Technische Universität München
TUM School of Management

Strategies and Policy Design: Three Essays on Renewable Energy Integration

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Vollständiger Abdruck der von der TUM School of Management der Technischen Universität München zur Erlangung des akademischen Grades eines Doktors der Wirtschafts- und Sozialwissenschaften (Dr. rer. pol.) genehmigten Dissertation.

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Die Dissertation wurde am 08.07.2022 bei der Technischen Universität München eingereicht und durch die TUM School of Management am 15.09.2022 angenommen.

Acknowledgements

I sincerely want to thank my first supervisor, Prof. Dr. Gunther Friedl, for being so supportive throughout my doctoral studies. Your advice, your feedback and also your trust in my work and abilities were incredibly motivating and helpful. Your open attitude towards new thoughts and ideas combined with the amazing flexibility and freedom you provided for my research and my personal development made me fall in love with academia. I am so thankful, that I received the opportunity to follow my interests and develop many new skills with your support. I am still learning new things on a daily basis along the early responsibilities you trusted me with during many research projects over the years. These experiences definitely helped me to become a truly independent researcher ready for new challenges.

I thank Prof. Dr. Svetlana Ikonnikova for interesting discussions during webinars and ACE lunches at the TUM and for heading my examination committee. Furthermore, I want to thank Prof. Hua Liao, Ph.D. for providing feedback and recommendations on my first paper in the early days of my academic journey when I visited him and his amazing team in Beijing. I am very thankful that you welcomed me so warmly within your research group and further motivated me to continue my path in academia.

My studies in the last years would not have been half as enjoyable, if it was not for my great colleagues at the Chair of Management Accounting. My colleagues perfectly combine bright minds with an awkwardly sarcastic humor. Even if my time at our faculty will have to end at some point to hopefully continue in academia somewhere else, I will always remember the many great moments and laughs we had. You made it special. I owe a special thanks to Dr. Peter Schäfer for always having time to share his genius mind whenever I was stuck. I also want to specially thank Prof. Dr. Sebastian Schwenen as well as Dr. David Matthäus, Dr. Friedrich Walcher, Prof. Dr. Gunther Glenk, Yanis Gamarra, Matthias Regier and Magnus Schauf for their incredibly valuable feedback, support and academic advice in so many occasions. I could not thank you enough for that. Another special thanks goes out to Ursula Steffl and Patricia

Norum for always covering my back with all the administrative tasks that came along, especially for our TUMfast scholarship program. Furthermore, I thank my student assistants Nikolai Milanov, Niklas Kluger and Hamitcan Canan.

However, there was nobody contributing more to this dissertation than my parents Ingrid and Herbert Blaschke. I truly am the luckiest person on earth to have received so much devotion and support following my dreams and interests. I also want to thank my brother Konstantin for the countless rather informal discussions about research in general. At this point I want to send some motivation for his current doctoral studies: If I should get this degree, it should be easy for you!

Last but not least, I want to express my deepest gratitude to my girlfriend, Elisabeth Hofmeister. Elisabeth, you raised me up whenever I felt like giving up and you cooled me down whenever I was too motivated with my work neglecting the need to sleep. Without you, I would have failed. Thank you so much for all your support and for reading, discussing and revising my entire dissertation. I am so grateful we met.

Abstract

This dissertation contributes three essays to tackle the challenges of integrating renewable energy sources. Renewable energy sources like photovoltaic power or wind energy could replace fossil fuels and by that reduce carbon emissions. The first essay uncovers structural barriers to residential demand side management with household devices. By simulating different taxation schemes, I can show that a dynamic tax mechanism could increase the incentives for households to participate in ecologically beneficial load shifting. The second essay shows that power suppliers could help decentralized storage systems to improve their charging strategy by taking over a few hours of price risk. By pre-announcing prices, power suppliers could utilize the storage capacities to balance renewable over- and underproduction and further integrate a higher share of renewable energy sources. The third essay contributes a method to calculate the value of carbon savings and innovation coming from subsidizing green technologies. The essay shows that the innovation effects of subsidizing electric vehicles are significant. However, the ecological value can not solely justify the corresponding government spending of the subsidy. My dissertation extends existing economic literature, specifically in the fields of sustainability and policy design by investigating regulations, subsidies and taxes in the energy and transportation sector. The three independent essays within this dissertation offer solutions and clarifications for policymakers to derive measures that efficiently foster the integration of renewable energies. By that, I hope to make a contribution in fighting climate change and enabling a quicker and broader adaption of renewable technologies for a sustainable future.

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1.1 Motivation and Background

"...the world is reaching the tipping point beyond which climate change may become irreversible. If this happens, we risk denying present and future generations the right to a healthy and sustainable planet - the whole of humanity stands to lose. On the other hand, climate change is an unprecedented opportunity for governments, investors, firms and citizens to work together to develop and deploy low-carbon technologies, which can sustain growth within our planetary boundaries. Shifting towards low-carbon energy systems can avert climate catastrophe while creating new opportunities for investment, growth and employment."
Kofi Annan, Former Secretary-General of UN in an interview within "The Guardian" published on the 3rd of May 2015 (The Guardian & Annan, 2015).

"We are the first generation to feel the effect of climate change and the last generation who can do something about it."
Barack Obama, President of the United States of America published via Twitter on 23rd of September 2014 (Obama, 2014).

Climate change and the corresponding global warming are one of the biggest threats to our planet. The fatal consequences of global warming might extinct thousands of species (see for example Root *et al.*, 2003 or Bellard *et al.*, 2012) around the globe and cause human deaths and health issues (see for example Patz *et al.*, 2005). Resulting in economic and agricultural catastrophes, the consequences of global warming are a serious threat especially for developing countries (see Rosenzweig & Parry, 1994, Wheeler & von Braun, 2013, Tol, 2018). However, as the above quotes state, there are measures and solutions to this threat as long as mankind reacts now and not later.

Especially politicians have the duty to consider future generations and act far-sighted as the development of low-carbon technologies might need decades, long after their political career, to finally pay off. Without pointing out these long-term effects to politicians and the public, our societies might have simply continued with the status-quo risking the planet as a home for our children and grandchildren. However, paving the way towards carbon neutrality now is essential in order to have a chance to trigger changing processes in time. Therefore, it is of major importance that research enriches our understanding of the effects of current political measures in tackling carbon emissions. By uncovering political or structural problems and showing potential solutions, I dedicated myself and this dissertation towards assisting politicians and the regulatory landscape on our way to a more sustainable future.

Politicians and the regulatory landscape already recognized the urgency of policy actions in climate matters. Under this urgency, the Paris Agreement of 2015 marked a global milestone in the international efforts to fight global warming. 196 countries signed this treaty to significantly reduce green house gas emissions in order to keep temperature rising below $1.5 - 2°C$ compared to pre-industrial levels (United Nations Climate Change, 2015). Just recently, the Glasgow climate conference in 2021 affirmed this political will with stricter goals and more detailed targets to reduce green house gas emissions (BBC, 2021). Green house gas emissions have various sources. As mentioned by Kofi Annan in the quote at the beginning of this chapter (The Guardian & Annan, 2015), the energy systems are the main sources of green house gases. As illustrated in Figure 1.1, burning fuel for generating electricity as well as to power vehicles in the transport sector are the two largest carbon emitting factors within the United States (United States Environmental Protection Agency, 2020). Having that detrimental impact, the electricity sector as well as mobility and transport emissions are frequently discussed in political and public debates.

The electric vehicle has emerged as a promising solution with the potential to decarbonize the mobility sector. With the latest electric vehicle sales numbers skyrocketing, electric drivetrains are already of major importance for individual mobility in many countries around the world (see for example International Energy Agency, 2021). The technology might further also decarbonize

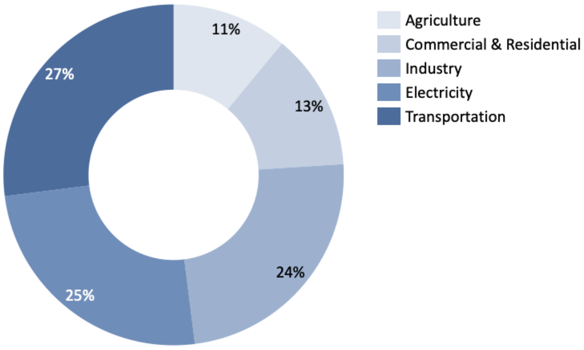


Figure 1.1: Illustration based on data of United States Environmental Protection Agency (2020) showing the share of human caused carbon emissions distinguished by economic sectors within the United States.

public and (in the long run) heavy transport. Without any tailpipe emissions, the electric vehicle only depends on a low-carbon electricity supply to keep a small carbon footprint (McCarthy & Yang, 2010, Doucette & McCulloch, 2011, Hawkins *et al.*, 2013, Faria *et al.*, 2013, Graff Zivin *et al.*, 2014, McLaren *et al.*, 2016, Nocera & Cavallaro, 2016, Rupp *et al.*, 2019). Hence, a low-carbon electricity supply with renewable energy sources could be key for both decarbonizing transportation and decarbonizing electricity consumption. Therefore, political measures and regulations to foster a transition towards integrating a higher share of renewable energy sources are tremendously important to solve the challenges within the electricity and the transportation sector.

Integrating a higher share of renewable power sources comes with multiple challenges. The output of these renewable power sources fluctuates with the weather and daytimes and cannot be rescheduled or terminated. Since supply is therefore inherently inflexible, balancing demand and supply becomes increasingly difficult. To overcome these difficulties, additional flexibility measures like grid enhancements, energy storage or demand side management need to be installed (Lund *et al.*, 2015, Cruz *et al.*, 2018, Zappa *et al.*, 2019).

Grid enhancements help to diversify the power supply between different locations and integrate a higher share of renewable energy sources (see Bayer *et al.*, 2018, Allard *et al.*, 2020). Especially windy or sunny regions could then supply power to regions currently lacking renewable power production. However, grid enhancements can not shift power across time and have therefore limited flexibility potential. Contrary, energy storage systems can shift electric power from times of renewable overproduction to times of high demand without renewable energy. Therefore, energy storage systems are frequently evaluated in academic literature (see for example Yekini

Suberu *et al.*, 2014, Luo *et al.*, 2015, Gallo *et al.*, 2016, Yang *et al.*, 2018, Comello & Reichelstein, 2019). The third measure, demand side management, is shifting demand from times of low renewable production to times of high renewable production (see for example Finn *et al.*, 2013, Caprino *et al.*, 2014, Shrouf *et al.*, 2014, Finn & Fitzpatrick, 2014, Behrangrad, 2015, Blaschke, 2022, Leinauer *et al.*, 2022).

All three measures combined could provide apparent ways to align supply and demand even with an inflexible supply. Therefore, all options likely provide efficient solutions to increase the share of renewable energies. Figure 1.2 illustrates the electricity system including challenges and flexibility measures. Concluding from that, the integration of higher shares of renewable energy requires policies and regulations to not only foster the installation of renewable energies but also the installation of flexibility measures.

To foster the installation of flexibility measures, policy systems and regulations aim to increase the attractiveness and profitability of these flexibility measures. Economic profitability is essential when it comes to trigger investments in green alternatives accordingly. Incentivizing investments in green alternative technologies is required to allow consumers to act in a more environmentally friendly way. Only if policies create green alternatives and incentivize consumers to use these alternatives, carbon emissions can be decreased significantly. Whether these mechanisms work, whether they incentivize efficiently, and whether consumers react accordingly is of major importance for a successful energy transition. Hence, research within this field is of major importance for a sustainable future of our planet. Therefore, I dedicate this thesis to policy issues and regulatory measures within this field. In the following subchapter, I give an overview of the related research.

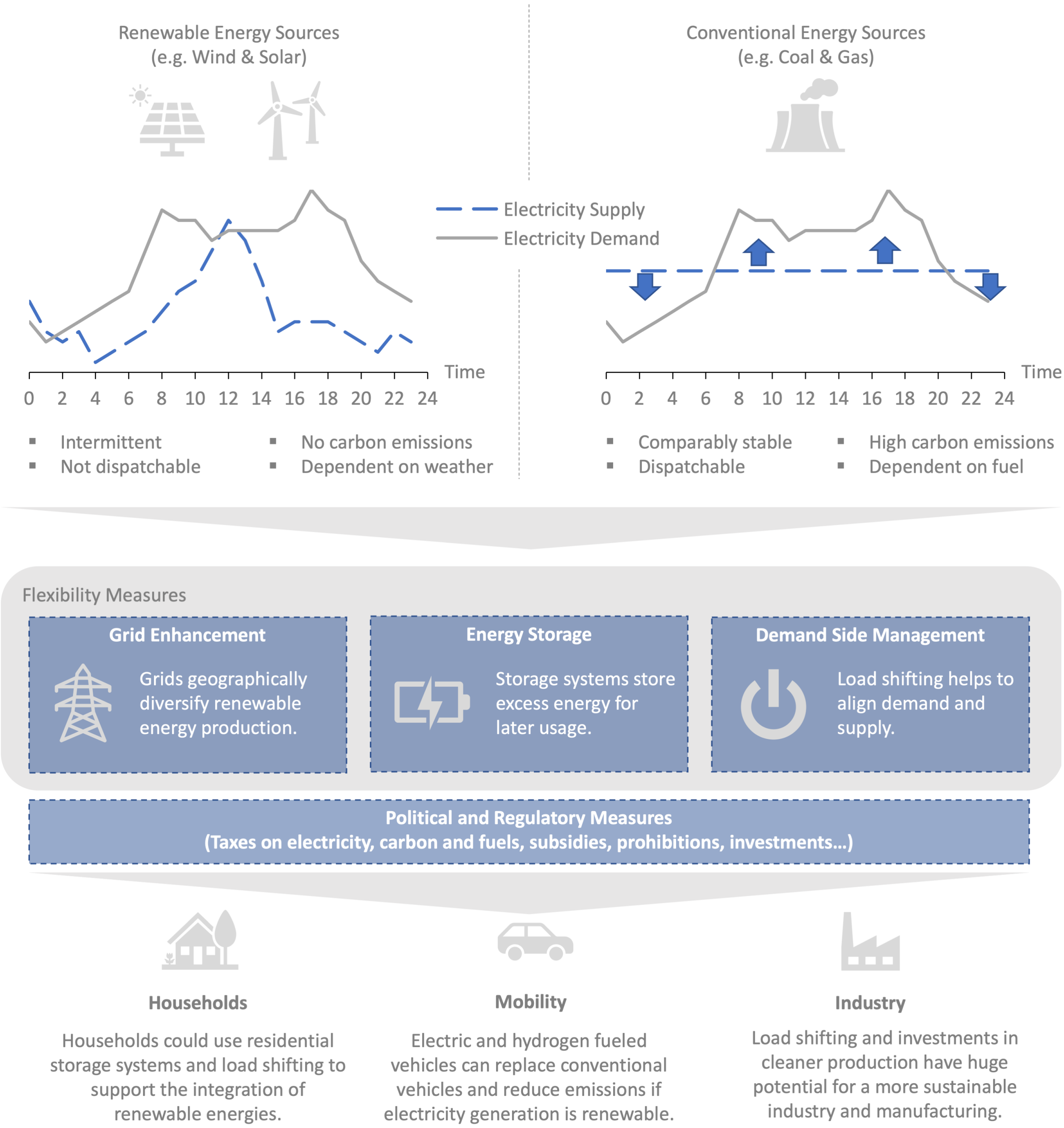


Figure 1.2: Symbolic illustration of the problems of integrating renewable energy and the flexibility measures to enable a higher share of renewable energy within the electricity grid and the mobility sector.

1.2 Objectives and Literature

I build my dissertation across various disciplines including technical as well as socio-economic research streams. These research streams are very multi-facetted with varying methods and perspectives: Some papers might use a very technical approach with complex system models while other politically motivated macroeconomic papers might use for example game theory to investigate problems within the energy sector. Some papers might investigate a rural micro-grid while other papers investigate the infrastructure within a whole continent. Hence, approaches and solutions change with the technical and geographic scope as well as the perspectives taken. Additionally, approaches and solutions interact with each other making the underlying problems dependent on multiple variables and measures within the system. Therefore, there are multiple ways and combinations of flexibility measures that might solve a problem. The most prominent flexibility measures frequently suggested to manage high renewable energy systems are grid enhancement, energy storage and demand side management (see for example Lund *et al.*, 2015, Cruz *et al.*, 2018, Zappa *et al.*, 2019).

Grid enhancement aims to integrate a higher share of renewable energy across regions (see papers like Bayer *et al.*, 2018 or Allard *et al.*, 2020). Renewable sources within one region share the same weather. Balancing local over- or under-production with connections between local grids tackles local supply problems. Tackling this local supply problems could allow to integrate more renewable energies as the need for conventional power sources to balance times of lower production shrinks.

Other papers focus on the flexibility provided by storage systems (see for example Yekini Suberu *et al.*, 2014, Luo *et al.*, 2015, Gallo *et al.*, 2016, Yang *et al.*, 2018, Comello & Reichelstein, 2019). While storage systems are probably the most obvious solution for balancing fluctuations and over- or under-production of renewable energy, they require a lot of expensive material, production and installation cost. Therefore, many papers evaluate the cost efficiency or discuss different technologies and sizes. Tackling cost issues and finding an affordable path to integrate higher shares of renewable electricity is frequently in the focus of these studies.

This is probably a reason why demand side management is so popular in academic research. At first sight, demand side management does not require huge upfront investments as it only needs consumers to change their demand. However, to enable consumers to actively participate in load shifting activities, new metering, communication and information infrastructure needs to be installed (Strbac, 2008). Rescheduling loads is very complex and comes with certain costs and disutility for the consumer. Therefore, incentive schemes and suitable business models must compensate the consumers for their efforts, for example with reduced electricity costs (see Behrangrad, 2015, Blaschke, 2022, Leinauer *et al.*, 2022). However, in both households (see for example Finn *et al.*, 2013, Caprino *et al.*, 2014, Blaschke, 2022) as well as industry (see for example Shrouf *et al.*, 2014, Finn & Fitzpatrick, 2014), demand side management could be an effective measure to utilize a higher share of renewable energies.

The transition of the energy sector towards more sustainable alternatives is a complex and multi-faceted task with almost endless topics and subtasks. A thorough literature review within the very prominent fields of demand side management, energy storage and mobility transition unveiled the research gaps for three different essays numbered I-III. In the following, I give an overview of the literature, the research gaps as well as the corresponding objectives used within the essays. I start off with essay I in the field of residential load shifting with household appliances.

The first essay builds on literature evaluating the opportunities of demand side management, in particular the concepts of dynamic electricity prices. The concepts as described for example by Finn *et al.* (2011), Di Giorgio & Liberati (2014) or Miller *et al.* (2017) use dynamic electricity prices to incentivize consumers to shift loads to times with renewable overproduction and when energy is cheap. In this essay, I simulate different household devices similar to Gottwalt *et al.* (2011), Katz *et al.* (2018) and Voulis *et al.* (2019) to uncover the potential savings of the household if a smart controller would take over the task of shifting loads. Following pricing signals from the energy exchange, dynamic tariffs would enable the residential household sector to make a contribution to the energy transition and further integrate a higher share of intermitting renewable electricity like photovoltaic power and wind energy.

The concept, however, is controversially discussed for example by Allcott & Rogers (2014), Bradley *et al.* (2016), Goulden *et al.* (2018), Frontier Economics Ltd & BET Büro für Energiewirtschaft und technische Planung GmbH (2016). Papers like Bradley *et al.* (2016) and Goulden *et al.* (2018) question that consumers would be willing to steadily monitor the energy prices for inconvenient manual load shifts. Allcott & Rogers (2014) find that consumers would most certainly let manual energy saving actions decay after some time.

Since consumers are unwilling to manually shift loads, automatic control units and smart appliances will probably take over the task of shifting power consumption based on pricing signals (Gottwalt *et al.*, 2011, Di Giorgio & Pimpinella, 2012). Hence, it is of major importance to ensure cost savings on the electricity bill outweigh the cost of installation of smart technology. However, the savings of shifting loads highly depend on the volatility of prices the households face. If the price changes are only within the range of a few cents, the incentive for households to invest in automatic load shifting technology is low.

According to research of O'Connell *et al.* (2014), Jansen *et al.* (2015) and Eid *et al.* (2016), low price volatility is especially a problem when 'per-unit' taxation further decreases the relative volatility. These taxes - some of them introduced to foster the uptake of renewable energy production - are charged on a 'per-unit' basis. 'per-unit' taxation means that taxes are charged in a static manner independent from exchange prices and current renewable energy production. If taxes charged independent from the renewable energy production, the volatility of retail prices is reduced as major shares of the retail electricity prices are due to taxes and levies. Even in the case of high price volatility on the energy exchange, the volatility impacts retail energy prices far less than proportional.

While these taxes and levies generally aim to fund and foster renewable energy production and improve their integration into the grid, the current status-quo of 'per-unit' taxation schemes reduces price volatility and weakens the pricing signal for residential consumers (O'Connell *et al.*, 2014, Jansen *et al.*, 2015, Eid *et al.*, 2016). If pricing signals decrease, there are less incentives for consumers to invest in automatic load shifting technologies. By decreasing the saving potential of automatic load shifting, the taxes meant to foster the renewable energy transition could actually curb their adoption. By curbing the adoption of load shifting, 'per-unit' taxation also curbs the integration of more renewable energy.

Following this literature, Katz *et al.* (2018) and Voulis *et al.* (2019) brought up the opportunities of 'ad-valorem' taxation. 'Ad-valorem' taxation is based on prices at the energy exchange and moves up and down dependent on current prices driven by demand and conventional and renewable power supply. The higher the prices, the higher the taxes charged. Hence, the taxes increase incentives for load shifting if they dynamically increase relative to electricity exchange prices.

Frontier Economics Ltd & BET Büro für Energiewirtschaft und technische Planung GmbH (2016) question the effectiveness of 'ad-valorem' taxation for small consumers as the minimum price incentive to foster load shifting behavior with price insensitive consumers would be unknown. However, they do not consider automatic load shifting devices that could be perfectly price elastic. Perfectly price elastic automatic devices could react already to the slightest changes in electricity prices. However, the costs of smart load shifting technology still need to be covered with these savings.

Previous literature did not investigate whether installing automatic control units to introduce dynamic pricing with smart appliances would actually be profitable from a consumer's perspective. Additionally, the effect of the taxation scheme on the profitability of automatic load shifting is still not clear. This lays the ground for the following new research questions: First, what extent of price volatility on the energy exchange would be required to compensate for additional costs of smart metering within households? Second, could 'ad-valorem' taxation lead to a sufficient increase in retail price volatility to promote load shifting within households? And third, what are financial risks imposed on the households with the introduction of a dynamic tariff in each taxation regime?

Since a major share of the price components of residential electricity are due to taxes and levies, I investigate the potential savings in these two different taxation settings: 'ad-valorem' taxation and 'per-unit' taxation. The essay uncovers the saving potential for households but also offers actionable tax recommendations and policy solutions. These tax recommendations and policy solutions could make automated demand side management in households profitable. By making automated demand side management with household devices profitable, households would have a direct incentive to invest in such smart controlling technology. This smart controlling technology could then enable residential households - one of the biggest electricity consuming sectors (compare United States Environmental Protection Agency, 2020) - to participate and contribute in the integration of a higher share of renewable energy and towards a sustainable energy transition.

Essay II aims to optimize the operational charging strategies of residential battery storage systems within households. These residential storage systems could also be used to balance renewable production. Electricity providers could pre-announce electricity prices to incentivize and control residential storage systems accordingly. Building on previous literature of Nottrott *et al.* (2013), Hanna *et al.* (2014), Silvente *et al.* (2015), Lorenzi & Silva (2016), Yoon & Kim

(2016), Abdulla *et al.* (2016) and Chitsaz *et al.* (2018), the essay could help to pave the way in building tariff structures that enable decentralized storage systems to participate in load shifting activities for the integration of a higher share of renewable electricity.

With the rise of photovoltaic technology, a large number of households use a photovoltaic roof to reduce the electricity bill by self-consuming the generated power. Households with a photovoltaic roof could additionally use a battery storage system to further increase self-consumption. A battery storage system could store excess energy of the photovoltaic unit in times of low demand to satisfy demand and increase self-consumption at later times when photovoltaic generation is low (see for example Matallanas *et al.*, 2012, Di Giorgio & Liberati, 2014, Ratnam *et al.*, 2015). Hence, more and more households might be willing to install such residential battery storage systems creating a significant amount of residential storage capacity.

This residential storage capacity might be used by energy providers to balance renewable production and integrate a higher share of renewable energy. However, energy providers would have to adapt the operational charging strategy of these decentralized battery storage systems to balance renewable over- or under-production. To incentivize such changes in the operational charging strategy, electricity providers would have to offer some economic benefits to households.

The general economic benefits of residential battery storage systems are a frequently researched topic (see for example Weniger *et al.*, 2014, Hoppmann *et al.*, 2014, Li & Danzer, 2014, Naumann *et al.*, 2015, Muenzel *et al.*, 2015, Matallanas *et al.*, 2012, Di Giorgio & Liberati, 2014). Papers like Sani Hassan *et al.* (2017), Erdinc (2014), Babacan *et al.* (2017), Dufo-López (2015) and Klein *et al.* (2019) introduce dynamic pricing into the operational strategies of battery storage systems. Within a dynamic electricity tariff, the battery may additionally consider charging in times of low prices and discharge in times of high prices to further minimize the electricity bill. To optimally exploit these price fluctuations, the battery requires information on future prices, load demand and photovoltaic production. If this information is lacking, the battery may not respond to the pricing signals of the power provider appropriately. Information on future prices, load demand and photovoltaic production, however, is either not available or frequently deviates from forecasts.

