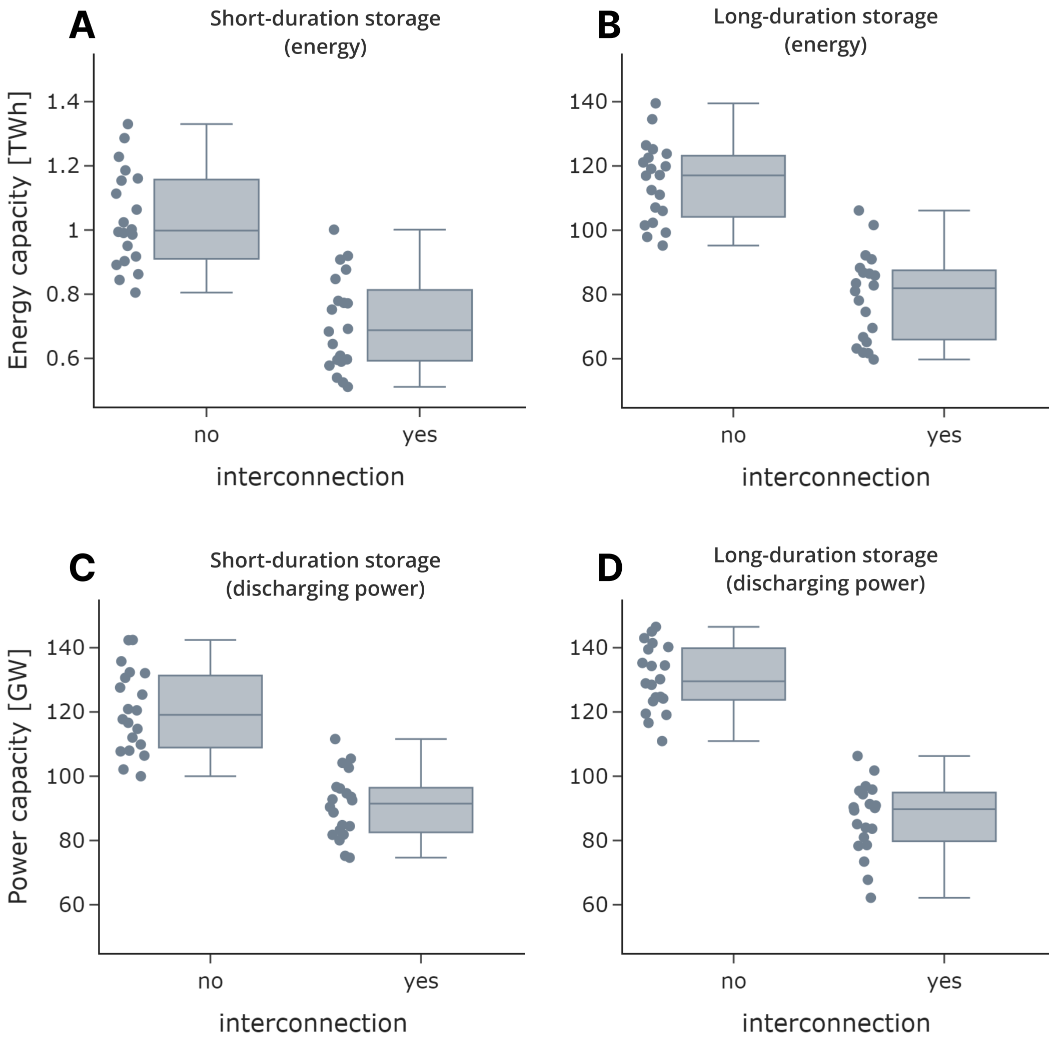
Model results can be interpreted as the outcomes of an idealized, frictionless central European electricity market in which all generators maximize their profits. Real-world market outcomes may differ from this benchmark because of various frictions, i.e., limited information of market actors or barriers to market entry. Note that single countries do not possess individual objective functions, but costs are minimized for the overall interconnected power sector.

For robustness, we do not perform our analysis only for a single weather year only, but for ten different ones covering nearly three decades, i.e., 1989, 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, and 2016. Between these weather years, the time series of renewables, load, and hydro inflow time series differ.

2.3 Results

Employing a factor separation approach in combination with a numerical energy sector model, we determine by how much interconnection between countries decreases the overall optimal storage energy and power capacity of the energy system (Section 2.3.1). Afterward, we attribute the change in storage capacity to different drivers (Section 2.3.2) and explain the key mechanisms (Section 2.3.3).

2.3.1 Geographical balancing reduces optimal storage power and energy capacity



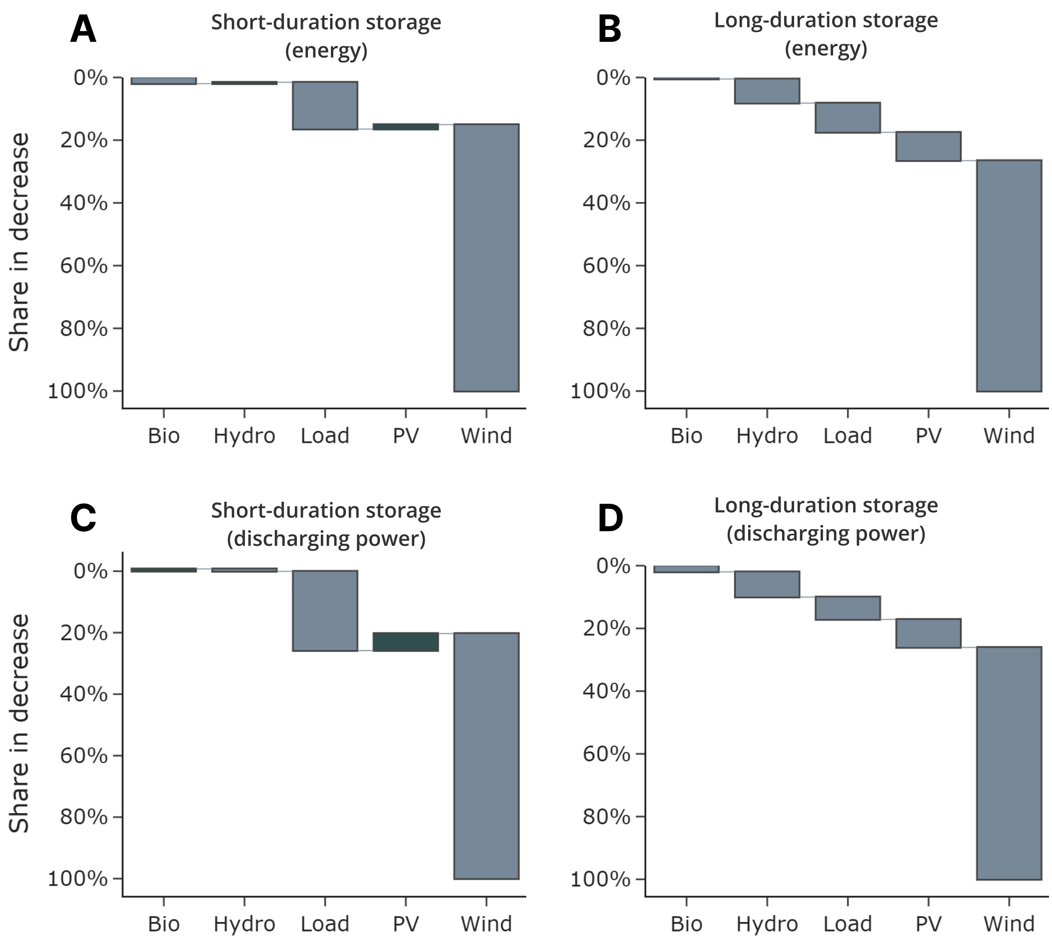
Notes: The figure shows energy capacities (Panel A and B) and discharging power (Panel C and D) capacities of short- and long-duration storage aggregated over all countries. Every dot is the scenario result based on one weather year. The middle bar shows the median value. The box shows the interquartile range (IQR), which are all values between the 1st and 3rd quartile. The whiskers show the range of values beyond the IQR, with a maximum of 1,5 x IQR below the 1st quartile and above the 3rd quartile.

Figure 2.1: Aggregate installed storage energy and discharging power capacity

We find that aggregated optimal storage capacity is substantially lower in an interconnected system than in a system of isolated countries (Figure 2.1). This applies to both short- and long-duration storage, as well as to storage discharging power and energy. Interconnection reduces optimal energy capacity need of short- and long-duration storage on average by 31% over all years modeled. Discharging power, on average, decreases by 25% for short-duration and by 33% for long-duration storage. This translates to a reduction of 36 TWh in storage energy and 74 Gigawatt (GW) in storage discharging power (short- and long-duration storage combined) for the modeled interconnected central European power sector with 100% RES.

These results confirm previous findings in the literature that a system with interconnection requires less storage than a system without or put differently, that geographical balancing of variable renewable electricity generation across countries mitigates storage needs. We show that this also holds in a scenario with 100% renewable energy. The variation of results between weather years is substantial, as optimal long-duration storage varies between 95 TWh and 140 TWh depending on the weather year. However, our results indicate that the storage-reducing effect of interconnection is robust to different weather years.

2.3.2 Wind power is the largest driver for mitigating storage needs



Notes: The figure shows the average relative contributions of different factors to the reduction in storage energy (Panel A and B) and discharging power (Panel C and D) capacity due to interconnection. The average is taken over all ten weather years included in the analysis.

Figure 2.2: Relative factor contribution to storage mitigation

Using counterfactual scenarios and a factorization method (more information in Section 2.2.1), we can attribute the decrease in optimal storage needs to individual factors. Wind power contributes by far the most, namely 80%, to reducing storage discharging power and energy (Figure 2.2).

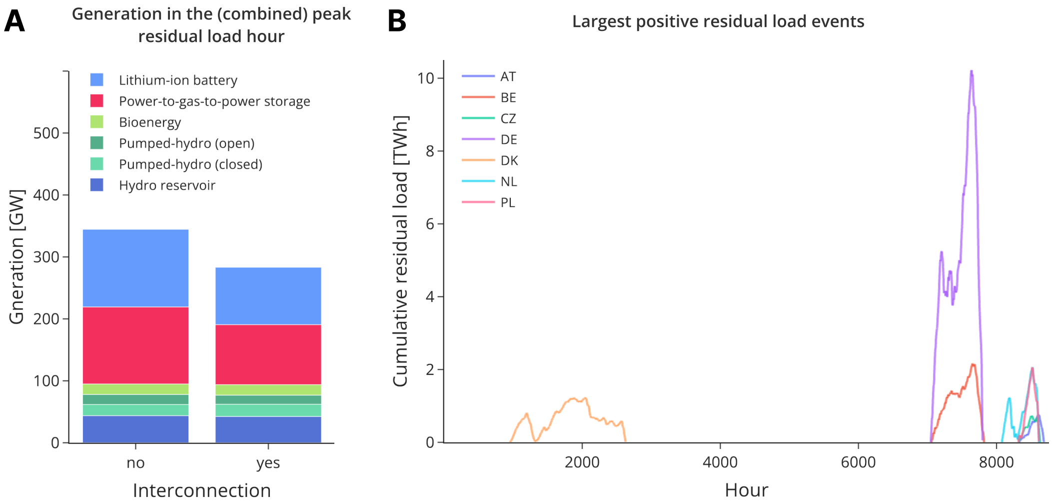
Especially for short-duration storage, differences in load profiles also contribute substantially to the storage-mitigating effect of interconnection. These account for 26% of the decrease in short-duration storage discharging power (Figure 2.2, Panel C). In contrast, differences in solar PV have, on average, a small increasing effect on short-duration storage energy and discharging power. However, this effect is strongly heterogeneous, depending on the weather year. For instance, solar PV can explain in some years up to 13% of the drop in storage energy and 8% of the drop in discharging capacity, yet in turn, has even a storage-increasing effect in other years (Figure A.2). Allowing for transmission between countries may increase optimal overall solar PV investments, all other factors being constant and homogenized; this is because capacities grow in countries with higher solar PV full load hours, i.e., with lower solar PV costs. In turn, the need for short-duration storage then increases compared to a setting without transmission between countries because of higher diurnal fluctuations.

In the case of long-duration storage, all investigated factors contribute to the reduction of optimal storage investments enabled by interconnection. While wind power is again clearly dominating, differences in hydropower capacity, load curves, and solar PV time series almost equally contribute to reducing storage needs.

While Figure 2.2 depicts average values, using ten weather years, results for individual years vary (see Figure A.2 for more detail). Especially the contribution of wind power strongly differs between weather years. However, the relative contributions of the factors are qualitatively robust. In all analyzed weather years, we find that wind power is the dominating factor.

Figure 2.2 shows the already aggregated factors. In the supplemental information A.5, we provide further information on the magnitude of all factors from the factorization in all weather years (Figure A.3) and in weather year 2016 (Figure A.4).

2.3.3 An explanation of key mechanisms



Notes: Panel A: The left bar shows the sum of electricity generation in the different countries' peak residual load hours, while the right bar shows the system-wide generation in the peak residual load hour of the interconnected system. Both bars depict the aggregate values of all countries. Panel B: Each country's largest positive residual load event is depicted. Countries with large hydro reservoirs are excluded as they have fundamentally different residual load events. Due to the existence of reservoirs, they accumulate large positive residual load events over the year. Both panels show results of the weather year 2016.

Figure 2.3: The drivers of reduced storage need: peak residual load hours and positive residual events

To explain these results, we illustrate the key mechanisms using the weather year 2016. We turn to the peak residual load hour as a central driver to explain the drop in optimal storage discharging power capacity through interconnection. The peak residual load hour is defined as the hour in which residual load (i.e., load minus generation by variable renewable sources) is largest in a year. In an energy system based on 100% renewables and high shares of wind and solar PV, load in that critical hour has to be provided mainly by storage. Hence, the residual load peak hour determines the required storage discharging power capacity.

When we compare an energy system without and with interconnection, the following thinking applies. In a system without interconnection, every country has to satisfy its own peak residual hourly load. Therefore, the overall (sum of all countries) storage discharging power needed in this system is simply the sum of all the countries' individual peak residual loads minus other existing generation options, such as bioenergy or hydro reservoirs. This simple addition is not true for an interconnected system if the countries' peak residual load hours do not coincide temporarily. Then, peak residual load hours in individual countries can potentially be compensated by geographical balancing, i.e., imports. Therefore, the overall storage discharging power needed in an interconnected system is most likely smaller than the sum of the countries' peak residual loads.

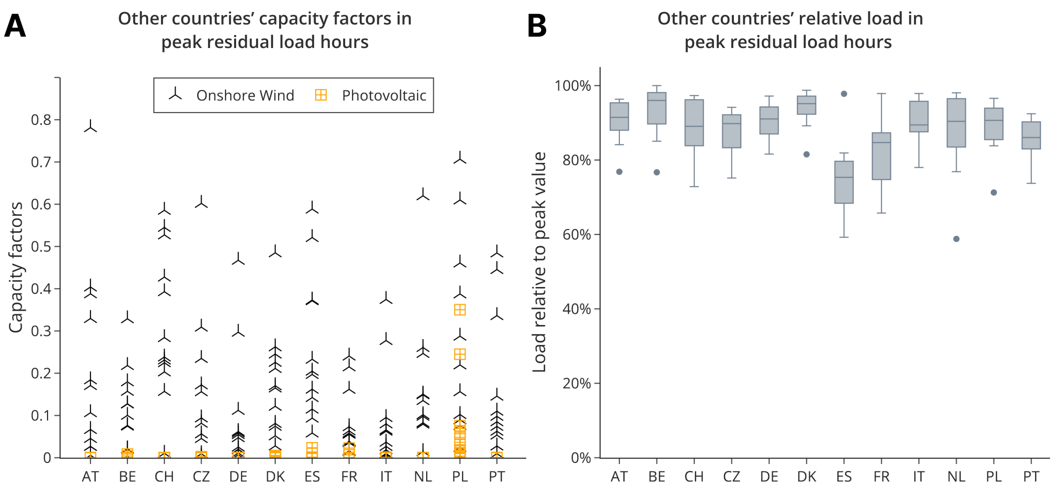
The left bar of Figure 2.3, Panel A, shows the sum of electricity generation in the different countries' peak residual load hours, while the right bar shows the system-wide generation in the peak residual load hour of the interconnected system. The two differ because peak residual load hours do not align in the different countries. Implicitly, this reasoning assumes that there would be no limit on interconnection capacity between countries. In our case, net transfer capacities (NTC) are limited, so the residual peaks cannot be balanced out completely. Yet, even with limited interconnection, the non-aligned peak residual load hours of the different countries help to reduce residual storage discharging power needs.

A similar reasoning applies to explain the reduced need for storage energy. The size of needed storage energy is correlated to the largest positive residual load event. We define a positive residual load event as a series of consecutive hours in which the cumulative residual load stays above zero. It may be interrupted by hours of negative residual load as long as the cumulative negative residual load does not outweigh the positive one. As soon as it does, the positive residual load event is terminated. These events typically occur when sunshine and wind are absent for long periods.

An energy system with interconnection needs less storage energy if the countries' largest positive residual load events do not fully coincide. In this case, geographical balancing can help to flatten out these events. On the contrary, in a system without interconnection, all these events have to be covered in and by each country individually; hence, the aggregate storage energy needs in a system without interconnection is the sum of every country's largest positive residual load event, and, therefore, higher than in a system with interconnection. Figure 2.3, Panel B, depicts the large positive residual load events for the year 2016 for different countries. Although some events overlap between the countries, many do not, and thus, interconnection helps reduce the need for storage energy capacity.

As shown in the previous section, wind power is the principal factor that drives down storage needs when interconnection between countries is possible. Peak residual load and the largest positive residual load event largely determine storage needs. Therefore, the decrease in peak residual load and also in the largest residual load events are largely driven by the heterogeneity of wind power between countries. This can be confirmed in the data. In the hour of a country's highest residual load, onshore wind power capacity factors of most countries are still relatively high, so geographical balancing could help to make use of them (Figure 2.4, Panel A). In contrast, this is hardly the case for solar PV capacity factors. The peak residual load hour of most European countries is likely to be in the winter when demand is high, but solar PV feed-in is low. Thus, wind power can contribute more to covering the peak residual hour than solar PV.

Load profiles also differ to some extent, such that relatively lower loads in other countries in combination with transmission can help to relieve the peak demand in a given country. During a peak residual load hour in a given country, we show the load (not residual load) relative to its maximal value in that year (Figure 2.4, Panel B). Most countries have to cover their own load and have limited space to provide electricity for export. Most values range above 80%. Therefore, differences in load



Notes: Panel A shows hourly capacity factors of all other countries in the peak residual load hour of the country shown on the horizontal axis. Panel B shows the range of relative loads of all other countries in the peak residual load hour of the country shown on the horizontal axis. The middle bar shows the median value. The box shows the interquartile range (IQR), which are all values between the 1st and 3rd quartile. The whiskers show the range of values beyond the IQR, with a maximum of 1,5 x IQR below the 1st quartile and above the 3rd quartile. Both panels show results of the weather year 2016.

Figure 2.4: Illustration of main drivers: wind power, solar PV, and load

profiles provide a positive but limited flexibility potential related to (peak) residual load balancing using interconnection.

Hydropower, a combined factor of hydro reservoirs, pumped-hydro, and run-of-river, has only a limited influence on storage reduction through interconnection. It could, in general, be an important provider of flexibility to the system. Yet, the reason for its limited importance is that installed hydro capacities are not big enough to substantially reduce the need for storage power and energy capacity (see Table A.3). This result may change under the assumption that hydropower capacity could be extended far beyond current levels. Then, the factor hydropower could play a bigger role in geographic balancing. This is also true for bioenergy, which we do not discuss here explicitly due to its minor effect.

2.4 Discussion

2.4.1 Interconnection decreases storage needs

Identifying future electricity storage needs is highly relevant for planning deeply decarbonized, 100% renewable power systems (T. Brown et al., 2018). Using an open-source numerical model, our results show that optimal electricity storage capacity in an application to twelve central European countries substantially decreases when interconnection between countries is allowed. Compared to a setting without interconnection, short- and long-duration storage energy capacity decreases by 31%; storage discharging power, on average, declines by 25% and 33%, respectively. These values hold for an average of ten weather years, covering three decades of historical data. Our outcomes corroborate and extend findings in the previous literature and show that the storage-mitigating effect of geographical balancing also holds in a with 100% renewable energy. Yet, we go a step further by also disentangling and quantifying how the mitigation of storage needs is driven by different factors. To do so, we employ a factorization approach used, for instance, in climate modeling (Lunt et al., 2021). To the best of our knowledge, this is the first time such an approach is adapted to a quantitative power sector model analysis.

2.4.2 Wind power is the most important factor

We find that wind power is by far the most important factor in reducing optimal storage needs through geographical balancing. Its heterogeneity between countries accounts, on average, for around 80% of reductions in storage energy and discharging power capacity needs. The main reason is that during peak residual load hours of a given country, which largely determine electricity storage needs, wind power availability in neighboring countries is still relatively high. Accordingly, geographical balancing helps to make better use of unevenly distributed wind generation potentials in an interconnected system during such periods. Differences in the profiles of solar PV and load, as well as in power plant portfolios (hydropower and bioenergy), contribute to the mitigation of storage needs to a much smaller extent. Though our analysis focuses on central Europe, we expect that qualitatively similar findings could also be derived for other non-island countries in temperate climate zones where wind power plays an important role in the energy mix.

2.4.3 Conclusions on geographical balancing and modeling

Our analysis fosters the grasp of the benefits of geographical balancing and its drivers. The findings may also be useful for energy system planners and policymakers. We reiterate the benefits of the European interconnection and argue that strengthening it should stay an energy policy priority if a potential shortage of long-duration electricity storage is a concern. Then, policymakers and system planners may particularly focus on such interconnection projects that facilitate the integration of wind power.

Finally, some modeling-related conclusions can be drawn. Any model analysis where wind power plays a role should properly consider geographical balancing in case storage capacities are of interest. Our analysis also indicates the importance of using more than one weather year in energy modeling with high shares of variable renewables. Not least, we hope to inspire other researchers to use factorization methods in energy modeling applications more widely.

2.4.4 Limitations

As with any numerical analysis, our investigation comes with some limitations. First, we may underestimate storage needs due to averaging over specific weather years. In real-world systems, planners may pick only scenarios with the highest storage need to derive robust storage capacity needs. Likewise, planners may also want to consider an extreme renewable energy drought for storage dimensioning, i.e., a period with low wind and solar availability. In case such a renewable energy drought similarly affects all countries of an interconnection, the storage-mitigating effects may decrease. Second, we exclude demand-side flexibility options. In particular, we do not consider future sector coupling technologies such as battery-electric vehicles or heat pumps, which may induce substantial additional electricity demand but possibly also new flexibility options. Temporally inflexible sector coupling options may substantially increase storage needs (Schill and Zerrahn, 2020). Thus, we might overestimate the role of interconnection in mitigating storage. The interaction of sector coupling with storage mitigation via geographical balancing appears to be a promising area for future research. Third, optimization model results depend on input parameter assumptions. In particular, we assume fixed interconnection capacities (Table A.4) and do not aim to determine the optimal amount of interconnection capacity investments. For such an analysis, a more detailed network model that considers optimal power flows over individual lines should be used. Larger interconnection capacities than assumed here could increase the storage-mitigating effect of interconnection as additional flexibility from other countries would become available. We show average utilization rates of interconnections in Section A.5. Moreover, our analysis does not differentiate between the “level” and “pattern” effects of wind and solar PV profiles. In our counterfactual scenarios, we implicitly change both the patterns and the levels of wind and solar PV availability. Further analysis could disentangle these two factors and quantify this relative importance to better understand what exactly drives storage mitigation through wind and solar PV.

3

Flexible heat pumps: must-have or nice to have in a power sector with renewables?

This chapter is based on A. Roth, D. Kirchem, et al. (2023). "Flexible Heat Pumps: Must-Have or Nice to Have in a Power Sector with Renewables?" *arXiv preprint* arXiv:2307.12918 [econ.GN]. DOI: 10.48550/arXiv.2307.12918

3.1 Introduction[1]

In light of the climate crisis, heat pumps are regarded as a central technology to reduce GHG emissions in the heating sector (IEA, 2022). When powered with electricity from RES, heat pumps can displace traditional heating technologies such as oil- and gas-fired heating and thus mitigate GHG emissions. In addition, the Russian invasion of Ukraine has led to a further political push in Europe, but especially Germany, to reduce the dependence on Russian natural gas imports. In Germany, natural gas is, at the moment, still the principal source of residential heating. The electrification of heating can therefore be seen as a critical measure to reduce the use of natural gas.

In Germany, policymakers aim for an accelerated roll-out of decentralized heat pumps, with a declared target of six million installed heat pumps by the year 2030 (A. Roth and Schill, 2023b). Given the current stock of around 1.5 million heat pumps, such a transition implies an increase in the electricity demand. So far, it is not yet understood how an increased heat pump stock affects the power sector in detail, considering that the electricity needs for mobility, hydrogen production, and other energy services will also increase. One common concern is that heat pumps constitute an additional burden on the power sector if they are operated in an inflexible manner. Given that electricity load profiles often coincide with heat demand profiles, inflexible heat pumps could add to existing load peaks and thus increase the need for firm generation capacity or electricity storage. Therefore, we explore the power sector effects of different German heat pump roll-out scenarios. In particular, we focus on different degrees of temporal flexibility in heat pump operations by varying the heat storage capacities assumed to be attached to heat pumps. To do so, we apply the open-source capacity expansion model DIETER to the central European power sector for various scenarios of the year 2030.

Previous studies have highlighted the important role of heat pumps in the decarbonization of the heating sector. A recent study shows that deploying heat pumps is one of the fastest strategies to reduce natural gas consumption in the German heating sector. Several studies investigate the potential of heat pumps to facilitate the integration of RES in the power sector (Bernath, Deac, and Sensfuß, 2019; Papaefthymiou, Hasche, and Nabe, 2012; Hedegaard and Münster, 2013; Ruhnau, Hirth, and Praktiknjo, 2020; Chen et al., 2021). For example, analyses show that a roll-out of heat pumps aligns well with additional investments into wind power deployment (Ruhnau, Hirth, and Praktiknjo, 2020; Chen et al., 2021). With respect to the flexibility of heat pumps and optimal heat storage size, the picture is inconclusive. Investigating heat storage sizes, a study finds that an optimal heat storage capacity for Spain and the UK lies between 12 and 14 hours (Lizana et al., 2023). An older analysis of wind power deployment in Denmark finds that the flexible operation of heat pumps provides only moderate system benefits and that even inflexible heat pumps enable a higher share of wind power energy (Hedegaard and Münster, 2013). A study for Germany points out

[1]Our colleague Adeline Guéret is thanked for supporting the calculations described in section 3.4.3, as well as various colleagues of the Ariadne project for feedback on an earlier draft. Financial support from the German Federal Ministry of Education and Research (BMBF) via the Kopernikus project Ariadne (FKZ 03SFK5N0) is gratefully acknowledged.

that the power system cost savings from flexible electric heating with night storage in Germany is moderate because renewable availability patterns do not align well with heat demand profiles (Schill and Zerrahn, 2020). The seasonal demand pattern gives flexible electric heating a disadvantage compared to other sector coupling options without this seasonality, such as electric vehicles. This finding is also supported by another study (Kröger, Peper, and Rehtanz, 2023) that identifies a larger potential for load shifting in electric vehicles than in heat pumps. Another study focuses on the role of flexible, large-scale, centralized heat pumps in district heating grids (Bernath, Deac, and Sensfuß, 2019), finding a correlation between RES expansion and the choice of heating technologies. With higher deployment of RES, large heat pumps become more competitive. Including other flexibility options in the analysis might reduce the value of flexibility in the heating sector. Other studies focus on the competition of the flexibility provided by heat pumps with electricity storage units. In power systems with an 80 percent renewable share or higher, the flexible use of heat pumps reduces the investment needs for short-term electricity storage significantly (Hilpert, 2020). The substitutional nature between pumped hydro storage and thermal storage is also highlighted in the literature (Ruhnau, Hirth, and Praktiknjo, 2020).

Our paper adds to the existing body of literature by investigating the power sector effects of decentralized heat pumps in detail, specifically accounting for different levels of temporal flexibility facilitated via heat storage. We do so with an open-source capacity expansion model that considers the hourly variability of renewable generation as well as electricity and heat demand over a full year, also accounting for additional loads related to electric vehicles and the production of green hydrogen. To the best of our knowledge, such an analysis has not been done so far. We investigate how different roll-out paths of heat pumps with different heat storage sizes impact the optimal capacity investment and dispatch decisions in the power system. In contrast to prior studies, we also examine how increases in natural gas prices impact the power system effects of an accelerated heat pump roll-out. To check the robustness of our results, we carry out numerous sensitivity analyses with alternative assumptions on relevant input parameters such as renewable availability, including an extended drought period, natural gas prices, and a German coal phase-out.

3.2 Methods

Power sector model DIETER In this study, we use the power sector model DIETER (Dispatch and Investment Evaluation Tool with Endogenous Renewables).[2] It is an open-source linear program to determine the least-cost investment and dispatch decisions for all electricity generation and storage technologies. DIETER not only covers the traditional electricity sector but also includes a detailed space heating module, e-mobility, and flexible hydrogen production options. The model minimizes total system costs and considers all subsequent hours of a year to accurately capture renewable energy variability and storage use. Input data for DIETER include time series of electric load, heat

[2]The model code can be accessed here: https://gitlab.com/diw-evu/projects/heatpumps_2030.

demand, electric vehicle charging, hydrogen demand, and capacity factors of renewable energies. Cost assumptions and technology investment constraints are further inputs.

Heat sector The space heating sector is included in Germany using twelve classes of residential buildings categorized by two size classes (single-/two-family homes and multi-family buildings) and six age classes, which correspond to varying energy efficiency levels (Schill and Zerrahn, 2020). We exogenously specify the proportion of space heating, which is covered by two different types of heat pumps for each scenario. Based on these inputs and assumptions, the model optimizes the hourly use of electricity by heat pumps. We assume that heat pumps can be combined with buffer thermal energy storage of different sizes, which we vary between scenarios.

Figure 3.1 depicts how heat pumps are modeled in DIETER. The heating energy generated by a heat pump is determined by its coefficient of performance (COP) and the amount of environmental heat available. How much heating energy is provided to the building depends on the heat outflow from the buffer storage, which cannot exceed the total amount of heating energy stored plus the storage inflow in the same hour. Finally, the heat storage outflow feeds both the space heating demand and the hot water demand. We only consider decentralized heat pumps with decentralized thermal energy storage. Centralized large heat pumps supplying district heating grids and centralized seasonal heat storage are not considered.

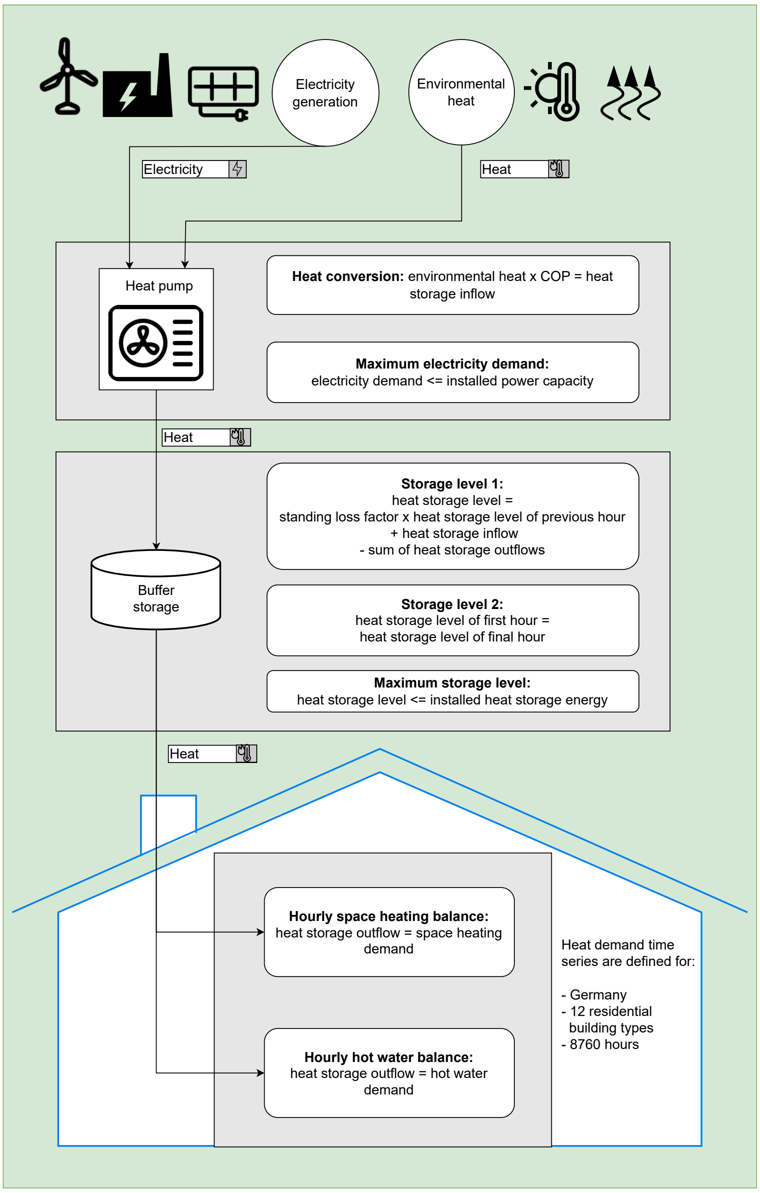


Figure 3.1: Heat module in DIETER

Sector coupling As the electrification of other sectors is a policy target in Germany, we also account for electric mobility and green hydrogen. The additional system load of electric vehicles enters the model as an electricity demand time series. Cars are assumed to charge with a balanced, yet not wholesale market price-driven time profile determined by the open-source tool “emobpy“ (Gaete-Morales, Kramer, et al., 2021) (for further details, see B.1.1). The model also has to satisfy a given yearly demand for green hydrogen via electrolysis. The hourly hydrogen production profile is endogenously optimized, with given electrolysis capacity and assuming hydrogen storage at no cost. We provide the equations that describe the simple hydrogen model in B.1.2.

Geographical scope We conduct the study focused on Germany and its neighboring countries, including Denmark, Poland, Czechia, Austria, Switzerland, France, Luxembourg, Belgium, the Netherlands, and Italy. To keep the model tractable while still taking into account the effects of the European interconnection, we optimize investment decisions only for Germany while assuming fixed power plant fleets for other countries, and also do not model sector coupling explicitly for other countries than Germany.

3.3 Data and scenario assumptions

3.3.1 Input data sources

Time series data for the electric load in Germany and renewable energy availability profiles for all countries are taken from the "Open Power System Data" platform, using the weather year 2016 for renewables and the year 2019 for load (Wiese et al., 2019). German load time series are scaled to the expected yearly electricity load in 2030 according to the medium scenario (B) of the German Grid Development Plan NEP 2019 (Bundesnetzagentur, 2018). Load data for other countries is derived from the TYNDP 2020 (ENTSO-E, 2018b), based on the scenario "Distributed Energy" and the climate year 1984. Cost and technology parameters of electricity generation and storage technologies are depicted in Table B.3 in the Supplemental Information. We assume that electrolysis happens at a conversion factor of 71 percent; hence 1 Kilowatt hour (kWh) of electricity is transformed into 0.71 kWh of hydrogen. The relevant technical assumptions related to heating technologies as well as gas-based electricity generation technologies for the ex-post analysis of natural gas savings are shown in Table 3.1. The estimation of natural gas and emission savings due to heat pumps is based on this data (more information in Section 3.4.3).

Table 3.1: Relevant parameters for comparison of gas savings due to heat pumps

Parameter	Value
Overnight investment costs [EUR/kW$_{th}$]	
Air-sourced heat pumps	850
Ground-sourced heat pumps	1400
Gas boilers	296
Efficiencies	
Open-cycle gas turbine	0.4
Combined-cycle gas turbine	0.542
Gas boilers	0.9
Technical lifetime of heat pumps [Years]	20
Interest rate	0.04
Annuity factor	0.074
Emission factor [t CO_2-eq / MWh$_{th}$]	0.2

3.3.2 Scenario assumptions

We refer to our main set of scenario assumptions as “baseline”. In the following, we briefly sketch the most important features of this scenario. Whenever we deviate from the baseline, for example, when we present sensitivity analyses, we make this explicitly clear.

Heating sector We distinguish between four scenarios of the overall heat pump stock in the year 2030. In the *reference roll-out*, we assume 1.7 million decentralized heat pumps in 2030, based on the assumption that the historic shares of heat pumps in different building types remain constant, based on (Schill and Zerrahn, 2020). In the *slow roll-out*, the number of heat pumps reaches 3.9 million by 2030. Here, the additional heat pumps are installed exclusively in single- and two-family homes of the two highest energy efficiency categories. In the *mid roll-out*, 6.5 million heat pumps are installed by 2030. Unlike the previous scenario, single- and two-family homes from the next worst energy efficiency class are also fitted with heat pumps. In the *fast roll-out*, heat pumps are additionally installed in multi-family homes of the same energy efficiency classes, which increases their total number to 7.5 million by 2030. Table 3.2 provides an overview of the heat pump roll-outs. In the most ambitious scenario, decentralized heat pumps provide nearly a quarter of total space heating and domestic hot water needs (Table 3.2).

Across all building types, air-source heat pumps account for 75% of installed heat pumps across all building classes, with ground-source heat pumps accounting for the remaining 25%. While ground-source heat pumps are more energy-efficient, air-source heat pumps are cheaper to install. We assume that all heat pumps are combined with thermal energy storage. We conduct analyses with varying thermal storage capacities ranging from 0 to 168 hours (0, 2, 6, 24, and 168 hours). For instance, a heat storage of two hours could deliver the maximum heat output for two consecutive hours.

Table 3.2: Heat pump data

		Reference	**Slow**	**Mid**	**Fast**
Number of installed heat pumps	[million]	1.7	3.9	6.5	7.5
Heat pump power rating	[GW_e]	8.5	17.4	28.9	40.1
Heat pump thermal rating	[GW_{th}]	19.6	40.1	66.6	92.6
Share of air-sourced heat pumps		0.75	0.75	0.75	0.75
Share of ground-sourced heat pumps		0.25	0.25	0.25	0.25
Heat supplied by heat pumps	[TWh_{th}]	24.7	45.9	103.1	142.6

Note: Heat includes space heating and domestic hot water.

We model 12 different building archetypes, which we distinguish by year of construction (six classes: before 1957, four periods between 1958 and 2019, and after 2019) and housing type (two classes: one -& two-family homes and multi-family homes). Depending on the year of construction, the building archetypes are characterized by different energy efficiency levels: younger buildings have a lower annual heating requirement, and buildings constructed after 2020 are characterized as passive houses. Table B.1 illustrates the building stock assumptions for 2030, which are based on (Schill and Zerrahn, 2020).

Generation capacity bounds In accordance with the 2030 German Grid Development Plan (NEP 2030) (Bundesnetzagentur, 2018), we assume that fossil-fuel power plant capacity expansion in Germany is limited. In sensitivity analyses with a German coal phase-out, we assume the upper capacity limit for hard coal and lignite to be zero. Regarding RES, we fix capacities of run-of-river hydropower and bioenergy under the assumption that their potential for further capacity expansion is exhausted. Furthermore, we align upper capacity bounds for on- and offshore wind energy with the current German government targets of 115 GW for onshore wind and 30 GW for offshore wind in the baseline scenarios. In the sensitivity analysis, we remove these limits. Capacities for other countries are fixed based on the Ten-Year Network Development Plan (TYNDP) (ENTSO-E, 2018b) of the European Transmission System Operators. Electrolysis capacity is fixed at 10 GW_e. Table B.2 provides an overview of the lower and upper capacity extension limits in Germany and fixed capacities in other countries.

Sector coupling demand In Germany, we take into account electric loads related to sector coupling. To incorporate the impact of e-mobility, we include a fleet of 12.5 million electric cars, which require approximately 29 TWh of electricity annually. Additionally, we account for 28 TWh of hydrogen demand in Germany, which must be generated by domestic electrolysis. This results in an additional electricity demand of around 39 TWh. The assumption is based on the target set in the German National Hydrogen Strategy 2020 to build up an electrolysis capacity of six GW, and scaled by the new target of 10 GW declared in 2022. Due to the assumed free hydrogen storage, electrolyzers can operate with some degree of flexibility to produce the above-mentioned total amount of hydrogen over the course of the year. In countries other than Germany, additional loads related to sector coupling are included in the electric load time series data provided by ENTSO-E.

Renewable energy constraint In all scenarios, 80 percent of the yearly electricity consumption in Germany, including electric vehicles and electrolysis, has to be covered by RES. That is in line with the goal of the current German government coalition. In addition, the electricity demand by heat pumps has to be entirely met by additional RES over the course of a year (but not every single hour). That means that the entire yearly electricity demand of heat pumps has to be generated by RES, not necessarily that RES in Germany can supply enough electricity for heat pumps every hour. In other countries, we do not assume any renewable energy targets.

Fuel and carbon prices For fuel prices, see table B.3. We further assume a carbon emission cost of 130 Euro per ton of CO_2 for 2030 (R. Pietzcker et al., 2021). This cost is associated with the emission factor of fossil-based heating and electricity generation technologies and is considered a variable generating cost, along with fuel expenses.

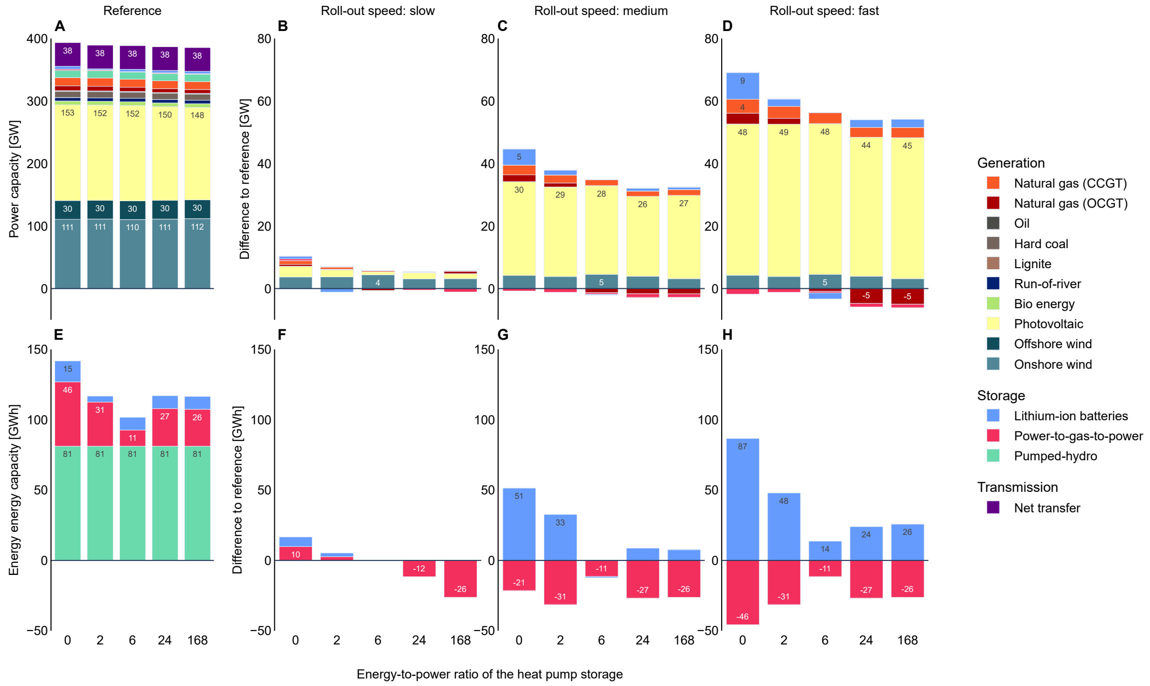
3.4 Results

3.4.1 Results for baseline assumptions

The baseline scenario includes expansion limits of 115 GW for onshore wind power and 30 GW for offshore wind power, has no regulated phase-out of coal-fired power plants, and assumes a natural gas price of 50 Euro per MWh. We show the effects of alternative assumptions in the subsequent section 3.4.2.

3.4.1.1 Heat storage reduces electricity generation and storage capacity investments

Expanding the stock of heat pumps requires additional investments into electricity generation infrastructure. We first look at the case of temporally inflexible heat pumps, i.e., heat pumps with no attached heat storage. These have to consume electricity exactly at the time of heat demand (left rows in Figure 3.2). In the reference roll-out scenario, the stock of heat pumps only increases slightly above the level of 2022. In this reference scenario and under baseline assumptions, the German electricity sector requires renewable power plant capacities of 111 GW onshore wind, 30 GW offshore wind, and 153 GW of solar PV (3.2, Panel A) to reach the goal of 80% renewable energy. Further, 10 GW of hard coal and 21 GW of gas-fired power plants are installed.



Notes: Absolute values in the reference scenarios (panel A & E) and changes caused by the roll-out of heat pumps with different heat storage sizes.

Figure 3.2: Optimal capacity investments under baseline assumptions

An increasing roll-out of heat pumps requires higher generation capacity additions. In the scenario *fast* with the highest roll-out of around 7.5 million heat pumps (Panel D), there is a need for an additional 48 GW of solar PV capacity to generate the electricity the heat pumps need over the year. This capacity expansion is driven by the fact that the additional electricity demand by heat pumps has to be covered 100% by renewable energy. At the same time, wind power capacity can hardly be expanded because of the assumed expansion limit of 115 GW.

The effects of heat pumps on firm electricity generation and storage capacities are smaller, with eight GW of additional gas power plants (close and open cycle together) and nine GW of battery storage in terms of power rating (Panel D) as well as 87 acGWh energy capacity (Panel H). This aligns well with the expansion of solar PV and respective increases in diurnal fluctuations of electricity generation. The growth in batteries, in turn, is crowding out power-to-gas-to-power storage, which is substituted completely in the *fast* scenario.

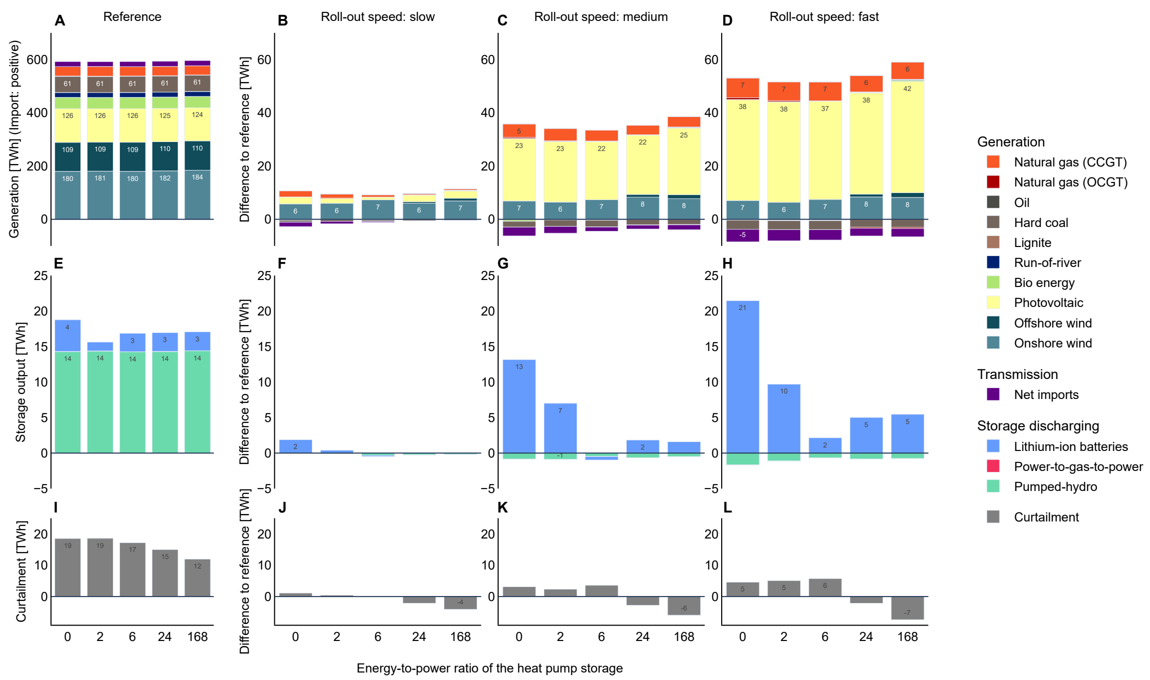
In the scenarios *slow* and *mid* (Panel B & C), in which fewer additional heat pumps are installed, results are qualitatively similar but require overall lower capacity additions. For instance, scenario *slow* requires 3.5 GW of solar PV and 3.7 GW of onshore wind, and hardly any additional power plant capacities (Panel B).

