On the economics of real-time pricing in low-carbon electricity markets:

Efficiency and feasibility in the presence of policy-induced variable renewable energy supply

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Summary

Price responsive demand is increasingly considered as an integral part of low-carbon electricity markets, where accommodating the large share of variable renewable electricity generation from wind and solar power will be pivotal for efficiency and supply reliability. Exposing consumers to the variation in the marginal costs of electricity supply through real-time retail prices is to many economists the most intuitive solution to achieve this. The economic evaluation of implementing real-time pricing in low-carbon electricity markets requires a proper understanding of how climate policy instruments and variable renewable generation interact on the related welfare as well as distributional effects.

This thesis provides insights on this interaction, by identifying the major drivers and explaining the basic economic mechanisms underlying the effects of real-time retail pricing on transforming electricity markets. To this end, comparative static welfare analyses are conducted, by using a simple electricity market modeling framework to simulate long-run market equilibria and applying empirical market data.

In doing so, this thesis sheds light on crucial issues regarding the timing and feasibility of introducing real-time pricing, both of which are relevant to regulators and market actors. The optimal timing of rolling out real-time pricing is found to be complicated by a non-linear relationship between policy-induced variable renewable technology deployment and the gross welfare gains from real-time pricing. This result challenges existing rollout strategies, since it implies that real-time pricing does not necessarily become more beneficial in the presence than in the absence of large-scale variable renewable generation. Moreover, growing variable renewable deployment renders full-fledged real-time pricing virtually inevitable, as it allows for making efficient use of installed renewable capacity, and thus increasingly outperforms second-best pricing schemes, which are often considered less complex and therefore more feasible.

Besides the complexity of real-time pricing, its potentially adverse distributional effects are another important acceptance barrier, which this thesis addresses. Variable renewable electricity supply is shown to significantly attenuate these distributional effects, within and across consumer sectors, since reducing the influence of individual demand patterns on consumption costs. Most consumers might thus not have to expect significant consumption cost increases from real-time pricing in low-carbon electricity markets. Targeted rollouts of real-time pricing to large consumers, which are often considered efficient at low renewable supply shares, are, however, found to result in negative pecuniary externalities across consumer sectors, affecting particularly residential consumers. Such cross-sectoral distributional effects could foster

already existing acceptance problems of dynamic pricing schemes. In addition to this, many consumers may make non-optimal tariff choices and decide not to switch to real-time pricing for a variety of reasons. This thesis shows that the resulting unrealized welfare gains could be substantial and rapidly growing with variable renewable market penetration, particularly if mostly residential and commercial consumers do not adopt real-time pricing. It is therefore argued that the potential welfare losses from low adoption rates could justify corrective measures, if tariff choices are indeed non-optimal on average.

Furthermore, several findings in this thesis highlight the complementarity of real-time pricing and climate or renewable policies. This thesis particularly contributes to assessing the cost-effectiveness of renewable support instruments, by illustrating the circumstances under which renewable output subsidies can be more efficient than capacity subsidies in achieving a certain renewable supply target. Putting previous research on this topic into perspective, this seemingly counterintuitive result can obtain, if consumers are real-time priced and can thus react to the negative wholesale prices induced by output subsidies during periods of high variable renewable generation.

Addressing the potential influence of other technological factors on the effects of real-time pricing, this thesis analyzes the relevance of costs and price effects resulting from rapid changes in thermal-plant operation, caused by variable renewable generation. While these effects can decisively modify the evolution of efficiency gains from real-time pricing found in this thesis, it can be illustrated that they likely become negligible under reasonable assumptions about the dynamics in fuel prices, in the carbon price and the generation portfolio.

Concluding with a thorough discussion on future research avenues, this thesis argues that since knowledge about retail tariff choice is lacking, it remains fundamentally uncertain whether the efficiency potential of real-time pricing can actually be realized. Understanding and investigating the determinants of retail tariff choice hence appear to be the next important steps for advancing the economics of real-time pricing.

Zusammenfassung

Eine preiselastische Stromnachfrage wird zunehmend als essentielle Voraussetzung eines an Kohlendioxidemission armen Strommarktes erachtet. Sowohl die Effizienz als auch die Versorgungssicherheit dieses Marktes wird maßgeblich durch die Integration fluktuierender Stromerzeugung seitens variabler erneuerbarer Energien bestimmt werden. Echtzeittarife, die Stromkonsumenten die Variation der marginalen Erzeugungskosten signalisieren, stellen eine in dieser Hinsicht intuitive Lösung dar. Eine ökonomische Bewertung solcher Tarife in sich wandelnden Märkten erfordert das Verständnis über die Wechselwirkung klimapolitischer Instrumente und variabler, erneuerbarer Stromerzeugung auf die mit Echtzeittarifen einhergehenden Wohlfahrts- und Verteilungseffekte.

Die vorliegende Arbeit beleuchtet diese Interaktion, indem sie entscheidende Einflussfaktoren der Wohlfahrts- und Verteilungseffekte von Echtzeitpreisen in sich verändernden Strommärkten identifiziert und die zugrundeliegenden ökonomische Mechanismen erklärt. Um dies zu erreichen werden komparativ statische Wohlfahrtsanalysen mittels eines einfachen Strommarktmodells durchgeführt, welches auf Basis empirischer Marktdaten langfristige Gleichgewichte im Strommarkt simuliert.

Somit gibt diese Dissertation Antworten auf wesentliche Themen bezüglich des Timings und der Durchführbarkeit der Markteinführung von Echtzeittarifen. Insbesondere kann sich die optimale Terminierung der Einführung von Echtzeittarifen als komplex erweisen angesichts des nicht-linearen Zusammenhangs zwischen der Diffusion variabler erneuerbare Erzeugungstechnologien und den mit Echtzeittarifen verbundenen Wohlfahrtsgewinnen. Dadurch geht die Einführung von Echtzeittarifen, entgegen weitverbreiteter Intuition und gegenwärtiger Pläne bezüglich ihrer Markteinführung, nicht notwendigerweise mit höheren Wohlfahrtsgewinnen einher, sobald ein hoher Anteil variabler erneuerbarer Energieerzeugung im Markt erreicht ist. Darüber hinaus scheinen Echtzeittarife mit der Marktpenetration variabler Erzeugungstechnologien zunehmend alternativlos zu werden, da es eine effiziente Nutzung installierter erneuerbarer Kapazität erlaubt, so dass weniger komplexe und deswegen als praktikabler erachtete dynamischer Stromtarifmodelle signifikant ineffizienter werden.

Echtzeittarife werden jedoch nicht nur wegen ihrer Komplexität, sondern auch wegen ihrer möglicherweise negativen Verteilungseffekte als impraktikabel erachtet. Es kann jedoch gezeigt werden, dass solche Verteilungseffekte, die sowohl innerhalb eines Konsumentensegments als auch sektorenübergreifend entstehen, durch variable Stromerzeugung abgeschwächt werden können. Dies ist darauf zurückzuführen, dass eine zunehmend fluktuierende Erzeugung den Einfluss individueller Nachfragemuster auf die jeweiligen Kosten des Stromkonsums abmildert. Die meisten Stromkonsumenten wären daher keinen signifikanten Kostensteigerungen durch Echtzeittarife in einem von erneuerbaren Energien dominierten Strommarkt ausgesetzt. Eine selektive Einführung von Echtzeittarifen, die oft aus plausiblen Effizienzgründen für relativ große Konsumenten angedacht wird, kann wiederum signifikante negative Vertei-

lungseffekte auf Konsumenten anderer Sektoren haben, insbesondere solange der Anteil variabler erneuerbarer Stromerzeugung relativ gering ist. Dadurch könnten bestehende Akzeptanzprobleme hinsichtlich der Einführung von Echtzeittarifen verstärkt werden. Zudem könnten viele Konsumenten nicht optimale Tarifentscheidungen treffen und Echtzeittarife aufgrund verschiedener Faktoren ablehnen. Wie die vorliegende Arbeit zeigt, könnten dadurch substanzielle Wohlfahrtsgewinne nicht realisiert werden, insbesondere wenn Konsumenten des Haushalts- und Dienstleistungssektors Echtzeittarife ablehnen. Diese entgangenen Wohlfahrtsgewinne steigen zudem stark mit dem Anteil erneuerbarer Erzeugung an. Die potenziellen Wohlfahrtsverluste durch geringe Akzeptanzraten könnten somit Interventionen rechtfertigen, die der Korrektur nicht optimaler Tarifentscheidungen dienen können.

Viele Ergebnisse dieser Dissertation unterstreichen überdies die Komplementarität von Echtzeittarifen und Klima- beziehungsweise erneuerbarer Förderpolitiken. Die vorliegende Arbeit trägt insbesondere zur Bewertung der Kosteneffektivität erneuerbarer Förderpolitiken bei, indem sie aufzeigt unter welchen Umständen erneuerbare Erzeugungssubventionen gegebene Einspeiseziele effizienter erreichen können als entsprechend Kapazitätssubventionen. Dieses scheinbar kontraintuitive Ergebnis kommt zustande sobald Echtzeittarife eingeführt sind und Konsumenten somit durch negative Strompreise in Phasen hoher variabler Stromerzeugung einen Anreiz erhalten ihre Nachfrage zu erhöhen.

Um den möglichen Einfluss weiterer technologischer Faktoren auf die Effekte von Echtzeittarifen zu adressieren, wird in dieser Arbeit die Relevanz von Kosten- und Preiseffekten analysiert, die durch rapide Änderungen in der Stromerzeugung thermischer Kraftwerke entstehen, und die durch variable erneuerbare Erzeugung verstärkt werden können. Während diese Effekte die Entwicklung der Wohlfahrtseffekte von Echtzeittarifen stark beeinflussen können, kann gezeigt werden, dass ihr Einfluss unter realistischen Annahmen hinsichtlich der Dynamik von Energiepreisen, CO_2 Preisen und des Erzeugungsportfolios vernachlässigbar werden.

Die vorliegende Arbeit schließt mit einer ausführlichen Diskussion möglicher weiterer Forschungsthemen bezüglich der Einführung von Echtzeittarifen ab. Hierbei wird aufgezeigt, dass das Wissen über mögliche Einflussfaktoren auf Tarifentscheidungen fehlt und daher eine grundsätzliche Unsicherheit darüber besteht, ob und inwiefern die möglichen Effizienzgewinne durch Echtzeittarife überhaupt realisierbar sind. Die Analyse der Determinanten von Tarifentscheidungen ergibt sich somit als wichtiger nächster Schritt in der Ökonomik der Echtzeittarife.

List of Papers

The main chapters **2** to **5** of this dissertation base on separate research papers. They are the result of collaborations between the author of the dissertation, his Post-Doc supervisor Michael Pahle, and other colleagues as indicated.

Chapter 2 is based on the preprint of Gambardella, C., Pahle, M. and Schill, W.-P. (2019). *Do Benefits from Dynamic Tariffing Rise? Welfare Effects of Real-Time Retail Pricing under Carbon Taxation and Variable Renewable Electricity Supply.* Environmental and Resource Economics, Volume 75, Issue 1, Pages 183-213, DOI: `https://doi.org/10.1007/s10640-019-00393-0`. The final version is published under a CC-BY 4.0 license.

Chapter 3 is based on the preprint of Gambardella, C. and Pahle, M. (2018). *Time-Varying Electricity Pricing and Consumer Heterogeneity: Welfare and Distributional Effects with Variable Renewable Supply.* Energy Economics. Vol. 76, Pages 257-273, DOI: `https://doi.org/10.1016/j.eneco.2018.08.020`.

Chapter 4 is based on Pahle, M., Schill, W.-P., Gambardella, C. and Tietjen, O. (2016). *Renewable Energy Support, Negative Prices, and Real-time Pricing.* This article first appeared in The Energy Journal under a CC-BY 4.0 license, Vol. 37, Special Issue 3, Pages 147-169, 2016, DOI: `https://doi.org/10.5547/01956574.37.SI3.mpah` - Reproduced by permission of the International Association for Energy Economics (IAEE).

Chapter 5 is based on Schill, W.-P., Pahle, M., Gambardella, C. (2017). *Start-up costs of thermal power plants in markets with increasing shares of variable renewable generation.* Published in Nature Energy 2 (17050), Pages 1-6, DOI: `https://doi.org/10.1038/nenergy.2017.50`.

Contents

Chapter 1

Introduction

> *The medieval notion of the just price as an ethical norm, with its implication that the price of a commodity or service that is nominally in some sense the same should not vary according to the circumstances of the moment, has a strong appeal even today.*
> – William Vickrey (1971)[1]

The low-carbon transformation of the electricity sector in economies striving for mitigating anthropogenic climate change through reducing greenhouse gas emissions is widely considered to require a fundamental change in electricity consumer behavior (Borenstein, 2012a; Mills and Wiser, 2014; CEER, 2014; ACER, 2014; FERC, 2016a; BMWi, 2016). In order to ensure reliability and efficiency in low-carbon electricity markets, consumers are supposed to become exposed to the actual variation in the marginal costs of electricity supply through real-time retail pricing (RTP). This is due for basically three reasons (cf. Borenstein and Holland, 2005; EC, 2011; IPCC, 2014); First, most consumers usually face a constant price that does not reflect the typically large temporal (and locational) variation in the marginal costs of electricity supply. Second, most of the electricity supply in low-carbon economies is assumed to be variable and uncertain, since being generated from weather dependent variable renewable energy sources (VRE) such as wind and solar power. Third, final energy demand is envisioned to be electrified and covered largely by VRE generation.

This thesis aims to improve the understanding of why the need or social benefit of real-time retail pricing increases and how relevant feasibility constraints might become in transforming electricity markets. To do so, it identifies and explains the basic economic mechanisms as well as major drivers underlying the welfare and distributional effects of implementing RTP, focusing on the interaction of climate policies and variable renewable electricity generation.

[1] Vickrey, William (1971). Responsive Pricing of Public Utility Services. *The Bell Journal of Economics and Management Science* 2 (1), 337-346.

Many economists have long regarded real-time retail pricing as the intuitive, albeit rather hypothetical, first-best, since it exposes electricity consumers to the social marginal costs of supply as they occur (e.g. Vickrey, 1971). Peak-load pricing theory, which has long been the standard tool to analyze and model efficient allocation in electricity markets, is based on the assumption of real-time price responsive demand Boiteux (1960). In practice, however, electricity demand behaves mostly price inelastic as most consumers are flat priced due to the lack of enabling technologies such as advanced meters that could provide real-time information on prices. Yet, progress in information and communication technology (ICT) has made RTP technologically feasible by significantly reducing the costs of advanced-metering infrastructure (AMI) and of automated response devices that reduce consumers' transaction costs of reacting to frequent price variations (Joskow and Wolfram, 2012).

Additionally, the gross benefits of rolling out AMI and RTP are widely expected to increase substantially with the market penetration of VRE technologies (Kopsakangas Savolainen and Svento, 2012; Leautier, 2014; Mills and Wiser, 2014; Connect Energy Economics, 2015). The most common economic intuition behind this expectation is that large-scale VRE generation increases the variability in electricity supply and the corresponding costs, thereby increasing the inefficiency arising from time-invariant retail pricing (e.g. Leautier, 2014). Intuitively, time-invariant or flat pricing is inefficient since it induces consumers to consume "too little" or "too much" in low or high cost periods, such that a higher volatility in the marginal supply costs raises the efficiency gains from pricing schemes that enable optimal consumption behavior.

For these reasons AMI and RTP are increasingly seen as an economic option to integrate the growing share of variable renewable electricity generation in many power systems. In fact, AMI is already being rolled out at large-scale in several electricity markets in the U.S[2] and Europe[3], for instance. Nevertheless, current assessments of implementing real-time pricing, on which such rollout decisions might base, do by no means provide a coherent analysis of both the welfare and distributional effects involved in a transforming electricity market. In particular, a clear understanding is lacking of how variable renewable electricity generation and the policy instruments to induce it interact on both the

[2] As of 2015 roughly 43% of residential customers, that is 57 million out of 132 million residential meters, have already been equipped with AMI, although it is not clear what type of technology exactly has been rolled out. Data is available from the U.S. Energy Information Administration (EIA):`https://www.eia.gov/electricity/annual/html/epa_10_10.html` [last accessed: 10/17/17]

[3] In Europe, several member states such as Denmark and Spain aim for equipping at least to 80% of electricity consumers with smart-meters by 2020, based on non-mandatory targets defined in the EU regulation 2009/72/EC. A detailed overview of member state specific rollout policies is provided by The Joint Research Center of the European Commission (JRC) at `http://ses.jrc.ec.europa.eu/smart-metering-deployment-european-union` [last accessed 10/17/17].

efficiency and feasibility of RTP.

For instance, how do decreasing market values of wind or solar generation assets affect the evolution of either a carbon tax or renewable subsidies, and how does this feed back to electricity prices and the potential efficiency gains from RTP in the long-run? How do different types of consumers benefit or lose from introducing RTP, if electricity supply and prices start to correlate less or more with individual demand patterns than in markets with mostly non-variable electricity generation? What are the welfare gains left on the table, if residential consumers prefer flat rates over rather complex time-varying tariffs, despite growing VRE deployment? How does RTP affect the cost-effectiveness of climate or renewable support policies? These questions indicate the relevance of including the interaction between policy instruments and VRE generation effects when analyzing the economic and political implications of introducing real-time price responsive demand. They also convey the scope of topics addressed in this thesis and hint towards crucial issues, which market actors and regulators alike might face in transforming electricity markets.

One of these crucial issues addressed in chapter 2 of this thesis regards the optimal timing of implementing RTP schemes, if accounting for the dynamics in the efficiency gains from RTP caused by the diffusion of VRE. The differing regulatory practices concerning the pace and comprehensiveness of rolling out AMI in the different EU electricity markets exemplifies both the relevance of this aspect and the uncertainty about an adequate economic evaluation (cf. ACER, 2014). Challenging the common intuition that VRE deployment implies higher benefits from implementing RTP, chapter 2 shows that if VRE investments are carbon-tax-induced, then the gross welfare gains from RTP could actually be far smaller in the presence than in the absence of large-scale VRE supply. Due to this I argue that it might be efficient to postpone the ongoing or planned rollouts of AMI in many European and U.S. jurisdictions until VRE supply shares have reached a critical level.

While the efficiency gains from RTP are nevertheless shown to increase substantially with VRE deployment, realizing these gains and implementing RTP may prove infeasible for several reasons, as discussed in the sections below. Feasibility concerns regarding RTP and the potential implications of infeasibility thus represent an important issue in the literature, to which the research in this thesis contributes also. Specifically, chapter 2 analyzes the relative performance of second-best time-varying pricing schemes, which is motivated by the common concern that most consumers might perceive full-fledged real-time retail pricing schemes as overwhelmingly complex (Duetschke and Paetz, 2013). Some economists therefore suggest to implement less complex time-varying pricing schemes, which expose consumers to less price variation, while still achieving significant efficiency gains (Holland and Mansur, 2006; Borenstein, 2007b; Blonz, 2016). It can be shown, however, that such second-best

pricing schemes perform increasingly badly relative to real-time pricing, and may therefore fail as an adequate alternative to RTP under growing VRE deployment rates. The reason for this is that allocative efficiency increasingly depends on providing incentives to make efficient use of installed VRE capacity when it is available for electricity generation, which requires a pricing scheme of high temporal granularity.

The distributional consequences of implementing RTP are often perceived as yet another important acceptance barrier to many consumers (Borenstein, 2007b, 2013; Andersen et al., 2014; Blonz, 2016). Chapter 3 thus explores and highlights the effect of variable renewable generation on the potential distributional effects among residential customers, which stem from the redistribution of consumption costs. It is illustrated that variable generation attenuates the distributional effects of RTP by making hourly price patterns more random, such that individual demand patterns likely correlate less with price on average. Due to this, the risk of being exposed to high prices and higher consumption costs under RTP than under flat tariffs is reduced.

Many, particularly residential customers may nonetheless tend to make non-optimal tariff choices and could prefer not to enroll in RTP programs even if it would benefit them. Simultaneously, regulators and retail firms could primarily target the largest, typically industrial customers when rolling out AMI and RTP programs as in the case of Germany, for instance, due to the relatively high net benefits even at low VRE market penetration rates (Leautier, 2014). Chapter 3 thus analyzes the welfare consequences of either selective RTP adoption and consumer targeted RTP rollouts. It is found that selective RTP adoption could result in substantial amounts of unrealized welfare gains, which increase with VRE deployment, and that targeted implementations to certain consumer groups could cause adverse distributional affects across consumer sectors, especially when VRE supply shares are relatively low. Corrective measures to address non-optimal retail tariff choices could thus become increasingly relevant in low-carbon power markets. Moreover, the negative cross-sectoral effects highlight the importance of considering potential distributional consequences when evaluating targeted rollouts of RTP in the short run, since these might have a lasting impact on the social acceptance of RTP and hence, in turn, on market efficiency in the long run.

Several findings in this thesis, however, indicate the complementarity of real-time pricing and climate or renewable policies. A comprehensive adoption of RTP could thus strongly improve the cost-effectiveness of renewable policies, as particularly the work in chapter 4 illustrates (cf. Kopsakangas Savolainen and Svento, 2012; Mills and Wiser, 2014). This chapter focuses on and contributes to the comparative assessment of renewable support schemes in markets, by assuming that RTP is implemented. Specifically, it demonstrates under which circumstances a certain VRE supply share target can be achieved more ef-

ficiently with renewable output subsidies, such as renewable market premia, than with renewable capacity subsidies. While this result appears counterintuitive at first glance, it exploits the simple mechanism that real-time price responsive demand can result in sufficiently large VRE capacity savings in the presence of negative prices induced by VRE output subsidization. Thereby, chapter 4 puts previous conclusions in this regard into perspective (cf. Fischer and Newell, 2008; Fell and Linn, 2013; Green and Léautier, 2015).

The economic modeling approach taken to investigate the research topics in this thesis can, of course, not capture all of the relevant real-world complexities, that might matter qualitatively and quantitatively. Acknowledging this, chapter 5 complements the research presented in chapter 2 to 4, by investigating the role of quasi-fixed generation costs at high shares of renewable energy supply, which represent one of several omitted factors that could affect the efficiency gains from RTP. Quasi-fixed costs accrue from changes in plant operation and are commonly seen to increase significantly with variable renewable generation, which could have a significant influence on the evolution of wholesale and retail electricity prices. However, the findings in chapter 5 do not confirm this, implying that the omission of quasi-fixed costs may not significantly bias the welfare effects of RTP found in this thesis.

Nevertheless, the potential caveats of the presented research are thoroughly discussed where necessary and particularly in the concluding sections 6.2 and 6.4, where avenues for further research are derived from the identified limitations. Specifically, it is argued that while advanced metering infrastructure will likely be rolled out at large scale in several European and U.S. markets, the question arises whether it will be used and how the efficiency potential of real-time pricing can actually be unlocked. This leads to the conclusion that understanding and investigating the determinants of retail tariff choice appears to be the next important step for advancing the economics of real-time pricing.

The following sections of this chapter provide the theoretical background on the methodological approach taken and clarifies the most important drivers and caveats to the welfare analyses in this thesis. Section 1.1 relates my research to the key issues addressed in the economic literature on time-varying retail pricing. Section 1.2 touches upon the research topics that are rather specific to the economic analysis of real-time pricing in the low-carbon electricity market. Section 1.3 concludes by spelling out the central objectives and research questions addressed by this thesis.

1.1 Economics of time-varying retail pricing

The findings in this thesis shed new light on key topics in the economic literature on time-varying pricing, which have thus far not been addressed within the context of the low-carbon electricity market. Section 1.1.1 explains that the deployment of variable renewable technologies increases the relative inefficiency of consuming "too little" during periods of high supply, and how this modifies the welfare implications of RTP in the presence of reliability and resource adequacy standards. In doing so, the section specifies the structural modeling approach taken in this thesis, which largely builds upon standard peak-load pricing theory, the traditional model to analyze the efficiency of electricity markets. Section 1.1.2 and 1.1.3 describe how this thesis provides new insights on questions related to the feasibility of RTP by accounting for induced variable renewable generation. The specific feasibility topics addressed comprise of the welfare and distributional implications of targeted RTP rollouts, consumer acceptance barriers and non-optimal tariff choices as well as of the introduction of second-best alternatives to real-time pricing.