Some papers propose real-time charging strategies in dynamic models that account for prediction errors or missing information a battery strategy is based on (see Di Giorgio *et al.*, n.d., Bao *et al.*, 2012, Bedi *et al.*, 2017, Di Giorgio *et al.*, 2017, Li *et al.*, 2016). Lujano-Rojas *et al.* (2017) use an autoregressive moving-average model (ARMA) to evaluate the effects of forecasting errors in energy prices with stand-alone lead-acid batteries. Other papers like Nottrott *et al.* (2013), Silvente *et al.* (2015), Lorenzi & Silva (2016), Yoon & Kim (2016), Abdulla *et al.* (2016), Hanna *et al.* (2014) or Chitsaz *et al.* (2018) optimize battery strategies with a rolling forecast horizon window. With the information of this rolling forecast horizon window, the battery adapts and optimizes its charging strategy.

Power providers may pre-announce and guarantee prices within such a rolling horizon window for a certain period of time, for example the next five hours. This would foster load shifting through storage systems according to their pricing signals and allow the power provider to utilize residential storages for load balancing. However, this would also require the power provider to lift the risk of price changes on the energy exchange from its customers.

To avoid high risks due to unplanned price changes, the power provider intends to keep the horizon for the pre-announcement as short as possible, but sufficiently long to enable beneficial charging strategies. Further reducing the need for external information with a learning battery that incorporates the production and consumption data of the last year could help to reduce risks and improve the strategy of the battery. Previous literature could not yet answer whether there is a minimum horizon of price pre-announcements required for a battery system to generate significant savings via load shifting. Apart from that, it remains unclear how sensitive the electricity costs of a household would be towards the length of the pre-announcement period.

With my second essay, I tackle the following questions: Is there a minimum horizon of price pre-announcements required for a battery system to generate significant savings via load shifting? How sensitive are the electricity costs of a household towards this length of the pre-announcement period? By investigating different pre-announcement periods, this essay sheds light on the potential of price guarantees within tariffs to improve the integration of renewable energy. Applied to thousands or even millions of household storage systems, these pre-announcements could have the potential to significantly provide flexibility and increase the share of renewable energy within the system.

Essay III investigates the integration of renewable alternatives in the mobility sector following a call of Gillingham & Stock (2018) to enrich our understanding of subsidy-induced innovation especially for the case of electric vehicles. The essay builds on economic growth literature combined with the learning concepts of Arrow (1962) applied to subsidies on electric vehicles.

Electric vehicles are the most prominent alternative to conventional fuel powered vehicles and one of the most promising measures to reduce carbon emission in the mobility sector.

Therefore, many governments either tax conventional vehicles or subsidize electric vehicles. Subsidizing electric vehicles should increase the adoption and sales of the new technology. However, subsidies in the mobility sector are frequently under public debate. Especially the United States, China and Germany spend huge sums of money to foster the electric drivetrain and battery technology. With governmental bonuses of up to $7.500 federal tax credit in the United States, ¥22.500 in China or €9.000 in Germany [1] for purchasing an electric vehicle, critics claim these subsidies to be inefficient and costly in abating carbon emissions considering the large governmental spendings (see for example Holland *et al.*, 2016, Sheldon & Dua, 2019, Xing *et al.*, 2021).

When calculating the expected carbon abatement during production and operation of an electric vehicle (see for example Chandra *et al.*, 2010, Doucette & McCulloch, 2011, Faria *et al.*, 2013, Messagie *et al.*, 2014, Bickert *et al.*, 2015, Rangaraju *et al.*, 2015), the costs to subsidize an electric vehicle per saved carbon ton are comparably uncompetitive (see Chandra *et al.*, 2010, Van Vliet *et al.*, 2011, Michalek *et al.*, 2011, Bollinger & Gillingham, 2014, Huse & Lucinda, 2014, Newbery, 2018, Yan, 2018). The costs of alternative carbon abatement measures, offsetting carbon at the cap and trade systems or even the comparably high cost estimations of IWG (2021) for the social costs of carbon are below the prices of reducing a ton of carbon emissions with an electric vehicle subsidy. This could wrongfully lead to the conclusion that every vehicle subsidy is inefficient. However, as pointed out by Gillingham & Stock (2018), subsidizing an electric vehicle now might foster innovation and development, triggering a quicker and broader adoption of many more electric vehicles in the future. Therefore, the value of the subsidy is not only defined by the emission reductions of the subsidized vehicle but also by the innovation and the following emission reductions in the future.

Following the growth models of Acemoglu *et al.* (2012) and Acemoglu *et al.* (2016), the evaluations of Bollinger & Gillingham (2014) and Newbery (2018) or the work of Vogt-Schilb *et al.* (2018), more costly investments in clean technology could have an especially high potential in preventing carbon emissions. Investing in the more expensive carbon abatement measures now could then be the optimal strategy as these measures would have a high abatement potential

[1]See respective subsidies 2020 in U.S. Department of Energy (2021), Ministry of Finance of the People's Republic of China (2020), Bundesministerium für Wirtschaft und Klimaschutz (2021).

in the future. Investing now into these measures allows the technology to evolve and improve earlier with cumulative experience and learning rates (see for example Spence, 1981, Fudenberg & Tirole, 1983, Ghemawat & Spence, 1985). One of the core implications of this literature stream for my case is that it could be beneficial to accept negative short-run marginal profits with subsidies in order to gain technological improvements under positive learning rates.

Weiss *et al.* (2012), Matteson & Williams (2015), Nykvist & Nilsson (2015), Schmidt *et al.* (2017), Kittner *et al.* (2017), Ziegler *et al.* (2021) and Ziegler & Trancik (2021) found promising learning rates in battery technology and electric vehicles. Ziegler & Trancik (2021), for example, found a price decrease of 20% upon a doubling of cumulative market size. Hence, subsidies could speed up the cumulative production and the corresponding learning and technology development if they trigger price elastic consumer responses as observed by many studies like Chandra *et al.* (2010), Jenn *et al.* (2013, 2018), Palmer *et al.* (2018) or Yan (2018). Jenn *et al.* (2018), for example, observed average sales increases of 2.6% for electric vehicles for every $1,000 offered as a rebate or tax credit. However, it remains questionable whether the learning and technology improvement for carbon abatement is worth spending these rebates and tax credits for electric vehicles.

Therefore, it is worth looking into another stream of literature evaluating the emission reduction potential of electric vehicles (see Samaras & Meisterling, 2008, Stephan & Sullivan, 2008, McCarthy & Yang, 2010, Van Vliet *et al.*, 2011, Hawkins *et al.*, 2013, Graff Zivin *et al.*, 2014, Archsmith *et al.*, 2015, Holland *et al.*, 2016, Knobloch *et al.*, 2020). What almost all papers in this discipline have in common is that they emphasize the dependency on clean power production for an electric vehicle to be environmentally beneficial. A very prominent paper of Holland *et al.* (2016), for example, finds environmental benefits of electric vehicles worth $2,785 with the clean power production in California but huge environmental damages up to $4,964 in North Dakota with electricity being produced from coal powered plants. A big stream of literature (see for example Chandra *et al.*, 2010, Van Vliet *et al.*, 2011, Michalek *et al.*, 2011, Bollinger & Gillingham, 2014, Huse & Lucinda, 2014, Newbery, 2018, Yan, 2018) sets these emission reductions into perspective by investigating the efficiency of subsidies and the corresponding carbon abatement cost.

However, as pointed out by Gillingham & Stock (2018), past studies on electric vehicle subsidization did not include the effects of "learning by doing" and economies of scale within the subsidy, that provide additional value to technology development. The important question that arises from this is whether subsidy-induced innovation could indeed justify governmental spending?

Within this third essay, I introduce a new method based on a simpler version of the Bass (1969) adoption model for consumer durables in combination with the concept of "learning by doing" of Arrow (1962). I calculate the value of innovation triggered by subsidies using price elasticities and learning rates and showcase this method by evaluating the governmental subsidy programs for electric vehicles in the United States, China and Germany. Calculating the value of innovation triggered by a subsidy, this essay offers a method for policymakers to evaluate the efficiency of subsidies in green technologies. With limited financial resources to foster the uptake of more sustainable energy alternatives, this essay could be of major importance to channel investments into the most promising technologies.

1.3 Methodologies

For every essay, I use a different method that I considered to be most appropriate to solve the formal problem and answer the respective research questions. While all three essays used a quantitative assessment with simulations, the specific models varied with the underlying problem of the essay. In the following, I will summarize the method approaches chosen for each essay.

Essay I extends the models of Gottwalt *et al.* (2011), Katz *et al.* (2018) and Voulis *et al.* (2019) to simulate load shifting with common household devices under different price volatilities and taxation schemes. Therefore, I iterate through the different scenarios and adjust the underlying residential electricity price inputs to reflect the hypothetical changes in volatility and taxation scheme. Within every iteration, I individually minimize the electricity bill of 100 artificially created household load patterns formulated as a deterministic mixed integer linear program over a single year. Every household load pattern is composed from a set of household devices that need to run under specific conditions dependent on the categorization of the device.

I categorize household devices regarding their need for direct interaction with the consumer into ‘manual’, ‘semi-automatic’ or ‘automatic’. Devices like the TV or a lightbulb are categorized as ‘manual’ and are not suited for automatic load shifting. Devices that do not require any user interaction are categorized as ‘automatic’. ‘Automatic’ devices (for example fridge or freezer) work with a thermal storage and simply operate within the pre-defined range of their operating temperature. Devices that do require user interaction but can switch on and off without are categorized as 'semi-automatic'.'Semi-automatic' devices require external data input and the consumer needs to prepare their operation manually (for example loading the washing machine or dishwasher).

Therefore, the automatic controller can shift the operation of these devices only within predefined limits that have been drawn for each household according to usage statistics and power load probability distributions. Letting the automatic controller shift only within these conditions, reduces the load shifting potential but considers the inelasticity in electricity consumption as consumers would most likely not accept utility losses with load shifts disrupting their daily habits. Therefore, this essay provides a comparably realistic evaluation that is close to real world application and reliable for policy recommendation.

Within essay II, I extend previous literature on optimizations under uncertainty (Nottrott *et al.*, 2013, Lorenzi & Silva, 2016, Yoon & Kim, 2016, Abdulla *et al.*, 2016, Hanna *et al.*, 2014, Chitsaz *et al.*, 2018). I formulate a deterministic mixed integer linear optimization program to find the optimal charging strategy of a residential battery storage minimizing the total annual net electricity bill of a household with a photovoltaic roof. For every hour over a year, I optimize the setup to minimize the electricity costs over a rolling horizon of forecast information regarding the photovoltaic production as well as the household's load demand. After each timestep, new forecasts appear within the rolling horizon and the actual values of the past timestep are included in the learning set for the next forecast. The optimal battery charging strategy for the current hour is actually carried out and used for further evaluation and learning.

With new forecasts and price data available, the charging strategy changes for the following hours in the next iteration. With that, I create a highly realistic simulation of a storage system in a household in which these parameters are also most likely to be unknown in advance. The power provider announces future prices within a certain pre-announcement horizon. With this additional information, the battery is able to change the charging strategy to optimally exploit price changes, reduce pressure on the grid and integrate renewable energy according to the pricing signals given. Within this essay, I value the efficacy of the resulting charging strategies by the differences in the net electricity bills compared to the optimal deterministic strategy under perfect information. The difference in electricity bills therefore represents the value of additional pre-announced price information. With this focus, the essay provides insights into optimal dynamic tariff structures under uncertainty that could foster a more grid friendly operation of residential battery storages and help to integrate more renewable energy into the grid.

Essay III introduces a new method to calculate the value of innovation triggered by subsidies. By simulating the phase-out of a subsidy using price elasticities, I calculate the subsequent sales decline. This sales decline slows down innovation with learning effects depending on the cumulative sales and production (see cumulative experience and learning rates literature of Arrow, 1962, Spence, 1981, Fudenberg & Tirole, 1983, Ghemawat & Spence, 1985). Given the learning rates on cumulative sales and production (see Weiss *et al.*, 2012, Matteson & Williams, 2015, Nykvist & Nilsson, 2015, Schmidt *et al.*, 2017, Kittner *et al.*, 2017, Ziegler *et al.*, 2021, Ziegler & Trancik, 2021), I can extract the subsidy-induced innovation within the projected technology adoption curve. The projected technology adoption curve is fitted towards an S-shaped curve following the adoption model for consumer durables by Bass (1969). Simulating a scenario of the adoption curve with and one scenario without subsidy allows me to determine the effects and, hence, the innovative value of the subsidy.

Within this essay, I showcase this method by evaluating the governmental subsidy programs for electric vehicles in the United States, China and Germany. I consider changes in the electricity mix, fuel and carbon certificate prices to accommodate for the changing energy systems and the environmental footprint of installed power capacities in the future. With these inputs, I can simulate each country's hourly electricity production in a merit order to calculate the carbon emissions of the marginal electricity demand of electric vehicles. Valued with the social cost of carbon, the reduction of carbon emissions has societal ecological value. I discount these future societal ecological values of carbon abatement and compare them to the costs of the current subsidy programs. With this approach, the essay not only evaluates the subsidy programs of electric vehicles in the most important automobile markets, but also offers a new method that can be adapted to other subsidy programs that help to reduce carbon emissions and integrate renewable energy.

1.4 Results and Contributions

The different simulations and policy studies within this dissertation offer important results that advance our knowledge on how to construct tariff structures and policy incentivization schemes for a successful energy transition. Based on my models and findings, researchers and policy makers could further improve current tariff, taxation and subsidy schemes to enable a higher share of renewable energy within the grid. In the following, I provide an overview of the main findings and contributions of each of the essays.

Essay I determines the price volatility necessary for automatic load shifting to cover the cost of the associated smart metering within a household. The essay shows that current price volatility does not allow sufficient savings to compensate for additional metering costs. The results of the essay indicate that a change towards an 'ad-valorem' electricity taxation dependent on exchange prices could make residential demand-side management profitable. A regulatory change towards an 'ad-valorem' taxation regime would increase the retail price volatility and thereby enable households to economically participate in automatic load shifting activities. Enabling households to participate in load shifting activities could lift huge potential for further integrating renewable energy capacities.

If a mandatory switch to dynamic tariffs were to be imposed by official regulation, households with no smart devices would suffer only slightly higher total bills. Simulating worst case scenarios for inflexible consumers, I can show that the potential price risk for consumers that do not react to pricing signals because of a lack of smart devices, is almost negligible. As consumption patterns suggest, these households consume in times of both high and low prices. With this mix, the households could almost cancel out higher payments at peak times even without any load shifts. This is a very important finding as these results help policymakers to anticipate the effects of dynamic retail prices on electricity and derive the implications of different taxation settings also from a social perspective of low-income households with less advanced devices.

This essay extends the models of Gottwalt *et al.* (2011), Katz *et al.* (2018) and Voulis *et al.* (2019) to advance our knowledge of tariff structures for demand side management. The proposed solution of automated load shifting under 'ad-valorem' taxation regime also contributes solutions to the structural and consumer behavioral problems mentioned in previous literature (see for example Allcott & Rogers, 2014, Bradley *et al.*, 2016, Goulden *et al.*, 2018). An 'ad-valorem' taxation regime could enable smart household appliances to profitably shift loads without the need for consumer interaction. Hence, the proposed solution of this essay would allow even price insensitive households to shift loads and thereby lift huge load shifting potential to integrate further renewable energy sources.

Essay II values pre-announced price information for a household with a photovoltaic roof and a battery storage system. Without predictions for supply and demand, the battery storage would not be able to adapt its charging strategy to optimally exploit renewable production. With this essay, I can show that electricity suppliers would only have to pre-announce their prices for a 3-8 hour period in order to allow the battery storage to find an almost optimal charging strategy. This finding is especially important as the number of residential storage systems might increase in the future if more and more residential photovoltaic units are installed. With an increasing number of residential storage systems, the potential to use these residential storages to balance renewable overproduction grows day by day.

I argue that electricity suppliers and grid operators could therefore have an incentive to announce certain prices in advance. By announcing prices in advance, the electricity suppliers could control the charging strategy of residential battery storage systems that minimize the household's electricity bill. This essay shows, that even a short pre-announcement horizon could be sufficient to integrate thousands and probably soon millions of residential storage systems into a smart grid. These huge capacities could enable the integration of a higher share of renewable energy within the grid.

Extending the previous research of Nottrott *et al.* (2013), Silvente *et al.* (2015), Lorenzi & Silva (2016), Yoon & Kim (2016), Abdulla *et al.* (2016), Hanna *et al.* (2014) and Chitsaz *et al.* (2018), my essay shows that pre-announcements beyond a 3-8 hour horizon would only have a marginal impact on the resulting savings for consumers and would not change the battery charging strategy. If energy providers would only have to take over the pricing risks for such a short horizon in advance, influencing the charging strategy with electricity storages is not that risky. My findings and the proposed model help households and electricity providers to assess dynamic electricity tariffs and determine optimal structures for demand-side management. Applying my findings to future electricity tariffs could enable electricity providers to integrate huge balancing potential in form of residential storage systems and thereby contribute to a successful renewable energy transition.

Essay III contributes a new method to calculate the ecological value of subsidy programs. Subsidy programs on products usually increase their sales leading to economies of scale as well as new innovations. New innovations improve the product and further accelerate the adoption with cumulative experience and learning rates. Hence, subsidies offer additional societal value in form of a quicker innovation of the desired good.

To correctly evaluate current and future subsidy programs, it is very important to consider subsidy-induced innovation. The essay presents a method to calculate this subsidy-induced innovation and enables policymakers to foresee the innovation triggered. By valuing this innovation, the method allows to measure and evaluate the efficiency of subsidy programs. Knowing the true ecological and economical value of subsidy programs is key to decide and adapt policies. As these policies frequently cost billions of dollars (see U.S. Department of Energy, 2021, Ministry of Finance of the People's Republic of China, 2020, Bundesministerium für Wirtschaft und Klimaschutz, 2021), this approach could have a tremendous economic and also ecological impact considering the limited resources for sustainable measures.

I showcase this method by evaluating the governmental subsidy programs for electric vehicles in the United States, China and Germany. Since these countries subsidize, produce and also drive a major share of the electric vehicles worldwide, their subsidy programs and the induced innovation have enormous impact on the development of electric vehicles in all other countries as well. The essay shows that subsidizing an electric vehicle now could have positive effects for the electric vehicle adoption in the near future. The underlying value of innovation within a subsidy could even outweigh the value of the actual carbon savings of the subsidized vehicle. Hence, this innovation effect justifies subsidies way higher than the value of carbon abatement by the vehicle. However, at least in the case of the United States and Germany, the resulting value of carbon reductions could not justify the expenses from a sole ecological perspective. Indeed, the subsidy might still be justifiable for economic welfare reasons as all of these countries also have major shares of the global vehicle production and need to secure jobs in that industry. By considering the value of innovation induced by these subsidies, my essay could help policymakers to a better understanding of the effects resulting from their subsidy decisions.

1.5 Structure of the Dissertation

I conducted three independent research projects with differing objectives and methods used. Table 1.1 provides an overview over the three essays with their topics and main contributions. Since all of these three essays are meant to be published in academic journals individually, every essay is written independently. This includes the explanation of key concepts or definitions that might be provided repeatedly in more than one essay. This allows the reader to either read this dissertation as provided or also review the essays in another order or outside of the dissertation once the essays are published in journals.

Chapter 2 consists of Essay I (published in Energy Policy Vol. 164, May 2022, please see `https://www.sciencedirect.com/science/article/pii/S0301421522001033` for the formatted version). Here, I analyze the opportunities of demand side management in residential households under different taxation settings. Chapter 3 comprises Essay II that evaluates the horizon dynamic tariff prices should be pre-announced in order to use distributed battery storage systems for balancing over- or under-capacities within the grid. Chapter 4 consists of Essay III that develops and showcases a new method to calculate the value of subsidy-induced innovation of fostering the uptake of electric vehicles. Within Chapter 5, I conclude my findings and suggest new fields and topics for future research.

Table 1.1: Dissertation Overview

Reserach topics:	Sustainability, Flexibility Measures, Renewable Energies, Smart Grid, Digitalization		
Essays	Chapter 2 (Essay I)	Chapter 3 (Essay II)	Chapter 4 (Essay III)
Title	Dynamic Pricing of Electricity: Enabling Demand Response in Domestic Households	How Households Benefit From Pre-announced Electricity Price Information: A Rolling Horizon Simulation With a Battery Storage System	Innovation Trigger or Political Symbolism: How Green are Subsidies in Electric Vehicles?
Structural or Policy Problem	Residential load shifting is not profitable as volatility in prices is too low due to a high share of taxes charged on electricity.	Decentralized storage systems will not optimize their charging strategy to support a higher share of renewable production unless they receive pricing signals in advance.	Subsidies on electric vehicles require huge governmental spendings that can only be justified if subsidy-induced innovation is very high.
Research question	Could a change towards 'ad-valorem' taxation on electricity incentivize residential load shifting with smart devices?	How long should electricity providers pre-announce prices in advance that energy storage systems can adapt their charging strategy?	Can subsidy-induced innovation and learning justify the expenses related to technology bound subsidies?
Main Contribution	The simulation of different taxation schemes unveils that 'ad-valorem' taxation could incentivize residential demand side management with smart devices.	Electricity providers only need to pre-announce prices for a rather short horizon of 3-8 hours in order to incentivize battery storage systems to adapt the charging strategy accordingly.	The contributed method shows that the subsidy-induced innovation in electric vehicles can not justify the governmental spendings from a sole ecological perspective.

2 | Dynamic Pricing of Electricity: Enabling Demand Response in Domestic Households

Fluctuations in retail energy prices may incentivize domestic households to adapt their load pattern in order to minimize the cost of electricity. This paper determines the price volatility necessary for automatic load shifting to cover the cost of the associated smart metering within a household. This study shows that current price volatility does not allow sufficient savings to compensate for additional metering costs. However, results indicate that a change towards an 'ad-valorem' electricity taxation dependent on exchange prices could make residential demand-side management profitable. At the same time, the potential price risk for consumers that do not react to pricing signals because of a lack of smart devices, is almost negligible. As consumption patterns suggest, these households consume in times of both high and low prices, thereby almost canceling out higher payments at peak times even without any load shifts. With these results, policymakers can anticipate the effects of dynamic retail prices on electricity and derive the implications of different taxation settings.

Keywords: Energy taxes, Demand response, Dynamic tariff, Smart meter, Smart appliances, Residential, Taxation mechanism, Financial incentives.

Published in Energy Policy Vol. 164, May 2022, please see `https://www.sciencedirect.com/science/article/pii/S0301421522001033` **for the formatted version.**

2.1 Introduction

Governments around the world promote the installation of renewable energy sources like wind and solar energy. The output of these renewable power sources fluctuates with the weather and daytimes and cannot be rescheduled or terminated. Since supply is therefore inherently inflexible, shifting demand from times of low renewable production to times of high renewable production is an apparent way to align supply and demand.

This alignment could be induced by dynamic tariffs that incentivize consumers to shift loads to times with renewable overproduction and when energy is cheap (Finn *et al.*, 2011, Di Giorgio & Liberati, 2014, Miller *et al.*, 2017). The generated savings hereby depend on the volatility of retail prices. The higher the volatility, the higher the savings in shifting loads. This study evaluates this volatility by comparing the savings and risks within a 'per-unit' to an 'ad-valorem' taxation of electricity in the light of potential smart load shifting from a household perspective.

A major share of retail electricity prices are due to taxes and levies, whereas many of these taxes and levies aim to foster renewable energy production and improve their integration into the grid. Since these taxes are charged on a 'per-unit' basis, even high price volatility on the energy exchange impacts retail energy prices far less than proportional. Frequent and significant changes in retail prices, however, are necessary to incentivize load shifting. The 'per-unit' taxation, therefore, actually weakens the pricing signal for residential consumers in proportional terms (O'Connell *et al.*, 2014, Jansen *et al.*, 2015, Eid *et al.*, 2016). In the way these taxes for the renewable energy transition are imposed, they do actually curb the adoption of load shifting and thereby the integration of renewable energy.

'Ad-valorem' taxation, on the other hand, is based on prices at the energy exchange. The higher the prices, the higher the taxes charged. As a result, volatility in exchange prices has a proportional influence on taxes and thereby a greater impact on the volatility of the retail price passed on to domestic households. This taxation mechanism would strengthen the pricing signal, incentivize load shifting accordingly and might justify investments in smart load shifting technology.

These investments in smart technology are crucial for an adoption of load shifting in the domestic household sector. Consumers want to avoid the steady monitoring of energy prices for inconvenient load shifts (see for example Bradley *et al.*, 2016, Goulden *et al.*, 2018) and also let manual energy saving actions decay after some time (Allcott & Rogers, 2014). Therefore, automatic control units and smart appliances likely take over the task of shifting power consumption based on pricing signals (Gottwalt *et al.*, 2011, Di Giorgio & Pimpinella, 2012). Given inelastic demand and a competitive retail sector, the additional costs of these investments are presumably to be borne by the consumers.