Equipping heat pumps with heat storage reduces the need for electricity generation and storage capacities. With a heat storage capacity of two hours of maximum heat pump output, there is hardly an effect on the optimal installed solar PV capacity (Panel D, second column), but it reduces the need for battery storage: the additional power rating of battery storage is reduced by seven GW (two GW instead of nine GW, Panel D). This is because short-duration electricity and heat storage serve as complements, especially when it comes to taking up daily solar PV surplus generation peaks. If the heat storage capacity becomes larger than two hours, this further decreases the capacity needs for solar PV as well as open-cycle gas turbines (OCGT), which are used to supply peak residual loads. As heat storage helps balancing the fluctuations of solar generation, heat demand profiles, and the overall system load, other additional peak supply capacities are not needed. Increasing the heat storage capacity beyond two hours requires even fewer additional fixed power plant capacities (such as gas power plants). Yet, the overall effects remain moderate even if heat storage becomes very large (168 hours, i.e., one week).

The effects of additional heat storage on optimal battery storage energy capacities (lower row of panels Figure 3.2) are even more pronounced. Compared to the fully inflexible 0-hour heat storage scenario, the additionally needed battery storage energy capacity is 39 GWh lower with two hours of heat storage (48 GWh instead of 87 GWh, Panel H). Heat storage of six hours makes heat pumps so flexible that they can be rolled out almost without any complementary battery storage. While in the case without heat storage, a maximum of 87 GWh of additional battery storage is installed (scenario “fast”), this need is diminished to 14 GWh by a six hour heat storage. Larger heat storage conversely causes optimal battery storage energy capacity to increase again slightly, but this is compensated by lower long-duration electricity storage needs (power-to-gas-to-power). For any roll-out path, we see that *less* long-duration electricity storage is needed when more heat pumps are rolled out. That is because batteries and heat storage replace long-duration electricity storage. Note that in all of these scenarios, pumped-hydro storage capacities in Germany are assumed to be fixed.

3.4.1.2 Heat storage helps to integrate renewable electricity

The impact of an increased heat pump roll-out on the optimal yearly dispatch of generation and storage capacities is largely in line with its impact on optimal capacities (Figure 3.3). Yet, the share of onshore wind power in additional electricity generated is larger than its share in additional capacity, as it comes with higher full-load hours than PV. As the time profiles of solar PV and heat pump load only align to some extent, the expansion of heat pumps triggers additional generation by gas-fired power plants and increased battery storage use. Similar to optimal investment, larger heat storage capacities decrease the use of batteries. Beyond a six-hour heat storage capacity, battery storage use increases again, in line with slightly increasing generation from solar PV. Net imports of electricity slightly decrease with the roll-out of heat pumps, especially when they do not come with heat storage, i.e., are operated in an inflexible manner. As renewable generation capacity expansion that goes along with the heat pump roll-out causes increasing renewable surplus generation events, especially solar PV peaks at noon, these surpluses are partly exported, especially in case of inflexible heat pump operation. Accordingly, net imports decrease.

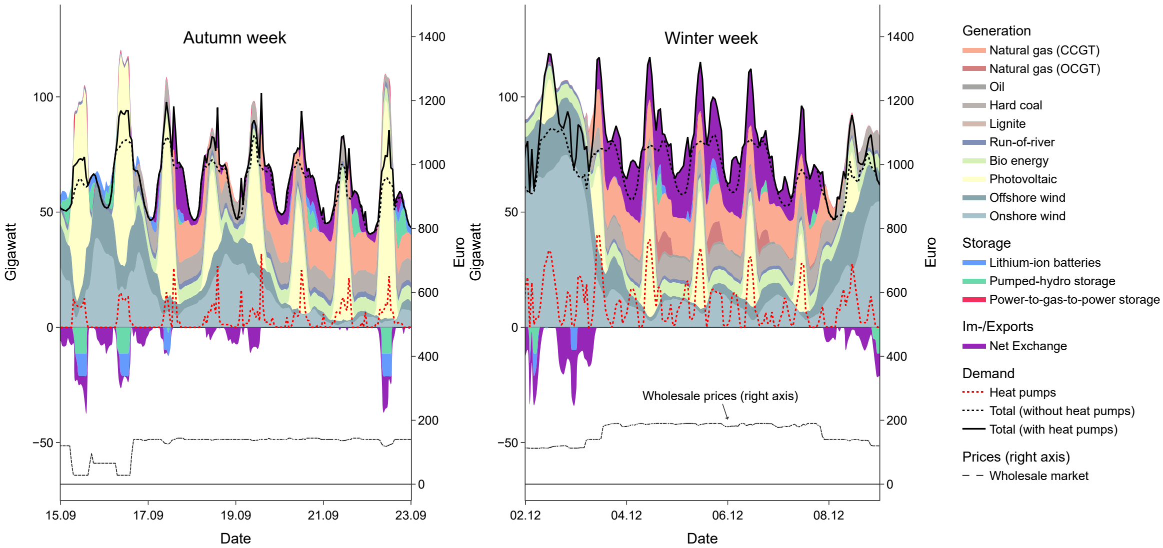


Notes: Absolute values in the reference scenarios (Panel A & E) and changes caused by the roll-out of heat pumps with different heat storage sizes.

Figure 3.3: Yearly electricity generation by source under baseline assumptions

Figure 3.4 provides an illustration of hourly electricity generation and heat pump operation in combination with additional heat pumps. The figure depicts two exemplary weeks in the baseline scenario, with a *fast* roll-out and two hours of heat storage. The diurnal fluctuations of solar PV generation are visible. In contrast, wind power generation has less regular, yet longer variability patterns. In hours of low wind and solar PV generation, gas-fired power plants and imports cover the remaining residual load. Even with only two hours of heat storage capacity, heat pumps can align a substantial part of their electricity consumption with PV peak generation periods. This indicates that even small heat storage capacities already improve the integration of heat pumps into the system. Hours of electricity exports, storage charging, and heat pump use often coincide, which are also hours with relatively low prices. Conversely, heat pumps largely avoid drawing electricity from the grid during hours when imports take place, which often coincides with hours of low renewable generation and relatively high prices.

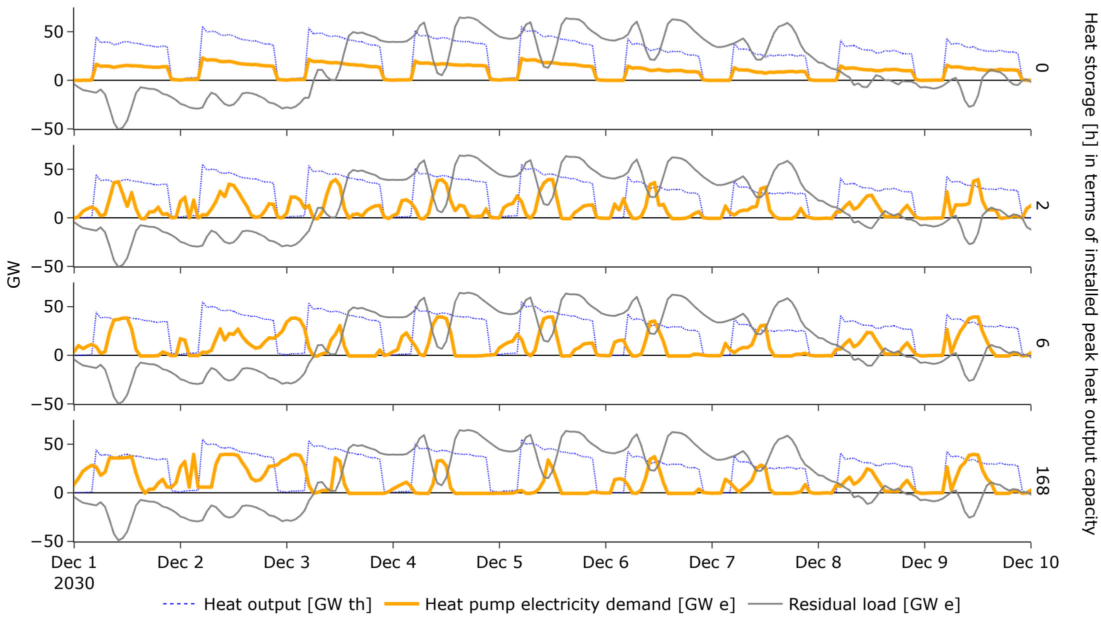
Given our model setup, heat pumps are operated in a way to minimize system cost, which can be interpreted as if they are following (wholesale) market price signals. Heat pumps can align their electricity consumption better with periods of low residual load (which goes along with low prices) when they are equipped with heat storage. As visible in Figure 3.5, there is a strong alignment of heat pump electricity intake and relatively low residual load levels. While heat pumps with no heat storage are inflexible electricity consumers, even small two-hour thermal storage makes them



Notes: Two exemplary weeks are shown for the *fast* roll-out of heat pumps with two hours of heat storage.

Figure 3.4: Hourly electricity generation and heat pump operation in two exemplary weeks

sufficiently flexible that they can adjust their demand to the overall system to a considerable extent. If heat storage is expanded further (rows “6” and “168” of Figure 3.5), heat output and electricity intake are even less correlated. However, as shown before, the effects on optimal storage capacity installation are comparatively small beyond six hours of heat storage (Figure 3.2).



Notes: The figure shows the electricity demand of heat pumps, their heat output, and the residual load in the *baseline* scenario with a *fast* roll-out.

Figure 3.5: Heat pump operation compared to the residual load with different heat storage durations

3.4.1.3 Electricity sector costs

With respect to electricity sector costs, our analysis focuses on additional system costs caused by the heat pump expansion. We relate these costs to the additional heating energy provided (Figure 3.6). More heat pumps lead to additional costs for the electricity sector. We find a cost increase of around four ct/kWh of additional heating energy provided in the fast roll-out scenario with two hours of heat storage. That is because the expansion of heat pumps triggers additional investments into electricity generation and storage infrastructure. This increase in electricity sector costs is much lower than average consumer prices for natural gas in Germany.

Electricity sector costs decrease with larger heat storage. This decrease is very small between a day (24 hours) and a week of heat storage (168 hours), hinting at the fact that heat storage is primarily used to balance daily fluctuations. That is, the marginal electricity sector cost savings decrease with larger heat storage. The power sector cost effect is largest when the heat storage capacity is increased from zero hours to two hours.

Figure 3.6 does not include the installation costs of heat pumps and heat storage, but only the costs related to the electricity sector, such as investment and operational costs of generation and electricity storage capacities. Therefore, we can interpret these figures as opportunity costs of heat storage. Taking the fast roll-out path as an example, an introduction of heat storage of six hours

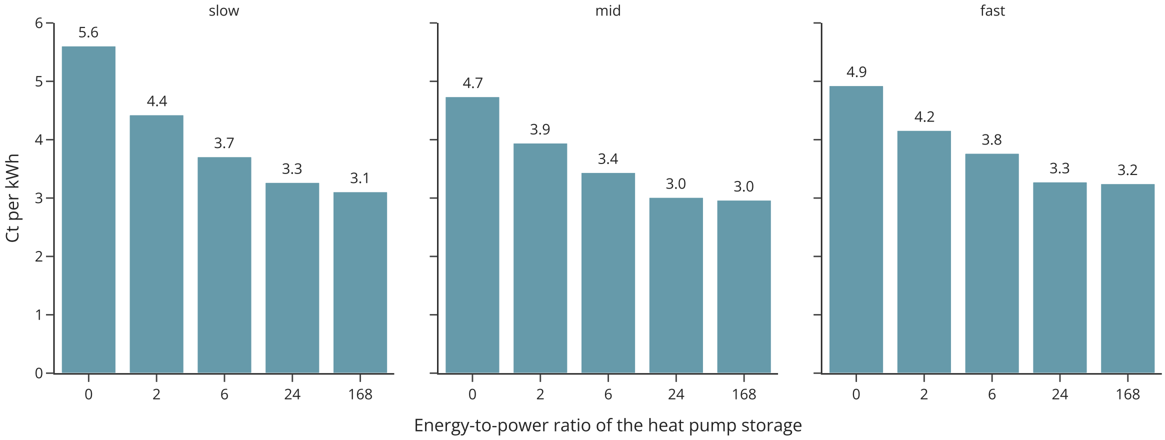


Figure 3.6: Additional electricity sector costs per MWh of additional heating energy provided for different roll-out scenarios and heat storage durations

comes with a reduction of around 10 Euro per MWh_{th} of the additional heat provided. This is a benchmark of how cheap heat storage would have to become in order to lower overall system costs.

3.4.2 Sensitivity analyses

In addition to our baseline scenario runs in which we vary the roll-out speed of heat pumps and heat storage durations (see sections above), we conduct several sensitivity analyses. Those help us judge how strongly our results hinge on certain fundamental model assumptions. Table 3.3 provides an overview of all sensitivity analyses conducted.

Table 3.3: Overview of sensitivity analyses

	Name	Description
1	*no wind cap*	No upper capacity on capacity on- and offshore wind investment in Germany.
2	*gas100*	Natural gas price set to 100 Euro per MWh.
3	*gas150*	Natural gas price set to 150 Euro per MWh.
4	*coal phase-out*	No coal-fired plants allowed to operate by 2030.
5	*coal phase-out + gas100*	Combination of 2 and 4.
6	*coal phase-out + gas150*	Combination of 3 and 4.
7	*RE drought*	All renewable energy capacity factors in one winter week are set to zero.
8	*RE drought + coal phase-out*	Combination of 4 and 7.

In the following, we briefly present the different sensitivity analyses and discuss their results in terms of capacity investments (Figure 3.7), dispatch (Figure 3.8), and additional system costs of heating provided (Figure 3.9).

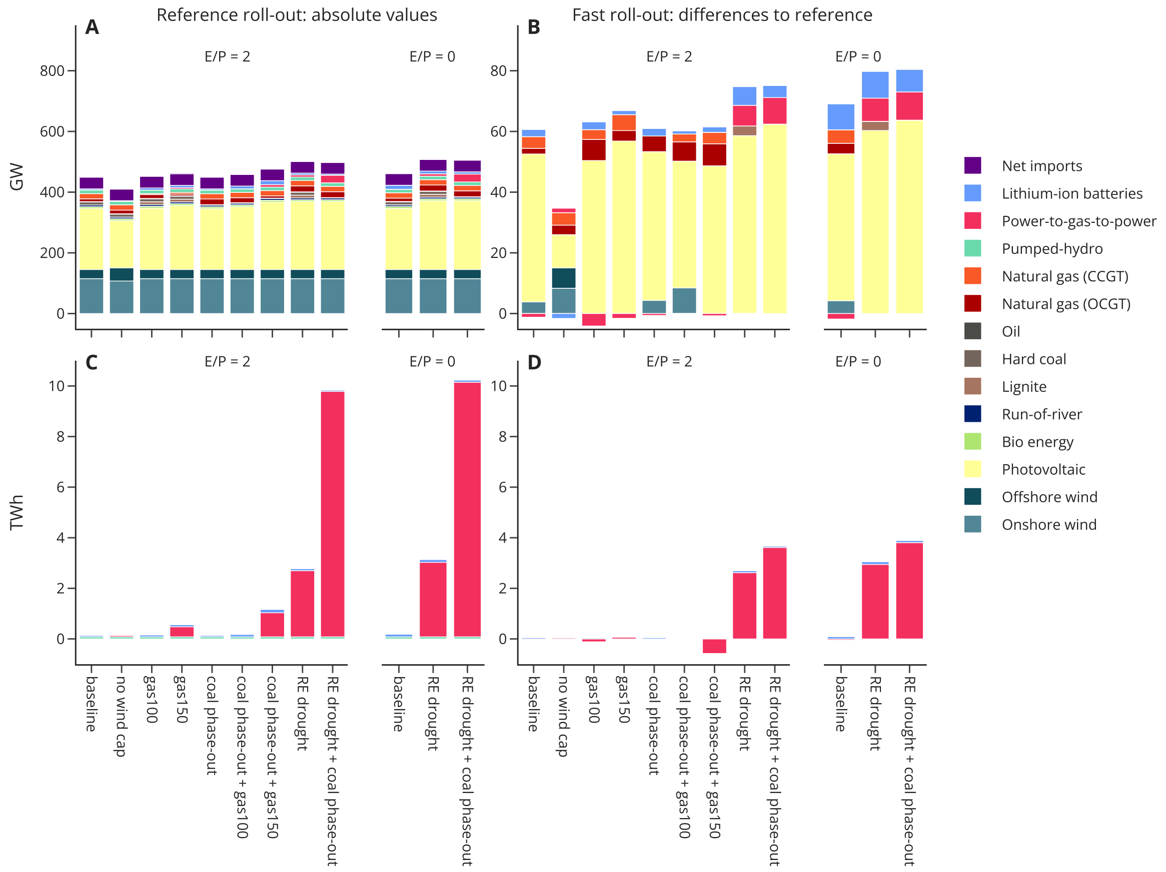


Figure 3.7: Capacity investments in different sensitivity analyses

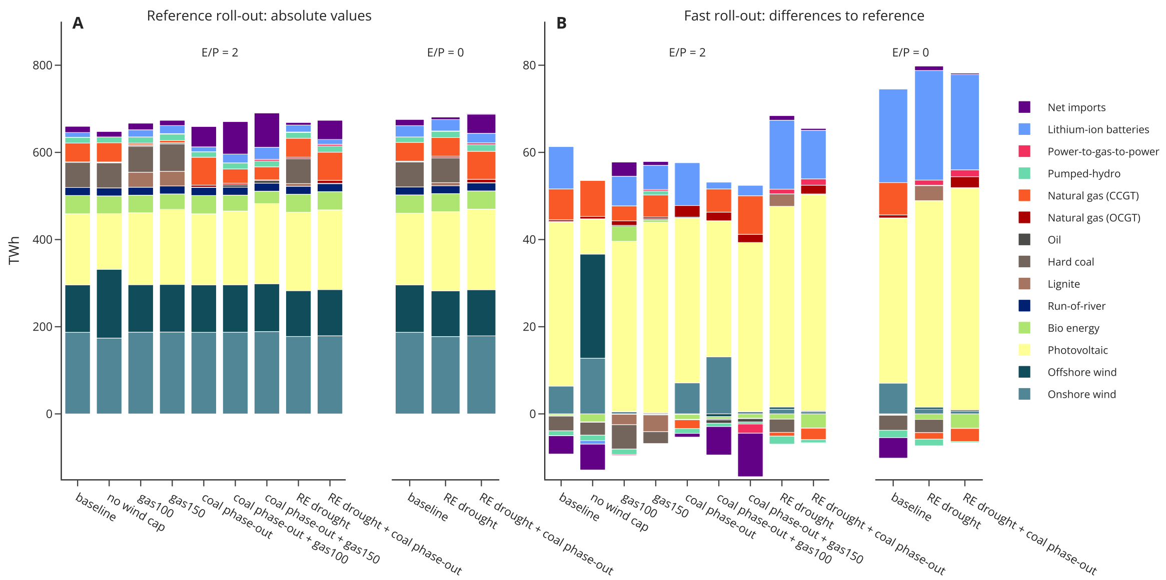
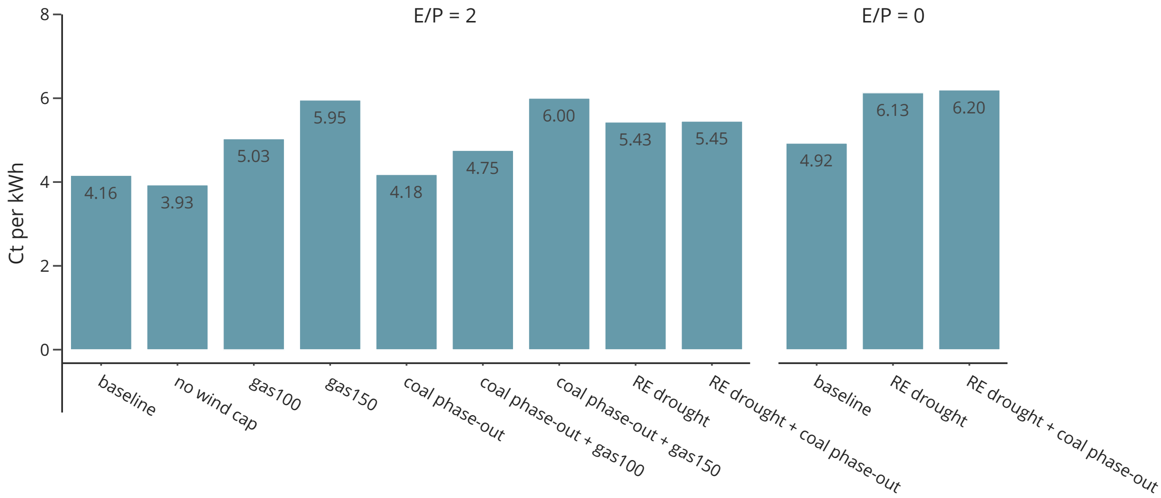


Figure 3.8: Yearly electricity generation and curtailment in different sensitivity analyses



Notes: The figure shows the additional system costs per heating energy provided [in Euro cent per kWh] of 5.8 million additional heat pumps in different sensitivity scenarios (with heat storage durations of zero or two hours as shown below the labels).

Figure 3.9: Additional power system costs of heating energy provided (space heating and domestic hot water) in different sensitivity analyses

No capacity expansion limit of wind energy (*no wind cap*) In the baseline scenarios, we set an upper limit for on- and offshore wind power capacity expansion in Germany of 115 GW and 30 GW, respectively. This appears to be more policy relevant in a 2030 perspective as compared to assuming unbounded wind power expansion potentials, considering real-world constraints related to regulation, land availability and public acceptance. In a sensitivity analysis, we drop this upper limit so that investments into on- and offshore wind power are unconstrained.

The removal of the upper cap for wind power leads to higher overall wind capacities and lower PV capacity expansion, even in the reference roll-out scenario (Figure 3.7, Panel A). This in turn reduces overall capacity requirements. Investments into onshore wind energy even decrease slightly, but are overcompensated by additional offshore wind capacities. These changes correspond with a higher yearly generation of offshore wind energy in the reference roll-out scenario (Figure 3.8, Panel A) compared to the baseline scenario. Given this reference, an additional roll-out of heat pumps leads to a substantial expansion of wind onshore and particularly offshore capacities, yet far fewer additional PV capacities (Figure 3.7, Panel B) than in the baseline. In consequence, additional dispatch consists mainly of offshore wind energy instead of solar PV (Figure 3.8, Panel B). The increased use of wind power hints to the fact that its availability aligns better with the seasonality of the heating demand than solar PV. Optimal storage energy installation rarely changes in comparison to the baseline (Figure 3.7, Panel C and D). Despite the relatively large shift between wind power and PV, overall system costs barely change compared to the baseline setting (Figure 3.9). This implies that a roll-out of heat pumps can also be combined with solar PV capacity expansion in case of binding wind power capacity limits with little additional costs, making use of the flexibility provided by the European interconnection.

Sustained high gas prices (*gas100* and *gas150*) As a consequence of the Russian invasion of Ukraine, the natural gas supply structure of Europe was fundamentally changed. For the foreseeable future, Germany will not import any more Russian gas, but will rely on more costly imports of liquefied natural gas (LNG) from other regions. Although wholesale gas prices have been falling strongly since their peak levels of over 300 Euro per MWh in August 2022 and range by the time of writing at around 30 Euro per MWh, it remains possible that new spikes arise in the near future. In our set of baseline scenarios, we assume a natural gas price of 50 Euro per MWh. We introduce two alternative scenarios, *gas100* and *gas150*, in which we assume natural natural gas prices of 100 or 150 Euro per MWh.

Higher gas prices barely alter the optimal capacity expansion in the reference roll-out. Even a fast heat pump roll-out leads to very similar capacity installations compared to baseline assumptions, with slightly increased solar PV (for a gas price of 150 Euro per MWh) and even slightly more additional gas power plants. This is because with a reference roll-out, the capacity of gas-fired power plants is higher under baseline assumptions (Figure 3.7, Panel A) than in the sensitivities with higher gas prices, where nearly no gas-fired power plants are built. Thus, additional heat pumps have a slightly larger effect in these scenarios. Regarding yearly energy generation, the higher gas prices drive out natural gas in the reference roll-out and lead to slightly less additional dispatch by gas power plants in the fast roll-out scenario. Overall, we do not observe substantial changes compared to our baseline scenario. Nonetheless, the additional power system costs per heating unit increase substantially compared to the baseline because of more expensive natural gas.

Coal phase-out (*coal phase-out*) In the baseline scenarios, we allow coal-fired power plants to generate electricity in 2030, in accordance with the currently planned German coal phase-out by 2038. However, the current governmental coalition agreed to "ideally bring forward" the coal phase-out to 2030. Although this agreement has not yet been translated into binding law, we aim to analyze the power sector consequences of an earlier coal phase-out combined with a faster heat pump roll-out. Hence, in this sensitivity analysis, we assume that electricity generation by coal-fired power plants is not possible.

In the reference roll-out, coal-fired power plants that are present in the baseline scenario would be mainly replaced by gas-fired generation. For a fast roll-out of heat pumps, the additional capacity needs hardly differ from those in the baseline, as heat pumps also do not trigger an expansion of coal-fired power plant capacities under baseline assumptions. In terms of dispatch, generation by coal-fired power plants in the reference roll-out scenario is mainly compensated by gas-fired (CCGT) plants, as well as by increased net imports. Expanding heat pumps leads to largely similar dispatch effects as in the baseline. Power system costs increase only very slightly.

We also combine the coal phase-out with higher gas prices (scenarios *coal phase-out + gas100* and *coal phase-out + gas150*). In consequence, we see slightly higher solar PV capacity installations in the reference roll-out. Additional capacities in the fast roll-out barely differ from those under baseline assumptions. In terms of dispatch, results do not differ too much from the baseline either. For the reference roll-out, the missing coal-fired generation is partly displaced by electricity net imports. Yet, these net imports diminish with additional heat pumps in the fast roll-out. Overall, additional dispatch does not vary strongly between these sensitivity scenarios and the baseline. Yet, the combination of a coal phase-out and higher gas prices lead to considerably higher power system costs because of higher production costs of gas-fired power plants, which often are the marginal plant.

A week of a renewable energy drought (*RE drought*) As the share of variable renewable energy increases, the security of supply during prolonged periods with low renewable energy supply becomes an increasing concern. Therefore, we assess how a week of a severe renewable energy drought in Europe would affect our results. To simulate an extreme case of such a week, we artificially set wind and solar PV capacity factors to zero in all modeled countries during one winter week.

Because of this massive input parameter modification, this sensitivity analysis substantially impacts our results. Effects on generation capacities are generally limited for the reference roll-out, yet substantial long-duration storage capacities (power-to-gas-to-power) are needed. In contrast to the baseline, where almost no long-duration storage is installed, 2.6 TWh of energy capacity are installed in the *RE drought* scenario already in the reference roll-out of heat pumps. In the fast roll-out scenario, another 2.6 TWh are added, a substantial difference from the baseline, in which long-duration energy storage capacity remains unaltered in the fast roll-out. Also, the fast roll-out of heat pumps triggers significantly higher solar PV capacity additions: over 58 GW instead of 48 GW in the baseline. In terms of dispatch, the fast roll-out of heat pumps leads to a higher use of solar PV generation and short-duration electricity storage compared to the baseline. Considering the binding minimum renewable energy share constraint, the addition of PV capacity is required to compensate for the missing generation from renewables (largely wind power) during the drought week. As wind power capacities are capped, additional solar PV capacities are installed, which in turn trigger additional short-duration storage capacities to integrate optimally the electricity generated by solar PV. Including a renewable energy drought accordingly also leads to higher system cost increases of a fast heat pump roll-out of 6.1 cent per kWh heat provided. This can be explained by additional capacity investments needed as well as the dispatch of gas-fired power plants in the week of energy drought.

Combining the scenarios *RE drought* with *coal phase-out*, we find very similar capacity expansion results. The biggest difference is, however, that already in the reference roll-out scneario 9.7 TWh of long-duration electricity storage are installed. This is because coal-fired power plants are missing as a firm generation technology, and also the generation capacities of gas-fired power plants cannot be increased further. In the fast roll-out of heat pumps, generation capacities are similar to *RE drought*, yet even more additional long-duration electricity storage is installed: an additional 3.6 TWh instead of 2.6 TWh for the *RE drought* only and almost zero in the baseline. Dispatch in the scenario *RE drought + coal phase-out* does not greatly change from *RE drought*, and power system costs only increase mildly.

For *baseline*, *RE drought*, and *RE drought + coal phase-out*, we ran additional sensitivity analyses assuming zero heat storage instead of heat storage with an energy-to-power ratio of two in all the other scenarios. Generation capacity changes are very limited and differ barely from the respective scenario with an E/P of two. We see slightly higher capacity investments into solar PV, as well as short- and long-duration storage. Concerning yearly electricity generation, we find that the absence of heat storage leads to a more intensive use of short-duration electricity storage. This can already be detected in the fast roll-out of heat pumps in the baseline scenario, and the use is further increased in the scenarios *RE drought* and *RE drought + coal phase-out*. The overall impact on costs remains limited. That is, small-scale heat storage reduces overall system costs in all sensitivities investigated here, but mildly so.

Summarizing the results of our extensive sensitivity analyses shows that the principal results and insights remain largely robust. Adding a considerable number of heat pumps to the German power sector leads to substantial capacity investments into mainly solar PV to fulfill the renewable energy constraint. Additional investments into gas-fired power plant capacities and short-duration lithium-ion storage capacities are also optimal. If the expansion of heat pumps could be accompanied by unlimited wind power expansion, this would lead to favorable results compared to a setting where the additional energy is largely supplied by solar PV. Yet, overall costs decrease only to a small extent when relying more on wind power. Overall, sensitivity scenarios point to the fact that, especially when a renewable energy drought is present, firm generation and storage capacities are most strongly expanded compared to the baseline.

3.4.3 Natural gas and carbon emission savings

Based on the power sector optimization results, we can also examine the effects on natural gas usage and carbon emissions of an accelerated roll-out of heat pumps. In doing so, we compare the reference roll-out of 1.7 million heat pumps with 2.2 million additional heat pumps in the slow roll-out scenario and 5.8 million additional heat pumps in the fast roll-out scenario. The underlying assumptions for the calculation of gas and emission savings are stated in Table 3.1. Table 3.4 summarizes the results.

Under the assumption that each heat pump replaces one gas boiler with a thermal efficiency of 0.9[3], additional heat pumps displace around 24 TWh_{th} of natural gas in case of a slow roll-out and around 131 TWh_{th} with a fast roll-out. At the same time, natural gas usage for electricity generation increases in both scenarios, but this is by far overcompensated by the large natural gas

[3] A thermal efficiency of 0.9 means that 1 kWh of natural gas will be transformed to 0.9 kWh of heat.

savings in the heating sector, leading to total savings of up to 117 TWh_{th} of natural gas (fast roll-out). In the scenarios with gas prices of 100 Euro or 150 Euro per MWh_{th}, gas usage for electricity generation drops compared to the scenario with a price of 50 Euro. That leads to slightly larger total yearly natural gas savings of up to 122 TWh_{th}. To put these numbers into perspective, 120 TWh of natural gas correspond to around 14 percent of Germany's overall natural gas consumption in 2022, or around a third of private and commercial natural gas demand, or to around 100 shipments of large LNG tankers. In general, we find that all scenarios lead to a substantial reduction in natural gas consumption, which is mainly driven by the substitution of gas boilers with heat pumps. The additional natural gas consumption in the electricity sector has a minor effect. Note that this is also a consequence of our renewable energy constraint which requires that the roll-out of heat pumps goes along with a corresponding expansion of yearly renewable electricity generation.

We also observe a general decrease in overall costs in all scenarios. Here, overall costs include the increase in power system costs due to higher electricity demand, the total annualized overnight investment costs of the additional heat pumps against the savings in natural gas expenditures, CO_2 emission costs, as well as investment costs of replaced natural gas boilers. Overall cost savings are 2.3 billion Euro per year in the fast toll-out scenario and a 50 Euro per MWh gas price; assuming a higher gas price of 150 Euro per MWh_{th}, cost savings increase to nearly 14 billion Euro per year.

The reduced consumption of natural gas leads to lower CO_2 emissions. In a fast roll-out scenario of heat pumps, CO_2 emission savings of 23-24 million tons CO_2-eq can be expected under different gas price assumptions, strongly exceeding the emission savings of around four million tons CO_2-eq in the slow roll-out. 24 million tons of CO_2 correspond to around three percent of Germany's overall CO_2 emissions of the year 2021, or around a third of the CO_2 emissions of German households in the building sector. Hence, an ambitious heat pump roll-out as described in this paper could make a sizeable contribution to Germany's strategy to reduce emissions. A further expansion of heat pumps beyond 2030 would lead to even higher reductions of carbon emissions.

Table 3.4: Yearly saving of natural gas, CO_2 emissions, and costs related to heat pumps (Changes and savings in relation to reference scenario)

Gas price	EUR/MWh	50		100		150	
Heat pump roll-out		slow	fast	slow	fast	slow	fast
Natural gas displaced by additional heat pumps	TWh_{th}	-23.5	-131.0	-23.5	-131.0	-23.5	-131.0
Additional electricity generated from natural gas	TWh	38.5	44.4	0.9	5.1	0.4	5.6
Additional gas usage for electricity	TWh_{th}	+2.9	+14.0	+0.7	+8.9	+0.6	+10.2
Total change in gas usage	**TWh_{th}**	**-20.6**	**-117.0**	**-22.8**	**-122.0**	**-22.9**	**-120.7**
Total change in emissions	**Mio t CO_2-eq**	**-4.1**	**-23.4**	**-4.6**	**-24.4**	**-4.6**	**-24.1**
Change in overall costs	**billion EUR**	**-0.1**	**-2.3**	**-1.1**	**-8.0**	**-2.2**	**-13.7**

3.5 Discussion and conclusion

As heat pumps are considered a key technology in the heating transition, their potential future impact on the electricity sector is of interest. We determine the impacts of different roll-out paths of decentralized heat pumps in Germany, combined with thermal buffer storage of different sizes, on the central European power sector. We find that the addition of nearly six million heat pumps in Germany would require additional investments of around 48 GW of solar PV capacity, regardless of the assumed size of the attached heat storage. These results are partly driven by the assumption that the additional electricity consumption of heat pumps has to be covered by additional renewable electricity on a yearly basis and that the expansion of wind power is limited to 115 GW (offshore) and 30 GW (offshore), respectively. Our results suggest that the need for additional firm capacities remains limited, such as gas-fired power plants and lithium-ion batteries, which can provide flexible generation in times of low renewable energy generation. This is true even if heat pumps are operated in an inflexible way, as heat pumps benefit from the European interconnection.

The need to expand electricity storage capacities can be reduced by coupling decentralized heat pumps with thermal storage. Already small buffer heat storage of two hours enables heat pumps to align electricity consumption with the residual load to a sizable extent. This results in substantial power system cost savings compared to a system with inflexible heat pumps. We find the largest mitigation of electricity storage needs in a setting with a heat storage capacity of six hours. To sum up, operating heat pumps in a temporally flexible manner cannot be considered to be a “must-have” in the power sector modeled here, but it appears to be desirable.

Sensitivity analyses show that results are generally robust against changes in key scenario assumptions. Assuming unconstrained expansion potentials for wind power substantially reduces solar PV capacity deployment, but not overall costs, since wind energy aligns better with heat demand (compare Ruhnau, Hirth, and Praktiknjo, 2020). A complete coal phase-out in the electricity sector does not have major effects, but requires additional dispatchable generation capacity from natural gas to satisfy load peaks. A further increase in gas prices changes these results only slightly but increases power system costs substantially. Considering a week-long, pan-European renewable energy drought requires that the expansion of heat pumps is accompanied by a substantial expansion in long-duration electricity storage capacity to satisfy the additional electricity demand of heat pumps.

We further find that an accelerated replacement of gas boilers with heat pumps (fast roll-out scenario) can bring about yearly natural gas savings of up to 122 TWh_{th}, already accounting for increased gas usage in the electricity sector. This corresponds to around a third of private and commercial natural gas demand in Germany and corroborates related findings by Altermatt et al. (2023). Overall yearly cost savings depend, among other factors, on the natural gas price and range between around two and 14 billion for different natural gas price assumptions. CO_2 emissions decrease by 23-24 million tons per year.

As with any model-based analysis, our study has limitations. For example, we implicitly assume perfect distribution and transmission grids within countries, which limits our analysis with respect to any kind of grid congestion caused by heat pumps. In some distribution grid settings, the effect of heat pumps on grid congestion may be more severe than the impacts on system-wide generation capacities and dispatch modeled here. Furthermore, the size of the heat buffer storage is exogenously varied and not an endogenous investment decision in the model. That means that we cannot draw conclusions regarding the optimal heat storage capacity from this analysis. Yet, our results show that even relatively small heat storage capacities may already have substantially positive power system effects. Further, flexibly operating heat pumps requires incentives for consumers in the real world. Finding ways of exposing heat pump operators to wholesale market price signals, either directly or indirectly via aggregators, appears to be important in this respect. Next, our analysis could be expanded by allowing for optimal generation capacity expansion in other European countries in order to assess the potential interactions of capacity expansion in Germany and abroad. This has been left out in this analysis for numerical reasons and to improve tractability. Furthermore, Germany is not the only country pushing for an accelerated roll-out of heat pumps. Future analysis could include similar developments in other European countries to obtain more comprehensive insights into a wider European heating transition.

In summary, we find the power sector impacts of an accelerated heat pump roll-out in Germany to be moderate and manageable, even under the assumption that the electric load from heat pumps is met by a corresponding expansion of renewable electricity generation in a yearly balance. If wind energy cannot be expanded beyond certain limits, additional solar PV capacity can be deployed instead without substantially increasing the overall system costs. This is despite a seasonal mismatch of solar PV generation and heat demand profiles, which can be mitigated via the European interconnection. In general, operating heat pumps in a temporally flexible manner entails power sector benefits. Even relatively small heat storage already facilitates lower electricity storage needs and power system costs. Yet, such flexible operations do not appear to be a “must-have” in the scenarios modeled here. Overall, the need to add firm generation and storage capacities still remains limited, even in a less optimistic setting if heat pumps are operated as fully inflexible loads.

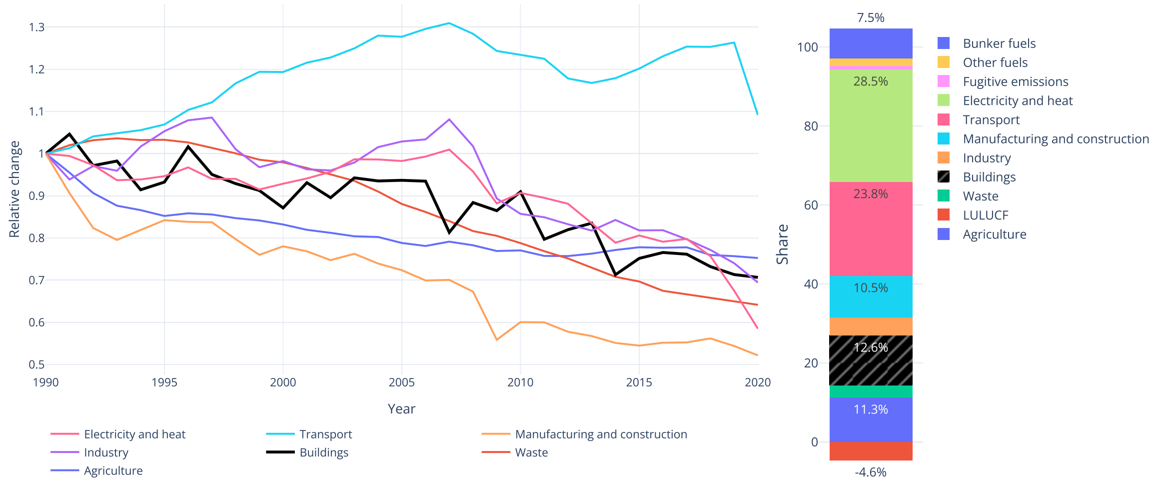
4

Power sector impacts of a simultaneous European heat pump rollout

This chapter is based on A. Roth (2023). “Power Sector Impacts of a Simultaneous European Heat Pump Rollout”. *arXiv preprint* arXiv:2312.06589 [econ.GN]. DOI: 10.48550/arXiv.2312.06589

4.1 Introduction

To limit the increase of global mean temperature and mitigate its consequences, European countries have decided to decrease their GHG emissions in the coming decades, achieving a net-zero economy in 2050 (European Climate Law, 2021). Reaching this goal requires decreasing GHG emissions in all sectors of the economy. The building sector, mainly heating and cooling, contributes significantly to carbon emissions (Figure 4.1b). Despite some progress in recent years (Figure 4.1a), further reductions are needed, especially in large countries such as Germany, which still rely heavily on fossil fuel heating systems. One solution to decrease GHG emissions in the building sector is to deploy non-fossil heating technologies, such as heat pumps. This study focuses on a simultaneous and substantial rollout of heat pumps in several central European countries and assesses the challenges for the power sector.



(a) Relative development (1990 = 1) **(b)** Shares in 2019

Source: Own illustration based on Ritchie, Rosado, and Roser (2023).

Figure 4.1: Sectoral GHG emissions in the EU 27

As the building sector is responsible for around 13% of total GHG emissions in the EU (Figure 4.1b), the role of this sector in reducing its overall emissions is paramount.[1] Several technological options exist that are already mature and widely available to decarbonize the building sector (Climate Action Tracker, 2022). On the demand side, insulation, for instance, can reduce the overall energy needs of buildings, while on the supply side, traditional fossil fuel heating solutions have to be replaced. Among others, heat pumps are considered a crucial technology to achieve decarbonization (IEA, 2022). A heat pump extracts heat from a source, such as the ambient air

[1]Importantly, these reported emissions from the building sector only cover emissions directly emitted at the building, while emissions from the generation of electricity and heat in power plants are reported in *Electricity and heat*. On top of that, emissions associated with the construction of buildings are also not contained. Hence, the overall share of building-related emissions is larger than shown in Figure 4.1b.

or the ground, and transports it to a destination where it is needed, such as a water-based heating system within a building. Most heat supplied by a heat pump is harvested from the environment, while the electricity is mainly used to transfer and lift the heat to a useful temperature level (IEA, 2022). Therefore, heat pumps possess two essential features: they are efficient and operate directly with electricity. Mainly due to the latter, their usage lends itself perfectly to a decarbonized energy system, relying almost exclusively on renewable electricity, in which heat pumps can be run directly without an intermediary energy carrier.

However, an ambitious deployment of heat pumps does not come without challenges. Apart from possible electricity transmission and distribution grid requirements, the direct use of electricity by heat pumps, mentioned above as an advantage, also poses challenges for the power sector. The rollout would not only lead to an increase in electricity demand - which would have to be covered by additional generation capacities - but could also lead to more elevated peak loads in the power sector, requiring additional flexibility. This flexibility could be attained, for instance, by firm generation capacities (fossil, renewable, or storage), interconnection between countries, or by thermal energy storage of heat pumps. As higher shares of renewable electricity already increase the need for flexibility options, heat pumps possibly add to this need.

Several studies assess the effects of heat pumps on the power sector. Early on, Hedegaard and Balyk (2013) point out the benefits of flexible operation of heat pumps. In a recent working paper, A. Roth, Kirchem, et al. (2023) analyze the additional generation capacities needed for different heat pump rollout speeds in Germany and the impact of thermal energy storage. However, only a deployment in Germany is considered, and capacity expansion in neighboring countries is not modeled. Altermatt et al. (2023) assess an even more ambitious heat pump rollout path for Germany, yet neither explicitly modeling the electricity sector nor accounting for other countries. Concerning the flexibility of heat pumps, Kröger, Peper, and Rehtanz (2023), using a detailed modeling approach for small- and large-scale heat pumps, quantify additional peak loads through heat pumps and shifting potentials through thermal energy storage. Yet, the heat pump expansion is limited to Germany, and no capacity expansion effects are estimated. In a case study of the British and Spanish market, Lizana et al. (2023) determine the optimal thermal energy storage size to shift peak power demand, yet neither explicitly modeling the electricity sector. With respect to additional peak loads generated by heat pumps, Charitopoulos et al. (2023) claim that heat demand peaks are often considerably lower than values widely cited in the literature, that deep electrification of heating can be achieved with moderately higher electricity load peaks, and that thermal energy storage plays an important role in shifting loads. On the other hand, Buonocore et al. (2022) conclude that a poorly executed electrification of heat in the United States (US) would require a massive expansion of renewable energies. Using a regression-based approach in the UK, Deakin et al. (2021) estimate the additional peak demand of heat pumps, while Chen et al. (2021) conclude that the electrification of heat is cost-effective compared to other solutions, but lead to considerable additional demand that has to be met - in their study - by wind energy installations. Finally, Hilpert (2020) highlight the importance of flexible heat pump operation in 100% renewable energy systems, relating well to the findings of other studies.

As highlighted above, most of the literature (1) assesses heat pump deployment only in single countries, (2) does not account for interconnection, or (3) considers only a single weather year. Hence, this study assesses a parallel and ambitious heat pump rollout in several countries and aims to identify its effects on the power sector in a midterm 2030 setting. While large-scale studies have simulated decarbonization pathways for Europe, including heat pumps, this study seeks to isolate the heat pump effect on the electricity system. I assess the required power plant additions, especially the firm capacity additions. I estimate the impact of an important source of flexibility: I study how a small thermal energy storage attached to the heat pumps influences the residual load and, therefore, generation capacity needs. I also assess how much flexibility can be provided by interconnection between countries. Crucially, I study how strongly cold spells are correlated in Europe and how they overlap with the residual load. I do not base my analysis on a single weather year but consider six different weather years. By relying on several years, I not only improve the stability of the results but also provide an intuition for the variability of heat demand and its impact in Europe. Finally, I run several robustness checks to assess the robustness of my results.

4.2 Model and Data

My analysis builds on several tools and data sources mentioned in this section. While the functioning of the overall power sector model is explained in Section 4.2.1.2, the following subsection briefly explains the fundamentals of the heat module used.

4.2.1 Model

4.2.1.1 Heating

I use a straightforward approach to model the interaction between heat demand for space and water in buildings and the power sector. As explained in the subsequent Subsection 4.2.2 on data, I use as a crucial input the heat demand for space and water for different house categories at every hour of the year and in every country. Exogenously, I assume a share $s_{bt,st,hpt}$ of which heat demand $hd_{bt,st,h}$ has to be covered by heat generated $HO_{bt,st,htp,h}$ by heat pumps in every hour h of the year.[2] As the heat demand is exogenously given, it is assumed to be totally inelastic. In the present model set-up, the model has to fulfill that heat demand and has no possibility of not serving it.

$$HO_{hp,st,h} = s_{bt,st,hpt} \times hd_{bt,st,h}, \tag{4.1}$$

[2]If not differently noted, all parameters, variables, and equations mentioned in this section apply equally to every country. For the reason of simplicity and readability, I omit a country-specific subscript.

where *bt* is the *building type* (single-family, multifamily, or commercial), *st* the type of heat sink (space or water), and *hpt* the type of heat pump (air-sourced, ground-sourced, water-sourced).

As heat pumps can be equipped with thermal energy storage, the following equation governs the state of charge HL of that storage:

$$HL_{bt,st,hpt,h} = HL_{bt,st,hpt,h-1} + HI_{bt,st,hpt,h} - HO_{bt,st,hpt,h}. \tag{4.2}$$

The state of charge HL increases with heat supplied HI and decreases with heat output HO. The required heat output $HO_{bt,st,hpt,h}$ of the heat pump can either be met using heat from thermal storage HL or generating it HI. Obviously, the state of charge is always 0 ($HL = 0$) if heat pumps do not have thermal energy storage. In that case, heat output HO and heat generated HI are equal every hour. The size of the thermal storage, hence the maximum of HL, is determined by an exogenously set *energy-to-power* ratio $ep_{bt,st,hpt}$ that relates the maximum heat output (the installed heat output capacity) to the size of the thermal energy storage.