1.1.1 Reliability standards, resource adequacy and real-time pricing

The reliable operation of the bulk power system can be regarded as the prime regulatory challenge in liberalized electricity markets, since "[...]modern society has come to depend on reliable electricity as an essential resource for [...] nearly all aspects of modern life" (FERC, 2016b). Power system failures resulting in local or even cascading black-outs can thus entail significant costs to society. Accordingly, electricity markets' ability or inability to attain an optimal level of reliability is a core issue in power market economics. A closely related topic is considered with the efficiency implications of administratively determined reliability standards, which are common in many markets and induce excess generation capacity. This section outlines how the research on RTP in this thesis contributes to this crucial topic and, in doing so, traces the analysis of RTP and reliability back to the standard economic model of electricity markets, which is provided by the theory of peak-load pricing (Boiteux, 1960).

Avoiding costly black-outs requires to continuously balance electricity demand and supply so as to warrant a stable grid frequency. In practice, keeping injections and withdrawals from the power grid in balance at every instant is complicated by *stochastic* supply and demand fluctuations, lack of economic storage capacity and mainly price inelastic demand. The provision of security of supply through ancillary services, typically lies in the responsibility of transmission or independent system operators. Measures to achieve a certain level

of supply security comprise of, for instance, procuring balancing power (operating reserves), activating balancing (reserve) energy and managing transmission congestions through re-dispatching generation units and counter-trading (see for instance BnetzA, 2016). Direct load control is usually a measure of last resort. All of these short-term security of supply measure depend fundamentally on the adequacy of installed generation and transmission capacity, that is on resource adequacy (Stoft, 2002).

Evidently, reliability is not an issue in a deterministic setting, in which *all* consumers are facing electricity spot prices in real-time so that price based clearing of electricity demand and supply is always warranted. Under these assumptions, standard peak-load pricing theory derives welfare optimal prices, that is Ramsey prices, which exceed the short-run marginal costs of electricity supply during peak demand periods (Boiteux, 1960). The resulting average price spike contributes to induce just enough generation capacity to cover peak-demand under all contingencies. Hence, standard peak-load pricing theory implies a convergence towards a long-run equilibrium in the electricity market, where demand induces sufficient capacity investment incentives just by signaling its willingness to pay for electricity such that resources are always adequate and supply security warranted (Crew et al., 1995).

While this theory is still fundamental to most economic electricity market analyses, including the research in this thesis, it's implications are subject of intense academic and political debate. More specifically, both the realization of optimal Ramsey prices and existence of stable long-run equilibria under real market conditions is highly contested ever since the liberalization of electricity markets. Skeptics thus suspect a "missing money problem", meaning that common electricity markets are incapable of providing sufficient investment incentives in generation (and transmission) capacity. The fact that most consumers cannot be rationed by price to available supply during periods of scarce generation resources and can accordingly not signal their valuation for being served electricity, is crucial for this argument Cramton et al. (2013). This is why the lack of price responsive demand is also considered as the "fundamental market flaw" (Stoft, 2002). Full-blown real-time retail pricing would, of course, not only reveal consumers' willingness to pay for the commodity electricity, but also for the service of providing this electricity at a certain level of reliability (cf. Kirschen and Strbac, 2004).[4] However, even then the price spikes necessary to incentivize sufficient capacity investment may not materialize, since they are widely considered as politically infeasible. Many jurisdictions have therefore implemented wholesale price caps, in order to protect consumers from high prices. These caps are usually well below any level close to the average

[4] Additionally, some economists perceive reliability provision in electricity markets as a public good problem, e.g. Cramton et al. (2013). Since consumers cannot be excluded from enjoying a given level of service reliability, each consumer has an incentive to conceal her true willingness to pay for reliability.

value lost for not consuming a unit of electricity in the event of curtailment (Stoft, 2002; Kirschen and Strbac, 2004; Joskow and Tirole, 2007; Cramton et al., 2013).

Although building largely on standard peak-load pricing theory, models of real-time retail pricing like the one introduced in chapter 2can explain inefficient capacity investment in common electricity markets without drawing on political economy reasons. Their main purpose is in fact to analyze the gradual changes in long- and short-run market efficiency, resulting from reducing the share of flat priced consumers and increasing the share time-varyingly priced consumers. Using the assumption of the coexistence of flat and real-time priced consumers, it can be formally shown that generation capacity in the competitive market equilibrium is either too high or too low compared to the social optimum analyzed in peak-load pricing theory (Borenstein and Holland, 2005).[5]

The RTP modeling framework further allows for incorporating and analyzing the effects of counteracting regulatory measures such as planning reserve margins and the introduction of programs to curb peak-demand, as is done in chapter 2 (Allcott, 2012). Guided by the intuition that resource adequacy does not unfold endogenously in electricity markets, many regulatory authorities have implemented reliability targets, which are often enforced through planning reserve margins (Pfeifenberger et al., 2013). Planning reserve margins basically mandate excess generation capacity in proportion to expected peak demand. To induce planning reserve margin targets, several U.S. and European electricity market systems[6] are or will be complemented by centralized capacity markets, which provide a secure flow of revenues from selling "firm" generation capacity (cf. Cramton et al., 2013). Excess generation capacity, which stands idle most of the time, is costly, however, and related cost savings have been found to constitute the largest part of the efficiency gains from introducing real-time pricing (Allcott, 2012; Blonz, 2016). Put differently, flat tariffs are inefficient mainly because of incentivizing consumers to consume "too much" during high price periods where capacity is scarce. This has spurred regulators' interest in peak-pricing schemes or peak-time rebates to incentivize peak-demand reductions Faruqui et al. (2012).[7] However, as a

[5]Installed capacity can never be optimal in the presence of flat priced consumers and is in fact not even second-best optimal under certain conditions. Borenstein and Holland (2005) illustrate that this result obtains because flat electricity rates are non-optimal in the competitive equilibrium, since they do not reflect the relative distortion in consumption at different demand levels. This depends crucially on the assumed demand function and whether the elasticity to price varies with demand. If competitive equilibrium flat rates are "too low", installed capacity are shown to be "too high" and vice versa.

[6]Prominent examples include the Pennsylvania-Jersey-Maryland market (PJM) in the U.S. or the French, Italian and U.K. capacity markets in Europe.

[7]Skepticism regarding the feasibility of full-fledged real-time pricing may also be involved, as is further explained in section 1.1.3.

general finding, this thesis shows that making efficient use of installed VRE capacity when it is highly available will become substantially more important to allocative efficiency in low-carbon electricity markets than mitigating the inefficiency arising from "overconsumption" during periods of scarce generation resources.[8] Further details on this are given in section 1.1.3.

1.1.2 Tariff choice and consumer acceptance barriers of real-time pricing

While it is intuitive that introducing real-time retail pricing can improve allocative efficiency in electricity markets, it is less clear whether potential efficiency gains can actually be realized or it is net beneficial. This fundamentally hinges on the RTP related costs and on consumers' willingness to adopt RTP schemes, that is on the determinants of their tariff choice. Individual tariff choice as such is not analyzed and RTP is assumed to come at no costs throughout this thesis. However, factors influencing it and the potential welfare consequences of acceptance barriers to implementing RTP are studied and discussed in this thesis.

Transaction costs, risk aversion as well as consumers' ability to optimally react to price variations have long been considered as crucial feasibility barriers to real-time retail pricing schemes (cf. Vickrey, 1971). Focus has particularly been put on electricity consumers' aversion to the risk of increasing and volatile consumption costs due to switching from flat to real-time pricing. Findings obtained for non-renewable electricity markets usually hint towards considerable adverse distributional effects and selection problems within every consumer segment (Borenstein, 2007b,a; Andersen et al., 2014). Specifically, it has been shown that the median customer in the residential, commercial or industrial sector, respectively, would in many cases refrain from a tariff switch, since facing higher consumption costs. Changes in consumption costs accrue because switching from flat to real-time pricing entails the redistribution of consumption costs between those consumers who consume most of their electricity during high price periods, and those consumers, who cross-subsidize the former since consuming relatively little electricity during high price periods Borenstein (2007b).

While the distributional effects of RTP could thus indeed pose a crucial feasibility barrier in non-renewable electricity markets, chapter **3** illustrates that the distributional impacts of RTP could actually become negligible in low-carbon electricity markets, due to the high variability of renewable electricity supply.

[8] This result follows partially from the fact that variable generation capacity will naturally reduce the amount of peak-load generation capacity required for complying with a given planning reserve margin constraint (cf. Milligan et al., 2011). Potential savings in excess capacity due to peak- or real-time pricing decrease accordingly.

Applying residential consumption data as well as wind and solar generation data from Germany, it is found that the majority of consumers of the sample would face only marginally changing consumption costs from introducing RTP as soon as electricity stems mostly from variable renewable generation. Increased (weather-dependent) variability in supply implies a more random fluctuation in wholesale electricity prices, which simply reduces the covariation of individual demand and real-time price. High demand for electricity may thus less and less coincide with high electricity prices, if average VRE generation is relatively high during high demand periods. This result may not necessarily hold for every consumer class or type, however, since it crucially depends on the specific covariation of individual demand patterns and VRE generation profiles.

Chapter 3 does not only provide new insights on the intra-sectoral impacts but also on the distributional effects across different consumer classes. Cross-sectoral distributional effects can result from targeted rollouts of RTP to the largest, usually industrial consumers, as is currently planned planned in the German and other European electricity market, for instance.[9] Targeting the largest consumers appears reasonable in terms of efficiency, especially in the near term where VRE deployment is low, since the cost-benefit ratio of introducing RTP is typically relatively favorable for this type of consumer (cf. Leautier, 2014). However, since consumer targeting could raise distributional issues, it could potentially hamper a widespread consumer acceptance of RTP in the mid to long term as the analysis in chapter 3 reveals. Specifically, it illustrates that residential and commercial consumers could be harmed, if only industrial, consumers are put on RTP. The resulting change in industrial consumption behavior can inflate the retail rates faced the remaining flat-priced consumers of other sectors, as it causes wholesale prices to rise stronger during off-peak periods than it causes them to fall during peak-periods. Large-scale VRE supply is shown to moderate or even suppress this negative pecuniary externality. This implies that targeted implementations of RTP could be more harmful to certain consumer groups in the near term, where VRE supply shares are low, than in the long-term, thus challenging current or recommended rollout-strategies in several jurisdictions.

Yet, even if the distributional implications became irrelevant in low-carbon electricity markets, many consumers could nonetheless refrain from switching to RTP due to having relatively high transaction costs and/or because of

[9] While Germany is leading in the number of smart-grid demonstration as well as research and development projects (cf. Gangale et al., 2017), the German government has decided, based on the Act on the Digitisation of the Energy Transition, to roll out smart meters selectively, focusing on very large consumers in the near term. For further details on the Act on the Digitisation of the Energy Transition, please refer to: `http://www.bundesrat.de/SharedDocs/drucksachen/2016/0301-0400/349-16.pdf?__blob=publicationFile&v=1` [last accessed 10/17/17].

misperceiving their benefits from it. The role of transaction costs and cognitive biases in electricity consumer decision making gains increasing attention, particularly in the behavioral economics literature on energy efficiency and electricity consumption (Ito and Reguant, 2016; Jessoe and Rapson, 2014). In section 6.4, I will therefore review the growing body of empirical studies, providing knowledge about the influence of these factors on decision making and discuss why and how they could affect individual tariff choice. Given acceptance rates of RTP schemes among residential and commercial consumers may indeed turn out to be non-optimally low, chapter 3 goes on to demonstrate that this could result in significant amounts of unrealized efficiency gains, especially for growing VRE supply shares (cf. section 1.2.4). Corrective measures to remedy non-optimal tariff choices may therefore become increasingly justified in low-carbon electricity markets.

1.1.3 Time-varying retail pricing schemes and variable renewable electricity generation

In theory, real-time retail pricing represents the first-best among a variety of time-varying pricing schemes, since it exposes consumers to the social marginal costs of electricity supply as they occur. In practice, however, regulators and suppliers will face a trade-off between the feasibility and efficiency of a retail pricing scheme. Full-fledged real-time pricing is often regarded as infeasible, due to its complexity and the cost risk involved for customers, as explained in the previous section. Accordingly, implementing less complex and less risky second-best schemes is often proposed. Based on the findings in this thesis, I provide arguments for why second- or third-best pricing schemes might become inefficient and inadequate alternatives to RTP in markets deploying high shares of variable renewable technologies.

Each pricing scheme is characterized by a specific complexity-efficiency-relationship, along which different schemes can be compared (Faruqui et al., 2012). Intuitively, the more accurate a retail rate reflects the actual costs of electricity supply at a given point in time (and location in the grid), the more efficient it is to implement compared to less accurate rates, ceteris paribus. The accuracy of a rate is determined by its temporal (and locational) granularity and timeliness, which refers to the degree of its variation over time and to how far in advance of actual consumption it is set, respectively (Borenstein, 2012b). While implementing pricing schemes with higher temporal granularity and timeliness are thus more efficient than other schemes, they are also perceived as more complex due to higher consumption cost risk and volatility as well as higher transaction costs involved (Faruqui et al., 2012; Borenstein, 2007a,b). The more retail prices vary over time, the higher a consumer's transaction costs of keeping informed about price changes and adjust consumption accordingly.

Being exposed to price variations can moreover imply to face more frequent changes in individual consumption costs, depending on individual demand habits and the volatility in the underlying reference price.

Time-of-Use tariffs (TOU) are located at the low end of this complexity-efficiency-spectrum, as retail prices only vary between night- and daytime or between different blocks of hours during the day, which are set to reflect characteristic price-demand variations in these periods (Faruqui and Sergici, 2010; Faruqui et al., 2012). TOU rates are usually determined months or even a year ahead of electricity consumption, often with little adjustment between seasons (Borenstein, 2012b). Thus reflecting little of the actual variation in supply costs, TOU rates are considered to induce moderate efficiency rewards at moderate risks and complexity. Monthly adjusted TOU rates have been found to perform reasonably well in systems based on non-variable generation, however, since achieving a large portion of the potential efficiency gains obtained under real-time pricing (Holland and Mansur, 2006; Borenstein, 2007b). But predefining TOU blocks that reflect characteristic load and, thus, average wholesale price variations (e.g. off-peak, shoulder-peak and peak-periods) could become rather difficult as soon as supply becomes increasingly variable and random with the diffusion of VRE technologies. The relatively "coarse" variation of TOU rates, even if monthly adjusted, appears rather inadequate for incentivizing proper consumer response to more frequently and rapidly changing supply conditions under large-scale variable renewable electricity generation (cf. Cappers et al., 2012; Faruqui et al., 2012).

A more efficient alternative than TOU tariffs is *Critical or Variable Peak Pricing* (CPP and VPP). Peak-pricing schemes are primarily implemented to address reliability problems in a power system and to reduce the amount of excess generation capacity. This is achieved through incentivizing consumers to curb demand during tight market situations by providing very high retail prices that signal capacity scarcity. CPP rates as well as the number and the window of event-days,i.e. the expected peak-demand period, are determined *ex-ante.* On event days, enrolled customers face a peak-charge during peak-demand hours, which is usually a multiple of their otherwise constant rate (or TOU rates). Under variable peak pricing, these peak-charges are adjusted to the actual degree of capacity scarcity, implying that the number and time-frame of event days also varies accordingly. Introducing VPP would therefore probably yield higher efficiency gains than CPP.

Some quantitative findings suggest that peak-pricing schemes could in fact capture the bulk of efficiency gains from introducing RTP (Allcott, 2012; Borenstein, 2013; Blonz, 2016). The underlying reason is that "overconsumption" during high price hours and the resulting excess generation capacity represent the main source of inefficiency arising from flat tariffs. For this reason and its manageable degree of complexity, peak-pricing is already applied in

some markets in the U.S. and is often considered as the more feasibly alternative to RTP (Faruqui et al., 2012; Blonz, 2016). In chapter 2, I can show, however, that this assessment might mainly hold for conventional electricity markets, which are based on non-renewable generation technologies. Specifically, I find that if renewable technologies supply electricity at large-scale, only a relatively small fraction of the potential efficiency gains from RTP are obtained from curbing peak-demand and mitigating "overconsumption" during peak-periods through variable peak prices. The lion's share of efficiency gains from introducing RTP accrues from avoiding "underconsumption" during off-peak periods , during which capital intensive VRE generation assets supply electricity at almost zero-marginal cost. Making efficient use of installed VRE capacity by incentivizing demand increases during periods of abundant VRE supply thus becomes more important for allocative efficiency in low-carbon electricity markets. This might only be achieved through full-fledged real-time pricing, since accurately reflecting the social marginal costs of supply at every instant.

1.2 Real-time retail pricing in low-carbon electricity markets

To give regulators and market actors economically sound guidance on when to implement which option that serves to integrate variable renewable electricity generation in existing power systems, requires a thorough understanding of the factors and underlying mechanisms driving the efficiency gains as well as distributional effects of each integration option. By analyzing how the efficiency and distributional effects of introducing real-time pricing evolve with the deployment of variable renewable energy sources in low-carbon electricity markets, this thesis contributes to the rigor of cost-benefit analyses and feasibility assessments of this integration option. This chapter highlights four important factors influencing the dynamics in the efficiency and distributional effects of real-time retail pricing, which are given by *i)* climate and renewable policy instruments, *ii)* the supply characteristics of variable renewable technologies, *iii)* the trade-offs against other integration options and *iv)* long-run changes in consumer behavior. Each of the following sections hence briefly outlines the main mechanisms through which these factors can affect the welfare and distributional impacts of introducing real-time pricing. In doing so, the implications of omitted factors in the analyses of the main chapters in this thesis are clarified.

1.2.1 Interaction of climate and renewable policy and real-time price responsive demand

While investigating the effects of RTP under climate or renewable support policy induced renewable electricity is the overarching focus of this thesis, the interaction of such policies and the implementation of real-time pricing is shown to be twofold. On the one hand, price responsive demand can improve the cost-effectiveness of policy instruments. Renewable subsidies or carbon taxation can, on the other hand, result in different market outcomes and thus entail different wholesale and retail price effects, which feed back to the welfare effects of introducing real-time pricing.

The cost-effectiveness of policy instruments to induce carbon-emission-free technologies is an important topic in the environmental economics literature (Palmer and Burtraw, 2005; Fischer and Newell, 2008; Fell and Linn, 2013; Green and Léautier, 2015). Much attention is paid to the relative performance of carbon emissions taxation and different types of renewable support policies such as renewable portfolio standards. In the absence of externalities other than the negative externality from carbon dioxide emissions this typically boils down to the conclusion that implementing a Pigouvian tax achieves a certain emission reduction target most efficiently (Palmer and Burtraw, 2005; Fell and Linn, 2013). In the presence of both the carbon emission externality and positive externalities from learning-by-doing or research and development in renewable technologies, combinations of renewable support policies and carbon taxation can be found optimal in reducing carbon emissions to a certain level (Fischer and Newell, 2008; Kalkuhl et al., 2013). In a second-best setting, where, due to political economy reasons, the negative externality cannot be internalized directly or optimally through Pigouvian taxation but only by renewable subsidization (e.g. Kalkuhl et al., 2013), the focus lies on the relative efficiency of different renewable subsidy schemes (Palmer and Burtraw, 2005; Green and Léautier, 2015; Fell and Linn, 2013; Newbery, 2016).

The work in in chapter 2 contributes rather generally to the cost-effectiveness literature, by illustrating that raising the share of real-time priced consumers increases the profitability and therefore investment in renewable capacity at a given carbon tax (cf. Sioshansi and Short, 2009; Kopsakangas Savolainen and Svento, 2012; Fell and Linn, 2013; Mills and Wiser, 2014). This replicates the rather general finding that RTP and VRE generation are complementary in the sense that RTP allows for making better use of VRE generation assets. Compared to a market with price inelastic demand behavior, VRE generation assets make higher short-run profits, since real-time priced consumers raise demand when supply from wind and solar generators is high and wholesale prices correspondingly low, such that average demand and price are comparatively high. Chapter 2 further shows that this complementarity is self-enforcing as

the incremental welfare gains from RTP do not level off but grow almost linearly as the renewable supply share increases. Moreover, welfare gains from RTP are found to increase faster, the higher the initial level of renewable deployment. Model applications to thermal-based power systems instead show that raising the RTP share is decreasingly welfare improving (Borenstein, 2005; Holland and Mansur, 2006).

The work presented in chapter 4 assesses the cost-effectiveness of different renewable support schemes, where one of many crucial issues regards the inefficiency of renewable output subsidies. Specifically, it tackles the question whether renewable capacity subsidies are more efficient in achieving a certain VRE capacity target than output subsidies when real-time priced consumers. Renewable output subsidies like the renewable market premia in Germany, for instance, can incentivize generators to supply electricity at a negative wholesale price, which is equal to the subsidy received. Negative wholesale prices can accelerate the decrease in the marginal economic value of variable renewables with renewable capacity entry, such that levies to finance VRE subsidies can correspondingly increase relatively fast. Accordingly, for such a situation it can be shown that the deadweight losses from levies become comparatively large for given levels of variable renewable capacity, and that it would be more efficient to avoid negative wholesale prices, by providing a financial rather than physical dispatch insurance, i.e. by compensating renewable generators for being curtailed Green and Léautier (2015).[10] Based on similar reasoning, Newbery (2016) argues in favor of market determined payments for available renewable *capacity*, which could serve to refinance capital costs while keeping generators exposed to correct short-run signal.

The findings in chapter 4 put this intuitive argument into perspective, by illustrating that output subsides can in fact be more efficient in achieving a given renewable target than capacity subsides under certain assumptions. Taking into account that renewable targets are often defined as shares in total consumption, and that negative prices can incentivize real-time priced consumers to increase demand during high VRE generation, results for the German market suggest that a given target can be reached at considerably lower VRE capacity investment and less costs than under capacity subsidization. These cost savings are sufficiently large to overcompensate the higher deadweight losses from the levies needed to finance VRE output subsidies. The higher

[10] In fact, providing *ex-post* financial dispatch insurance is what German transmission system operators are increasingly practicing when curtailing particularly wind generators and remunerating 95% of their lost revenues, in order to remedy locational imbalances in the transmission grid BnetzA (2016).it is argued that while advanced metering infrastructure will likely be rolled out at large scale in several European and U.S. markets, the question arises whether it will be used and how the efficiency potential of real-time pricing can actually be unlocked. This leads to the conclusion that understanding and investigating the determinants of retail tariff choice appears to be the next important step for advancing the economics of real-time pricing.

the VRE supply share target the higher becomes the relative efficiency gap between output and capacity subsidization.

Finally, the sensitivity analyses in chapter 2 and 3 shed some light on the relative efficiency of carbon taxation and renewable subsidies. These findings relate to the aforementioned differential retail price effects of different policies. In particular,for a given VRE supply share the welfare gains from RTP are found to be larger under carbon taxation than under levy-financed renewable subsidies. Under carbon taxation RTP consumers face a tax-mark up only during periods, in which carbon emitting technologies set the wholesale price. In periods of high renewable supply they face almost zero-prices, which is not the case if renewable subsidies are financed through levies included in the retail rates. Levies constitute a constant tax-wedge between real-time retail rates and wholesale prices, which can become rather large at high renewable supply shares. The resulting dead-weight-loss can only partially be mitigated through introducing RTP, implying that corresponding efficiency gains are lower than under carbon-tax-induced VRE supply.

1.2.2 Variable renewable integration costs, market value dynamics and the benefits of real-time pricing

As pointed out before, the rising interest in unlocking price responsive electricity demand is fundamentally driven by the challenges to integrate weather-dependent electricity generation from wind and solar power in existing power systems. These integration challenges are operationalized through the *integration costs* or *market value* of variable renewable energy technologies in the energy economics and engineering literature (Lamont, 2008; Joskow, 2011; Milligan et al., 2011; Hirth et al., 2015). This section outlines how VRE integration costs and market value dynamics translate into the welfare gains from real-time price responsive demand.

The temporal as well as locational variability and uncertainty of electricity generation from wind and solar power is widely considered to require adaptations in power system operations and infrastructure investments. These adaptations come at additional costs, also termed *integration costs*. Following Hirth et al. (2015), integration costs can be decomposed into "balancing", "grid-related" and "profile" costs, which respectively arise from uncertainty in VRE supply, the spread in the locational value of electricity and changes in the operation of and investment in the remaining non-variable generation portfolio.[11] Importantly, integration costs accrue for every generation technology and are

[11]Balancing costs result from forecasting errors, i.e. from uncertainty in VRE supply and reflect the marginal costs from activating balancing energy and procuring balancing power, for instance, in order to remedy short-term demand and supply imbalances. Grid related costs comprise of the shadow value of scarce transmission capacity, the spread in the locational value of electricity and the opportunity costs from transmitting energy from

contingent on the respective power system (Milligan et al., 2011). The potential savings in integration costs is what constitutes the additional economic value of options to cope with the supply characteristics of VRE technologies, including real-time price responsive demand. Hence, if VRE integration costs increase with VRE deployment, then the value of real-time price responsive demand should also increase, ceteris paribus.