In the context of avoiding welfare losses, the following research questions are of major importance: First, what extent of price volatility on the energy exchange would be required to compensate for additional costs of smart metering within households? Second, could 'ad-valorem' taxation lead to a sufficient increase in retail price volatility to promote load shifting within households? And third, what are financial risks imposed on the households with the introduction of a dynamic tariff in each taxation regime?

This study extends the models of Gottwalt *et al.* (2011), Katz *et al.* (2018) and Voulis *et al.* (2019) to simulate common household devices and identify the price volatility necessary to compensate for additional cost of smart metering in a German case study. This paper evaluates the potential of 'ad-valorem' taxation and compares the price risks of dynamic tariffs in each taxation regime to develop a policy recommendation. The results help legislators to better anticipate the effects of a change towards 'ad-valorem' electricity taxation and the introduction of dynamic tariffs for households per se. Additionally, producers of household appliances may use this approach to evaluate the benefit of load shifting features within their products and, in so doing, assess the demand for specific functions related to load shifting.

Jansen *et al.* (2015) discuss the introduction of 'ad-valorem' taxation but do not provide an evaluation of the potential within households. Frontier Economics Ltd & BET Büro für Energiewirtschaft und technische Planung GmbH (2016) question the effectiveness of 'ad-valorem' taxation for small consumers since the minimum price incentive to foster load shifting behavior with price insensitive consumers would be unknown and unpredictable. However, they do not specifically evaluate automatic load shifting, which is by nature perfectly price sensitive and does not require a minimum price incentive besides coverage of additional costs of smart metering. Katz *et al.* (2018) suggest dynamic electricity taxes for households to overcome perceived switching costs towards a dynamic tariff but do not provide a detailed evaluation of common household devices or consider the costs of smart metering. Voulis *et al.* (2019) find increasing incentives for load shifting with the introduction of 'ad-valorem' taxation in a case study of heat pumps, yet they do not evaluate household devices or compare the savings to costs of smart metering. In summary, the previous literature emphasizes the necessity of smart metering technology but has not yet considered its operative costs. All of the above papers lack a detailed evaluation of the specifics of common household devices and therefore cannot provide a clear policy recommendation for the household sector.

The paper is organized as follows: Section 2.2 describes the general methodology and formally sets out the optimization problem, for which the input parameters and assumptions are described in section 2.3. Section 2.4 then presents and discusses the results, while section 2.5 offers a conclusion.

2.2 Methodology and Problem Description

2.2.1 General Description

This study presents a deterministic mixed integer linear program to minimize the total yearly electricity costs of 100 created household load patterns under different price volatilities. These price volatilities result from either an increase in exchange price volatility within the 'per-unit' taxation or from a switch to 'ad-valorem' taxation. However, all simulated scenarios consume the same amount of electricity. They only differ in terms of the time the electricity is consumed and the respective price. As a solver, this study uses the inbuilt CPLEX solver of the General Algebraic Modeling System (GAMS) optimization software (version 25.0.2 win64). Section 2.2.2 states the program while section 2.2.3 describes the approach to vary price volatility.

2.2.2 Problem Formalization

A household's electricity consumption is driven by its devices and the consumer's personal preferences in using them. This minimization shifts the operation of electrical devices to periods when energy is cheapest. The model limits the shifts of each individual device to its scope of operation and a specific consumer usage pattern. By that, this paper determines a realistic load shifting potential, which is realizable without changes in the consumer's behavior. Table 2.1 lists the symbols used in the optimization.

Table 2.1: Symbols used in the mathematical formulation of the minimization problem.

Parameter	**Description**
t	Time-step
T	Number of time-steps within a year
D_A	An automatically operating device
D_{S}	A semi-automatically operating device
D_{all}	Set of all modeled devices
C	Total electricity costs of the household with all modeled devices of the set D_{all}
$q(t)$	Total electric consumption of all devices D_{all} within time t
q_D^T	Total yearly electricity consumption in kWh of a single device D
$p(t)$	Price of electricity in €per kWh at time t
$\theta_D(t)$	Time proportion within time-step t while device D is operating
θ_D^T	Total yearly time a single device D is operating
ω_D	Wattage that device D consumes during operation
$L_{D_{\mathrm{S}}}$	Length of a single cycle of a semi-automatic device D_{S} in hours
$\chi_{D_{\mathrm{S}}}$	Yearly number of cycles of semi-automatic device D_{S}
$\rho_{D_{\mathrm{S}}}(t)$	Flexibility indicator of semi-automatic device D_{S} at time t
$\Upsilon^1_{D_{\mathrm{S}}}(t)$	Switch-on event of semi-automatic device D_{S}: $1 = 1 \mathrel{\widehat{=}}$ On, $1 = 0 \mathrel{\widehat{=}}$ Off
$\tau_{D_A}(t)$	Temperature of 'automatic' device D_A at time t
$\Delta\tau^0_{D_A}$	Temperature losses of 'automatic' device D_A within one time step t
$\Delta\tau^1_{D_A}$	Temperature gains via operation of device D_A within one time step t
$\Delta\tau^C_{D_A}(t)$	Consumption of temperature for device D_A at time t
$\tau^{min}_{D_A}$	Minimum temperature of device D_A
$\tau^{max}_{D_A}$	Maximum temperature of device D_A
$\tau^{init}_{D_A}$	Initial and final temperature of device D_A in $t = 0$ and $t = T$
$E(t)$	Energy in the battery of the electric vehicle at time t in kWh
E^{min}	Minimum energy in the battery of the electric vehicle
E^{max}	Maximum energy in the battery of the electric vehicle
E^{Charge}	Power in kWh the electric vehicle can charge within one timestep t
$E^{Consumption}$	Power consumption of the electric vehicle in kWh per km
$E^{maxC}(t)$	Maximum charge the electric vehicle could have reached in time t
$\Delta E(t)$	Consumption of the electric vehicle's battery at time t
$\rho_{EV}(t)$	Flexibility indicator whether the electric vehicle is plugged in at time t
d	Driven distance of the electric vehicle of a single trip
d^{max}	Maximum distance of the electric vehicle for a single trip
v	Average speed of the electric vehicle
t_{off}	Time the electric vehicle leaves the household for a trip
t_{on}	Time the electric vehicle arrives back at the household from a trip

Electricity costs C are calculated with the electricity consumption $q(t)$ of the hour multiplied by the respective price $p(t)$. The objective function is defined as:

$$\min_{q(t)} \ C = \sum_{t \in T} q(t) \cdot p(t). \tag{2.1}$$

The total electricity consumption is calculated by aggregating the loads of all simulated electrical devices. The individual load of each device D is calculated with the wattage ω_D of the device and the status indicator $\theta_D(t)$, which indicates whether a device is operating during a timestep. A device, which is currently off, has $\theta_D(t) = 0$ and a operating device $\theta_D(t) = 1$. A value between 0 and 1 indicates that the device is operating for a percentage share of time within this timestep:

$$q(t) = \sum_{D \in D_{all}} \theta_D(t) \cdot \omega_D, \qquad \theta_D(t) \in [0, 1]. \tag{2.2}$$

To avoid utility losses to the consumer, the only devices considered for automatic load shifting are those where the consumers do not face any, or only minor, changes to their lifestyle if the devices are switched on and off automatically. Previous literature categorized devices according to their need for interaction with the consumer, and hereby whether the devices are suitable for being controlled by an automatic system or not (see Gottwalt *et al.*, 2011).

Due to the need for direct interaction with the consumer, devices like the TV or a lightbulb are categorized as ‘manual’ and are not suited for automatic load shifting. Devices that do not require any user interaction are categorized as ‘automatic’. Devices that do require user interaction but switch on and off without are categorized as ‘semi-automatic’.

In the following, this study introduces specific conditions for each device category suitable for automatic load shifting. Section 2.2.2.1 states conditions for ‘automatic’ devices, while section 2.2.2.2 adds conditions applied to ‘semi-automatic’ devices. Section 2.2.2.3 adds the conditions for an electric vehicle.

2.2.2.1 Conditions for ‘Automatic’ Devices

Within this study, the household devices categorized as ‘automatic’ work with a thermal storage (for example fridge and freezer). They simply operate within the pre-defined range of their operating temperature without the need for any consumer interaction (similar to Voulis *et al.* (2019)). The model defines these ranges with the minimum $\tau_{D_A}^{min}$ and maximum temperature

$\tau_{D_A}^{max}$ of the devices so that $\tau_{D_A}^{min} \leq \tau_{D_A}(t) \leq \tau_{D_A}^{max}$ is always valid. The simulation starts and ends with the device at the initial temperature level $\tau_{D_A}^{init}$. Current temperature $\tau_{D_A}(t)$ is given by temperature consumption $\Delta\tau_{D_A}^{C}(t)$ (only for the hot water of the immersion heater and the air conditioning in specific hours), temperature losses $\Delta\tau_{D_A}^{0}$ and temperature gains $\Delta\tau_{D_A}^{1}$ when the device is operating:

$$\tau_{D_A}(t) = \tau_{D_A}(t-1) - \Delta\tau_{D_A}^{C}(t) - \Delta\tau_{D_A}^{0} + \Delta\tau_{D_A}^{1} \cdot \theta_{D_A}(t). \tag{2.3}$$

2.2.2.2 Conditions for 'Semi-Automatic' Devices

'Semi-automatic' devices require external data input and the consumer needs to prepare their operation manually (for example loading the washing machine or dishwasher). However, within the consumer's given timespan, these 'semi-automatic' devices are able to operate in conjunction with a smart controller. All 'semi-automatic' devices considered in this study cannot be disrupted during their operation. Once they were started by the automatic controller, they will have to operate and complete their cycle. Whether the device is operating within an hour is then given by the switch on event $\Upsilon_{D_\mathrm{S}}^{1}(t)$ and the length L_{D_S} a cycle takes:

$$\theta_{D_\mathrm{S}}(t) = \sum_{\mathrm{j}=t}^{L_{D_\mathrm{S}}+t} \Upsilon_{D_\mathrm{S}}^{1}(t), \qquad \mathrm{j}, L_{D_\mathrm{S}} \in \mathbb{N}, \Upsilon_{D_\mathrm{S}}^{1}(t) \in \big[0;1\big]. \tag{2.4}$$

To account for consumer preferences, the model limits the operation to the timespan between simulated loading and deloading events as indicated by the flexibility state $\rho_{D_\mathrm{S}}(t)$:

$$\theta_{D_\mathrm{S}}(t) \leq \rho_{D_\mathrm{S}}(t), \qquad \rho_{D_\mathrm{S}}(t) \in \big[0;1\big]. \tag{2.5}$$

If $\rho_{D_\mathrm{S}}(t) = 1$, a device D_S is prepared by the consumer and therefore ready to operate. If $\rho_{D_\mathrm{S}}(t) = 0$ the device D_S needs to be finished with its operation. With another binary variable during optimization, the program assures that the device does not switch on multiple times without consumer interaction in between.

2.2.2.3 Conditions for an Electric Vehicle

The inbuilt battery of the electric vehicle offers the flexibility to pause charging when prices increase and continue as soon as prices drop. The electric vehicle can only charge when the consumer is not driving, as stated in the first case of Equation 2.6. The current state of charge $E(t)$ of the battery can be described by the previous state of charge $E(t-1)$, the charging rate E^{Charge} and the indicator $\theta_{D_{EV}}(t)$ whether the electric vehicle is currently charging with $\theta_{D_{EV}}(t) \in [0,1]$.

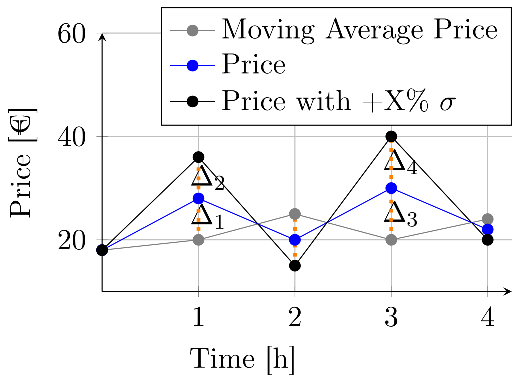
Most electric vehicles recharge as soon as they are plugged in. With information on future trips, a smart controller is able to schedule the charging to the cheapest hours. Thereby, it would be sufficient to only charge the power needed for the next trip. However, consumers might prefer a fully charged battery whenever they begin a journey to preserve some flexibility, even if it reduces the potential savings made by the smart controller. For this reason, the second case of Equation 2.6 states the condition to always fully charge the battery prior to the next trip. In case of insufficient time for charging to full capacity, the smart controller would still maximize the state of charge regardless of electricity prices at the time. The current maximum state of charge $E^{maxC}(t)$ is the benchmark to be reached, calculated as if the electric vehicle would start recharging immediately after returning from a trip. The third case describes the electricity consumption while the electric vehicle is in motion:

$$E(t) = \begin{cases} E(t-1) + E^{Charge} \cdot \theta_{D_{EV}}(t) & if\, \rho_{D_{EV}}(t) > 0 \\ \min\left[E^{max}, E^{maxC}(t)\right] - \Delta E(t) & if\, \rho_{D_{EV}}(t) - \rho_{D_{EV}}(t-1) < 0 \\ E(t-1) - \Delta E(t) & else. \end{cases} \tag{2.6}$$

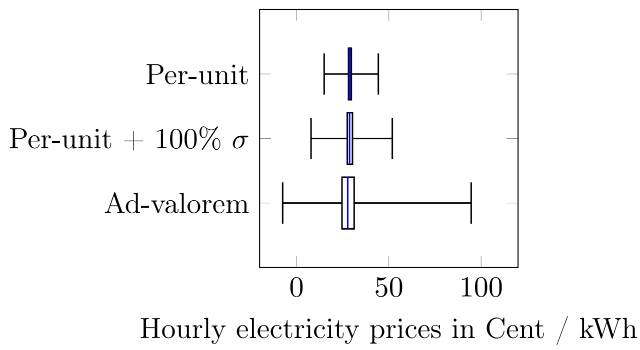
The battery cannot discharge more than the energy $E(t)$ it currently stores and cannot be charged to more than its maximum capacity E^{max} so that $E^{min} \leq E(t) \leq E^{max}$ is always valid.

2.2.3 Increasing Price Volatility

Short-term volatility in electricity prices is essential when it comes to generating savings via load shifting with smart appliances. Within the 'per-unit' taxation setting, the moving average price of 12 hours before and 12 hours after every timestep serves as a reference to measure and manipulate this short-term volatility. Considering this time window, this moving average includes a complete day-night shift spanning across the most likely load shifting window. Hence, it is a suitable reference for the short-term price volatility the household could utilize when shifting loads. The difference between this moving average and the current exchange price is then used to relatively manipulate the price volatility. While prices above this moving average



(A) Principle of increasing price volatility along the moving average.



(B) Exemplary statistics of the generated dynamic electricity prices.

FIGURE 2.1: The process of increasing the short-term price volatility and the resulting volatility in retail prices.

(peaks) would be increased, prices below the moving average (valleys) would be decreased even further. Fig. 2.1a illustrates this mechanism, while the following equation defines the price $p(t)_\sigma$ for an increase in volatility σ:

$$p(t)_\sigma = p(t) + \sigma \cdot \left(p(t) - \sum_{i=-12}^{12} p(t+i) \right) \tag{2.7}$$

In this 'per-unit' taxation setting, retail prices are solely influenced by changes in exchange price volatility, while taxes stay constant. In the 'ad-valorem' taxation setting, the taxes dynamically increase or decrease with the exchange market prices. The boxplots in Fig. 2.1b illustrate the resulting variation in prices.

2.3 Input, Data and Assumptions

2.3.1 Input for Household Devices

Devices that have a low ownership rate or are insignificant due to their low consumption are not considered within this study. This paper simulates German households as a case study. The devices used as well as their operation habits should be representative for many other countries as well. Table 2.2 lists electrical household devices with their particular category and their ownership rate in the German market.

TABLE 2.2: Statistics of common household devices in Germany: a device categorization based on consumer interaction.

Device	Category[a]	Ownership rate[b].
Fridge	Automatic	99.9%
Freezer	Automatic	51.6%
Immersion heater	Automatic	38.4%
Air conditioning	Automatic	3.14% - 8.21%
Dishwasher	Semi-Automatic	71.5%
Washing machine	Semi-Automatic	96.4%
Tumble dryer	Semi-Automatic	42.2%
Electric vehicle	Specific	-

[a]These categories depend on the parameters governing my simulations. Other studies might use different categories, probably due to different time-interval resolutions, as suggested by Beaudin & Zareipour (2015).
[b]The ownership rates are based on Statistisches Bundesamt (2018) for all devices except the immersion heater, which is stated from EnergieAgentur.NRW (2015), and the air conditioning taken from Kenkmann *et al.* (2019).

Washing machine and tumble dryer present a difficulty for load shifting, as the operation of the latter is dependent on the former and requires intermediate consumer interaction. The ‘washer-dryer’ combines a washing machine with a tumble dryer, so that additional user interaction is omitted. For this reason, this paper simulates the washer-dryer instead of the two separate devices as one of the common ‘semi-automatic’ devices in a future smart home.

The fridge, freezer, immersion heater and air conditioning are simulated as ‘automatic’ devices. While the ownership rate of air conditioning is still comparably low in Germany, it is commonly owned in warmer countries and thus worth to include in this study. Considering the expected increase in future ownership rate and the significance regarding the power consumption, the electric vehicle is part of these simulations as well. The following subsections describe the input parameters for the ‘automatic’ and ‘semi-automatic’ devices and the electric vehicle.

2.3.1.1 Input for ‘Automatic’ Devices

This study uses the average technical specifications of devices labeled with at least a ‘good’ grading within the latest tests of Stiftung Warentest (2021) to create a representative fridge (integrated and freestanding since 08/2018), freezer (since 09/2018) and air conditioning system (all fixed mounted split devices of the 06/2020 test) for these simulations. Table 2.3 states the resulting average values together with the inputs for the immersion heater. These 'automatic' devices can shift their operation within the range of their internal temperature limits. The total annual consumption $q^T_{D_A}$ of an 'automatic' device is the sum of the hourly loads over the year:

$$q^T_{D_A} = \sum_t^T \theta_{D_A}(t) \cdot \omega_{D_A}. \tag{2.8}$$

For reasons of simplicity, this study does not specifically simulate consumer events like opening the fridge/freezer, placing warmer goods inside or the power consumption of small features like the light or display. These losses, however, are included in the producer's given statistics for the annual consumption $q^T_{D_A}$. Knowing the expected annual consumption $q^T_{D_A}$ and the wattage ω_{D_A}, the yearly operating time $\theta^T_{D_A}$ can be calculated with:

$$\theta^T_{D_A} = q^T_{D_A} / \omega_{D_A}. \tag{2.9}$$

The temperature with operating and non-operating times is then defined in an equation as:

$$\tau^{end}_{D_A} = \tau^{init}_{D_A} + \theta^T_{D_A} \cdot \Delta\tau^1_{D_A} - T \cdot \Delta\tau^0_{D_A} - \sum_t^T \Delta\tau^C_{D_A}(t). \tag{2.10}$$

The immersion heater loses substantial temperature as soon as the consumer uses hot water. As a proxy for this energy consumption this study uses the reference tapping cycle of Energy Saving Trust (2008). Given in kWh, the profile is converted with $\omega_{D_A} = m \cdot c \cdot \Delta Temperature$ into temperature changes in a 150 litre tank with mass m of water to be constant at $1kg/l$ and specific heat capacity c to be $0.00116617kWh/kg$.

For the air conditioning, this study uses outside air temperature data as a proxy for the heat load within an hour. With the data of climate research stations provided by Deutscher Wetterdienst (2021), this papers simulates air conditioning systems in or near the four biggest German cities Berlin (dataset 433, in the east), Hamburg (dataset 1975, in the north), Munich (dataset 3379, in the south) and Cologne (dataset 2968, in the west). Due to their geographical allocation and population density, these citiy-areas should be representative for a large proportion of German households and simultaneously project a good range of climatic differences.

The current room temperature $\tau_{AC}(t)$ changes according to the outside air temperature $\tau^{air}_{AC}(t)$ and the inertia factor $\beta_{AC} = 50\%$. This study assumes air conditioning in Germany to be solely

TABLE 2.3: Input variables and assumptions for the fridge, freezer, immersion heater and air conditioning.

Variable	Fridge	Freezer	Immersion heater	Air conditioning
Initial temperature $\tau_{D_A}^{init}$	$+4°C$	$-21°C$	$+50°C$	$+18°C$
Maximum temperature $\tau_{D_A}^{max}$ [a]	$+6°C$	$-16°C$	$+82°C$	$+24°C$
Minimal temperature $\tau_{D_A}^{min}$ [a]	$+3°C$	$-27°C$	$+35°C$	$+18°C$
Temperature losses $\Delta\tau_{D_A}^{0}$ [b]	$+0.75°C$	$+0.46°C$	$-0.28°C$	-
Temperature consumption $\Delta\tau_{D_A}^{C}(t)$ [c]	$0°C$	$0°C$	hourly	hourly
Wattage ω_{D_A} of the device [d]	87 W	153 W	1600 W	2440 W
Yearly energy consumption $\sum_t^T q(t)[D_A]$ [d]	85.67 kWh	221 kWh	-	95 kWh
Temperature change $\Delta\tau_{D_A}^{1}$ per t of operation [e]	$-6.64°C$	$-2.79°C$	$+9.15°C$	$-26.84°C$

[a] The temperature ranges for fridge and freezer are based on Pfeifroth *et al.* (2012). For the immersion heater, this study refers to Nehrir *et al.* (1999). The ranges for the air conditioning are based on the recommendations of World Health Organization (1990).
[b] For the fridge and freezer calculated with the temperature ranges of Pfeifroth *et al.* (2012) and a 4-hour / 24-hour storage capacity based on the power blackout food recommendations of United States Department of Agriculture (2013). this study uses half of the observed average loss rate of Finn *et al.* (2011), as their system uses twice the storage capacity used in this study. For the air conditioning, this paper uses hourly air temperature data instead of constant losses.
[c] This paper does not consider specific consumption patterns for the fridge and the freezer. The consumption for the immersion heater is based on Energy Saving Trust (2008). Air temperature data of Deutscher Wetterdienst (2021) serves as a proxy for the air conditioning usage.
[d] Average specifications of fridges, freezers and air conditioning tested by Stiftung Warentest (2021). For the immersion heater, this study assumes half the wattage of Finn *et al.* (2011).
[e] Calculated with Equation (2.10) for the fridge and freezer. For the immersion heater, the rising temperature can be calculated with the wattage. For the air conditioning, this study uses the wattage, the yearly energy consumption and the average heat load (see Equation 2.12) across the simulated cities. The average result is equivalent to a 4.47°C decrease in temperature within 10 minutes of operating the air conditioning.

used for cooling, as heating would be highly inefficient and cost intensive at colder temperatures. Hence, this study assumes the room temperature to always stay above the minimum temperature τ_{AC}^{min}:

$$\tau_{AC}(t) = \max\left[\tau_{AC}(t-1)\cdot\beta_{AC} + (1-\beta_{AC})\cdot\tau_{AC}^{air}(t), \tau_{AC}^{min}\right] \tag{2.11}$$

Since the outside air temperature $\tau_{AC}^{air}(t)$ might be either heating up or cooling down the room, a vector of the hourly heat loads $\Delta\tau_{AC}^{C}(t)$ is used in equation 2.3 similarly to the hourly changing consumption of the immersion heater. By using this case distinction, this study assures that the problem itself remains feasible for every timestep:

$$\Delta\tau_{AC}^{C}(t) = \begin{cases} \tau_{AC}(t) - \tau_{AC}^{max} + \max\left[\tau_{AC}(t) - \tau_{AC}(t-1), 0\right] & if\, \tau_{AC}(t) > \tau_{AC}^{max} \\ \tau_{AC}(t) - \min\left[\tau_{AC}(t-1), \tau_{AC}^{max}\right] & else. \end{cases} \tag{2.12}$$

2.3.1.2 Input for 'Semi-Automatic' Devices

Almost all households in Germany are charged based on a flat electricity tariff. Therefore, consumers currently do not derive any advantage from load shifting. Hence, historic load profiles are not distorted by incentivation and represent the maximum convenience load pattern of the consumers. Peaks in a load pattern can be interpreted as the times during which the consumers prefer to operate devices. In order to generate a common activity pattern, this study tests two consumption profiles, a standard representative load profile for a household in 2017 provided by EnergieNetze Bayern & BDEW Bundesverband der Energie- und Wasserwirtschaft e.V. (2018) as well as an average profile created out of 74 German households provided by Tjaden *et al.* (2015). The minimum load - representing the base load without user activity - within the profiles is removed, so as to obtain an 'activity-pattern' of the consumers in every hour.