To generate heat $HI_{bt,st,hpt,h}$, heat pumps use electricity $E_{bt,st,hpt,h}$. The sink-, heat pump-, and hour-specific coefficient of performance (COP) determines that process and, hence, the efficiency of the heat pump. The higher the COP, the more heat is generated with the same electricity input:

$$HI_{bt,st,hpt,h} = cop_{st,hpt,h} \times E_{bt,st,hpt,h}. \tag{4.3}$$

With the present model formulation, I treat space and water heating separately using different COPs. The COP for water is generally lower due to the higher temperature needed compared to space heating. While this formulation is probably slightly unrealistic for many houses with a single heat pump system to serve space and water heating, my specification determines the electricity needed more precisely. In any case, the difference to a model in which the entire heat of a house is served with the same COP is not substantial, as overall heat demand for water is relatively small compared to space heat demand.

The installed capacity of the heat pumps, with respect to heat output, electricity input, and thermal energy storage, is not determined based on cost-optimally but is set to satisfy heat demand every hour. Therefore, its size is chosen to meet the peak heat demand, given the COP of that hour, in the absence of thermal energy storage.

4.2.1.2 Power sector

To measure the impact of a heat pump rollout on the power sector, I use the electricity sector model DIETER (Zerrahn and Schill, 2017; Schill and Zerrahn, 2018; Gaete-Morales, Kittel, et al., 2021), which derives optimal dispatch and investment decisions. This model has been used in numerous peer-reviewed publications (e.g. H. C. Gils, Gardian, Kittel, Schill, Murmann, et al., 2022; A. Roth and Schill, 2023b; Kirchem and Schill, 2023). DIETER is a linear cost-minimization model that takes all 8760 consecutive hours of a year into account and optimizes investment and dispatch of the power sector. The model does not contain a detailed grid but assumes a "copper plate" within a country, while a net-transfer capacity (NTC) model is used between countries. Important endogenous variables are the capacity installation of power plants and storage, the dispatch, as well as the power flow between countries. For a detailed model formulation, I refer to Gaete-Morales, Kittel, et al. (2021). For this analysis, the subsequent features and assumptions characterize the model. Unless differently stated, these hold for all model runs.

Generation In terms of generation technologies, the following are present in this analysis: *variable renewables*: solar PV, onshore and offshore wind power, run-of-river hydropower; *dispatchable renewables:* bioenergy, reservoir hydropower; *non-renewables:* nuclear power, gas-fired power (closed-cycle turbine) (CCGT), lignite, hard coal, oil, other.

Storage Lithium-ion batteries, power-to-gas-to-power (p2g2p) storage, pumped-hydro storage: with inflow (open PHS) and without inflow (closed PHS).

Capacity bounds In principle, capacity installations of the different generation and storage technologies are not restricted. However, to increase the realism of the scenarios, I restrict certain technologies with upper and lower bounds. Whenever I impose bounds, I use the values given by *ERAA 2021*, using the year 2025 to take values as close as possible to current values (Table C.2). Solar PV, on- and offshore wind have no upper capacity bounds, but lower bounds are set according to European Resource Adequacy Assessment (ERAA). All hydro technologies (run-or-river, open and closed PHS, reservoir) are fixed. Gas power plants have lower bounds but are not restricted to their upper bounds. In this manner, I allow for the addition of capacity while avoiding (unlikely) decommissioning until 2030. Similarly, I fix the values of hard coal and lignite power plants to account for the existing fleet that will not be further expanded but is likely to stay in operation as a backup. The capacities of nuclear power are also fixed, with the idea in mind that changes (additions or decommissioning) are unlikely until 2030. All remaining technologies (oil, other) have upper bounds, yet no lower bounds. The power and energy capacities of battery and hydrogen storage are unconstrained. Please note that some of these assumption are altered in the robustness checks. All capacity bounds are shown in Table C.2.

Generation bounds No bounds for yearly total generation are set for any technology except for bioenergy, for which I constrain generation to 2022 values (Ember, 2023).

Net-transfer capacities The net-transfer capacities between countries are fixed exogenously and are based on *ERAA 2021*, using the year 2025.

Renewable electricity share No minimum share of renewable electricity production on total electricity production or consumption is assumed.

CO_2 price A price of 150 Euro per ton of CO_2 emitted is assumed.

Countries The scenarios entail the following nine countries: Austria, Belgium, Denmark, France, Germany, Italy, Luxembourg, Netherlands, and Switzerland[3].

4.2.2 Data

Technology and costs For the technology and cost data, I rely primarily on Gaete-Morales, Kittel, et al. (2021). Table C.1 shows the values.

Heating demand time series Relying on the *When2Heat* dataset (Ruhnau, Hirth, and Praktiknjo, 2019) and its latest update and extension (Ruhnau and Muessel, 2022), I use the total national space and water gas heat demand. The database provides hourly profiles of heat demand differentiated between different building types (single family, multifamily, commercial) and sink (space and water), and hourly COPs for different types of heat pumps (air-sourced, ground-sourced, ground-water-sourced), separated for sinks. The heat demand data are available for the years 2009–2015.[3]

Renewable availability and electricity demand time series The data provided by ENTSO-E, used in *ERAA 2021*, has time series of renewable availability, hydro inflows *(Pan-European Climate Database)*, and electricity demand for different weather years of all European countries. Specifically, I rely on the machine-friendly version of De Felice (2022).

4.3 Scenarios

Given the features and assumptions in the previous section, I model the heat pump deployment by requiring a certain share, 25%, of total heat demand to be covered by heat pumps. Please note that for simplicity, I assume the same share for single-family houses, multiple-family houses, and commercial buildings, as well as space and water. I also consider only one type of heat pump, air-sourced, to cover the heat, with the idea that air-sourced heat pumps (ASHPs) currently dominate the market. It is important to mention that I do not model heat demand in a strict bottom-up way. Therefore, I do not assume anything about the part of existing electricity demand used to generate heat or the remaining heat demand not covered by the model. Therefore, the model and scenario definitions implicitly assume that I only assess the effect of *additional* heat pumps that cover 25% of total building heat demand *additionally*.

Table 4.1 provides an overview of the definition of my *base* scenarios. As a reference, I conduct a scenario run in which no heat has to be covered by heat pumps. In the two other scenarios, 25% of the heat has to be covered by heat pumps with varying sizes of thermal energy storage. In one scenario,

[3]As heat demand data for Switzerland is missing, Switzerland is part of the analysis and optimization, yet not heat pump rollout is simulated there.

all heat pumps are equipped with thermal energy storage sized at two hours of the maximum heat output. In the other scenario, this size is zero; hence, no thermal energy storage is available. I assume that heat pump owners are faced with wholesale electricity prices and operate their heat pumps in a system-friendly way. The advantage of thermal energy storage is the possibility of moving electric demand induced by heat demand to hours, in which the residual load (total load minus the generation of variable renewable electricity) is lower; hence, prices are lower. Another advantage of moving heat pump load away from hours of heat demand (and likely lower temperatures) is that heat pumps can possibly generate heat in hours of higher temperatures, therefore higher COPs, lowering the overall electricity demand of heat pumps.

Every scenario run is conducted for six weather years (2009-2014). To adequately capture the heating period in each year, I do not run the model from January to December, as it is commonly done in energy system modeling, but from July to June. If a specific weather year is mentioned in the following, I refer to the period starting in July and ending in June of the following year. For instance, the year 2009 would refer to the period July 2009 to June 2010.

Table 4.1: Definition of *base* scenarios

Heat share	E/P ratio of thermal storage
0%	-
25%	0
25%	2

To check the robustness of my results, additional scenario runs are employed, in which specific assumptions are varied (Table 4.2). For all robustness checks, a scenario with no heat pumps and a scenario with 25% heat covered by heat pumps is conducted. In all runs, heat pumps are equipped with a two-hour thermal heat storage. All scenarios are run for six weather years.

The scenario *gas_free* removes the lower bounds of gas-fired power plants, checking whether the model would prefer to install less CCGT capacity. *no_nuc* assumes a nuclear power plant fleet that is 50% lower than current values, assessing the impact of a partial nuclear phase-out. *no_coal* assumes a total decommissioning of lignite and hard coal-fired power plants. *no_ntc* is a counterfactual scenario in which no power flows between countries are possible, estimating the importance of cross-border electricity trade. As wind power might face expansion restrictions, *wind_cap* is a scenario in which wind on- and offshore capacities can only be expanded by 50% beyond ERAA 2021 values.

4.4 Results & Discussion

Before showing and discussing the principal model outcomes of the scenarios, a few fundamental facts about heat pumps and heat demand regarding the scenarios are presented; then, hours and periods of peak heat demand are analyzed; and, finally, the main outcomes, primarily generation capacities, are shown.

Table 4.2: Robustness checks

Scenario	Description
gas_free	No capacity (lower or upper) for gas-fired power plants.
half_nuc	Nuclear power plant capacities fixed at 50% lower value compared to *base*.
no_coal	No hard coal or lignite power plants.
no_ntc	No electricity flow between countries.
wind_cap	Upper bounds for on- and offshore wind power capacity at 50% above ERAA 2021 values.

In the *base* scenario, 25% of total space and water heating is supplied by ASHPs, leading to a substantial electricity demand (Figure 4.2). For instance, Germany would need to cover around 52 TWh in addition to its already existing load of 555 TWh, roughly an increase of ten percent. As explained in section 4.2, the size of the heat pumps in terms of electricity input, heat output, and thermal storage capacities are not determined endogenously but are set so that heat demand can be covered in every hour, even without thermal storage. With these assumptions in mind, Table 4.3 depicts the installed heat pump capacities that would follow the requirement to cover 25% of total building heat demand with ASHPs. Relevant for the electricity sector is the installed electricity input capacity of heat pumps, which would reach almost 40 GW in Germany and over 20 GW in France.

Country	Heat output (GW_{th})	Heat storage (GWh_{th})	Electricity input (GW_{el})
AT	5.5	11.0	3.5
BE	8.8	17.7	5.1
CH	0.0	0.0	0.0
DE	63.8	127.5	39.7
DK	3.9	7.8	1.9
FR	41.1	82.2	20.9
IT	29.2	58.4	13.9
LU	0.7	1.3	0.4
NL	12.5	25.0	6.8
All	165.4	330.9	92.0

Table 4.3: Heat pump capacities

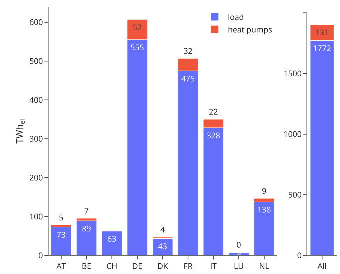
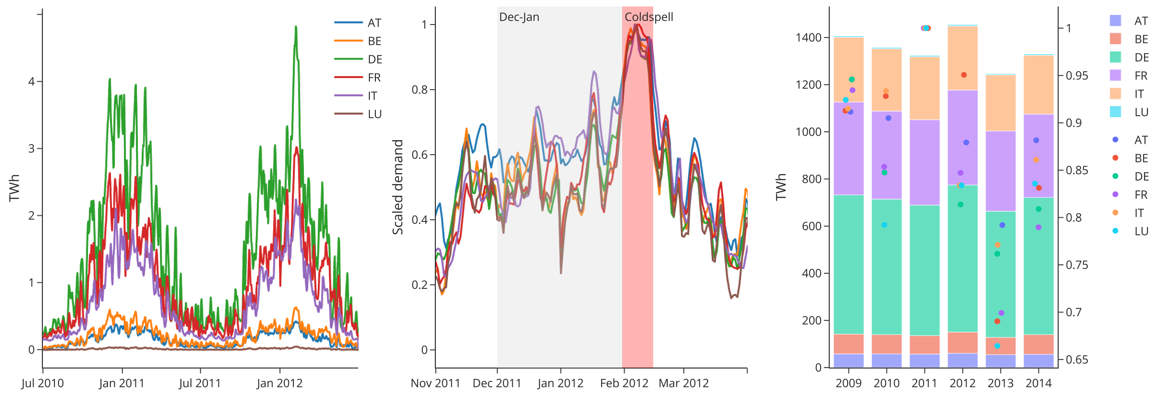


Figure 4.2: Yearly electricity demand

Note: The values depicted result from the *base* scenario with thermal energy storage of two hours and the weather year 2009.

4.4.1 Heat demand peaks and total heat demand do not align

As mentioned above, a simultaneous heat pump rollout could pose several challenges for the European electricity sector in terms of overall electricity needed and additional peak loads. Regarding these questions, a sensible approach is to first look at the overall structure and principal characteristics of heat demand for the countries included in my analysis (Figure 4.3). Not surprisingly, heat demand increases in winter in all countries (Figure 4.3a). The figure also reveals the dimensions of energy needed for residential and commercial heating of buildings: at the peak, almost five TWh of thermal energy were used per day for space and water heating in Germany in residential and commercial buildings in the year 2012. Despite the correlational appearance of heat demand, suggested by Figure 4.3a, heat demand patterns are more nuanced. The winter of 2011-2012 serves as a good example, in which heat demand showed only a partial correlation in the months of December and January. Yet, a cold spell hit the continent in mid-February, and heating demand surged simultaneously. Scaled to its maximum yearly value, total daily heat demand peaked in all countries around the same time (Figure 4.3b). Two insights for the energy system might arise: even a mild winter can be a strain if it contains a short cold spell, while moderately cold winters might be less of a challenge if they do not go beyond the expected. Related to this question, no clear relationship can be found between total heating energy needed and peak heating needed: Figure 4.3c shows the yearly (July-June) heating demand for each country in bars (left axis), while the dots depict the maximal hourly heat demand, scaled to the overall maximum heat demand of the period 2009-2014 (right axis). The hour of maximum heat demand in the period 2009-2014 occurred in all countries in 2011. In other years, the respective maximum heat hours show considerably lower values. Interestingly, 2011 was clearly not among the coldest years, as overall heat demand is lower than in years before and after. As peak heat demand was the highest, peak and total heat demand do not need to coincide.

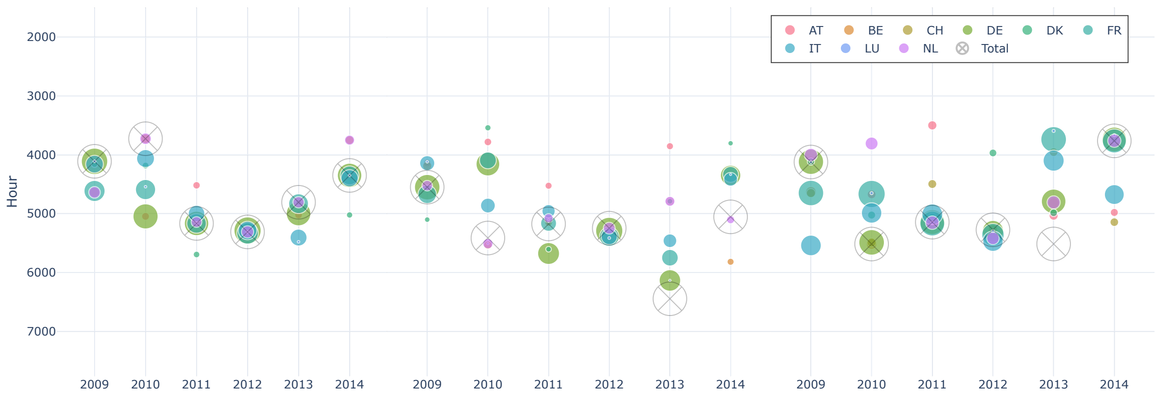


(a) Daily **(b)** Daily scaled to max. per year **(c)** Yearly and max. hour

Note: In panel (c), yearly heat demand is shown on the left axis. The maximum hourly heat demand, scaled to the overall maximum hourly heat demand of the entire period, is depicted on the right axis.

Figure 4.3: Heat demand

4.4.2 Heat pump load peaks do not necessarily align with residual load peaks



(a) Maximum heat demand **(b)** Maximum heat pump load **(c)** Maximum residual load

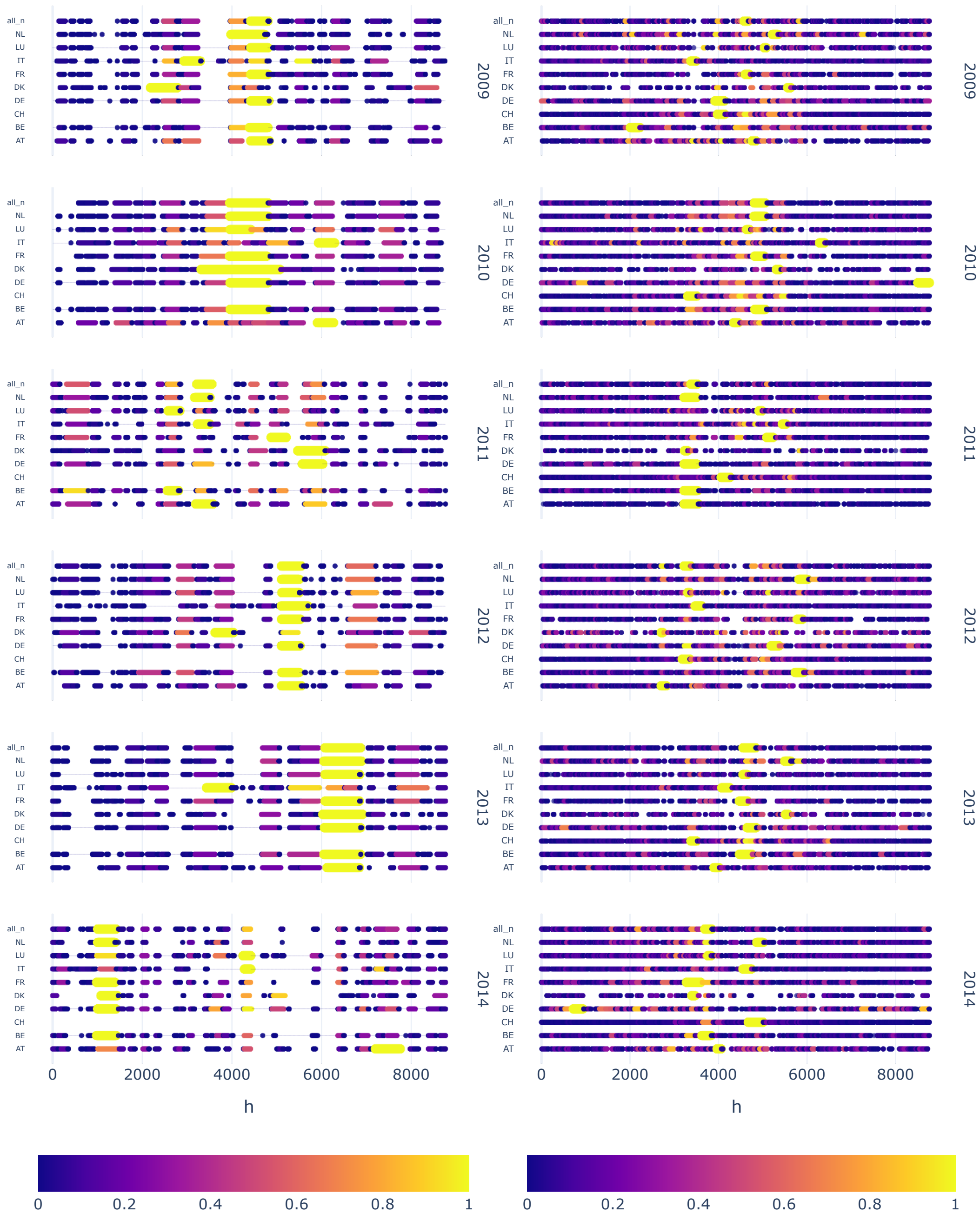
Note: The values depicted results from the *base* scenario with thermal energy storage of two hours. *Total* refers to the hour in which the sum of all countries is at its maximum. The size of that associated gray marker is not to scale. In panel (c), the residual load does not contain the electricity demand of heat pumps.

Figure 4.4: Maximum heat demand, heat pump load, and residual load: size and hour

However, it is important to acknowledge that the analysis of peak heat demand, even for several countries, does not fully capture the actual challenge for the electricity sector. While cold spells could lead to severe peak loads by heat pumps, consequences would be limited if these hours were accompanied by a high generation of renewable electricity. Therefore, it is helpful to analyze the relationship between the residual load, defined as electricity demand minus the generation of all variable RES (photovoltaic, wind on- and offshore, and hydro run-of-river), and peak heat demand (Figure 4.4): the occurrence of the hour of the maximum heat demand of every country in every year, as well as its relative size (indicated by the diameter of the circle) is depicted (4.4a), as well as the hour of maximum heat pump load (4.4b), and the hour of the maximum residual load (4.4c). The hour of maximum heat demand can be found in the winter months. Varying between the years, hours of maximum heat demand normally occur between the hours 4000 and 5500 (starting July 1st). In some years (like 2012), there is a coincidence of all maximum hours, while in other years (like 2010), no alignment can be seen. In many years, the hour in which the sum of heat demand of all countries is maximal also coincides with the maximum hour in the individual countries. As Figure 4.4 depicts values of a scenario in which heat pumps are equipped with thermal energy storage of two hours, the maximum heat pump load (4.4b) does not necessarily coincide with the maximum heat demand (4.4a). In some countries and in some years, the maximum heat pump load and maximum heat demand align, such as in the year 2012. However, for many years, the maximum heat pump load is at a different hour than the maximum heat demand, suggesting that the model has used thermal energy storage to disentangle heat demand and heat pump lead. For the impact on the power sector, though, it is relevant to see whether the maximum heat pump load coincides with the maximum residual load. Only if they fall together, the power sector would be strained, and additional (firm) generation capacity would be needed to cover the load. Like heat demand, all maximum residual load events can be found in the winter period (4.4c). The exact occurrences of the peak residual load hours vary quite strongly between years. Just like heat demand, they fall together in all countries in some years (2012), while they do not in others (2013). Most importantly, in many years and many countries, including the sum of all countries, maximum heat load and maximum residual do not align, suggesting a possible limited impact on the power sector. Yet, for the years 2011 and 2012, they align very well (roughly after the hour 5000), which should reflect a higher need for firm capacity in these years. The alignment could exist because wind speeds could be correlated with temperatures, and the existing electricity demand could already cover part of the heat demand, hence peaking in the same hour. It is also important to mention that the figure depicts only the hours of maximum heat demand, heat pump load, and residual load. However, the hours with the second, third, etc. highest values could show a different correlational structure. Hence, Figure 4.4 only shows a limited picture.

4.4.3 Periods of positive residual load and heat deviation overlap sometimes

However, the analysis of coincidence between the maximum heat pump load and residual load draws only a partial picture. The challenge for the energy system does not only arise from single hours of high (residual) load but also from more extended periods of low temperatures on the one side and longer periods of a positive residual load on the other side (Figure 4.5). If these two types of periods fall together, heat pumps add strain to the power sector. To analyze the occurrence of these two types of periods, the *maximum heat deviation events*, defined as the cumulative sum of positive differences between the hourly heat demand and its average value are depicted (Figure 4.5a). When heat demand falls below its average value, a “new” event starts. Therefore, it is likely that the true length of the cold periods is underestimated. The difference from the average is a good indicator of “cold spells” creating possible difficulties for the power sector. For better visualization and comparability, the summed energy value of each event is related to the value of the maximum event in each country and year. The event with the largest positive heat demand deviation is labeled with a “1”, and all the others, respectively, have values between zero and one depending on their relative size. Like in the analysis of hours of maximum heat demand, the maximum heat deviation events often align between countries, suggesting that they are driven by the same weather patterns. Please note, though, that the gravity of the events can be quite different between countries, as only the relative value to the maximum event of each country in each year is shown here. Years like 2010 and 2013 show how strongly heat deviation events can be correlated, suggesting that all countries were affected by the same weather events. Conversely, years like 2011 and 2014 depict shorter and less correlated events. Yet, maximum events in one country happen often in parallel to near-maximum events in other countries. With respect to positive residual load events, the picture looks a bit different (Figure 4.5b). Periods of consecutive positive residual loads are shorter than heat deviation events. Yet, it is important to remember that the yellow events are only the biggest and are terminated when



(a) Maximum heat devition events

(b) Maximum residual load event

Note: all_n refers to the sum of all countries.

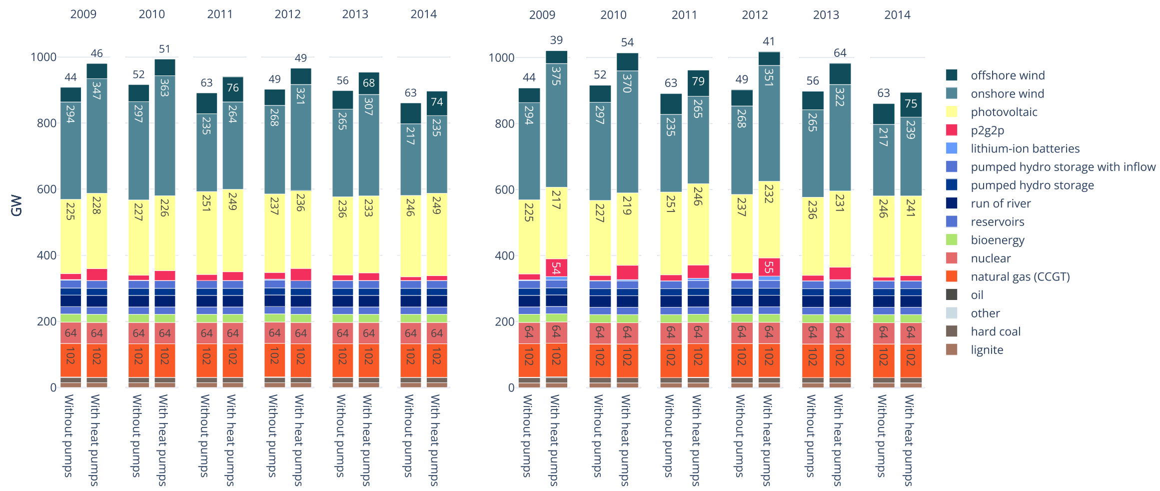
Figure 4.5: Maximum heat deviation and residual load events

the residual load turns negative. Therefore, if not accounting for these short periods of negative residual load, one could define these positive residual load events even longer.

Relevant to the power sector is whether there is an overlap between heat demand events and residual load events. Similarly to the previous analysis of maximum hours, the answer is mixed:

while in some years, a clear overlap between the largest (and close-to-largest) residual load events and heat events (such as in 2010 and 2011) can be seen, in other years they do not fall together (such in 2014). This finding, combined with the insights drawn from Figure 4.4, again shows the need to use several years in any energy system analysis to properly account for all possible phenomena and interactions. If the analysis of several years is not feasible, a careful study of weather years, which includes renewable energy availability and temperatures, is necessary to choose the appropriate year.

4.4.4 Thermal energy storage reduces the need for firm generation capacity



(a) Two hour thermal storage

(b) No thermal storage

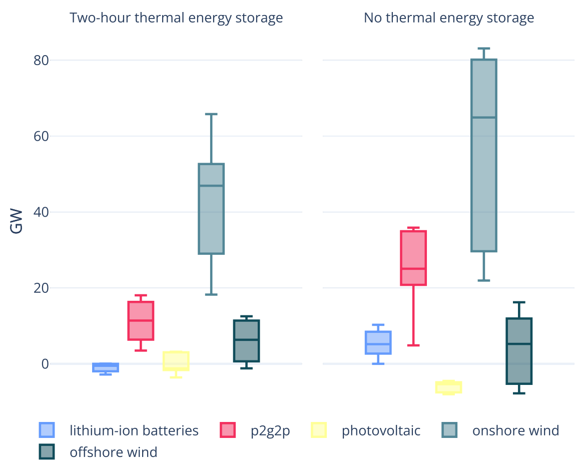
Figure 4.6: Overview generation capacities

A substantial rollout of heat pumps requires additional electricity, hence additional power plant capacities. Figure 4.6 depicts total generation capacities in all countries, with and without heat pumps, for all weather years. Already in the scenarios without heat pumps, the electricity sector is rather wind-focused (217-297 GW), with capacity varying quite strongly between weather years. Solar PV is also installed at a sizable dimension (225-246 GW). As assumed for the *base* scenario, nuclear power, as well as coal (lignite and hard) are fixed, while gas-fired power has a lower bound. As the model chooses to keep the capacity of gas-fired power plants at that lower bound, it suggests that even lower capacities could be cost-optimal (see Section 4.4.5).

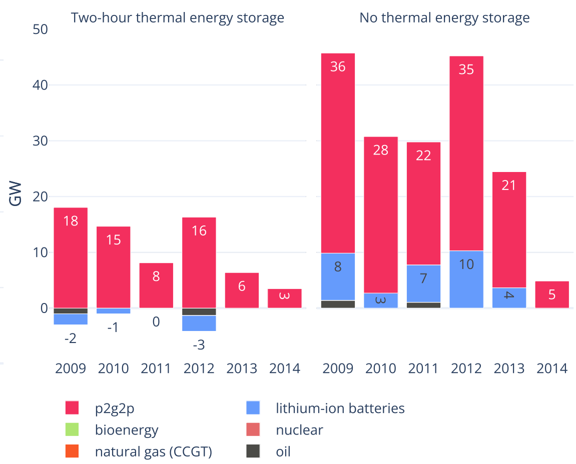
The introduction of additional heat pumps leads primarily to more onshore wind power (20 to 80 GW) and p2g2p storage (5 to almost 40 GW). Figure 4.6 shows the totals for every weather year, while Figure 4.7 depicts the changes as a box plot. P2g2p storage can be seen as a “proxy” for firm capacities. Interestingly, the model favors p2g2p storage over expanding gas-fired power plants, likely because of high CO_2 prices. Offshore wind power is also added in some years, yet at lower levels, due to the relatively high costs.

As shown in Figure 4.7a, equipping heat pumps with two-hour thermal energy storage leads to sizable differences in added capacities. While in the case of no thermal storage, the deployment of heat pumps leads to additional onshore wind capacities of between around 20 and 80 GW, these additional capacities are reduced to 20 to around 65 GW in the case of a two-hour thermal energy storage. Equally, the additions of p2g2p and lithium-ion battery storage and offshore wind power are smaller or even negative. Depending on the weather year, the onshore wind power capacity is expanded between 10 and 30%, while solar PV changes hardly.

Zooming in on only the firm capacities, the difference between the two scenarios is quite visible (Figure 4.7b). The two-hour thermal storage can avoid almost 20 GW of additional firm capacities, in my scenarios, mainly p2g2p storage. If no thermal storage is allowed, sizable capacities of lithium-ion battery storage are added with the deployment of heat pumps, which add intraday flexibility. Allowing for the thermal energy storage, the additional lithium-ion batteries are not needed, as the thermal energy storage takes over that role, and even a reduction in lithium-ion batteries with the rollout of heat pumps can be seen.



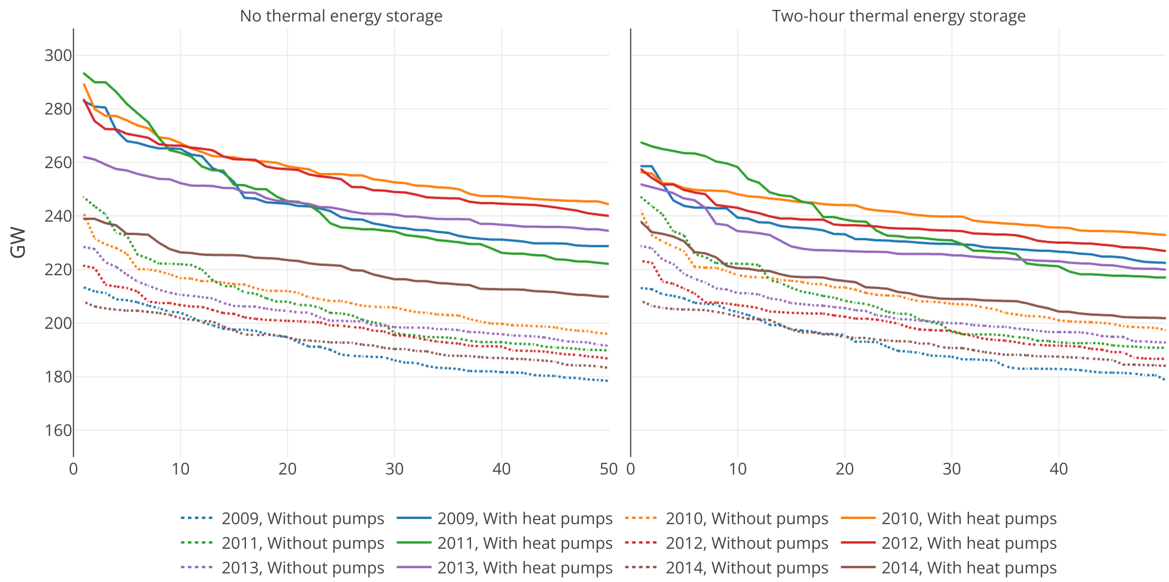
(a) All capacities



(b) Firm capacities, per year

Figure 4.7: Changes in aggregated generation capacities

The effect of the thermal energy storage can also be nicely seen with the analysis of residual load duration curves (Figure 4.8). The figure depicts the first 50 hours of the residual load duration curves of the entire "system", hence all countries. The dotted lines are the curves without the heat pump load, while the solid lines refer to the residual load duration curves with the heat pump load included. The left panel, the setting without thermal energy storage, reveals the direct impact of the heat pump load on the residual load. For instance, in the year 2009, there is a difference of almost 70 GW in residual load: heat pumps can add a lot of residual load! Not surprisingly, results differ quite substantially between years. The right panel displays the residual load duration curves in the scenario in which heat pumps are equipped with thermal energy storage of two hours. Compared to the left panel, the dotted lines, which are residual load duration curves without heat pump load, are almost the same. However, the solid lines are placed considerably lower, which shows that heat pumps in that scenario add considerably less residual load. For instance, in the year 2009, the difference between the two lines is considerably smaller, and the load added by heat pumps is now less than 50 GW. The effect visualized in this figure fits well with the results about additional firm generation capacities (Figure 4.7b), discussed above, and shows the importance of even — rather small — thermal storage for smoothing heating demand.



Note: The figure depicts the residual load duration curves of the "system", hence of all countries combined.

Figure 4.8: Residual load duration curves

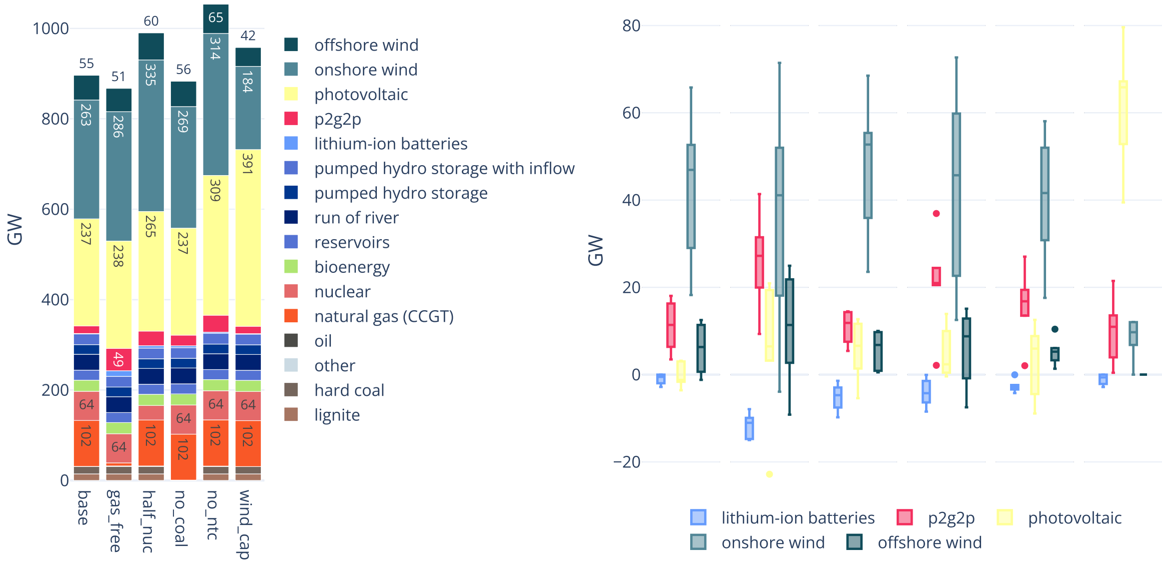
4.4.5 Further results and robustness checks

To better understand the quality of the results presented, a number of robustness checks are conducted in which some core assumptions of the model are varied. In the following, the generation capacity results and the impact on total system costs are presented and discussed.

Section 4.3 describes the assumptions of the additional scenario runs. Please remember that all robustness scenarios (Table 4.2) are conducted with heat pumps that have a two-hour thermal energy storage available. With respect to generation capacities, Figure 4.9 provides an overview of the capacities installed without heat pumps (4.9a) and the changes due to heat pump deployment (4.9b). Several insights are paramount: if capacities of gas power plants are not fixed (scenario *gas_free*), the model chooses to remove them entirely and invests mainly in additional p2g2p storage and onshore wind plants (compared to scenario *base*). That effect can be explained by the high CO_2, which renders, in turn, the operation of gas-power power plants costly. Regarding p2g2p storage, the scenarios *half_nuc*, *no_coal*, and *no_ntc* foresee higher investments to replace either missing firm capacity or due to the removed flexibility without electricity exchange. The scenarios *half_nuc* and *no_ntc* foresee considerably higher capacities of onshore wind power to replace missing energy generation and trade. The scenario *no_ntc* also foresees considerably higher solar PV capacities, not surprising as every country has to work in autonomy and therefore requires an overall more balanced power plant portfolio. Finally, the scenario *wind_cap* leads to very high capacities of solar PV compared to *base*, to replace the electricity formerly generated by onshore wind power.

The deployment of heat pumps has different effects on installed generation and storage discharge capacities (Figure 4.9b). Compared to the *base* scenario, additional on- and offshore wind power capacities are relatively similar, which is also not too surprising given the restrictions of the model and the high CO_2 price: (onshore) wind power is the most cost-effective technology to provide the additional electricity needed. In the scenario *wind_cap*, the heat pump rollout leads to mainly additional solar PV capacity, as on- and offshore wind capacities are already close to or at their respective upper bounds. Regarding the firm capacities, comparable dynamics can be seen in most scenarios, and several insights can be drawn: the additional heat pumps require additional firm capacities, which are provided by the p2g2p storage. Depending on the year, the assumed heat pump rollout can require between a few and almost 20 GW of additional p2g2p storage (in the *base* scenario). With higher capacities of p2g2p storage, lithium-ion batteries are pushed out of the system. In a system without interconnection (scenario *no_ntc*), the additional p2g2p capacities are similar to the ones in *base*, suggesting that interconnection provides only little additional flexibility to cope with the heat pump load. This aligns with the insights from the previous section 4.4.2, which demonstrated that heat demand peaks and strong heating periods overlapped between many countries. The two scenarios *gas_free* and *no_coal* trigger unsurprisingly additional investments into p2g2p storage to replace the missing firm capacities. The scenario *half_nuc* is similar to *base*, suggesting that the nuclear power plants (mostly in France) are indeed not crucial in delivering firm capacities to cover peak loads from heat pumps.

With respect to the different scenarios, total system costs are similar in the scenarios *base*, *half_nuc*, and *no_coal*, with even lower values in the latter two (Figure 4.10). The most expensive scenarios are *no_ntc* and *wind_cap*. Especially in the latter, the additional heat pumps increase system costs considerably. In the former, total system costs are on a higher overall level, but the introduction of heat pumps leads to a similar cost increase as in the *base* scenario, suggesting that an interconnected system does not provide much flexibility to cover the additional heat pump load. For the *wind_cap* scenario, costs without heat pumps are not much higher compared to the scenario *base*, yet increase substantially with the heat pump rollout, showing the compatibility of (onshore) wind power and heat pumps (cf Ruhnau, Hirth, and Praktiknjo, 2020). The impact of thermal heat storage on total system costs is small. Finally, Figure 4.10 shows again the variability of results with respect to weather years. Consistently, the year 2010 constitutes an upper outlier, while 2014 is a lower outlier. Further figures on the total electricity generation (Figure C.3) and on all residual load duration curves (Figure C.2) can be found in the appendix.



(a) Average generation capacities without heat pumps

(b) Capacity changes

Figure 4.9: Generation capacities in the robustness checks

The introduction of heat pumps leads to an increase in total system costs of around 5 billion Euro, as additional generation capacities need to be installed and additional electricity generated. These costs just reflect the costs of the electricity sector and do not account for the costs of heat pumps, for instance. As shown in Figure 4.3c, total heat demand in my system ranges around 1,300 TWh. If heat pumps would cover 25% of that demand, they would supply around 325 TWh of heat, translating to a price of 15.5 Euro per MWh. That price level is well below current wholesale prices of natural gas (around 40 Euro per MWh at the time of writing), assuming that the heat supplied with heat pumps had been previously generated by only burning natural gas with an efficiency of 100%. This calculation does not even account for the CO_2 price to be added to the gas bill. Therefore, it is evident, at least in terms of variable costs, that the additional expenses for the electricity sector costs are very favorable compared to the expenses for natural gas needed to generate the same amount of heat.

Figure 4.10: Total system costs

4.4.6 Limitations

As in any model-based analysis, my results depend strongly on data and scenario assumptions. Regarding the modeling of heat, I make several simplifying assumptions such that I do not model the detailed physical properties of heat pumps, only considering one heat pump technology, and also abstracting from potential flexibility by existing heat pumps as I only model additional units. Also, I exogenously set the share of heat covered by heat pumps and assume the size of the thermal energy storage instead of determining these variables endogenously. I abstract from any market incentives for consumers to operate heat pumps in a system-optimal way but assume they act in a system-friendly manner. My analysis could also be improved by adding more countries and weather years. Finally, I abstract from any detailed transmission and distribution grid modeling.

4.5 Conclusion

Heat pumps are a cornerstone in decarbonizing the heat supply of European buildings. Yet, their deployment does not come without challenges for the power sector. The present analysis evaluates a simultaneous heat pump rollout in several European countries, which allows several conclusions to be drawn. First, an ambitious rollout requires the installation of additional electricity generation capacities. Covering 25% of total heat demand in buildings by air-sourced heat pumps would require around 50 GW of additional onshore wind power capacity, alongside additional storage and firm capacities of far lower magnitude. In the case of expansion limits of onshore wind, the additional electricity could also be supplied by solar PV in combination with storage. Second, the flexibility of heat pumps is critical. Even a small thermal energy storage in combination with a system-friendly operation of heat pumps leads to a sizable reduction in peak loads and, therefore, firm capacity needs. Third, the interconnection between countries does not substantially help to reduce generation (and firm) capacities, as cold spell events are correlated. Hence, fourth, it is paramount to understand properly the nexus of heat demand and renewable energy supply in order to adequately assess the challenges of a further electrification of heat. Fifth, the additional costs of the electricity sector are very favorable compared to expenses for natural gas to generate a similar amount of heat. Finally, the present analysis shows again the variability of results with respect to different weather years. Thus, the statements of policy-informing studies should be interpreted with the insight in mind that results might strongly vary depending on weather data. The choice of the "right" weather year, the usage of multiple weather years, or even better, the modeling of multi-year periods periods are possible ways forward.

5

Not only a mild winter: German consumers change their behavior to save natural gas

This chapter is based on A. Roth and F. Schmidt (2023). "Not Only a Mild Winter: German Consumers Change Their Behavior to Save Natural Gas". *Joule*, S2542435123001733. DOI: 10.1016/j.joule.2023.05.001

5.1 Introduction[1]

By the start of the 2022/2023 heating season, Germany and many other European countries found themselves facing a potential gas supply shortage in the wake of Russia's invasion of Ukraine. In search of a response, authorities called on residential and commercial sectors to save natural gas. Exploiting winter 2022/23 as a "natural experiment", we shed light on the magnitude of behavioral gas savings using open data and a machine learning method. Despite being exposed to incomplete price signals, we find significant behavioral gas savings by German households and businesses, contributing to closing the supply gap. We uncover temperature-dependent saving dynamics and discuss the potential roles of different drivers of this change. Finally, we highlight the pivotal role of a timely and continuous provision of openly accessible data and analysis to inform the general public as well as policymakers.

5.2 Context

The Russian invasion of Ukraine in February 2022 has created an unprecedented supply crunch in European natural gas markets. Up until February 2022, Russia had been Europe's largest supplier of natural gas, expanding its position in prior years. Doubting the reliability of Russia's gas supplies, the question of whether enough gas would have been supplied to the European market led to spiraling wholesale gas prices. At the end of August 2022, prices peaked at over 300 Euro per MWh at the benchmark hub TTF after Russia stopped delivering gas through its Nord Stream 1 pipeline (TradingEconomics.com, 2023). Slowly rising in the months prior to the invasion, prices had been fluctuating around 20 Euro per MWh in recent years (TradingEconomics.com, 2023). Following the closure of Nord Stream 1, the security of supply was called into question with respect to the upcoming winter of 2022/23 (Murphy, 2022).

Within a year, (Central) Europe's gas supply structure changed radically. While historically, around 40% of all gas imported to Germany had been coming through Russian pipelines, this number dropped to almost 0% by the end of 2022 (Schill and A. Roth, 2023). Much of the Russian supply was substituted by additional pipeline imports from Norway and liquefied natural gas (LNG) shipments from other countries. The remaining potential shortfall gave rise to a discussion on how much gas could and would be saved by whom.

With respect to gas consumption, there are three principal groups: gas-fired power plants, large industrial consumers, and the residential and commercial sectors, which comprise households and small- and medium-sized businesses. Gas-fired power plants consume gas for electricity production, yet some also supply heat to district heating networks. Large industrial consumers use gas either as feedstock or source of process heat. The residential and commercial sectors need gas predominantly to satisfy heat demand.

[1]Wolf-Peter Schill is thanked for his very helpful comments and remarks. This work benefited from a research grant by the German Federal Ministry of Education and Research (BMBF) via the Kopernikus project Ariadne (FKZ 03SFK5N0).

These consumer groups are different in terms of the price signals they receive, as well as the potential for and consequences of gas demand reductions or enforced curtailment. Gas-fired power plants usually buy gas short-term to serve peak electricity demand and thus react immediately to price signals in both electricity and gas markets. Provided there is sufficient alternative electricity supply, e.g. from coal-fired power plants, gas demand from the power sector is rather flexible. Large industrial consumers, unless protected by long-term gas supply contracts or comprehensive hedging, are similarly exposed to price changes in the spot market and therefore have an incentive to reduce gas consumption in case of a supply crunch. At least in the short run, the industry can reduce its gas consumption by curbing production, substituting the energy carrier, or buying alternative upstream products. Mostly supplied under fixed-price contracts, residential and commercial consumers do not bear the consequences of rising prices in the spot market until a contract has to be renewed. Even in the case of an acute gas shortage, it is not clear whether a controlled gas curtailment of supply to residential and commercial sectors in the distribution grids would have been possible, as it would have been challenging to implement for various technical (Winkelhahn, 2022; Murphy, 2022) and political reasons.

In the face of a looming gas shortage, the public debate initially concentrated on industry halting production, leading to a strong economic downturn, the size of which was debated controversially among economists (Bachmann et al., 2022; Krebs, 2022). To avoid dire economic consequences of production cutbacks of industrial consumers and because of limited means for the government to impose rationing, voluntary savings by residential and commercial sectors eventually gained importance in closing the gas supply gap.

5.3 Gas savings from changes in behaviour

Since the beginning of the gas supply crunch, Germany has been the focus of discussion due to its large economy and relatively high dependence on Russian gas imports. In September 2022, the German Federal Network Agency *Bundesnetzagentur* announced that a 20% reduction in gas consumption (compared to the average consumption of the preceding four years) would have been necessary to avoid an acute gas shortage (Bundesnetzagentur, 2022).