Increasing integration costs of VRE generation assets in turn imply a decrease in the market values of these assets, as integration costs can be interpreted as the part of the potential market value that is lost due to output variability and uncertainty (Hirth et al., 2015). The market value or marginal value of a generation asset equals the stream of expected marginal revenues from supplying electricity with this asset (Lamont, 2008).[12] In this thesis, changes in the welfare effects of introducing real-time pricing at different stages of VRE market penetration are mostly explained on the basis of the dynamics in VRE market values.

The non-monotonous change in the welfare gains from RTP found in chapter 2 and 3 can thus mainly be explained by the declining market value of both wind and solar generation assets as they diffuse in the market. It is particularly shown that introducing real-time pricing can be less beneficial in the presence than in the absence of high VRE deployment. This result has direct implications for the optimal timing of rolling out advanced metering infrastructure and real-time pricing schemes in transforming markets. Hence, in difference to current practice in many EU and U.S. electricity markets, it might be more efficient to defer large-scale roll-outs of AMI and RTP until VRE supply shares have reached a very high level. The reason for this result is that carbon-tax-induced VRE deployment, as assumed in chapter 2 and 3, entails two opposing effects on the wholesale price distribution. Specifically, wholesale prices inflate on average with VRE deployment, while they also drop to zero during an increasing fraction of periods, where electricity demand can be fully supplied by VRE technologies supplying electricity at near-zero marginal costs. As is explained in more detail in chapter 2, these opposing price effects gradually increase the extent to which flat priced consumers consume "too little" during low price periods, such that the efficiency gains from switching to real-time pricing increase correspondingly. That is the spread between the average and

a VRE source to the consumer. Profile costs include all costs linked to changes in the operation of and investment in the remaining non-variable generation portfolio, caused by the variability in wind or solar output. Non-variable plants incur costs from changing their output levels, i.e. from ramping up (down) or starting up (shutting down), in response to the rapid changes in wind or solar electricity generation. Moreover, VRE supply reduces the utilization of non-variable technologies, thereby raising the average cost per unit of energy generated from these technologies. shifts investment towards technologies with relatively low fixed and high marginal costs

[12] Put differently, the market value of a technology is the average price of electricity supplied by this technology (Helm and Mier, 2016).

hourly wholesale price increases with VRE deployment especially during low price periods due to the inflation in the average wholesale price.

The average wholesale price increases, in turn, because of the decrease in the market value of VRE technologies, which represents the main mechanism driving most of the results found in this thesis. A decrease in the market values of VRE generation assets is a quite robust finding in the related literature and is mainly a result of VRE output variability, not uncertainty (Lamont, 2008; Bushnell, 2010; Mills and Wiser, 2012; Green and Léautier, 2015). The variability in wind speeds or solar radiation implies that usually only a relatively small fraction of installed VRE capacity is on average available for generating electricity, and that high VRE availability does decreasingly often coincide with high electricity price periods at growing VRE deployment.[13] Put simply, the average VRE generator produces much when prices are low and vice versa. The larger the amount of VRE capacity in the market, the lower the prices and revenues in periods of high VRE capacity availability, and thus the marginal value per unit of wind or solar capacity. Consequently, the larger VRE capacity entry is in equilibrium, the larger the average wholesale price has to be in order to allow for this capacity to break even, if assuming perfect competition (cf. Hirth et al., 2015).[14]

Several other influencing factors have been ignored in the welfare analysis in chapter 2 to 4, as including these lies beyond the scope of the work presented in this thesis. For instance, price and cost effects attributable to wind and solar output uncertainty are not accounted for in all of the analyses. Moreover, the presented welfare results do not include the environmental benefits (or damages) from deploying VRE technologies such as the avoided (or created) social damages from carbon-dioxide emissions, which could imply even higher (lower) benefits from RTP given its complementarity to VRE deployment discussed in the previous section.[15] The caveats of omitting these and other factors are

[13]While the latter may mainly hold for wind powered generation, it does not necessarily hold for solar powered technologies, whose output pattern can correlate strongly with load patterns. Thus, at least at low penetration rates, solar electricity generation can most of the time coincide with high prices (cf. Lamont, 2008).

[14]The non-renewable generation technology portfolio changes accordingly towards low fixed, high marginal cost generation technologies. These technology portfolio changes are largely climate policy induced in this case, but also result from the crowding-out effect on non-renewable, high fixed and low marginal cost technologies. This crowding-out effect obtains, since VRE technologies typically have the lowest (short-run) marginal costs of supply in the market such that increasing VRE generation reduces the load factor of other technologies. This leads to a gradual increase in the levelized costs of electricity (LCOE) supplied by non-renewable technologies, making them more expensive relative to VRE technologies in addition to carbon taxation or renewable subsidization. Hirth et al. (cf. 2015) interpret this crowding-out effect as the "utilization effect", which increases the "profile cost"-component of VRE integration costs. In sum, all of the mentioned effects imply that the average costs of electricity supply increase with VRE deployment, which is reflected in the corresponding increase of the average electricity price found in the main chapters 2, 3 and 4.

[15]The environmental effects of RTP are contextual, of course, and thus ambiguous, if

separately discussed in each chapter as well as in the concluding section 6.2.

The analyses also abstract from integration costs that arise from changes in quasi-fixed costs of thermal power plant operation caused by variable generation. Variable generation is often considered to increase quasi-fixed costs by increasing the frequency of ramping or start-up and shutdown operations of dispatchable, i.e. non-variable generation plants. However, the work presented in section 5 analyzes whether this actually holds under realistic transition path scenarios for the German power system, applying a unit commitment model approach. The analysis shows that the amount of quasi-fixed costs stemming from more frequent start-up operations increases only insignificantly and constitutes a marginal portion of total system costs. The bias from omitting quasi-fixed costs in the welfare analysis of RTP in the core chapters thus seems to be rather small.

Moreover, trade-offs to alternative technological or regulatory options that facilitate the integration of VRE and mitigate corresponding costs are also mostly ignored in the welfare analyses below. How this can affect the findings in this thesis and which alternative integration options compete with rolling out AMI and enabling real-time price responsive demand is discussed in the subsequent section.

1.2.3 Trade-offs between real-time pricing and other VRE integration options

Implementing real-time pricing does not only generate benefits but also costs and thus competes with several market based and technological options to accommodate variable renewable electricity supply. In this section I briefly review the most relevant trade-offs to other so-called flexibility or integration options, in order to clarify how to interpret the welfare results presented in chapter 2 to 4.

Integration options can prevent or remedy the locational and temporal imbalances between demand and supply arising from both the typically uneven dispersion of installed VRE capacity and the unforeseen as well as frequent changes in VRE generation. Supply-sided integration options comprise of expanding the capacity of the transmission grid, of storage facilities and of flexible peak-load generation technologies (e.g. Bertsch et al., 2016; Brouwer et al., 2016). Expanding the transmission capacity to adjacent markets or within markets serves to remedy bottlenecks in transporting electricity from source to consumer, and thereby to correct locational imbalances. Such locational

considering all stages of the transition. That is, introducing RTP could also imply an increase in environmental damages and thus comparatively lower welfare gains at low VRE supply shares and high supply shares of coal or lignite fired base-load technologies.

imbalances could occur more frequently with VRE deployment due to surplus generation of wind turbines, for instance, which are often clustered at the best, i.e. windy sites, yet not necessarily at demand centers. Grid- or small-scale storage technologies such as pumped hydroelectric storage, grid-connected batteries or batteries in electric vehicles allow for shifting electricity demand or supply over time, and therefore serve to mitigate temporal demand and supply imbalances at a certain location in the grid. Peak-load generation technologies such as combined cycle gas turbine (CCGT) are able to respond quickly to rapid changes in supply conditions at relatively low quasi-fixed costs, which are caused by changes in plant operation. As the costs of peak-generation capacity are typically relatively low, they can be refinanced even if generation units are rarely utilized, often rendering peak-load technologies a robust least-cost integration option (Green and Vasilakos, 2010; Kopsakangas Savolainen and Svento, 2012; Brouwer et al., 2016; Bertsch et al., 2016; IEA, 2016).

In fact, the welfare analyses in chapter 2, 3 and 4 only account for the potential trade-off between implementing RTP and expanding peak-load generation capacity. While this simplification keeps the methodological approach tractable, it also implies that estimated welfare effects can be downward or upward biased, depending on the degree to which RTP would reduce the need for transmission grid expansion or investing in storage capacities, and vice versa. Exposing consumers to location- and time-varying prices would possibly reduce the need to build new transmission lines and to invest in storage capacity, by incentivizing demand adjustments to the current and local supply conditions. Like storage technologies, price responsive demand could particularly serve to make better use of installed VRE capacity during periods and at locations of high wind or solar output and accordingly low prices; a feature that becomes increasingly important to establishing market efficiency at very high shares of VRE generation, as explained before in section 1.1.1 and 1.1.3.

However, the extent to which these trade-offs matter depends on the stage of VRE market penetration and whether different options are actually substitutes or indeed complements. Accommodating VRE generation through both transmission and storage capacity expansion is often found to be relatively expensive at low VRE shares, yet each option becomes increasingly economic at very high VRE deployment rates (Mills and Wiser, 2014; Cochran et al., 2014; Brouwer et al., 2016; MIT Energy Initiative, 2016). Hence, savings in *additional* investment in transmission or storage capacity through implementing RTP may only become substantial at large-scale VRE deployment. Moreover, demand- and supply-sided flexibility options are not necessarily substitutes but also complements. Distributed behind-the-meter storage facilities such as electric heaters and vehicles or small-scale batteries could become increasingly economic with the implementation of RTP and vice versa (see also section 6.2).

Compared to these technological options, regulatory and market design adjust-

ments aimed at integrating VRE generation can be regarded as a least-cost integration option (Cochran et al., 2014; Pérez-Arriaga et al., 2017). The welfare effects of technological integration options and the extent to which each creates savings in the other option could be less significant, if such adjustments would be accounted for. The amount of additional balancing power to cope with VRE uncertainty, for instance, could be significantly reduced by scheduling auctions for electricity closer to real-time, by allowing for sub-hourly products or by consolidating balancing and control areas (GE Energy, 2010; Müsgens et al., 2014; BnetzA, 2016). Better coordination among transmission system operators regarding redispatch schedules and balancing needs could significantly reduce the overall costs of transmission congestion management (Kunz and Zerrahn, 2016). And by making better use of existing transmission capacity, improved coordination protocols may further reduce the need for expanding transmission capacity (Lew et al., 2010). This could also be achieved through providing incentives to allocate particularly VRE generation resources more efficiently or evenly across locations in the grid by introducing locational marginal pricing, for example, which would moreover reduce the costs from remedying transmission congestions (Green, 2007; Mills and Wiser, 2014).

1.2.4 Long- and short run perspective on electricity consumer behavior

Dynamics in consumer behavior can have a crucial influence on the welfare effects of time-varying retail pricing. Welfare changes from introducing RTP are typically very sensitive to the size and temporal pattern of electricity demand as well as to the level of own-price elasticity. Both the electrification of final energy demand in low-carbon economies and the ongoing progress in information and communication technologies could have a lasting effect on these behavioral parameters. Properly assessing the implementation of RTP in a transforming power sector therefore necessitates to consider the interaction of behavioral changes and VRE technology diffusion. This section outlines the potential implications of changes in demand size, patterns and the sensitivity to price.

The electrification of final energy demand could weaken the argument for consumer targeted implementations of RTP as well as it could increase the need for interventions to correct non-optimal tariff choices (cf. 1.1.2). The reasoning for targeted rollouts of advanced meters and real-time pricing is usually based on demand size, since the annual or average demand size of a consumer type gives an indication of the cost-benefit ratio from exposing this type of consumer to real-time prices (e.g. Leautier, 2014). The larger the average level of consumption, the larger is the average level of "over-" and "underconsumption" under flat rates, and thus the benefits from RTP. In many cases

this would imply to target industrial and large commercial customers with RTP programs.[16] However, the large-scale electrification of space-heating and transportation could change this by causing demand sizes of different consumer groups to converge quite rapidly. A widespread utilization of electrified space heating and the diffusion of electric mobility could substantially raise average electricity demand, particularly in the residential sector (Green and Staffell, 2017).[17] Larger average demand levels would, in turn, imply higher efficiency losses from non-optimal tariff choices against enrolling in RTP, possibly justifying corrective interventions.

Individual demand patterns and their specific covariation with wholesale prices are, however, just as important as average demand size in influencing the potential efficiency losses from non-optimal tariff choice. This is illustrated by the analysis in chapter 3, which rests on the simple intuition that a higher covariation of demand and wholesale price also implies higher inefficiency from flat tariffs, since "over-" and "underconsumption" during high and low price periods is then also relatively high (Borenstein, 2005; Holland and Mansur, 2006; Borenstein, 2013). The efficiency gains from introducing RTP to consumers, who consume relatively much when prices are high and vice versa, are therefore comparatively large. Demand patterns and their covariation with price could be significantly altered in low-carbon electricity markets due to both variable generation and the electrification of final energy demand. Chapter 3 highlights the influence of variable generation on the covariation between consumer-specific demand and price. In particular, for the German market it is shown that *current* residential and commercial demand patterns covary quite "favorably" with wind and solar generation patterns, such that high residential and commercial demand often coincides with high wind and/or solar power availability, and therefore with relatively low prices. The welfare gains from introducing RTP to these consumer types are therefore found to increase relatively fast with VRE market penetration. The electrification of final energy demand could, in addition to this, significantly change individual demand patterns (cf. Hayn et al., 2014; Boßmann and Staffell, 2015). It is unclear, however, as to how the usage of electrical heaters (power-to-heat) or electric vehicles, for instance, could alter the consumer-specific demand and VRE output covariation, and thus the potential efficiency gains from introducing RTP.

The most important driver of the efficiency gains from RTP, however, is the

[16] This intuition has also guided German regulation on the rollout schedule of advanced meters, mentioned before, which is given by the Act on the Digitization of the Energy Transition. According to this act, advanced metering infrastructure is supposed to be rolled out to the largest commercial and industrial consumers in the near-term, whereas smaller consumers should be gradually equipped with advanced meters in the mid to long term.

[17] Simulating different electrification scenarios for the UK, Green and Staffell (2017) find that average residential electricity demand would roughly triple and double due to electric space heating and electric vehicle charging, respectively.

elasticity to price (own- and cross-price elasticity), which does not only become clear from the sensitivity analyses in chapter 2 and 3, but has been demonstrated in many case studies (cf. Borenstein and Holland, 2005; Allcott, 2011, 2012; Leautier, 2014). More and more evidence from field experiments suggests that electricity consumers' sensitivity to price signals can rise significantly, if they are provided with adequate, easy digestible consumption related information and "smart-appliances" allowing for automated response (Ito, 2014; Jessoe and Rapson, 2014; Sallee, 2014; Bollinger and Hartmann, 2015).[18] How the benefits from real-time pricing schemes change at different stages of the low-carbon transformation thus does not only depend on the market diffusion of VRE but also on the diffusion of technologies which provide these services. This applies to all of the aforementioned factors, potentially influencing consumer behavior.

This section therefore clarifies that the co-dynamic between behavioral changes and VRE diffusion is essential to the assessment of RTP impacts. Nevertheless, including behavioral changes would go beyond the scope of this thesis, but the results presented in the main chapters will, in part, provide some indication of their potential impacts on the electricity market and welfare outcomes.

1.3 Outline and objectives of the thesis

The objective of this thesis is to improve the evaluation of the efficiency and feasibility of real-time retail pricing in low-carbon electricity markets. In order to do so, this thesis identifies and explains the basic mechanisms underlying the interaction of variable renewable electricity generation and climate policy instruments in a tractable model framework. Thereby it aims to provide useful insights on key regulation and market design issues in transforming electricity markets, which are addressed by the following research questions and answered in the four scientific articles included in this thesis:

1. What factors determine the optimal-timing of rolling out real-time retail pricing programs?

2. How does induced variable renewable electricity supply affect the benefits of real-time retail pricing?

[18] Jessoe and Rapson (2014), for instance, can show that advanced meters featured with inhome-displays providing easily digestible information on individual energy consumption costs in real-time, at the appliance level, may increase short-term own-price elasticity by as much as three standard deviations. Similarly, Bollinger and Hartmann (2015) find that price elasticities could double, if consumers of their sample are equipped with smart-thermostats. Such smart-appliances allow for automated response to price signals, thereby reducing consumers' costs to stay informed about price and reacting to it and thus increase their responsiveness to price variations.

3. How do second-best pricing schemes perform relative to real-time pricing at low and high shares of renewable electricity supply?
4. What are the potential distributional impacts of real-time pricing on households and how are they affected by variable electricity supply?
5. How do consumer-specific demand patterns influence the welfare effects of non-optimal tariff choice leading to low real-time pricing adoption?
6. What are the welfare and distributional implications of targeted rollouts of real-time pricing, if accounting for consumer heterogeneity?
7. How does the introduction of real-time pricing affect the cost-effectiveness and relative efficiency of renewable support schemes?
8. How do quasi-fixed costs of electricity generation change with increasing variable renewable generation and what is their relevance in evaluating real-time pricing?

Chapter 2 addresses research questions 1 to 3 and, thus, lays out the basic interaction of climate policy and variable renewable electricity supply on the welfare gains from real-time pricing. Results are derived from comparative static welfare analyses, which are based on a deterministic, partial-equilibrium model of a perfectly competitive electricity wholesale and retail market system, which is also developed in this chapter. The model is calibrated to German market and time-series data and represents the main tool used throughout chapters 2, 3 and 4 in modified versions that fit the specific research questions.

The findings in chapter 2 are twofold: first, welfare gains from real-time pricing change non-monotonously, that is in a U-shaped fashion with carbon taxation such that RTP does not necessarily become more beneficial in the presence than in the absence of variable electricity generation. This finding puts the common assumption into perspective, which suggests that the benefits from RTP rise monotonously with the market diffusion of renewable technologies, and therefore challenges the timing of the large-scale AMI and RTP rollout planned for the near to mid term in many EU and U.S markets; second, although regulators may find less complex, second-best alternatives to real-time pricing such as variable peak pricing more feasible, the results of chapter 2 illustrate that the implementation of full-fledged real-time pricing becomes necessary in markets with large variable renewable supply shares. For the most part, allocative efficiency will then depend on consumers' ability to absorb occasionally abundant supply from variably generating technologies rather than on reducing demand during periods of scarce supply resources.

Chapter 3 focuses on key feasibility issues of introducing real-time retail pricing at large-scale, by studying its potentially adverse distributional effects

and the welfare consequences of low consumer acceptance as well as targeted rollouts. Implementing RTP is often considered politically infeasible, since a large number of consumers could face higher consumption costs. Based on German residential consumer data chapter 3 illustrates, however, that such concerns could become less relevant in low-carbon electricity markets, where these adverse distributional effects could be attenuated by variable renewable electricity supply. This results simply from the fact that individual demand patterns start to covary less with real-time prices as aggregate supply becomes increasingly weather dependent and variable. Consumers thus would mostly face negligible changes in their electricity bills.

Particularly residential and small commercial customers might, however, be prone to make non-optimal tariff choices, possibly resulting in rather low RTP adoption. It is shown that the amount of unrealized welfare gains from low RTP adoption by these consumer types is comparatively high due to their volatile demand patterns compared to industrial demand patterns, for instance. Variable renewable market penetration can significantly increase these unrealized welfare gains in particular since solar generation peaks often coincide with residential and commercial demand peaks. This could increasingly justify corrective measures aimed at non-optimal tariff choices. In the near term, where VRE shares are relatively low, a targeted rollout of RTP to the largest, usually industrial consumers often seems efficient, if accounting for both related costs and benefits. While this intuition often guides current rollout strategies, as in Germany for instance, it is shown that such consumer targeting can indeed harm residential and commercial customers, by increasing their consumption cost particularly in the near term, where variable renewable supply shares are low. It is argued that this could prove detrimental to a wider acceptance of RTP and thus potentially also to market efficiency in the long-run. Hence, while targeted rollouts could prove efficient in the near term, regulators and retail firms might also have to consider their cross-sectoral distributional impacts and dynamic efficiency.

Chapter 4 evaluates the relative performance of renewable output and capacity subsidies in the presence of real-time priced consumers, which is motivated by the growing incidence of negative wholesale prices and their detrimental effect on the market value of variable renewable assets in electricity markets deploying high shares of renewable technologies. Since output subsidies can entail negative wholesale prices such that market values of variable renewable assets depreciate faster with renewable market penetration than under capacity subsidies, previous findings suggest that output subsidies are, intuitively, less cost-effective in inducing a certain amount of renewable capacity. The findings in chapter 4 put this result into relation, by showing that output subsides can actually be more efficient than capacity subsidies, if assuming that renewable targets are defined as shares in total supply and that consumers

absorb abundant renewable electricity when real-time prices become negative. Renewable targets are then achieved with less renewable capacity entry and at correspondingly less costs than under capacity subsidization. These cost savings are large enough to outweigh the relatively large deadweight losses arising from the higher surcharges to refinance renewable output subsidies.

Chapter 5 analyzes the effect of variable renewable electricity generation on the start-up costs of thermal power plants, which are otherwise ignored in the welfare analyses of chapter 2, 3 and 4. Start-up costs constitute a major component of quasi-fixed costs, which arise from start-up, shutdown or ramping operations of dispatchable generation plants. Changes in start-up costs caused by VRE electricity supply could modify the evolution of efficiency gains from real-time pricing, by inducing additional changes in wholesale prices and retail prices. This could imply that the welfare effects found in the core chapters are systematically underestimated. However, applying a unit commitment modeling approach which incorporates very high technological detail and various technology diffusion and fuel-price scenarios for Germany, it can be shown that start-up costs increase only negligibly and therefore have a minor effect on overall generation costs and electricity prices. Hence, the main welfare results found in this thesis appear to be robust in this respect.

Finally, Chapter 6 summarizes the main findings and the conclusions drawn from them. Simultaneously, the results are put into perspective when discussing the methodological approach taken in this thesis, which particularly focuses on the crucial trade-offs left out in the welfare analyses. In doing so, the chapter also provides a comprehensive outlook on possible future research topics based on both the main findings and on the limitations of this thesis.

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Chapter 2

Do Benefits from Dynamic Tariffing Rise? Welfare Effects of Real-Time Retail Pricing under Carbon Taxation and Variable Renewable Electricity Supply[1]

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Do Benefits from Dynamic Tariffing Rise? Welfare Effects of Real-Time Retail Pricing under Carbon Taxation and Variable Renewable Electricity Supply

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Abstract

We apply a stylized real-time pricing model and simulate long-run electricity market equilibria with carbon-tax-induced variable renewable technology investment to analyze the timing of rolling-out real-time retail pricing and the relative performance of variable peak pricing. Our findings suggest that rolling out costly advance metering infrastructure and real-time pricing should occur at a relatively late stage of renewable electricity market penetration, casting doubt on the efficiency of current practice in many European and U.S. markets. Specifically, we find a U-shaped association between carbon taxation and the gross benefits from introducing real-time retail pricing, implying they can actually be larger in the absence than in the presence of large-scale variable renewable energy supply. The result is not driven by corresponding changes in wholesale price volatility but by opposing effects on the long-run wholesale price distribution caused by generation portfolio adjustments. We further find that variable peak pricing becomes relatively inefficient with growing variable renewable generation, since allocative efficiency then mostly depends on increasing demand when renewable electricity is highly available, rather than on curbing demand when generation capacities are scarce. This result weakens the case for less complex second-best alternatives to real-time retail pricing.