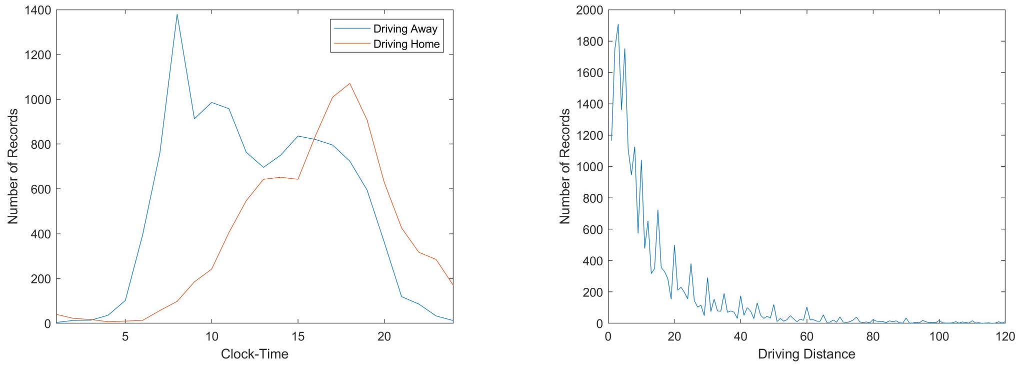
From this, a probability function is generated to determine the times where the consumers most likely operate their 'semi-automatic' devices. The start and end events are distributed with respect to this probability function until the number χ_{D_S} of cycles within a year is reached. The algorithms create 100 annual household patterns for each device while ensuring that only realistic and feasible flexibility windows are generated. A new cycle, for example, cannot be commenced until the previous cycle finished. For reasons of simplicity and since the resulting savings between the two consumption patterns did not significantly differ, this paper further only presents the results with the consumption patterns based on the profile of EnergieNetze Bayern & BDEW Bundesverband der Energie- und Wasserwirtschaft e.V. (2018). The input variables for the dishwasher and washer-dryer are summarized in Table 2.4.

2.3.1.3 Input for the Electric Vehicle

To simulate the power consumption of the electric vehicle, this study uses driving data from year 2016 provided by the German Mobility Panel (Zumkeller *et al.*, 2018). The data are filtered, so that only records are used where the main vehicle is a car (Code 41 in the dataset) and where

TABLE 2.4: The average specifications of the devices tested by Stiftung Warentest (2021) since 2019 with 'good' grading for the input parameters for the dishwasher and washer-dryer .

Variable	Dishwasher	Washer-dryer
Yearly power consumption $\sum_t^T \theta_{D_\mathrm{S}}(t)$	286 kWh	1224 kWh
Wattage ω_{D_S}	340 W	510 W
Number χ_{D_S} of cycles per year	280	200
Length L_{D_S} of each cycle	3 hours	12 hours



(A) Trips of vehicles leaving the household and returning grouped by daytimes.

(B) Trips of vehicles grouped by distance of the trip.

FIGURE 2.2: Input data for simulating electric vehicle trips during the simulation after manual filtering.

the driver is either assumed to leave the household (Codes of purpose 1,3,4,5,6,11) or intends to return to the household (Code 7). All records with a single distance greater than 120 km (round trip) are excluded, since the simulation assumes a maximum range of 240 km and the household to be the only place to charge the electric vehicle. The remaining 21,383 dataset records are used to generate a distribution of the usage of the electric vehicle, this being configured in relation to the likelihood of the vehicle departing from or arriving back at the household, as well as the driven distance (see Fig. 2.2).

The algorithm first draws the time at which the car leaves the household and another one at which it returns according to the probability distributions for a random day in the year. Its return needs to be on the same day as its departure or within a period of 18 hours. By that, the possible driving timeframes are usually limited to one day. By repeatedly drawing random days and on and off times, the algorithm generates a boolean electric vehicle occupancy pattern, whereby $\rho_{D_{EV}}(t) = 1$ indicates that the electric vehicle is plugged in and is capable of being charged. $\rho_{D_{EV}}(t) = 0$ indicates that the car is on a trip and cannot be charged.

For every journey undertaken by the electric vehicle the driving distance distribution is used to draw a distance that is achievable within the previously configured timeframe. The possible distances d within the distribution are limited by the timespan between leaving the household t_{off} and returning t_{on} at average speed v as well as the the maximum distance d^{max} of the electric vehicle:

$$d \leq \min\left[\frac{(t_{on} - t_{off}) \cdot v}{2}, \frac{d^{max}}{2}\right]. \tag{2.13}$$

Once the vehicle returns at home, the state of charge of the battery is reduced by the electricity consumed, based on the distance driven (two-way):

$$\Delta E(t) = d \cdot 2 \cdot E^{Consumption}. \tag{2.14}$$

This is repeated until the average distance of 10,300 km/year (Frenzel *et al.*, 2015) for a battery electric vehicle is either reached or exceeded. The resulting profiles are validated by checking the maximum state of charge $E^{maxC}(t)$ that the battery could have at any given time. If it is greater than the electricity needed for the next trip, the profile is valid. The maximum state of charge possible at a specific time t is defined by:

$$E^{maxC}(t) \begin{cases} min\left[E^{maxC}(t-1) + E^{Charge}, E^{max}\right] & if \rho_{D_{EV}}(t) > 0 \\ E^{maxC}(t-1) - \Delta E(t) & else. \end{cases} \tag{2.15}$$

The assumptions of the vehicle attributes are derived from the most popular electric cars currently on the market. Based on these assumptions and driving data the algorithm generates 100 electric vehicle consumption patterns as described above. The input values for the electric vehicle are summarized in Table 2.5.

2.3.2 Market Exchange Prices, Taxes and Levies

Retail electricity prices in Germany include the costs relating to electricity exchange, transport and distribution, as well as approximately 55% of multiple taxes and levies (Bundesverband der Energie- und Wasserwirtschaft e.V., 2018). This study uses the day-ahead spot prices of the European Power Exchange (Epex Spot SE, 2018) of the year 2017 for the German market to

Table 2.5: Input variables for the electric vehicle.

Variable	**Electric Vehicle**
Charging power E^{Charge}	11.00 kW
Maximum battery capacity E^{max}	31.00 kWh
Power consumption $E^{Consumption}$	12.92 kWh[a]
Initial battery state of charge $E(t)$ for $t = 0$	15.50 kWh
Average speed in driving v	32.70 km/h [b]
Average distance per year	10,300 km [c]

[a]Per 100 km, assuming 240 km maximum distance with a 31 kWh battery.
[b]Average speed of motorized individual traffic for cities as stated in Ahrens *et al.* (2016).
[c]Based on Frenzel *et al.* (2015).

create artificial dynamic prices. The spot prices of 2017 are cleared for the summer time shift and adjusted to align them with the statistics of Bundesverband der Energie- und Wasserwirtschaft e.V. (2018). This ensures that the consumer almost pays the same total bill as he would have in a flat tariff. The static costs titled 'purchasing and sales' by Bundesverband der Energie- und Wasserwirtschaft e.V. (2018) are replaced with dynamic spot market prices $p(t)_{SPOT}$ thereby generating a dynamic tariff, where the taxes and levies p_{TL} are added on top. The status quo consists of adding the renewable energy fee (6.88 Cents/kWh), grid-fees (7.5 Cents/kWh) and the other taxes and levies (4.514 Cents/kWh) on a per-unit basis. Value-added tax p_{VAT} is then charged with 19% on top:

$$p(t) = [p(t)_{SPOT} + alignment + p_{TL}] \cdot (1 + p_{VAT}) \tag{2.16}$$

This 'per-unit' taxation is charged regardless of whether spot market prices on the energy exchange are positive or negative. An alternative approach would be to charge the taxes based on the day-ahead prices of the spot market as suggested for the renewable energy fee by Frontier Economics Ltd & BET Büro für Energiewirtschaft und technische Planung GmbH (2016). This 'ad-valorem' taxation is only charged when the prices on the spot market $p(t)_{SPOT}$ are positive. The tax rate is set by the historic proportion of taxes and levies p_{TL} charged compared to 'purchasing and sales' costs p_{PS}.

$$p(t) = \left[(p(t)_{SPOT} + alignment) \cdot \frac{p_{TL}}{p_{PS}}\right] \cdot (1 + p_{VAT}). \tag{2.17}$$

2.3.3 Costs of Smart Metering

To incentivize load shifting, the associated costs need to be covered. Since the automatic controller and the smart devices shift loads without any user interaction, it is assumed that consumers do not face any disutility. However, smart devices, controllers and meters always require some level of upfront investment and incur operating costs.

The study assumes annually fixed recurring costs for smart metering to be between 48€ and 88€ per year, based on the calculations of Liebe *et al.* (2015) for a household consuming 4,000 kWh - 6,000 kWh or more than 6,000 kWh per year. Similar to Liebe *et al.* (2015), this paper assumes a household with an electric vehicle or an electric immersion heater to consume above the 6,000 kWh mark and charged with 88€ per year. Households without these devices are assumed to be below the mark and therefore charged at 48€ instead of 88€ per year. This study does not consider further maintaining costs or other operational expenses.

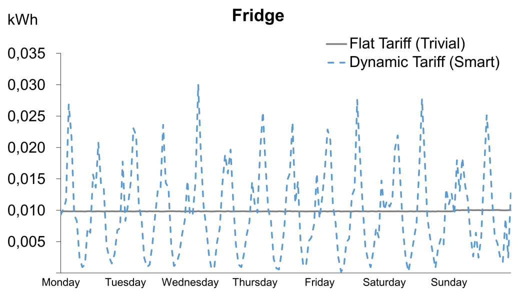
2.4 Results and Discussion

2.4.1 Load shifts with a Dynamic Tariff

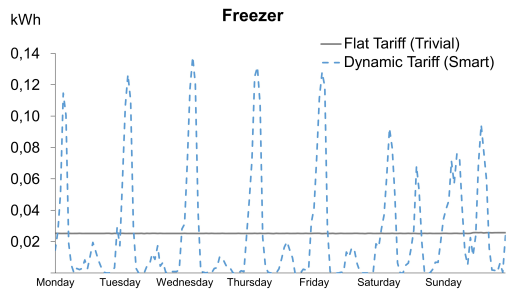
Fig. 2.3 illustrates the average patterns of the devices simulated for a future smart household. In a flat tariff, the fridge and freezer would constantly cool, leading to an evenly distribution in usage. In a dynamic tariff, fridge and freezer use their thermal inertia to pre-cool and make use of the hours with the cheapest electricity prices. Very similar to that, the immersion heater pre-heats during the night to satisfy the hot water demand in the morning.

The air conditioning shows only minor load shifts within the simulation of German households. The low number of hot days with air temperatures above 24°C leads to a low overall usage of the air conditioning system limiting the opportunities to shift loads. This might be substantially different in hotter climatic regions. However, if air temperatures rise to a level that forces the air conditioning to almost run continuously, the flexibility potential to shift loads diminishes again. Hence, it depends on the individual specifics of every region whether air conditioning systems are a relevant device for a load shifting household.

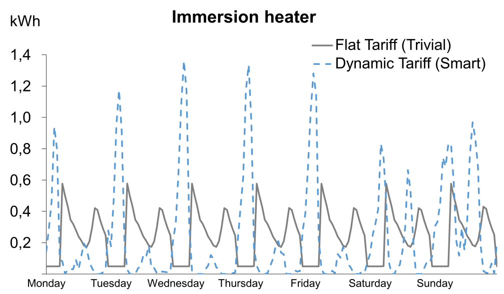
In contrast to the previous devices, the dishwasher, washer-dryer and the electric vehicle allow for delaying load shifts. Since these devices require the manual preparation by the consumer,



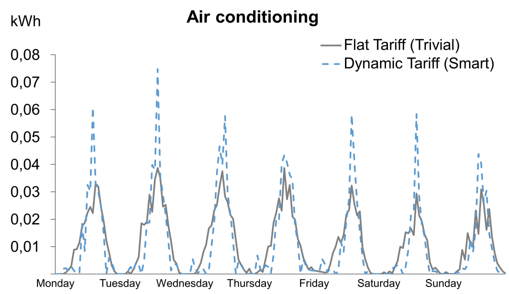
(A) Average weekly pattern of the fridge.



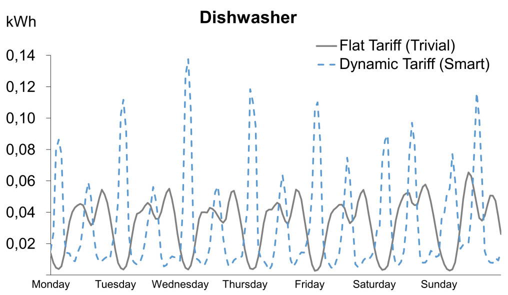
(B) Average weekly pattern of the freezer.



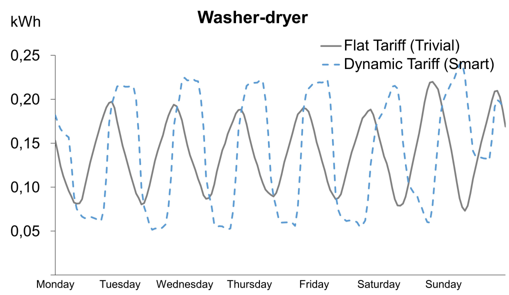
(C) Average weekly pattern of the immersion heating.



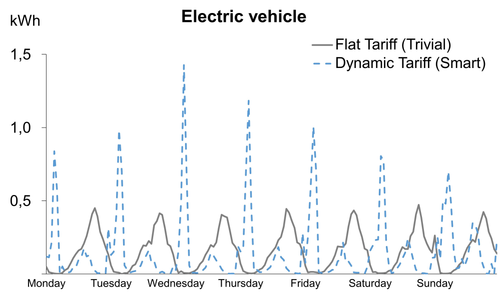
(D) Average weekly pattern of the air conditioning.



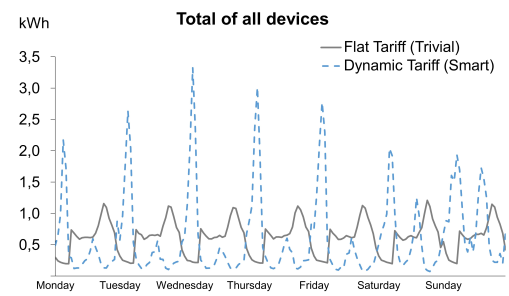
(E) Average weekly pattern of the dishwasher.



(F) Average weekly pattern of the washer-dryer.



(G) Average weekly pattern of the electric vehicle.



(H) Average weekly pattern of all automatic and semi-automatic devices as well as the electric vehicle.

Figure 2.3: Average weekly patterns of the individual devices either in a flat tariff without smart load shifting or a dynamic tariff with smart load shifting.

they can not pre-run their cycle but shift their operation to later times instead, when energy is cheap.

The daily pattern of the aggregated load of all devices (see Fig. 2.3h) is largely influenced by the load shifts of the immersion heater and the electric vehicle. While the daily pattern repeats during the week, it slightly changes on the weekends due to differing consumer usage behaviour and price changes.

2.4.2 Potential Savings: Flat Tariff vs. Dynamic Tariff

For the financial comparison with a flat tariff, this study assumes a constant electricity price of 29.23 Cents per kWh as charged to households on average in 2017 (Bundesverband der Energie- und Wasserwirtschaft e.V., 2018). Since prices stay the same for the whole year, there is no reason to shift loads from a consumer perspective. The dynamic tariff, on the other hand, allows price minimizing shifts. Fig. 2.4 illustrates the average annual savings of every device with a dynamic tariff.

While the washer-dryer consumes a major share of the electricity within the household, it cannot offer flexibility. Since the device is simulated at 200 cycles per year with 12 hours per cycle, the time remaining for shifted operation is somewhat limited. Thus, the potential savings are rather meagre between 6.82€ and 11.94€ per year depending on the usage patterns. While the dishwasher can offer more flexibility, it is not as significant regarding the power consumption, leading to savings between 2.93€ and 4.23€ per year. Smart charging the electric vehicle leads to savings between 16.80€ and 27.55€ per year depending on the driving patterns of the consumer. The electric immersion heater offers the highest saving potential, but is one of the least common devices due to cheaper substitutes like gas powered heaters.

Due to low electricity consumption, the automatic cooling devices show very little saving potential in absolute terms. The freezer offers a potential in savings of only 4€ per year. A smart fridge would even undercut this with savings of less than 1€ per year. The air conditioning varies depnding on the location with a range between 0.18€ in Hamburg (in the north of Germany) to 1.39€ in Munich (in the south of Germany). Compared to the 19,992€ of average household income in 2017 (1,666€ per month, see WSI Verteilungsmonitor, 2019) these savings are not significant. In fact, on average, consumers would expect savings of 45€ (3.80€ per month) from

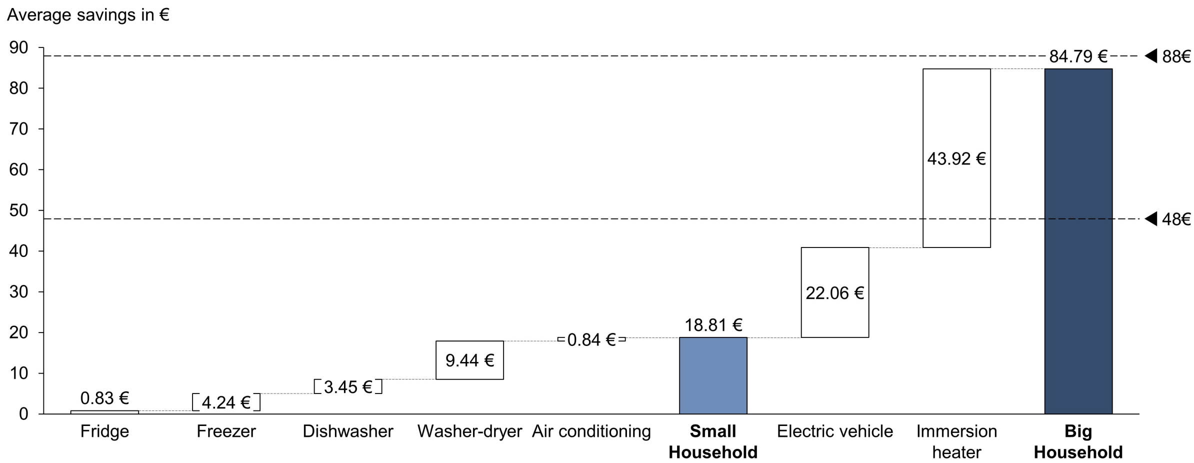


Figure 2.4: Average savings of annual electricity costs incurred in the operation of common household devices with a smart controller in a dynamic tariff compared to a flat tariff.

a smart fridge (Pfeifroth *et al.*, 2012). This illustrates the enormous gap between the actual potential in savings under current price volatility and the expectations of consumers.

As illustrated in Fig. 2.4, the current price volatility would not be sufficient to cover the fixed costs of smart metering. Neither the combination of devices designed for the 'small' household with metering costs of 48€, nor all of the devices together with metering costs of 88€ can generate sufficient savings. In conclusion, households have no incentive to switch to a dynamic tariff under current price volatility.

2.4.3 Sensitivity on Short Term Price Volatility and 'Ad-Valorem' Taxation

Since this study only considers automated load shifting with no or only minor user interaction, there is no minimum price movement required to trigger load shifting. Whereas a human would not react to every pricing signal, the automatic controller would consider even the smallest changes in the prices to minimize the costs of electricity. Therefore, increasing price volatility will not change the strategy of the smart controller per se. However, due to larger price gaps, the strategy will have a more significant impact on the total electricity bill.

This study increases the price volatility in a constant 'per-unit' taxation regime and calculates the potential savings compared to the flat tariff as illustrated in Fig. 2.5. A household with all of the devices evaluated will cover the fixed metering costs of 88€ at approximately 6% higher price volatility. The small household (with no electric vehicle or immersion heater) would need approximately 235% higher price volatility and is therefore far from covering the 48€ in metering

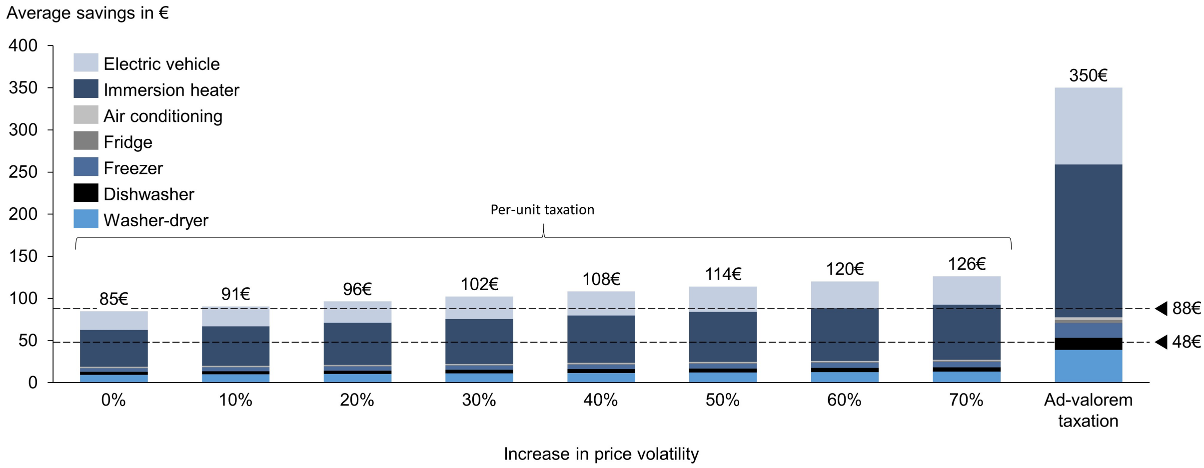


FIGURE 2.5: Comparison of average savings for the operation of common household devices with a smart controller under a 'per-unit' taxation regime with different price volatility and 'ad-valorem' taxation regime.

costs. Thus, a switch to a dynamic tariff is less relevant for smaller households within a 'per-unit' taxation regime as their required increase in price volatility is unlikely to be achieved.

One way to achieve high price volatility is to change the taxation towards an 'ad-valorem' taxation regime as illustrated in the last bar of Fig. 2.5. If new regulations lead to a switch towards this taxation regime, the saving potential of load shifting within households increases considerably. The 'ad-valorem' taxation would thereby enable the smart controller to cover the operating costs of 48€ or 88€ even at current observed price volatility levels. While a dynamic tariff under 'ad-valorem' taxation would already pay off the 88€ with a single electric immersion heater, households using all these smart devices would on average save 350€.

The simulations indicate that most households will not be able to generate the necessary savings to cover metering costs under 'per-unit' taxation. Therefore, especially small households will not switch to a dynamic tariff as long as the taxation regime is not changed in favor of 'ad-valorem' taxation. Unless this condition is met, smart features for load shifting in fridges, freezers, dishwashers and washer-dryers as well as air conditioning systems will not find a market.

2.4.4 Risk Evaluation Within a Dynamic Tariff Under 'Ad-Valorem' Taxation

To conclude with a policy recommendation, it is necessary to evaluate the risks of 'ad-valorem' taxation in a setting where the consumer is subject to a dynamic tariff but might not operate smart devices. Trivial devices would start their operation as soon as they are plugged in by the consumer, since they are not governed by any intelligent control systems. The operation could then fall into more expensive hours and in so doing increase the electricity bill. A change to 'ad-valorem' taxation might then be disadvantageous for the household. Therefore, these simulations are run on the same inputs again, although every device is forced to commence operating immediately.

Fig. 2.6 illustrates the difference in the electricity bill in a dynamic tariff compared to a flat tariff whereas the households use either 'trivial' or 'smart' devices for both taxation regimes. The range of the box plot marks the best case when the household is fully smart equipped as well as the worst case when only trivial devices are used. A household using only trivial devices would thereby face slightly increased costs in a dynamic tariff compared to a flat tariff.

While households with trivial devices might consume at times with higher prices, they also consume electricity at times when it is cheap anyway. By consuming the energy when plugged in, the resulting mix of cheap and expensive electricity only leads to very small cost risks. The potential cost risks under 'ad-valorem' taxation are slightly higher since the taxes charged on the prices have additional negative effects for households with trivial devices. However, these risks could still be assumed to be negligible compared to the high advantages in potential savings if households use smart devices.

The cost-optimal scheduling of a smart household, on the other hand, avoids almost any high-priced times and explicitly shifts power to the cheapest hours. Hence, the resulting price mix benefits more from short-term price movements. The potential savings up to 89€ and 366€ as indicated by the left side whiskers of the box plots by far outweigh the potential losses. A mandatory dynamic pricing tariff would probably lead to slightly higher electricity bills for households without smart devices. The potential benefits for households with smart devices, on the other hand, offsets the risks by far, especially with 'ad-valorem' taxation.

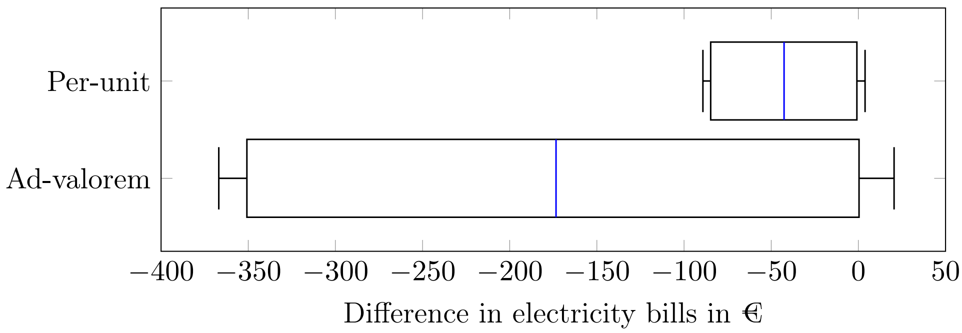


FIGURE 2.6: Difference in the annual electricity bill under a dynamic tariff compared to a flat tariff with scenarios of no smart devices and all devices being smart.