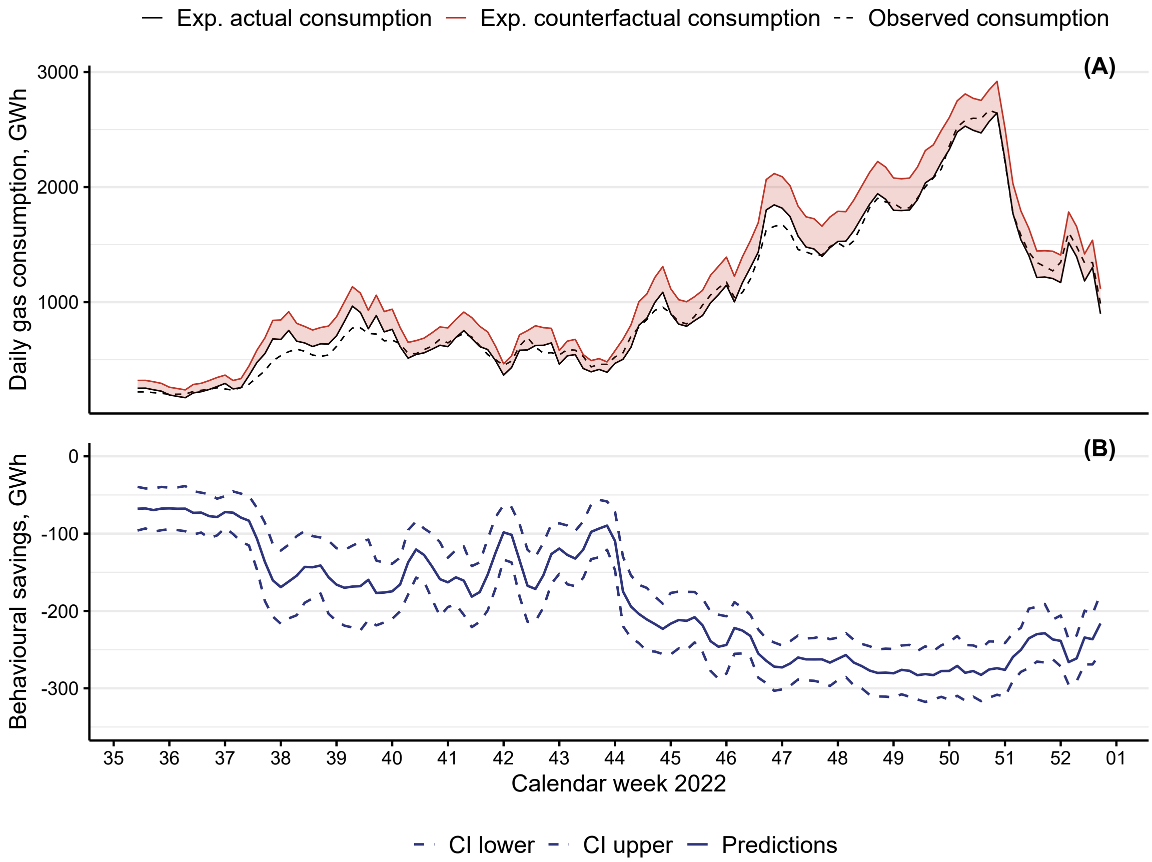
In the following, we aim to shed light on the efforts by residential and commercial sectors to save gas. The strong dependency of residential and commercial gas demand on weather conditions implies that relatively warmer or colder weather has a large effect on whether the target is actually achievable or not. Building on a rich literature on the relationship between heat demand, gas demand, temperatures and prices (Henley and Peirson, 1997; Wojdyga, 2008; Ruhnau, Stiewe, et al., 2022; Bantle and Wiersich, 2022), we use a very flexible machine learning method to isolate those gas demand drivers that are not governed by weather variations. We subsume these drivers as the *behavioral component*.

The method used in this commentary to estimate savings is a causal forest, which has two important features: (1) It is fully non-parametric and data-driven, and (2) it allows isolating savings effects differentiated by temperature. Causal forests (Athey and Imbens, 2017) extend a classic machine learning algorithm, random forests Breiman, 2001. The general idea of random forests is to partition the data set based on values of explanatory variables and fit local models within these partitions, which are together capable of representing non-linear relationships without having to specify a functional form. Causal forests extend this concept by using the same logic as a tool to identify local saving effects. We provide extensive explanations, details, and robustness checks of our model in the Supplemental Information (D.2) section. The causal forest model enables us to *predict* daily behavioral savings depending on the weather conditions of the day. In order to control for weather conditions, we include mean, minimum and maximum temperatures of a given day as well as several lags to control for thermal inertia. Irradiation effects are proxied by sunshine duration, and we include month and weekend/holiday indicators to account for behavioral variations.

Our model allows us to recover two alternative scenarios of *estimated* consumption. The first scenario is the estimated *actual* consumption, including behavioral savings. The second scenario is the estimated *counterfactual* consumption, which would be expected in the absence of the savings. By design, the difference between these two scenarios yields our estimate of *behavioral savings*. By focusing on estimated counterfactual consumption and estimated actual consumption (instead of *observed* consumption), we ensure a like-for-like comparison and that our savings are not driven by random error. This assumes implicitly that the model errors, given by the difference between the estimated actual consumption and the observed consumption, would have been the same in the absence of behavioral savings.

In the upper panel of Figure 5.1, the estimated actual consumption is depicted as a solid black line, while a solid red line represents the estimated counterfactual consumption (in the absence of savings). The dashed black line gives the observed consumption. We start measuring the savings effect as of September 2022, when the risk of a supply shortage became pressing with the start of the heating period and the end of Nord Stream deliveries. Nonetheless, our model allows for the possibility of behavioral savings from the beginning of the Russian invasion of Ukraine on 24 February 2022. We discuss the implications of this assumption in detail in the Supplemental Information section (D.2).

Gas consumption has been going up as expected with colder temperatures (Figure 5.1). With the beginning of the heating season in September, we see that German residential and commercial sectors have consistently saved between 66 and 285 GWh of gas per day. As revealed in the lower panel of Figure 5.1, estimated savings are statistically significant for all days in the September to December period. December 2022 was exceptionally cold, also reflected by spiking gas demands. Around the Christmas period, savings efforts diminished. Cumulatively, we estimate that households and commercial sectors have saved ca. 23 TWh [95% CI: 18.7; 27.3] by changing their behavior from the beginning of September until the end of December 2022.

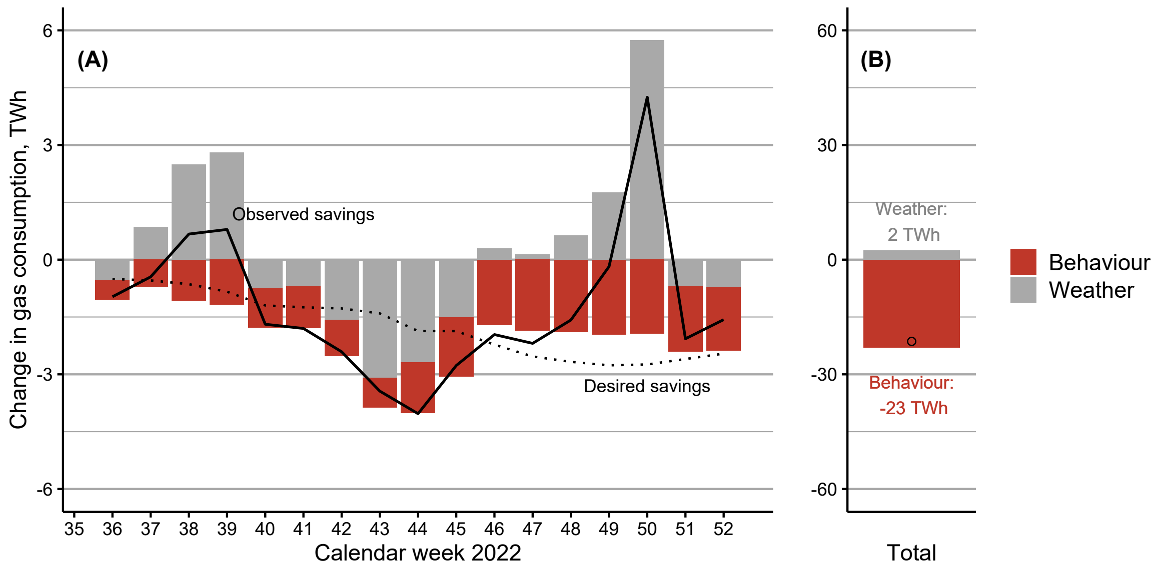


Notes: The *upper panel* (**A**) shows the modeled actual and counterfactual gas consumption paths from September 2022 - December 2022. The solid line in the *lower panel* (**B**) gives the estimated behavioral savings (corresponding to the shaded area in the upper panel). The dashed lines define the 95% confidence interval of the estimated savings.

Figure 5.1: Actual and counterfactual gas consumption

Relying on the results above, we can attribute the differences in gas consumption between 2022 and the average of the period 2018-2021 to different effects (Figure 5.2). The weather effect (grey) is computed as the difference between the 2018-2021 average consumption and the estimated counterfactual consumption in 2022. Behavioral savings (red) result from the difference between estimated actual and counterfactual consumption. The sum of weather and behavioral savings does not add up to the total difference in consumption, represented by the solid line, due to the unobserved error component discussed above. The 20% savings target defined by German Federal Network Agency is reflected by the dashed line.

Total savings compared to the average of 2018-2021 varied substantially between different weeks (Figure 5.2). This variation is mostly driven by the weather component. Meanwhile, the behavioral component remains relatively stable, slightly increasing over time. Compared to 2018-2021, we observe two cold spells: one in September (as of calendar week 36) and one in mid-December (as of calendar week 50), in which the weather component drove up gas consumption. Even in these colder



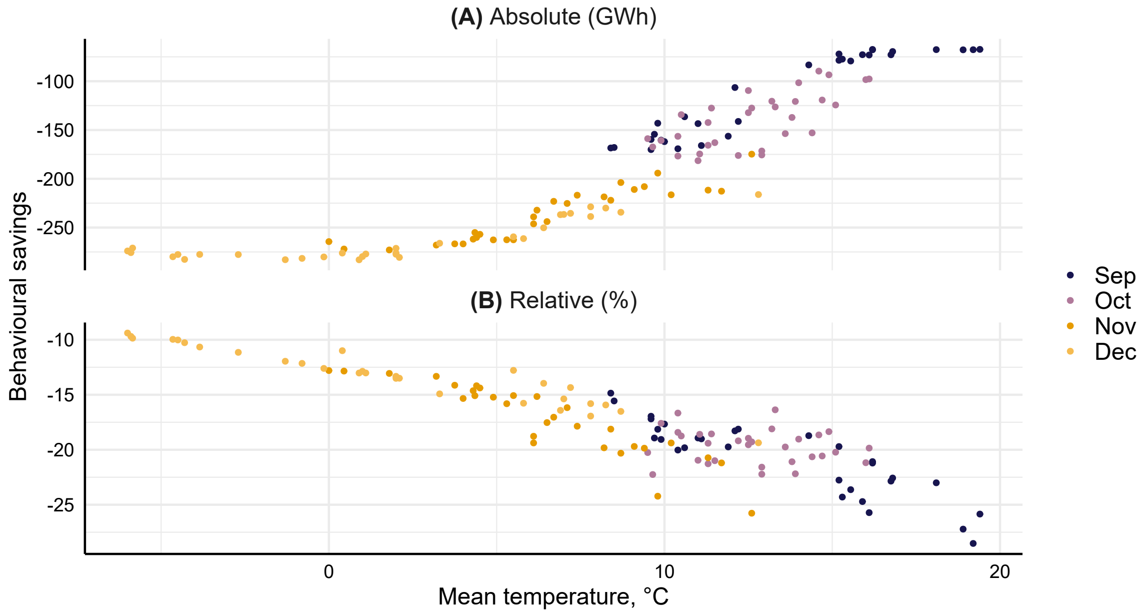
Notes: Weekly savings in 2022 compared to 2018-21 consumption, disaggregated into behavioral and weather component *(left)*; disaggregated quantity-accumulated savings *(right)*

Figure 5.2: Gas savings disaggregated into weather and behavioral components vs 2018-21 average

periods, estimated behavioral savings did not change much. In the last two weeks of the year, savings decreased slightly compared to the previous weeks. This may be explained either by the Christmas period or by a reduced urgency, as it became increasingly evident by December that a gas shortage in the winter of 2022/23 would be rather unlikely. Gas storage levels remained well above the range of previous years.

On aggregate, we find that the weather effect alone did not play a significant role when comparing the September to December 2022 gas consumption with previous years (right panel of Figure 5.2). At least for the first half of the winter, this is possibly at odds with other analyses asserting that a comparably mild winter induced most savings Blas, 2023. Consistent behavioral savings contrast highly variable weather-related savings. Especially the cold spell in December offset most of the savings by weather due to milder temperatures in the weeks before. However, the weather may have had an indirect effect, as a colder winter would have made it even harder for households to save gas in the same way.

The winter months of 2022 also shed light on the savings dynamics of the residential and commercial sectors relative to temperatures. We find a negative relationship between relative gas savings, defined as absolute gas savings divided by estimated counterfactual consumption, and temperature (lower panel, Figure 5.3). The residential and commercial sectors seem to relatively easily suppress their heating demand when temperatures are rather mild. These levels of relative savings cannot be carried over to lower temperatures. If outside temperatures are around 12°C, decreasing heating efforts by a certain amount will have a much lower effect on room temperatures compared to a situation when outside temperatures range around 0°C.



Notes: Relative behavioral savings are defined as absolute behavioral savings divided by estimated counterfactual consumption.

Figure 5.3: Correlation between behavioral savings and mean temperature

Regarding the relevance of averting a gas shortage, relative savings are, however, only of minor importance. Therefore, we highlight the substantial and consistent absolute savings during cold temperature days (upper panel of Figure 5.3). Although they fell short of the targeted 20% goal by the federal regulator, they added more to adverting a gas shortage than the higher relative savings in autumn.

5.4 Conclusions and outlook

Winter 2022/23 happened to be a "natural experiment" for Europe and Germany on how the economy would react to a gas supply crunch or even a looming shortage. It tested the capacity and willingness of households and commercial consumers to cut gas demand mainly used for heating. Using a data-driven causal forest model, we can show that residential and commercial sectors have reduced their gas consumption. In contrast, the weather had even an increasing effect.

The reasons for these savings could be manifold, including but not limited to increased prices, clear communication by officials, changed expectations, and political conviction and solidarity.

As most of Germany's residential and commercial sectors face fixed price regimes, wholesale market price spikes usually do not affect consumers directly. Short-lived price hikes on the wholesale market typically do not translate into higher long-term retail tariffs. For the prolonged price increase in the wake of the Russian invasion of Ukraine, average retail prices only reacted sluggishly (Ruhnau, Stiewe, et al., 2022). Furthermore, staggered contractual periods and the unavailability of individual-level consumption data make it challenging to compute precise price elasticities at the retail level. Notwithstanding, higher prices have certainly affected the estimated behavioral savings. Yet, the precise impact of prices on German residential and commercial sectors remains, for the moment, opaque.

As we observe savings despite incomplete price signals, we suggest they might have also been driven by a response to public communication. As September came to an end, Germany had experienced a colder start into autumn than usual, and the German Federal Network Agency, *Bundesnetzagentur*, and its president urged residential and commercial sectors to reduce consumption. Consequently, the agency released the aforementioned target of a 20% demand reduction. The president repeated this plea several times. In addition, consumers could have saved additionally in expectation of higher prices. Clear communication by the Federal Network Agency raised public awareness of the role of storage levels and their effect on wholesale prices and, eventually, contract prices. Consumers are likely to have understood that lower consumption levels today would keep storage levels sufficiently high in order to avoid costly additional imports. Other reasons might have played a role as well. Some consumers could have regarded saving gas as a part of responsible civil behavior. Political beliefs towards the support of Ukraine (or Russia) could also have (de-)motivated the savings behavior of some households.

Importantly, we want to highlight the essential role of continuous and timely data provision and analysis for public debate and policymaking. Transparency and publicly available data are crucial for consumers and policymakers, not only to better understand the topic but also to track whether measures and their efforts have any effect. In autumn 2022, little publicly available evidence existed on whether and how strong the residential and commercial sectors would help in savings gas to avoid a potential gas shortage in the winter months. Several platforms began to publish analyses on various aspects of the energy crunch, such as consumption data, storage levels, prices etc. On the "Open Energy Tracker" (Schill and A. Roth, 2023), we have been tracking behavioral gas savings of residential and commercial sectors since October 2022, providing the public with timely insights. The results and methods in this commentary are based on those published in a less elaborate form on the "Open Energy Tracker".

Despite the impact that data and analyses might have already had on policy and consumer behavior in this gas crisis, improved data quality, e.g., by means of an accelerated smart meter roll-out, could yield further benefits. It could enhance the quality of the analysis by uncovering drivers of consumer behavior and thereby increase the policy relevance of real-time analyses. It could also allow for more direct pricing mechanisms that prompt an immediate consumer response to wholesale market developments.

Finally, all results in this piece can only be regarded as a snapshot in time, and a complete picture will only emerge in a continued analysis. The estimates presented in this commentary will be continuously updated online (Schill and A. Roth, 2023). We believe that with a data-driven analysis of events, the public and policymakers have an important tool at hand to assess the success of saving efforts and their policies.

6

Do Wind Turbines Have Adverse Health Impacts?

This chapter is based on C. Krekel, J. Rode, and A. Roth (2023). "Do Wind Turbines Have Adverse Health Impacts?" *DIW Discussion Papers* 2054. DOI: http://hdl.handle.net/10419/279485

6.1 Introduction[1]

Wind power is considered key in the transition towards net zero. About 100 GW of onshore capacity – roughly 500,000 wind turbines – were built in Europe between 2011 and 2020 alone, satisfying about 7% of Europe's electricity demand as of 2020 (WindEurope, 2021). Wind power is expected to contribute large shares to electricity supply in Europe (Child et al., 2019) and worldwide (IEA, 2021) by 2050, making it the most important renewable energy after solar.

Yet, wind power is not without controversy. Although its importance is generally acknowledged, local residents often strongly oppose new wind turbines near their homes, a phenomenon referred to as *not-in-my-backyard effect* which is seen as a major contributing factor behind the slow expansion of wind power. In fact, negative impacts on house prices and the subjective wellbeing of nearby residents have been documented (cf. Heintzelman and Tuttle, 2012; Gibbons, 2015; Dröes and Koster, 2016; von Möllendorff and Welsch, 2017; Krekel and Zerrahn, 2017). Importantly, local residents regularly cite concerns about adverse health impacts of wind turbines as one reason behind their opposition, and these concerns have led to a heated debate about potential public health consequences of living close to installations. In fact, Baxter, Morzaria, and Hirsch (2013) find that health concerns are the strongest predictor for local resistance. However, systematic, causal evidence on potential health externalities is scarce.

In this paper, we ask: do wind turbines have systematic, negative causal effects on the health of nearby residents? If so, which health dimensions are affected and by how much? And are effects, if any, spatially or temporally limited? To answer these questions, we use quasi-experimental methods and representative longitudinal household data from Germany – a country with a fast expansion of wind power in recent decades and hence a suitable case study – linked to a nationwide dataset on wind turbines, based on precise geographical coordinates, covering the universe of almost 24,000 installations built in Germany between 2000 and 2017.

In theory, adverse health impacts of onshore wind turbines may be driven by several factors.[2] First, and most important, there are concerns about the technology, with visual pollution from both shadow flicker and night-time anti-aircraft lights, as well as noise pollution from both audible and (especially) sub-audible (low-frequency or infra) sound as often cited mechanisms. Whether feared or actually realised, these may result in worry, anxiety, and sleep disturbances, thereby resulting in mental or physical health issues (cf. Bolin et al., 2011; Onakpoya et al., 2014; Freiberg et al., 2019). Besides technological concerns, residents may feel overwhelmed and annoyed by not having been involved in local planning and decision-making processes, aspects of fairness and procedural justice (cf. Pohl, Gabriel, and Hübner, 2018; van Kamp and van den Berg, 2021; Ki et al., 2022). Once installations have been built, they may feel disturbed by violations of their natural landscape

[1]Richard Layard, Ekaterina Oparina, Stefan Pichler, Michael Neugart, and Falk Laser are thanked for their comments and suggestions on an earlier draft. Jonas Witte, Niall Maher, Isaac Parkes, and Marc Mosch are thanked for their excellent research assistance. This work profited from the support of the Chair of International Economics at TU Darmstadt.

[2]For general reviews of wind turbine externalities, see Mattmann, Logar, and Brouwer (2016) or Zerrahn (2017).

preferences or their psychological attachment to their places of residence (cf. Devine-Wright, 2005; Jobert, Laborgne, and Mimler, 2007; Wolsink, 2007; Waldo, 2012).[3] Each of these factors may provoke negative emotional reactions and stress, leading to, if sufficiently strong, adverse health impacts.

To provide systematic, causal evidence on such health externalities, we link the health outcomes of household members to the nearest wind turbine based on precise geographical coordinates of both households and installations. We measure general, mental, and physical health using the 12-Item Short Form Survey (SF-12) (RAND, 2022), a routine instrument for monitoring health in the general population. In addition, we measure self-assessed health and the number of doctor visits as a retrospective behavioural outcome, as well as the frequency of experiencing negative emotions, sleep satisfaction, and the number of hours of sleep as cited mechanisms behind potential health problems. To estimate causal effects, we exploit the staggered rollout of installations over a two-decade period in a spatial difference-in-differences design, using two-way fixed-effects estimators and, in addition, the robust estimator by Sun and Abraham (2021) to explicitly account for potential treatment effect heterogeneity due to changing technology over time (cf. Goodman-Bacon, 2021).[4] Depending on outcome and treatment and control radii, our estimation samples include between 700 and 1,963 individuals who are treated by between 111 and 462 wind turbines, distributed across the entire country, who are compared to a control group of between 8,002 and 10,533 individuals.[5]

We are the first to study the direct health effects of wind turbines using quasi-experimental methods and nationwide data on households and installations that span over two decades, while explicitly accounting for potential treatment effect heterogeneity due to changing technology over time. We find no evidence of negative effects on either general, mental, or physical health – neither on aggregate nor on any of the different mental or physical health sub-scales – in the SF-12. There is no evidence for dynamic effects over time nor for cumulative effects. We do not detect impacts on self-assessed health or the number of doctor visits either. When looking at often cited mechanisms in the literature, we find no evidence that residents living closer to installations experience more negative emotions, are less satisfied with their sleep, or sleep fewer hours than residents living further away. In our baseline specification, we use a treatment group within 4,000 meters and a control group between 4,000 and 8,000 meters to the nearest installation. Individuals within 4,000 meters are previously shown to experience negative externalities of wind turbines on their subjective wellbeing (cf. Krekel and Zerrahn, 2017). Our results are robust to different treatment and control radii as well as different bins around plants, to different plant sizes, and to accounting for residential sorting. Taken together, our findings cast doubt on health externalities on the local population, which has important implications for the public and scientific debate around wind power.

[3]A similar argument can be made for residents who hold lower environmental attitudes (Hobman and Ashworth, 2013), who have less experience in and knowledge of renewables (Aitken, 2010), or who hold more conservative political beliefs (Eltham, Harrison, and Allen, 2008; Karlstrom and Ryghaug, 2014).

[4]As an alternative to Sun and Abraham (2021), we also use the estimator by Gardner (2022) as a robustness check, which confirms our results.

[5]An *ex-post* power calculation confirms that our study is sufficiently powered to detect a small effect size, if present.

Suicide is an extreme outcome of mental distress (Harris and Barraclough, 1997), and has been used as an objective measure of adverse mental health impacts of environmental stressors, for example air pollution in the US (Molitor, Mullins, and White, 2023) or high temperatures in Mexico and the US (Burke et al., 2018). The paper most closely related to ours is Zou (2020), who studies the impact of wind turbines on suicides by exploiting administrative data on 800 new utility-scale wind farms and official suicide rates at the county level in the US from 2001 to 2013. The author uses a spatial difference-in-differences design and two-way fixed-effects estimators, finding significant increases in suicides in counties closer to wind farms. However, impacts are small and detectable only for individuals between 15 to 19 and for those over 80 years of age. Leveraging additional survey data, the author shows that increases in suicides are likely driven by sleep insufficiency.[6] Exploiting administrative data on suicide rates at the county level in Germany during our observation period and replicating our analysis on health outcomes for suicides, we do not find evidence of effects on suicides.

We contribute to a body of evidence that is – despite a clear, theoretical causal chain from environmental stressor to health – largely inconclusive and that relies mostly on cross-sectional analyses and local case studies.[7] Most studies find that being located close to a wind turbine is associated with increases in noise annoyance (Bakker et al., 2012; Michaud et al., 2016; Pohl, Gabriel, and Hübner, 2018; Radun et al., 2022), health concerns (especially when installations are visible) (Michaud et al., 2016), sleep disturbances (Bakker et al., 2012; Turunen et al., 2021; van Kamp and van den Berg, 2021), and increases in psychological distress (Bakker et al., 2012), with similar patterns across countries (Hübner et al., 2019). Besides issues of causality and a focus on local case studies, a common concern with many of these studies is that they are often framed as or are seemingly related to wind turbines, which may elicit attitude expression rather than the reporting of genuine impacts. Given the quality of the evidence base, meta-analyses and systematic reviews are, likewise, inconclusive (Bolin et al., 2011; Knopper and Olson, 2011), concluding that “experimental and observational studies investigating the relationship between wind turbine noise and health are warranted” (Onakpoya et al., 2014) and that “more high-quality research is needed” (Freiberg et al., 2019). In a systematic review, J. H. Schmidt and Klokker (2014) find that exposure to wind turbines increases the risk of annoyance and sleep disturbance, yet find no conclusive evidence of other claimed health effects, noting that “selection bias and information bias of differing magnitudes were found to be present in all current studies.” Given this inconclusive evidence base, the World Health Organization, in its *Environmental Noise Guidelines*, takes a cautionary stance, and recommends “reducing noise levels produced by wind turbines below 45 dB L_{den} [decibel day-evening-night-

[6] In a study not related to health, Brunner, Hoen, and Hyman (2022) use a spatial difference-in-differences design that exploits the nationwide rollout of wind turbines in the US between 1995 and 2016. The authors estimate the causal effects of wind turbines on test scores, high-school completion, and long-run outcomes of local students, finding precisely estimated zero effects. Like our paper, the authors use both two-way fixed-effects estimators and the robust estimator by Sun and Abraham (2021).

[7] There is also a proliferating grey and pseudo-scientific literature suggesting that proximity to wind turbines is causing a wide range of health issues, from autism to cancer or even death. We limit our literature review to peer-reviewed articles.

weighted sound pressure level], as wind turbine noise above this level is associated with adverse health effects" and that "policy-makers implement suitable measures to reduce noise exposure [...] above the guideline values". However, it also acknowledges that the quality of evidence is "low" or even entirely missing (WHO, 2018).

Interestingly, some studies point towards psychological salience, personality, and individual differences to explain some of these findings. For example, Crichton and Petrie (2015) show that concerns about adverse health impacts created by the media may trigger symptom reporting, while Taylor et al. (2013) find perceived symptoms only amongst residents who score high in terms of neuroticism, negative affect, and frustration intolerance. Similarly, Jalali et al. (2016) find reported sleep disturbances only amongst residents who have negative attitudes towards wind turbines, concerns about property devaluations, and who can see installations from their homes.

We also contribute to the literature in health, environmental, and public economics that looks at the external effects of infrastructure, either directly on health and health-related quality of life, such as freeways and associated congestion (Currie, Neidell, and Schmieder, 2009; Brinkman and Lin, 2022) or shale gas development and fracking (Hill, 2018), or indirectly via noise pollution, such as airports or neighborhood structure (Bilger and Carrieri, 2012; Boes, Nüesch, and Stillman, 2013); via air pollution such as industrial facilities, power plants, or heating and agricultural systems (Agarwal, Banternghansa, and Bui, 2010; Luechinger, 2014; Currie, Davis, et al., 2015; Sheldon and Sankaran, 2017; Fan, He, and Zhou, 2020), or the impacts of air quality on health and societal welfare more generally (Currie, Neidell, and Schmieder, 2009; Muller, Mendelsohn, and Nordhaus, 2011; Coneus and C. K. Spiess, 2012; Tanaka, 2015; Deryugina et al., 2019; Anderson, 2020; Giaccerini, Kopinska, and Palma, 2021), and specifically, the societal benefits and costs of wind power (Cullen, 2013; Novan, 2015). Our paper adds a particular type of infrastructure – renewable energy facilities, specifically wind turbines – that is being deployed in many countries at fast pace in close proximity to households.

6.2 Data

6.2.1 Health

Our health data come from the German Socio-Economic Panel (SOEP), a representative panel of private households in Germany (SOEP, 2021). It has been conducted annually since 1984 and includes almost 40,000 individuals living in more than 19,000 households in its most recent 2022 wave. Importantly, the panel provides, besides interview dates, the exact geographical coordinates of every household in every year since 2000, which allows us to merge the health outcomes of individuals living in a representative sample of German households with data on wind turbines based on precise geographical information and timing (Goebel, Grabka, et al., 2019).[8]

[8]The SOEP is subject to rigorous data protection: it is not possible to derive household data from geographical coordinates as both are not visible to the researcher at the same time. See Goebel and Pauer (2014) for details.

We select several health outcomes. Our main outcomes come from the 12-Item Short Form Survey (SF-12) (RAND, 2022), which is incorporated into the SOEP every second year (i.e. 2000, 2002, 2004, ..., and so on). It includes summary scales for *general health*, *mental health*, and *physical health*, alongside respective sub-scales.[9] The SF-12 is a standard instrument on health-related quality of life, allowing for group comparisons involving multiple health dimensions. It relies on self-reporting and is widely used in healthcare for monitoring and assessment of health outcomes in general and patient populations (Ware, Kosinski, and Keller, 1995). All scales from the SF-12 are normalized to be between zero and 100, with a mean of 50 and a standard deviation of 10 (cf. Andersen, Mühlbacher, and Nübling, 2007).

Moreover, we obtain data on the subjective *self-assessed health* of individuals and, as a retrospective behavioral outcome, the reported *number of doctor visits* in the year prior to their interview, both of which are asked every year. The former is obtained from a five-point Likert scale question that asks "How would you describe your current health?", with answers ranging from five ("Very good") to one ("Bad"). The latter is obtained from a question that asks "Have you gone to a doctor within the last year? If yes, please state how often." Finally, we obtain data on the frequency of experiencing certain emotions, sleep satisfaction, and the number of hours of sleep to look at often cited mechanisms through which adverse health impacts of wind turbines may come about, in particular those related to noise pollution from both audible and (especially) sub-audible (low-frequency or infra) sound.

Besides these outcomes, we select a wide range of demographic and socio-economic characteristics as covariates, including marital status, employment status, log annual net household income, the ownership status of the dwelling and its log annual rent, as well as the number of adults and children in the household.[10]. Importantly, neither surveys nor questions are framed as being related to the presence of wind turbines, so that priming of respondents is of no concern.

Appendix Table E.1 shows summary statistics for outcomes and covariates in our baseline specification. Overall, individuals in our estimation sample are 71% married, 34% full-time and 12% part-time employed (with a median annual net household income of about €31,200), 4% unemployed, 70% owning their dwelling and 30% renting, and have, on average, slightly less than three individuals in their household.[11] Individuals in our sample also tend to be rather healthy: for our main outcomes based on the SF-12, individuals have mental and physical health scores above the median of 50 (which can be interpreted as a cut-off for being healthier as opposed to unhealthier), and they themselves assess their health as good (though not necessary very good). The median number

[9]For mental health, these are *role-emotional* and *social functioning*, which are defined as the extent to which individuals are capable of mastering work or other daily and social activities without being affected by emotional problems, as well as *general mental health* and *vitality*, which are defined as the absence of mental disorder and fatigue. For physical health, these are *role-physical* and *physical functioning* as well as *bodily pain*. Each sub-scale is obtained from a five-point Likert scale, whereby the respective summary scale combines these with equal weights.

[10]The SOEP asks renters to report their actual and owners to report their *estimated* rent in the hypothetical case in which they would not own their dwelling. We combine both in a single variable.

[11]As described in Section 6.3.2, our sample is restricted to individuals living in rural areas (where wind turbines are more common). Our results are robust to lifting this restriction.

of doctor visits in the last year is four. Note that the divergence between mean and median for some of our health outcomes suggests that there is a longer tail of individuals who have below-average health.

6.2.2 Wind Turbines

Our data on wind turbines come from Unnewehr et al. (2021) and include all 23,628 onshore wind turbines connected to the grid in Germany from 2000 to the end of 2017. In particular, the data contain information on the exact location of each installation in form of precise geographical coordinates, the starting year of operation, and further details such as hub height, rotor diameter, and installed capacity in GW.

The exact location of each installation is essential for our analysis, and we carried out extensive plausibility checks to ensure high data quality. In particular, we drew a 10% random sample of wind turbines and then verified the location of each randomly drawn installation based on satellite imagery from Google Earth. We found that about 95% of installations had the correct geographical coordinates.[12] We conclude that our data on wind turbines are of high quality.

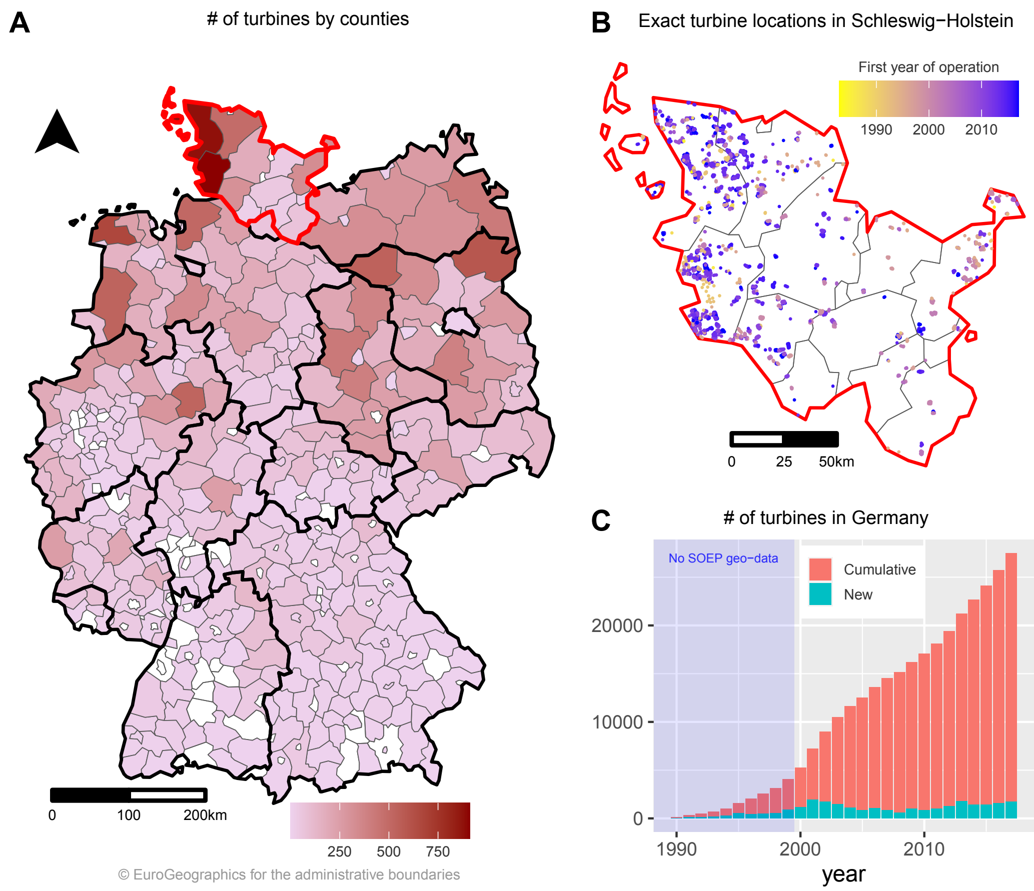
Based on our data, Figure 6.1 shows the diffusion of onshore wind turbines in Germany until 2017. In particular, Panel A shows the geographical distribution of wind turbines at the level of counties (NUTS-3 areas) in Germany, whereby counties colored in darker shades of red exhibit more installations. We observe that 327 out of 401 counties had installations by the end of 2017. Most can be found in the north of Germany, near the sea where wind intensity tends to be highest, especially in the federal states of *Lower Saxony*, *Mecklenburg-Western Pomerania*, and *Schleswig-Holstein*, which are adjacent to the North Sea, as well as to a lesser extent in the federal states of *Brandenburg* and *Saxony-Anhalt*, which are landlocked yet still in the north of the country.

Panel B shows, as an example, the exact location of each wind turbine in the federal state of *Schleswig-Holstein*, whereby installations that are older are colored in yellow, and those that are newer are colored in blue. In total, there were 3,310 installations in *Schleswig-Holstein* at the end of 2017.[13]

Finally, Panel C plots the annual number of cumulative and new installations in Germany since 1990. While new builds increased in the 1990s, their number peaked in 2002, two years after the German *Renewable Energy Sources Act* established an attractive feed-in-tariff system for electricity generated from wind power. After fewer new builds in 2008 and an increase in the following years, the number of new builds per year remained roughly stable at around 1,500 between 2013 and 2017. Our analysis focuses on the period between 2000 and 2017, for which the SOEP provides the precise geographical coordinates of every household in every year.

[12] More specifically, 93.9% of the random draw had exactly the same geographical coordinates as in Google Earth. For 1.4% of the draw, the geographical coordinates were almost the same. For the rest, we found that 2.8% of installations no longer existed, while 1.6% could not be found, 0.1% were under construction, and 0.25% came with similar geographical coordinates as another installation nearby.

[13] Appendix Figure E.1 shows the exact locations of all 27,739 onshore wind turbines connected to the grid in Germany through the end of 2017.



Panel A shows the geographical distribution of wind turbines across counties (NUTS-3 areas: *Landkreise und Kreisfreie Städte*) in Germany in 2017. The thick black lines indicate the borders of federal states (NUTS-1 regions), whereas the thick red line indicates the border of the federal state of *Schleswig-Holstein*, the most northern German state. *Panel B* is a close-up of *Schleswig-Holstein* and shows, as an example, the exact location of each installation in that federal state, whereby each dot indicates one installation, colored by the first year of operation. *Panel C* plots the annual number of cumulative and new installations in Germany since 1990.

Figure 6.1: Diffusion of Onshore Wind Turbines in Germany until 2017.

Appendix Table E.2 shows summary statistics for wind turbines in our baseline specification. On average, wind turbines have a power capacity of 1.6 GW (standard deviation of 0.8), a hub height of 88.4 meters (standard deviation of 32.2), and a rotor diameter of 76.2 meters (standard deviation of 23.3). Appendix Table E.3 then shows how these summary statistics have evolved over time during our observation period: capacity has almost doubled, from 1.3 GW in 2002 to 2.4 in 2015, and so have hub height (from 75.7 meters in 2002 to 122.1 in 2015) and rotor diameter (from 64.2 meters to 112.2).

6.2.3 Estimation Sample

Our estimation sample consists of all individuals who are interviewed from 2000 through 2017 (for whom we have precise geographical coordinates), who have at least one pre-treatment and one post-treatment observation, and who have no missings on either outcomes or covariates. The number of observations in our estimation sample depends on the availability of outcomes in a given year (some are available every year, others only every second) and on our treatment and control radii.

In our baseline specification, which uses a treatment group within 4,000 meters and a control group between 4,000 and 8,000 meters to the nearest installation, we have 700 individuals in our treatment group and 8,002 individuals in our control group for our main outcomes based on the SF-12, being treated by 111 wind turbines. For self-assessed health and the number of doctor visits, this amounts to 1,510 individuals in our treatment group and 10,533 individuals in our control group being treated by 399 wind turbines. For a treatment group within 6,000 meters, we have 902 treated and 8,002 controlled individuals for our main outcomes, being treated by 116 wind turbines. For self-assessed health and the number of doctor visits, there are 1,963 treated and 10,533 controlled individuals, being treated by 462 wind turbines.

To ascertain whether our study is sufficiently powered to detect a small effect size, we conduct an *ex-post* power calculation. In particular, we assume a small effect size of $d = 0.2$, an error probability of $\alpha = 0.05$, and a power of $1-\beta = 0.95$. This yields a required total sample size of 1,084 individuals, with 542 individuals in the treatment group and in the control group. As our group sizes exceed this threshold for each of our outcomes, we conclude that our study is sufficiently powered to detect a small effect size, if present.

6.3 Empirical Strategy

6.3.1 Model

Our empirical strategy rests on a spatial difference-in-differences design that compares the health outcomes of individuals living in households near wind turbines with those of individuals living further away, from before to after the start date of operation. We begin with the following regression model:

$$\begin{aligned} Y_{ijd,t} = &\beta_0 + \beta_1(1\{Near\}_{ijd} \times 1\{Operating\}_{ij,t}) + \beta_2 1\{Near\}_{ijd} + \beta_3 1\{Operating\}_{ij,t} \\ &+ \beta_4' X_{ijd,t} + r + s + t + s \times t + u_i + \epsilon_{ijd,t} \end{aligned} \tag{6.1}$$

where $Y_{ijd,t}$ is the health outcome of individual i in year t, given the nearest installation j and its distance d to the household of the individual. The indicator $1\{Near\}_{ijd}$ is a time-invariant dummy that takes on one if the household is located within distance band $[0; d]$ meters to the installation (i.e. our treatment group), and zero if it is located within distance band $(d; x]$ meters (i.e. our control group, whereby $x > d$). That is, individuals in our control group are located close to an installation but not close enough to be treated. The indicator $1\{Operating\}_{ij,t}$ is a time-varying dummy that takes on one if the installation is operational in a given year and zero else.[14] The vector $X_{ijd,t}$ are time-varying covariates, including demographic and socio-economic characteristics. The variables r, s, and t are county, federal state, and year fixed effects,[15] whereas u_i is an individual fixed effect. Together, r, s, t, and u_i net out time-invariant unobserved heterogeneity at the county, federal state, year, and individual level. We also include interactions between federal state and year fixed effects to flexibly account for trends in health across federal states over time. Because plants determine treatment, we cluster robust standard errors at the plant level.

Equation 6.1 implements our spatial difference-in-differences design as a two-way fixed-effects estimator, generalizing the canonical difference-in-differences design to treatment at multiple points in time.[16] Noting that $1\{Near\}_{ijd}$ and u_i as well as $1\{Operating\}_{ij,t}$ and t are collinear, and defining $D_{ijd,t} = (1\{Near\}_{ijd} \times 1\{Operating\}_{ij,t})$, Equation 6.1 can be rewritten as:

$$Y_{ijd,t} = \beta_0 + \beta_1 D_{ijd,t} + \beta_2' X_{ijd,t} + r + s + t + s \times t + u_i + \epsilon_{ijd,t} \tag{6.2}$$

As we are also interested in whether individuals adapt to nearby installations or whether continued exposure potentially aggravates adverse health impacts, we also estimate this model as an event study:

$$Y_{ijd,t} = \beta_0 + \sum_l \beta_1^l D_{ijd,t}^l + \beta_2' X_{ijd,t} + r + s + t + s \times t + u_i + \epsilon_{ijd,t} \tag{6.3}$$

where $D_{ijd,t}^l$ is a set of dummies that take on one for the l^{th} lead before (i.e. from $l = -6$ to $l = -1$) or lag after construction (i.e. from $l = 0$ to $l = 8$), and zero otherwise.[17]

We are interested in β_1 in Equation 6.2 and β_1^l in Equation 6.3, which can be interpreted as the average causal effects on health from being located within distance band $[0; d]$ meters to the nearest wind turbine if our identifying assumptions in Section 6.3.2 are satisfied.

[14]We use the start date of operation to define our time dummy, as adverse health impacts are mostly attributed to the operation rather than construction of installations. Note that the construction (excluding planning and project management) of a wind turbine is rather fast: for example, it only takes about two months to build a smaller, ten GW wind farm and about six months for a larger, 50 GW farm, each comprising several wind turbines (EWEA, 2023). As Figure 6.2 shows, we find no evidence for anticipation effects (adverse health effects prior to treatment) that could be attributed to construction.

[15]In Germany, there are 401 counties (NUTS-3 areas) and 16 federal states (NUTS-1 regions).

[16]This closely resembles the model by Currie, Davis, et al. (2015) for estimating the causal effect of toxic plant closings on health, the main difference being that our model takes the level of analysis from the aggregate to the individual level.

[17]We normalize the year of first treatment as $t = 0$ and use the pre-treatment year $t = -1$ as the reference category in our regression. Note that, due to sample size i.e., a small number of individuals many years before and many years after treatment, we trim observations before the sixth lead and after the eighth lag.

6.3.1.1 Treatment Effect Heterogeneity

de Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), Goodman-Bacon (2021), Sun and Abraham (2021), Athey and Imbens (2022), and Borusyak, Jaravel, and J. Spiess (2023) show that Equations 6.2 and 6.3 yield unbiased estimates of β_1 and β_1^l only if treatment effects are homogeneous.[18] This may not be true in our case: we exploit the staggered rollout of installations over a two-decade period during which technology may have changed. In fact, Appendix Table E.3 shows that capacity, as well as hub height and rotor diameter of wind turbines, almost doubled between 2002 and 2015, suggesting that treatment effects may be heterogeneous during our observation period.

In essence, Equations 6.2 and 6.3 may yield biased estimates of β_1 and β_1^l as they compare individuals who are being treated at the time not only to those who are later treated or who are never treated but also to those who were earlier treated.[19] However, individuals who were earlier treated may have been exposed to a different technology, resulting in, for example, different trajectories of adaptation to nearby installations. The direction of potential bias is not *ex-ante* clear.[20]

To eliminate potential bias, we adopt the robust estimator by Sun and Abraham (2021) for difference-in-differences with treatment at multiple points in time, which formalizes this setting as an event study. This approach has several advantages in our case: first, it allows us to show an unbiased common trend between treated and controlled pre-treatment, by looking at leads, as well as an unbiased trajectory of adaptation to nearby installations post-treatment, by looking at lags. We can then aggregate lags into a single parameter to obtain an unbiased average effect. Second, it allows us to elicit the extent of bias arising from treatment effect heterogeneity, by directly comparing estimates from our two-way fixed-effects estimator in Equation 6.3 with those from Sun and Abraham (2021), which is a contribution in its own right.

Sun and Abraham (2021) use cohort-specific average treatment effects on the treated as building blocks, which in our case can be defined as $CATT_{e,l} = E[Y^1_{ijd,e+l} - Y^0_{ijd,e+l} | E_{ijd} = e]$, where $E_{ijd} = min\{t : D_{ijd,t} = 1\}$ is the year of first treatment, individuals in cohort $e \in \{1, 2, ...T, \infty\}$ are first treated in year $\{i : E_{ijd} = e\}$ (with ∞ denoting cohorts that are never treated), and $Y^1_{ijd,e+l}$ and $Y^0_{ijd,e+l}$ are potential outcomes of treatment and control group, respectively.[21] Hence, $CATT_{e,l}$ is the average treatment effect l periods relative to the year of first treatment for the cohort of individuals who are first treated in year e. The authors show that, for a non-empty cohort e, some pre-periods $s < e$, and some set of non-empty control cohorts $C \subseteq \{c : e + l < c \leq T\}$, an estimate $\hat{\delta}_{e,l}$ of $CATT_{e,l}$ can be obtained from:

[18] See also de Chaisemartin and D'Haultfœuille (2022) and J. Roth et al. (2023) for recent reviews of this issue.

[19] Individuals who are always treated are generally excluded, as they do not allow for inference.

[20] Accounting for potential treatment effect heterogeneity over time, we also look at heterogeneous treatment effects by plant size in Section 6.5.