JEL classification: D04, D12, D47, D61, H23, L94, Q42

Keywords: Real-time pricing; Variable renewable electricity; Carbon tax; Welfare analysis; Partial equilibrium modeling

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1. Introduction

Facing the challenge to accommodate increasing shares of variable renewable electricity supply, regulators, academia and practitioners have recognized price responsive demand as an integral part of low-carbon power markets (Joskow, 2012; Kopsakangas Savolainen and Svento, 2012; Mills and Wiser, 2014; ACER, 2014; CEER, 2014; IEA, 2016; BMWi, 2016; The White House, 2016; CAISO, 2017). Several jurisdictions in the U.S. and Europe have recently initiated or are already in the process of rolling-out advanced metering infrastructure (AMI) at large scale, which would technically allow consumers to receive price signals in real-time. Many economists consider it intuitive that electricity demand decisions should be guided by time-varying prices that reflect the typically high temporal (and locational) variation in marginal costs of supply. In many instances, they have therefore illustrated the substantial allocative inefficiency arising from flat retail tariffs, which most consumers face in almost every electricity market so far (Borenstein and Holland, 2005; Borenstein, 2005; Holland and Mansur, 2006; Joskow and Tirole, 2007; Allcott, 2011, 2012).

Based on the plausible intuition that price volatility increases the inefficiency caused by flat tariffing, the efficiency gains from changing to real-time retail pricing (RTP) are widely expected to rise significantly with the diffusion of variable renewable energy technologies (VRE) such as wind or solar power (Allcott, 2011; Borenstein, 2012; Leautier, 2014; Mills and Wiser, 2014; ACER, 2014; IEA, 2016). The costs linked to the introduction of RTP might still be relatively high compared to the potential benefits, however, raising the question of whether a large-scale roll-out of AMI and RTP schemes might be well-timed at current or anticipated levels of renewable market penetration in the aforementioned markets. In addition to this, decision makers face the trade-off between the feasibility of and the potential efficiency gains from different time-varying pricing schemes. While time-varying pricing schemes with less temporal granularity than RTP appear less complex and hence more feasible, much of the achievable welfare gains might be left on the table under second-best retail tariffing. This paper thus tries to provide insights on both the prospective benefits of RTP and its performance compared to less complex forms of time-varying pricing in a transforming electricity market.

We therefore start by analyzing how the welfare gains from introducing RTP change at different stages of induced VRE market penetration, and which economic mechanisms underlie these changes. We do so by applying the deterministic model framework by Borenstein and Holland (2005), which mimics a competitive wholesale and retail market with given shares of real-time and flat priced

consumers, and adjust it to include carbon-tax-induced investment in variable renewable generation technologies. We calibrate the model to German market data as well as long-run technology and fuel cost projections. Simulating long-run equilibria, we conduct a comparative static welfare analysis of increasing RTP consumer shares for gradually increasing VRE supply shares and carbon taxes. Our research thereby complements related studies, which ignore potential timing issues by comparing welfare changes from RTP only at either zero or very high VRE supply shares, instead of accounting for the different stages of VRE market penetration (Chao, 2011; Kopsakangas Savolainen and Svento, 2012; Fell and Linn, 2013; Brouwer et al., 2016).

Although VRE investments are in practice often driven by direct subsidies or tax breaks, assuming carbon-tax-induced investment simplifies the welfare analysis by leaving out further welfare effects from consumption distortions arising from renewable surcharges, for instance (cf. Green and Léautier, 2015). Accounting for these distortions would only blur, yet would not change the mechanisms underlying our welfare results found below. Our sensitivity analyses prove that the major outcomes and mechanisms obtain qualitatively, if VRE investment is incentivized also by direct renewable subsidies.

Our first set of results suggests that the welfare gains from raising the share of real-time priced consumers change in a U-shaped fashion with the carbon tax. Introducing RTP may therefore actually yield less benefits in presence than in absence of VRE supply until the carbon tax and VRE share reach a critical level. This result puts previous findings into perspective which suggest that the benefits from RTP strictly increase with the VRE supply share, but have been obtained by abstracting from endogenous VRE investment (e.g. Mills and Wiser, 2014).

By contrast, assuming carbon tax driven VRE market entry proves crucial in our analysis, since it results in two opposing effects on the long-run wholesale price distribution, which explain the non-monotonous change in the benefits from RTP. Specifically, the average wholesale price is shown to inflate significantly to allow for increasing capacity investment in variably generating renewable technologies, while growing VRE supply occasionally depresses wholesale prices to zero. Consumers switching to RTP under large-scale VRE deployment therefore pay higher prices most of the time, yet also much lower prices than before switching during the remaining periods. This is different if VRE supply is absent or only makes up a very low share in total supply, since the average wholesale price level is then also relatively low. Tariff switching consumers then mostly face lower prices than before switching to RTP, while the average spread between their previous flat rate and the RTP rate is also way smaller. Consequently, characteristic changes

in the distribution of retail price spreads are essentially driving the changes in the welfare gains from RTP at different VRE penetration rates.

Importantly, the effect on retail price spreads puts the widely held assumption into focus, which considers wholesale price volatility as the primary driver of RTP benefits (e.g. Allcott, 2011; Borenstein, 2012; Leautier, 2014; ACER, 2014; IEA, 2016). Moreover, while increased price volatility appears to be one of the main arguments for introducing time-varying pricing at large scale VRE supply, we do not observe a clear association between wholesale price volatility and the benefits from RTP. Instead, we can show that relatively high welfare gains from RTP can obtain even if price volatility is relatively low and vice versa.

In the second part of this paper we analyze the relative performance of variable peak pricing, in order to address the crucial issue of feasibility of implementing RTP at a large-scale. While most economists regard real-time retail pricing as the intuitive first-best, they have always been well aware of the potential reasons which could render such pricing schemes infeasible in practice (cf. Vickrey, 1971). Due to its high temporal granularity, one particularly important implementation barrier of RTP regards its complexity and the corresponding transaction costs involved for electricity consumers. This has motivated research on second-best alternatives capable of realizing most of the efficiency gains from RTP, which are, however, less temporally granular, hence simpler and therefore easier to implement. Critical peak pricing (CPP), under which consumers are occasionally exposed to very high, predetermined prices during peak-demand periods, appears to be a particular popular alternative in U.S markets (Borenstein, 2007; Faruqui and Sergici, 2010; Faruqui et al., 2012). Case specific studies indeed find that peak-pricing schemes could achieve the lion's share of the benefits from RTP in markets mostly supplied by dispatchable, fossil-fueled technologies (Allcott, 2012; Blonz, 2016). By reducing "overconsumption" when generation capacity is scarce, i.e by curbing peak demand, CPP can yield substantial cost savings in costly peak-generation capacity, standing idle most of the time.

However, in the presence of large-scale VRE deployment, most of the benefits from RTP might actually stem from incentivizing demand increases during periods in which VRE supply depresses prices to almost zero (cf. Kopsakangas Savolainen and Svento, 2012). This could render peak-retail-pricing less of an efficient second-best alternative to RTP. We therefore analyze the relative performance of peak-retail-pricing scheme for increasing VRE supply shares. Specifically, we quantify the portion of welfare gains from RTP, which could be obtained from implementing variable peak pricing (VPP). As it reflects the actual rather than a predetermined scarcity value of electricity supply, VPP is theoretically more efficient than CPP.

To add practical relevance and robustness to the analysis, we account for the existence of planning reserve margins, which are common in many U.S. markets and reflect administratively determined reliability standards[1] (Pfeifenberger et al., 2013). Planning reserve margins serve to induce excess peak generation capacity and thus could in principle increase the relative benefits from introducing VPP.

We nonetheless find that curbing peak demand via variable peak pricing captures only a small portion of the potential welfare gains from full-fledged RTP as soon as VRE supply electricity at large-scale. Allocative efficiency depends increasingly on incentivizing consumers to increase demand during periods of abundant VRE supply, when prices drop to zero. Consequently, time-varying pricing schemes addressing only "overconsumption" during high price periods might become obsolete to certain degree as VRE supply shares grow, leaving full-fledged RTP as the only reasonable choice in low-carbon power markets.

The paper proceeds as follows. In section 2 we present further political and regulatory background on key assumptions and embed our work in the related literature. Subsequently, we present an adaptation of the partial equilibrium model of dynamic retail pricing by Borenstein and Holland (2005) and Allcott (2012) in section 3. Data, calibration and central simulation results are presented in sections 4 and 5, respectively. Section 6 concludes.

2. Model

We employ a two-stage wholesale and retail electricity market model largely building on Borenstein and Holland (2005) and Allcott (2012), but also incorporate carbon tax driven investments and a detailed representation of variable renewable generation technologies. The details of the model are described below. For the numerical application, we formulate it as a mixed complementarity problem in GAMS (Rutherford, 1995). The code is available as open-source using the acronym LORETTA ("LOng-run Electricity market model with Time-varying retail TAriffing").[2]

2.1. Electricity demand

Wholesale electricity supply has to match aggregate demand $\overline{Q}_t(p)$ in each hour $t \in T$. In line with previous work, we assume that consumers have the

[1] Most regulatory authorities seek to fulfill an explicitly defined reliability requirement such as the 0.1 day/year (one-day-in-ten-years) Loss-of Load-Expectation (LOLE) standard, for instance.

[2] The code for LORETTA version 1.0.0, which we use here, is available at: https://www.pik-potsdam.de/research/sustainable-solutions/models/loretta

same underlying demand in t, $Q_t(p)$ with $\frac{\partial Q_t}{\partial p} < 0$. An exogenously given share of consumers, $\alpha \in [0,1]$, consists of RTP customers facing an hourly varying retail electricity price p_t, while the remaining $(1-\alpha)$ flat rate consumers pay the time-invariant tariff $\bar{p}$. Additionally, consumers pay separately for generation capacity and reserves. While flat rate consumers always pay the constant capacity mark-up pc per unit of electricity, RTP consumers pay either the time-varying capacity price[3] pc_t or the same constant mark-up as flat rate consumers. That is, RTP consumers either face scarcity prices or they do not, which is described in more detail in section 2.4. Hence, in each period t RTP customers consume $\alpha Q_t(p_t, pc_t)$ or $\alpha Q_t(p_t, pc)$ units of electricity and flat rate consumption equals $(1-\alpha) Q_t(\bar{p}, pc)$, yielding hourly aggregate wholesale and retail demand as $\overline{Q}_t(p_t, \bar{p}, pc_t, pc) = \alpha Q_t(p_t, pc_t) + (1-\alpha) Q_t(\bar{p}, pc)$ or $\overline{Q}_t(p_t, \bar{p}, pc) = \alpha Q_t(p_t, pc) + (1-\alpha) Q_t(\bar{p}, pc)$, respectively. Increasing α makes aggregate demand more reactive to the time-variation of prices, so that it rotates around the point $\left(\overline{Q}_t(p_t, \bar{p}, pc_t, pc), \bar{p}\right)$.[4] For the simulation, we assume an isoelastic demand function, $Q_t(p) = a_t p^{\epsilon}$, where $\epsilon < 0$ is the constant own-price elasticity and a_t a scaling parameter capturing structural demand variations over time. This gives hourly aggregate demand under scarcity pricing, for instance, as $\overline{Q}_t(p_t, \bar{p}, pc_t, pc) = [\alpha (p_t + pc_t)^{\epsilon} + (1-\alpha)(\bar{p} + pc)^{\epsilon}] a_t$.

2.2. Electricity supply and capacity investment

There are I generation technologies available indexed by $i = \{1, \ldots, I\}$ where $V \subset I$ and $NV \subset I$ is the subset of variable renewable (VRE) technologies and non-variable, carbon dioxide (CO_2) emitting technologies,[5] respectively. Installed capacity of each non-variable technology i K_i^{NV} is always fully available, that is $av_{it}^{NV} = 1 \; \forall i \in NV, \; t \in T$, whereas capacity of VRE technology i K_i^{V} is time-varyingly available, capturing varying wind speeds or solar radiation, for instance, such that $av_{it} = [0,1] \; \forall i \in V, \; t \in T$. Up to available capacity $av_{it} K_i$, technology i produces each megawatt hour (MWh) of electricity at constant marginal costs

[3] This is a slight deviation from the representation of dynamic retail capacity prices in Allcott (2012), where both the energy and capacity component are subsumed under one hourly scarcity price. We explain this modification below.

[4] Since for $p_t > \bar{p}$ ($p_t < \bar{p}$) total demand $\overline{Q}_t(\cdot)$will be lower (higher) after α has increased.

[5] This implies that we abstract from non-variable and carbon non-emitting technologies such as nuclear energy. Doing so allows us to model strictly increasing VRE entry under carbon taxation and thereby to focus on its effects on the benefits of RTP. It further reflects particularly the German market situation in the long-run, which we simulate and where a nuclear-phase out has been determined. Moreover, this assumption may be justified by possibly decreasing profitability of nuclear energy technologies due to lower full load hours and/or increasing quasi-fixed costs following from more frequent starting and shut down operations with high VRE shares.

$mc_i(\tau)$, where τ is the exogenous per unit carbon dioxide emissions tax which increases marginal production costs of non-variable technology i by $\frac{\partial mc_i^{NV}}{\partial \tau} > 0$. Annuitized fixed costs of capacity amount to fc_i units per megawatt (MW) and year. Non-variable technologies can be ordered by increasing marginal production costs $mc_i^{NV} > mc_j^{NV}\ \forall i > j$ and decreasing annual fixed costs $fc_i^{NV} < fc_j^{NV}\ \forall i > j$, principally allowing for entry of each technology type in the long-run equilibrium (Crew et al., 1995).[6] Since VRE technologies produce at negligible or zero marginal costs without emitting carbon dioxide (CO_2), that is $mc_i^V = 0$ and $\frac{\partial mc_i^V}{\partial \tau} = 0\ \forall i \in V$, they become relatively cheaper than non-variable technologies as the carbon taxτ is raised from zero. Likewise, non-variable technology i becomes relatively cheaper than technology j given that $\frac{\partial mc_i}{\partial \tau} < \frac{\partial mc_j}{\partial \tau} \forall i \neq j$, resulting in corresponding portfolio changes.

By maximizing total annual profits $\pi_i(q_{it}, K_i \mid w_t, r)$ under perfect foresight and perfect competition and thus taking wholesale electricity price w_t as given, generators decide upon investment in capacity K_i of technology i and output q_{it}. Output choice always bases on available installed capacity such that $q_{it} \leq av_{it}K_i\ \forall t, i$. In addition to their short-run profits from energy sales $q_{it}(w_t - mc_i)$, non-variable technologies receive a separate, uniform capacity payment r, which is determined in the capacity market equilibrium discussed below. This gives their total annual profit as

$$\pi_i^{NV}(q_{it}, K_i \mid w_t, r) = \sum_t^T \left[w_t - mc_i^{NV}\right] q_{it}^{NV} + rK_i^{NV} - fc_i^{NV}K_i^{NV}. \quad (1)$$

Each VRE technology $i \in V$ fully depends on remuneration from energy sales and thus makes annual profits equal to

$$\pi_i^V(q_{it}, K_i \mid w_t) = \sum_t^T \left[w_t - mc_i^V\right] q_{it}^V - fc_i^V K_i^V. \quad (2)$$

Each generator using technology i optimally produces at capacity and supplies $q_{it} = av_{it}K_i$ each time marginal revenue is larger than marginal costs, that is $w_t > mc_i$. If $w_t = mc_i$, a generator is indifferent between any output level, that is $q_{it} \geq 0$, but produces nothing if $w_t < mc_i$.[7] Hence, each generating unit has

[6] While variable technologies are at the low end of marginal cost assumptions, their *effective* annualized fixed costs per kW are usually relatively high due their low average capacity availability. This enables entry of higher marginal/higher nominal fixed cost technologies in the long run equilibrium.

[7] With constant marginal costs mc_i profit increases monotonically with output q_{it} given that $w_t > mc_i$ and is therefore maximized if producing at full available capacity.

an inverse L-shaped supply curve so that aggregate wholesale supply is a step function (merit order) where each plateau reflects the constant marginal costs of all technologies present in equilibrium (cf. Holland and Mansur, 2006).

Under perfect competition, generators invest in capacity of non-variable technology i until (annualized) the fixed costs per unit of capacity fc_i equal the accumulated short-run profits $\sum_t^T [w_t - mc_i]$ plus the price of capacity and reserves r[8]

$$\sum_t^T \left[w_t - mc_i^{NV}\right] + r \quad = \quad fc_i^{NV}, \forall i \in NV. \tag{3}$$

Likewise, generators invest in VRE capacity of technology i until the fixed costs fc_i equal the respective stream of short-run profits $\sum_t^T [w_t - mc_i]$ weighted by the hourly varying capacity factor av_{it}

$$\sum_t^T \left[w_t - mc_i^V\right] av_{it} \quad = \quad fc_{i,}^V \forall i \in V. \tag{4}$$

As indicated above, we assume that investment in VRE technologies only becomes profitable, if they become sufficiently cheap through increasing the carbon tax. Equation (4) implies that VRE profitability is strongly determined by the technology specific correlation of capacity availability av_{it} with the wholesale price w_t (Lamont, 2008). If more capacity of the same VRE technology type enters the market, wholesale prices drop particularly when av_{it} is relatively high, resulting in decreasing profitability. Hence, if a certain VRE share is supposed to materialize in the long-run equilibrium, wholesale prices have to rise disproportionately in periods, where av_{it} is relatively low. As shown by Green and Léautier (2015), this also implies that supportive measures, such as the carbon tax in our case, likely require to rise disproportionately with the VRE market penetration, *ceteris paribus.* In combination with the typically low average availability of VRE sources, av_{it}, this decreasing profitability effect has the important implication that equilibrium wholesale prices settle at relatively high levels on average in presence of VRE market entry. This crucially drives the differences found in the benefits from real-time retail pricing in a market with and without VRE supply.

[8]Reformulating (3) yields each generators competitive capacity market bid as $r^{bid} = fc_i - \sum_t^T [w_t - mc_i], \forall i \in NV$. The technology with the lowest earnings to refinance capacity costs will set the capacity market equilibrium price defined below.

2.3. The variable peak pricing and capacity market mechanism

In order to partial out the efficiency effects of variable peak pricing (VPP), we model a retail market in which RTP consumers either face or do not face high prices when non-variable generation capacity gets scarce. The two cases serve to separate those efficiency gains from the overall efficiency gains, which are solely attributable to the savings in peak-load generation capacity. To add some realism to the analysis, we impose a planning reserve margin (PRM) constraint, which requires installed non-variable capacity in excess of (net) peak demand by m percent. Scarcity is thus defined by the exogenous reliability standard, i.e. by the bindingness of the PRM constraint. The amount of excess capacity entry depends on the PRM level, i.e. on m. This set up basically mimics the effect of a perfectly competitive market for installed capacity.

To incorporate the different scarcity pricing mechanisms, we adopt the approach by Allcott (2012), where the PRM constraint is either imposed on non-variable generation capacity K^{NV} or on non-variable *hourly output* q_{it}^{NV}. We denote the latter case as the *Dynamic Installed Capacity* (DICAP) regime[9], where the corresponding PRM constraint is formally given by

$$\sum_{i}^{NV} q_{it}^{NV} \leq \frac{\sum_i^{NV} K_i^{NV}}{(1+m)}, \forall t, \tag{5}$$

noting that in equilibrium $\sum_i^{NV} q_{it}^{NV}$ is equal to aggregate net demand, $\overline{Q}_t^D\left(p_t, \bar{p}, pc_t, pc\right) - \sum_i^V q_{it}$, i.e. total demand less supply from VRE technologies. Constraint (5) thus implies that the hourly aggregate supply curve becomes inelastic each time aggregate net demand exceeds installed non-variable capacity *less* reserves, $\frac{\sum_i^{NV} K_i^{NV}}{(1+m)}$.[10] The associated KKT multiplier, ρ_t, reflects the time-varying shadow value of non-variable generation capacity, K^{NV}, including reserves, in a particular hour t, such that the corresponding dual feasibility and complementary

[9]Note, however, that DICAP does not reflect VPP as such. Under DICAP RTP consumers face time-varying retail prices in all periods, whereas under VPP schemes, customers usually face time-invariant rates during off-peak periods, so during most of the time.

[10]Note that this conceptually differs from the "Augmented/Operational Reserve Demand Curve"-approach by Hogan (2005) in two ways. First, the constraint bites only if the (long-run) *planning reserve margin* is reached in any given hour as opposed to a *short-run operational reserve margin* (cf. Allcott, 2012). Second, investment in firm capacity and reserves is incentivized through infra-marginal rents as well as the forward capacity payment r, yet not through occasional *scarcity rents*.

slackness condition hold in equilibrium, i.e.

$$\rho_t \geq 0, \qquad \rho_t \left[\overline{Q}_t \left(p_t, \bar{p}, pc_t, pc \right) - \sum_i^V q_{it} - \frac{\sum_i^{NV} K_i^{NV}}{(1+m)} \right] = 0, \qquad \forall t. \tag{6}$$

The KKT multiplier, ρ_t, equals the scarcity price at the intersection of net demand and the inelastic part of the supply curve each time the PRM constraint (5) binds, which RTP consumers are assumed to face via the real-time capacity retail price, pc_t (see section 2.4). Exactly like VPP, this incentivizes RTP consumers to curb their demand during periods of scarce resources. This is the main difference to the CICAP regime presented in the following.

Note that since available supply always exceeds demand, wholesale price, w_t, never exceeds the marginal production costs of the most expensive technology deployed in equilibrium.[11] Accordingly, generators do not face ρ_t as it occurs, which therefore does not influence their output decisions. Instead, they are assumed to receive a single forward payment per unit of installed capacity, r, which equals the stream of scarcity prices, $\sum_t^T \rho_t$, and thus influences only their investment decision regarding non-variable generation capacity, K_i^{NV} (cf. eq. (3)).[12] The capacity payment, r, can be interpreted as the uniform clearing price of a forward capacity market auction, which would provide a secure return on investments in non-variable generation capacity (cf. Cramton et al., 2013).

Under the *Constant Installed Capacity* regime (CICAP), RTP consumers do not face a time-varying capacity price, but pay a flat retail price for capacity, pc. Correspondingly, RTP consumers do not reduce consumption when non-variable capacity is scarce, which is therefore installed in larger amounts than under DICAP. This mechanism is included via another market clearing condition, postulating that non-variable capacity, K^{NV}, always exceeds aggregate net demand by at least m percent:

$$(1+m) \left[\overline{Q}_t \left(p_t, \bar{p}, pc \right) - \sum_i^V q_{it} \right] \leq \sum_i^{NV} K_i^{NV}, \forall t. \tag{7}$$

Note that the market clearing condition (7) differs from (5) only with regard

[11] Consequently, the highest marginal cost technology denoted I cannot gain short run profits, since w_t can never rise above mc_I^{NV}. Therefore, in accordance with the zero-profit conditions implied in the assumptions above, the capacity market equilibrium price r^* will always equate the fixed cost annuity of the most expensive marginal cost technology I deployed in equilibrium.

[12] This represents a slight modification of the approach used by Allcott (2012) where scarcity prices are included in the hourly wholesale prices and thus short-run profits of all technologies. We do so mainly since we want to model a capacity market mechanism not providing VRE capacity remuneration.

to the time-varying capacity price, pc_t, since all consumers face a.time-invariant retail capacity price pc instead. This implies that there is a unique, time-invariant shadow price, ρ, such that the corresponding dual feasibility and complementary slackness condition hold in equilibrium

$$\rho \geq 0, \qquad \rho\left(1+m\right)\left[\overline{Q}_t\left(p_t, \bar{p}, pc\right) - \sum_i^V q_{it}\right] - \sum_i^{NV} K_i^{NV} = 0. \tag{8}$$

In this case, the shadow price ρ equals the equilibrium capacity payment, r, paid to each unit of installed capacity from non-variable generation technologies. Since non-variable technology capacity scarcity majorly depends on the exogenous PRM, the respective shadow prices of both (5) and (7) reflect the social value of lost load (VoLL), given the exogenously determined level of reliability.

Comparing the efficiency gains accruing under either CICAP or DICAP, as done in section (5.3) below, thus allows for determining the relative performance of variable peak pricing and full fledged real-time retail pricing (DICAP).

As mentioned above, previous findings suggest that most of the efficiency gains of RTP can be obtained through variable peak prices, that is, through mitigating the distortion from "overconsumption" under flat pricing in high price periods and saving in costly peak-generation capacity. Under large-scale VRE deployment, however, inefficiency from flat pricing may rather stem from "underconsumption" than from consuming "too much", since a significant portion of total electricity is supplied at zero marginal costs, yet high investment costs. Given this is the case, variable peak pricing would leave the lions share of efficiency gains from RTP unrealized and might thus become not a real alternative.