2.5 Conclusions and Policy Implications

This paper evaluates the economic benefits of automated load shifting with common household devices and investigates the effects of a change towards 'ad-valorem' taxation of electricity, based on market prices. Historic electricity load profiles and driving patterns are used to create realistic consumption patterns and to simulate the flexibility and saving potential of every device. The simulations show that current price volatility is not sufficient to cover the additional costs of smart metering technology. A regulatory change towards an 'ad-valorem' taxation regime would increase the retail price volatility and thereby enable households to economically participate in automatic load shifting activities.

If a mandatory switch to dynamic tariffs in a 'per-unit' taxation were to be imposed by official regulation, households with no smart devices would suffer only slightly higher total bills. As soon as the household devices react to prices, they generate some savings but will most likely not offset the higher costs of smart metering technology in a 'per-unit' taxation. Only 'ad-valorem' taxation would elevate the potential savings to a level that would consequently incentivize load shifting and investments in smart technology while the risks for households without smart devices remain comparably low.

Further research could evaluate the consumer's willingness to manually shift loads if an 'ad-valorem' taxation regime leads to large price fluctuations. A welfare analysis and a tax-authorities' perspective on a shift towards 'ad-valorem' taxation would be another interesting area for following research: As a fully smart equipped household consumes at times where market exchange prices are approximately 35% lower, the taxes and levies paid by the household would also shrink by approximately 20%. These losses in tax revenues might challenge the tax authorities and also distort the profitability and therefore the incentive for certain investments, for example in storage or the grid. However, incentivizing load shifts with a changed taxation regime might pay off, if the load shifting triggered leads to a higher share and cheaper integration of renewable energy while reducing the need for extensive grid investments or storage facilities.

3 How Households Benefit From Pre-announced Electricity Price Information: A Rolling Horizon Simulation With a Battery Storage System

The operational strategy of a residential energy storage system in a dynamic electricity tariff critically depends on the availability of information on future prices. If the storage charges electricity in times of low prices and discharges in times of high prices, households can reduce their electricity bill while potentially decreasing imbalances in the grid at the same time. Electricity providers may pre-announce and guarantee prices for a certain time period, e.g. the next six hours, to incentivize grid-serving use of storage systems. This paper aims to value pre-announced price information for a household with a photovoltaic roof system and a battery storage in a German case study. To determine the sensitivity of a household's electricity bill towards limited external information on future prices, I evaluate different pre-announcement periods for prices with simulations in a rolling horizon approach. I use autoregressive integrated moving average (ARIMA) forecasts to predict the photovoltaic production, the household's consumption as well as electricity prices beyond the information given by the provider. Results indicate that pre-announced external price information of a 3-8 hour period is of major value for a statistically trained system. Pre-announcements beyond this period only have a marginal impact on the resulting savings for consumers. My findings and the proposed model help households and electricity providers to assess dynamic electricity tariffs and determine optimal structures for demand-side management.

Keywords: Dynamic Prices, Forecasts, Battery Storage, Arbitrage, Optimization.

3.1 Introduction

A large number of households in Germany use a photovoltaic roof to either sell power to the grid or to reduce the electricity bill by self-consuming the power. Some households using photovoltaic systems save additional electricity costs by installing a battery system. The battery system stores excess energy and increases self-consumption to further avoid costly purchases from the electricity provider. Within a dynamic electricity tariff, the battery may charge in times of low prices and discharge in times of high prices according to the pricing signals given by the provider.

To optimally exploit price fluctuations, the battery requires information on future prices, load demand and photovoltaic production. Without these inputs, the battery may not respond to the pricing signals of the electricity provider appropriately. Electricity providers may therefore pre-announce and guarantee prices for a certain period of time, e.g. the next six hours, to foster load shifting through storage systems according to their pricing signals. Thereby, the electricity provider lifts the risk of price changes on the energy exchange from its customers. Hence, the electricity provider intends to keep the horizon for the pre-announcement sufficiently long to enable beneficial charging strategies yet as short as possible to avoid high risks due to unplanned price changes.

This raises the following questions: What is the horizon of price pre-announcements required for a battery system to generate significant savings via load shifting? How sensitive are the electricity costs of a household towards this length of the pre-announcement period?

Previous literature already developed operational strategies for demand-side management with a battery storage system together with photovoltaic units (see Matallanas *et al.*, 2012, Di Giorgio & Liberati, 2014, Ratnam *et al.*, 2015) and their usage in dynamic pricing environments (for example Sani Hassan *et al.*, 2017, Erdinc, 2014, Babacan *et al.*, 2017, Dufo-López, 2015, Klein *et al.*, 2019). Some papers like (Nottrott *et al.*, 2013, Lorenzi & Silva, 2016, Yoon & Kim, 2016, Abdulla *et al.*, 2016, Hanna *et al.*, 2014, Chitsaz *et al.*, 2018) optimize battery strategies with a rolling forecast horizon window (usually 24 hours) to account for the lack of information, but have a different focus than the horizon length with price information uncertainty. Silvente *et al.* (2015) evaluate the effects of uncertainty in demand and production via a rolling horizon optimization in a microgrid. Lujano-Rojas *et al.* (2017) investigate effects of forecasted errors in energy prices with stand-alone lead-acid batteries. So far, it is unknown to what extent future price information enhances the profitability of a residential photovoltaic-plus-battery system under a dynamic power tariff in a household setting.

I determine the additional saving potential by a battery of a household with a photovoltaic roof receiving pre-announced dynamic electricity prices. Therefore, I create a linear cost minimization program with a rolling horizon to simulate the charging strategy of a battery storage system. The battery storage receives ARIMA predictions for photovoltaic production and load demand whereas prices are pre-announced by the electricity provider for a limited horizon and are forecasted beyond. I calculate the incremental savings a battery would realize with an additional hour in the price pre-announcement horizon. By that, I value price information on the consumer side and evaluate the sensitivity of battery savings towards the length of the price pre-announcement horizon. This information is crucial to assure the effectiveness of pricing signals in dynamic electricity tariffs and to evaluate and forecast the potential load shifting activities of smart battery storage systems. My findings could help electricity providers and policy makers to conceptualize regulations and dynamic tariffs with pre-announced prices. These pre-announced dynamic tariffs could then enable millions of decentralized storage systems to participate in the integration of a higher share of renewable energy. My results help electricity providers to minimize the risk burden, that comes with these pre-announced prices.

Chapter 3.2 describes the setting and presents the formal optimization problem for the cost minimizing approach. Chapter 3.3 describes the inputs used in the simulation. Chapter 3.4 presents and discusses the simulation results followed by a wrap up and conclusion in Chapter 3.5.

Nomenclature

p^-	Return of selling electricity to the grid, € / kWh
$p^+(t)$	Price of buying electricity from the grid at time t, € / kWh
p^+_{AbsTax}	Static absolute tax and levies on electricity, € / kWh
p^+_{DynTax}	Dynamic tax rate in the electricity retail price, %
p^+_{Margin}	Margin of the power supplier on the electricity retail price, € / kWh
$p^+_{Spot}(t)$	Spot prices from the exchange market at time t, € / kWh
p^+_{Static}	Electricity price in a static tariff, € / kWh
p^+_{VAT}	Value added tax on electricity retail prices, %
S^B	Size of the battery storage system, kWh
S^{PV}	Size of the photovoltaic rooftop, kWp
t	Index of the current time-step
T	Number of time-steps in the optimization horizon, Hours
$\beta(t)$	Capacity factor of installed photovoltaic system at time t, kWh / kWp
ϵ	Feed-in limitation of the photovoltaic system, %
μ	Charging losses by charging the battery, %
τ^-	Maximum charging power, kW
τ^+	Maximum discharging power, kW
Υ	Total net electricity costs of a household, €
${\chi^+}_B(t)$	Power inflow from the battery storage system at time t, kWh
${\chi^-}_B(t)$	Power outflow to feed the battery storage system at time t, kWh
${\chi^+}_G(t)$	Power inflow from the grid at time t, kWh
${\chi^-}_G(t)$	Power outflow to feed the grid at time t, kWh
${\chi^-}_H(t)$	Power outflow to the household at time t, kWh
${\chi^+}_{PV}(t)$	Power inflow from the photovoltaic unit at time t, kWh
${\chi^-}_W(t)$	Power wasted at time t, kWh
$\Omega(t)$	State of charge of the battery at time t, kWh

3.2 Problem description and formalization

I formulate a deterministic mixed integer linear optimization program to minimize the total annual net electricity bill of a household with a photovoltaic rooftop and a battery. The optimization problem is solved iteratively for every hour in the year via a rolling horizon approach. The inputs regarding photovoltaic production and load demand are forecasted.

Figure 3.1 illustrates the rolling horizon approach with an optimization horizon, a pre-announcement horizon and an execution timestep. The optimization horizon comprises the price pre-announcement and forecast information over which the battery determines the optimal charging strategy. The electricity provider announces future prices only for the time of the pre-announcement horizon. For the rest of the optimization horizon, the battery storage optimizes its operation strategy according to ARIMA forecasts (see Chapter 3.3.3) instead of pre-announced prices. The forecasts are updated after each timestep, as the actual values of the past timestep are included in the learning set for the next forecast. Only the solution for the current hour is actually executed and used for further evaluation (see execution timestep in Figure 3.1), while the charging strategy for the following hours might be updated in the next iteration as soon as new forecasts or price data are available. This ensures a highly realistic simulation of a storage system in a household in which these parameters are also most likely to be unknown in advance.

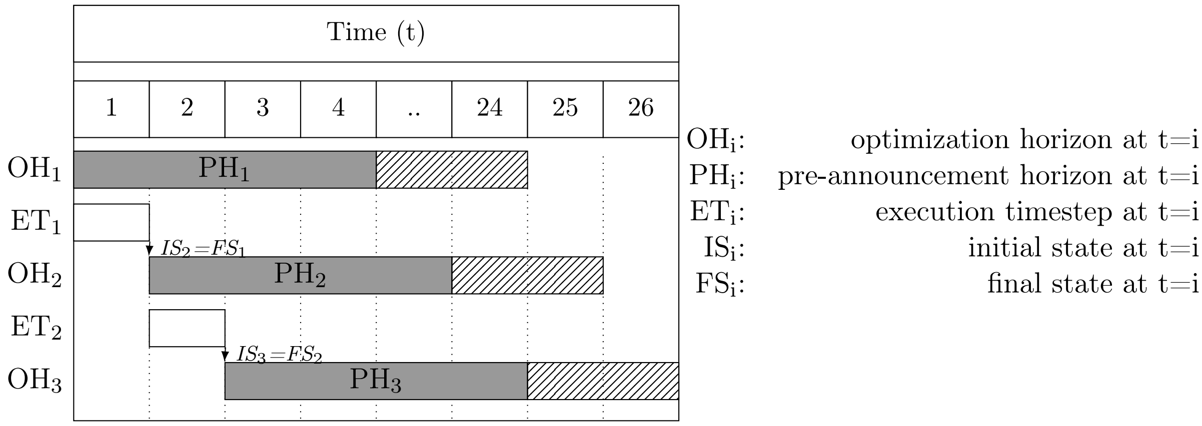


FIGURE 3.1: Representation of the rolling horizon approach with price pre-announcement and optimization horizon.

I distinguish between two settings: The first setting limits the optimization horizon to the length of the pre-announcement horizon. The second setting uses price forecasts beyond the pre-announcement horizon and optimizes 24 hours. By that, I isolate the additional value of price information from the additional value gained via a longer optimization horizon that allows considering more sophisticated strategies. If the optimization horizon is longer than 24 hours the forecast repeats itself until the vectors of all the inputs match in length.

Each optimization minimizes the net electricity costs Υ within the current optimization horizon. The net electricity costs Υ include the costs of buying energy subtracted by the returns of selling energy. The costs of buying energy are determined through the product of current power prices $p^+(t)$ and load ${\chi^+}_G(t)$ consumed from the grid. The energy ${\chi^-}_G(t)$ sold to the grid on the other hand is valued with the contracted remuneration rate p^-. Hence, the net electricity costs equal:

$$\Upsilon = \sum_{t=1}^{T} p^+(t) \cdot {\chi^+}_G(t) - p^- \cdot {\chi^-}_G(t). \tag{3.1}$$

The photovoltaic output ${\chi^+}_{PV}(t)$ equals a given capacity factor $\beta(t)$ multiplied by the size of the photovoltaic system S^{PV}:

$${\chi^+}_{PV}(t) = S^{PV} \cdot \beta(t). \tag{3.2}$$

The household's load demand ${\chi^-}_H(t)$ is satisfied either by photovoltaic production ${\chi^+}_{PV}(t)$, purchases from the grid ${\chi^+}_G(t)$ or previously stored power ${\chi^+}_B(t)$ from the battery. Excess power might be fed to the grid as ${\chi^-}_G(t)$, stored as ${\chi^-}_B(t)$ in the battery or simply wasted as ${\chi^-}_W(t)$ if none of the previous options are applicable. To ensure that the total power of all sources equals the total power used, I restrict the optimization problem with such condition:

$$\begin{aligned} &{\chi^+}_{PV}(t) + {\chi^+}_B(t) + {\chi^+}_G(t) = {\chi^-}_H(t) + {\chi^-}_B(t) + {\chi^-}_G(t) + {\chi^-}_W(t), \\ \textit{where} \quad &{\chi^+}_{PV}(t), {\chi^+}_B(t), {\chi^+}_G(t), {\chi^-}_H(t), {\chi^-}_B(t), {\chi^-}_G(t), {\chi^-}_W(t) \in \mathbb{Z}^+. \end{aligned} \tag{3.3}$$

The power fed to the grid is limited to the current photovoltaic production ${\chi^+}_{PV}(t)$ or the regulatory feed-in-limit ϵ for the respective photovoltaic size S^{PV}:

$${\chi^-}_G(t) \leq \min\left({\chi^+}_{PV}(t); S^{PV} \cdot \epsilon\right). \tag{3.4}$$

To prevent endless grid purchases at times of negative prices, the wasted electricity ${\chi^-}_W(t)$ is limited to the overproduction of the photovoltaic unit that cannot be fed to the grid,

$${\chi^-}_W(t) \leq {\chi^+}_{PV}(t) - \min\left({\chi^+}_{PV}(t); S^{PV} \cdot \epsilon\right). \tag{3.5}$$

The battery state of charge $\Omega(t)$ is always larger than or equal to zero and cannot be above the battery‘s capacity S^B. Power ${\chi^-}_B(t)$ that is stored into the battery is assumed to be subject to charging losses μ. The state of charge $\Omega(t)$ a battery offers after t is defined as:

$$\Omega(t) = \Omega(t-1) - {\chi^+}_B(t) + {\chi^-}_B(t) \cdot (1-\mu)\,, \qquad \Omega(t) \in [0, S^B]. \tag{3.6}$$

The formalized problem technically allows to simultaneously charge and discharge the battery at the cost of loosing power due to charging losses. Indeed, this enables the battery to get rid of a small amount of previously stored energy when it wants to maximize power purchases from the grid in periods of negative prices. Since these earnings are negligibly small, I do not introduce a condition to prevent this in order to keep the problem linear instead of quadratic. The power ${\chi^-}_B(t)$ charged to the battery and the power ${\chi^+}_B(t)$ discharged from battery within one timestep are limited by the net effective charging power τ^- and discharging power τ^+:

$${\chi^-}_B(t) \in [0, \tau^-], {\chi^+}_B(t) \in [0, \tau^+]. \tag{3.7}$$

While the rolling horizon approach optimizes the charging strategy for a limited optimization horizon, the battery continues operation beyond that horizon. To prevent the battery from discharging completely towards the end of each optimization horizon, I value the remaining power stored $\Omega(T)$ with the mean of the current horizon's electricity prices. If situations arise where the optimization program is indifferent to storing energy earlier or later, I incentivize the optimization program with a minor additional return to store energy immediatly. This enables the battery to consider the uncertainty of future photovoltaic production with a preference for a positive net charging energy (battery inflow ${\chi^-}_B(t)$ - battery outflow ${\chi^+}_B(t)$) in otherwise indifferent strategy decisions. The objective function is then defined as:

$$\min \Upsilon - \left[\Omega(T) \cdot \frac{\sum_{t=1}^{T} p^+(t)}{T}\right] - \left[\sum_{t=1}^{T} \left({\chi^-}_B(t) - {\chi^+}_B(t)\right) \cdot \frac{1}{t \cdot 10^5}\right]. \tag{3.8}$$

For each length of the price pre-announcement horizon, I use the resulting operational strategies to determine the net electricity bill over the whole year. The differences in the net electricity bills represent the value of additional pre-announced price information. Because the focus of this study is on the economic aspects of price pre-announcements, I refrain from considering technical details such as losses of the inverters, battery degradation and solar panel aging.

3.3 Input and Assumptions

3.3.1 Photovoltaic roof, storage system and household consumption

For the photovoltaic production of the household, I use hourly capacity factors from the MERRA-2-dataset for 2018 with the common photovoltaic default values for system loss (10%), Tilt (35°) and Azimuth (180°) and query the capacity factors on renewable.ninja for the location of the Technical University of Munich, Germany (Latitude of 48.1496, Longitude of 11.5678). I insert one hour with a production of 0 kW at the beginning and delete the last hour of the data in order to align the UTC time of the dataset to the German time. The size of the photovoltaic roof is based on an own analysis of the publicly available databases of German transmission system operators (Netztransparenz.de, n.d.). On average, the installed photovoltaic roofs since August 2014 until 2018 below a size of 10 kWp - as required for the remuneration - have a nominal capacity of 6.65 kWp with a median of 6.48 kWp.

The power from the photovoltaic roof sold to the grid is compensated with a feed-in remuneration based on the photovoltaic remuneration for small rooftop installations in April 2018 in Germany (Bundesnetzagentur, 2019). I limit the feed-in into the grid relative to installed photovoltaic power as legally required according to §6 (2) of the Renewable Energy Act (Erneuerbare-Energien-Gesetz - EEG) in Germany.

The battery size is derived from the monitoring of installations of residential battery systems in Germany with an average of 1 kWh usable capacity per kWp of photovoltaic power (Figgener *et al.*, 2018). For the load profile of the household, I use the dataset 37 provided by Tjaden *et al.* (2015) with a total yearly demand of 3,466 kWh as this total demand should represent a common single family household.

Table 3.1 lists the input parameters for the simulation.

3.3.2 Electric power prices

To simulate the pricing signals of the electricity provider, I generate a dynamic electricity retail rate that is linked to exchange prices and add margin and taxes on top of these. I use the 2018 epexspot DE/AT and DE/LU day-ahead data (Epex Spot SE, 2019) as an indicator for

TABLE 3.1: Input parameters and assumptions for the photovoltaic roof and the storage system as well as the applied settings for the remuneration of photovoltaic feed-in into the grid.

Parameter	Description	Value
S^{PV}	System size of the photovoltaic roof	6.5 kWp
S^{B}	System size of the battery	6.5 kWh
p^{-}	Feed-in remuneration of photovoltaic power	0.122 €/kWh
ϵ	Limit of the feed-in into the grid	70%
τ^{-}	Maximal charging power of the battery	6.5 kW
τ^{+}	Maximal discharging power of the battery	6.5 kW
μ	Charging losses of the battery	5%

price fluctuations within the dynamic electricity tariff. I add a 0.02 €/kWh margin p^{+}_{Margin} for the retailer and 0.0474 €/kWh of absolute charged taxes p^{+}_{AbsTax} on a per-unit basis (see (Bundesnetzagentur & Bundeskartellamt, 2018)). As recommended by Jansen *et al.* (2015), the renewable energy surcharge and the grid fees increase and decrease as an ad-valorem dynamic tax based on the prices $p^{+}_{Spot}(t)$ of the exchange market. The value added tax p^{+}_{VAT} of 19% is added on top. The dynamic retail price $p^{+}(t)$ is then calculated by:

$$p^{+}(t) = \left[p^{+}_{Spot}(t) \cdot \left(1 + p^{+}_{DynTax}\right) + p^{+}_{AbsTax} + p^{+}_{Margin}\right] \cdot \left(1 + p^{+}_{VAT}\right) \tag{3.9}$$

To determine an appropriate overall relative tax rate, I solve for the dynamic tax rate p^{+}_{DynTax} to let the household pay the equal amount as it would do in a static setting with a static electricity price p^{+}_{Static} over the whole 8760 hours. Therefore, the following equation must be valid:

$$\sum_{t=1}^{8760} p^{+}_{Static} \cdot \chi^{-}{}_{H}(t) = \sum_{t=1}^{8760} p^{+}(t) \cdot \chi^{-}{}_{H}(t) \tag{3.10}$$

Negative values on the spot market prices $p^{+}_{Spot}(t)$ do not result in negative taxes but simply lead to no dynamic tax for that specific timestep.

3.3.3 Forecasts

Seasonal ARIMA forecasts within a 24 hour rolling horizon predict the photovoltaic production, the load pattern of the household as well as the price fluctuations on the energy exchange. By minimizing the Akaike information criterion (AIC), I fit the ARIMA model to the training data of the previous year 2017. I argue that a freshly installed storage controller would most probably have no data of the previous load pattern of the specific household but might be trained with a standardized load pattern instead. Therefore, I use a synthetic standard H0 profile by Bundesverband der Energie- und Wasserwirtschaft (2018) for a household located in Bavaria, Germany. The resulting seasonal ARIMA parameters are stated in Table 3.2.

Table 3.2: Seasonal ARIMA model parameters with the autoregressive order p, the difference order d and the moving average order q. The seasonal elements of the model are stated with the the seasonal autoregressive order P, the seasonal difference order D and the seasonal moving average order Q. The mean absolute percentage errors (MAPE) measure the quality of the forecast by adding up the errors of the predicted values within the 24 hour rolling horizon for each of the 8760 hours.

Parameter	p	d	q	Seasonality	P	D	Q	MAPE
Pattern of the household load demand	5	1	1	week	0	1	0	5558.7
Pattern of the photovoltaic production	4	0	0	day	2	1	0	8963
Pattern of exchange price fluctuations	2	0	1	day	2	1	0	2596.4

3.4 Results and discussion

Figure 3.2 illustrates the savings of price pre-announcements as the difference in the total electricity bill compared to the setting when no future prices or forecasts are known to the system and only the current values are used to determine a strategy (when optimization horizon = 1). I compare the scenarios with and without photovoltaic unit and distinguish between the savings with an optimization horizon equal to the pre-announcement horizon and the savings in an optimization with a minimum optimization horizon of 24 hours.

The solid lines show the savings where the optimization horizon is limited to the length of the price pre-announcement, meaning that photovoltaic and demand forecasts are limited to the length of price information. The bold dotted lines show the savings with a 24 hour optimization horizon where the missing price information is forecasted similar to the photovoltaic production and load demand.

With an increasing pre-announcement horizon, the savings gradually increase and converge to the value of the optimal strategy with perfect price information (pre-announcement horizon = 8760). The optimal strategy with perfect price information, however, is still not optimal in retrospect since photovoltaic data and load demand were still forecasted with errors.

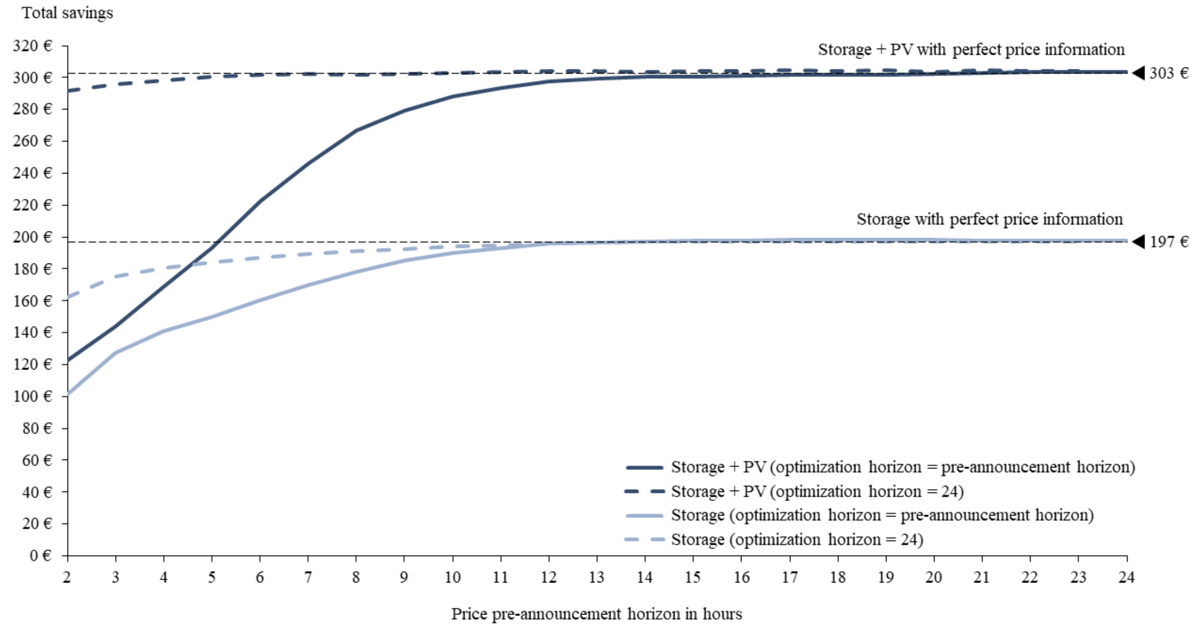


Figure 3.2: Savings realized by the adaption of the battery strategy according to external price information depending on the price pre-announcement horizon.