[21] The data structure of our event study can be described as *hybrid* (Miller, 2022), considering that treatment occurs at multiple points in time and that it includes both individuals who are later treated and individuals who are never treated.

$$\hat{\delta}_{e,l} = \frac{\frac{1}{N}\sum_{i=1}^{N}(Y_{ijd,e+l} - Y_{ijd,s}) \times 1\{E_{ijd} = e\}}{\frac{1}{N}\sum_{i=1}^{N} 1\{E_{ijd} = e\}} - \frac{\frac{1}{N}\sum_{i=1}^{N}(Y_{ijd,e+l} - Y_{ijd,s}) \times 1\{E_{ijd} \in C\}}{\frac{1}{N}\sum_{i=1}^{N} 1\{E_{ijd} \in C\}} \tag{6.4}$$

Then, estimates of the l^{th} lead before or lag after construction, $\hat{\beta}_1^l$, can be calculated as weighted averages of $\hat{\delta}_{e,l}$ using estimated weights $\hat{PR}\{E_{ijd} = e|E_{ijd} \in [-l, T-l]\}$, which are obtained from sample shares of each cohort in relevant periods l:

$$\hat{\beta}_1^l = \sum_l \sum_e \hat{\delta}_{e,l}\hat{PR}\{E_{ijd} = e|E_{ijd} \in [-l, T-l]\} \tag{6.5}$$

Finally, an overall estimate, $\hat{\beta}_1$, can be calculated as the average across all lags after construction. Sun and Abraham (2021) show that, if our identifying assumptions in Section 6.3.2 are satisfied, $\hat{\delta}_{e,l}$ is a consistent estimate of $CATT_{e,l}$ and sample shares $\hat{PR}\{E_{ijd} = e|E_{ijd} \in [-l, T-l]\}$ are consistent estimates of population shares, implying that $\hat{\beta}_1^l$ and $\hat{\beta}_1$ are consistent estimates even if treatment effects are heterogeneous.

Note that, regardless of our estimator, we assume that treatment is an absorbing state, i.e. once a wind turbine becomes operational, it remains so until the end of our observation period.[22]

Appendix Figure E.2, Panel A, shows the number of individuals who are treated by year in our estimation sample; Panel B the number of individuals who are never treated, exemplary for our outcome *self-assessed health*, which is available in every year. Appendix Figure E.3 replicates this figure for *general health* in the SF-12, which is available every second year. As seen in both cases, the number of individuals who are treated is almost constant during our observation period, except for a slight increase in 2016 and a much stronger increase around 2002, when the feed-in-tariff system for electricity generated from wind power was established in Germany. In line with this, Panel C shows the cumulative density of individuals who are treated by year, with a much steeper increase during the first years of our observation period. Finally, Appendix Figure E.4 shows the share of individuals who are treated by one, two, or more newly built wind turbines. Most are treated by one turbine or wind farms with less than five turbines.

6.3.2 Identification

We choose our control group to be close enough to installation j to capture highly localized area conditions such as local demography, labor markets, deprivation, or health clusters in its surroundings, yet far enough not to be treated.

[22] Our data on wind turbines do not include the date of decommissioning, if applicable. However, the average lifespan of a wind turbine is 20 years (EPA, 2013). Decommission is, therefore, likely to be a minor issue during our observation period. In any case, it is likely to bind our treatment effects from below. The same is true if wind turbines are taken off-grid for maintenance or repair (which usually takes only very short time).

As there exists no uniform legislation in Germany that could serve as a point of reference (like a mandated setback distance), we are agnostic and use different treatment radii, i.e. $d = \{2000, 3000, 4000, 5000, 6000\}$, as well as different control radii, i.e. $x = \{4500, 5000, 5500, 6000, 8000, 10000\}$. A treatment radius of $d = 4000$ and a control radius of $x = 8000$ are our default, as individuals within 4,000 meters are previously shown to experience negative externalities of wind turbines on their subjective wellbeing (cf. Krekel and Zerrahn, 2017). This is a common approach in the literature (cf. Gibbons, 2015; Krekel and Zerrahn, 2017), in case a treatment radius cannot be endogenously determined, for example by estimating how far a pollutant travels (cf. Currie, Davis, et al., 2015). It also allows us to test for spatial decay of potential wind turbine externalities on health.

Left with these treatment and control group definitions, our empirical strategy rests on two identifying assumptions:

1. ***Exogeneity of Treatment.*** Whether an individual is allocated to our treatment or control group is as good as random, conditional on time-varying covariates $X_{ijd,t}$, county and federal state fixed effects r and s, year fixed effects t, and individual fixed effects u_i. That is, $D_{ijd,t} \perp 0, 1 | X_{ijd,t}, r, s, t, u_i$. This also implies no anticipatory behavior prior to treatment.

2. ***Common Trend.*** In a hypothetical absence of treatment, our treatment group would have followed the same trend in health outcomes as our control group, conditional on time-varying covariates $X_{ijd,t}$, county and federal state fixed effects r and s, year fixed effects t, and individual fixed effects u_i. That is, $E[Y_{ijd,t} - Y_{ijd,t-1} | X_{ijd,t}, r, s, t, u_i, D_{ijd,t} = 1] = E[Y_{ijd,t} - Y_{ijd,t-1} | X_{ijd,t}, r, s, t, u_i, D_{ijd,t} = 0]$.

Regarding homogeneity of treatment, Appendix Table E.4 shows means and variances of our covariates separately for our default treatment and control group, including normalized differences between them. According to Imbens and Wooldridge (2009), a normalized difference greater than 0.25 suggests covariate imbalance. As seen, none of our covariates exceeds this value, implying that they are well-balanced between groups. Note that *not* controlling for time-varying covariates, county and federal state fixed effects, year fixed effects, and individual fixed effects in our regressions does not change our results (Appendix Figures E.5 and E.6). This suggests that exogeneity of treatment is likely satisfied, even unconditionally. As Figure 6.2 shows, we do not find evidence for anticipatory behavior prior to treatment.

Regarding common trend, we plot leads before the year of first treatment in our event studies, for our two-way fixed-effects estimator and for the robust estimator by Sun and Abraham (2021). As will be seen, none of these leads turns out significantly different from zero in our baseline specification, suggesting common trend behavior between treated and controlled pre-treatment.

A threat to identification may come from *endogenous sorting*. In particular, some individuals may be more likely to move away from wind turbines, for example because they are concerned about adverse health impacts or are experiencing them. Other individuals, however, may move towards wind turbines, where rental prices may be lower, potentially mispredicting adverse health impacts or even deliberately taking them into account. The direction of resulting bias is not *ex-ante* clear. Thus, in our baseline specification, we omit individuals who move and focus entirely on stayers.[23] Note that mobility in Germany is rather low compared to other countries: in the SOEP, only about 5% of individuals move every year.

Another threat to identification may come from *endogenous construction*. In particular, some individuals may be more likely to have wind turbines constructed nearby, while others may even construct installations themselves. For example, wind turbines may be more likely to be placed in deprived areas, where local resistance may be lower. On the other hand, private persons may be generating income from wind turbines, for example farmers who build a wind farm on their land or who lease their land to utilities to do so. To the extent that endogenous construction is correlated with health, as is found for deprivation and income (cf. Frijters, Haisken-DeNew, and Shields, 2005; Lindahl, 2005; Jones and Wildman, 2008), it may bias our estimates, the direction of which is again not *ex-ante* clear.

We deal with endogenous construction in three ways. First, recall that our control group is located within distance band $(d; x]$ meters to the nearest installation hence far enough not to be treated but close enough to capture highly localized area conditions such as deprivation and income. Second, we use different treatment and control radii d and x to capture different aspects of these conditions. Additionally, we control for county fixed effects r to capture localized area conditions such as local attitudes (as well as federal state fixed effects s and their interaction with years to capture regional socio-political conditions and their trends over time). Finally, we exclude farmers and urban counties, so that our estimation sample is restricted to a relatively homogeneous group of individuals living in rural areas.[24]

6.4 Results

We first look at average treatment effects. Table 6.1 shows the estimates from our baseline specification, which compares the health outcomes of individuals who are treated (i.e. living within 4,000 meters to the nearest newly built wind turbine) with those who are not (i.e. living between 4,000 and 8,000 meters). Panel A shows the estimates from our two-way fixed-effects estimator, Panel B those from the robust estimator by Sun and Abraham (2021). All models routinely control for time-varying covariates, county fixed effects, federal state times year fixed effects, and individual fixed effects. We standardized outcomes to have a mean of zero and a standard deviation of one (i.e. z-scores) for comparability.

We do not find a statistically significant effect of a newly built wind turbine on either the mental or physical health summary scale (Columns 2 and 3 in each panel), our main outcomes from the

[23]In a robustness check in Section 6.5, we return to the issue of endogenous sorting. As will be seen, our results remain robust to the inclusion of movers (Appendix Table E.5).

[24]Our results do not change when including urban counties (Appendix Figure E.7).

SF-12. If anything, we detect a *positive* effect on general health as an overall measure of health (Column 1). However, it is only small in size (about 6% SD), significant at the 5% level (i.e. P value of about 0.04 for each estimator), and should be de-emphasized due to the number of hypotheses we are testing. In particular, considering that we are testing five hypotheses, a standard Bonferroni correction suggests a critical value of $(0.10/5) = 0.02$ for a 10% level of statistical significance, which is clearly below our empirical P value. Going on, we do not find a statistically significant effect on self-assessed health (Column 4) or on the reported number of doctor visits (Column 5), a retrospective behavioral outcome that allows us to capture potential impacts that go beyond self-assessment. Estimates from our two-way fixed-effects estimator generally resemble those from the robust estimator by Sun and Abraham (2021).

Appendix Tables E.6 and E.7 disentangle the mental and physical health summary scales from the SF-12 into their respective sub-scales, which are *role-emotional* and *social functioning*, *general mental health*, and *vitality* for the mental health summary scale, and *role-physical* and *physical functioning* as well as *bodily pain* for the physical health summary scale. In line with our previous results, we do not find a statistically significant effect of a newly built wind turbine on any of these sub-scales.

Table 6.1: Average Treatment Effects.

(a) Two-Way Fixed-Effects Estimator.

	SF-12 Health Survey			Other Health Outcomes	
Dependent Variable:	General Health	Mental Health Summary Scale	Physical Health Summary Scale	Self-Assessed Health	Doctor Visits
	(1)	(2)	(3)	(4)	(5)
Variable					
Treated 0-4 km	0.06**	0.009	-0.002	0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Individual	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes	Yes
Statistics					
Adjusted R^2	0.591	0.484	0.668	0.601	0.357
Obs.	26,903	26,903	26,903	68,289	65,068
N treated	700	700	700	1,509	1,508
N never treated	8,002	8,002	8,002	10,533	8,767

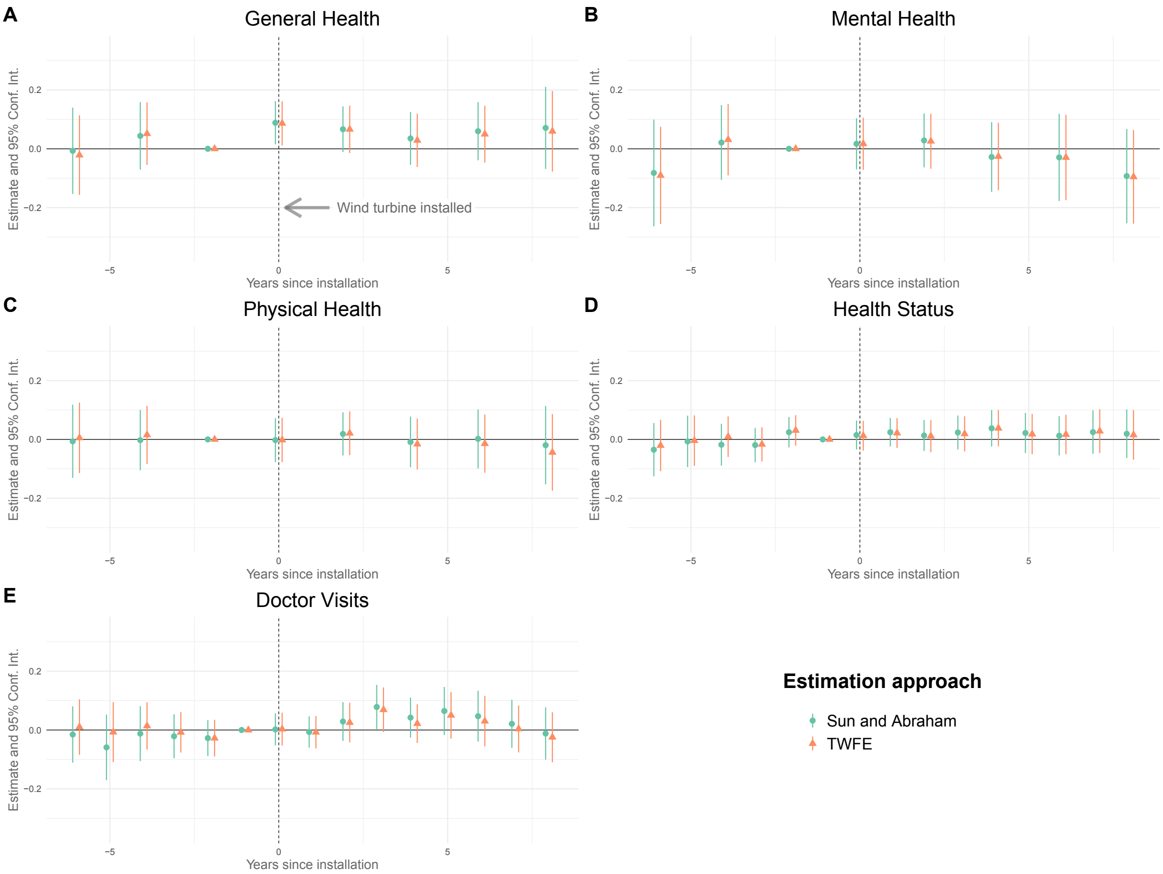
(b) Robust Estimator by Sun and Abraham (2021).

	SF-12 Health Survey			Other Health Outcomes	
Dependent Variable:	General Health	Mental Health Summary Scale	Physical Health Summary Scale	Self-Assessed Health	Doctor Visits
	(1)	(2)	(3)	(4)	(5)
Variable					
Treated 0-4 km	0.07**	-0.007	0.0009	0.02	0.03
	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Individual	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes	Yes
Statistics					
Adjusted R^2	0.591	0.485	0.668	0.601	0.357
Obs.	26,903	26,903	26,903	68,289	65,068
N treated	700	700	700	1,509	1,508
N never treated	8,002	8,002	8,002	10,533	8,767

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant) standard-errors in parentheses; treatment group 0-4 km; control group 4-8 km.
Outcomes in z-scores; more indicates better health (but for doctoral visits more indicates worse).

Next, we move from static to dynamic effects and look at treatment over time. Figure 6.2 shows the estimates from our baseline specification implemented as an event study, with six leads before and eight lags after a new wind turbine is built, whereby the period in which an installation is built is normalized to zero and the first lead serves as the reference category. Panels A to E plot these leads and lags for each of our outcomes in Table 6.1. The remainder is the same as before.

A visual inspection of the leads indicates no difference in time trends between our treatment and control groups in any of the panels, suggesting common trend behavior pre-treatment.



Outcomes are in z-scores. Higher values indicate better health (but for doctor visits higher indicates worse)

Figure 6.2: Dynamic average treatment effects for two-way fixed-effects estimator and robust estimator by Sun and Abraham (2021). Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).

Again, we do not find a statistically significant effect of a newly built wind turbine on either the mental or physical health summary scales from the SF-12, neither for any lead nor for any lag. We also do not find a consistent effect on self-assessed health or on the reported number of doctor visits. We observe that the small, positive effect on general health is only significant in the year in which a new wind turbine is built (i.e. P value of about 0.02 for each estimator), with no evidence of a lasting positive effect on general health. Considering that we are testing 15 hypotheses (i.e. six leads and eight lags), a standard Bonferroni correction suggests a critical value of $(0.10/15) = 0.007$ for a 10% level of statistical significance, which is again below our empirical P value. Estimates from our two-way fixed-effects estimator once more resemble those from the robust estimator by Sun and Abraham (2021).

It could be the case that potential effects only emerge from more than one turbine. Appendix Figure E.8 replicates Figure 6.2 for different treatment intensities, i.e. being treated by one, two to five, or more than five wind turbines, using the robust estimator by Sun and Abraham (2021), to capture potential cumulative impacts, for example by wind farms. As before, we do not find a statistically significant effect of one or several newly built wind turbines on any of our health outcomes.[25]

Perhaps effects only manifest themselves for different age groups. Appendix Figure E.9 replicates Figure 6.2 for different age groups, defined as younger (between 18 and 40 years), middle-aged (between 41 and 59 years), and older (from 60 years of age onwards). Again, we do not detect consistent impacts on any of these age groups for any of our outcomes.

Although we are unable to detect impacts on our health outcomes, there may still be externalities from newly built wind turbines, though perhaps not sufficiently strong to manifest themselves in adverse health impacts. Because noise annoyances and sleep disturbances are often cited as mechanisms through which adverse health impacts may come about, we also look at the *frequency of experiencing certain emotions* (i.e. happiness, sadness, anxiety, and anger) as well as *sleep satisfaction* and the *number of hours of sleep* on a normal weekday and a normal weekend day as additional outcomes.[26]

Appendix Figure E.10 replicates Figure 6.2 for these additional outcomes. As seen, we again do not find consistent evidence of systematic, statistically significant effects on either happiness, sadness, anxiety, or anger, nor on the number of hours respondents report to sleep or their sleep satisfaction.

6.5 Robustness

We conduct a series of tests to investigate the robustness of our results. If not stated otherwise, estimates are based on the robust estimator by Sun and Abraham (2021), a treatment group that lives within 4,000 meters to the nearest newly built wind turbine, and a control group that lives between 4,000 and 8,000 meters, i.e. our baseline specification.[27] For consistency, we conduct each robustness check for each of our health outcomes.

[25]There is indication for a temporal effect on doctor visits from 2-5 turbines but in this case the common trend assumption does not hold.

[26]The frequency of experiencing certain emotions is obtained from a five-point Likert scale question that asks “Please indicate for each feeling how often or rarely you experienced this feeling in the last four weeks: angry, worried, happy, and sad”, with answers including one (“Very rarely”), two (“Rarely”), three (“Occasionally”), four (“Often”), and five (“Very often”). Moreover, sleep satisfaction is obtained from an eleven-point Likert scale question that asks “How satisfied are you with your sleep?”, with answers ranging from zero (“Completely dissatisfied”) to ten (“Completely satisfied”). Finally, the number of hours of sleep is obtained from free-text questions that ask “How many hours do you sleep on average on a normal day during the working week? How many hours on a normal weekend day?”.

[27]We also implemented the two-stage difference-in-differences framework by Gardner (2022) and Gardner and Butts (2022) as an alternative to Sun and Abraham (2021). In essence, this framework identifies group and period effects in a first stage from the sample of untreated observations, then, in the second stage, it identifies treatment effects by comparing treated and untreated outcomes after removing these group and period effects. We obtain qualitatively similar results using this framework (Appendix Figure E.11).

We first look at our standard errors, which, in our baseline specification, are clustered at the plant level, where randomization takes place. Appendix Table E.5 Column 1 shows that clustering our standard errors at the level of households, i.e. at a lower, and hence, less conservative level, does not change our results.[28] Next, we look at endogenous sorting. Recall that we focused on stayers in our baseline specification as movers may move towards or away from installations, depending on preferences, potentially biasing our estimates. Movers may also bias our estimates because moving itself may have health effects. Column 2, however, shows that including movers leaves our results unchanged, suggesting that endogenous sorting is, if anything, only a minor concern. Also recall that we trim observations before the sixth lead and after the eighth lag in our baseline specification, as these are only identified by few observations. We now include these observations in Column 3, thus also capturing potential effects that may occur many years after a new wind turbine was built. As shown, there is no evidence for such effects as our results remain unchanged. Finally, in Columns 4 and 5, we split our estimation sample into the years before and after 2010, i.e. the years in which wind power was still relatively novel and later years, whereas in Columns 6 and 7, we differentiate small from large plants, i.e. plants with a hub height below 100 meters from those with a hub height above. Especially for the latter, a potential concern could be that for a given treatment and control radius, plants with a higher hub height may contaminate our control group, thereby reducing our treatment effect. Focusing on smaller plants should mitigate such concerns.[29] As shown, there are no statistically significant treatment effects (at the 5% level) across Columns 4 to 7.[30]

Next, we look at whether modifying our control group changes our results. What if individuals in our control group living close to an installation (but just outside our treatment radius) are also, though minorly, affected by its presence? To answer this question, in Appendix Figure E.14, we narrow our control group to individuals living in 500-meter bins between 4,000 and 6,000 meters to the nearest newly built wind turbine. As before, we do not find consistent evidence of adverse health impacts across bins. In Figure E.15, we then further adjust our control group, by selectively including individuals living further away, as it could be the case that adverse health impacts (for example, due to low-frequency noise emissions) may manifest themselves only at distances greater than 4,000 meters. As before, we find no consistent evidence of such impacts.

Next, we change our treatment radius. Although a treatment radius of 4,000 meters in our baseline specification seems reasonable, and is shown to capture negative externalities of newly built wind turbines on the subjective wellbeing of nearby residents (cf. Krekel and Zerrahn, 2017), we vary our treatment radius in Figure E.16. As seen, we also do not find systematic evidence of adverse health impacts at 2,000, 3,000, or 6,000 meters. There is some evidence of a higher number of reported doctor visits two, three, and four years after a new wind turbine was built at a distance of

[28] Clustering our standard errors at the plant times year level does not change our results either (Appendix Figure E.12).

[29] In another robustness check, we additionally controlled for hub height, which left our results unchanged (Appendix Figure E.6).

[30] Appendix Figure E.13 shows dynamic treatment effects over time when splitting our estimation sample into the years before and after 2010. Again, we find no consistent evidence of adverse health impacts for any lag after a new wind turbine was built.

2,000 meters, but in this case we also observe a potential violation of the common trend assumption prior to treatment. Note that, for a distance of 2,000 meters, the size of the treatment group drops: here, we only observe 318 individuals in our treatment group for our bi-annual health outcomes (i.e. the SF-12) and 584 for our annual outcomes (i.e. self-assessed health and the reported number of doctor visits).

Finally, Appendix Figure E.5 shows that excluding and including various fixed effects (i.e. individual, year, county and federal state, and their interactions) does not change our results; results also do not change with the inclusion of fixed effects for different distance bins around newly built wind turbines (e.g. a fixed effect for all households that are located within 1,000 meters to the nearest installation, another for all households that are located within 1,000-2,000 meters, and so on).

6.6 Additional Analysis: Suicides

We move on to an alternative approach for measuring potential adverse health impacts of wind turbines. In particular, we use suicide rates as an objective measure of adverse mental health impacts, as has been used for air pollution in the US (Molitor, Mullins, and White, 2023) or high temperatures in the US and Mexico (Burke et al., 2018). The advantage of information on suicides is that it relies on administrative records as opposed to self-reports and that it is consistently measured across a population over time. In doing so, we follow Zou (2020), who exploits administrative data on 800 wind farms and suicides at the county level in the US from 2001 to 2013 in a spatial difference-in-differences design and two-way fixed-effects estimators. The author finds significant increases in suicide rates in counties closer to wind farms. In what follows, we replicate our analysis for annual suicides per million population in the 401 counties in Germany. The Statistical Offices of the German federal states provided us with the data.

We control for covariates shown in Appendix Table E.8. These include unemployment per capita, GDP per capita, and the average age, which are obtained from INKAR (2023).[31] Further, we include county and federal state times year fixed effects.[32]

Table 6.2 Column 1 shows our baseline results using the robust estimator by Sun and Abraham (2021). It shows differences in suicides per million population between treated counties (those with

[31] Appendix Table E.9 shows normalized differences between treated and never-treated counties. Note that we are not particularly concerned about differences greater than 0.25 for GDP per capita as our county fixed effects account for GDP imbalances which should mainly be time-invariant. We also control for the log-transformed level of suicides, lagged by 10 years. As we trim our data to observations with six leads before and eight lags after a new wind turbine was built, we only include lagged suicide information before treatment.

[32] County fixed effects capture time-invariant county-specific determinants of suicides, whereas federal state times year fixed effects control for characteristics that vary on the state level and change over time, for example changes in the health care system.

at least one new wind turbine) *versus* untreated counties (those with no wind turbines).[33] In our baseline specification, we focus on non-urban counties as wind turbines are mainly installed there.[34] We observe no statistically significant differences in suicides between treated and untreated counties.

Table 6.2: Wind turbines on suicides.

Treatment	At least one turbine	Ten or more turbines	0.1 or more turbines per sqkm
Dependent Variable:		Suicides per million population	
	(1)	(2)	(3)
Variable			
ATT	0.49	0.41	1.5
	(1.1)	(1.3)	(1.6)
Controls	Yes	Yes	Yes
Fixed-effects			
County	Yes	Yes	Yes
State-Year	Yes	Yes	Yes
Statistics			
Adjusted R^2	0.959	0.929	0.940
Observations	1,190	2,843	6,273
N treated	73	126	71
N never treated	20	136	324

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (county) standard-errors in parentheses;
Controls are GDP per capita, unemployment rate, average age and the log of number of suicides lagged by 10 years.
In column (1), we focus on non-urban areas only and neglect counties with a turbine installed in 2000.
In column (2), we neglect observations with between 1 and 9 turbines and those with 10 or more turbines in 2000.
In column (3), we neglect counties with more than 0.1 turbines per sqkm in 2000.
In column (3), we also neglect observations between 0.075 and 0.1 turbines per sqkm.

Next, we move to dynamic effects and look at treatment over time. Appendix Figure E.19, Panel A, shows the estimates from our baseline specification implemented as an event study, with six leads before and eight lags after the first wind turbine is built.[35] A visual inspection of the leads indicates no difference in time trends between our treatment and control groups, which suggests common trend behavior pre-treatment.[36]

Suicides are extreme events. It could be the case that potential effects only emerge from more than one installation. Thus, we increase the threshold that we regard as treatment. In Table 6.2,

[33] Appendix Figure E.17 Panel A illustrates that there are many counties with at least one wind turbine in 2000, i.e. always treated counties. In our estimations, we focus on counties without a wind turbine in 2000 as only these allow us to estimate potential causal effects on suicides from a new wind turbine. Appendix Figure E.17, Panel C, gives a first indication that the average number of suicides per million between counties with and without turbines in 2000 follows a similar trend. Figure E.18, Panel A, shows the number of counties that are treated by year; Panel B the number of counties that are never treated. We observe that the number of counties that are treated is largest at the beginning of our observation period. In line with this observation, Panel C shows the cumulative density of individuals that are treated by year, with a much steeper increase during the first years, as for our self-reported health outcomes.

[34] Concentrating on non-urban counties allows us to analyze a homogeneous group of counties. Nevertheless, we include urban counties in a robustness check below.

[35] As before, the period in which an installation is built is normalized to zero.

[36] Appendix Figure E.19 also indicates a common trend before treatment based on the two-way fixed effects estimator.

Columns 2 and 3 reveal no effect, neither for ten or more installations nor for counties that reach an installation density of 0.1 or more per square kilometer.[37] The threshold of 0.1 installations per square kilometer indicates a high turbine density. The value lies between the 90th percentile value of 0.09 installations per square kilometer and the 95th percentile value of 0.13 installations per square kilometer (for the pooled dataset of counties between 2000 and 2017). A visual inspection of the corresponding event studies in Appendix Figure E.19, Panels B and C, reveals no difference in time trends between our treatment and control groups, neither before nor after treatment, for both alternative treatment thresholds. The only noticeable exception is the third lead in case of counties that had ten or more turbines installed in 2000, which turns out significant with our two-way fixed-effects estimator only.

Table E.10 shows that our results are robust in various dimensions. We look at the treatment threshold of at least one wind turbine. In Column 1, we find no effects using the log-transformed level of suicides as an outcome. This approach allows for capturing potentially heterogeneous effects for counties with different suicide levels. In Columns 2 and 3, we focus on suicides per million population again, controlling for the number and the log-transformed number of wind turbines, respectively. Still, we find no evidence for effects of wind turbines on suicides. In Column 4, we include urban areas. Again, there is no evidence of effects. In Column 5, we only focus on the years between 2000 and 2009 (when wind turbines were smaller), and in Column 6, the years between 2010 and 2017 (when they were larger). There is no evidence of effects in either period. In Column 7, we also look at wind turbines nearby a county (within 4,000 meters) as treatment.[38] Again, this alternative definition of treatment does not reveal any effects. Finally, in Column 8, we also include counties with a wind turbine in 2000, i.e. always-treated counties. This approach only reveals a correlation but allows for including counties in the north of Germany, where installations are common due to more favorable wind conditions near the North Sea. If there is an effect of wind turbines on suicides, we would still expect significant effects. Again, we find no difference in suicides per population between counties with and those without wind turbines. We conclude that we find no evidence of adverse health impacts of wind turbines on suicides as an extreme measure of negative mental health outcomes.

6.7 Discussion and Conclusion

It is estimated that, by 2050, wind power will become the most important renewable energy after solar (IEA, 2021). Despite its importance in the transition towards net zero, there is a heated, ongoing

[37]We drop observations close to thresholds. In Column 2, we neglect observations with between one and nine installations and counties with an installation in 2000. In Column 3, we drop counties with more than 0.1 installations per square kilometer in 2000 and observations with between 0.075 and 0.1 installations per square kilometer. In Table 6.1 Columns 2 and 3, we include urban counties in order to have a large enough control group.

[38]Appendix Figure E.17 Panel B is a close-up of the federal state of *Schleswig-Holstein*. For example, blue dots indicate a wind turbine relevant for *Pinneberg* county (in yellow). Here, we consider not only blue dots within the county but also those within 4,000 meters distance to the county border.

debate about potential adverse health impacts of wind turbines on nearby residents, which in many cases manifests itself in vocal resistance against new installations locally. This resistance is often based on a body of evidence that is largely inconclusive and that relies mostly on cross-sectional analyses and local case studies.

This paper set out to determine whether wind turbines have systematic, negative causal effects on the health of nearby residents and, if so, which health dimensions are affected and by how much. It also asked whether effects, if any, are spatially or temporally limited.

For this, we used representative longitudinal household data linked, based on precise geographical coordinates, to a nationwide dataset on wind turbines and a spatial difference-in-differences design that exploited the staggered rollout of installations in Germany, a country that witnessed a fast expansion of wind power since the year 2000. We used both two-way fixed-effects estimators and the robust estimator by Sun and Abraham (2021) to explicitly account for potential treatment effect heterogeneity due to changing technology over time. To our knowledge, we are the first to do so.

We do not find evidence of temporary or even permanent negative effects on either general, mental, or physical health in the 12-Item Short Form Survey (SF-12) (RAND, 2022). There are also no effects on self-assessed health or on the number of doctor visits of nearby residents. Often cited mechanisms through which adverse health impacts of wind turbines may come about include visual and, in particular, noise pollution, potentially resulting in annoyance and sleep disturbances. When looking at the frequency of experiencing negative emotions, sleep satisfaction, and the number of hours of sleep, however, we do not find impacts. Finally, by exploiting administrative data on suicide rates at the county level in Germany during our observation period and by replicating our analysis on health outcomes for suicide rates, we also do not find impacts. Our results are robust to different treatment and control radii as well as different bins around plants, to different plant sizes, and to accounting for residential sorting. By calculating statistical power *ex post*, we confirm that our study is sufficiently powered to detect a small effect size, if present.

While these findings cast doubt on systematic, causal negative effects of wind turbines on the local population, our study has several limitations that warrant readers' attention. For one, while reliance on secondary data and quasi-experimental methods avoids priming respondents and ensures external validity, our sample size and inference are limited when it comes to residents who live in very close proximity to installations, i.e. below 2,000 meters. Similarly, our sample size requires us, in most cases, to estimate average treatment effects. Although these are most relevant for policy applications, they may cast potentially important heterogeneities. For example, theory and evidence in psychology shows that some individuals are more sensitive to (changes in) their environment than others (Pluess et al., 2023). Likewise, individuals who score high in terms of neuroticism, negative affect, and frustration intolerance (Taylor et al., 2013), or who already have a negative predisposition towards wind turbines pre-treatment (Jalali et al., 2016), have been suggested to react more adversely to new installations. Unfortunately, we have no data to capture such individual differences. Finally, the context of Germany itself, in terms of culture and political climate where residents are generally aware of climate change and favorably disposed toward renewable energy, may itself impose limitations when it comes to transferability of findings to other countries.

Although we find no evidence of adverse health impacts, this does not preclude that other externalities do not exist. Negative impacts on the house prices and the subjective wellbeing of nearby residents, for example, are well documented (cf. Gibbons, 2015; Krekel and Zerrahn, 2017). Furthermore, concern or fear of potential negative health consequences is a real phenomenon (cf. Michaud et al., 2016), with actual consequences, including local protests or voting outcomes (cf. Financial Times, 2021). However, recent studies suggest that residents develop more favorable attitudes towards the technology *after* having been exposed to it (cf. Bayulgen et al., 2021; Urpelainen and Zhang, 2022), suggesting learning about one's preferences or rationalization *ex-post*. In fact, Baxter, Morzaria, and Hirsch (2013) find that residents in communities without wind turbines are *more* concerned about the technology and show *lower* support than residents in communities with installations. Finally, wind turbines can also have positive externalities, for example on local fiscal outcomes or air pollution, which for a balanced assessment need to be taken into account (Kahn, 2013).

In any case, local resistance may slow the transition to renewable energy and risks missing climate action goals, which is why these concerns must be taken seriously and addressed by policy, for example by actively involving resident communities in local planning and decision-making processes and disseminating targeted, factual information grounded in scientific evidence regarding potential impacts. Promising avenues for future research include how to achieve fairness and procedural justice during new build projects, as well as distributional equity in sharing the burden of external effects amongst the general population.

A

Appendix to Chapter 2

A.1 Assumptions and data

A.1.1 Time series

All time series concerning generation (capacity factors for solar PV, wind on- and offshore, inflow series for hydropower plants) are taken from ENTSO-E's "Pan-European Climate Database (PECD)" (De Felice, 2020). The load data is taken from ENTSO-E's "Mid-term Adequacy Forecast (MAF) 2020" (ENTSO-E, 2018a).

A.1.2 Techno-economic parameters for technologies with endogenous capacities

Table A.1: Technical and costs assumptions of installable generation technologies

Technology	Thermal efficiency [%]	Overnight investment costs [EUR/kW]	Technical Lifetime [years]
Bioenergy	0.487	1951	30
Run-of-river	0.9	600	25
PV	1	3000	50
Wind offshore	1	2,506	25
Wind onshore	1	1,182	25

Table A.2: Technical and cost assumptions of installable storage technologies

Technology	Marginal costs of storing in [EUR/MW]	Marginal costs of storing out [EUR/MW]	Efficiency storing in [%]	Efficiency storing out [%]	Efficiency self-discharge [%]	Overnight investment costs in energy [EUR/kWh]	Overnight investment costs in capacity charge [EUR/kW]	Overnight investment costs in capacity discharge [EUR/kW]	Technical lifetime [years]
Lithium-Ion	0.5	0.5	92	92	100	200	150	150	13
Power-to-gas-to-power	0.5	0.5	50	50	100	1	3000	3000	20
Pumped-hydro	0.5	0.5	80	80	100	80	1100	1100	60
Reservoir	-	0.1	-	95	100	10	-	200	50

For the principal technical and cost parameters, we rely on previous research (Gaete-Morales, Kittel, et al., 2021), and these are shown in Tables A.1 and A.2. For all technologies (generation and storage), we assume an interest rate for calculating investment annuities of 4%. The assumed power of installed bioenergy capacities is provided by ENTSO-E (ENTSO-E, 2018a).

A.1.3 Exogenous generation and storage capacities

Table A.3: Assumptions on exogenous generation and storage capacities

Technology	Variable	AT	BE	CH	CZ	DE	DK	ES	FR	IT	NL	PL	PT
Bioenergy	Power [GW]	0.50	0.62	0	0.40	7.75	1.72	0.51	1.93	1.54	0.46	0.85	0.61
Run-of-River	Power [GW]	5.56	0.17	0.64	0.33	3.99	0.01	1.16	10.96	10.65	0.04	0.44	2.86
Pumped-hydro (closed)	Discharging power [GW]	0	1.31	3.99	0.69	6.06	0	3.33	1.96	4.01	0	1.32	0
	Charging power [GW]	0	1.15	3.94	0.65	6.07	0	3.14	1.95	4.07	0	1.49	0
	Energy [GWh]	0	5.30	670	3.70	355	0	95.40	10	22.40	0	6.34	0
Pumped-hydro (open)	Discharging power [GW]	3.46	0	0	0.47	1.64	0	2.68	1.85	3.57	0	0.18	2.95
	Charging power [GW]	2.56	0	0	0.44	1.36	0	2.42	1.85	2.34	0	0.17	2.70
	Energy [GWh]	1722	0	0	2	417	0	6185	90	382	0	2	1966
Reservoir	Discharging power [GW]	2.43	0	8.15	0.70	1.30	0	10.97	8.48	9.96	0	0.18	3.49
	Energy [GWh]	762	0	8155	3	258	0	11840	10000	5649	0	1	1187

A.1.4 Interconnection capacities

Table A.4: Installed Net Transfer Capacities (NTC) in model runs with interconnection

link	Installed capacity [MW]
AT_CH	1700
AT_CZ	1100
AT_DE	7500
AT_IT	1470
BE_DE	1000
BE_FR	5050
BE_NL	4900
CH_DE	5300
CH_FR	4000
CH_IT	4850
CZ_DE	2300
CZ_PL	700
DE_DK	4000
DE_FR	4800
DE_NL	5000
DE_PL	3750
DK_PL	500
ES_FR	9000
ES_PT	4350
FR_IT	3255

The assumed Net Transfer Capacities (NTC) provided in Table A.4 are taken from from the TYNDP 2018 (Appendix IV - Cross-border capacities, NTC ST 2040) (ENTSO-E, 2018a).

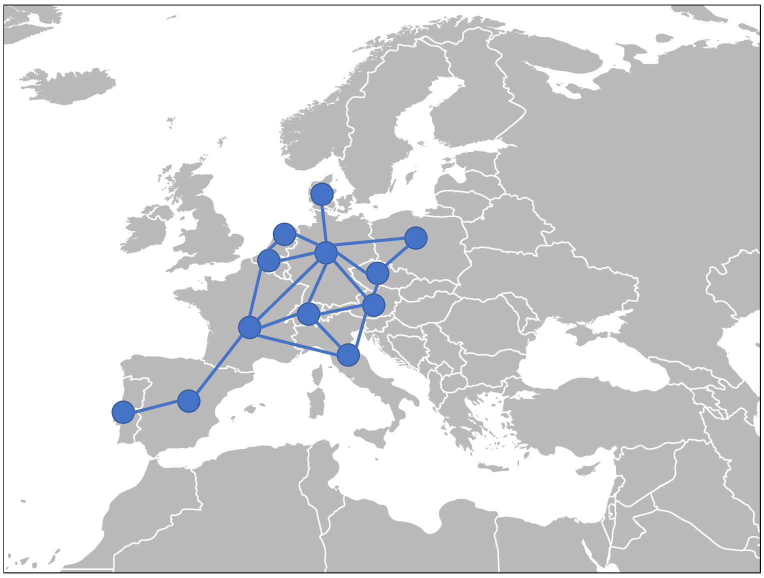


Figure A.1: Geographic scope of the model and existing interconnections (related to STAR Methods)

Figure A.1 depicts the countries that are part of the model and the respective interconnections between them.

A.2 Model

Our analysis is model-based, using the open-source capacity expansion model DIETER. A short introduction is provided in section 2.2.3, more details are provided in previous publications (Zerrahn and Schill, 2017; Gaete-Morales, Kittel, et al., 2021). For illustrative reasons, we provide below the formulation of two key equations of the model: the objective function and the energy balance. Before, we provide a non-exhaustive nomenclature of sets, variables, and parameters used in these equations. Variables are defined with uppercase letters and parameters with lowercase letters.

Sets n is the set of countries, h the set hours, dis the set of dispatchable generators, nd the set of non-dispatchable generators, and sto the set of storage technologies.

Electricity generation and flows [MWh] $G_{n,dis,h}$ is the generation of the dispatchable generation technology dis in country n in hour h. STO^{out} is the electricity generation (by discharge) of storage technologies, STO^{in} is the charging, and RSV^{out} is the electricity generation (by outflows) of reservoirs. $F_{l,h}$ is the electric energy sent over line l in hour h.

Installed generation capacities [MW] N is the installed capacity of a generation technology. N^{p-out} is the installed discharging capacity of storage technologies, N^{p-in} is the installed charging capacity of storage technologies.

Energy installation variables [MWh] N^e is the installed energy capacity of storage technologies.

Costs [Euro/MW(h)] c^m are marginal costs of generation, c^i annualized investment costs of installation power and energy capacities (generation and storage), c^{fix} are the respective annual fixed costs.

Objective function DIETER minimizes the total cost Z, consisting of variable generation costs (first term), investment costs of dispatchable and non-dispatchable generators (second term), as well as fixed and variable costs of storage (third term). The objective function of the model is given as:

$$
\begin{aligned}
Z = \sum_n \Bigg[\sum_h \Bigg[\sum_{dis} c^m_{n,dis} G_{n,dis,h} + \sum_{sto} c^m_{n,sto} \left(STO^{out}_{n,sto,h} + STO^{in}_{n,sto,h} \right) \\
&+ c^m_{n,rsv} RSV^{out}_{n,rsv,h} \Bigg] \\
&+ \sum_{dis} \left[\left(c^i_{n,dis} + c^{fix}_{n,dis} \right) N_{n,dis} \right] + \sum_{nd} \left[\left(c^i_{n,nd} + c^{fix}_{n,nd} \right) N_{n,nd} \right] \\
&+ \sum_{sto} \Bigg[\left(c^{i,p-out}_{n,sto} + c^{fix,p-out}_{n,sto} \right) N^{p-out}_{n,sto} + \left(c^{i,p-in}_{n,sto} + c^{fix,p-in}_{n,sto} \right) N^{p-in}_{n,sto} \\
&+ \left(c^{i,e}_{n,sto} + c^{fix,e}_{n,sto} \right) N^e_{n,sto} \Bigg] \Bigg] \qquad \text{(A.1)}
\end{aligned}
$$

Those fixed variables (NTC capacities, installed capacities of hydro and bioenergy), and some nomenclature details, are omitted in the objective function for the reader's convenience. The full objective function is provided in the model code.

Energy balance The wholesale energy balance reads as follows:

$$
\begin{aligned}
& d_{n,h} + \sum_{sto} STO^{in}_{n,sto,h} \\
&= \\
& \sum_{dis} G_{n,dis,h} + \sum_{nd} G_{n,nd,h} + \sum_{sto} STO^{out}_{n,sto,h} + \sum_{rsv} RSV^{out}_{n,rsv,h} \\
&+ \sum_l i_{l,n} F_{l,h} \qquad \forall n, h \qquad \text{(A.2)}
\end{aligned}
$$

The left-hand side is total electricity demand in hour h at node n plus charging of storage technologies; the right-hand side is the total generation, including storage discharging, plus net imports: $F_{l,h}$ represents the directed flow on line l. If $F_{l,n} > 0$, electricity flows from the source to the sink of the line and reversed for $F_{l,n} < 0$. With the incidence parameter $i_{l,n} \in \{-1, 0, 1\}$, source, and sink are exogenously defined.

A.3 Background on factorization

To identify the importance of different factors that reduce optimal storage need through interconnection, we (1) define several counterfactual scenarios and (2) then attribute the overall change to different factors using a "factorization" method (Stein and Alpert, 1993; Lunt et al., 2021).

To explain the principles of factorization, we borrow an example used in another paper (Lunt et al., 2021). Using a case study from the field of climate science, we aim to explain why oceans around three million years ago were warmer than today. Assuming that two important factors are atmospheric CO_2 concentration and the extent and volume of large ice sheets, we apply a climate model and run several counterfactual scenarios. Both factors can have two kinds of states: CO_2 concentration can be low or high, and ice sheets can be small or large. Comparing different model outcomes, we can identify a "sole" CO_2 and ice sheet effect, but also an interaction effect between CO_2 concentration and ice sheet extension on ocean temperature.

Following the notation introduced in previous research (Schär and Kröner, 2017), we describe the different scenarios in the following way: in f_0, ice sheets are small, and CO_2 is low. In the scenario f_1, the ice sheets are large, but CO_2 concentration is low. In scenario f_2, ice sheets are small, but CO_2 concentration is high. Finally, in scenario f_{12}, ice sheets are large, and CO_2 concentration is high.

The factorization method on which we rely on (Stein and Alpert, 1993) that defines the impact of the different factors in the following way:

$$\hat{f}_1 = f_1 - f_0, \tag{A.3}$$

$$\hat{f}_2 = f_2 - f_0. \tag{A.4}$$

$\hat{f}_1$ is the sole contribution of ice sheets, $\hat{f}_2$ of CO_2 concentration to the change in ocean temperature. However, with this factorization approach, the sum of the individual effects does not (in general) add up to the overall effect:

$$\hat{f}_1 + \hat{f}_2 \neq f_{12} - f_0 \tag{A.5}$$

Thus, an "interaction effect" $\hat{f}_{12}$ is introduced, which captures the joint effect of ice sheets size and CO_2 concentration on ocean temperature (Stein and Alpert, 1993), such that $\hat{f}_1$, $\hat{f}_2$, and $\hat{f}_{12}$ add up to total the total effect $f_{12} - f_0$:

$$\begin{aligned}
& f_{12} - f_0 = \hat{f}_1 + \hat{f}_2 + \hat{f}_{12} \\
\Leftrightarrow \quad & \hat{f}_{12} = f_{12} - f_0 - \hat{f}_1 - \hat{f}_2 \\
\Leftrightarrow \quad & \hat{f}_{12} = f_{12} - f_0 - (f_1 - f_0) - (f_2 - f_0) \\
\Leftrightarrow \quad & \hat{f}_{12} = f_{12} - f_1 - f_2 + f_0
\end{aligned} \tag{A.6}$$

If interested in the overall effect of CO_2 concentration and ice sheets on ocean temperatures and not in the interaction term, $\hat{f}_{12}$ has to be "distributed" to the other factors $\hat{f}_1$ and $\hat{f}_2$. This distribution can be done in different ways. One possibility is to share that interaction term equally between the two factors that are involved in that interaction term. Following that logic, the total effect of the two factors becomes:

$$\hat{f}_1^{total} = f_1 - f_0 + \frac{1}{2}\hat{f}_{12} = \frac{1}{2}((f_1 - f_0) + (f_{12} - f2)) \tag{A.7}$$

$$\hat{f}_2^{total} = f_2 - f_0 + \frac{1}{2}\hat{f}_{12} = \frac{1}{2}((f_2 - f_0) + (f_{12} - f1)) \tag{A.8}$$

and capture the overall effect of ice sheets ($\hat{f}_1$) and CO_2 concentration ($\hat{f}_2$) on ocean temperatures. For a complete decomposition of factors, 2^n runs have to be conducted where n is the number of factors.