2.4. Retail market equilibrium

In the perfectly competitive retail market homogeneous retail firms buy electricity at wholesale prices w_t and sell it on to the final consumers either at the real-time price p_t or flat rate tariff $\bar{p}$. Additionally, retail firms have to procure non-variable capacity at price ρ under CICAP or at $\sum_t^T \rho_t$ under DICAP in proportion to net demand served plus the reserve margin, that is $(1+m)\left(Q_t\left(p\right) - \sum_i^V q_{it}\right)$. We abstract from transmission and distribution costs. Under CICAP retailers refinance total capacity market payments, $\rho K^{NV} = \rho\left(1+m\right)\left[\overline{Q}_{\hat{t}}\left(p_{\hat{t}}, \bar{p}, pc\right) - \sum_i^V q_{i\hat{t}}\right]$, by charging each consumer a constant and uniform capacity price pc per unit of consumed electricity. Under DICAP, RTP consumers pay a time-varying capacity price pc_t, while flat consumers remain on the time-invariant price pc. For each customer group, retailers now spread and refinance the total costs per unit of capacity and reserve demand, $(1+m)\sum_t^T \rho_t$, across scarcity hours where the PRM

constraint binds and $\rho_t > 0$ holds. Hence, while under CICAP total annual profits π^{rt} equal

$$\begin{aligned} \pi^{rt} &= \sum_t^T (p_t - w_t)\, \alpha Q_t\, (p_t, pc) \\ &+ (\bar{p} - w_t)\,(1-\alpha)\, Q_t\, (\bar{p}, pc) \\ &+ pc\overline{Q}_t\, (p_t, \bar{p}, pc) - \rho K^{NV}, \end{aligned} \tag{9}$$

while under DICAP π^{rt} is given by

$$\begin{aligned} \pi^{rt} &= \sum_t^T (p_t - w_t)\, \alpha Q_t\, (p_t, , pc_t) \\ &+ (\bar{p} - w_t)\,(1-\alpha)\, Q_t\, (\bar{p}, pc) \\ &+ pc_t \alpha Q_t\, (p_t, pc_t) - \rho_t\, (1+m)\, \alpha \left(Q_t\, (p_t, pc_t) - \sum_i^V q_{it} \right) \\ &+ pc\,(1-\alpha)\, Q_t\, (\bar{p}, pc) - \rho_t\, (1+m)\,(1-\alpha) \left(Q_t\, (\bar{p}, pc) - \sum_i^V q_{it} \right). \end{aligned} \tag{10}$$

The first and second term represent retail profits from selling electricity to RTP and flat rate consumers in (9) and (10), respectively, while the subsequent terms comprise profits from capacity sales. For given w_t and ρ or ρ_t, each retailer determines the retail real-time price p_t, the flat tariff $\bar{p}$, the constant and time-variant retail capacity price pc and pc_t, respectively, by maximizing π^{rt}. Free entry of retail firms and the absence of transaction costs of switching retailers, which we assume, imply that retailers earn zero-profits in equilibrium. Moreover, we exclude cross subsidization of costs in retail rates. Thus, the respective zero-profit condition $\sum_t^T (p_t - w_t)\, \alpha Q_t\, (p_t, pc, pc_t) = 0$ and $\sum_t^T (\bar{p} - w_t)\,(1-\alpha)\, Q_t\, (\bar{p}, pc) = 0$ with regard to the real-time electricity price p_t, and energy flat rate tariff $\bar{p}$ must hold under both DICAP and CICAP. This implies that the real-time retail price p_t equals the electricity wholesale price w_t in each period, that is $p_t = w_t\, \forall t$, while the competitive flat price $\bar{p}$ is a flat demand weighted average of w_t:

$$\bar{p} = \frac{\sum_t^T w_t Q_t\, (\bar{p}, pc)}{\sum_t^T Q_t\, (\bar{p}, pc)}. \tag{11}$$

Likewise, revenues from capacity and reserve sales have to equate corresponding costs in equilibrium, such that $\sum_t^T pc\overline{Q}_t\, (p_t, \bar{p}, pc) - \rho K^{NV} = 0$ has to hold under CICAP, giving the flat capacity price pc as the total demand weighted average of

total capacity market costs:

$$pc = \frac{\rho K^{NV}}{\sum_t^T \overline{Q}_t \left(p_t, \bar{p}, pc\right)}. \tag{12}$$

Breaking even with the costs of covering customers' net demand with sufficient capacity under DICAP implies that retailers determine the dynamic capacity price pc_t as to warrant $\sum_t^T pc_t \alpha Q_t \left(p_t, pc_t\right) - \rho_t \left(1+m\right) \alpha \left(Q_t \left(p_t, pc_t\right) - \sum_i^V q_{it}\right) = 0$, while the constant capacity price pc is chosen to yield $\sum_t^T pc \left(1-\alpha\right) Q_t \left(\bar{p}, pc\right) - \rho_t \left(1+m\right) \left(1-\alpha\right) \left(Q_t \left(\bar{p}, pc\right) - \sum_i^V q_{it}\right) = 0$. Therefore, since charging RTP consumers pc_t per unit of energy consumption during scarcity hour t, retailers can deflate their capacity market costs in $t, \rho_t \left(1+m\right) \alpha \left(Q_t \left(p_t, pc_t\right) - \sum_i^V q_{it}\right)$ by $Q_t \left(p_t, pc_t\right)$. For each t, pc_t is thus given as

$$pc_t = \frac{\left(1+m\right) \rho_t \left(Q_t \left(p_t, pc_t\right) - \sum_i^V q_{it}\right)}{Q_t \left(p_t, pc_t\right)}. \tag{13}$$

The flat capacity price pc is again a weighted average of the hourly capacity price ρ_t, where the weights now equal the ratio of hourly net demand plus reserves and total energy demand by the flat rate consumers only:

$$pc = \frac{\sum_t^T \left(1+m\right) \rho_t \left(Q_t \left(\bar{p}, pc\right) - \sum_i^V q_{it}\right)}{\sum_t^T Q_t \left(\bar{p}, pc\right)}. \tag{14}$$

The final hourly retail price for RTP consumers equals $p_t + pc_t$ under DICAP and $p_t + pc$ under CICAP. Flat rate customers pay $\bar{p} + pc$ each period and under both pricing regimes.[13]

2.5. Wholesale market equilibrium

Borenstein (2005) as well as Allcott (2012) demonstrate that the above model yields a unique long-run equilibrium in the wholesale, retail and capacity market. It is defined by the vector of installed capacity $\mathbf{K}$, the uniform capacity price for generators r, the flat electricity and capacity retail price $\bar{p}$ and pc. Moreover, it is defined by the set of equilibrium wholesale prices $\{w_t\}$ as well as retail prices $\{p_t\}$ and $\{pc_t\}$, which clear demand and supply in each hour t, that is

[13]Note that the competitive flat price $\bar{p}$ is not (second-best) optimal under general assumptions regarding the demand function, since optimal flat prices would reflect the relative consumption distortion in each hour, and thus would be a weighted average of the relative slopes of the demand curve (Borenstein and Holland, 2005). However, if assuming an isoelastic demand function, as is done in the simulations below, the competitive and second-best optimal flat price are equal.

$\overline{Q}_t\left(p_t, pc_t, \bar{p}, pc\right) = S\left(p_t\right) \forall t$ or $\overline{Q}_t\left(p_t, \bar{p}, pc\right) = S\left(p_t\right) \forall t$ under DICAP and CICAP, respectively, noting that the retail market equilibrium implies $w_t = p_t \forall t$.

The wholesale clearing prices and quantities can be described in more detail by first noting that hourly aggregate supply is an upward sloping step function of p_t due to the the clearly ranked marginal production costs $mc_i \in [0, mc_{NV}]$, where we now use the index $i = 0$ for denoting each technology from the variable technology subset V. For $0 \leq i \leq I$, the set of equilibrium electricity prices can be defined by the vertical segment between each step, $v_i = \{t : \ mc_i < p_t < mc_{i+1}\}$, and the horizontal segment representing the marginal costs of the marginal technology $h_i = \{t : \ p_t = mc_i\}$ (cf. Green and Léautier, 2015). Let $u_{it} \in [0, 1]$ denote the hourly degree of capacity utilization, that is the dispatch rate of technology i. Then on h_0, VRE technology $v \in [1, V]$ produces at the margin so that demand and supply clear at $\overline{Q}_t\left(\mathbf{p}\right) = \sum_{v=1}^{V} u_{v,t} av_{v,t} K_v$, where $\mathbf{p}$ denotes the retail price vector either under DICAP or CICAP. On h_i for $i \geq 2$, technology i produces at the margin and VRE technologies at available capacity, therefore $\overline{Q}_t\left(\mathbf{p}\right) = u_{i,t} K_i + \sum_{j=1}^{i-1} K_j + \sum_{v=1}^{V} av_{v,t} K_v$. On v_i demand intersects a vertical segment of the supply curve where technology $i \geq 1$ produces at capacity, while technology $i+1$ is not dispatched, which gives the equilibrium quantity as $\overline{Q}_t\left(\mathbf{p}\right) = \sum_{j=1}^{i} K_j + \sum_{v}^{V} av_{v,t} K_v$. Under DICAP, market clearing on v_I implies that demand is rationed by the scarcity price $pc_t > 0$, such that $\overline{Q}\left(p_t, pc_t, \bar{p}, , pc\right) = \frac{\sum_{i=1}^{I} K_i}{(1+m)} + \sum_{v}^{V} av_{v,t} K_v$.

Finally, recall that due to free entry each technology $i \in I$ of the long-run equilibrium capacity vector $\mathbf{K}$ earns zero-profits, that is $\pi_i = 0 \, \forall i$.

3. Welfare changes from real-time pricing under carbon-tax-induced variable renewable electricity supply

In this section, we briefly delineate the mechanisms through which carbon taxation and induced variable renewable generation affect the welfare changes from RTP. In order to do so, we start by defining and decomposing the aggregate welfare change from introducing real-time pricing, which represents the main variable analyzed in section 5.1.

3.1. Decomposition of consumer surplus changes from real-time pricing

Since retailers and generators make zero-profits in the long-run equilibrium, and since we abstract from RTP related costs, total welfare changes from changing the RTP share equal the consumer surplus changes of consumers who switch from flat to real-time pricing, of consumers who remain on the flat rate as well as of

consumers who are already real-time priced (Borenstein and Holland, 2005).[14] Increasing the share of RTP consumers from α^0 to α^1 entails corresponding changes in the equilibrium real-time retail price from $p_t^0 + pc_t^0$ to $p_t^1 + pc_t^1$ and in the flat rate from $\bar{p}^0 + pc^0$ to $\bar{p}^1 + pc^1$. Total net consumer surplus changes of *incumbent* RTP consumers, ΔCS^R, equal the sum of all hourly surplus changes $\sum_t^T \left[\int_{p_t^1+pc_t^1}^{p_t^0+pc_t^0} \alpha^0 a_t x^\epsilon dx\right]$, which under DICAP is given by

$$\Delta CS^R = \sum_t^T \left[\frac{\alpha^0 a_t}{\epsilon+1}\left(\left(p_t^0 + pc_t^0\right)^{\epsilon+1} - \left(p_t^1 + pc_t^1\right)^{\epsilon+1}\right)\right]. \tag{15}$$

Consumers who *switch* to RTP are paying $\bar{p}^0 + pc^0$ before and $p_t^1 + pc_t^1$ after switching, yielding hourly net surplus changes as $\int_{p_t^1+pc_t^1}^{\bar{p}^0+pc^0} (\alpha^1 - \alpha^0)\, a_t x^\epsilon dx$ and thus total surplus changes from switching as

$$\Delta CS^S = \sum_t^T \left[\frac{(\alpha^1 - \alpha^0)\, a_t}{\epsilon+1}\left(\left(\bar{p}^0 + pc^0\right)^{\epsilon+1} - \left(p_t^1 + pc_t^1\right)^{\epsilon+1}\right)\right]. \tag{16}$$

Under CICAP, RTP consumers do not face peak-load prices, therefore pc_t^1 has to be substituted by the constant capacity adder pc^1 in (15) and (16). Finally, hourly surplus changes for customers who *remain on the flat retail rate* equal $\int_{\bar{p}^1+pc^1}^{\bar{p}^0+pc^0} (1 - \alpha^1)\, a_t x^\epsilon dx$, giving their total consumer surplus gains as

$$\Delta CS^F = \sum_t^T \left[\frac{(1 - \alpha^1)\, a_t}{\epsilon+1}\left(\left(\bar{p}^0 + pc^0\right)^{\epsilon+1} - \left(\bar{p}^1 + pc^1\right)^{\epsilon+1}\right)\right]. \tag{17}$$

Borenstein and Holland (2005) demonstrate that under general assumptions, total welfare increases with the RTP share, i.e. $\Delta CS > 0$, although incumbent RTP consumer lose, i.e. $\Delta CS^R < 0$, while switching consumers benefit, i.e. $\Delta CS^S > 0$, and also make consumers who remain flat priced better off, i.e. $\Delta CS^F > 0$, since their changed consumption behavior exerts a positive pecuniary externality, that is the equilibrium flat rate decreases. In the numerical applications of their models, both Borenstein (2005) and Allcott (2012) show that the tariff switching gains ΔCS^S make up for the largest part of total welfare changes ΔCS. Hence, in the following we are particularly interested in how these switching gains are affected by carbon taxation and variable renewable energy supply.

[14] Importantly, since we do not compare net welfare but welfare gains from increasing the RTP share for different carbon tax equilibria, both the dead-weight-loss from taxation and the social benefits from internalizing the negative externality from carbon dioxide emissions do not matter in our analysis.

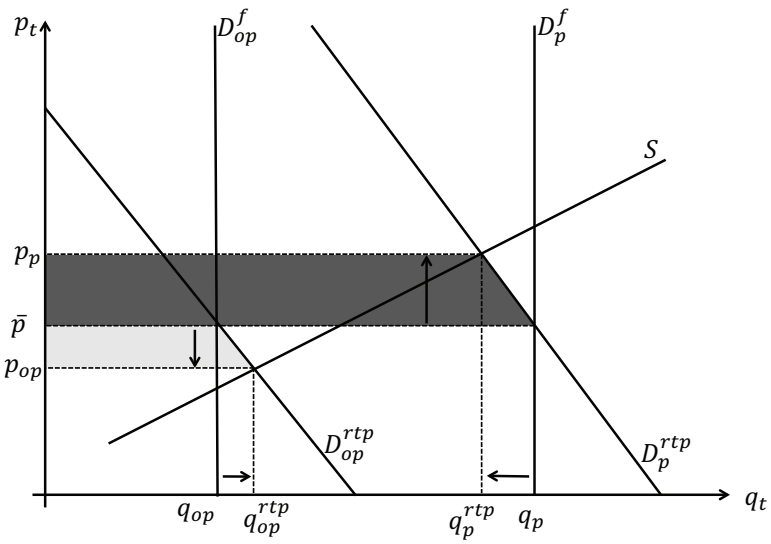
3.2. Effects of carbon taxation and variable generation on retail price spreads and tariff switching benefits

Hourly consumer surplus losses and gains from switching to RTP obtained during peak and off-peak periods are depicted by the dark and gray areas in each panel of Figure 1. Panel 1a and 1b give a stylized representation of the peak and off peak spot market equilibrium in the absence and the presence of carbon-tax-induced VRE supply, respectively.[15] Intuitively, consumers switching to RTP gain if their real-time retail rate, which equals the wholesale price w_t, is below their previous flat rate, i.e. $\bar{p} > p_t$, and lose if otherwise. To simplify notation, the capacity component is included in the respective retail rate $\bar{p}$ and p_t in the following. The weighted sum of Δp_t over all T periods determines the total consumer surplus gains from switching, ΔCS^S, as implied by equation (16). Thus, if changes in ΔCS^S differ across carbon tax scenarios, these differences must originate from changes in the distribution of hourly flat-to-real-time price spreads, $\Delta p_t = \bar{p} - p_t$, which can, in turn, be traced back to corresponding changes in both the wholesale price distribution and the long-run generation portfolio.

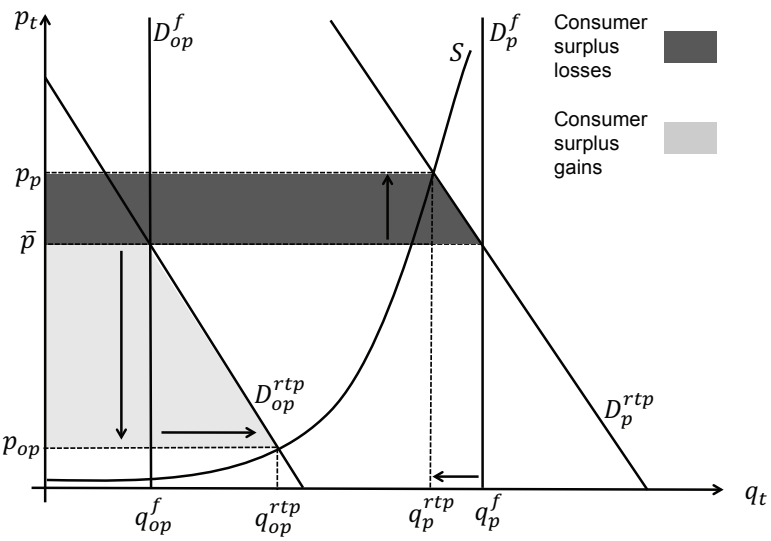
The generation portfolio effect of carbon taxation is reflected in the changed curvature of the aggregate marginal cost of supply curve, S, when moving from Panel 1a to 1b. The carbon tax drives up the marginal costs of supply from carbon-emitting generation technologies, which are at the same time gradually displaced by VRE generation technologies supplying electricity at almost zero-marginal costs. The aggregate supply curve thus becomes more convex as in Panel 1b.

The corresponding effect on the wholesale price distribution is indicated by the higher flat rate, $\bar{p}$, in Panel 1b, implying that wholesale prices reach a higher level on average and that demand D intersects supply at its steep part more frequently than in the absence of VRE generation. The price inflation is a result of both the relatively low average availability of wind and solar power for generating electricity, particularly when wholesale prices are high, and the accordingly decreasing profitability per unit of VRE capacity with increasing VRE market penetration

[15] The peak and off-peak equilibrium when consumers are flat priced is given by the intersection of the aggregate supply curve S with the peak and off-peak demand curve, D_p^f and D_{op}^f. When consumers become real-time priced, the respective demand curve rotates around the point $\left(D_p^f, \bar{p}\right)$ or $\left(D_{op}^f, \bar{p}\right)$, as described in section 2.1, such that the peak and off-peak equilibrium are accordingly given by the intersection of S with the peak and off-peak demand curve under RTP, D_p^{rtp} and D_{op}^{rtp}, respectively. The corresponding peak and off-peak wholesale and retail real-time price are given by p_p and p_{op}. When changing from the flat to the real-time pricing equilibrium, electricity consumption decreases during peak periods from q_p to q_p^{rtp}, and increases from q_{op} to q_{op}^{rtp} during off-peak periods.



(a) Wholesale spot market without VRE supply



(b) Wholesale spot market with VRE supply

Figure 1 Peak and off-peak wholesale spot market equilibrium with and without VRE supply

(cf. section 2.2). That is, the average wholesale price needs to increase disproportionately with increasing market penetration of VRE technologies, in order to allow for sufficient revenues per installed VRE generation unit.

While the generation portfolio effect changes the potential *size* of positive and negative price spreads, $\Delta p_t > 0$ and $\Delta p_t < 0$, the distribution of wholesale prices determines the relative *incidence* of $\Delta p_t > 0$ and $\Delta p_t < 0$. In combination, the described effects imply that positive retail price spreads can increase in size, yet can occur less frequently than in the absence of carbon taxation and VRE supply. That is, on the one hand, equilibrium wholesale prices rarely drop to relatively low levels or even zero, since they have to settle at relatively high levels on average. The flat rate inflation, on the other hand, implies that when prices actually settle at very low levels or even to zero, consumer surplus gains from switching to RTP can be considerably large, if compared to the case without supply from VRE technologies.

In consequence, the overall effect of carbon-tax-induced VRE supply on the total consumer surplus gains from switching to RTP can be ambiguous. While switching consumers would most of the time pay more than before switching, they would also face heavy price drops when their demand is occasionally supplied at almost zero-marginal generation costs, since facing a very high rate on the flat tariff contract. The more VRE capacity is installed, the more often it can fully supply demand at zero-marginal costs, while the flat rate paid before switching to RTP inflates further such that positive price spreads increase in size and relative frequency. In sum, this implies that there can be states in the transition towards high VRE supply shares at which the welfare gains from RTP could in fact be lower in the presence than in the absence of large-scale VRE deployment, and that they might only become much larger than in a conventional market, if the VRE supply share is sufficiently high. At what stage either case obtains greatly depends on the market specific covariation of aggregate demand and variable renewable output patterns, which provides the primary motivation to apply the above model numerically in the following.

4. Scenarios, data and calibration of the simulation

As mentioned initially, the above model serves as the basis for the numerical model LORETTA, which is applied to simulate counterfactual carbon tax and RTP scenarios. In order to analyze how carbon-tax-induced VRE supply[16] affects

[16] Gross supply equals net supply, since we neither model trade between adjacent markets nor do we include transmission losses or own-consumption of plants.

the welfare gains obtained from exposing consumers to real-time prices (DICAP), we define the zero-carbon-tax equilibrium as the base scenario and raise the carbon tax from zero up to EUR 450 per ton of CO_2 (tCO_2) in discrete steps. We particularly compare equilibria with VRE shares of about 48%, 57%, 63% and 68%, which cover long-run projections based on German CO_2 emissions mitigation targets (cf. DLR et al., 2012; Bertsch et al., 2016).[17]

Section 5.3 presents the second part of our analysis, in which we study the performance of variable peak pricing relative to RTP under growing VRE supply shares. To do so, we compute the ratio of welfare gains from changing from the CICAP to the DICAP regime to those obtained under DICAP, i.e. full RTP, for the same VRE share scenarios as before and for given RTP consumer shares.

We simulate competitive long-run equilibrium prices and quantities for a representative year, that is for 8760 hours, using the PATH solver algorithm (Ferris and Munson, 2000). We loosely calibrate the model to the German power system drawing on hourly price and load data of the German electricity spot market at the European Power Exchange (EPEX Spot SE) from 2013.[18] The stylized set of supply technologies comprises onshore wind power and solar photovoltaic (solar PV) as VRE technologies, lignite and hard coal as non-variable base- and mid-load technologies as well as combined cycle and open cycle gas turbines (CCGT and OCGT) as peak and super-peak technologies. To compute technology specific marginal generation costs, $mc_i = (f_i + e_i\tau)\,\eta_i^{-1} + c_i^{om}$, we use long-run projections on average fuel prices f_i and on operation and maintenance costs c_i^{om}, both taken from the IEA World Energy Outlook 2014 (IEA, 2014), as well as prospective energy conversion (thermal) efficiency rates η_i, based on a meta-study by Schröder et al. (2013). Fuel specific CO_2-efficiency factors e_i from Icha (2013) are used to determine marginal cost increases of carbon emitting technologies from corresponding increases in the carbon tax τ, i.e. $\frac{\partial mc_i^{NV}}{\partial \tau} = e_i\eta_i^{-1} > 0$. Each technology's annualized fixed costs fc_i, also taken from Schröder et al. (2013), consist of overnight construction costs for the most part. Table 1 includes all relevant cost parameters of the stylized technology portfolio used for the simulation. Additionally, we apply publicly available data from 2013 provided by the German TSOs[19],

[17]The corresponding carbon tax amount to EUR 150, EUR 250, EUR 350 and EUR 450 per tCO_2, respectively.

[18]EPEX clearing price data are publicly available at the Danish transmission system operator (TSO) Energinet.dk, while German load data can be obtained from the Network of European Transmission System Operators for Electricity (Entso-e).

[19]The German grid is owned and operated by four private transmission system operators (TSOs): Amprion, 50Hertz Transmission, TransnetBW and Tennet TSO. Installed VRE capacity data are publicly available and provided by netztransparenz.de, which is a data platform

to compute capacity factors av_{it} for all 8760 hours and each VRE technology. To do so, we divide hourly feed-in data from wind onshore and solar PV units by the respective installed capacity data.