With potential savings of approximately 303 € in case of perfect price information, the storage with a photovoltaic system seems to offer a higher saving potential compared to the 197 € without the photovoltaic system. However, these higher potential savings for a storage system with a photovoltaic unit mainly arise from the initially low performing battery strategy at a short optimization horizon. If the optimization horizon is too short, the optimal strategy might not consider storing the photovoltaic output for later usage. Consuming the power within the household, however, is usually the return maximizing strategy but requires longer optimization horizons. Therefore, it is necessary to distinguish between the savings that result from a longer optimization horizon and the savings that result from additional price information.

Figure 3.3 illustrates the savings with a 24 hour minimum optimization horizon and by that isolates the savings of additional price information. The system with a photovoltaic unit then generally realizes fewer savings than the system without photovoltaic unit. While the total savings in a perfect price information setting with a photovoltaic unit would only add up to 20.37 €, the system without photovoltaic unit generates savings up to 65.38 €. The lower effect of price information is due to the added uncertainty of photovoltaic production. Due to the uncertainty of photovoltaic production, the strategy with a photovoltaic unit is more vulnerable

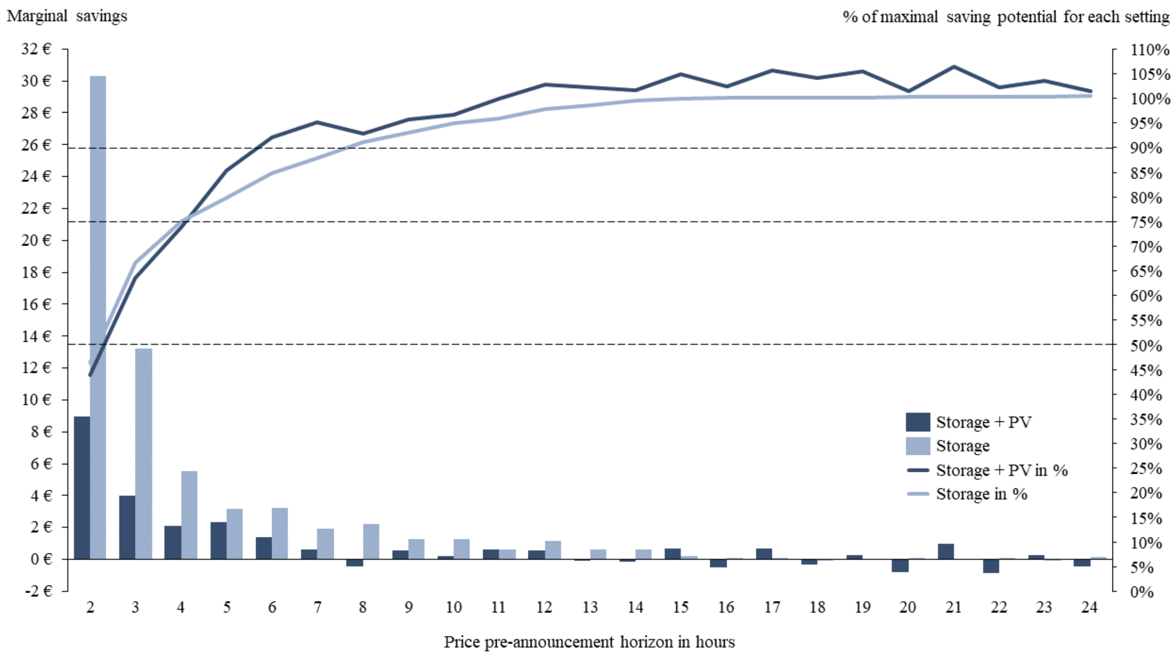


FIGURE 3.3: The value of price information of an additional hour within the optimization horizon.

to forecast errors. Additional price information then offers less saving potential, since forecast errors in photovoltaic production might lead to unprofitable strategies in the first place.

Different horizon lengths allow different strategy considerations. Whereas short horizons might be sufficient for storage strategies with only a few hours (e.g. to store afternoon photovoltaic production for use in the early evening hours), longer horizons allow the optimization with storing throughout the night or even for days. Depending on the timespan where the storage can supplant purchases from the grid, the system is able to bridge high price periods. The information when the high price period ends is essential to evaluate whether the storage can satisfy the demand until that point. Therefore, different hours in the horizon are of different value and the increments in value are neither constant nor strictly increasing or decreasing for every additional hour. This is indicated by Figure 3.3 in hour 12 of the setting without a photovoltaic unit. While the additional savings were already lower at hour 11, the following hours add again more value to the strategy. To decide whether the battery should charge for the next day as well, the system might even require pre-announcement horizons above 24 hours to compare the prices for both days. By that, price information further down in the optimization horizon might be more critical than the information of the early optimization period. However, the simulations show that the system usually optimizes its strategy within shorter horizons and reaches the majority of savings with far fewer hours of pre-announced information.

Fifty percent of potential savings are realized if the electricity provider announces the prices for 3 hours in advance. With 4 hours of pre-announcing prices, 75% of related savings can be realized. The system with a photovoltaic unit then exceeds the 90% mark after 6 hours whereas the system without photovoltaic unit requires 8 hours to reach this level. The values beyond the 100% mark result out of "lucky bets" on the production and demand forecasts where the limited price information leads the optimization program to follow a strategy that in the end turns out to be more profitable. With a longer price pre-announcement, however, the optimization program would choose a different strategy that turns out to be unprofitable when forecast errors for the photovoltaic output become apparent.

3.5 Conclusion

This paper determines the value of price information for a household in a dynamic electricity price tariff. I use a common domestic household load pattern together with photovoltaic data to generate ARIMA forecasts. Based on these forecasts and pre-announced price information by the electricity provider, the battery storage system schedules charging and discharging actions in a rolling horizon optimization. I iteratively increase the pre-announcement horizon and compare the resulting savings of the battery storage system. While the battery storage system would require perfect information of photovoltaic production, household load demand and electricity prices upfront to derive a perfect strategy, sufficiently good charging strategies could already be determined with a rather short pre-announcement period and forecasts. My results indicate that a price pre-announcement horizon of 3 hours by the electricity provider would be sufficient to realize 50% of potential savings. A maximum of 8 hours would be required to develop charging strategies with 90% of the maximal saving potential.

These findings contribute to our understanding of the potential of dynamic tariff concepts and charging strategies for battery storage systems under uncertainty. This study showcases the low information dependency if charging controllers are fed with past supply and demand data to generate forecasts, for example with an ARIMA approach. ARIMA forecasts might become less reliable in the future once renewable production pattern become more extreme and volatile due to climate change. While this could require more sophisticated forecasting methods, for example with learning from external weather forecasts, the general findings of this study should hold strong: Electricity providers could enable decentralized battery storage systems to balance renewable over- and underproduction by only taking over a few hours of price risk. Therefore, my findings are particularly important for the design of pricing tariffs and deliver valuable insights for electricity providers offering dynamic electricity tariffs. Households or consumer representatives might use my approach to determine the saving potential of their decentralized storage system once dynamic tariffs are introduced in the residential sector. Future research may determine a welfare maximizing price pre-announcement horizon by assessing electricity providers' benefits of favorable load shifting that is incentivized by price pre-announcements.

4 | Innovation Trigger or Political Symbolism: How Green are Subsidies in Electric Vehicles?

Subsidizing technology fosters product innovation that might lead to a quicker technology adoption. This innovation effect could justify subsidy expenses beyond the directly related social value of the subsidized good during its lifetime. This paper proposes a method to calculate the underlying value of innovation within a subsidy. The proposed calculation method uses price elasticities and learning rates to correct for effects that depend on the number of products sold, e.g. market saturation and learning. Correcting for these effects allows me to compare scenarios with and without subsidy and draw conclusions about the innovation effects. I showcase this method by evaluating the governmental subsidy programs for electric vehicles in the United States, China and Germany. The evaluation shows that the underlying ecological value of innovation within a subsidy might outweigh the value of the directly related carbon savings of the subsidized vehicles. At least for the federal subsidy programs in the United States and Germany, however, the ecological value could not justify the expenses.

Keywords: Subsidy Efficiency, Innovation, Learning, Electric Vehicles

4.1 Introduction

Reducing carbon emissions is on top of almost all developed countries' agendas. To reach their agendas' goals, many governments either tax pollution or subsidize cleaner alternatives. Subsidizing alternatives takes effect via increasing the adoption and sales of new technologies like photovoltaic power or alternative fuels. However, policymakers and economists discuss such political measures controversially.

In particular, subsidies in the mobility sector are currently in the spotlight of public debate: The electric vehicle is the symbol for the transition towards a clean mobility sector. Given governmental bonuses of up to \$7.500 federal tax credit in the United States, ¥22.500 in China or €9.000 in Germany [2] for purchasing an electric vehicle, critics highlight the large governmental spendings and claim these subsidies rather inefficient means to reduce carbon emissions (see for example Holland *et al.*, 2016, Sheldon & Dua, 2019, Xing *et al.*, 2021). However, current subsidies might foster innovation and development, triggering a quicker and broader adoption of electric vehicles in the future. Therefore, can subsidy-induced innovation justify governmental spending and silence the critics?

In this paper, I introduce a new method to calculate the value of innovation triggered by subsidies. By using price elasticities I simulate the sales decline following the phasing-out of a subsidy. This sales decline leads to a slow-down in innovation assuming that learning mostly depends on the cumulative sales and production. Calculating this innovation decline with learning rates, I can extract the subsidy-induced innovation within the projected technology adoption curve. The comparison of the technology adoption curves with and without subsidies uncovers the value of innovation created by the subsidy.

Within this study, I showcase this method by evaluating the governmental subsidy programs for electric vehicles in the United States, China and Germany. I simulate each country's hourly electricity production in a merit order considering changes in the electricity mix, fuel and carbon certificate prices to accommodate for the changing energy systems and the environmental footprint of installed power capacities. Together with the hourly national electricity demand, I calculate the carbon emission of the marginal electricity demand of electric vehicles. I consider

[2]See respective subsidies 2020 in U.S. Department of Energy, 2021, Ministry of Finance of the People's Republic of China, 2020, Bundesministerium für Wirtschaft und Klimaschutz, 2021.

all these long-term developments in energy systems to predict the ecological value of future electric vehicle purchases induced by current subsidies. By discounting the future ecological value, I draw conclusions about the economic efficiency of current subsidy programs.

Considering innovation effects in the evaluation of subsidy programs might justify subsidies into technologies with negative short-run effects but great potential in the long-run. My findings indicate that subsidy-induced innovation might add substantial value on top of the direct related positive externalities of the subsidized good. However, the innovation induced by governmental subsidy programs for electric vehicles in the United States and Germany could not justify the governmental spendings from a sole ecological perspective. The additional economic effects like securing local jobs, defending market power or tax revenues following the increased sales, however, might indeed close the gap and justify the governmental spendings accordingly. My method allows policymakers to calculate the ecological value of innovation and evaluate the innovative potential of subsidy programs. To the best of my knowledge this paper is the first to calculate the ecological value of innovation induced by a subsidy.

The paper is structured as follows: Chapter 4.2 gives an overview of the underlying literature. Chapter 4.3 states the problem formalization while Chapter 4.4 describes the assumptions and inputs. Chapter 4.5 states and discusses the results before Chapter 4.6 gives a final conclusion.

4.2 Literature

At the heart of this paper lies the notion that costly investments in clean technology could pay off with comparably lower carbon abatement costs in the future (see growth models of Acemoglu *et al.*, 2012 and Acemoglu *et al.*, 2016, evaluations of Bollinger & Gillingham, 2014 and Newbery, 2018 or the work of Vogt-Schilb *et al.*, 2018). For example Vogt-Schilb *et al.* (2018) argue, that investing in more expensive carbon abatement measures now could be the optimal strategy as these measures would have a high abatement potential in the future.

This high abatement potential might open up, if technology improves or prices decline with innovation, economies of scale, or, due to learning rates. Following the concept of learning by doing of Arrow (1962), a series of prominent research discussed the effects of cumulative experience and learning rates (e.g. Spence, 1981, Fudenberg & Tirole, 1983, Ghemawat & Spence, 1985). Specifically, Spence (1981) analyzed the competition within a market in which unit costs decline with cumulative production. Most notably, it could be beneficial for a firm to accept negative short-run marginal profits in order to gain market dominance in the future. The same effect might be drawn upon by governments when subsidizing certain technologies like electric vehicles under learning rates. Subsidies, that show negative short-run marginal effects as their direct carbon reductions are low and corresponding governmental spendings are high, might still be efficient. The subsidy might still pay off in the future if the total carbon saving potential of the technology is big enough, the price elasticity triggered by the subsidy is significant and the technology is showing promising learning rates.

Indeed, promising learning rates were found for battery technology and the electric vehicles these batteries will be used for (see Weiss *et al.*, 2012, Matteson & Williams, 2015, Nykvist & Nilsson, 2015, Schmidt *et al.*, 2017, Kittner *et al.*, 2017, Ziegler *et al.*, 2021, Ziegler & Trancik, 2021). Weiss *et al.* (2012) create ex-post learning rates and ex-ante price forecasts to discuss the price development of hybrid and battery electric vehicles. Nykvist & Nilsson (2015) analyze cost estimates for battery packs and find learning rates between 6-9% following a cumulative doubling of production. Kittner *et al.* (2017) develop a factor learning curve model to analyze the impact of innovation and deployment policies on the cost of energy storage technologies. Schmidt *et al.* (2017) use learning rates to project the future costs of electrical energy storage systems. A recent study of Ziegler & Trancik (2021) found a price decrease of 20% upon a doubling of cumulative market size.

Speeding up learning by increasing cumulative production with subsidies requires a price elastic consumer response. For my case of electric vehicles, previous literature already found such consumer response for subsidy programs or price declines (see Chandra *et al.*, 2010, Jenn *et al.*, 2013, 2018, Palmer *et al.*, 2018, Yan, 2018). For example, Jenn *et al.* (2018) observed average sales increases of 2.6% for electric vehicles for every $1,000 offered as a rebate or tax credit. Whether these rebates and tax credits are worth spending obviously depends on the carbon reductions associated with electric vehicles.

Over the years, many studies evaluated the emission reductions of electric vehicles with various different approaches and results (see Samaras & Meisterling, 2008, Stephan & Sullivan, 2008, McCarthy & Yang, 2010, Van Vliet *et al.*, 2011, Hawkins *et al.*, 2013, Graff Zivin *et al.*, 2014, Archsmith *et al.*, 2015, Holland *et al.*, 2016, Knobloch *et al.*, 2020). However, all studies emphasize the dependency on clean power production for an electric vehicle to be environmentally beneficial. Holland *et al.* (2016), for example, find environmental benefits of electric vehicles worth $2,785 with the clean power production in California but huge environmental damages up to $4,964 in North Dakota with electricity being produced from coal powered plants. Hence, the subsidies they propose vary drastically.

Some papers investigated the carbon abatement costs for certain subsidies in green technologies and electric vehicles (see e.g. Chandra *et al.*, 2010, Van Vliet *et al.*, 2011, Michalek *et al.*, 2011, Bollinger & Gillingham, 2014, Huse & Lucinda, 2014, Newbery, 2018, Yan, 2018). Huse & Lucinda (2014) investigate the Swedish Green Car Rebate and find costs of $109 per carbon ton to abate with less emitting vehicles. Van Vliet *et al.* (2011) calculate the costs for a battery electric vehicle in the Netherlands to be €1,900 per carbon ton at the time of their study and project €300-800 per ton in the future. van Benthem *et al.* (2008) and Bollinger & Gillingham (2014) investigate photovoltaic installation cost reductions in California induced by subsidies. Their results indicate that due to very low learning spillovers, the localized learning by doing could not justify the incentive program in the short-run. Newbery (2018) proposes a method to determine the justified subsidies for photovoltaic units and finds arguments to accelerate technology development with subsidies due to beneficial learning rates.

However, as pointed out by Gillingham & Stock (2018), past studies on electric vehicle subsidization did either not incorporate the changes in the electricity sector or the dynamics of innovation, learning by doing and economies of scale, that might be triggered by subsidizing electric vehicles. With the grids becoming cleaner every day, these dynamic innovation mechanisms might show a growing effect on the carbon reductions of the future that previous literature fails to incorporate. To the best of my knowledge, this paper is the first to address these innovation effects in a ceteris-paribus manner and to evaluate existing subsidy programs with the dynamics of induced future carbon reductions.

4.3 Problem Description and Formalization

4.3.1 Value of Innovation and Learning

My model uses price elasticities and learning rates to calculate the electric vehicle adoption in two scenarios: I simulate one scenario with subsidy and one scenario as if the subsidy would have been cancelled on December 31st 2019. Hence, I use 2020 as the year of reference to calculate the value V of the subsidy S including innovation and learning effects as the net present value of additional carbon reductions triggered by the subsidy in 2020 and later.

Therefore, I compare the emission reductions Δe_t^S of the electric vehicle stock N_t^S in a scenario with a subsidy to the emission reductions Δe_t of the stock N_t of electric vehicles in a scenario without subsidy. The value of the subsidy is then computed as the γ^t discounted social cost of carbon δ_t in year t of the additional carbon reductions:

$$V = \sum_{t \in T} (\Delta e_t^S \cdot N_t^S - \Delta e_t \cdot N_t) \cdot \delta_t \cdot \gamma^t. \tag{4.1}$$

The electric vehicle sales within a country are assumed to be a product of multiple factors (e.g. a better charging infrastructure, increased environmental awareness, higher taxes on gasoline or the subsidy). I assume that the product of these factors is politically constructed in a way to accomplish the underlying political electrification targets. The total number of cars N^{max} (conventional + electric) registered within each country remains the same and will be fully substituted with electric cars until 2050. While this is highly speculative, it is indeed a valid assumption as the governments frequently tighten their goals as well as many automobile manufacturers themselves announced to stop producing conventional vehicles until 2035. I fit these political electrification targets and past electric vehicle sales from 2010-2020 (see International Energy Agency, 2021) to a S-shaped adoption curve using a simpler version of the Bass (1969) adoption model for consumer durables. The S-shaped curve fitted by the variables k, n and y predicts the number N_t of electric vehicles on the road in year t under the current political measures and subsidies within a country:

$$N_t = N^{max} \cdot (1 - e^{-k*(t-2010)^n}) + y. \tag{4.2}$$

I assume that people will most likely switch to an electric vehicle when their old vehicle needs to be replaced. Hence, the number of electric vehicle sales within a year is limited by the replacements within the vehicle stock considering the lifetime of vehicles. However, I assume a 20% tolerance rate of the sales infrastructure and market fluctuations to account for the flexibility and potential of the vehicle sales markets in very optimistic years.

From this fitted S-curve (and the real vehicle sales data until 2020), I calculate the total growth factor F_t in year t as the change of electric vehicle sales ΔN_t (without replacements) between two years:

$$F_t = \frac{\Delta N_t^S}{\Delta N_{t-1}^S}. \tag{4.3}$$

This total growth includes the learning effects as well as market saturation effects that both depend on the number of electric vehicles already sold. If the number of electric vehicles sold changes due to the subsidy expiring, the total growth will be influenced by these two factors accordingly. Hence, I decompose the change in electric vehicle sales as a product of the learning factor F_t^λ, the market saturation factor F_t^M and the other independent trend factors F_t^O of the respective year:

$$F_t = F_t^\lambda \cdot F_t^M \cdot F_t^O. \tag{4.4}$$

I assume the consumers to react on the subsidy with static price elasticity. By removing the subsidy, the number of vehicle purchases therefore decreases accordingly. Indeed, the effect of price decreases due to learning and price decreases due to governmental subsidization might differ, e.g. as consumers might consider subsidies as a gift. For reasons of simplicity, however, I do not distinguish whether price changes result from governmental subsidization or economies of scale, learning by doing or anything else. The subsidy is expected to be fully deducted from the price of the vehicle without any appropriation by the producer.

I simulate a scenario with the subsidy and one as if the subsidy would have been cancelled. The vehicles electrified in 2020 without a subsidy are simply the actual historic electric vehicle purchases of 2020 diminished by the effect of the price elasticity ϵ due to the vehicle price P_t increasing with the expiration of the subsidy S (see first case of equation 4.5).

This decreased number of purchases will also decrease the learning and innovation for the upcoming years, leading to a slower adoption of electric vehicles as prices decline less and technology evolves slower. Market saturation, on the other hand, counteracts the adoption with an increasing share of electric vehicles as there are less vehicles left to be electrified. In a scenario without subsidy market saturation and the corresponding effects would kick in slower as there are less purchases without the subsidy incentive. Apart from that, assuming a lifetime of τ for every electric vehicle, the number of electric vehicles being replaced in a specific year will change as well. By correcting for these effects, I can calculate the lag within the S-curve resulting from the slowed down adoption in the scenario without subsidies.

Therefore, I reduce the growth factors F_t by their initial learning factors $F_t^{\lambda,S}$ and initial market saturation effects $F_t^{M,S}$ under subsidies in a ceteris paribus manner and multiply with the adjusted learning F_t^{λ} and adjusted market saturation F_t^{M} of the new vehicle stock without subsidies instead (see second case of equation 4.5):

$$\Delta N_t = \begin{cases} \frac{\Delta N_t^S}{1+\frac{S}{P_t}\cdot\epsilon} & if\, t = 2020 \\ \Delta N_{t-1}\cdot F_t \cdot \frac{F_t^{\lambda}}{F_t^{\lambda,S}}\cdot\frac{F_t^{M}}{F_t^{M,S}} & else. \end{cases} \tag{4.5}$$

The learning factor F_t^{λ} is the effect of innovation resulting from a doubling of cumulative production CP_t. I cumulate all vehicle electrifications ΔN_t together with the already replaced electric vehicles $\Delta N_{t-\tau}$ after their lifetime τ to calculate the cumulative production CP_t until year t like the following:

$$CP_t = \sum_{i=2010}^{t-1} \Delta N_i + \Delta N_{i-\tau} \tag{4.6}$$

I then compare the cumulative production CP_t of the current year to the cumulative production CP_{2019} of December 31st in 2019 before the scenarios diverge. The logarithm to the base of 2 states how often the cumulative production doubled since then. By multiplying the resulting cumulative doubling with the learning rate λ and the elasticity ϵ, I incorporate the increase of purchases due to price decreases and product improvements:

$$F_t^{\lambda} = 1 + \epsilon \cdot \left[1 - (1-\lambda)^{\log_2 \frac{CP_t}{CP_{2019}}}\right] \tag{4.7}$$

The market saturation factor F_t^{M} incorporates the share of electric vehicles on the road relative to the country's total vehicle stock N^{max} of all conventional and electric vehicles. Hence, the factor indicates the remaining fleet to be electrified. It is important to include this saturation factor to receive the desired S-shaped curve. Otherwise, product innovation and decreasing prices would skyrocket vehicle sales every year without any limit. As soon as all vehicles are electrified, however, market saturation should prevent further growth of the electric vehicle sales:

$$F_t^{M} = 1 + \left(1 - \frac{\sum_i^{t-1} \Delta N_i}{N^{max}}\right). \tag{4.8}$$

For reasons of simplicity, I do not consider non-linear effects like demand uncertainty or misconception in costs (see Cohen *et al.*, 2016, Andor *et al.*, 2020) that would also impact the adoption.

4.3.2 Calculation of Emission Reductions

The carbon emission reductions Δe_t are the difference between the emissions of operating an electric vehicle EV compared to a conventional vehicle CV in a specific year:

$$\Delta e_t = e_t^{EV} - e_t^{CV}. \tag{4.9}$$

I only consider operating emissions and neglect differences in the manufacturing process for simplicity reasons. The yearly operating emissions e_t^{EV} of the electric vehicle are simply calculated as the sum of all hourly emissions $e_t^{EV}(h)$ by the electric vehicle within the respective year:

$$e_t^{EV} = \sum_{h \in H} e_t^{EV}(h). \tag{4.10}$$

I calculate the hourly emissions $e_t^{EV}(h)$ as the marginal emissions of electricity production for an electric vehicle. The marginal emissions $e_t^{EV}(h)$ depend on the power sources Π used and their respective emission factors ξ_π. The increase in electricity demand caused by a high number of electric vehicles charging might require additional power sources to switch on their production. Hence, I use the marginal emissions not only of one car but the total electric vehicle stock N_t on the road and currently charging. The difference in produced electricity $\omega_\pi^{EV}(h)$ in a scenario with electric vehicles compared to the electricity production $\omega_\pi(h)$ in a scenario without electric vehicles determines the marginal emissions of all electric vehicles. By dividing by the number of vehicles within the electric vehicle stock N_t, I receive the average marginal emissions of an electric vehicle charging at a specific time:

$$e_t^{EV}(h) = \frac{\sum_{\pi \in \Pi} \xi_\pi \cdot \left[\omega_\pi^{EV}(h) - \omega_\pi(h)\right]}{N_t}. \tag{4.11}$$

The marginally used power sources for $\omega_\pi^{EV}(h)$ with electric vehicles and the used power sources for $\omega_\pi(h)$ without electric vehicles are both determined by an optimization for every time-step h. Hereby, I minimize the marginal costs of electricity production considering fuel costs θ_t^π and certificate prices θ_t^C of each power source π to simulate a cost minimizing merit order for every hour:

$$\min_{\omega_\pi(h)} \; \omega_\pi(h) \cdot \left[\theta_t^\pi + \theta_t^C\right]. \tag{4.12}$$

As a general condition, the electricity demand $\psi(h)$ needs to be satisfied by equivalent production for every hour:

$$\sum_{\pi \in \Pi} \omega_\pi(h) = \psi(h). \tag{4.13}$$

I limit the power production of a single power source by the installed capacities Ω_t^π and a capacity factor $\eta_\pi(h)$. Conventional power plants like coal and gas can be dispatched according to the demand and are therefore assumed to produce flexibly up to the total installed production capacities Ω_t^π. Intermittent power sources like photovoltaic systems and wind turbines additionally rely on the capacity factor $\eta_\pi(h)$ representing the weather conditions and daytime within a specific hour:

$$0 \leq \omega_\pi(h) \leq \Omega_t^\pi \cdot \eta_\pi(h). \tag{4.14}$$

When deciding whether to replace an existing conventional vehicle with an electric vehicle, the marginal emissions seem the intuitive measure to compare both options. By speeding up the electric vehicle adoption with a subsidy, the corresponding energy production increases by this additional electricity demand. At least in the short run, this additional electricity demand might require more conventional power plants to switch on at times when electric vehicles need to charge. Therefore, as long as simply replacing a vehicle with another conventional vehicle is the standard, the arguments of a marginal evaluation of both options seem fair.