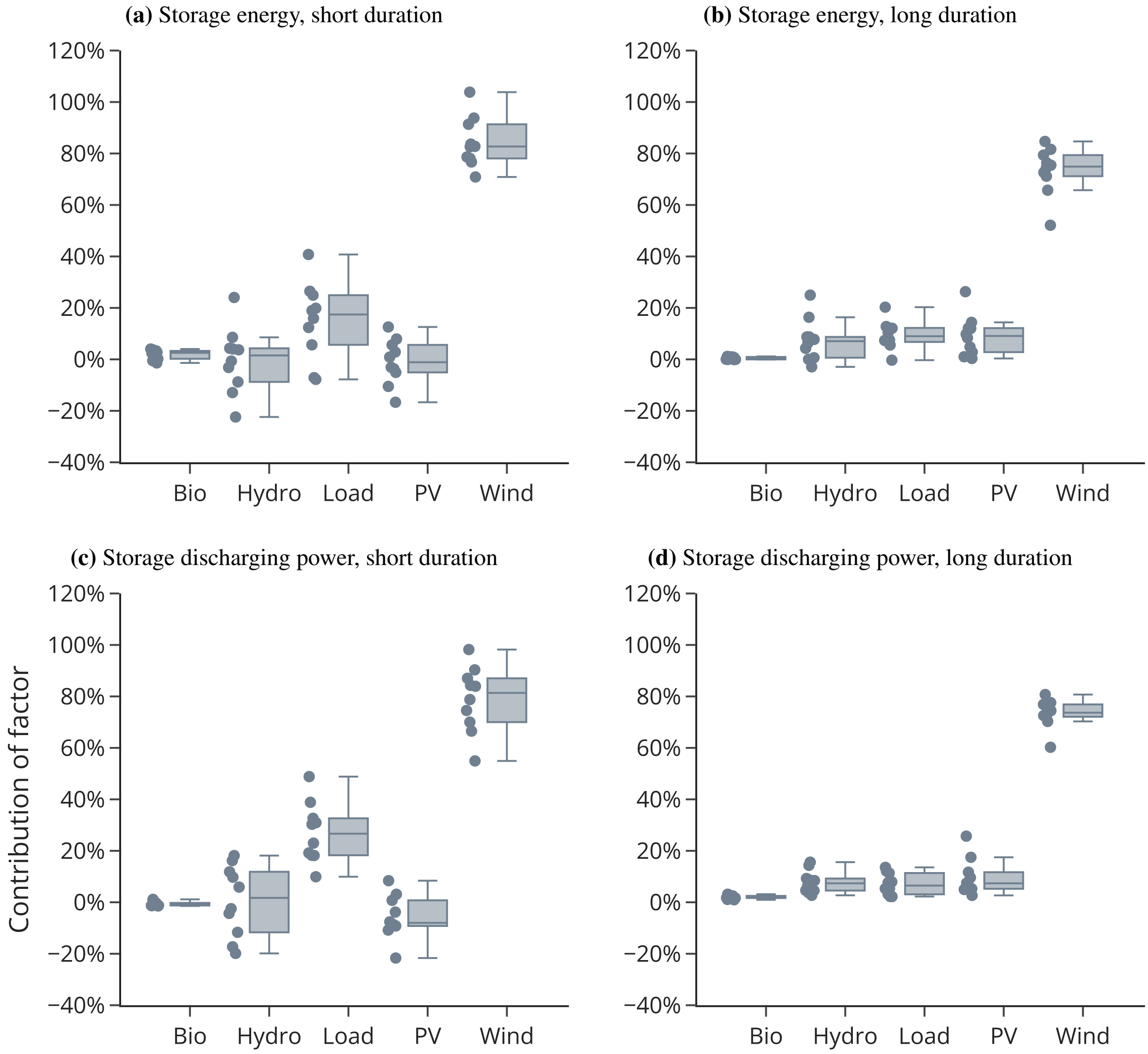
A.4 Overview of scenario runs

Table A.5: Overview of scenario runs

Run	Identifier	(1) Interconnection	(2) Wind	(3) Solar PV	(4) Load	(5) Hydro	(6) Bio
1	f_0	no	harmonized	harmonized	harmonized	harmonized	harmonized
2	f_1	yes	harmonized	harmonized	harmonized	harmonized	harmonized
3	f_2	no	not harmonized	harmonized	harmonized	harmonized	harmonized
4	f_3	no	harmonized	not harmonized	harmonized	harmonized	harmonized
5	f_4	no	harmonized	harmonized	not harmonized	harmonized	harmonized
6	f_5	no	harmonized	harmonized	harmonized	not harmonized	harmonized
7	f_6	no	harmonized	harmonized	harmonized	harmonized	not harmonized
8	f_{12}	yes	not harmonized	harmonized	harmonized	harmonized	harmonized
9	f_{13}	yes	harmonized	not harmonized	harmonized	harmonized	harmonized
...	...	...	...	...	...	...	...
63	f_{23456}	no	not harmonized	not harmonized	not harmonized	not harmonized	not harmonized
64	f_{123456}	yes	not harmonized	not harmonized	not harmonized	not harmonized	not harmonized

Table A.5 provides an intuition of which scenario runs are performed and how they are defined. For every weather year, 64 runs are needed for a complete factorization.

A.5 Further results



Notes: Every dot is the scenario result based on one weather year. The middle bar shows the median value. The box shows the interquartile range (IQR), which are all values between the 1st and 3rd quartile. The whiskers show the range of values beyond the IQR, with a maximum of 1,5 x IQR below the 1st quartile and above the 3rd quartile.

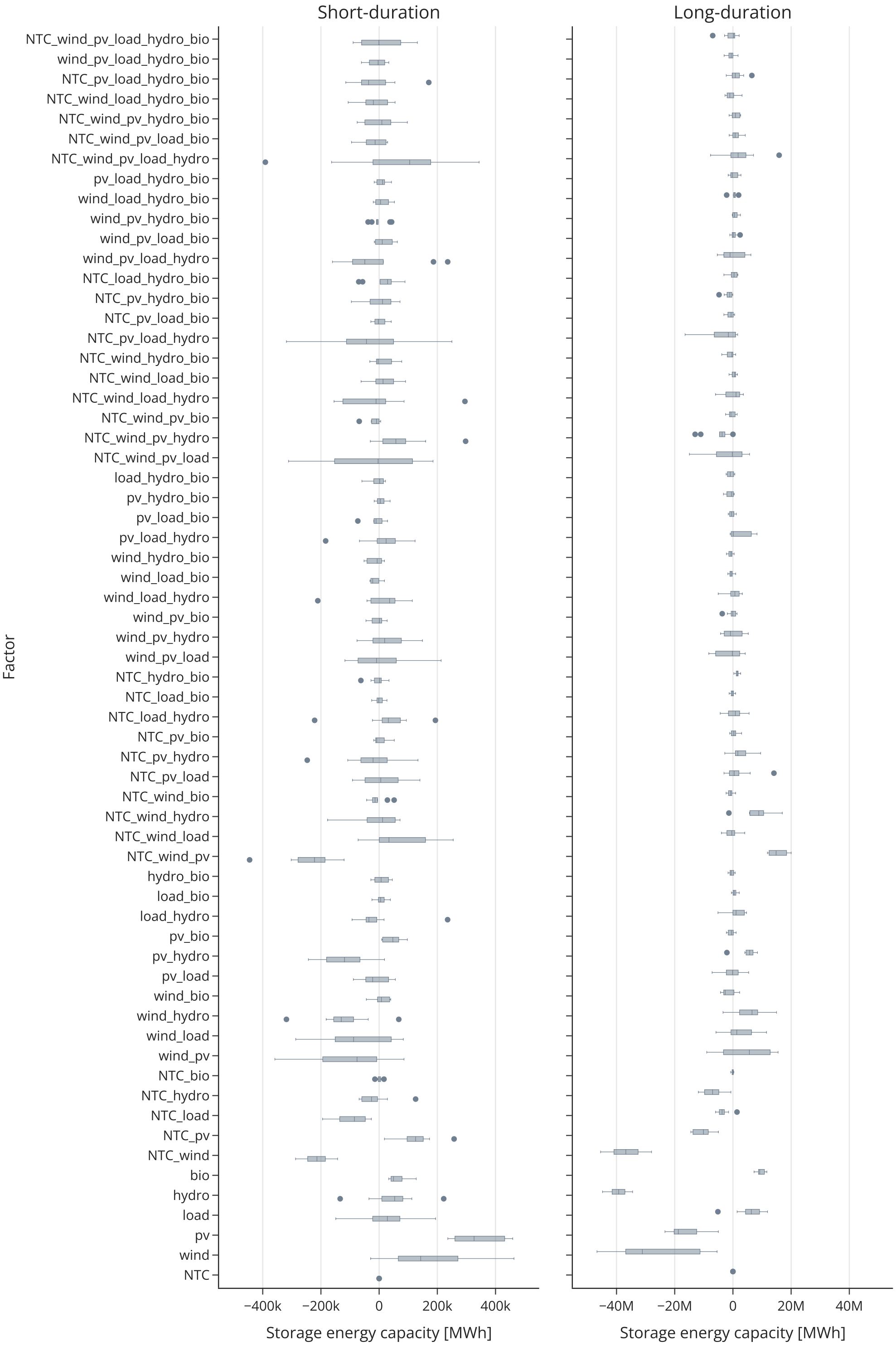
Figure A.2: Relative contribution of different factors to the change in storage energy and discharging power capacity related to interconnection

Heterogeneity in wind power explains between 55% and 104% of short-duration storage energy and discharging power capacity reduction and 52% to 85% of long-duration storage capacity reductions, respectively. At the other end of the spectrum, country-specific differences in installed bioenergy hardly have an effect. Differences in hydropower, load time series, and PV profiles have varying contributions, especially for short-duration storage. The effect of hydropower ranges between -22% and +24% for storage energy and -20% and +18% for storage discharging power (Figure A.2).

We find similar outcomes for solar PV. The effect of different solar PV capacity factors through interconnection on aggregate optimal short-duration storage energy or discharging capacity varies between -17% and +13%, or -22% and 8%, respectively. This contrasts with the results for wind power, which always decreases storage needs.

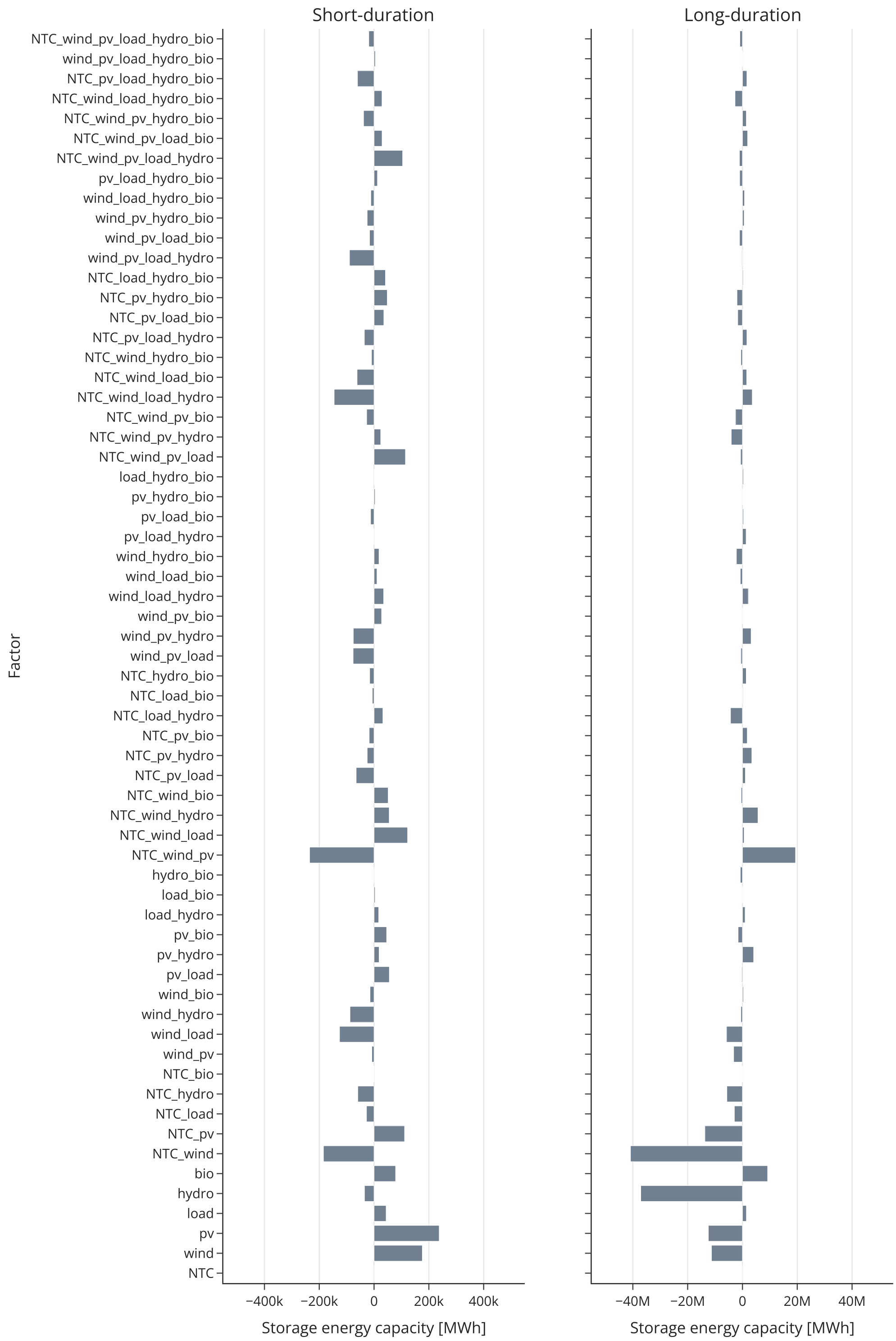
Negative percentage values indicate that the current heterogeneous mix of hydro capacities (run-of-river, reservoirs, and pumped hydro) may even increase optimal storage needs compared to a setting with equal relative shares, thus harmonized installations. Exploring this combined technology effect in detail merits further investigation.

Overall, the influence of different weather years on the composition of the factors is more pronounced for short-duration than for long-duration storage.



Notes: Differentiated by short- and long-duration, the strength of each individual factor is depicted, covering all 10 weather years. If below zero, a factor negatively impacts aggregate optimal storage energy capacity. If above zero, a factor increases aggregate optimal storage energy capacity.

Figure A.3: Impact of all factors on storage energy capacity in all years



Notes: Differentiated by short- and long-duration, the strength of each individual factor is depicted for the weather year 2016. If below zero, a factor negatively impacts aggregate optimal storage energy capacity. If above zero, a factor increases aggregate optimal storage energy capacity.

Figure A.4: Impact of all factors on storage energy capacity in 2016

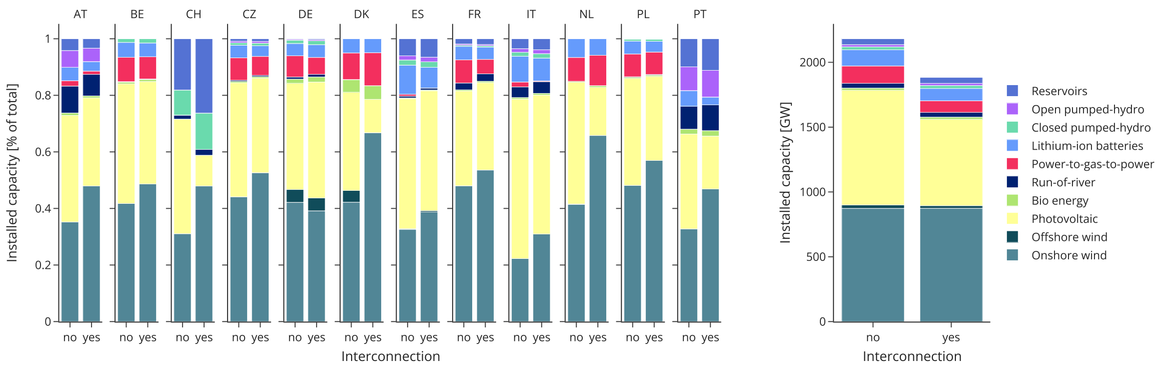
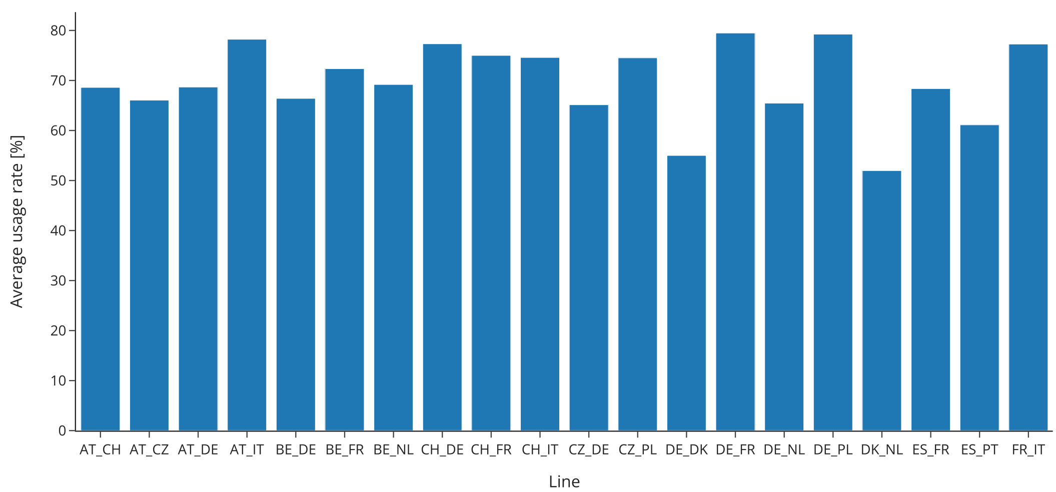


Figure A.5: Installed power plant and storage discharging capacities for scenarios with or without interconnection

Figure A.5 shows optimal generation and storage capacities for scenarios with and without interconnection. While solar PV and onshore wind power dominate the capacity mix in all countries, the share of onshore wind power increases in scenarios with interconnection compared to the setting with isolated power systems in all countries (left panel). This further corroborates our conclusion that geographical balancing particularly helps to smooth wind power variability across countries. The Figure also shows that the overall generation capacity decreases in a setting with interconnection (right panel). This is largely driven by a lower need for solar PV generation capacity, enabled by lower curtailment and better (cross-border) use of installed wind power capacities.



Notes: Data of the weather year 2016 shown.

Figure A.6: Average hourly usage rates of interconnections

Average utilization rates of the modeled interconnections are both relatively high and homogeneous, with values between around 50% and 80% (Figure A.6). Such high usage rates imply that the NTC expansion assumed by ENTSO-E (ENTSO-E, 2018a) for 2040 may not be sufficient for the fully renewable central European power sector modeled here. The connections between Germany and its neighbors France, Poland, and Switzerland, as well as the lines between Austria and Italy and between France and Italy, are most heavily used. This indicates that further extensions of these connections would be particularly desirable. In contrast, interconnections between Denmark and the Netherlands as well as Denmark and Germany are relatively under-utilized.

B

Appendix to Chapter 3

B.1 Model

B.1.1 Electric vehicles

In this analysis, we include battery electric vehicle (BEV) time series using the emobpy tool Gaete-Morales, Kramer, et al., 2021. The dataset Gaete-Morales, 2021 used has been created utilizing data from the "Mobilität in Deutschland" survey, distinguishing between commuter and spontaneous drivers and incorporating various factors such as trip frequencies, distances, trip duration, departure times, charging station availability, and charging strategies, as well as the use of popular BEV models.

The dataset encompassed multiple charging strategies. For this research, we select the "immediate-balanced" approach to reflect the electricity drawn from the grid. Under this charging strategy, the vehicles' batteries are charged upon arriving at charging stations, with a constant and often lower power rating than the charging station. This approach ensured that the BEV reached a 100% state of charge just before commencing the next trip. The selected time series are scaled to represent the demand for 12.5 million battery electric vehicles with an annual electricity demand of 29 TWh (see Figure B.1).

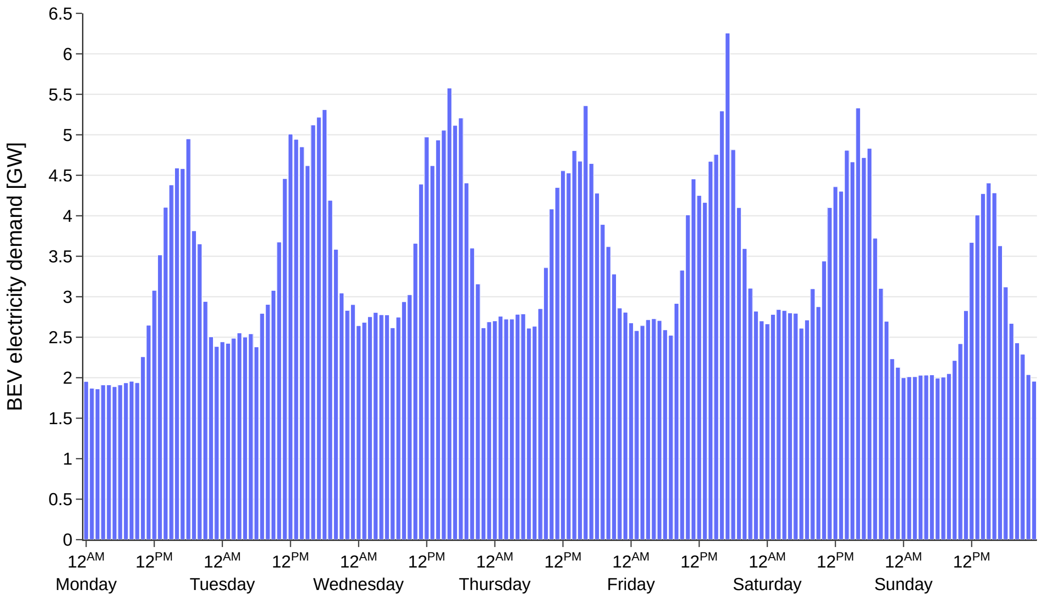


Figure B.1: Hourly average electricity demand of 12.5 million BEV for a representative week.

B.1.2 Green hydrogen

The production of green hydrogen is modeled in a simple way, following the approach described in Zerrahn, Schill, and Kemfert, 2018. We assume that a given hydrogen demand $h2^{demand}$ of 28 TWh has to be covered by electrolysis over the course of a year (Equation B.1). That is, we implicitly assume a temporally flexible hydrogen demand or unlimited hydrogen storage. In contrast, investments into electrolysis capacity are modeled endogenously (Equation B.3).

$$h2^{demand} = \sum^{h} H2_h^{prod} \tag{B.1}$$

$$H2_h^{prod} = H2_h^{elec} \times 0.71 \tag{B.2}$$

$$H2_h^{elec} \leq INV^{H2} \tag{B.3}$$

B.2 Tables

Table B.1: Building archetypes and heating energy demand assumptions for Germany in 2030

Year of construction	**Overall number of buildings** [million]	**Annual heating energy demand** [kWh/m^2]	**Floor area** [million m^2]
One- & two-family houses			
Before 1957	1.41	276	247
1958-1978	2.46	203	431
1979-1994	2.55	153	446
1995-2009	3.02	112	528
2010-2019	1.75	66	306
After 2019	2.15	15	375
Multi-family houses			
Before 1957	0.34	223	170
1958-1978	0.64	164	322
1979-1994	0.46	130	230
1995-2009	0.47	103	239
2010-2019	0.36	51	181
After 2019	0.46	11	232

Table B.2: Assumptions on capacity bounds [in GW]

Country	**Germany**		**Austria**	**Belgium**	**Switzerland**	**Czech Republic**	**Denmark**	**France**	**Luxembourg**	**Italy**	**Netherlands**	**Poland**
Technology	**Lower**	**Upper**	**fixed capacities**									
Run-of-river hydro	5.60	5.60	6.14	0.15	4.11	0.40	0	13.64	0.05	5.64	0.05	0.54
Nuclear	0	0	0	0	1.19	4.04	0	58.21	0	0	0.49	0
Lignite	0	0 / 9.3	0	0	0	3.89	0	0	0	0	0	6.32
Hard coal	0	0 / 9.8	0	0.62	0	0.37	0.77	0	0	0	0	9.88
Natural gas (CCGT)	0	17.60	2.82	7.61	0	1.35	0	6.55	0	38.67	8.65	5.00
Natural gas (OCGT)	0	19.60	0.59	1.08	0	0	0	0.88	0	5.40	0.64	0
Oil	0	1.20	0.17	0	0	0.01	0	0	0	0	0	0
Other	0	0	0.95	1.32	0.89	1.23	0.24	1.87	0.03	5.99	3.77	6.82
Bio energy	6.00	6.00	0.60	0.21	1.20	1.06	0.67	2.56	0.05	4.93	0.54	1.41
Onshore wind	56.00	115 / +Inf	10.00	5.93	1.25	3.00	5.48	44.11	0.35	19.05	8.30	11.28
Offshore wind	7.77	30 / +Inf	0	4.30	0	0	4.78	3.00	0	0.60	6.72	0.90
Solar PV	59.00	+Inf	15.00	13.92	11.00	10.50	4.75	42.63	0.25	49.33	15.46	12.19
Lithium-ion batteries												
... power in/out	0	+Inf	0.53	0.90	0.39	0.50	0.44	3.10	0.06	1.56	0.75	0.25
... energy [GWh]	0	+Inf	0.53	0.90	0.39	0.50	0.44	3.10	0.06	1.56	0.75	0.25
Power-to-gas-to-power												
... power in/out	0	+Inf	0	0	0	0	0	0	0	0	0	0
... energy [GWh]	0	+Inf	0	0	0	0	0	0	0	0	0	0
Pumped hydro storage												
... power in/out	11.60	11.60	5.70	1.40	3.99	1.16	0	3.50	1.31	11.90	0	1.50
... energy [GWh]	81.20	81.20	39.88	9.77	27.92	8.11	0	24.50	9.17	83.29	0	10.51
Reservoirs												
... power out	2.94	2.94	7.83	0	8.15	1.17	0	10.09	0	13.07	0	0.36
... energy [TWh]	0	0	15.66	0	16.30	2.34	0	20.19	0	26.13	0	0.73
Electrolysis	10	10	0	0	0	0	0	0	0	0	0	0

Notes: Based on Bundesnetzagentur (Bundesnetzagentur, 2018) and ENTSO-E (ENTSO-E, 2018b). If two numbers are present, the first one refers to the baseline scenario, while the second refers to sensitivity analyses. All numbers are provided in GW, except for storage energy, which is provided in GWh or TWh.

Table B.3: Cost and technology parameters

(a) Electricity storage

Technology	Interest rates	Lifetime [years]	Availability	Overnight costs energy [1000 EUR]	Overnight costs charging power [1000 EUR]	Overnight costs discharging power [1000 EUR]	Efficiency charging	Efficiency discharging	Marginal costs charging [EUR]	Marginal costs discharging [EUR]
Li-ion battery	0.04	20	0.98	142	80	80	0.96	0.96	0.5	0.5
Pumped hydro		80	0.89	10	550	550	0.97	0.91	0.5	0.5
Power-to-gas-to-power		25	0.95	2	550	435	0.73	0.42	0.5	0.5

(b) Electricity generation

Technology	Interest rates	Lifetime [years]	Availability	Overnight costs [1000 EUR]	Fixed costs [1000 EUR]	Efficiency	Carbon content [t/MWh]	Fuel costs [EUR/MWh]
Run-of-river	0.04	50	1.00	3,000	30	0.90	0.00	0
Nuclear		40	0.91	6,000	30	0.34	0.00	3.4
Lignite		35	0.95	1,500	30	0.38	0.40	5.5
Hard coal		35	0.96	1,300	30	0.43	0.34	8.3
Closed-cycle gas turbine		25	0.96	800	20	0.54	0.20	30.0
Open-cycle gas turbine		25	0.95	400	15	0.40	0.20	30.0
Oil		25	0.90	400	6.7	0.35	0.27	29.0
Other		30	0.90	1,500	30	0.35	0.35	18.1
Bioenergy		30	1.00	1,951	100	0.49	0.00	32.5
Wind onshore		25	1.00	1,182	35	1.00	0.00	0
Wind offshore		25	1.00	2,506	100	1.00	0.00	0
Solar photovoltaic		25	1.00	400	25	1.00	0.00	0

C

Appendix to Chapter 4

Capacity bounds, costs, and technical parameters

Table C.1: Cost and technology parameters

(a) Electricity storage and reservoirs

Technology	Interest rates [years]	Lifetime [years]	Availability [years]	Overnight costs energy [1000 EUR]	Overnight costs charging power [1000 EUR]	Overnight costs discharging power [1000 EUR]	Efficiency charging	Efficiency discharging	Marginal costs charging [EUR]	Marginal costs discharging [EUR]
Lithium-ion batteries	0.04	20	0.98	300	50	10	0.97	0.97	0.3	0.3
Power-to-gas-to-power		23	0.95	0.2	305	850	0.73	0.6	1.2	1.2
Pumped hydro (open/closed)		80	0.98	10	550	550	0.97	0.91	0.56	0.56
Hydro reservoirs		50	0.98	10	200	-	1.00	0.95	0	0.1

(b) Electricity generation

Technology	Interest rates	Lifetime [years]	Availability	Overnight costs [1000 EUR]	Fixed costs [1000 EUR]	Efficiency	Carbon content [t/MWh]	Fuel costs [EUR/MWh]
Closed-cycle gas turbine	0.04	25	0.96	830	28	0.61	0.20	26.0
Bioenergy		25	1.00	900	9	0.45	0.00	10.0
Hard coal		35	0.96	1,300	30	0.43	0.34	10.1
Lignite		35	0.95	1,500	30	0.38	0.40	4.0
Nuclear		40	0.91	6,000	30	0.34	0.00	1.7
Oil		25	0.90	400	7	0.35	0.27	41.7
Other		30	0.90	1,500	30	0.35	0.35	18.1
Solar photovoltaic		40	1.00	597	10	1.00	0.00	0.0
Wind onshore		50	1.00	3,000	30	0.90	0.00	0.0
Wind offshore		30	1.00	1,795	39	1.00	0.00	0.0
Run-of-river		30	1.00	1,036	13	1.00	0.00	0.0

Table C.2: Assumptions on capacity bounds [in GW]

Technology	**Austria**		**Belgium**		**Denmark**		**France**		**Germany**		**Italy**		**Luxembourg**		**Netherlands**		**Switzerland**	
	low	up	low	up	low	up	low	up	low	up	low	up	low	up	low	up	low	up
Natural gas (CCGT)	4.0	inf	8.1	inf	4.0	inf	7.2	inf	25.4	inf	40.5	inf	0	inf	12.4	inf	0	inf
Oil	0	0.16	0	0.2	0	2.5	0	1.3	0	1.0	0	0	0	0	0	0	0	0
Other	0	0.96	0	1.4	0	1.3	0	5.7	0	8.8	0	6.4	0	0.1	0	4.2	0	0.6
Hard coal	0	0	0	0	1.2	1.2	0	0	12.3	12.3	0	0	0	0	2.7	2.7	0	0
Lignite	0	0	0	0	0	0	0	0	14.6	14.5	0	0	0	0	0	0	0	0
Nuclear	0	0	0	0	0	0	61.8	61.8	0	0	0	0	0	0	0.5	0.5	2.2	2.2
Bioenergy	0.6	0.6	0.9	0.9	6.8	6.8	2.3	2.3	7.2	7.2	4.5	4.5	0.08	0.08	1.9	1.9	0.4	0.4
Run-of-river hydro	6.1	6.1	0.1	0.1	0	0	13.6	13.6	4.7	4.7	6.2	6.2	0.04	38	0.04	0.04	4.2	4.2
Solar PV	5.0	inf	7.5	inf	15.4	inf	18.2	inf	74.5	inf	28.6	inf	0.3	inf	18.7	inf	5.5	inf
Onshore wind	5.5	inf	3.6	inf	16.4	inf	24.1	inf	64.0	inf	15.7	inf	0.3	inf	6.0	inf	0.2	inf
Offshore wind	0	inf	2.3	inf	10.0	inf	2.5	inf	11.1	inf	0.3	inf	0	inf	5.9	inf	0	inf
Lithium-ion batteries																		
... power in/out	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf
... energy [GWh]	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf
Power-to-gas-to-power																		
... power in/out	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf
... energy [GWh]	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf	0	inf
Pumped hydro storage (closed)																		
... power in	0.3	0.3	1.2	1.2	0	0	2.0	2.0	7.4	7.4	7.4	7.4	1.0	1.0	0	0	1.9	1.9
... power out	0.3	0.3	1.2	1.2	0	0	2.0	2.0	7.4	7.4	7.3	7.3	1.3	1.3	0	0	1.9	1.9
... energy [GWh]	1.8	1.8	5.3	5.3	0	0	10	10	242	242	70.4	70.4	5.0	5.0	0	0	70	70
Pumped hydro storage (open)																		
... power in	5.2	5.2	0	0	0	0	1.9	1.9	1.4	1.4	2.1	2.1	0	0	0	0	2.1	2.1
... power out	6.0	6.0	0	0	0	0	1.9	1.9	1.6	1.6	3.3	3.3	0	0	0	0	10.7	10.7
... energy [GWh]	1,732	1,732	0	0	0	0	90	90	417	417	309	309	0	0	0	0	8,800	8,800
Reservoirs																		
... power out	2.5	2.5	0	0	0	0	8.9	8.9	1.3	1.3	9.6	9.6	0	0	0	0	0	0
... energy [TWh]	0.8	0.8	0	0	0	0	10	10	0.2	0.2	5.6	5.6	0	0	0	0	0	0

Results

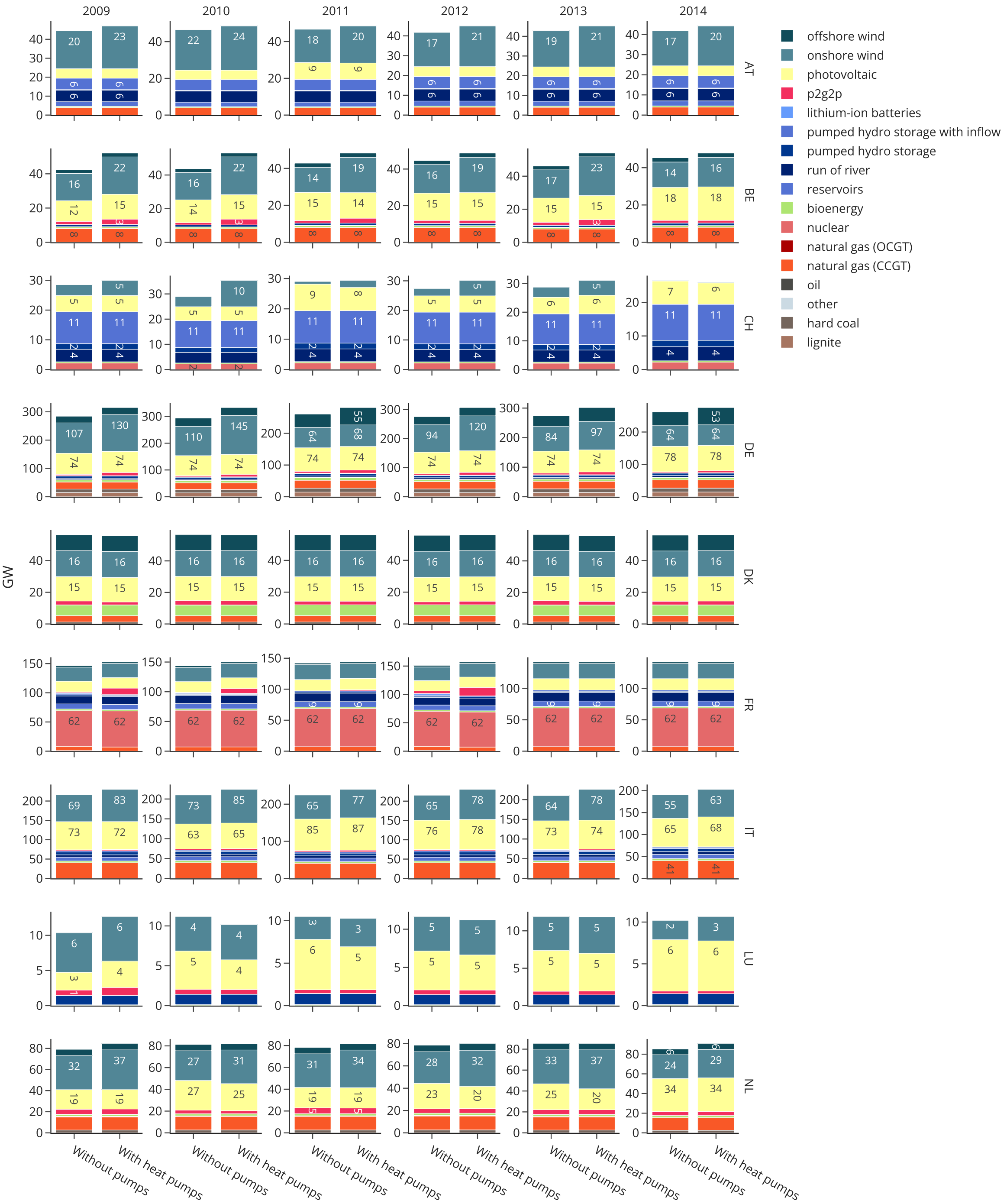


Figure C.1: Generation capacities of all countries

Figure C.1 depicts the generation capacities of all countries in all assessed weather years for the *base* scenarios with thermal heat storage of 2 hours.

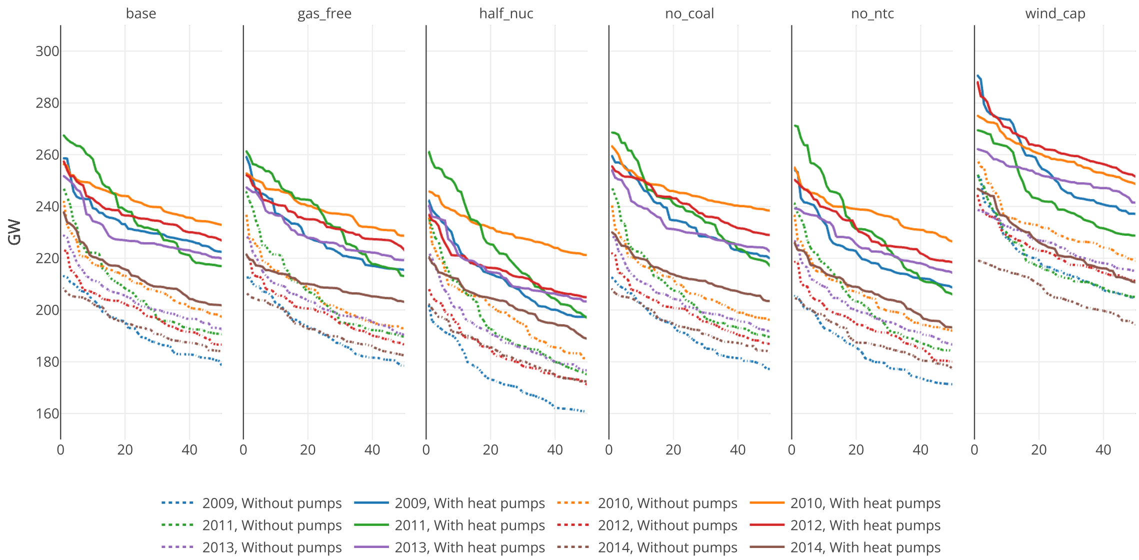


Figure C.2: All residual load curves

Figure C.2 depicts the residual load duration curves in all scenarios and all years, with and without a heat pump rollout. The jump caused by heat pumps is clearly visible, showing itself in the differences in firm generation capacities (see Figure 4.9). While the patterns are relatively similar in all scenarios, *wind_cap* shows a clearly higher level as the missing wind power pushes up the residual load duration curve.

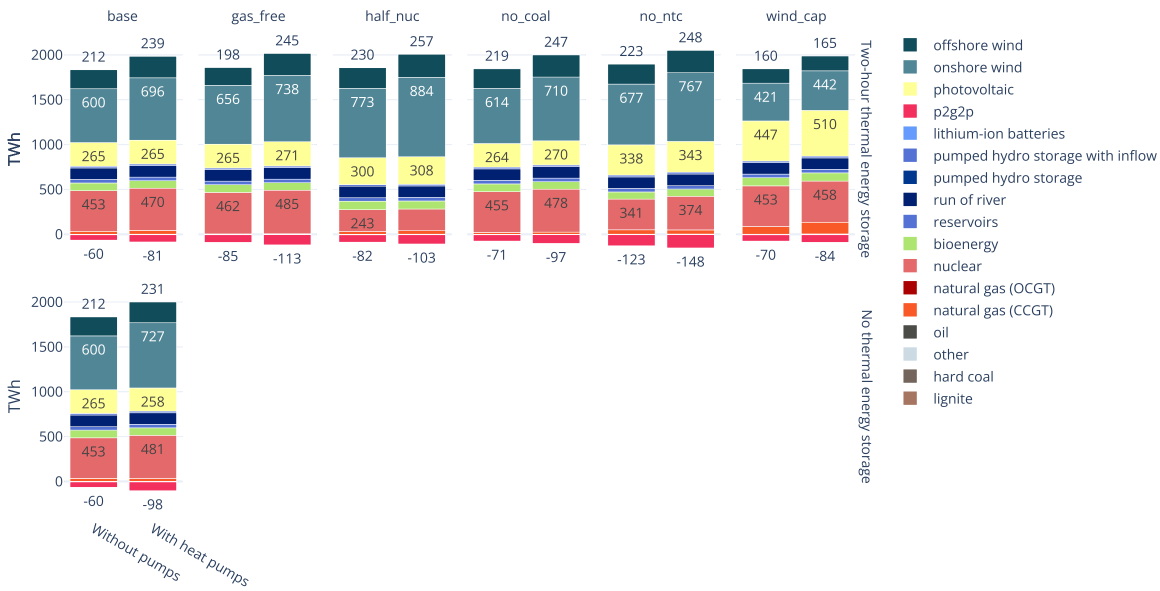


Figure C.3: Electricity generation (average all years)

Figure C.3 shows total electricity generation by technology as an average over all years. Storage technologies have negative values as discharging minus charging is shown, considering inefficiencies.

D

Appendix to Chapter 5

This section provides details on the deployed methodology and presents supplemental results. Section D.1 discusses data sources and provides some summary statistics. Section D.2 gives a methodological introduction to local linear causal trees. Section D.3 contrasts it with alternative approaches. Section D.4 provides supplemental results on robustness.

D.1 Data and descriptive statistics

D.1.1 Gas consumption data

Instantaneous gas consumption metering for residential and commercial customers is still rare in Germany, such that accurate day-by-day consumption profiles for individual households or business units are unavailable (ACER, 2022). In the absence of directly metered data, the German Network Agency relies on residual load data published by the German gas exchange Trading Hub Europe (THE). The residual load is derived by taking the difference between gas inflows and gas outflows from the network to downstream networks, storages, other countries, or large-scale customers (BDEW, 2021). These data are by design for the whole German market area and hence our analysis cannot take into account any spatial differentiation between consumption patterns. Very recent data are subject to revisions, and final data for a given date are only available after ca. 1.5 months.[1] Therefore, at the time of writing, the last available month of final data is December 2022. The publicly available dataset includes the years 2018-2022.

D.1.2 Weather data and other controls

Residential and commercial gas demand is heavily driven by heating demand inducing a high dependence on outside air temperatures and other weather variables. Germany's National Meteorological Service (DWD) publishes dozens of weather parameters for hundreds of weather stations daily. They are available through an application programming interface (API) that permits downloading specific data with custom programming scripts. We implemented our download routine in Python (see Section D.5 below). While the model described in the next section could potentially deal with a large number of covariates by means of regularisation methods such as a least absolute shrinkage and selection operator (LASSO), a regularised regression method that constrains the L_1 norm of the coefficient vector helping to select only important regressors, we restrict ourselves to a concise set that accounts for a very large share of the gas demand variation in the control period.

For each day and every weather station, we access the average temperature, as well as the maximum and minimum temperatures. The latter accounts for extreme temperature changes during a single day. To control for thermal inertia, three lags of average, minimum, and maximum

[1] THE publishes final data according to 'M+2M-10WD', which means that final data for the current month 'M' are published two months later ('+2M') minus 10 working days ('-10WD'). This information is provided in a data Excel file available at www.tradinghub.eu/en-gb/Publications/Transparency/Aggregated-consumption-data. Hence, for December 2022, final data have been available since the 15th of February.

temperatures are added to the model[2] Solar irradiation might be conducive to heating demand reductions not only through its effect on air temperatures. We proxy solar irradiation by the sunshine duration per day in hours. As discussed in the previous subsection, the gas demand data is only available at a national level. Hence, we need to aggregate the covariates spatially. Other studies use population-weighting to average across spatially disaggregated reanalysis data, a blend of historical data points and model outputs (Ruhnau, Stiewe, et al., 2022). For simplicity, we choose to take the median across weather stations. We prefer the median over a simple average so as to not introduce biases from extreme observations, such as measurements from Germany's highest mountain *Zugspitze*. Lastly, we include fixed effects for months and weekends as well as national holidays.

D.1.3 Summary statistics

In Table D.1, we present a few key statistics of our data set. We distinguish between 2018-2021, the business-as-usual period, and 2022, the year subject to behavioral savings. It is evident from the top panel that average gas consumption is somewhat lower in 2022 compared to previous years. For the weather variables in the following panels, the statistics are quite close to each other, indicating good *overlap*, a key requirement for the validity of the method discussed in the next section (Wager and Athey, 2018). For exposition, we plot the mean temperature in the September to December 2022 period against the mean, minimum and maximum temperatures of the same period in 2018-2021 in Figure D.1

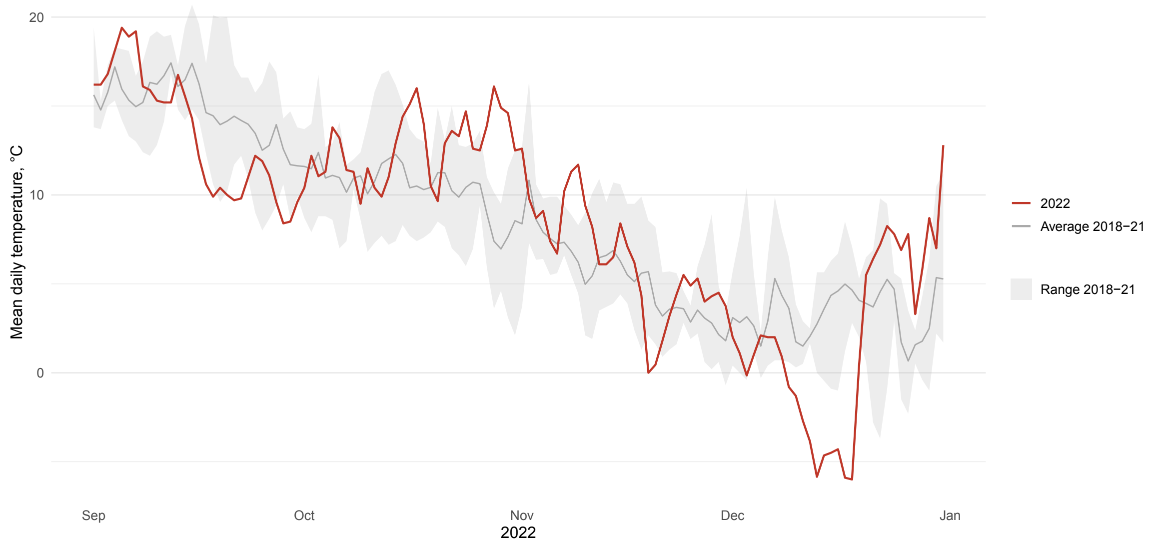


Figure D.1: Mean temperatures

[2]The German building stock equipped with gas-fired heating has varying degrees of insulation. By allowing the model to choose the relative importance of temperatures on preceding days non-parametrically, it accounts flexibly for the average impact of insulation on gas demand.

Table D.1: Selected summary statistics

Variable	Statistic	2018-2021	2022
Gas consumption	avg	1088.44	966.66
	min	165.35	162.93
	max	3273.74	2668.29
	std	764.83	726.95
Mean temperature	avg	10.18	10.61
	min	-9.6	-6
	max	27.2	26.2
	std	7.06	7.03
Minimum temperature	avg	5.63	5.83
	min	-13.7	-10
	max	18.2	16.95
	std	5.99	5.87
Maximum temperature	avg	14.8	15.43
	min	-6	-3
	max	35.5	35.6
	std	8.48	8.46
Sunshine duration	avg	4.96	5.54
	min	0	0
	max	15.23	14.65
	std	4.33	4.38

Figure D.2 shows the relationship between gas consumption and the daily mean temperature differentiated by calendar month (color) and period (marker shape). The figure demonstrates the non-linear relationship between mean temperature and gas consumption.

D.2 Model description

As evident from Figure D.2, the relationship between weather variables and gas consumption is non-linear. Traditional methods, such as heating degree day corrections or parametric polynomial models, may introduce biases, especially at the boundary of the support.

We deploy a fully data-driven, non-parametric approach that can not only deal with non-linearities in the relationship between covariates and gas consumption but also with *heterogeneity* in behavioral savings conditional on the covariates, such as temperature or month. Non-parametric models do not require the formulation of a functional relationship between relevant factors, the covariates, and the variable of interest. Causal forests pioneered by (Wager and Athey, 2018), and refined with doubly-robust techniques in (Athey, Tibshirani, and Wager, 2019), extend a classical machine learning method, random forests (Breiman, 2001). We provide short explanations of these terms below.