Table 1 Technology cost assumptions

Cost parameters	Technology						
	Wind	Solar PV	Lignite	Coal	CCGT	OCGT	OCGT Oil
Annualized fixed costs fc_i [kEUR /(MW*a)]	136.43	76.49	145.85	125.40	88.65	49.32	40.32
Marginal production costs mc_i [EUR /MWh$_{el}$]	0.10	0.10	18.19	33.80	64.41	96.76	173.94
CO_2-efficiency $e_i\eta_i$ [tCO_2/MWh$_{el}$]	0.00	0.00	0.88	0.73	0.33	0.51	0.68
Thermal efficiency η_i [MWh$_{el}$/MWh$_{th}$]	1.00	1.00	0.45	0.46	0.61	0.39	0.39

Notes: Marginal production costs are shown in Euro per megawatt hour (MWh) for a carbon tax equating zero, i.e. mc_i shown consist of fuel and variable operations and management costs only. Annualized specific fixed costs (per MW and year) comprise overnight investment as well as fixed operation and maintenance costs. Cost annuities are calculated with a risk-free interest rate of 7%, assuming lifetimes of 25 years for wind turbines solar PV, OCGT and CCGT, and 35 years for lignite and hard coal plants. While taking on a long-run perspective, prospected average fuel costs base on the "new policies scenario" for Europe, reflecting IEA fuel price projections for 2030 (IEA, 2014).

Using the isoelastic demand function described in chapter 3.1, our numerical model results are largely driven by the parameter assumptions regarding own-price elasticity, ϵ, and the distribution of the demand shifter, a_t. The demand shifter captures the characteristic seasonal and hourly aggregate consumption pattern and its distribution over 8760 hours is computed by using the mentioned price and load time series data. Since electricity demand in Germany is mostly non-responsive to price, we assume that $\alpha = 0$ and solve for a_t, by first calculating the break-even retail flat rate from the real spot price time-series and inserting this flat-price and hourly load into the demand equation in 3.1 (cf. Borenstein, 2005).[20] Finally, in the base case we set own-price elasticity ϵ to -0.05 which is at the low end of empirical estimates (cf. Faruqui and Sergici, 2010; Allcott, 2011). Whether our qualitative findings hold for higher levels of price elasticity is checked in Appendix Appendix C. We also conduct sensitivity analyses regarding the impact of the PRM by running additional simulations assuming a PRM of zero

initiated by the German TSOs.

[20]In contrast to Borenstein (2005) but without loss of relevant information, we do not adjust hourly price data to yield zero-profits of installed generation capacity.

and of 15% of net peak demand (see Appendix Appendix B). In the base case the PRM is set to 5% of net peak demand.

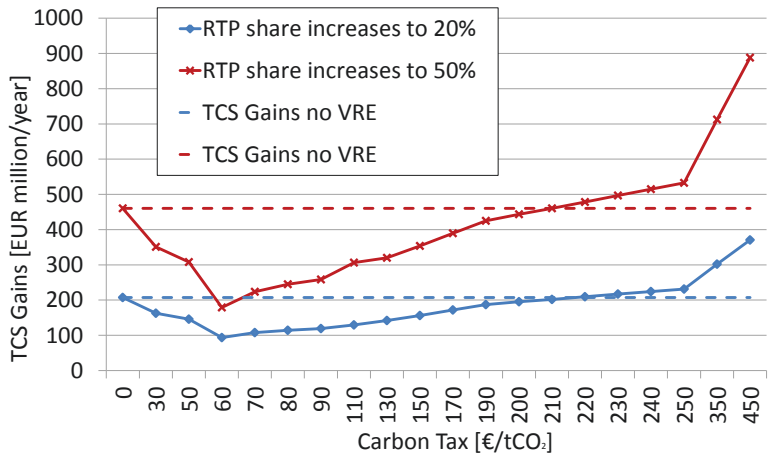
5. Results

5.1. Welfare effects of introducing RTP under carbon-tax-induced VRE supply

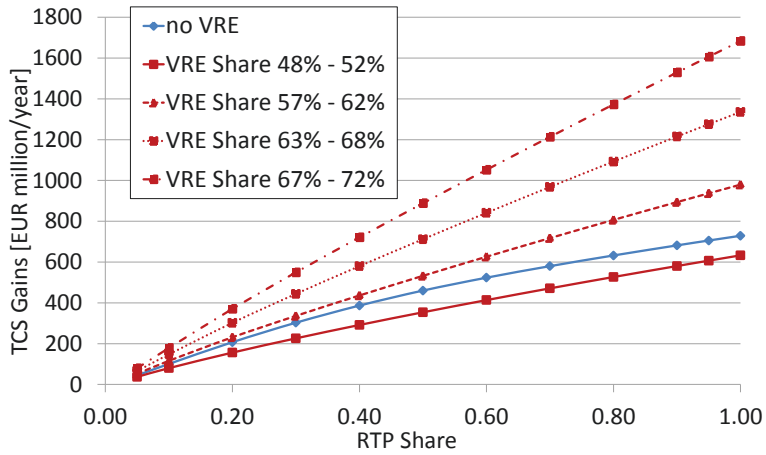
Panel 2a illustrates the main result that the annual welfare gains from introducing RTP change non-monotonously with the carbon tax τ. Specifically, Panel 2a shows that the total annual consumer surplus gains (TCS) from raising the RTP share α from 1% to either 20% (blue curve) or 50% (red curve) follow a U-shaped curve across increasing carbon tax levels. As τ is raised from zero up to EUR 450 per ton of CO_2 emissions in discrete steps, the TCS gains initially drop and reach a minimum as soon as the carbon tax equals EUR 60/ton. At this tax level VRE capacity starts to enter the market, which is discussed in more detail in the following section. Beyond this minimum, TCS gains strictly rise with the carbon tax and corresponding equilibrium VRE supply share. Contrary to common intuition, this implies that RTP can be less beneficial at relatively high amounts of variable renewable electricity generation than in their absence. This changes only after τ reaches EUR 210/ton, yielding a VRE supply share of about 54%, which is indicated by the intersection of the dashed horizontal lines with the solid curves, respectively.[21] At EUR 450/ton, where the VRE supply share reaches between 67% and 72% in total supply depending on the RTP share, the welfare gains from RTP are roughly twice as large as in the zero-tax scenario.

Moreover, Panel 2b illustrates the complementarity between growing VRE supply and real-time price responsive demand, since showing that the TCS gains from raising the RTP share from 1% up to 100% under low and high carbon taxes diverge. Particularly tariff switching consumers' benefits increase at an increasing rate, as can be taken from column 6 in Table 2, which shows the decomposed total annual consumer surplus gains for increases in α from 1% to 20% and 50% and selected carbon tax levels. This finding complements previous findings, which show that increases in the welfare gains from RTP level off at higher RTP shares. Introducing RTP and VRE supply interact such that VRE supply shares increase with the RTP share by roughly 4 to 5 percentage points in each carbon tax scenario, as is indicated by the VRE share range in the legend of Figure 2b as

[21] Table C.5 in Appendix Appendix C implies that these findings are robust for higher own-price elasticity assumptions, since the annual welfare gains from given increases in the RTP share are directly proportional to$|\epsilon|$ in each tax scenario. Likewise, Table B.4 in Appendix Appendix B shows that variations in the PRM do not qualitatively alter the U-shaped association between τ and ΔCS.



(a) TCS gains from increasing the RTP share from 1% to 20% or to 50% for increasing carbon taxation and VRE supply shares



(b) TCS gains from increasing the RTP share from 1% for selected VRE share (carbon tax) scenarios

Figure 2 Total annual consumer surplus gains from increasing the RTP share from 1% for varying carbon taxes and VRE shares in total supply under the DICAP scheme

well as by the bracketed numbers of column 1 in Table 3 below. This, in turn, lets the welfare gains from a given increase in the RTP share α grow at an increasing rate, since more VRE supply implies that the wholesale price is increasingly often decreased to zero. The growth in VRE capacity and supply results from the increased demand of RTP consumers reacting to the low prices during times of high VRE supply, implying that VRE technologies make higher short-run profits at a given carbon tax level.

Importantly, we do not find a clearly positive association between the welfare

Table 2 Total and decomposed annual consumer surplus changes from increasing the RTP share from 1% for varying carbon tax levels and VRE supply shares

Carbon tax τ (VRE share in total supply)	RTP consumer share	Annual consumer surplus change [EUR million/year]			
[EUR /tCO_2]	α	Total	Incumbent RTP Consumers	Flat Rate Consumers	Switchers to RTP
0	20%	207.35	-0.89	12.32	195.91
0	50%	460.29	-3.10	66.67	396.73
150 (49%)	20%	156.23	-2.25	17.73	140.74
150 (50%)	50%	353.85	-3.01	31.08	325.77
250 (58%)	20%	231.49	-1.88	22.38	211.00
250 (60%)	50%	532.61	-2.82	36.92	498.50
350 (64%)	20%	302.23	-1.51	20.57	283.18
350 (65%)	50%	712.07	-2.63	39.22	675.48
450 (68%)	20%	370.62	-1.22	17.65	354.19
450 (70%)	50%	888.19	-2.52	41.24	849.48

Note. - This table shows the annual total, incumbent RTP, flat rate and switching consumer surplus gains from raising the share of real-time priced consumers from 1% to 20% and 50% for different carbon tax levels and VRE supply shares in total supply (in brackets).

gains from RTP and wholesale price volatility as has been suggested in related work (e.g. Allcott, 2011; Leautier, 2014). This questions the common intuition that VRE supply increases the efficiency gains from RTP because of increasing price volatility. As can can be taken from column 11 in Table 3 below for selected scenarios, the standard deviation of the real-time retail price, $\sigma\left(p_t + pc_t\right)$, is strictly larger without than with VRE supply, given the RTP share α equals 1%.[22] RTP thus becomes more beneficial at sufficiently high VRE supply shares although wholesale prices become less volatile than in the absence of VRE supply.

While the efficiency gains from RTP appear to be less driven by the variance of price itself, we previously showed that consumer surplus gains from switching to RTP constitute the largest part of aggregate consumer surplus gains from RTP. As follows from expression (16), consumer surplus gains from switching are deter-

[22]Moreover, $\sigma\left(p_t + pc_t\right)$ strictly decreases until the VRE supply share reaches 48% in total supply, as indicated by Table 3, from where it starts to rise again, while TCS gains from RTP already start to rise again once VRE capacity enters the market (cf. section 5.2). Möbius and Müsgens (2015) find a similar, non-montonous change in wholesale price variance for growing VRE deployment. The association between VRE market entry, volatility and TCS gains appears to fit intuition better, if α is equal to 50% (compare $\sigma\left(p_t + pc_t\right)$ in Table 3). However, the differences in the standard deviation seem relatively small compared to the large differences in the TCS gains.

mined by the spreads between the flat rate, $\bar{p} + pc$, and the real-time retail prices, $p_t + pc_t$, paid before and after tariff switching, respectively. This indicates that changes in the welfare gains from RTP rather depend on characteristic changes in the distribution of retail price spreads. Hence, in the subsequent section we analyze how carbon taxation and VRE capacity entry affect the long-run distribution of retail price spreads.

5.2. Wholesale and retail price effects

This section demonstrates that carbon taxation entails two opposing effects on the distribution of hourly retail price spreads faced by tariff switching consumers, which mainly explain the non-monotonous change in welfare gains from RTP found above. The changes in the retail price spread pattern can, in turn, be traced back to characteristic wholesale price effects resulting from generation portfolio changes, which follow the mechanisms outlined in section 3.2.

An increasing carbon tax changes the long-run generation technology portfolio in two intuitive ways. First, it fosters investment in carbon-free variable renewable technologies with zero marginal supply costs, yet relatively high fixed investment costs. Second, within the remaining fossil-fueled generation technologies, it induces a gradual switch from carbon and capital intensive base-load technologies to natural gas fired peak-load technologies characterized by relatively low fixed investment costs, yet high marginal costs. The wholesale electricity price distribution changes accordingly such that both the average price level and the incidence of zero-prices increase simultaneously with VRE capacity entry.

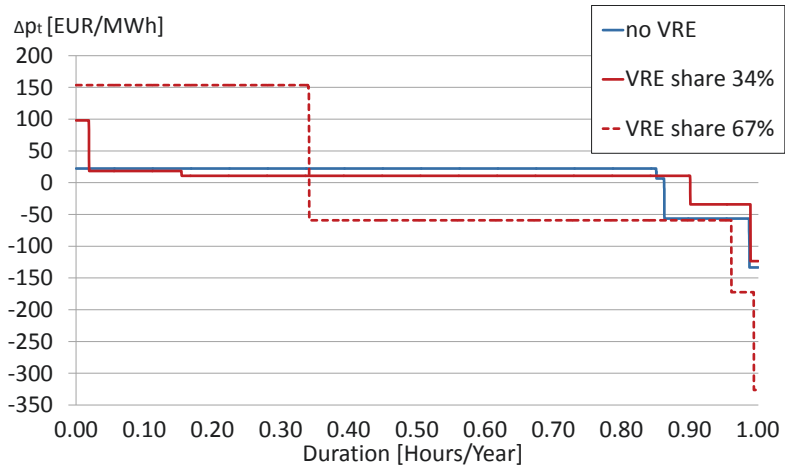
More specifically, Table 3 shows that up to the value of EUR 60/ton, the carbon tax only raises the marginal costs of carbon emitting technologies without inducing any VRE entry. Intuitively and importantly, the marginal generation costs of relatively carbon-intensive (base-load) technologies, such as lignite fired plants, increase faster with the tax than the marginal costs of originally more expensively generating mid- and peak-load technologies, e.g. natural gas CCGT plants. Accordingly, "off-peak" wholesale prices rise also faster than peak prices and, thus, converge. As a consequence, a consumer switching to RTP when the carbon tax is equal to EUR 60/ton will, on average, face a much lower price decrease during off-peak hours than a consumer switching in absence of carbon taxation. That is, the positive retail price spread, defined as $\Delta p_t = (\bar{p} + pc) - (p_t + pc_t) > 0$, faced by switching consumers decreases by 30% from about 22 to 15.3 EUR per MWh, while the average retail price increase, $\Delta p_t < 0$, changes only slightly (compare column 12 for row 1 and 2 in Table 3). Therefore, total annual welfare gains from RTP decrease until the carbon tax reaches EUR 60/ton, as

Table 3 Selected simulation results

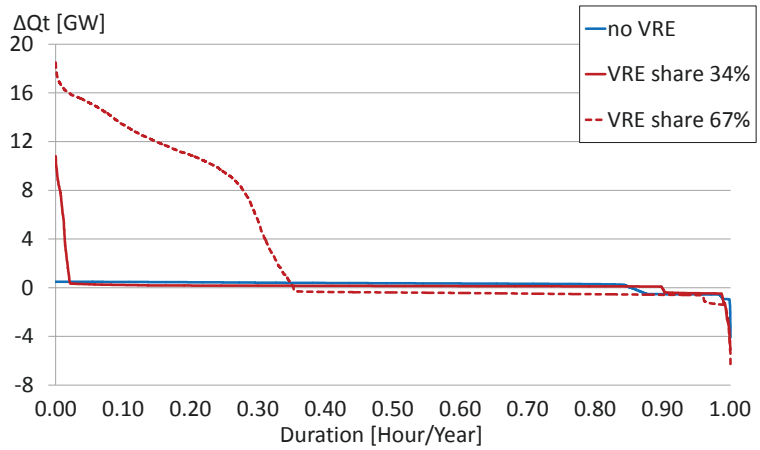
CO2 tax (VRE supply share)	Equilibrium Capacity [GW]							Total annual costs	Flat rate	$\sigma(p_t + pc_t)$	Mean (Max) $\Delta p_t > 0$	Off-peak price duration
[EUR/tCO_2]	Wind	CCGT	Solar PV	OCGT	OCGT Oil	Lignite	Total	[EUR million]	[EUR/MWh]		[EUR/MWh]	[% of 8760 hours]
							$\alpha = 1\%$					
0				4.62	9.96	64.29	78.88	18,694.15	40.39	454.93	22.00 (22.21)	85.07
60 (3%)	5.80	12.12	3.79	4.17	5.49	49.06	80.43	40,910.24	92.07	452.58	15.34 (21.09)	89.57
70 (34%)	62.62	31.50	50.81	10.34	7.83	19.02	182.12	43,485.50	98.18	436.16	13.67 (98.08)	90.00
150 (48%)	89.58	48.98	83.07	10.31	8.12		240.06	49,840.56	113.35	442.60	113.17 (113.25)	12.19
450 (67%)	168.93	48.04	103.72	8.84	8.23		337.77	66,582.72	153.76	445.31	153.57 (153.66)	34.16
							$\alpha = 50\%$					
0				2.75	3.34	64.11	70.20	18,256.87	40.10	116.09	21.35 (21.92)	83.18
60 (3%)	5.94	11.69	4.10	2.52	3.17	49.23	76.66	40,740.34	91.91	55.25	15.37 (21.09)	88.58
70 (35%)	64.62	31.74	51.79	9.70	3.41	18.42	179.66	43,273.05	98.04	85.82	13.65 (98.08)	89.75
150 (50%)	91.59	48.44	84.89	9.74	3.76		238.43	49,504.41	113.21	105.02	104.34 (113.11)	13.21
450 (70%)	172.13	47.10	104.98	8.27	3.73		336.22	65,738.94	153.76	167.13	147.83 (153.66)	35.00

Note.- This table shows selected long-run equilibrium results regarding the technology specific installed capacity, the total annual costs of electricity production, the retail flat rate $\bar{p}$, i.e. the (flat) demand-weighted average of the wholesale price, the standard deviation of real-time retail prices $\sigma(p_t + pc_t)$, the mean and maximum positive retail price spread Δp_t, faced by tariff switching consumers, and the relative frequency of hours within a representative year, during which real-time retail prices fall below the flat rate, i.e. "off-peak prices periods". Values are shown for scenarios in which the RTP share α remains unchanged at 1% (upper 5 rows) and in which it equals 50% (lower five rows). Note that hard coal capacity never enters in equilibrium under the cost assumptions given in Table 1.

discussed in the previous section and shown in Figure 2.



(a) Ranked distribution of hourly retail price spreads faced by consumers switching to RTP, if VRE shares equal zero, 34% (EUR 70/tonCO_2) and 67% (EUR 450/ton CO_2) in total supply



(b) Ranked distribution of hourly total demand changes when the RTP share increases to 20%, if VRE shares equal zero, 34% (EUR 70/tonCO_2) and 67% (EUR 450/ton CO_2) in total supply

Figure 3 Ranked hourly retail price spreads and total consumption changes from increasing the RTP share from 1% to 20% for varying VRE supply shares (under DICAP)

Welfare gains start to rise again at EUR 70 per ton of CO_2, following an abrupt change in the long-run generation technology portfolio from lignite (base-load) towards CCGT (mid-load) and large-scale wind and solar PV capacity entry. Specifically, lignite capacity is reduced by 70% to about 19 GW, whereas natural gas fired CCGT capacity triples to 32 GW compared to the equilibrium EUR

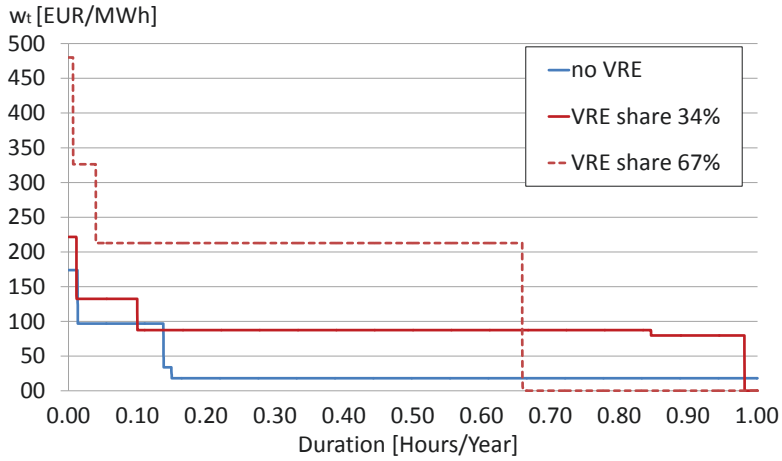


Figure 4 Ranked distribution of hourly wholesale electricity prices, p_t, when $\alpha = 1\%$, if VRE supply shares equal zero, 34% (EUR 70/ton of CO_2) and 67% (EUR 450/ton of CO_2) in total supply

60/ton.[23] Installed solar PV and wind capacity more than tenfolds to about 51 GW and 63 GW, respectively. The VRE supply share in total supply surges from almost zero to 34%, accordingly.

These portfolio effects result in a characteristic shape of the long-run wholesale price distribution under large-scale VRE deployment, which is mirrored by the distribution of retail price spreads, Δp_t. Wholesale prices reach comparatively high levels during most periods, while dropping to almost zero during few periods, which is illustrated by the solid red graph in Figure 4, giving the corresponding ranked distributions of wholesale prices, w_t. As the blue graph in this Figure indicates, this is quite the opposite to the wholesale price distribution in the absence of carbon taxation and VRE supply, where wholesale prices mostly settle at the rather low levels. That is, the lignite technology sets the price to 18 EUR per MWh during roughly 83% of all hours, while peak technologies, i.e gas and oil fired OCGT units, raise the wholesale price to about 96.8 and 173.9 EUR per MWh in the remaining periods. In contrast to this, high marginal cost technologies (mostly CCGT) set the wholesale price almost all of the time to about EUR 87.5 per MWh, despite the relatively high VRE supply share of 34% at EUR 70/ton. Low, or actually almost zero prices materialize only during 2% of the time, as indicated by the by the drop at the right end of the red solid graph in Figure 4, which is when VRE technologies fully serve demand. Accordingly, the demand-weighted average wholesale price, which in equilibrium equals the flat rate, $\bar{p} + pc$,

[23] At 75 EUR /tCO_2 the lignite technology is completely crowded out of the market.

more than doubles from EUR 40.39 to about 98.2 per MWh.

As explained in section 3.2, this price inflation is required to allow for sufficient revenues for installed wind and solar capacity, which is on average only available to generate electricity for 19% or 10% of the time, respectively.[24] Yet, it also almost halves the average, positive retail price spread, $\Delta p_t > 0$, faced by tariff switching consumers to 13.67 EUR per MWh compared to the zero-tax scenario, and reduces it by roughly 10% compared to the EUR 60/ton scenario (compare first three rows in column 12 of Table 3). Accordingly, in most instances$\Delta p_t > 0$ at EUR 70/ton is lower than the retail price spread under zero carbon taxation, as indicated by the red and blue solid graph in Figure 3a, which represent the ranked distribution of retail price spreads in either scenario. As a consequence, introducing RTP still remains less beneficial at a relatively high VRE supply share, as observed in the preceding section.

However, despite the lower average price spread, RTP becomes more beneficial than at EUR 60/ton, since during 2% of the time VRE set the wholesale price to almost zero such that the maximum spread jumps from about 21.1 to 91.8 EUR per MWh (see bracketed numbers in column 12 of Table 3). Apparently, these few heavy price drops suffice to outweigh the negative consumer surplus effects of facing relatively low price drops.

As the carbon tax and VRE entry level increase further, both the wholesale price inflation and incidence of zero-prices increase such that at some point RTP becomes indeed more beneficial at high VRE shares than in their absence. As discussed, the annual total welfare gains from introducing RTP are roughly twice as large at a carbon tax of 450/ton and a VRE share of 68%. The red dashed graph in Figure 3a shows that this holds although in about 76% of the time consumers switching at this high VRE share actually face price increases, i.e. $\Delta p_t < 0$, of about 73 EUR per MWh on average. The proportion of zero-wholesale price periods, however, increases to about 34%, while in the remaining time prices settle mostly at 212 EUR per MWh.[25] The corresponding flat retail rate, $\bar{p} + pc$, increases to 153.8 EUR per MWh (see third row in Table 3), implying that switching consumers face comparatively heavy price drops of about the same size on average in the remaining time. These price drops are roughly seven times

[24] Average capacity factors do not differ by much in other years since 2010, for which we have data available, too.

[25] Marginal production costs of CCGT to 212 EUR /MWh at 450 EUR /tCO_2. Between 4% to 10% of the time OCGT gas and oil plants, representing the highest marginal production cost technologies in our simulation, have to supply electricity, raising the wholesale price to even higher levels of up to 480 EUR /MWh.

larger than in absence of VRE supply and lead to correspondingly large increases in consumption, which are indicated by the hump of the red dashed graph in Figure 3b, showing the ranked distribution of total consumption changes when the RTP share increases from 1% to 20%.