The arguments however turn as soon as the electric vehicle becomes the standard: The ecological footprint of an electric oven, for example, is most likely evaluated with the average electricity mix and not the marginal electricity consumption as burning wood is outdated and not an alternative any longer. Similarly, perceiving the electricity demand of electric vehicles as additional marginal demand becomes debatable in the long run as it will establish as the standard. All electric appliances within a grid simply share the same electricity mix and have no real order in which they are supplied with electricity. Using an average or a marginal approach might have strong effects as the marginal electricity consumption is served from the currently most expensive and usually more carbon intensive power sources at the end of the merit order.

Therefore, I use a mixed approach. For the short-run until 2030 I stick to the marginal emissions along with previous literature comparing emissions of vehicles (see Holland *et al.*, 2016). For the years after 2030 I linearly decrease the emissions of 2030 to zero until 2050 or 2060 considering the governmental targets of carbon neutrality within the electricity sector as described in Chapter 4.4.1.

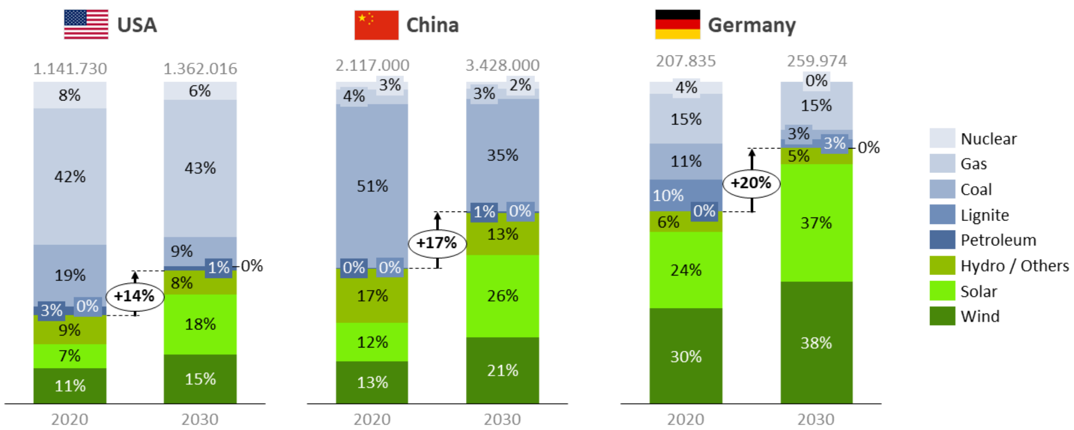


FIGURE 4.1: Development of the installed capacities from 2020 to 2030 for the United States, China & Germany based on United States Energy Information, 2020, Energy Research Institute of Academy of Macroeconomic Research/NDRC, 2020, SMARD Bundesnetzagentur, 2021, Drees *et al.*, 2021.

4.4 Input and Assumptions

4.4.1 Electricity supply and carbon emissions

For the energy production, I use current and projected production capacities installed in each country. I distinguish these capacities into dispatchable and undispatchable power sources. All conventional power plants within this simulation are dispatchable and fully flexible to decrease or increase their power production up to 100% of the installed capacity. Solar and wind capacities, however, rely on the time, weather and the season. To simulate the intermittency and account for seasonal variation of wind and solar power, I use a yearly pattern of 8760 hourly capacity factors $\eta_\pi(h)$ (deleting the 29th February from leap years) normalized by the installed capacity in the respective years. By normalizing with the installed capacities, I can adjust the production patterns to the planned installations in future scenarios as planned by the respective governments. To derive a reference demand curve without electric vehicles, I add up all power production and deduct the demand curves of electric vehicles on the road in 2020. Hence, I neglect electricity imports or exports and solely focus on the production within the country. A detailed description of the used datasets for each country is stated in A.4. Figure 4.1 illustrates the change in installed capacities.

I use yearly fuel price projections θ_t^π for the fuel the conventional power plants burn. By burning fuel, these conventional power plants emit carbon according to their respective efficiency / carbon emission factors ξ_π. To offset these carbon emissions, some power plants additionally acquire carbon certificates with rates θ_t^C. These rates come on top of the fuel costs and are therefore influencing the merit order of marginal costs of production. A.5 states the specifics of generating the merit order of electricity production for each respective country.

4.4.2 Electric Vehicle Consumption Patterns

To derive technical specifications for the electric vehicle that are representative for the respective country, I base my assumptions on electric vehicle registration data. For electricity consumption of respective electric vehicles, I use country specific measurement and testing data as a reference. I weight the consumption data by the local market share of the specific model to calculate the country specific average power consumption per 100 miles. While differences in the measurement procedures do not allow for comparisons across countries, it is a good approach to incorporate also the specifics of the driving behavior within the respective country. I consider the workplace and the private residence as the places to charge. Hence, I stick to a charging power W^{max} of 11kW in all countries as it is frequently available also with AC charging at almost any charging location and very common across many car manufacturers. A summary of the technical specifications and assumption for the electric vehicles can be found in Table A.1.

I use datasets of car trips to generate representative charging patterns for each country. The distance d driven during each trip and the consumption $\overline{\psi}$ per 100 miles determine the charging demand ($= \frac{d}{100} \cdot \overline{\psi}$) after the journey. The charging power W^{max} ultimately determines the timespan the vehicle needs to charge after the trip. I aggregate all charging actions into a weekly charging pattern and normalize it with the average weekly distance ($= d^t/52$) to receive an average weekly demand curve for a single vehicle. Figure 4.2 illustrates the resulting consumption profiles. A.6 describes the generation of the driving pattern and the corresponding electricity consumption in more detail.

4.4.3 Number of Vehicles, Learning Rates & Subsidies

I assume the total number of vehicles on the road to remain at the same level. Hence, I use current vehicle registration data and interim targets to derive the likely electric vehicle uptake curve. U.S. Department of Transportation Federal Highway Administration (n.d.) reports 107.180.635 registered vehicles in 2019 within the United States. The State Council of the People's Republic

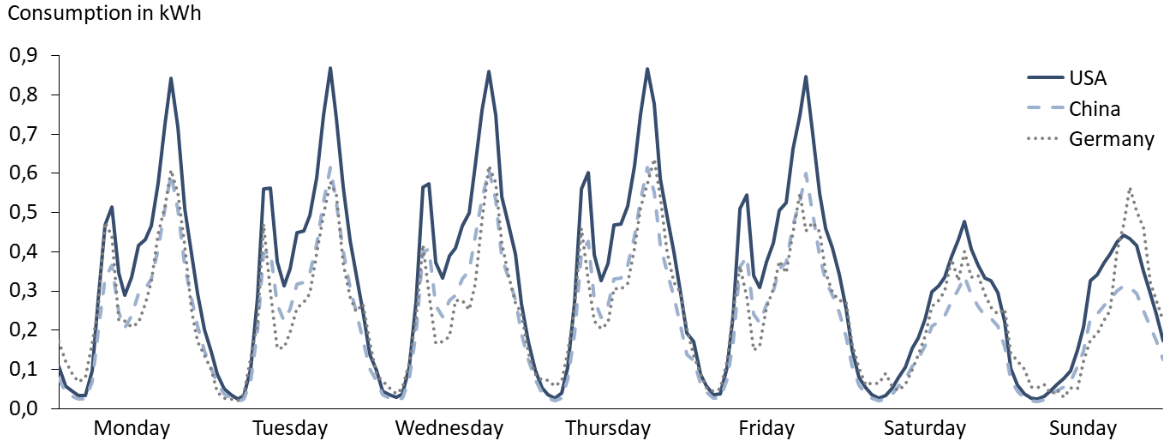


FIGURE 4.2: Average consumption profile of an electric vehicle in kWh based on vehicle driving data generated on data of U.S. Department of Transportation Federal Highway Administration (2017) for the United States and China as well as Zumkeller *et al.* (2018) for Germany.

of China (2021) report a total of 270.000.000 motor vehicles at the end of 2020 in China. For Germany, I calculate with a total number of 48.248.584 passenger cars (see registered passenger cars on the first of January 2021 by Kraftfahrt-Bundesamt, 2021). Additionally, the recently elected government announced an interim target of 15 million fully electrified vehicles until 2030 within their coalition agreement (see SPD & Die Grünen & FDP, 2021).

As previous literature shows, electric vehicles (specifically the battery packs as one of the main cost drivers) underly learning rates dependent on the cumulative production. Nykvist & Nilsson (2015) identify a learning rate of 6-9% following the cumulative doubling of production. Kittner *et al.* (2017) find a learning rate of 16.9%. Matteson & Williams (2015) assume learning rates between 9.5-22% found for consumer electronics to be applicable for batteries. A recent study of Ziegler & Trancik (2021) found a price decrease of 20% upon a doubling of cumulative market size. Within this study, I use a learning rate of 22% to illustrate the maximum range of innovation value within technology deployment via subsidies.

These learnings have a bigger influence if price elasticity is high, as the initial price increase when the subsidy ends leads to a stronger reduction in sales. Jenn *et al.* (2018) observed average sales increases of 2.6% for electric vehicles for every \$1,000 offered as a rebate or tax credit. I convert their finding into a relative measure by using the average list prices of electric vehicles sold in 2020 within the United States, I receive a price elasticity of $\epsilon = \frac{2.6\%}{\frac{\$1000}{P_{2020}}} = 1.32$. The elasticity could differ between countries. For reasons of simplicity, however, I use this measure for all countries when prices increase or decrease and assume the purchasing behavior to be independent from the absolute prices.

For the United States, I simulate a termination of the federal tax credit with $7500 for battery electric vehicles (see U.S. Department of Energy, 2021) without additional state level subsidies. In China, cars with a range higher than 400km qualify for ¥22.500 while cars below would only receive ¥16.200 if they fulfill the other criteria (see Now-gmbh, 2020). I simply assume a homogeneous subsidization of ¥19.000 per car. Within Germany the programs distinguish according to the net list price. While battery electric vehicles above €40.000 qualify for €7.500 in subsidies, vehicles below even receive €9.000 in subsidies. For reasons of simplicity, I assume a homogeneous subsidy of €8.000 in Germany and do not consider tax effects. For the scenario with subsidization, I assume all these subsidies to be paid constantly for every vehicle before completely fading out in 2025.

4.4.4 Social Cost of Carbon & Discount Rate

To evaluate the economic efficiency of subsidies, I compare their carbon abatement costs to the social cost of carbon. The social cost of carbon are the marginal costs of climate damages caused by the emission of an additional carbon ton. Therefore, they are a good measure to quantify the societal value of avoiding emissions. Reinstalled by the Biden administration, the social cost of carbon became a tool now frequently used to shape and challenge federal decision making. The Interagency Working Group issued the latest social cost of carbon calculations for 2020 dollars as a baseline (see IWG, 2021). I use the values with a 3% discount rate as suggested by IWG, 2021 and assume linear steps between their 5-year cost estimations.

4.5 Results and discussion

In the first step I calculate the share of electric vehicles both in the scenario with and without the subsidy as indicated in figure 4.3. The curves diverge as the reduced learning effect in the scenario without subsidy slows down the adoption of electric vehicles. By slowing down the adoption, the learning and product improvements develop slower as well, which makes the difference between the two scenarios greater every year. However, due to the constraint of a saturating market for vehicles, my model assumes the curves to converge again with increasing market saturation.The

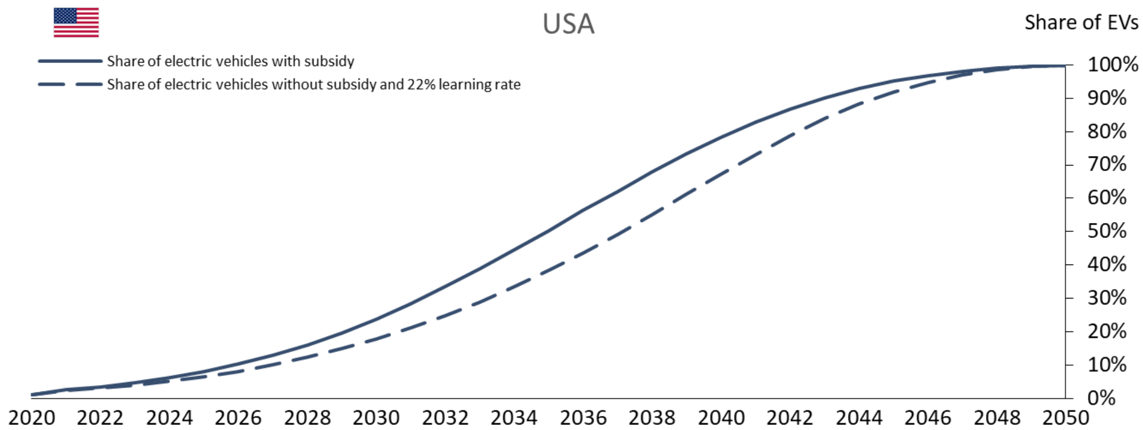


Figure 4.3: The electrification of passenger vehicles in the United States according to the political targets and the scenario corrected for the subsidy-induced learning, market saturation and replacements of vehicles taken out of service.

market saturation should counteract the learning effect as the share of conventional vehicles decreases and hence the number of vehicles to be electrified becomes smaller and smaller. In the scenario without subsidy, this market saturation effect kicks in with a delay but ultimately leads both curves to converge at the maximum of 100% electrification. By using a learning rate of 22%, I showcase the highest learning rate discussed in previous literature. Therefore, the curve without subsidy illustrates the highest effect the reduced learning without subsidy could result into. All the following illustrations and innovation values showcase the maximum innovation potential of the subsidy.

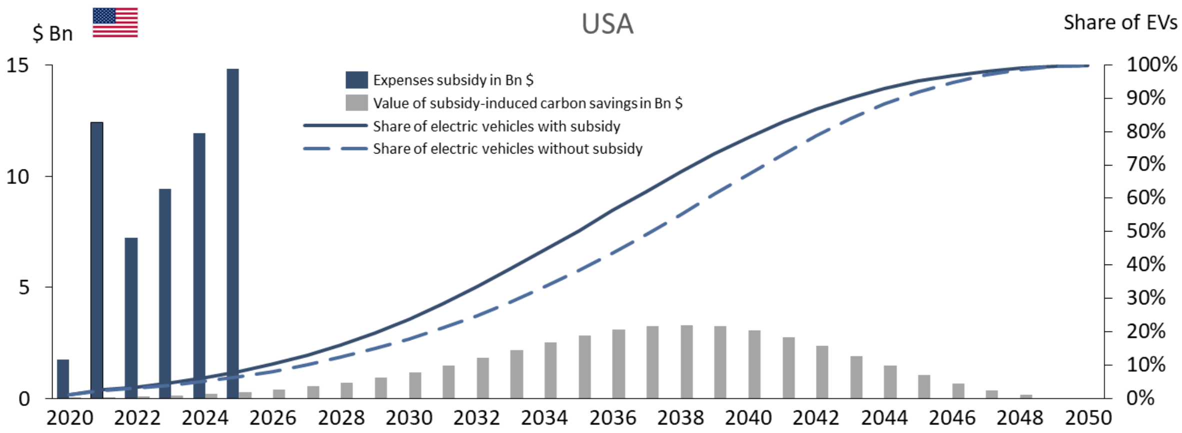
In a second step, I simulate both scenarios with the electricity production within the respective countries, allowing me to determine the additional carbon savings induced by the subsidy. The bars in figure 4.4 indicate the expenses and the corresponding social value of carbon abatement that can be attributed to the subsidy. I hereby assume, that the United States and Germany will continue to grant the subsidy for electric vehicles from 2020 until 2025 before the purchases of electric vehicles stabilize without these governmental subsidies. China however is optimistic to cut the subsidies already at the end of 2022 and still meeting electrification targets as the country invested from early on and has already a significant electric vehicle stock. The expenses in 2021 are exceptionally high in all three countries as the vehicle stocks are below the targeted S-curves and the algorithm needs to catch up to meet these targets.

The value of the subsidy indicated by the grey bars mainly depends on three factors. First, the value of the subsidy is almost perfectly linked to the difference between the two curves of the electric vehicle stock. The greater the difference of electric vehicles between the scenarios with and without subsidy, the higher is the value of the subsidy. Another driver are the marginal emission reductions of the electric vehicle depending largely on the emissions of the conventional vehicle. With comparably low fuel efficiency, conventional vehicles within the United States and China are predestined to be replaced by electric vehicles. The German electric cars show less marginal benefits as the conventional alternative is already comparably more efficient. The last big factor are the carbon emissions of the electricity production during the lifetime of the vehicle.

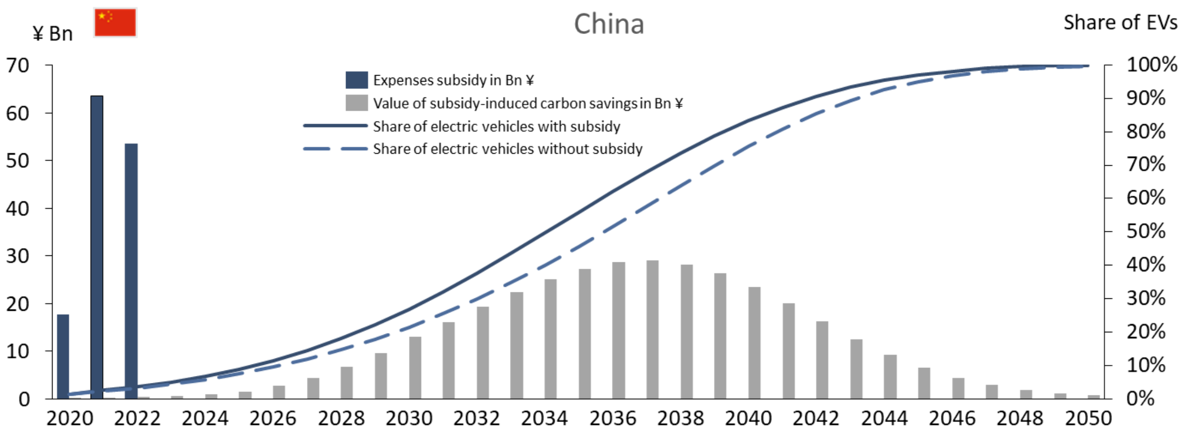
The future electricity production emits less carbon due to a higher share of renewable energy. However, the marginal electricity production for electric vehicles is served by production facilities that are able to provide the additional electricity at the time the vehicles charge, e.g. the evening hours. Hence, the additional demand is frequently served by conventional power plants. Figure 4.5 illustrates the resulting yearly emissions of operating an electric vehicle.

In the United States, the huge natural gas capacities completely satisfy the additional demand leading to constant emissions per electric vehicle in the next years. With no changes in the merit order (see A.1a), this is not about to change soon. In China, the adoption of more renewable capacities and the merit order changes (see A.1b) between 2025-2027 decrease the marginal emissions significantly. Despite the very high share of renewable energy in Germany, the marginal emissions are quite high resulting from the unfavorable marginal production via coal powered plants. Beginning with the nuclear phase-out, more and more marginal energy will be served by gas powered plants with a lower carbon footprint than the coal powered plants. While the total emissions might increase due to the nuclear phase out, the average marginal emissions of the electricity used for electric vehicles decrease. With growing prices for carbon certificates and the resulting shifts in the merit order (see A.1c), Germany can decrease the marginal emissions significantly over time.

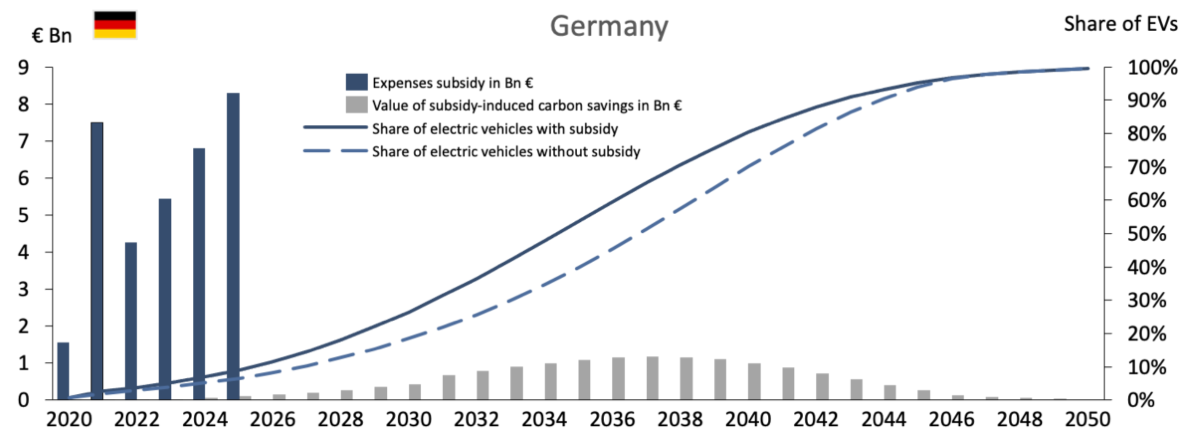
By discounting the expenses and the value of the corresponding carbon savings, I can determine the ecological net present value of each subsidy. As illustrated in figure 4.6, the value of subsidy-induced innovation exceeds the value of direct carbon savings of the subsidized vehicle in all three countries. However, the total ecological value of the subsidy can neither in the United States nor in Germany justify the current subsidy expenses. In the case of China, the ecological value by far outweighs the current costs of the subsidy. With only ¥19.000 ($\approx$ \$2980), the subsidy is comparably low and already expected to fade out at the end of 2022. Assuming that the electric vehicle sales develop according to the political electrification targets in China even



(A) The electrification of passenger vehicles in the United States with the subsidy-induced value and costs of carbon abatement.



(B) The electrification of passenger vehicles in China with the subsidy-induced value and costs of carbon abatement.



(C) The electrification of passenger vehicles in Germany with the subsidy-induced value and costs of carbon abatement.

FIGURE 4.4: The share of battery electric vehicles as well as the subsidy-induced value and costs of carbon abatement within the respective countries.

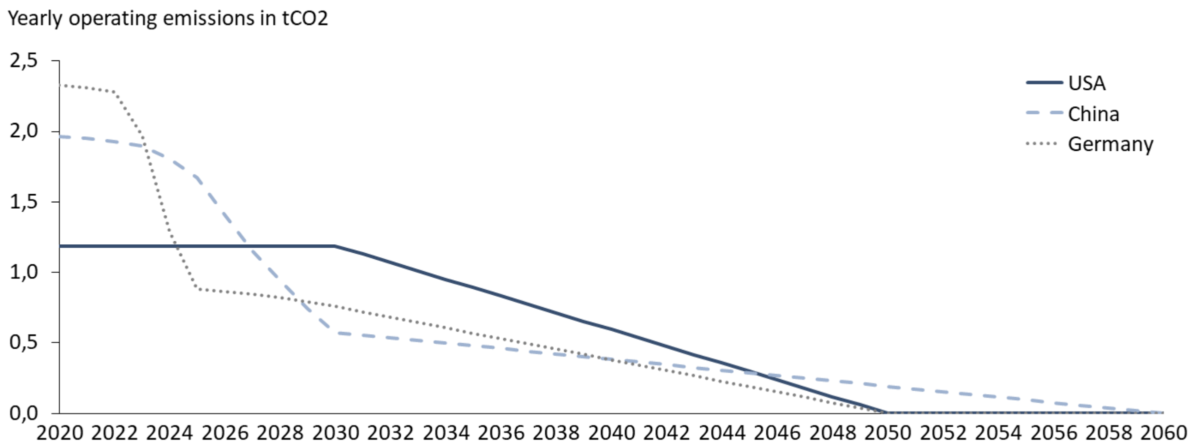


Figure 4.5: The emissions of the marginal electricity demand of operating an electric vehicle in the subsidized scenario.

without subsidy after 2022, the value of the current subsidy exceeds the expected costs between 2020-2022. Previous subsidies for electric vehicles, however, are not part of this calculation and probably a reason why China is confident to be able to stop subsidizing after 2022. Technological and innovation spill-over effects to other countries might increase the ecological value of the subsidy additionally.