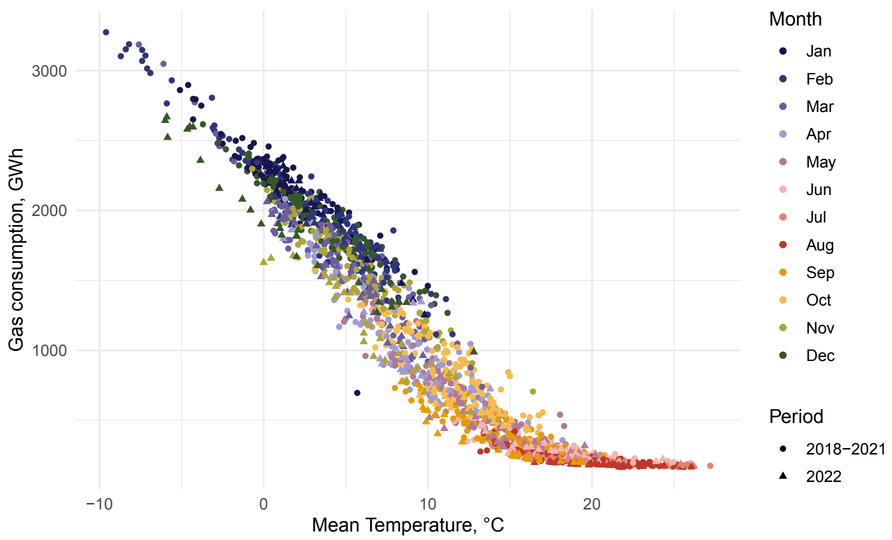


Figure D.2: Relationship between mean temperature and gas consumption by month and period

D.2.1 Random forests

Random forests predict a variable of interest conditional on a set of covariates by averaging over the predictions of a potentially large number of decision trees. A decision tree splits the data set into subsets, or neighborhoods, in the covariate domain. In our case, a simple tree could first divide the data set depending on whether a given observation has a mean temperature above or below 10 degrees Celsius. In the below 10 degrees subset, the next split could be based on whether an observation is from a calendar month before March or not. A completely different split could divide the above 10 degrees subset. Further splits may follow. The final subsets, or neighborhoods, are called *leaves*. For each leaf, the random forest algorithm fits a local model. In the classic implementation, this local model is a simple average of the variable of interest of all observations within this leaf. The more refined version used below fits a local linear model instead. The algorithm selects splitting rules in order to minimize some prediction error metric, such as the mean squared error. Taken together, the collection of local models can represent complicated non-linear relationships without having to specify a functional form. As shown (Breiman, 2001) that the average of a large number of decision trees estimated on bootstrap samples improves the predictive power, a forest usually consists of at least a few hundred decision trees.

D.2.2 Causal inference and causal forests

Causal forests use random forests to the *prediction* of treatment effects in a potential outcomes framework (e.g. Rubin, 2005). The *fundamental problem of causal inference* is that we cannot observe what would have happened to a treated unit in the absence of the treatment (Holland, 1986). In our case, the treatment corresponds to all factors discussed above regarding the looming supply crunch, assuming to start after 23/02/2022. In order to *identify* the treatment effect, i.e. the behavioral savings, modelers have different options ranging from structural models to randomized experiments. Observational studies, like the one at hand, aim to emulate the randomization of an experiment, e.g., by controlling for all factors that affect the propensity of being treated. Provided we can observe all such factors, the treatment assignment conditional on the covariates becomes as good as random. Two methods (of many) for controlling for the covariates affecting treatment selection are regression and inverse propensity score weighting (IPW). Combining the two leads to the class of *doubly robust* estimators that have the advantage of recovering the treatment effect even if only one of the two methods is correctly specified.

Much like a random forest, a causal forest splits the data set based on rules referring to covariate values. However, the objective sought to optimize by selecting the splits is different. We do not have data on the true treatment effect such that we cannot optimize a prediction error metric. Instead, the causal forest algorithm aims to determine neighborhoods in the covariate domain in such a way that the estimated treatment effects are as similar as possible within a neighborhood and as dissimilar as possible between neighborhoods (Tibshirani et al., 2023). The conditional average treatment effects are especially useful in a context like ours where the magnitude of behavioral savings is expected to vary significantly by weather conditions.

D.2.3 Model formulation and estimation

Let $Y_t(1)$ be the gas consumption in period t in the presence of behavioral savings and $Y_t(0)$ be the gas consumption in the same period in the absence of behavioral savings. Consequently, the observed consumption can be expressed by:

$$Y_t = W_t Y_t(1) + (1 - W_t) Y_t(0)$$

where $W_t \in \{0, 1\}$ indicates the presence of behavioral savings. In our base case, $W_t = 1$ for all $t \geq 24/02/2022$. We are interested in the effect of behavioral savings conditional on covariates $\mathbf{X}_t$ defined by:

$$\tau(x) = \mathbb{E}[Y_t(1) - Y_t(0) | \mathbf{X}_t = x] \tag{D.1}$$

Yet, $Y_t(1)$ and $Y_t(0)$ are not observable at the same time, such that the function $\tau(x)$ is not directly identifiable.

We assume *strict exogeneity* conditional on the covariates $\mathbf{X}_t$, i.e., there are no unobserved confounders of W_t and Y_t, and after controlling for the covariates the *treatment assignment* is as good as random.

$$\{Y_t(1), Y_t(0)\} \perp W_t | \mathbf{X}_t$$

We further assume that residential and commercial gas consumption Y_t on a day t follows the following partially linear model:

$$Y_t = \tau(\mathbf{X}_t)W_t + f(\mathbf{X}_t) + \varepsilon_t \tag{D.2}$$

The effect of behavioral savings on consumption is measured by a function $\tau(\cdot)$, which may depend on the covariates $\mathbf{X}_t$. $f(\mathbf{X}_t)$ is a potentially complicated function of the covariates and ε_t is an independently distributed error term. Double robustness, as discussed above, arises from the following reformulation (Athey, Tibshirani, and Wager, 2019):

$$Y_t - m(x) = \tau(x)(W_t - e(x)) + \varepsilon_t \tag{D.3}$$

where the regression component is $m(x) = \mathbb{E}[Y_t|\mathbf{X}_t = x] = f(x) + \tau(x)e(x)$ and the propensity score component is $e(x) = \mathbb{E}[W_t|\mathbf{X}_t = x]$. We build the model in two steps:

1. We estimate the nuisance functions $m(x)$ and $e(x)$ using local linear forests. A nuisance function is a function that is not of direct interest for the question at hand but needs to be estimated in order to identify the variable of interest. Local linear forests fit a linear model to the local observations in each leaf. They have proven superior for smooth, non-linear signals (Friedberg et al., 2021). A key feature of our predictions $\hat{m}(x)$ and $\hat{e}(x)$ is the *honesty* property. An honest tree divides the data into two subsamples. The first subsample is used to define the splitting rules and the second subsample is used for the estimation within a leaf. Only with *honest trees* the estimators have the desired asymptotic properties, such as consistency and asymptotic normality required for valid inference (Wager and Athey, 2018), e.g. used for the confidence intervals presented in the lower panel of Figure 5.1.

2. We use a causal forest to find neighborhoods for the treatment effects. In each neighborhood, we estimate D.3 where we replace $m(x)$ and $e(x)$ by $\hat{m}(x)$ and $\hat{e}(x)$.[3] The formulation has the advantage that we can still recover a good estimate of $\tau(\cdot)$ even if our estimates of the nuisance functions are noisy (Tibshirani et al., 2023). We obtain an estimated function $\hat{\tau}(x)$ according to (Wager and Athey, 2018; Tibshirani et al., 2023):[4]

$$\hat{\tau}(x) = \frac{\sum_{\{t:\mathbf{X}_t \in \mathcal{N}(x)\}}(W_t - \hat{e}(\mathbf{X}_t))(Y_t - \hat{m}(\mathbf{X_t}))}{\sum_{\{t:\mathbf{X}_t \in \mathcal{N}(x)\}}(W_t - \hat{e}(\mathbf{X}_t))^2}$$

   where $\mathcal{N}(x)$ refers to the neighborhood of a particular covariate realization x found by the causal tree.

The causal forest consists of $B = 10^4$ trees in total. For exposition, we show the tree $b = 1$ in Figure D.3

[3] For notational simplicity, we gloss over the fact that the prediction for t is made on the basis of all observations except for t. See Tibshirani et al., 2023 for details.

[4] We assume here that the local linear regression model is solved by ordinary least squares (OLS).

Figure D.3: $b = 1$ causal decision tree

D.3 Model fit

Before turning to the robustness checks, we further investigate the model output. The causal forest model discussed in the previous section is trained to predict the *savings effect* induced by the gas crisis. However, as shown in Figure 5.1, we can recover the expected gas consumption in either scenario from the model. We can use these expected gas consumption paths to compare them against the actual consumption in the pre-crisis period (2018-Feb 2022). While the aim of our model is not to maximize the in-sample fit of consumption in the pre-crisis period and it would still produce consistent estimates of the savings effect even if the relevant covariates only accounted for a small share of the observed variation in gas consumption, a good pre-crisis model fit makes it more unlikely that we omitted a *confounding* factor.[5] It is, therefore, informative to compare the pre-crisis fit of our model with alternative approaches. Note that in the pre-crisis period, actual consumption is modeled with the ($W_t = 0$) scenario of our model. We can recover the scenario by computing:

$$\hat{\mu}_t(x, 0) = \hat{m}(x) - \hat{\tau}(x)\hat{e}(x)$$

In the left panel of Figure D.4, we plot the predictions $\hat{\mu}_t(x, 0)$ against the observed consumption between January 2018 and 23 February 2022. We observe that the fitted values are very close two the black line, which indicates a perfect fit. We compute a root mean squared error (RSME) of

[5]A confounding factor is a covariate that affects both the likelihood for a particular day to be one with behavioral savings and the gas consumption. Such a factor, if omitted, induces a spurious behavioral savings effect.

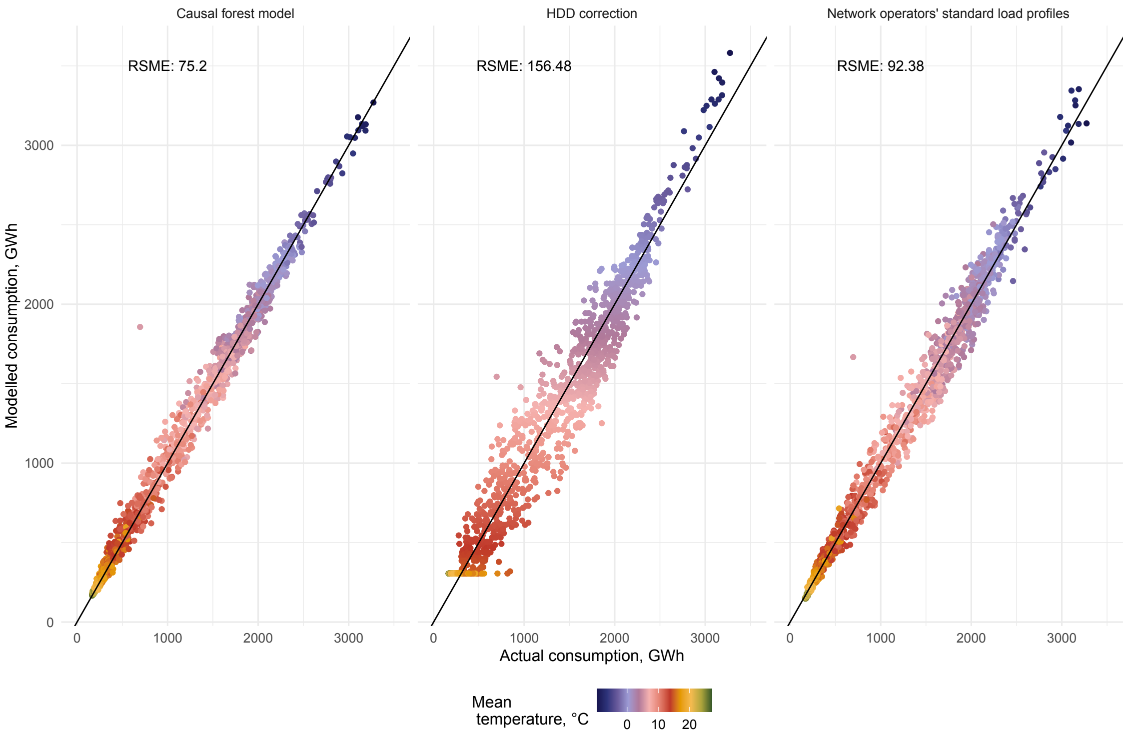


Figure D.4: Comparison of causal forest pre-crisis (2018-Feb 2022) fit to other methods

75.2 GWh. In comparison to other methods, such as a simple heating degree day (HDD) correction (middle panel), in which we regress the observed consumption on $\max(15 - T_t^{mean}, 0)$, or the standard load profiles (SLP) used by the network operators (left panel), we note that the causal forest fit is tighter, especially so for the lowest temperatures.[6]

D.4 Robustness

In contrast to prediction models, where evaluation metrics can be readily calculated on a validation dataset, the quality of the model for $\tau(x)$ cannot be readily evaluated in the same manner as the true values are not available. Following earlier approaches (Tibshirani et al., 2023), we conduct an auxiliary regression that helps to assess the causal forest fit and test the null hypothesis of no saving effect heterogeneity. We further conduct placebo tests (c.f. Athey and Imbens, 2017) and run a few sensitivities on the *treatment* start date.

[6] T_t^{mean} refers to the mean temperature on day t. Like the residual load data, the SLP predictions of the network operators have been retrieved from Trading Hub Europe as well (see Section D.1). We note that comparing these with our model outputs is not an exact like-for-like comparison as they at least partially rely on (historical) short-term temperature forecasts rather than historical realized temperature data. However, deviations tend to be small and forecasts are subject to repeated validation processes (BDEW, 2021). The SLP predictions result from a set of sigmoid functions with different parameters for different regions and building types and therefore are far more detailed than any sigmoid function-based model we could have built based on publicly available data.

Table D.2: Calibration test of causal forest with robust standard errors (HC3)

	Dependent variable: $(Y_t - \hat{m}_t)$
	α
Mean forest prediction ($\bar{\tau}$)	1.005^{***}
	(0.043)
Differential forest prediction ($\tau_t - \bar{\tau}$)	1.094^{***}
	(0.052)
	*p<0.1; **p<0.05; ***p<0.01

D.4.1 Omnibus test for causal forest fit

An omnibus test is a test for general model goodness-of-fit evaluation (Tibshirani et al., 2023). We fit a simple linear model regressing the estimated left-hand-side of D.3 on the mean predicted savings effect $\bar{\tau} = \sum_t \tau_t$ and the differential effect $\tau_t - \bar{\tau}$:

$$(Y_t - \hat{m}_t) = \alpha_0 \bar{\tau} + \alpha_1 (\tau_t - \bar{\tau}) + \nu_t$$

An α_0 value close to one suggests that the mean effect is correct, while α_1 close to one suggests additionally that the heterogeneity of the effect is well captured. As shown in Table D.2, both coefficients are fairly close to one and we conclude that the causal forest fit is adequate.

D.4.2 Placebo testing

Placebo testing is another standard technique in causal inference to test underlying model assumptions (Athey and Imbens, 2017). A very basic premise of our model is that the behavioral saving effects do not occur before the start of the energy crisis, the exact start of which is uncertain and subject to additional sensitivities in the next section.

Therefore, we run two sets of auxiliary models. We define $n_{savings}$ as the length of the set of days for which we suppose the presence of behavioral savings $\mathcal{T} = \{t : W_t = 1\}$, hence $n_{savings} = \sum_t W_t$. We define the set of control days as $C = \{t : W_t = 0\}$. For K times, we take a random sample $\mathcal{S}_k \subset C$ without replacement. In step (1) of the placebo test, we assign all days $t \in \mathcal{S}_k$ a dummy treatment $W'_t = 1$ and set $W'_t = 0 \; \forall t \in C \setminus \mathcal{S}_k$. We estimate our model over C with W_t replaced by W'_t. We store the average placebo-saving effect. In step (2), we estimate the original model over the set $\mathcal{T} \cup C \setminus \mathcal{S}_k$. We save the resulting *leave-n-out* average savings effect. We repeat steps (1) and (2) K times to obtain two distributions of average savings effects.

We use the *leave-n-out* estimation instead of our main specification of the model for the true savings effect to make our model comparable to the placebo draws in terms of statistical power. We set $K = 100$.

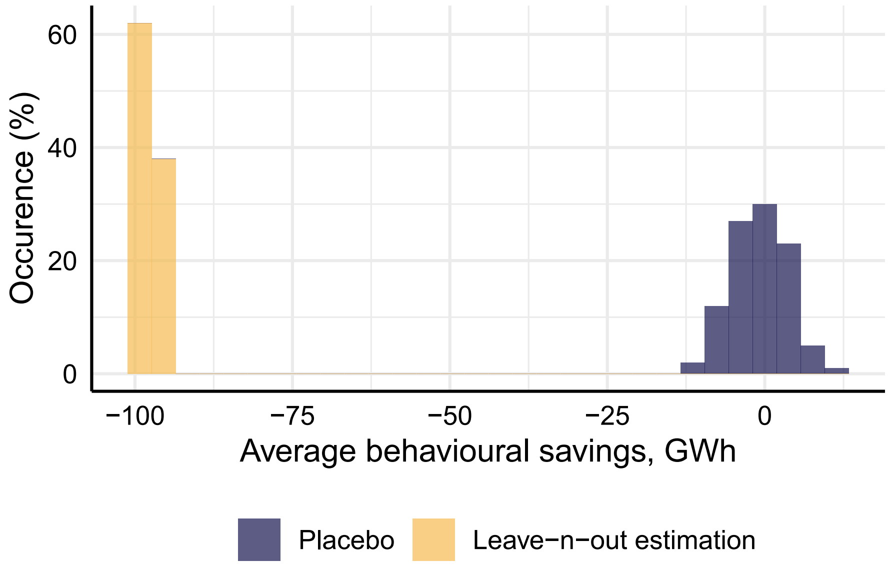


Figure D.5: Placebo test results

Figure D.5 shows the distributions of the Placebo runs in step (1) and the leave-n-out runs in step (2). While all runs in the latter render significant saving effects of around -96 GWh, the distribution of placebo runs is centered around 0 and only 4% of the estimated effects are statistically significant at the 10% level.

We are therefore confident to reject the hypothesis that the estimated savings effects above are just noise.

D.4.3 Crisis start sensitivities

We have chosen the day of the Russian invasion of Ukraine, 24 February 2022, as the start of our savings period, where $W_t = 1$. However, there are arguments for shifts in either direction. An earlier savings start could be supported by the fact that wholesale gas prices started rising above long-term average levels as early as September 2021 (Ruhnau, Stiewe, et al., 2022). On the other hand, the need for gas savings for households and commercial sectors only really became evident and a topic in the public domain in the Summer of 2022. Therefore, we test our assumption with respect to the start date by re-running our model with a monthly sequence of start dates beginning on 24 September 2021 and ending on 24 August 2022. For each iteration, we compute the total cumulative predicted savings in the period from 1 September 2022 until 31 December 2022.

Figure D.6 shows that the results are very robust to variations of the savings start date in 2022. For start dates in 2021, however, cumulative estimated savings from September 2022 to December 2022 decline rapidly, suggesting that households and commercial sectors did not react to the foreboding developments in wholesale markets at the time.

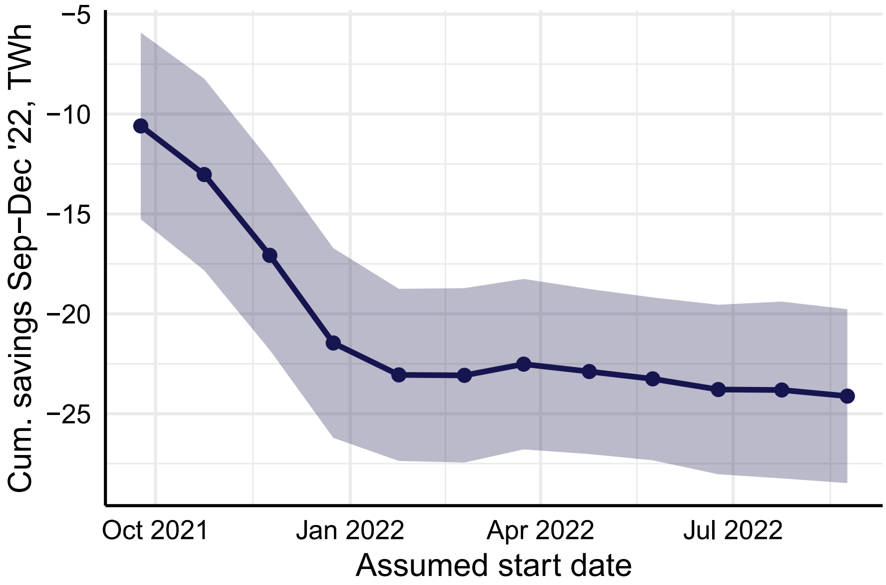


Figure D.6: Start date sensitivity

D.4.4 COVID-19

The pre-crisis period of our data set includes the COVID-19 pandemic. As households practiced social distancing, worked from home, and shops and offices remained closed, the heating behavior of residential and commercial sectors is likely to have changed compared to the pre-COVID period. Suppose that extended periods of isolation at home have led to more gas consumption, *ceteris paribus*, even offsetting the reduced demand by commercial buildings. If this were true, our model may deliver biased results as it exaggerates counterfactual gas demand compared to what would have been expected, as the world has gone back to normal in 2022, but for the gas crisis due to the Russian invasion of Ukraine.

Therefore, we conduct a sensitivity test in order to determine if our results hinge on a potential exaggeration of savings due to lockdowns. In Germany, the first lockdown started on 22 March 2020 and ended on 4 May 2020. A second lockdown began with lighter restrictions on 2 November 2020. By January, tighter restrictions were imposed and the lockdown was not lifted before 9 May 2021. Let $\mathcal{L} \subset C$ be the set of lockdown days in our pre-crisis data set. In the first step, we estimate our model over the set $\mathcal{T} \cup C \setminus \mathcal{L}$. Further, we define a broader set of pandemic days that comprises all days between 1 March 2020 and 31 December 2021. Let this set be denoted by $\mathcal{P}$. In a second step, we compute our model estimates over the set $\mathcal{T} \cup C \setminus \mathcal{P}$.

As shown in Table D.3, the effect of excluding the lockdown period is negligible. The effect of excluding the full pandemic period is a bit larger at ca. 7%. However, we do not think it is reasonable to exclude this period entirely. While it is very likely that heating behaviors have changed during the pandemic, it is also probable that at least a part of those changes continues to take effect today, e.g.

Table D.3: COVID-19 sensitivity

Scenario	Est. cum. behavioral savings	Change
Baseline	23.0 TWh	
Excl. lockdown days ($\mathcal{L}$)	22.7 TWh	-1.58%
Excl. all pandemic days ($\mathcal{P}$)	21.5 TWh	-7.09%

due to flexible working-from-home policies. We conclude that our model is not substantially biased by the inclusion of the COVID-19 period in the control set C.

D.5 Code

We wrote a Python script for gas consumption data downloads and *Deutscher Wetterdienst* API calls. All modeling steps and charting were conducted in R. We make all code available in this repository: gitlab.com/diw-evu/projects/gas-savings.

E

Appendix to Chapter 6

E.1 Health

E.1.1 Descriptives

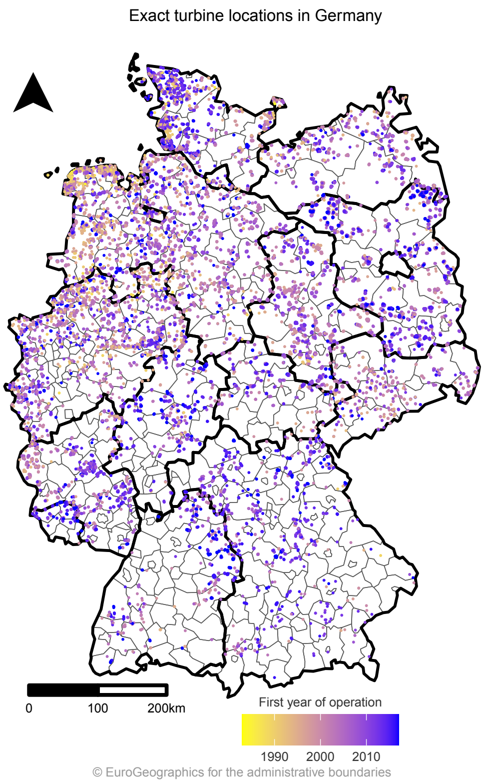


Figure E.1: Exact locations of on-shore wind turbines in Germany until 2017. Each dot indicates a turbine coloured by the first year of operation. Thick black lines indicate the borders of federal states.

Table E.1: Summary statistics.

Variable	Mean	Median	SD	Minimum	Maximum	Observations
Outcomes						
General Health	48.96	45.61	9.75	24.85	66.37	31395
Mental Health: Summary Scale	51.17	52.85	9.79	3.11	79.33	31395
... General	51.13	50.26	9.75	19.73	68.58	31395
... Role-Emotional Functioning	50.34	58.08	9.96	13.34	58.08	31395
... Social Functioning	50.20	57.12	9.97	14.69	57.12	31395
... Vitality	49.64	48.71	9.92	26.82	70.60	31395
Physical Health: Summary Scale	48.19	49.88	10.13	9.21	77.65	31395
... Role-Physical Functioning	49.02	50.27	10.39	21.92	59.72	31395
... Physical Functioning	48.54	50.58	10.35	27.25	58.35	31395
... Bodily Pain	49.17	50.64	10.25	23.00	59.85	31395
Self-Assessed Health	3.32	3.00	0.94	1.00	5.00	31395
Doctor Visits	9.72	4.00	15.45	0.00	396.00	30229
Covariates						
Age	53.50	54.00	16.70	16.00	99.00	31395
Gender [1: male, 2: female]	1.51	2.00	0.50	1.00	2.00	31395
Is Married	0.71	1.00	0.46	0.00	1.00	31395
Is in Civil Partnership	0.00	0.00	0.02	0.00	1.00	31395
Is Divorced	0.06	0.00	0.24	0.00	1.00	31395
Is Widowed	0.07	0.00	0.26	0.00	1.00	31395
Is Unemployed	0.04	0.00	0.20	0.00	1.00	31395
Is on Parental Leave	0.01	0.00	0.09	0.00	1.00	31395
Is in Training	0.02	0.00	0.14	0.00	1.00	31395
Is Part-Time Employed	0.12	0.00	0.33	0.00	1.00	31395
Is Full-Time Employed (baseline)	0.34	0.00	0.48	0.00	1.00	31395
Number of Individuals in Household	2.79	2.00	1.30	1.00	13.00	31395
Number of Children in Household	0.49	0.00	0.92	0.00	8.00	31395
Is Owner	0.70	1.00	0.46	0.00	1.00	31395
Is Renter (baseline)	0.30	0.00	0.46	0.00	1.00	31395
Annual Rent (in 1000)	4.34	2.40	5.73	0.00	119.99	31395
Annual Net Household Income (in 1000)	36.63	31.20	28.85	0.12	1199.99	31395

Summary statistics for outcomes are before standardising.

Table E.2: Wind power plants: summary statistics.

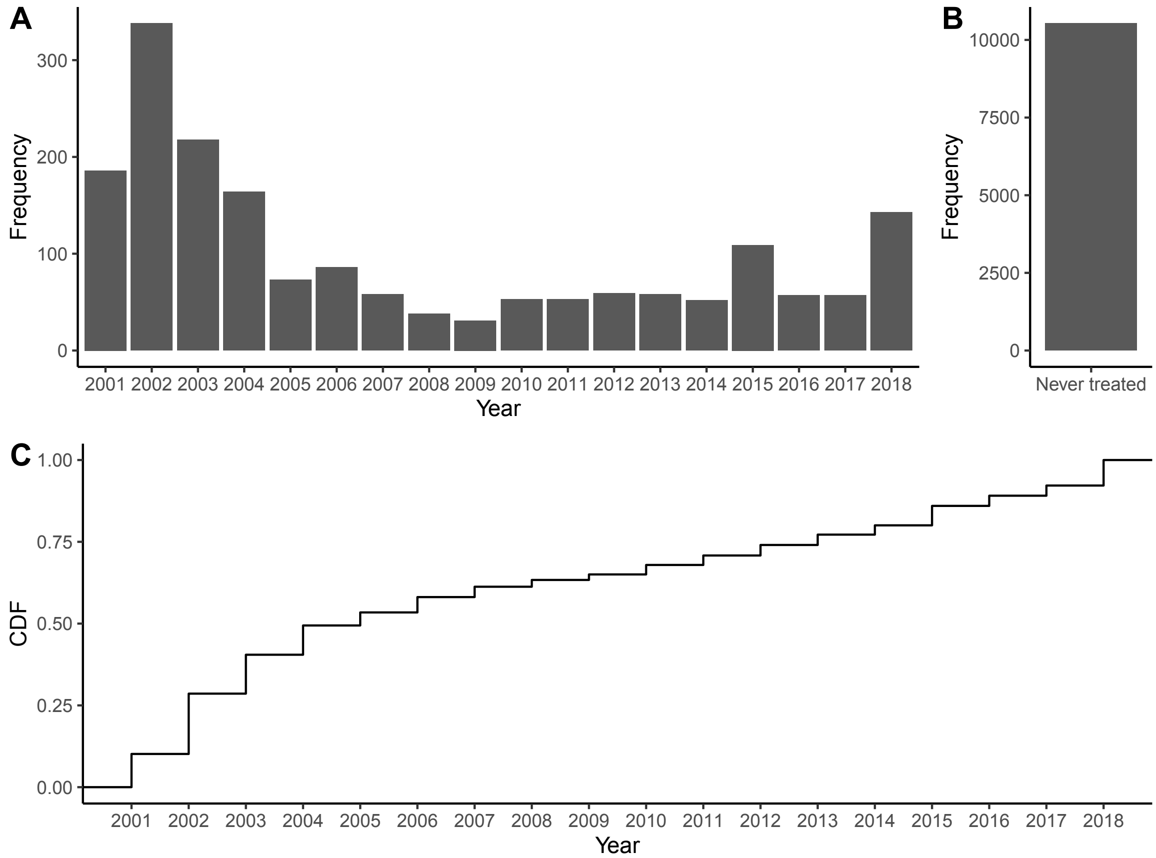
Variable	mean	md	sd	min	max
Power capacity [MW]	1.55	1.5	0.82	0	3.4
Hub height [m]	88.42	85.0	32.15	4	149.0
Rotor diameter [m]	76.23	77.0	23.26	6	126.0

Table E.3: Wind power plants: summary statistics per year.

Variable	year	mean	md	sd	min	max
Power capacity [MW]	2002	1.28	1.50	0.48	0.01	2.00
	2010	1.72	2.00	0.74	0.01	3.05
	2015	2.39	2.40	0.99	0.05	3.30
Hub height [m]	2002	75.71	74.00	18.07	10.00	100.00
	2010	98.11	98.00	34.29	10.00	138.00
	2015	122.06	140.00	35.36	32.00	149.00
Rotor diameter [m]	2002	64.24	70.00	15.44	6.00	80.00
	2010	75.74	82.00	15.17	48.00	101.00
	2015	112.24	115.35	12.84	77.00	126.00

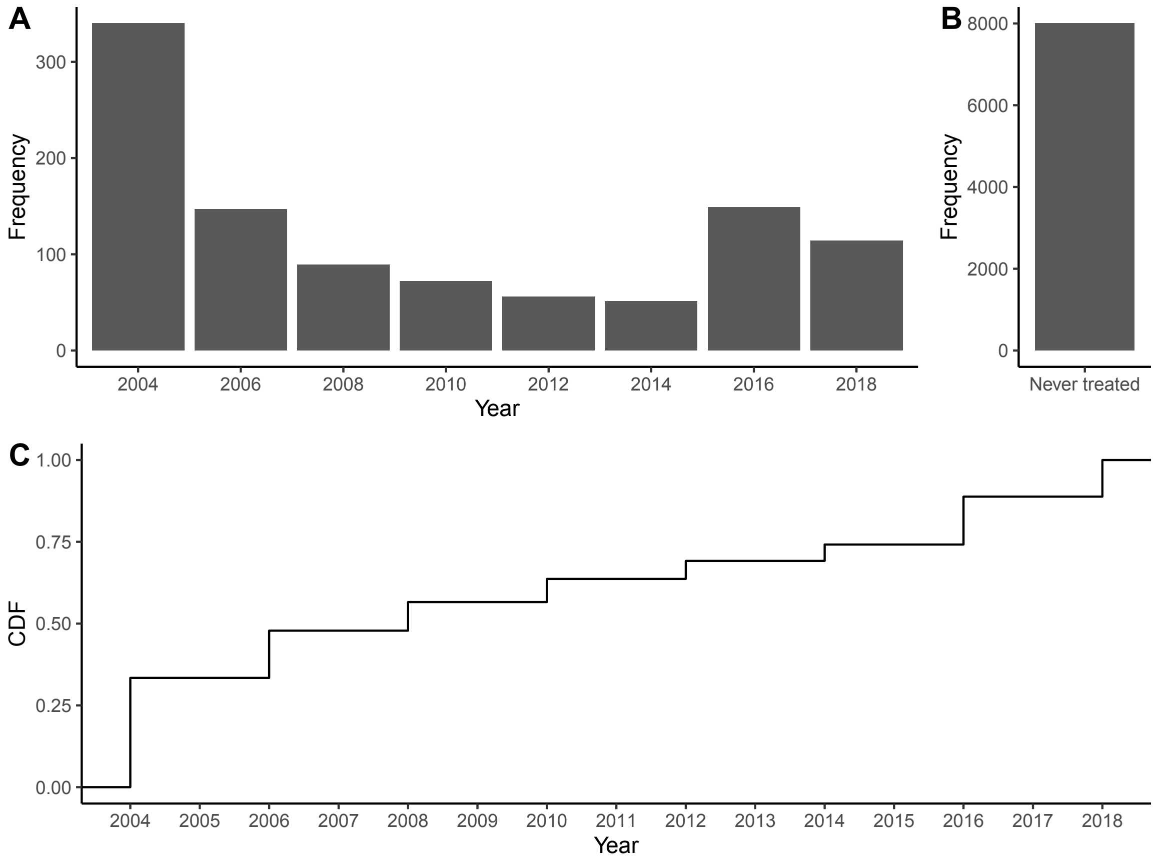
Table E.4: Normalised differences between treatment (4 km) and control (4-8 km) group.

	Mean		Variance		
Variable	Treatment	Control	Treatment	Control	Normalised Difference
Age	54.91	53.01	252.84	287.36	0.08
Gender [1: male, 2: female]	1.49	1.52	0.25	0.25	0.03
Is Married	0.74	0.69	0.19	0.21	0.08
Is in Civil Partnership	0	0	0	0	0
Is Divorced	0.05	0.06	0.05	0.06	0.03
Is Widowed	0.07	0.07	0.06	0.07	0.01
Is Unemployed	0.04	0.04	0.04	0.04	0.01
Is on Parental Leave	0	0.01	0	0.01	0.04
Is in Training	0.02	0.02	0.02	0.02	0.02
Is Part-Time Employed	0.11	0.12	0.1	0.11	0.03
Is Full-Time Employed (baseline)	0.35	0.34	0.23	0.23	0.01
Number of Individuals in Household	2.72	2.82	1.43	1.76	0.05
Number of Children in Household	0.41	0.52	0.69	0.89	0.09
Is Owner	0.77	0.67	0.18	0.22	0.15
Is Renter (baseline)	0.23	0.33	0.18	0.22	0.15
Annual Rent (in 1000)	4.38	4.33	30.03	33.86	0.01
Annual Net Household Income (in 1000)	35.09	37.17	420.58	976.04	0.06
Observations	8178	23217			



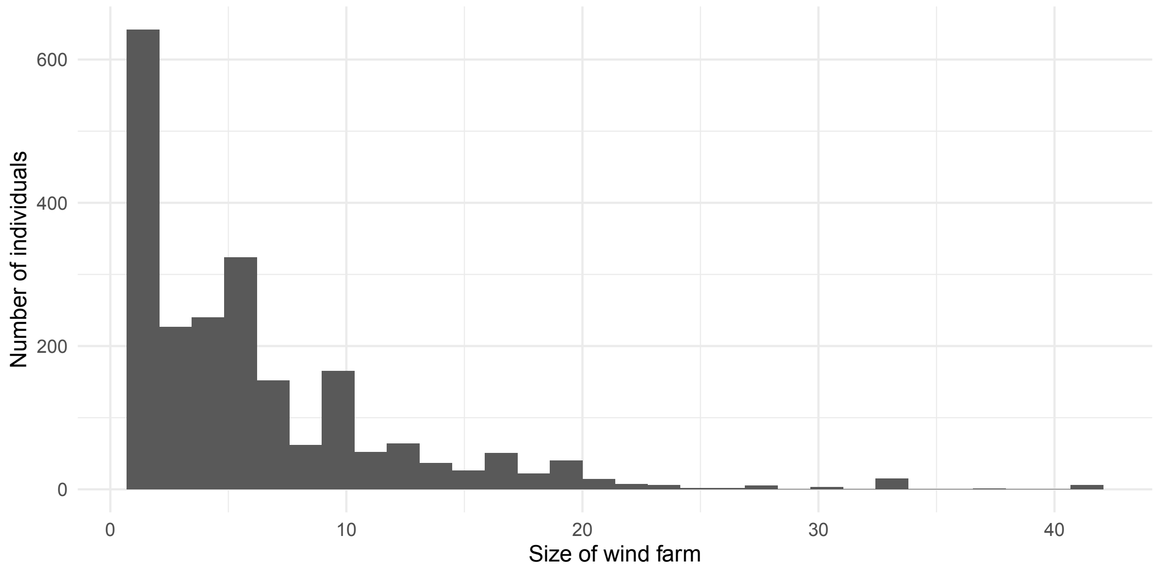
The figure relates to our baseline specification (0-4 km treatment group, 4-8 km control group, outcome: self-assessed health (Table 6.1 Column 4)). In *Panel A*, we show the frequency of firstly treated individuals (new wind turbine installed nearby individual by year). In *Panel B*, we show the frequency of never-treated individuals. *Panel C*, the cumulative density function of individuals from Panel A.

Figure E.2: Frequency (Panel A) and cumulative density (Panel B) of treated individuals by year and frequency of never treated individuals (Panel C) for outcome self-assessed health.



The figure relates to our baseline specification (0-4 km treatment group, 4-8 km control group, outcome: general health (Table 6.1 Column 1)). In *Panel A*, we show the frequency of firstly treated individuals (new wind turbine installed nearby individual by year). In *Panel B*, we show the frequency of never treated individuals. *Panel C*, the cumulative density function of individuals from Panel A.

Figure E.3: Frequency (Panel A) and cumulative density (Panel B) of treated individuals by year and frequency of never treated individuals (Panel C) for outcome general health.



The figure depicts the number of treated individuals by the size of the wind park. As seen, most individuals are treated by single wind turbines or by wind farms consisting of less than five wind turbines.

Figure E.4: Treatment intensity.

E.1.2 Results

E.1.2.1 Static

Table E.5: Robustness Checks.

	SF-12 Health Survey: General Health Summary Scale						
	SE Clust. at household (1)	Incl. movers (2)	Incl. all leads and lags (3)	Years < 2010 (4)	Years ≥ 2010 (5)	Small plants only (< 100m hub height) (6)	Large plants only (≥ 100m) (7)
Variables							
Treated 0-4 km	0.07*	0.07**	0.05	0.07	0.01	0.07*	0.05
	(0.04)	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)	(0.05)
Fixed-effects							
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Adjusted R^2	0.591	0.585	0.588	0.611	0.592	0.594	0.590
Obs.	26,903	41,051	27,731	10,724	14,432	25,405	24,707
N treated	700	923	700	385	197	417	280
N never treated	8,002	12,669	8,002	3,479	6,007	8,002	8,002

	SF-12 Health Survey: Mental Health Summary Scale						
	SE Clust. at household (1)	Incl. movers (2)	Incl. all leads and lags (3)	Years < 2010 (4)	Years ≥ 2010 (5)	Small plants only (< 100m hub height) (6)	Large plants only (≥ 100m) (7)
Variables							
Treated 0-4 km	-0.007	0.009	-0.03	0.03	0.02	-0.007	-0.006
	(0.05)	(0.03)	(0.04)	(0.05)	(0.08)	(0.05)	(0.05)
Fixed-effects							
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Adjusted R^2	0.485	0.481	0.485	0.508	0.487	0.479	0.483
Obs.	26,903	41,051	27,731	10,724	14,432	25,405	24,707
N treated	700	923	700	385	197	417	280
N never treated	8,002	12,669	8,002	3,479	6,007	8,002	8,002

	SF-12 Health Survey: Physical Health Summary Scale						
	SE Clust. at household (1)	Incl. movers (2)	Incl. all leads and lags (3)	Years < 2010 (4)	Years ≥ 2010 (5)	Small plants only (< 100m hub height) (6)	Large plants only (≥ 100m) (7)
Variables							
Treated 0-4 km	0.0009	0.006	-0.001	0.01	-0.10	0.01	-0.02
	(0.04)	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)	(0.05)
Fixed-effects							
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Adjusted R^2	0.668	0.663	0.664	0.683	0.675	0.670	0.672
Obs.	26,903	41,051	27,731	10,724	14,432	25,405	24,707
N treated	700	923	700	385	197	417	280
N never treated	8,002	12,669	8,002	3,479	6,007	8,002	8,002

	Self-Assessed Health						
	SE Clust. at household (1)	Incl. movers (2)	Incl. all leads and lags (3)	Years < 2010 (4)	Years ≥ 2010 (5)	Small plants only (< 100m hub height) (6)	Large plants only (≥ 100m) (7)
Variables							
Treated 0-4 km	0.02	0.009	0.02	0.05*	-0.02	0.03	-0.008
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)
Fixed-effects							
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Adjusted R^2	0.601	0.591	0.597	0.620	0.600	0.604	0.601
Obs.	68,289	101,396	71,869	32,488	32,558	63,774	58,944
N treated	1,509	2,038	1,510	1,062	378	1,023	481
N never treated	10,533	16,148	10,533	4,650	7,697	10,533	10,533

	Doctor Visits						
	SE Clust. at household (1)	Incl. movers (2)	Incl. all leads and lags (3)	Years < 2010 (4)	Years ≥ 2010 (5)	Small plants only (< 100m hub height) (6)	Large plants only (≥ 100m) (7)
Variables							
Treated 0-4 km	0.03	0.02	0.03	0.05*	-0.03	0.04	-0.009
	(0.03)	(0.02)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)
Fixed-effects							
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Adjusted R^2	0.357	0.339	0.346	0.366	0.363	0.357	0.348
Obs.	65,068	97,343	68,652	32,446	29,391	60,573	55,746
N treated	1,508	2,037	1,509	1,064	375	1,022	480
N never treated	8,767	13,941	8,767	4,647	5,933	8,767	8,767

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant, unless differently) standard errors in parentheses; treatment group 0-4 km; control group 4-8 km.

Table E.6: Average Treatment Effects: Mental Health.

	SF-12 Health Survey: Mental Health			
Dependent Variable:	General	Role-Emotional Functioning	Social Functioning	Vitality
	(1)	(2)	(3)	(4)
Variable				
Treated 0-4 km	0.02	-0.03	-0.007	-0.008
	(0.04)	(0.04)	(0.04)	(0.04)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Individual	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes
Statistics				
Adjusted R^2	0.484	0.470	0.431	0.452
Obs.	26,903	26,903	26,903	26,903
N treated	700	700	700	700
N never treated	8,002	8,002	8,002	8,002

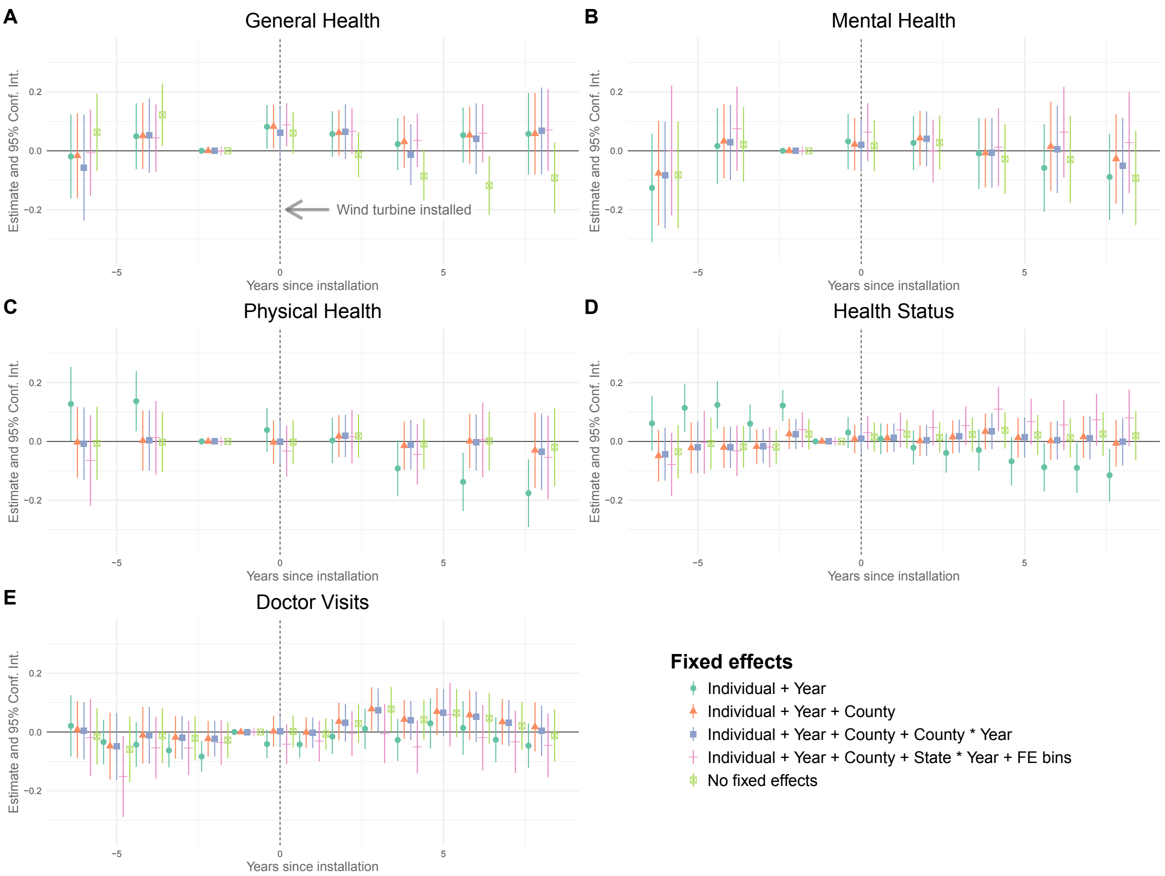
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant) standard-errors in parentheses; treatment group 0-4 km; control group 4-8 km.
Outcomes in z-scores; more indicates better health.

Table E.7: Average Treatment Effects: Physical Health.