Consequently, the observed changes in welfare effects from RTP reflect that as the share of VRE supply grows, flat rate consumers begin to "overconsume" more often, yet, at the same time "underconsume" heavily to an increasing extent during low price periods. Importantly, again, wholesale price volatility hardly indicates this mechanism, since we do not find significant differences in the standard deviation of wholesale prices between the low or high VRE share case. Instead, our analysis shows that it is the form of the price distribution rather than the variance of price itself, which determines the benefits of RTP.

5.3. Welfare, price and quantity effects of implementing variable peak pricing

This section analyzes the role of second-best alternatives to RTP in electricity markets with high VRE supply shares. We therefore quantify the proportion of the potential efficiency gains obtained under full-fledged RTP, which could be captured by variable peak pricing (VPP).

Importantly, we do not model VPP explicitly but different RTP schemes, under which RTP consumers either face the real-time capacity price pc_t (DICAP scheme), which increases during peak-demand periods, or they face the same constant capacity price pc that flat rate consumers face. As VPP schemes merely aim at incentivizing demand reductions during peak-demand periods so as to save in costly peak-load generation capacity, consumers face price variations, that is scarcity prices, only during these periods. Efficiency gains from introducing VPP thus arise exclusively from avoiding "overconsumption" during a few periods of scarce generation resources. The surplus changes from changing from constant (CICAP) to time-varying capacity pricing (DICAP), $\Delta CS\left(p_t, pc_t\right) - \Delta CS\left(p_t, pc\right)$, therefore reflect the consumer surplus gains that would be attributable to VPP. To assess its relative performance for different RTP and VRE supply shares, we compute the ratio of VPP to full RTP consumer surplus gains as follows:

$$\frac{\Delta CS\left(p_t, pc_t\right) - \Delta CS\left(p_t, pc\right)}{\Delta CS\left(p_t, pc_t\right)}. \tag{18}$$

Values for (18) are given by Figure 5a, which shows that the proportion of consumer surplus gains from VPP in total consumer surplus gains from RTP decreases as the VRE supply share grows. For example, if the the RTP amounts to 40%, this proportion amounts to roughly 50% of the total consumer surplus

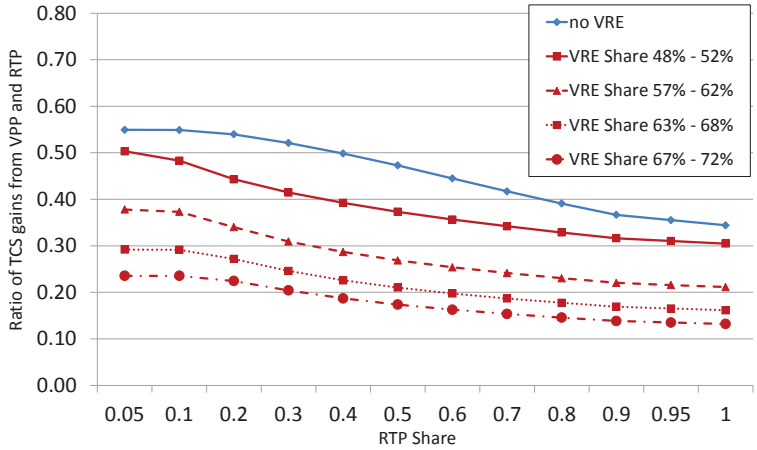
gains from RTP in absence of VRE supply (blue graph). If VRE supply up to 52% and 72% of total electricity (red solid and red dashed-dotted graph), this proportion decreases to roughly 40% and 19%, respectively. Hence, while in a non-renewable based market flat tariffing may thus indeed result in significant inefficiencies largely due to "overconsumption" during high price periods, they become relatively insignificant as VRE supply shares rise. That is, although VPP yields savings in capacity costs by reducing excess entry of peak-generation capacity, these benefits account for less and less of the total gains from RTP in a renewable based market.

Instead, efficiency losses from flat tariffing appear to mostly stem from "underconsumption" during low or even zero-price periods such that allocative efficiency appears to depend increasingly on raising consumption in periods of high renewable electricity supply rather than on reducing it during scarcity situations. This is indicated by the ranked electricity consumption changes caused by changing to full-fledged RTP, i.e. from CICAP to DICAP, which are shown in Figure 5b. RTP consumers increase consumption in all off-peak periods, since the constant capacity adder pc drops from their retail rate and where pc_t equals zero as the PRM constraint is not binding. The rising incidence of low and zero price periods in the presence of growing VRE supply shares (blue solid to red dashed-dotted graphs) again leads to heavy consumption increases and surplus gains, intuitively making VPP relatively less efficient than a pricing scheme that additionally exposes consumers to these low prices.[26]

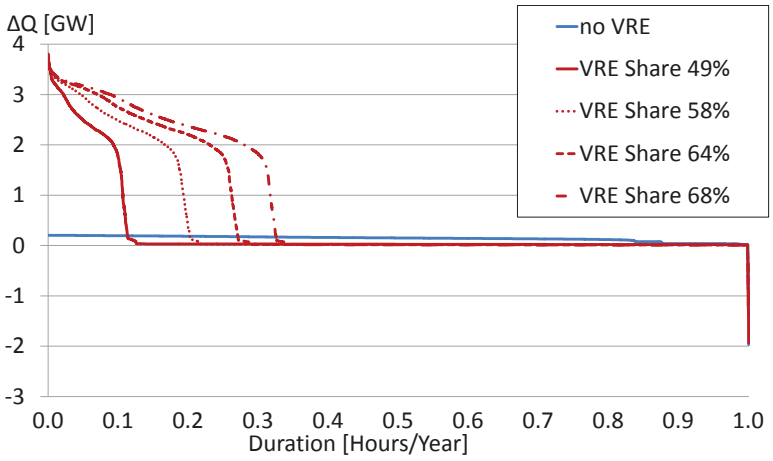
The planning reserve margin and the according level of excess capacity should positively affect the gains from introducing VPP. The above results are obtained for an exogenous planning reserve margin of 5% but also hold for a PRM of 15% of net peak-demand as shown by Table B.4 in the Appendix Appendix B.

Our results complement previous findings suggesting that the bulk of efficiency gains from implementing RTP could also be realized with pricing schemes of low time-granularity such as VPP, or that gains from curbing peak-demand through peak-pricing could even outweigh the gains from establishing a large share of

[26]The effect of time-varying capacity pricing on flat rate customers' annual surplus gains is ambiguous, since for any given flat price $\bar{p}$ the time-invariant capacity price pc can either rise or decline. As explained, firm capacity entry is lower under DICAP as RTP consumers now reduce demand when capacity is scarce entailing lower firm capacity costs $r \cdot K^{NV}$ for all consumers. This pecuniary externality causes flat customers' unit capacity price pc to shrink, ceteris paribus. Because RTP consumers can reduce their share in capacity payments by conserving energy though, pc can also rise even if overall firm capacity costs decrease, given that pc is simply a demand-weighted average of pc_t and since flat consumers' relative contribution to these costs rises sufficiently when moving from CICAP to DICAP.



(a) Total consumer surplus gains from variable peak pricing relative to total consumer surplus gains from real-time pricing



(b) Ranked distribution of total hourly demand changes from changing from CICAP to DICAP for varying VRE supply shares

Figure 5 Relative welfare effects of variable peak pricing for varying VRE supply shares

RTP consumers. As prices only vary occasionally in a rather predictable manner, VPP appears to be a preferable, since more feasible second-best solution to many utilities and regulatory authorities. However, as our results indicate the trade-off between efficiency and practicability has to be reconsidered with rising VRE market penetration, which renders full-fledged RTP as the only efficient pricing option.

5.4. Robustness and limitations

The welfare changes from RTP found in our analysis could be underestimated for several reasons. First, we omit the cross-price elasticity of demand and, thus, the effect of substituting demand in high price periods with demand in low price periods (demand shifting). This also includes effects of utilizing "behind-the-meter" storage facilities (e.g. small batteries) or other technologies that facilitate demand shifting (e.g. Power-to-Heat or electric vehicles). Given the large price spreads between off-peak and peak demand periods found when VRE technologies enter the market, it seems plausible that welfare gains from RTP could actually grow faster with the VRE supply share than in our simulations, if the cross-price elasticity of demand would be accounted for. Thus, while the welfare gains from RTP may still change in a U-shaped fashion with the carbon tax, they may exceed those obtained in the absence of VRE supply and carbon taxation at an earlier stage of VRE market penetration.

Additionally, we may underestimate the growth in the benefits from RTP by ignoring the locational variation in electricity prices. We therefore do not account for potential cost savings in transmission capacity expansion and congestion management caused by deploying VRE technologies. If consumers would face real-time prices that also reflect the locational constraints in the grid, some costly transmission lines might not have to be built and less generation plants might have to be re-dispatched ahead and behind of a congested line. If the related costs would rise sufficiently strong due to the deployment of wind and solar power in the system, RTP could entail relatively large efficiency gains even at very low VRE penetration rates.

The effect of long-run changes in demand patterns or consumption behavior is more complex to assess and appears ambiguous. On the one hand, progress in information and communication technology could affect the benefits from RTP positively by reducing the private transaction costs related to optimally adjusting demand to time-varying prices. For instance, advanced meters combined with in-home displays providing high frequency information not only about prices but about consumption costs at the appliance level could significantly increase consumers' elasticity to price, and thus the welfare gains from RTP (Jessoe and Rapson, 2014). Home automation and the utilization of smart-appliances able to communicate with advanced meters could amplify this positive effect (Bollinger and Hartmann, 2015).[27] On the other hand, dynamics in consumer behavior may

[27] Additionally, future demand for electricity could grow significantly due to the electrification of heating and transportation, which could also imply higher allocative efficiency gains from RTP

also reduce the potential benefits from introducing RTP. For instance, owners of rooftop solar PV capacity and small storage capacities could become more "attentive" to energy consumption related costs and adapt their behavior to the output profile of their PV unit (Sallee, 2014). To some extent such behavioral adjustments could reduce the efficiency gains from implementing real-time pricing.

Apart from this, we omit other relevant factors which could also significantly reduce the potential welfare gains from RTP. First, our model does not account for cross-border-trade with adjacent electricity markets. Accordingly, hourly price spreads may actually be lower than in our simulations. Second, we ignore any kind of grid- or utility-scale storage technology, the utilization of which could also have a dampening effect on hourly price spreads. Furthermore, we abstract from fossil-fuel price dynamics. Including these likely alters the respective equilibrium generation portfolios for given carbon tax scenarios from the ones simulated here. Specifically, the replacement of lignite by gas fueled technologies and entry of VRE technologies could occur at lower carbon tax levels than in our simulations. The change in the wholesale price distribution should, however, have the same direction as above, such that this simplification should have no qualitative implications.

Finally, our welfare results crucially hinge on the electricity price effects of carbon taxation. Direct renewable support policies such as feed-in-tariffs for renewable energy or renewable portfolio standards certainly would have different portfolio and price effects in the long-run equilibrium. In particular, renewable subsidy schemes can induce large-scale entry of VRE technologies, while allowing carbon intensive technologies with relatively low marginal generation costs like coal or lignite fired power plants to stay in the market at the same time.[28] Long-run wholesale prices could therefore reside at low levels most of the time and increasingly shift to zero as VRE supply shares rise. At first glance, this could render RTP always more beneficial in the presence than in the absence of VRE supply. This appears plausible as long as the consumption distortions from taxes or surcharges to refinance renewable subsidies are ignored. We check this by simulating equilibria with VRE capacity subsidization financed by renewable surcharges included in the retail rates. We find that welfare gains from RTP now change in a U-shaped with the VRE supply share, as is shown by Figure A.6a and A.6b in the Appendix Appendix A. This outcome mainly results from the time-invariant unit tax or surcharge to finance the subsidy to VRE capacity. The

(Boßmann and Staffell, 2015).

[28]This matches the current situation in the German electricity market where VRE have diffused rapidly due to fixed feed-in-tariffs, while lignite as well as hard coal technologies remain in the market and keep supplying most of the annually generated electricity.

tax increases with the VRE supply share and is added on top of both the retail real-time and flat rate, while wholesale prices indeed settle at low levels and increasingly drop to zero with rising VRE shares. The underlying mechanism are explained in more detail in the Appendix Appendix A.[29]

6. Conclusion

This paper contributes to the economic assessment of real-time retail pricing (RTP) in the presence of climate-policy-induced variable renewable electricity supply (VRE) in two ways. First, it analyzes the change in the gross welfare gains from introducing RTP for increasing VRE supply shares under carbon taxation. Second, it assesses the relative performance of RTP and variable peak pricing, which is widely considered a feasible and efficient second-best alternative to RTP.

Applying German market data to simulate long-run equilibria of a perfectly competitive wholesale and retail electricity market, we find a U-shaped relationship between the benefits of RTP and carbon emissions taxation. Contrasting common intuition, this implies that introducing RTP can be significantly more beneficial in the absence than in the presence of variable electricity generation unless it reaches a very high level. Importantly, this result cannot be explained by changes in wholesale price volatility as is often argued in the literature. Instead, our analysis illustrates that this result is majorly driven by a characteristic shift in the wholesale price distribution towards a higher mean and a simultaneous increase in the frequency of zero-prices. This shift stems from the generation portfolio effects of carbon taxation as well as of the supply characteristics of variable renewable technologies such as wind and solar power.

Furthermore, we find that variable peak pricing achieves only a small portion of the potential efficiency gains obtained under full-fledged RTP at high renewable deployment. The reason is that as variable renewable supply shares increase, most of the efficiency gains from introducing RTP result from incentivizing consumers to increase demand when supply from wind or solar resources is high and depresses wholesale prices to almost zero. Hence, allocative inefficiency from flat tariffing arises mostly from consuming "too little" during low-price periods rather than from consuming "too much" during peak-price periods.

[29]This result may be further complicated, if accounting for rising quasi-fixed costs, which accrue from start up, shut down and ramping operations and which generators usually include in their bids at the wholesale market. Increasing VRE supply may lead to growing quasi-fixed costs as non-variable plants may have to be started-up, curtailed or ramped up and down more often. If this would imply that positive price spreads for switching consumers become large, then the overall welfare gains from RTP may still change non-monotonously but would rise stronger with the VRE share than in the example of appendix Appendix A.

These findings provide guidance for decision makers on when to install costly advanced metering infrastructure (AMI) and to introduce which time-varying retail pricing scheme in transforming electricity markets. Our first result suggests that the ongoing and currently planned large-scale roll-out of AMI in many U.S. and European markets may not be well-timed, given the high investment costs involved and the private transaction costs linked to adjust particularly to RTP tariffing. In this regard, addressing the dynamics in electricity demand behavior will become highly relevant in future analyses on this topic. Behavioral changes might result from the electrification of future final energy demand as well as from the availability of smart-appliances that allow for automated demand response to price variations. Further research should additionally account for the potential welfare gains from both temporally and locationally varying electricity pricing, in order to capture the effects of geographically dispersed renewable generation capacity.

Our second result puts common feasibility considerations regarding RTP into perspective, by illustrating that most welfare gains would likely be left on the table under less complex, second-best alternatives to RTP. The realization of these welfare gains is, however, jeopardized by the potential reluctance of customers to adopt RTP. Specifically, consumers' tariff choice might be influenced by high individual transaction costs, inattention to consumption costs and misperceived benefits from time-varying prices. The determinants of tariff choice thus represent a crucial future research topic.

Appendix

Appendix A. Welfare gains from RTP with VRE capacity subsidization

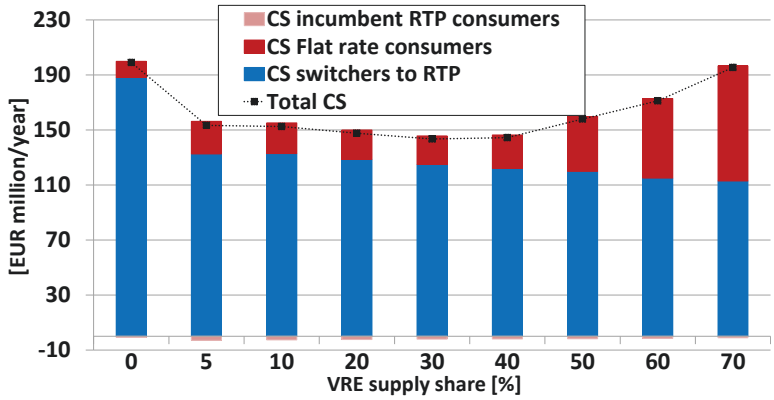
In this section we demonstrate that welfare gains from rising RTP shares also change non-monotonously with the VRE share if VRE capacity is subsidized.[30] Figure A.6a and A.6b show that up to a VRE share of 40%, TCS gains from raising the RTP share to 20% or 50% decrease compared to the levels obtained without VRE supply. From this point onward TCS gains rise again but remain below the level achieved without VRE supply when the RTP share is raised to

[30] To simulate this scenario, we use a modified version of the above model in order to determine endogenously the specific subsidy required to induce a given equilibrium VRE supply share. That is we nest the above MCP model in a "mathematical program with equilibrium constraints" (MPEC) as further explained in Pahle et al. (2016). We also exclude the PRM constraint and thus model a so called "energy-only market".

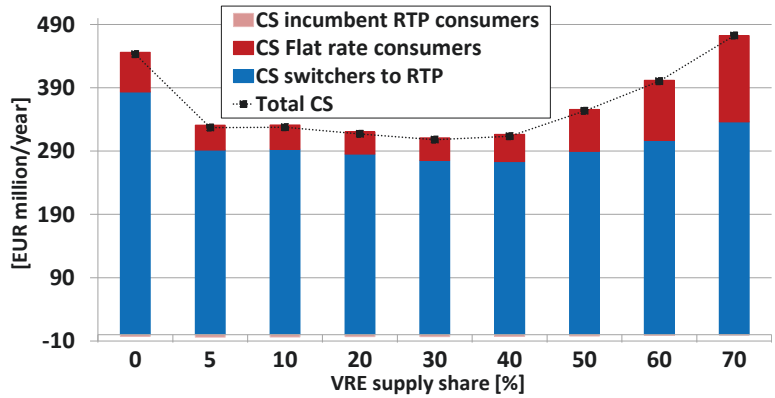
20%. When the RTP share is raised to 50%, corresponding TCS gains are lower than without VRE supply unless the VRE share amounts to 70% (Figure A.6b). Interestingly and in difference to the carbon tax scenarios, switching to RTP remains less beneficial than in the equilibrium without VRE supply (blue bars in Figure A.6). Flat rate consumers, however, increasingly benefit from a switch to RTP by other consumers with rising VRE shares (red bars in Figure A.6). Hence, overall welfare gains from RTP at higher VRE shares are more and more determined by the TCS gains of flat rate consumers and less by the benefits of consumers switching to RTP.

The above results now stem less from wholesale price changes but rather from the presence of a uniform per unit tax τ included in retail rates to finance the VRE subsidy. As each consumer pays τ per consumed unit of energy, this tax constitutes a time-invariant wedge between retail and wholesale electricity prices. Importantly, this wedge increases on average with VRE entry because of both VRE technologies set wholesale prices increasingly often to zero and the VRE subsidy as well as the corresponding tax rise simultaneously. The rise in subsidies follows from a decrease in short-run profits at the wholesale market by VRE technologies (cf. Lamont, 2008). As VRE market profitability declines disproportionately with VRE capacity entry, subsidies to refinance VRE capacity costs have to rise disproportionately with the given VRE target (cf. Green and Léautier, 2015). In the equilibria shown in Figure A.6, τ rises from EUR 3 to EUR 73 per MWh. Simultaneously, $\bar{p}$ drops from EUR 40 per MWh to around EUR 31 per MWh.

These changes in retail price components entail several effects on switching and flat rate consumers' surplus gains. Flat retail rates $\bar{p} + \tau$ increase with the VRE share as τ rises faster than $\bar{p}$ declines. This would make switching to RTP in principle more beneficial, if hourly RTP rates could drop to the marginal costs of supply. However, this is not the case due to the tax mark up that RTP consumers pay per unit of consumption. Instead, the majority of positive price spreads if switching to RTP, $\triangle p_t > 0$, declines at low VRE shares as shown by the solid red curve in Figure A.7. At relatively low VRE shares, VRE set prices relatively infrequently such that real-time retail prices mostly equal the marginal production costs of coal or lignite units plus the tax τ. The corresponding positive price spread for switching consumers therefore equals $\bar{p} - mc_i^{NV}$ most of the time, which is lower than without VRE entry, since $\bar{p}$ decreases (slightly) with increasing VRE shares. Hence, comparing the large plateaus of the blue and red solid graphs in Figure A.7 gives that $\bar{p} - mc_i^{NV}$ amounts to EUR 22 per MWh without VRE entry (blue graph) and EUR 21 per MWh with a 30% VRE share during about 85% of the time. When the equilibrium VRE share equals 70%, these price spreads fall to EUR 15



(a) Decomposed annual consumer surplus gains from raising the RTP share from 1% to 20% for VRE supply shares from 0% to 70%



(b) Decomposed annual consumer surplus gains from raising the RTP share from 1% to 50% for VRE supply shares from 0% to 70%

Figure A.6 Total annual consumer surplus gains from RTP share increases under VRE capacity subsidization

per MWh in about 60% of all hours (dashed red line in Figure A.7). In most of the remaining hours of this scenario, price spreads rise to $\bar{p} = 31$ EUR/MWh, which is when VRE supply sets wholesale prices to zero. Thus, as price spreads increase comparatively, TCS gains from switching become larger again (blue bars in Figure A.6), at least if the RTP share is raised to 50%, yet not as large as without VRE supply.

Flat rate consumers' benefits from higher RTP shares rise with the VRE share,

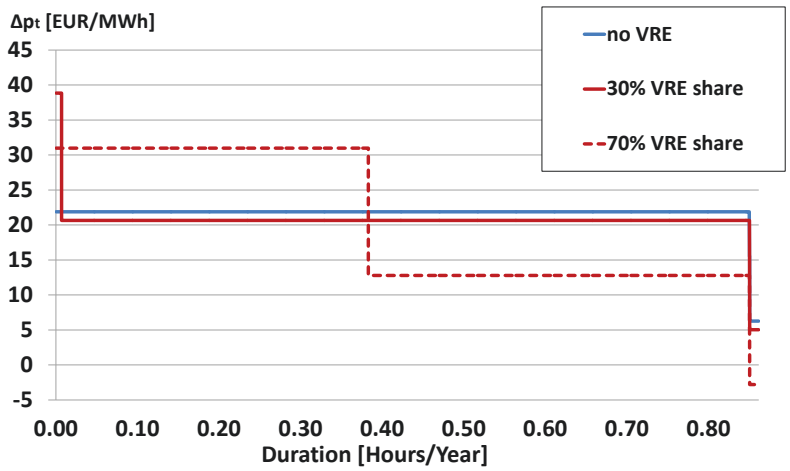


Figure A.7 Positive retail price spreads, i.e. $\bar{p} - p_t > 0$, at $\alpha = 1\%$ faced by consumers switching to RTP at 0%, 30% and 70% VRE supply shares in total supply

since their flat rate $\bar{p} + \tau$ declines more sharply when other consumer switch to RTP (not shown). As RTP consumers raise consumption when prices are low, wholesale prices rise during hours where a large part of VRE capacity supplies energy. VRE technologies thus become more profitable and less subsidies are needed to reach a given VRE share, so thatτ decreases. This positive pecuniary externality increases with the VRE share and thus leads to the increasing benefits of flat consumers for given RTP share increases. Simultaneously, $\bar{p}$ decreases with the RTP share as explained above, but the decrease does not differ by much for different VRE shares.

In consequence, welfare gains from RTP change non-monotonously with VRE supply shares either if VRE entry is carbon tax or subsidy induced, however, the mechanisms responsible for this result differ.

Appendix B. Impact of the planning reserve margin on the welfare gains from RTP and the relative welfare gains from VPP

Table B.4 illustrates that the PRM has a negligible quantitative, yet no qualitative impact on the welfare results found in the previous sections. In the absence of a PRM constraint, total annual consumer surplus gains from raising the RTP consumer share to 20% change non-monotonously as follows from comparing columns 2 to 4. If the PRM equals 15% under the DICAP scheme, annual consumer surplus gains are approximately 11% and about 4% higher than without PRM constraint and in the base case, respectively (cf. Table 2). Under the CICAP scheme, welfare gains from RTP are lower than under the DICAP scheme, which is not surprising

since savings in peak-generation capacity remain unrealized as RTP consumers do not face high prices when capacity is scarce, but the flat capacity price *pc*. Hence, RTP consumers also consume "too much" during peak-price periods such that the amount of installed peak-generation capacity is larger under CICAP than under DICAP. As before, the efficiency gains from changing from the CICAP to the DICAP scheme, which would actually represent the potential efficiency gains from introducing variable peak pricing as discussed in section5.3, make up a decreasing portion of the potential efficiency gains obtained under RTP (DICAP) when the VRE supply share increases. This can be taken from comparing the values in the last column.