The expenses exceeding the total ecological value could serve as a measure for environmental inefficiency since they can not be justified with current and future emission reductions. While the ecological benefits can not justify the expenses in the United States and Germany, this does not necessarily mean that these governments per se over-subsidize their vehicles. It might still be legitimate to grant these subsidies from an economic welfare perspective, for example to support the automobile industry. Assuming that these subsidies are needed for the industry to secure jobs and economic welfare, the economic benefits might make up for the discrepancy. However, it is still arguable whether restricting these subsidies to electric vehicles is efficient from an economic welfare perspective. I argue that car manufacturers could allocate subsidies best, if these subsidies would not be fully tied to electric vehicles. Subsidizing technologies like automated driving might be of greater economic value for the car manufacturing industry than economic subsidies hidden in environmental bonuses that are tied towards a specific drivetrain technology. This constraint towards a specific drivetrain technology limits the options for the automobile manufacturers to innovate with this subsidy efficiently. However, since political reasons might prevent subsidies for other technologies unrelated to carbon efficiency, it might be the politically best way to stabilize the automotive industry via ecological subsidies. This,

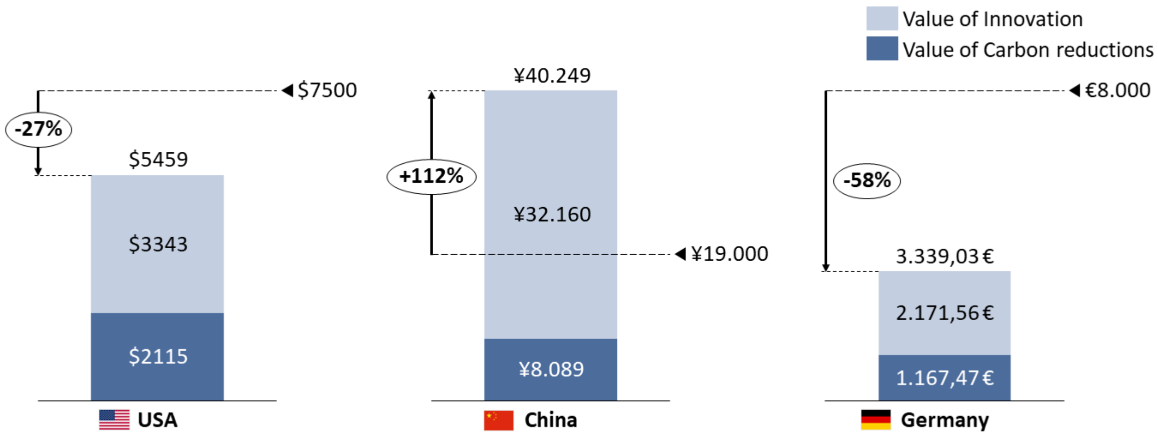


FIGURE 4.6: Comparison of the subsidy costs to the net present value of subsidy-induced carbon savings distinguished by the associated carbon abatements of the subsidized electric vehicle and the carbon abatements of the subsidy-induced electric vehicle adoption including innovation and learning effects.

however, would require the automotive industry to appropriate parts of the subsidy for economic reasons and not hand over the subsidies to the consumers, leading to an even lower ecological value.

Assuming that other measures would be cheaper to decrease carbon emissions, electric vehicles in the United States and Germany are over-subsidized. As long as the marginal ecological effects of subsidizing above the ecological value are positive, the expenses are still effective but probably not efficient from an environmental perspective.

4.6 Conclusion

This study aims to reveal the underlying value potential of innovation induced by a product subsidy. A subsidy might foster product innovation and development leading to a quicker adoption of the subsidized technology. I use price elasticities and learning rates from previous research to correct for effects that depend on the number of products sold in the past (market saturation, learning and replacements of products taken out of service). With that, I can compare a scenario without subsidies to the political targets the subsidies are installed to achieve. From the difference between the adoption curves with and without subsidy, I can value the underlying innovation effects. While this method does not allow to find effects resulting from subsidies, it does uncover policy inconsistencies under the assumption that the subsidies have the politically desired effects. These results might be of major importance for policy makers when drafting future subsidy programs. I showcase my method by evaluating subsidy programs to support the electric vehicle adoption in United States, China and Germany.

For each country, I compare the share of electric vehicles in scenarios with and without subsidy valued with the social cost of carbon saved. Hereby, I use a dynamic hourly merit order simulation considering carbon and fuel prices, available production capacities and renewable production data on country specific driving patterns to calculate the marginal emission reductions of the respective electric vehicles. With this approach, I can calculate the carbon savings of electric vehicles now and in future electricity mixes. By discounting these carbon savings, I determine the ecological value of the subsidy and compare it to the corresponding expenses.

Subsidizing an electric vehicle now could have huge effects for the electric vehicle adoption in the near future. I can show that the underlying value of innovation within a subsidy could outweigh the value of the actual carbon savings of the subsidized vehicle. By ignoring these innovation effects, many critics of subsidies might undervalue the beneficial effect that comes with these subsidies. However, at least in the case of the United States and Germany, the resulting ecological values could still not justify the expenses even with the highest learning rates. As discussed, the subsidy might still be justifiable for economic welfare reasons. However, since the subsidy is tied towards a specific drivetrain technology it will not necessarily foster a quicker development in technologies like automated driving that might be economically more attractive. Future research could adopt this model to other subsidies for example in residential renewable energy generation or the construction industry.

Concluding my findings, subsidies trigger innovation that could be of higher environmental value than many critics would assume. In the case of electric vehicles, the efficiency from an ecologic and as well as from an economic welfare perspective, is debatable. Hence, the subsidy schemes for electric vehicles in the United States and Germany might be at least partly due to political symbolism.

5 | Conclusion

5.1 Summary of Research Findings

This dissertation consists of three essays elaborating political or structural barriers towards the integration of more renewable power in the energy and transportation sector. In the following, I summarize these three essays.

In essay I, I propose changing the taxation of electricity. As more and more renewable energy sources feed in power intermittently, incentivizing households with dynamic electricity prices to participate in load shifting activities could have immense potential. Fluctuations in dynamic energy prices may - if volatile enough - incentivize domestic households to adapt their load pattern in order to minimize the cost of electricity. This study shows that current price volatility does not allow sufficient savings to compensate for additional metering costs occurring with the introduction of dynamic prices. The taxation mechanism has strong effects on the volatility of electricity prices. My results indicate that a change towards an 'ad-valorem' electricity taxation dependent on exchange prices could make residential demand-side management profitable.

I additionally check the potential price risk for consumers that do not react to pricing signals, for example because of a lack of smart devices. Their risk of facing dynamic electricity prices is almost negligible as consumption patterns suggest that they consume in times of both high and low prices canceling out higher payments at peak times even without any load shifts. With these results, policymakers can anticipate the effects of dynamic retail prices on electricity and derive the implications of different taxation settings.

Essay II investigates a more technical and structural issue for decentralized storage systems to actively participate and balance renewable over- and underproduction. The operational strategy of a decentralized energy storage systems critically depends on the availability of information on future prices, future renewable production and future demand. If storage systems do not have this information, they can not adapt their charging strategy to optimally exploit renewable energy production. Therefore, electricity providers may pre-announce and guarantee prices for a certain time period, e.g. the next five hours, to incentivize grid-serving use of storage systems. By incentivizing grid-serving use of storage systems, electricity providers may indirectly control the charging pattern of thousands or even millions of residential battery systems and by that lift huge potential to balance the intermittency of renewable production.

I value pre-announced price information for a household with a photovoltaic roof system and a battery storage in a German case study. To determine the sensitivity of a household's electricity bill towards limited external information on future prices, I evaluate different pre-announcement periods in a rolling horizon approach. I use autoregressive integrated moving average (ARIMA) forecasts to predict the photovoltaic production, the household's consumption as well as electricity prices beyond the information given by the provider. My results indicate that pre-announced external price information of a 3-8 hour period is of major value for a statistically trained system. Pre-announcements beyond this period only have a marginal impact on the resulting savings for consumers. With 3-8 hour periods, the risk electricity providers would have to take in order to control the charging patterns of decentralized battery storage systems is comparably small. My findings help both, households and electricity providers to assess dynamic tariff structures and optimize the usage of renewable power.

Essay III evaluates the efficiency of certain green technology fostering subsidies. These subsidies foster product innovation in green technologies that might lead to a quicker technology adoption. If green technology adapts earlier, governments could reduce probably millions of carbon tons by subsidizing promising green technologies now hoping for innovation effects in the future. These innovation effects could then justify subsidy expenses beyond the directly related social value of the current subsidized good. This paper proposes a method to calculate the underlying value of innovation within a subsidy. The proposed calculation method uses price elasticities and learning rates to correct for effects that depend on the number of products sold, e.g. market saturation and learning. Correcting for these effects allows me to compare scenarios with and without subsidy and draw conclusions about the innovation effects.

Within this essay III, I showcase this method by evaluating the governmental subsidy programs for electric vehicles in the United States, China and Germany. The evaluation shows that the underlying ecological value of innovation within a subsidy might outweigh the value of the directly related carbon savings of the subsidized vehicles. At least for the federal subsidy programs in the United States and Germany, however, the ecological value could not justify the expenses. Either way, this innovation valuing method could help policymakers to decide upon technologies considering their expected innovation potential. My findings could legitimize subsidies in very promising technologies that do not pay off in short-term but have huge potential in the future.

5.2 Future Research

All three essays provide important contributions to existing literature in the field of sustainability, economics and energy. Tackling policy and structural issues, however, is very complex and frequently shows effects on multiple parties within the whole economic and ecological system. While my essays provide answers within their specific economic or ecological area, various related questions remain open for future research. Therefore, investigating effects from a different viewpoint could add more insights into the issues related with certain structural and policy issues. In the following, I will shortly discuss further open questions related to each essay.

In essay I, I suggest shifting towards 'ad-valorem' electricity taxation dependent on the price on the energy exchange. While I can show the direct effects on the electricity bill of participating households, the corresponding change in tax income from a governmental perspective remains unanswered. Hence, a welfare analysis and a tax-authorities' perspective on a shift towards 'ad-valorem' taxation would be a very interesting area for following research. Further research could evaluate the consumer's willingness to manually shift loads if an 'ad-valorem' taxation regime leads to large price fluctuations. Previous papers like Bradley *et al.* (2016) and Goulden *et al.* (2018) question that consumers would be willing to steadily monitor the energy prices for inconvenient load shifts. Therefore, I expect consumers to not manually shift loads but let smart controllers take over this task. Smart controllers do not require a minimum price change to react to pricing signals.

However, these smart controllers can shift loads only with automatic and semi-automatic devices but can not change the consumer usage of manually operated devices. Therefore, I did not consider any price elasticity and behavioral changes from the consumers. If the price changes would increase with 'ad-valorem' taxation, some consumers might indeed change their behavior. Replicating behavioral studies like Allcott & Rogers (2014) under different taxation schemes would be interesting to consider the additional potential in load shifting coming from the price elasticity of the consumer.

In essay II, I evaluate the marginal improvements in the charging strategy of a decentralized battery when electricity providers would pre-announce future electricity prices for a few hours. I can show that a 3-8 hour pre-announcement horizon would already be sufficient for the battery to calculate an almost optimal charging strategy. This is a very important information for the electricity provider to incentivize and control the charging strategy of residential storage systems. However, further research could quantify the risks the electricity providers would bear with this 3-8 hour price pre-announcement. For the electricity providers it could be of major importance to evaluate those risks against the potential returns of price pre-announcements. The returns of price pre-announcements could be calculated as the reduction in costs for balancing grids or hedging certain price peaks and valleys that would otherwise occur. Future research may determine a welfare maximizing price pre-announcement horizon by assessing power providers' benefits of favorable load shifting that is incentivized by price pre-announcements.

Essay III provides a method to calculate the value of innovation induced by a subsidy. While I showcase this method for the subsidy of electric vehicles, future research could adopt this model to other subsidies in different sectors. The subsidization of photovoltaic rooftops, for example, would be an interesting application and could add further insights on top of the contributions of van Benthem *et al.* (2008) and Gillingham & Stock (2018). Another example could be subsidies within the construction industry using similar purchase incentive schemes to foster the installation of thermal insulation or less carbon intensive heating technologies. As these technologies might improve and become cheaper due to learning rates, subsidizing these technologies now might pay off with increasing purchases and installations in the future. Basically, future research could use my method with learning rates and price elasticities to calculate the value of innovation in almost any purchase incentivized subsidy-scheme. However, my proposed method does not consider spill-over effects to other countries. Other countries profit from these subsidies as well as the subsidy-induced innovation most likely does not stop at the border and could decrease prices and improve products also for the export. Since emissions and climate change are a global threat, determining the ecological value from a global perspective considering spill-over effects would be another very interesting area for future research.

All three essays contribute insights into current issues or barriers towards a more sustainable future. The essays answer specific research questions and open up solutions that could have tremendous impact on the energy transformation and a higher usage of renewable energy. These solutions, however, would benefit from perspectives considering tax-authorities, electricity suppliers and the consumers within households and industry.

5.3 Concluding Remarks

This dissertation contributes new knowledge and solutions for the integration of a higher share of renewable energy. Based on a thorough literature review, I uncover and tackle regulatory problems in residential electricity consumption and transportation. Electricity and transportation are two of the main sources for carbon emissions. Solving regulatory problems within these two fields could significantly reduce emissions and global warming. Considering the potential of integrating renewable alternatives, the essays within this dissertation focus on flexibility measures that could be accomplished with a smart grid in the electricity sector and subsidies to foster a higher share of electric vehicles within the individual transport sector.

Within the electricity sector, digitalization could open up great potentials in the integration of more renewable energies. Essay I and II within this dissertation directly elaborate on flexibility measures that might be improved by a digitalized smart grid with dynamic prices. With demand side management of automatic devices as well as optimizing charging strategies of battery storage systems, I research on flexibility potential in the residential sector that remained unused so far. My research contributes to lift this unused potential and integrate a higher share of renewable energy within the electricity mix.

With a higher share of renewable energy within the electricity mix, further opportunities in the transportation sector arise. With electricity becoming less carbon intensive, electrifying individual transport becomes a major factor in the decarbonization of mobility. This is another important matter within the political discussion that I contribute to. With my research I provide valuable insights to efficiently electrify individual transport with subsidies. I can show that there is significant value in subsidy-induced innovation beyond the direct related carbon savings of subsidized vehicles. This might justify subsidies in technologies with great carbon saving potential in the future.

My essays provide policymakers, consumers and other researchers with promising approaches to (1) incentivize households to participate in load shifting activities, (2) utilize decentralized storage systems to balance the intermittency of renewable energy production and (3) evaluate the ecological efficiency of subsidy programs fostering innovation in green technologies. With these contributions, I hope to enrich research as well as the political and regulatory landscape with new insights helping to tackle climate change and transform the energy systems for a sustainable future.

Appendix

A.4 Electricity supply and carbon emissions

For the United States, I use the net summer capacity from United States Energy Information (2020) for 2019 and their outlook of power plant builds and dismantles to determine the capacities until 2030. I assume petroleum capacities to decrease similarly to coal. For the hourly capacity factors I use the data of 2020 aggregated along all balancing authorities but exclude other non distinguished sources like pumped storage and reduce the reference demand accordingly. I clear out obvious outliers (hours 8303, and 2443-2446) by replacing them with the average of the two enclosing hours and remove the negative values within the photovoltaic production. Following the recent governmental announcements, I assume carbon neutral electricity until 2050.

For the installed capacity within China, I linearly interpolate the values taken from Energy Research Institute of Academy of Macroeconomic Research/NDRC (2020) between the years 2020 until 2030 without ocean power as it is only of minor importance due to its low total installed capacity. For the hourly data, I use the installed capacities within the provinces (taken from Thewindpower.net, 2021) and collect sample specifications and coordinates of power plants for each province. For these coordinates, I load the respective wind capacity factors from the MERRA-2 (global) database with renewables.ninja. I then calculate a weighted average hourly wind production pattern. I repeat this procedure with the solar installations in the provinces taken from Chinaenergyportal.org (2020) matched with coordinates taken from the global energy observatory by Google and various other web sources. Despite the petroleum plants, I assume the same utilization of conventional power-plants (coal utilization is derived from the weighted average in hard coal and lignite utilization) as in Germany to derive the reference demand curve without electric vehicles. For petroleum, I use the United States capacity utilizations. I assume carbon neutral electricity until 2060 due to the latest governmental statements.

For Germany, I calculate the installed capacities in 2020 as the average of the 1st of January 2020 and the 1st of January 2021 with the German grid authority data SMARD Bundesnetzagentur (2021). I exclude the pumped water storage as an energy source as it does not produce energy by itself as well as the other non-specified energy sources. The projections for the capacities until 2030 are calculated with a linear change towards the scenario B of Drees *et al.* (2021). Nuclear power sources are completely faded out after 2022 due to governmental regulatories. I derive the hourly capacity factors $\eta_{\pi}(h)$ as the average electricity production patterns in years 2016 to 2020 taken from SMARD Bundesnetzagentur (2021). I assume carbon neutral electricity until 2050 as stated in some governmental projections and roadmaps.

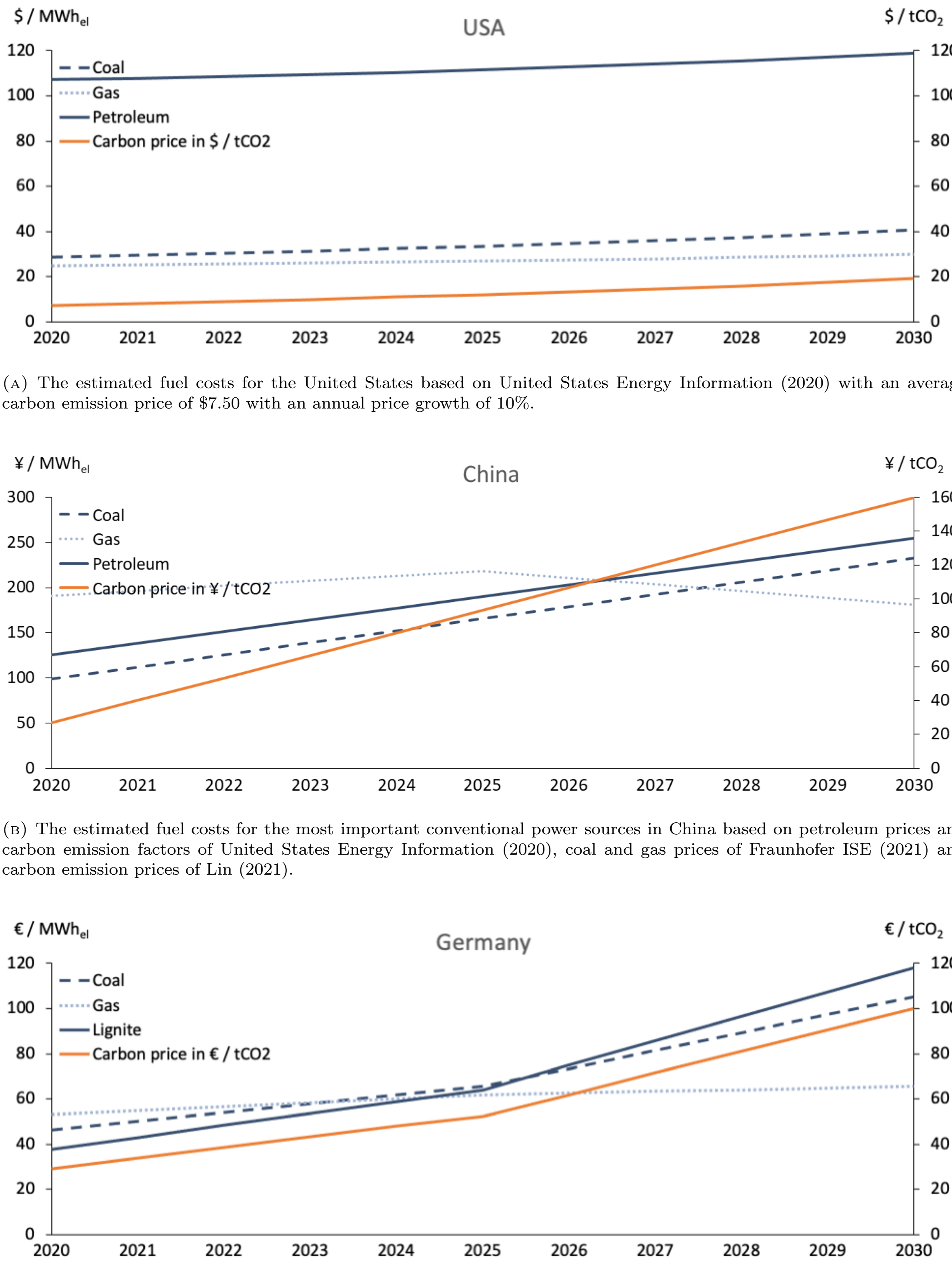
A.5 Development of the Merit Order with Electricity Prices

For the United States, I use the net electricity production, the fuel consumption, the carbon emissions and fuel price data of United States Energy Information (2020) for 2019 to derive the production costs per MWh for each power source. At the time this paper was written, eleven states in the United States had formed the "Regional Greenhouse Gas Initiative" (RGGI) to decrease carbon emission with a cap and trade mechanism. Assuming that more and more states might either join or build up similar systems, I calculate with an average carbon emission price of $7.50 with an annual price growth of 10%. Since the cleanest power source being natural gas is also the cheapest, I do not assume big changes in the merit order as the ranking in fuel prices might stay roughly the same.

In the past, China dispatched the generation hours amongst the installed capacities. For the future, I assume a change towards a merit order dispatching system as well as a more competitive cap and trade system. Regarding the carbon price forecasts I follow the projections of Lin (2021) with a linear increase up to ¥160 until 2030. Due to a lack of fuel price forecasts for China, I assume the same fuel prices for petroleum and the same emission factors of all power plants as in the (converted with the exchange rate ¥6,37 / $ of the time this paper was written). For the coal and natural gas prices I take the fuel prices of the German forecasts (converted with ¥7,20 / €) as I see more parallels to the German case without cheap wrecking gas.

In Germany, I generate merit order projections for electricity based on the fuel price projections, power plant efficiency factors and interpolated average carbon projections of Fraunhofer ISE

(2021) considering the emission factors of Icha & Kuhs (2020). Figure A.1 illustrates the changes in the pricing in the respective countries.



(A) The estimated fuel costs for the United States based on United States Energy Information (2020) with an average carbon emission price of $7.50 with an annual price growth of 10%.

(B) The estimated fuel costs for the most important conventional power sources in China based on petroleum prices and carbon emission factors of United States Energy Information (2020), coal and gas prices of Fraunhofer ISE (2021) and carbon emission prices of Lin (2021).

(C) The estimated fuel costs for Germany based on price projections of Fraunhofer ISE (2021) considering the emission factors of Icha & Kuhs (2020).

FIGURE A.1: Price development of the most important conventional energy sources within the respective countries until 2030 indicating the general merit order projections.

A.6 Generating consumption profiles of electric vehicles

U.S. Department of Transportation Federal Highway Administration (2017) offers a large dataset of trips for the United States, that I filter for private car trips. (TRPTRANS = 3,4,5,6 and DRVFLAG = 1). I aggregate all routes until the destination is either the home or the workplace of the driver (HHSTFIPS = 1,2,3,4). The cars are assumed to immediately begin charging with the given charging power W^{max}, creating a hourly charging pattern. With day and time given, I create a weekly profile that I repeat for a whole year and normalize to a single averaged electric vehicle consumption profile. As there are no publicly available trip databases for China, I reuse the American driving behavior also for China. However, I adjust for the average annual distance as well as the average consumption per mile. For Germany, Zumkeller *et al.* (2018) provides a representative dataset of individual trips that I filter for cars. I accumulate journeys that have been taken in a sequence until the consumer either reaches her workplace (purpose code 1) or returns back home (purpose code 7).

Table A.1: Assumptions for the electric vehicle inputs within the simulation.

Variable	**United States**	**China**	**Germany**
Average yearly distance d^t in miles	11599 [a]	7691 [b]	8452 [c]
Power consumption $\overline{\psi}$ per 100 miles in kWh [d]	24.78	26.54	25.84
Electric vehicles on the road 2020 (N_{2020})[e]	1.138.654	3.512.477	330.780
Average electric vehicle price (P_{2020})[f]	\$50,725.67	¥171,708.88	€38,477.38
Carbon emissions per mile of conventional vehicles in gCO_2[g]	358	373	333

[a] According to 2019 statistics of the Federal Highway Administration of the U.S. Department of Transportation (see U.S. Department of Transportation Federal Highway Administration, n.d.)

[b] calculated from 12377 kilometers as stated by Ou *et al.* (2020).

[c] calculated from 13602 kilometers as stated by the German governmental agency for traffic (Kraftfahrt-Bundesamt, 2020)

[d] Weighted average WLTP consumption of all listed battery electric vehicles sold in 2020 where technical specifications were available within the dataset of EVVolumes (2021). Data that was not available in EU WLTP but in CN GB is multiplied with a factor of 1.18 to adjust with the average discrepancy in the measurement procedures of those vehicles which had both measures given.

[e] Electric vehicle stock 2020 taken from International Energy Agency (2021)

[f] I use the databases of EVVolumes (2021) to derive the average list prices before subsidies of the electric vehicles purchased in 2020 within each respective country.

[g] Based on expected average well to tank and tank to wheel emissions of medium sized passenger cars in the respective countries between 2020 and 2030 according to Bieker (2021).

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