	SF-12 Health Survey: Physical Health		
Dependent Variable:	Role-Emotional Functioning	Physical Functioning	Bodily Pain
	(1)	(2)	(3)
Variable			
Treated 0-4 km	-0.01	-0.01	-0.03
	(0.03)	(0.03)	(0.04)
Controls	Yes	Yes	Yes
Fixed-effects			
Individual	Yes	Yes	Yes
County	Yes	Yes	Yes
State-Year	Yes	Yes	Yes
Statistics			
Adjusted R^2	0.545	0.658	0.522
Obs.	26,903	26,903	26,903
N treated	700	700	700
N never treated	8,002	8,002	8,002

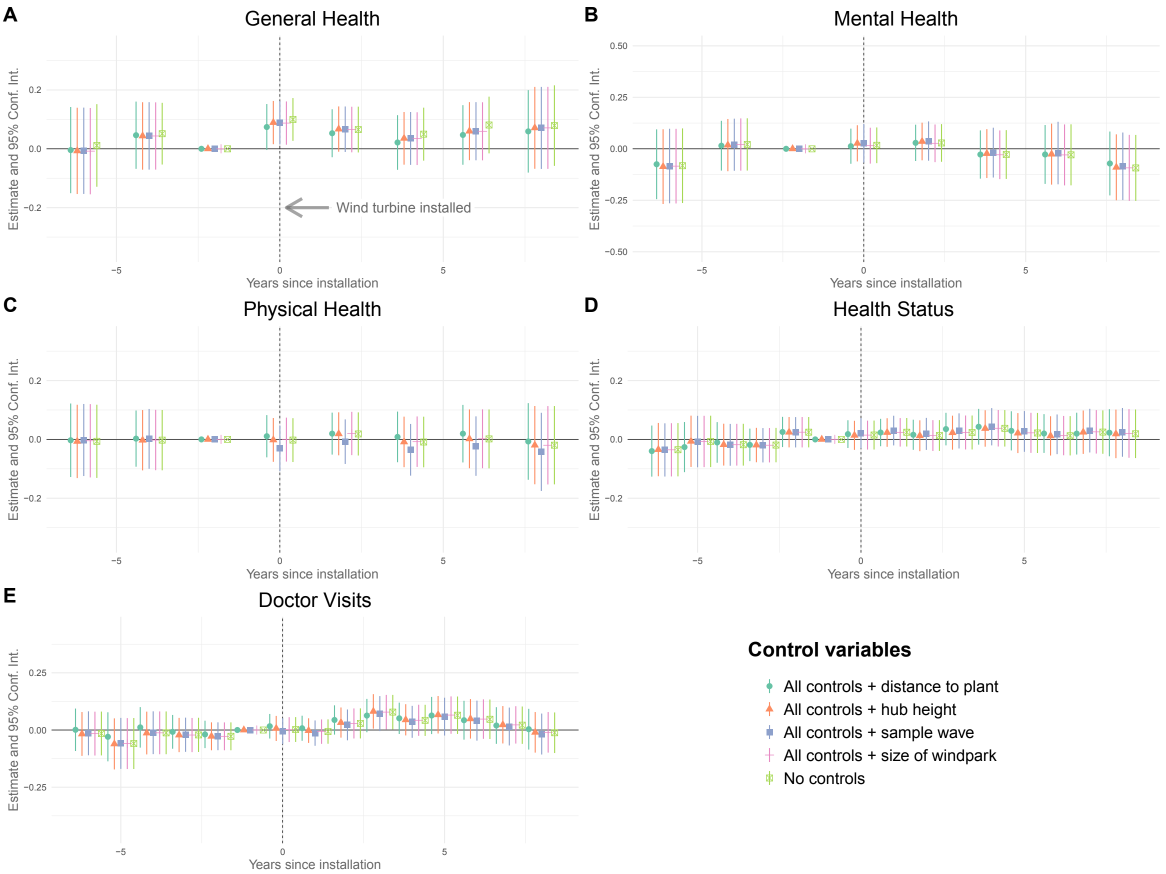
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant) standard-errors in parentheses; treatment group 0-4 km; control group 4-8 km.
Outcomes in z-scores; more indicates better health (but for bodily pain more indicates worse).

E.1.2.2 Dynamic



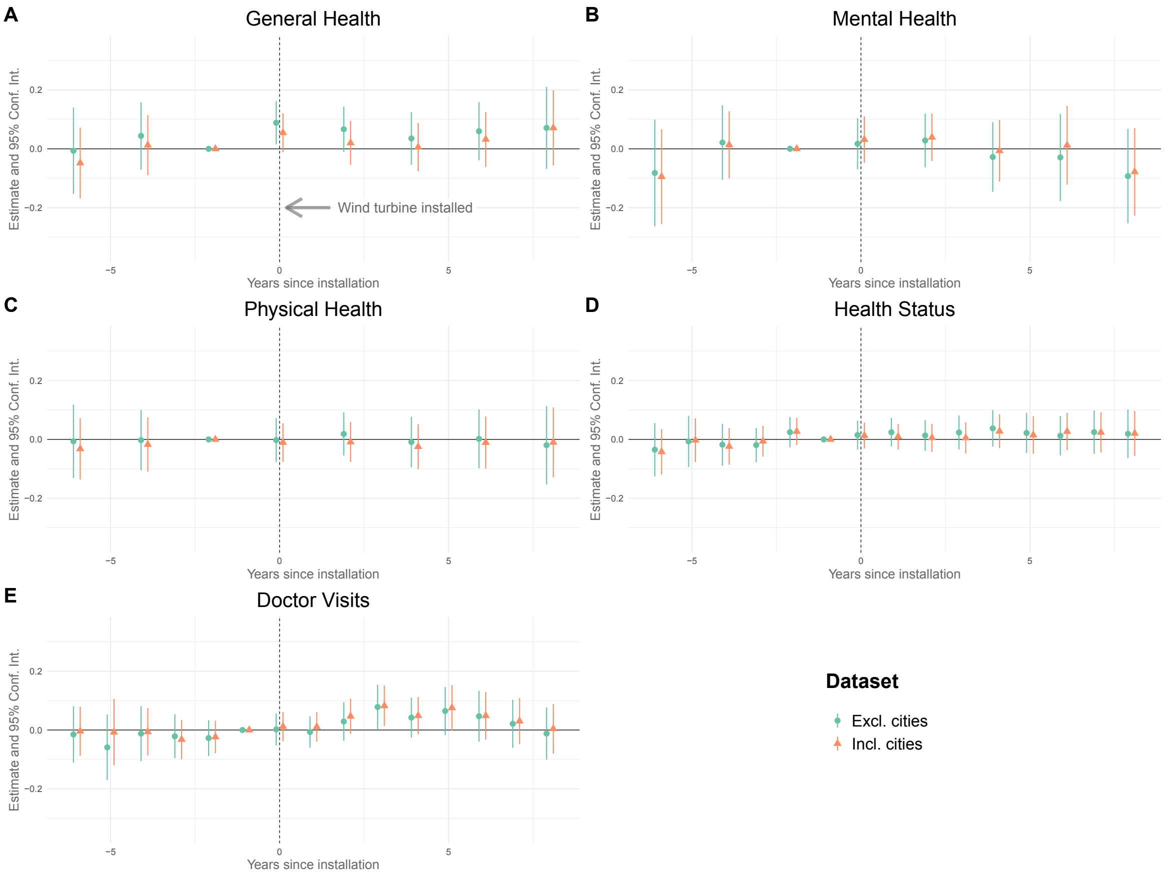
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.5: Dynamic effects for different fixed effects. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



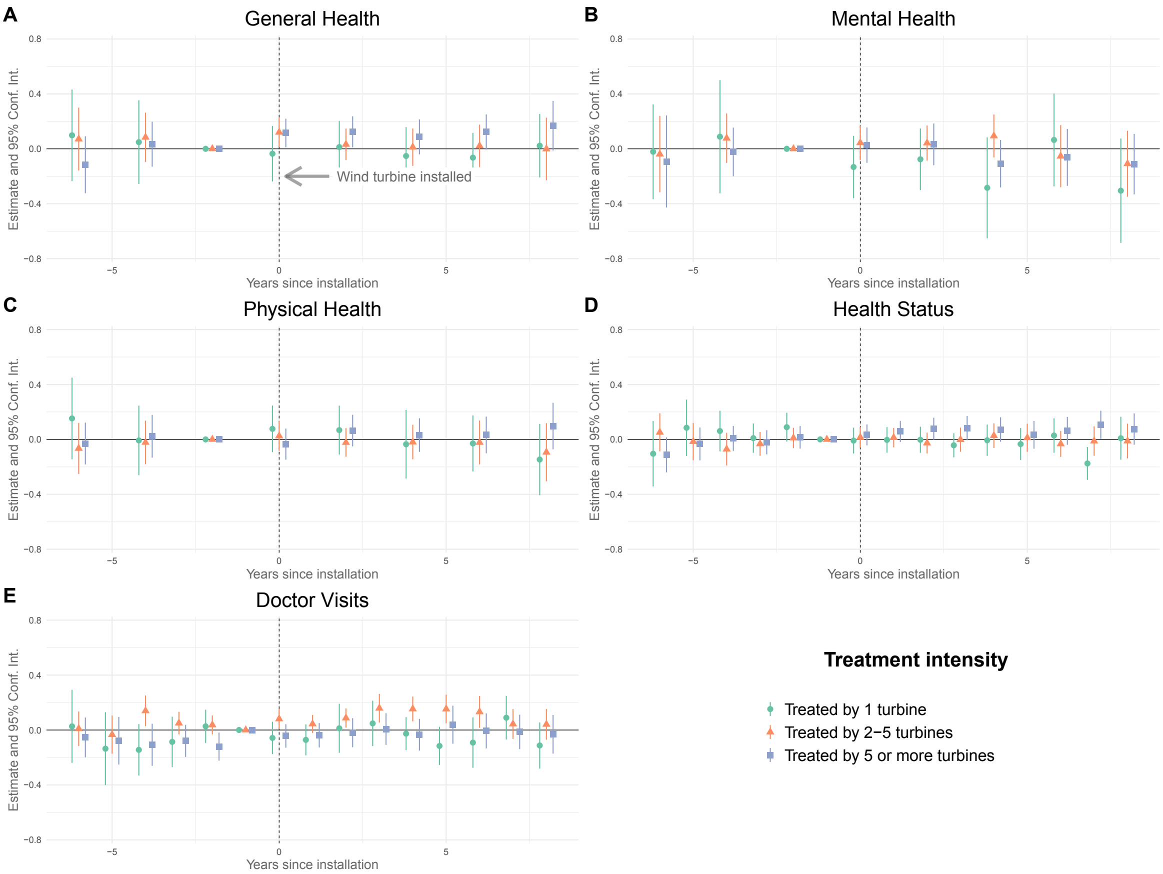
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.6: Dynamic effects for different control variables. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



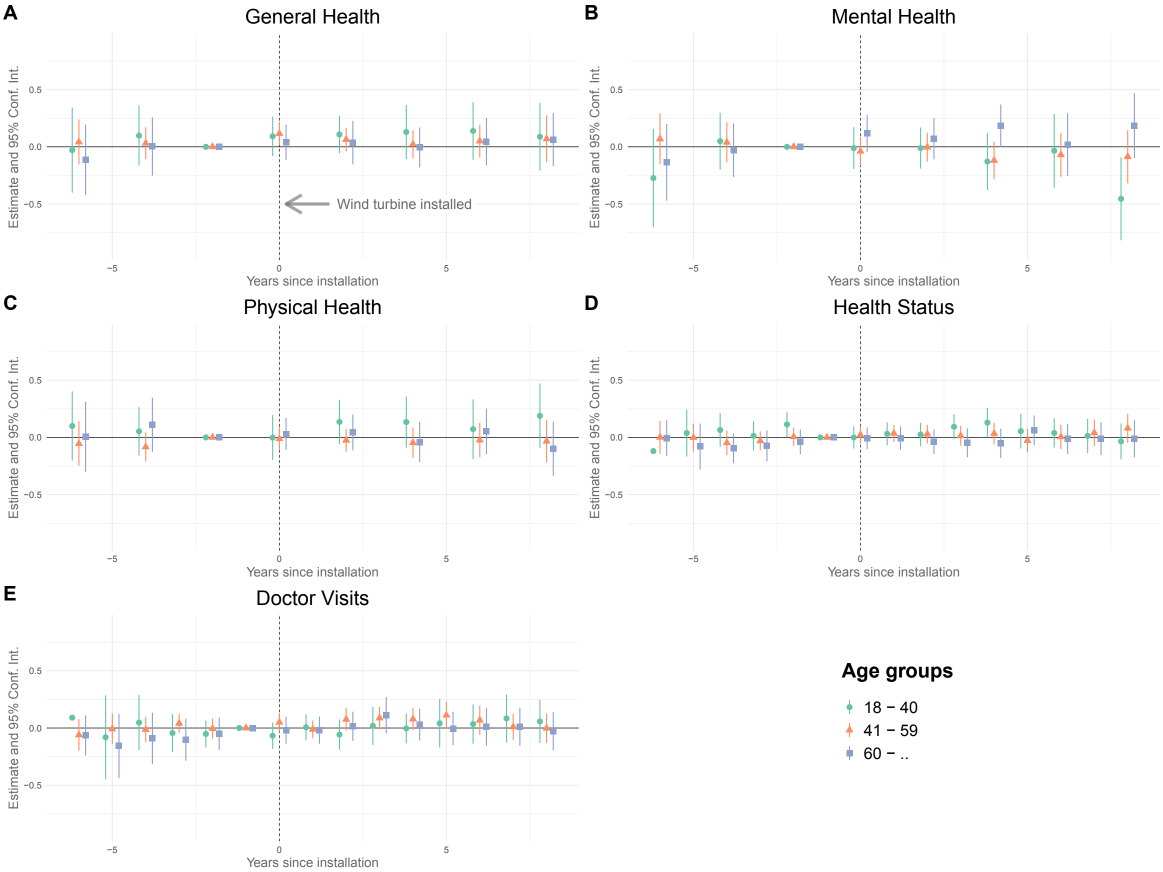
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.7: Dynamic effects for different samples, excl. and incl. cities. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



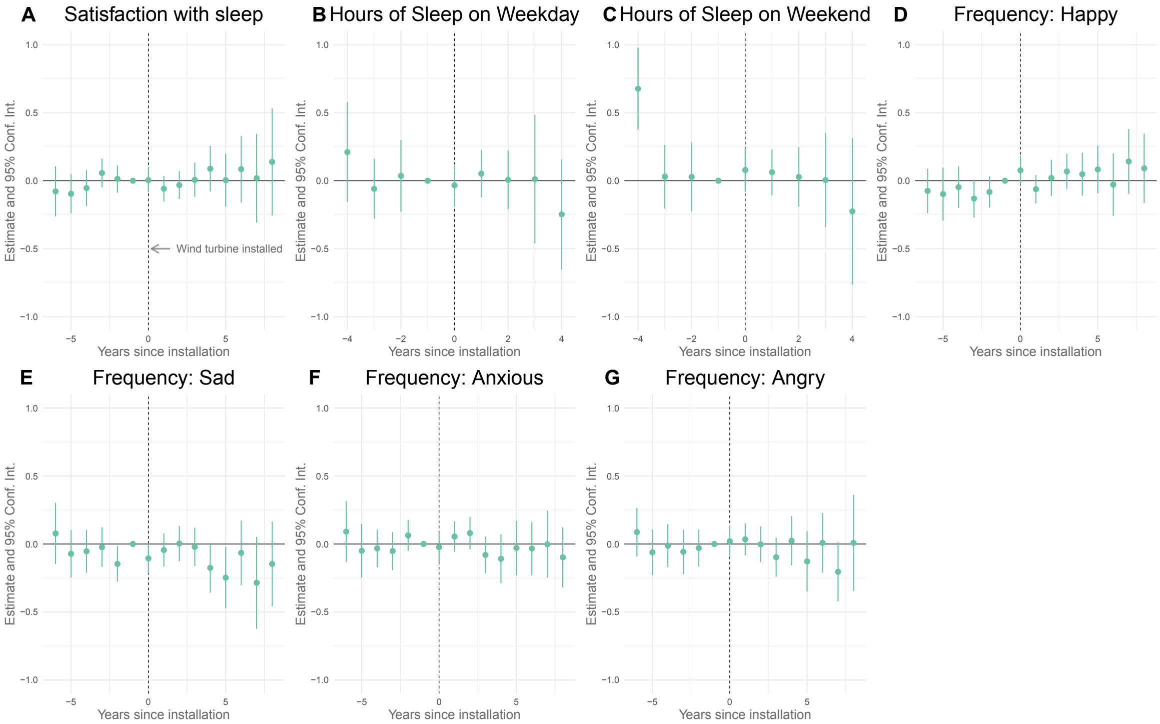
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.8: Treatment intensities. Difference in health outcomes between individuals living nearby one or several newly built wind turbines (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



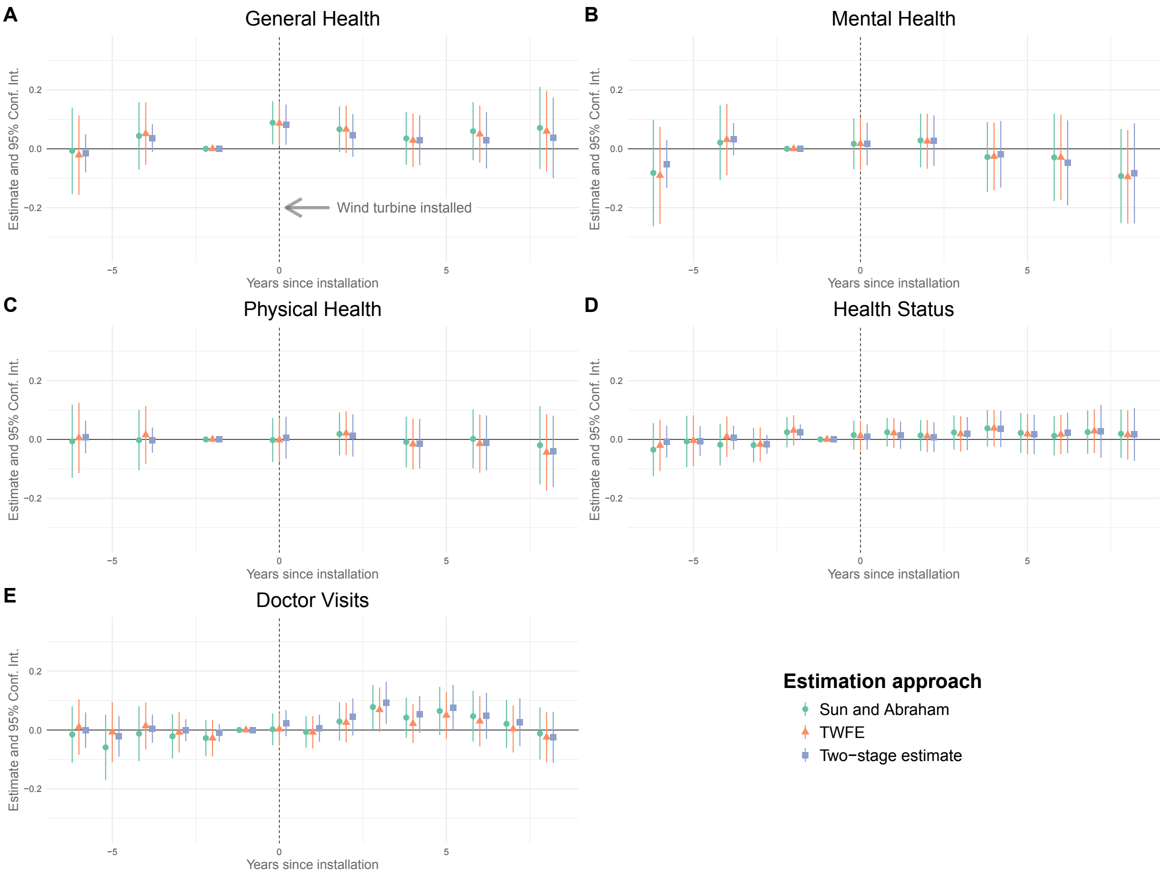
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.9: Dynamic effects for different age groups. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



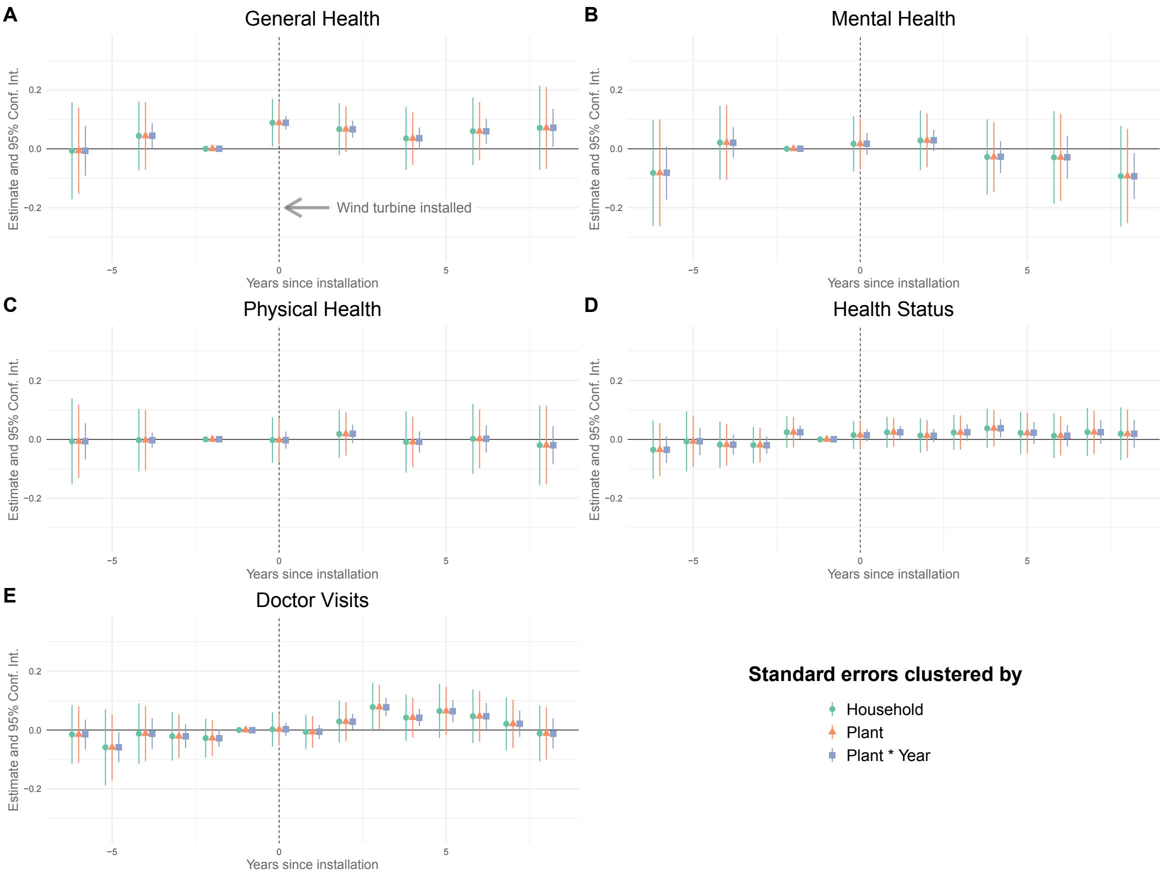
Sun-Abraham estimator. 0-4 km treatment group, 4-8 km control group. Panels A-C as of 2008 (until 2013 for B and C), Panels D-G as of 2007. Outcomes are in z-scores. More indicates better health (but for panels E, F, G more indicates worse).

Figure E.10: Different outcomes. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



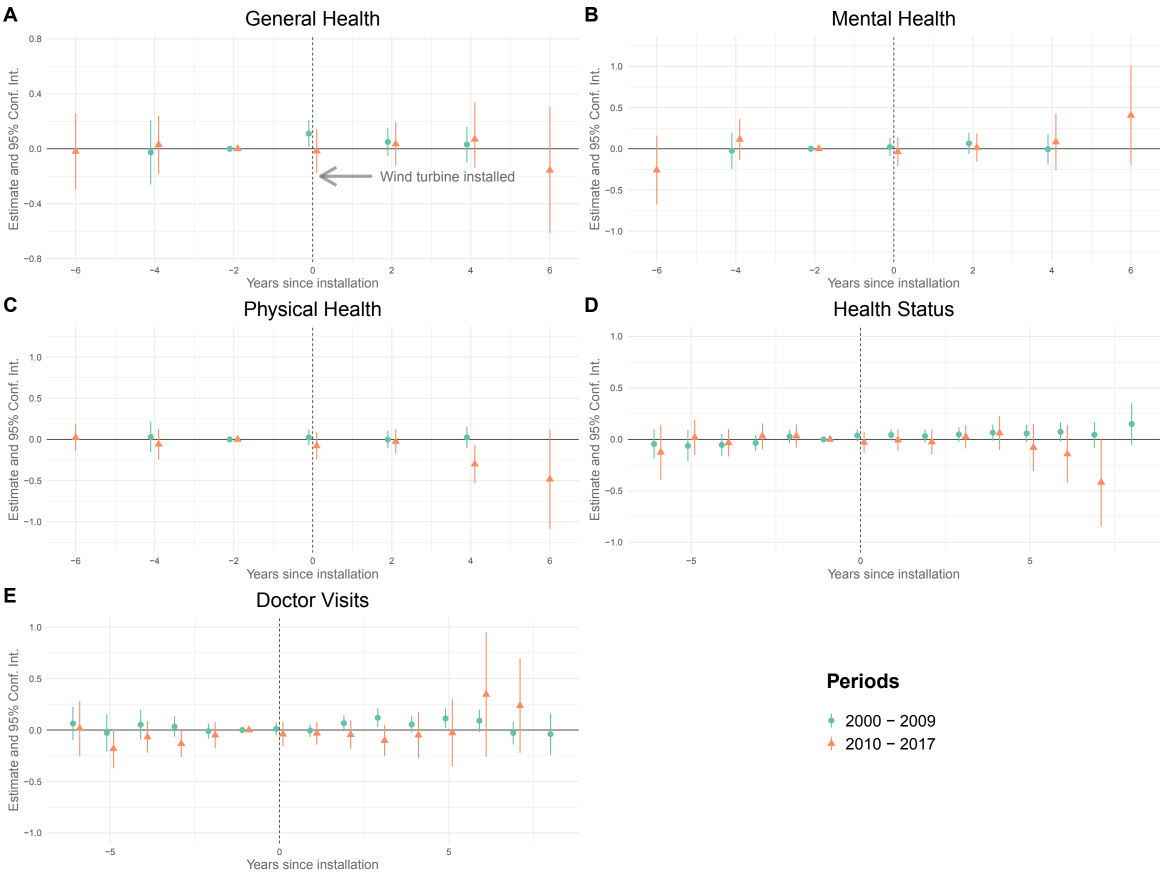
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.11: Dynamic effects (different estimators). Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



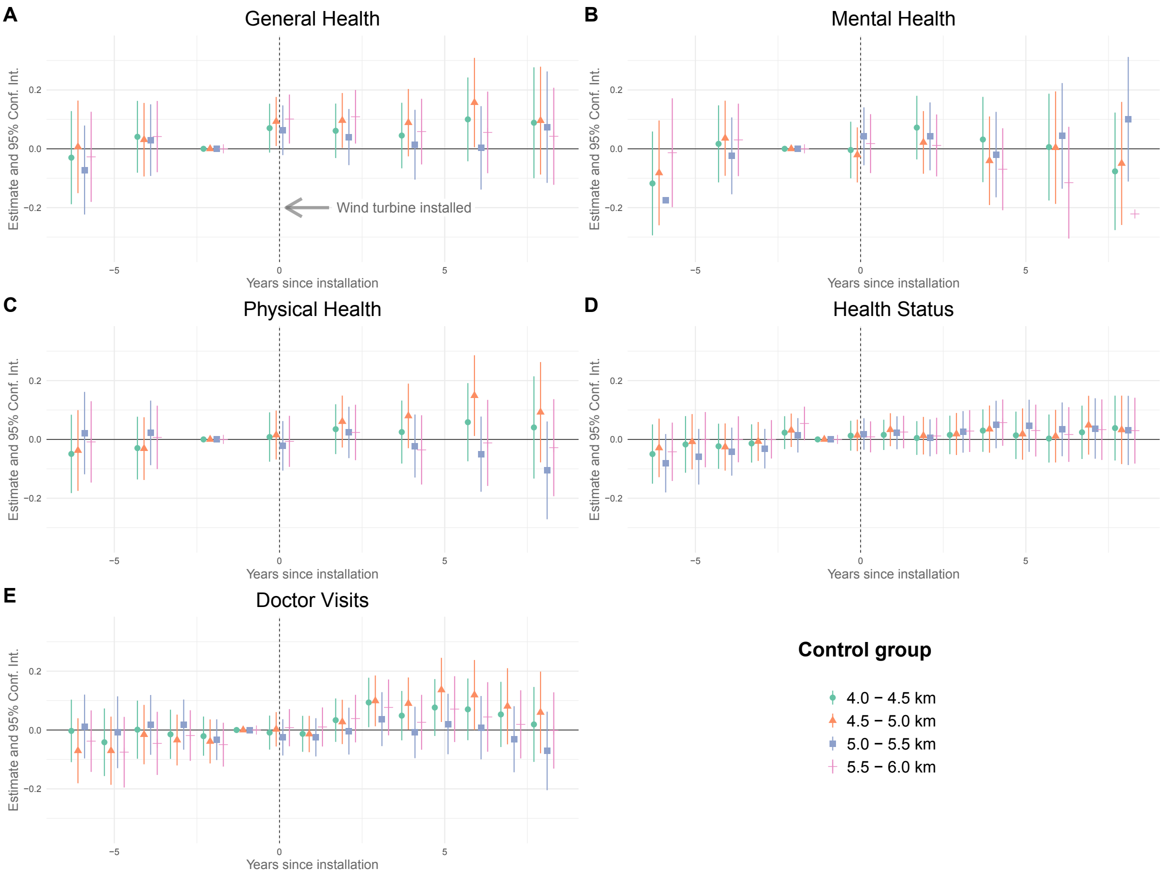
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.12: Dynamic effects for different clustering of standard errors. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



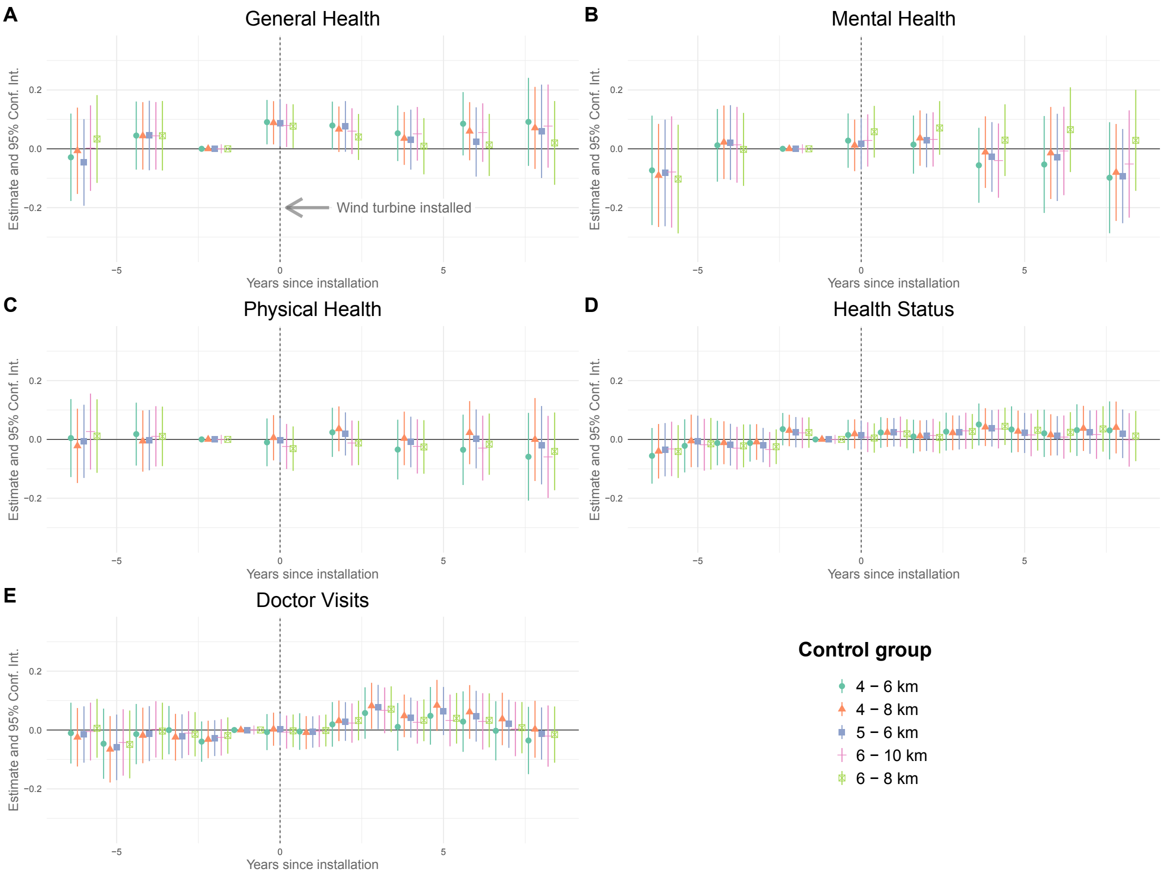
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.13: Dynamic effects for different sample periods. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters).



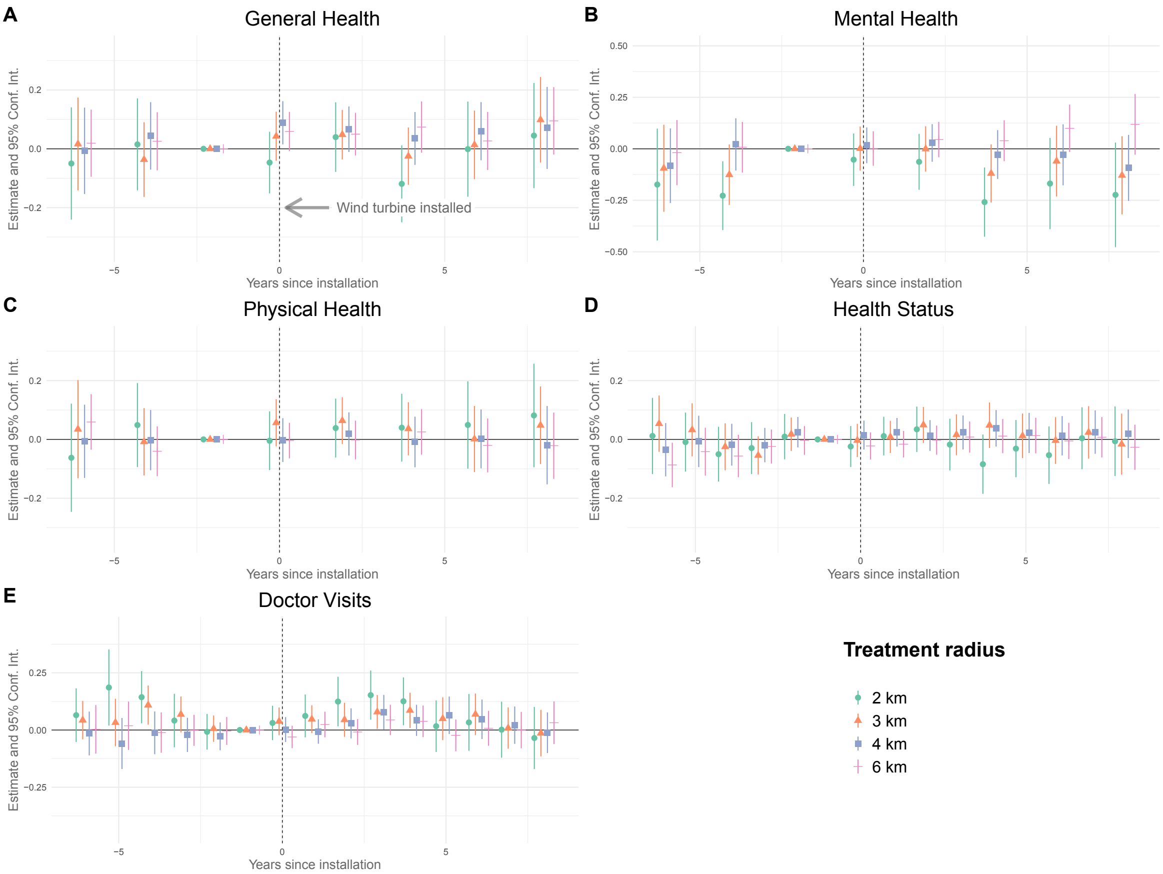
Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.14: Dynamic effects for different control groups. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 4,500 meters, within 4,000 and 5,000 meters, within 4,500 and 5,000 meters, within 5,000 and 5,500 meters, or within 5,500 and 6,000 meters).



Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.15: Dynamic effects for different control groups. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 meters) and individuals further away (i.e. between 4,000 and 6,000 meters, within 4,000 and 8,000 meters, or within 6,000 and 10,000 meters).

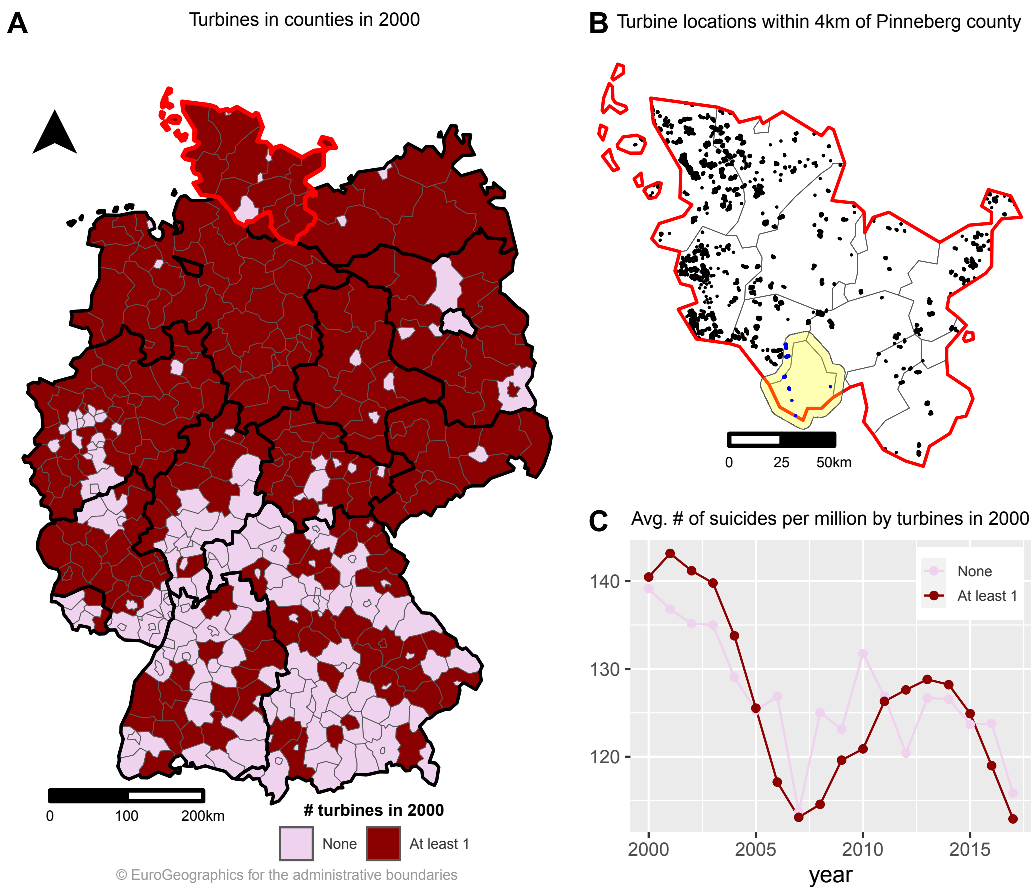


Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse).

Figure E.16: Dynamic effects for different treatment radii. Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 2,000 meters, within 3,000 meters or within 4,000 meters) and individuals further away (i.e. between 4,000 and 8,000 meters). For treatment of 6,000 meters, the control group is 6,000-10,000 meters.

E.2 Suicides

E.2.1 Descriptives



Panel A shows counties with and without wind turbines in Germany in 2000. The thick black lines indicate the borders of federal states (NUTS-1 regions), whereas the red thick line indicates the border of the federal state of *Schleswig-Holstein*, the most northern German state. *Panel B* is a close-up of *Schleswig-Holstein* and shows, as an example, the exact location of each installation in that federal state, where each dot indicates one installation. Blue dots highlight turbine locations within 4 km of *Pinneberg* county. *Panel C* plots the average number of suicides per million population by year for counties with and without turbines as of 2000.

Figure E.17: Counties with and without wind turbines in 2000, illustration of turbines nearby a county and average suicides by population over time for counties with and without turbines.

Table E.8: Summary statistics suicides

Variable	Mean	Median	SD	Minimum	Maximum	Observations
Outcomes						
Suicides per million population	128.91	126.38	34.48	22.70	273.98	1190
Covariates						
Unemployed per capita	0.03	0.02	0.01	0.01	0.11	1190
GDP per capita [in thousand EUR]	28.29	26.00	11.29	11.01	107.42	1190
Average age	42.26	42.31	1.75	37.36	48.71	1190

Table E.9: Normalised differences between treated and not treated counties

	Mean		Variance		
Variable	Treatment	Control	Treatment	Control	Normalised Difference
Unemployed per capita	0.03	0.03	0	0	0.03
GDP per capita [in thousand EUR]	30.34	25.8	177.02	56.62	0.3
Average age	42.07	42.5	3.2	2.84	0.17
Observations	539	651			

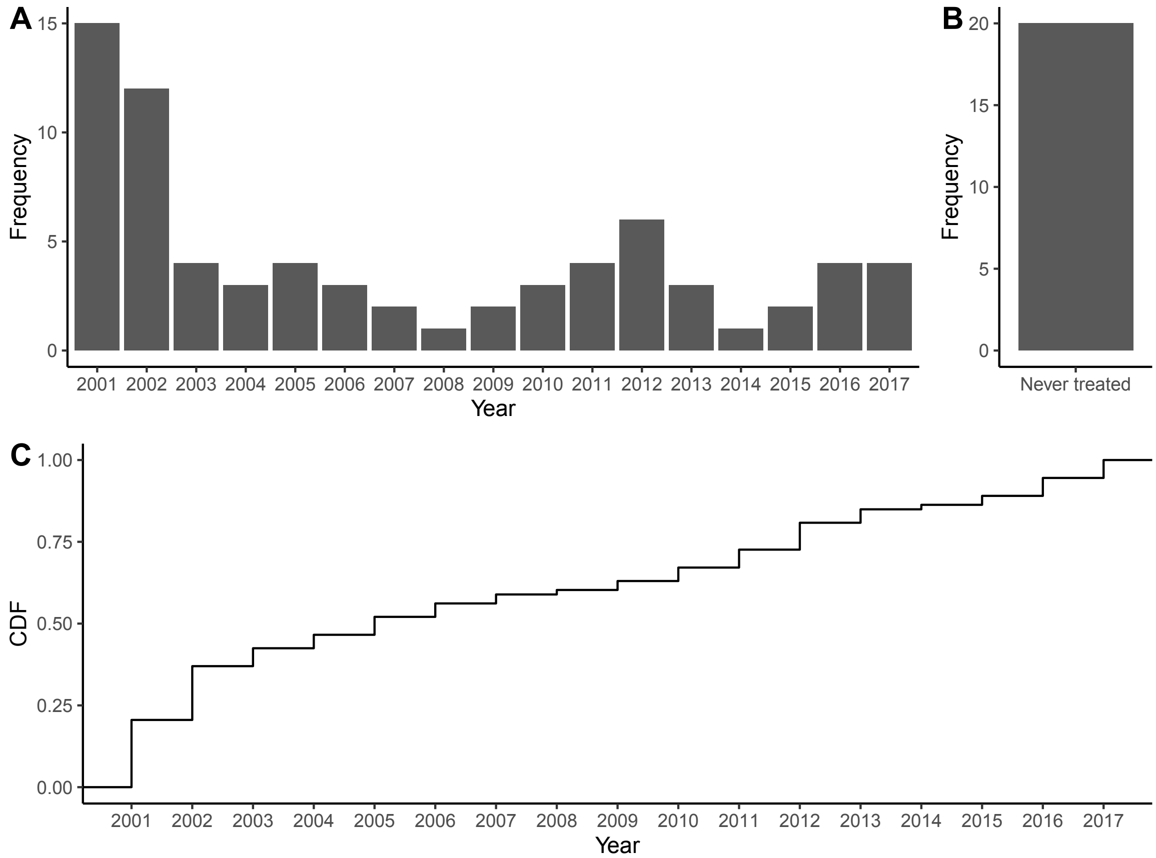


Figure E.18: Frequency (Panel A) and cumulative density (Panel B) of treated counties by year and frequency of never treated counties (Panel C).

E.2.2 Results

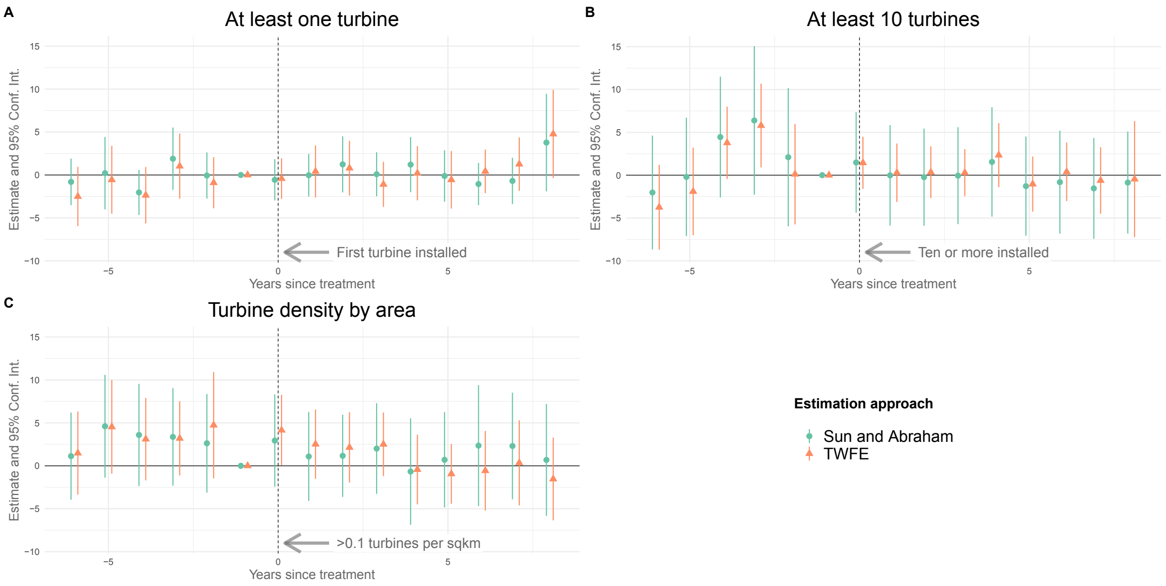
E.2.2.1 Static

Table E.10: Robustness of wind turbines on suicides.

Description	Other dependent variable	Controlling for intensity		With urban counties	Years 2000-2009	Years 2010-2017	Considering turbines within 4km	With counties with turbine in 2000
Dependent Variables:	ln(Suicides)	Suicides per million population						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable								
ATT	1.8×10^{-17}	-0.11	-0.78	-1.6	0.90	-3.4	-0.22	-0.39
	(2.6×10^{-17})	(1.4)	(2.2)	(1.1)	(1.3)	(2.9)	(1.4)	(0.93)
# Turbines		0.08						
		(0.08)						
ln(1 + #Turbines)			0.79					
			(1.0)					
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics								
Adjusted R^2	1	0.959	0.959	0.924	0.963	0.970	0.965	0.949
Observations	1,190	1,190	1,190	2,474	723	390	828	4,700
N treated	73	73	73	102	46	30	55	272
N never treated	20	20	20	74	39	20	11	20

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (county) standard-errors in parentheses;
Controls are GDP per capita, unemployment rate, average age and the log of number of suicides lagged by 10 years.
In columns (1-3, 5-8), we focus on non-urban areas only. In columns (1-7), we neglect counties with a turbine installed in 2000.

E.2.2.2 Dynamic



Standard errors are clustered at the county level. We control for GDP per capita, the unemployment rate and average age. In *Panel A*, we focus on non-urban areas only and also control for the log of number of suicides lagged by 10 years. We neglect counties that had a turbine already installed in 2000. In *Panel B*, we neglect observations with between 1 and 9 turbines installed and counties that had 10 or more turbines already installed in 2000. In *Panel C*, we neglect regions with more than 0.1 turbines per sqkm in 2000. We also drop observations with between 0.075 and 0.1 turbines per sqkm. Table 6.2 contains further details on the underlying estimations.

Figure E.19: Dynamic effects for wind turbines on suicides per 1,000,000 population for two estimation approaches. Difference between counties with a (new) wind turbine (Panel A), counties with at least 10 turbines (Panel B) or counties with at least 0.1 turbines per sqkm (Panel C) and counties without turbines.

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