Table B.4 Absolute and relative consumer surplus gains from RTP and VPP for a planning reserve margin (PRM) of zero and 15% (base case 5%) of net peak demand and for varying VRE supply shares under the DICAP and CICAP scheme

	Scenario								
Market Design	no PRM			CICAP	DICAP	CICAP	DICAP	CICAP	DICAP
VRE Share in total supply [%]	0	48	58	0	0	48	48	68	68
(Carbon tax in EUR/ton CO_2)	0	(150)	(250)	0	0	(150)	(150)	(450)	(450)
Annual consumer surplus change [EUR million/year]									
Incumbent RTP consumers	-0.84	-2.12	-1.77	0.50	-0.97	0.30	-2.46	0.46	-1.34
Switchers to RTP	188.26	137.27	207.43	54.22	211.34	61.54	149.54	242.61	364.11
Flat rate consumers	11.70	16.40	20.48	44.29	13.55	27.09	19.45	46.31	19.46
Total	199.10	151.55	226.14	99.01	223.92	88.92	166.52	289.38	382.24
Relative gains from VPP [%]	-	-	-	-	55.79	-	36.26	-	24.29

Note. - This table shows the total and decomposed annual welfare changes from increasing the share of real-time priced consumers, α, from 1% to 20% for a PRM of 15% of peak-demand as well as in absence of a PRM constraint ("no PRM"), either under full-fledged RTP, i.e. the DICAP scenario, or under RTP with a peak-price cap, i.e. the CICAP scheme, under which RTP consumers do not face scarcity prices. Results are respectively shown for a zero, 48% and 68% VRE supply share in equilibrium.

Appendix C. Impact of own-price elasticity assumptions

Total welfare gains from given increases in the RTP share rise proportional to own-price elasticity ϵ. This follows directly from comparing the corresponding values given in Table 2 and Table C.5, which also shows that welfare gains nonetheless change non-monotonously with the carbon tax.

Table C.5 Decomposed annual consumer surplus changes from increasing RTP under DICAP with higher price elasticity (base case $\epsilon = -0.05$)

Carbon tax τ (VRE share in total supply [%])	RTP consumer share	Annual consumer surplus change [EUR million/year] (EUR/year/customer)			
[EUR /tCO_2]	α	Total	Incumbent RTP consumers	Flat rate consumers	Switchers to RTP
		$\epsilon = -0.1$			
0	20%	396.44	-4.02	49.85	350.61
(0)		(8.81)	(-8.04)	(1.25)	(36.91)
150	20%	297.31	-5.04	36.70	265.65
(48)		(6.61)	(-10.09)	(0.92)	(27.96)
250	20%	449.16	-5.07	46.00	408.24
(57)		(9.98)	(-10.14)	(1.15)	(42.97)
		$\epsilon = -0.2$			
0	20%	836.00	-17.78	218.25	635.54
(0)		(18.58)	(-35.56)	(5.46)	(66.90)
150	20%	593.41	-11.29	84.65	520.06
(48)		(13.19)	(-22.59)	(2.12)	(54.74)
250	20%	928.44	-12.40	102.49	838.35
(57)		(20.63)	(-24.81)	(2.56)	(88.25)

Note. - This table shows the total and decomposed annual welfare gains from increasing the share of real-time priced consumers, α, to 20% obtained for higher own-price elasticity assumptions than in the base scenario, where ϵ equals 0.05. The top and lower three rows give values for doubling and quadrupling own-price elasticity ϵ to 0.1 and 0.2, respectively. Each row gives consumer surplus gains for a different carbon tax and VRE supply share scenario. The per capita surplus gains are derived from dividing the respective consumer surplus gains by the number of installed meters Germany, which amounted to about 50 million in 2013 (BnetzA, 2014).

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Chapter 3

Time-Varying Electricity Pricing and Consumer Heterogeneity: Welfare and Distributional Effects with Variable Renewable Supply[1]

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Time-Varying Electricity Pricing and Consumer Heterogeneity: Welfare and Distributional Effects with Variable Renewable Supply

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Abstract

Advanced metering infrastructure is being rolled out at large scale in many U.S. and European power markets, allowing for exposing consumers to time-varying electricity prices. The latter is considered crucial for coping with growing variable renewable electricity supply and essential for allocative efficiency in electricity markets. Yet, significant amounts of the potential efficiency gains from time-varying tariffing may be left unrealized, since many residential and commercial retail consumers could actually prefer to stick with the usual default, which is flat tariffing, in order to avoid potential consumption cost increases. We study how increasing variable renewable supply affects individual consumption cost changes from implementing real-time retail pricing among residential consumers, using consumption data from Germany and simulating long-run electricity market equilibria. We find that most customers face comparatively small bill changes at high renewable supply shares. We further analyze how consumer heterogeneity influences the unrealized welfare gains from rejecting real-time pricing. Applying synthetic residential, commercial and industrial demand profiles calibrated to German market data, we find that unrealized welfare gains are 18% to 57% larger, if mostly residential and commercial instead of industrial customers remain flat-priced. The corresponding unrealized welfare gains can more than quadruple to 1.1 bn EUR per year, if renewable supply shares increase. Additionally, targeted rollouts of real-time pricing can entail adverse distributional effects across consumer sectors. Particularly residential consumers can face rate increases, if mainly industrial consumers adopt real-time pricing.

JEL classification: D04, D12, D47, D61, H23, L94, Q42

Keywords: Real-time pricing; Electricity market; Variable renewable generation; Carbon taxation; Welfare analysis; Heterogeneous agents modeling

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1. Introduction

As the shares of variable electricity supply from wind and solar power continue to grow in many markets, exposing consumers to the time- and location-varying value of electricity is widely considered to yield increasing allocative efficiency gains. Electricity consumers are typically charged a fixed price which does not reflect the actual variation in the marginal costs of electricity. In the European and U.S. electricity markets, however, most customers will be equipped with advanced metering infrastructure in the medium run, allowing for the introduction of time-varying electricity tariffing, such as real-time retail pricing (RTP).

Though a widespread switch from fixed retail rates to RTP could increasingly benefit consumers on aggregate, particularly many residential and small commercial retail customers may actually prefer not to switch for several reasons. Especially loss aversion has been identified as a potentially major acceptance barrier to the adoption of RTP (Borenstein, 2007, 2013; Salies, 2013; Jessoe and Rapson, 2014). That is, consumers might tend to misperceive the potential benefits and rather try to avoid the potential electricity bill increases from being exposed to time-varying retail prices. Assuming that they would not adapt their consumption behavior, many consumers could indeed face higher consumption costs under RTP given that much of their consumption is cross-subsidized under their flat rate tariffing scheme (Borenstein, 2007). Customers consuming relatively little during high-price periods could bear some of other customers' consumption costs, who are on the same flat rate and consume relatively much when electricity is expensive. Studies analyzing the potential redistribution of consumption costs by using samples of residential, commercial or industrial customers have found that the median customer would actually lose and thus not opt for a RTP tariff (Borenstein, 2007, 2013; Andersen et al., 2014).

So far, however, research has neither addressed how these intra-sectoral distributional effects might change with growing variable renewable electricity supply (VRE), nor has there been an analysis on the welfare implications when heterogeneous consumers reject RTP in such a setting. Analyzing these issues seems necessary for two reasons. On the one hand, the distributional effects from RTP might be mitigated when electricity is mostly supplied by wind and solar power, since individual demand patterns may correlate less with prices, implying that most consumers might face smaller bill changes if put on RTP. As generation from variable renewables depends on erratic weather conditions, high demand periods can frequently coincide with low price periods, during which wind and/or solar electricity output is relatively high and vice versa. On the other hand, efficiency gains from comprehensive RTP adoption probably rise substantially with VRE as does, accordingly, the amount of welfare gains left on the table

from rejecting RTP (cf. Kopsakangas Savolainen and Svento, 2012; Gambardella et al., 2016). Additionally, consumer heterogeneity matters, that is it matters which type of consumer tends to reject RTP, as inefficiencies from flat pricing depend on individual or sector-specific demand characteristics (Holland and Mansur, 2006; Borenstein, 2013). If demand covaries relatively strongly with the wholesale price, consumption under flat pricing will deviate comparatively much from optimal consumption levels, adjusted to the actual marginal costs of supply. Aggregate residential and commercial electricity demand in the German or U.S. markets is typically high when prices and aggregate demand are high and vice versa. Instead, industrial consumers usually have a rather even demand pattern. Hence, the amount of unrealized welfare gains could be comparatively large, if, as suggested in the literature, mostly residential and small commercial customers stick with flat pricing, holding *average demand size* fixed.

The first part of this work therefore studies how increasing VRE deployment could influence the distributional effects from RTP among residential consumers. In the second part, we analyze the welfare implications of consumer heterogeneity and selective RTP adoption by comparing the potential unrealized welfare gains from low RTP adoption in the residential, commercial or industrial consumer sector for varying renewable supply shares. Specifically, we compare scenarios in which residential and commercial consumers remain mostly flat priced, while the industrial sector is fully real-time priced to the converse case. To estimate the potential electricity bill and consumer surplus changes from RTP, we simulate long-run wholesale and retail prices by applying a stylized model of a perfectly competitive wholesale and retail electricity market based on Borenstein and Holland (2005). The model is loosely calibrated to load and price data of the German electricity spot market from 2015, and to fossil-fueled generation parameters fitting the German power market setting. Investment in renewable generation technologies is carbon tax induced. Our model further captures sectoral consumer heterogeneity with regard to consumption size and patterns. Electricity demand thus consists of the three main customer segments of electricity markets; the residential, commercial and industrial sector. Characteristic consumption time series data is derived from synthetic load profiles for the German commercial and residential sector, as used by German transmission and distribution system operators. These profiles are calibrated to match the empirical annual consumption volumes and shares in aggregate electricity demand in Germany for 2015.

Using hourly data on residential consumption from Germany, we find that the distributional effects from implementing RTP are mitigated at high variable renewable supply shares. The distribution of bill changes compresses so that the majority of consumers faces only moderate electricity bill increases or decreases of less than 5%. Nonetheless, residential and small commercial consumers might still perceive to rather

lose from RTP and thus refrain from tariff switching.

Thus quantifying the welfare implications from selective RTP adoption, we find that the annually unrealized welfare gains could be roughly 18% to 57% larger, if residential and commercial consumers stick to flat pricing instead of industrial consumers. The difference in foregone welfare gains increases with the renewable supply share in absolute, yet not in relative terms. Specifically, this difference roughly doubles from 70 to 162 million EUR per year, making up 16% and 8% of the potential welfare gains from comprehensive RTP adoption, respectively, if VRE supply shares increase from zero to 75%. The total amount of unrealized welfare gains if residential and commercial consumers remain flat priced more than quadruples from 228 million to 1.1 billion EUR per year. Each of the 50.3 million electricity customers in Germany would thus miss out on surplus gains equal to 5 to 22 EUR per year, respectively. While these numbers are moderate, it is important to note that they do not reflect the possibly substantial increases in future (residential) electricity demand, which might result from utilizing electrified heating, cooling and transportation in low carbon power markets. The amount of unrealized welfare gains if residential and commercial customers reject RTP could therefore be much higher.

Importantly, we find that RTP adoption can entail negative cross-sectoral externalities, which partially explain the aforementioned difference in foregone welfare gains. More specifically, RTP adoption in the industrial sector can inflate flat rates in the residential and commercial sector. The corresponding losses translate into larger foregone welfare gains if these sectors remain flat priced. However, this negative pecuniary externality reduces with growing supply from variable renewables. Still, residential flat rate consumers can also be harmed at high VRE supply shares. So far, this aspect has not gained much attention in the literature, where it is argued that dynamic pricing programs should be targeted at large industrial or commercial customers with favorable cost-benefit ratios (cf. Leautier, 2014).[1] While this seems justified from a mere efficiency perspective, the distributional effects of selective RTP adoption across sectors may pose yet another acceptance barrier to implementing RTP programs.

This work contributes to the literature on both the distributional and welfare im-

[1]This is also reflected in current regulations and market practices. For instance, the German government has decided to roll-out smart-meters only to industrial and large commercial customers in the coming years. The medium run target is to provide real-time meters also to residential (and small commercial consumers), who consume at least six megawatt hours (MWh) per year, which is far above the current average residential consumption level of about 3.2 MWh annually. The critical peak pricing program by one of California's largest private utilities, Pacific Gas & Electric (PG&E), is targeted only at large industrial and commercial customers. The first real RTP program in Germany, initiated by NEXT Kraftwerke, a German trading company that aggregates distributed generation facilities, also focuses on large commercial customers (https://www.next-kraftwerke.de/virtuelles-kraftwerk/stromverbraucher/variabler-stromtarif).

pacts of real-time pricing in four major ways. First, by accounting for consumer heterogeneity at the sector level, we use a novel approach in the comparative welfare analysis of real-time pricing. Related studies have thus far relied on modeling a representative consumer whose demand pattern is based on aggregate, hourly load data (Borenstein, 2005; Allcott, 2012; Chao, 2011; Mills and Wiser, 2014). By applying heterogeneous consumption data instead, we are able to identify important economic mechanisms driving the welfare effects from implementing RTP and to simulate equilibrium effects more realistically. Importantly, as this also allows us to analyze potential cross-sectoral welfare effects, we complement previous work on the intra-sectoral distributional effects of real-time pricing, which focused either on the residential, commercial or industrial sector (Borenstein, 2007, 2012). Moreover, to our knowledge this is the first attempt to analyze the changes in the distributional effects resulting from carbon tax induced VRE deployment and corresponding changes in the long-run generation portfolio. Finally, we contribute to both the literature on real-time pricing and an increasing body of studies on the assessment of demand response as a technological option to integrate renewables (Mills and Wiser, 2014; Brouwer et al., 2016; Bertsch et al., 2016). In contrast to most other studies, we explicitly analyze the interaction of policy instruments driving endogenous variable renewable entry, such as carbon taxation, and renewable supply characteristics on consumer welfare.

The paper proceeds as follows: Section 2 briefly describes the partial equilibrium model used in the numerical simulations. Section 3 provides intuition on the main mechanisms arising from consumer heterogeneity, which drive the numerical welfare results. Section 4 describes the data. Numerical results are presented and discussed in Section 5. Section 6 discusses the main limitations of our approach and the robustness of our findings. Section 7 concludes.

2. An electricity market model with heterogeneous consumers

The formal model builds largely on Borenstein and Holland (2005) and Gambardella et al. (2016), and forms the basis of the numerical open source model LORETTA Version 1.0.1 (Gambardella, 2017), briefly described in section 4.2.

2.1. Demand

There are T periods indexed t and I consumer sectors (types) indexed $i \in I$, e.g. the industrial, commercial and residential consumer sector. All consumers have the same demand function $d_{it}(p, a_{it}) = a_{it}p^{\epsilon}$, with constant own-price elasticity $-1 < \epsilon < 0$. Consumers differ with regard to their characteristic demand pattern $\{a_{it}\}_t^T$, entering $d_{it}(p, a_{it})$ as a scale parameter in each period, which also reflects the respective consumption share in total demand, $\gamma_i \in [0, 1]$. Let $d_{it}(\bar{p}_i, a_{it})$ and $d_{it}(p_t, a_{it})$ denote

electricity demand by flat and real-time priced (RTP) consumers of type i in period $t \in T$, respectively. The exogenous share of RTP consumers in sector i, $\alpha_i \in [0,1]$, faces the retail real-time electricity price p_t varying over all t, while the remaining $(1-\alpha_i)$ flat rate consumers pay the time-invariant tariff (flat rate) $\bar{p}_i$.[2] In each period t, aggregate demand, $D_t(\mathbf{p})$, thus equals the sum of RTP and flat rate consumer demand of each consumer sector i, that is

$$D_t(\mathbf{p}) = \sum_i^I \left(\alpha_i d_{it}(p_t, a_{it}) + (1-\alpha_i)\, d_{it}(\bar{p}_i, a_{it})\right),$$

where $\mathbf{p}$ is the vector of retail prices. If the RTP share in sector i, α_i, increases, more consumers of type i reduce (increase) demand as soon as the real-time retail rate exceeds (falls below) the previously paid flat rate, i.e. as soon as $p_t > \bar{p}_i$ ($p_t < \bar{p}_i$). Hence, demand in sector i, $D_{it}(\bar{p}_i, p_t, a_{it})$, rotates around the point $(D_{it}(\bar{p}_i, p_t), \bar{p}_i)$ in each period t, as does aggregate demand $D_t(\mathbf{p})$. The larger demand a_{it} in sector i is on average, the larger is the change (rotation) in aggregate demand when α_i increases. For simplicity, we ignore that consumers could also differ regarding their elasticity to price (own- or cross-price elasticity).[3] The differences in scale and demand pattern thus mainly drive the differences in welfare changes from sectoral RTP adoption shown below.

2.2. Supply and capacity investment

There are $N+1$ generation technologies indexed by $n \in [0, N]$, comprising of conventional, fossil-fueled technologies and the variable renewable (VRE) generation technology $n = 0$, such as wind or solar power.[4] Up to capacity, each technology n generates electricity at constant marginal generation costs, c_n , expressed in EUR per megawatt-hour (MWh), and has constant, annuitized marginal fixed costs, fc_n, expressed in EUR per megawatt (MW) per year. Marginal generation costs of technology n are given as $c_n(f_n, c_n^{om}, \tau, e_n) = f_n + c_n^{om} + \tau e_n$ and thus consist of exogenous fossil-fuel costs, f_n, operation and maintenance cost, c_n^{om}, and carbon emission costs, τe_n, where τ is the exogenous tax (in EUR) per ton of carbon dioxide emissions and $e_n \in [0,1]$ is the technology-specific carbon emission factor per unit of electricity generated. Emitting

[2] Consumer type-specific flat tariffs imply that we ignore cross-subsidization of consumption between consumer groups.

[3] We also simulate scenarios, in which consumers also differ with respect to their own price elasticity.

[4] Without loss of relevant model mechanisms, we assume only one VRE technology mainly for notational simplicity. In the numerical application we assume one wind and solar generation technology, respectively. More importantly, we abstract from nonvariable and carbon emission free technologies, such as nuclear energy, as well as dispatchable renewable technologies such as biomass. This restrictive assumption matches the specific German long-run market situation and similar markets, where nuclear energy will be phased out.

no carbon dioxide (i.e. $e_0 = 0$) and having no input costs other than operation and maintenance costs (i.e. $f_0 = 0$), the renewable technology generates electricity at the almost zero marginal costs, that is $c_0 \leq c_{n\geq 1}$.

Installed capacity (in MW) of technology n is denoted k_n and cumulative installed capacity is $K = \sum_n^N k_n$, where N represents the supply technology with the highest marginal generation to fixed cost ratio in equilibrium. The availability of installed renewable capacity, $av_{0t} \in [0, 1]$, depends on varying wind speeds or solar radiation and varies accordingly in each period t, whereas conventional capacity is always fully available ($av_{nt} = 1$ for all $n > 0$).

Generators using technology n decide upon investment in capacity k_n and upon output q_{nt} (in MWh) in period t by maximizing total profits $\pi_n (q_{nt}, k_n, w_t) = \sum_t^T [w_t - c_n] q_{nt} - fc_n k_n$ under perfect competition, and thus take the electricity wholesale price w_t as given. In each t, output is limited by available capacity such that $q_{nt} \leq av_{nt} k_n$ for each technology n. If marginal revenue, w_t, exceeds marginal costs c_n, the competitive generator optimally produces at available capacity of technology n, i.e. $q_{nt} = av_{nt} k_n$, produces nothing if $w_t < c_n$, and is indifferent between any output level if $w_t = c_n$. Hence, each technology has an inverse L-shaped supply curve so that aggregate wholesale supply is a step function (merit order) where each plateau reflects the constant marginal costs of each supply technology present in equilibrium (cf. Holland and Mansur, 2006).

Competitive generators invest in capacity of technology n k_n until its marginal fixed costs fc_n equal the cumulated marginal short-run profits (or marginal value) $\sum_t^T av_{nt} [w_t - c_n]$, giving the first-order condition with regard to investment choice as:

$$\sum_t^T av_{nt} [w_t - c_n] \quad = \quad fc_n, \forall n \in N. \tag{1}$$

Marginal generation costs of fossil-fueled technologies, $c_n (f_n, c_n^{om}, \tau, e_n)$, rise linearly with the carbon tax τ, which therefore reduces the profitability of investments in fossil-fueled technologies relative to investments in renewable capacity, k_0. To allow for large-scale renewable supply in the long-run equilibrium under carbon taxation, the average wholesale electricity price $\bar{w}$ is required to increase sharply. This is mainly a consequence of the quite robust finding that cumulated marginal short-run profits of variable renewable technologies decrease more or less exponentially with variable renewable capacity expansion (cf. Lamont, 2008; Green and Léautier, 2015). The sharp drop in VRE short-run profits is mainly due to the wholesale price deflation particularly during periods of high resource availability av_{0t} (e.g. windy and/or sunny periods)[5]

[5]In other words, the idiosyncratic covariance of the renewable resource availability and wholesale price, which Lamont (2008) defines as the "system matching component", decreases with capacity

(Lamont, 2008). Accordingly, for condition (1) to hold, each increment in k_0 (or in renewable energy supply) requires an ever larger increase in the average wholesale price in periods, during which av_{0t} is relatively low and conventional technologies are setting the price. Beyond a certain VRE entry level, this can only be achieved through an exponentially increasing carbon tax, which sufficiently raises the marginal costs of conventional technologies and thereby also the average wholesale price level (cf. Kopsakangas Savolainen and Svento, 2012; Green and Léautier, 2015). As is explained in more detail below, this mechanism will induce very large electricity price spreads in few periods, determining consumers' surplus gains from adopting RTP at high renewable supply shares.

2.3. Electricity retail

We assume homogeneous retail firms sell electricity on to consumers under perfect competition, which they buy from the electricity wholesale market at the wholesale price w_t. Thus, having only electricity procurement costs, retailers choose the respective retail flat rate, $\bar{p}_i$, for each sector i and the real-time retail price, p_t, such as to maximize their total profit $\pi^r(p_t, \bar{p}_i, w_t)$. Total retail profits then read as:

$$\pi^r = \sum_t^T \sum_i^I \left[\alpha_i (p_t - w_t) d_{it}(p_t, a_{it}) + (1 - \alpha_i)(\bar{p}_i - w_t) d_{it}(\bar{p}_i, a_{it})\right]. \tag{2}$$

Retailers do not cross-finance consumption costs among real-time and flat priced consumers as well as among the I customer sectors. Since customers have no transaction costs from switching retailers, perfectly competitive retail firms make zero profits from selling electricity. In each period in equilibrium, retailers therefore set the real-time retail price for electricity equal to the real-time wholesale price, that is $p_t = w_t \ \forall t$. The group-specific competitive equilibrium flat rate equals the idiosyncratic demand weighted average of the wholesale price:

$$\bar{p}_i = \frac{\sum_t^T w_t d_{it}(\bar{p}_i, a_{it})}{\sum_t^T d_{it}(\bar{p}_i, a_{it})}. \tag{3}$$

In the numerical analysis that follows below, two mechanisms influencing $\bar{p}_i$ are important in explaining the sectoral and cross-sectoral welfare changes from differing sectoral RTP adoption rates. First, as $\bar{p}_i$ is a demand weighted average, it depends positively on $Cov(a_{it}, p_t)$, that is on the idiosyncratic covariance of the demand scale parameter a_{it} and the real-time retail price p_t, noting again that in equilibrium $p_t = w_t$. Rearranging (3) to derive the sectoral flat rate, $\bar{p}_i$, as a function of $Cov(a_{it}, p_t)$ by

entry of the renewable technology.

applying the definition of the sample covariance gives

$$\bar{p}_i = \frac{T\left(Cov\left(a_{it}, p_t\right) + \bar{p}_t \bar{a}_{it}\right)}{\sum_t^T a_{it}}, \tag{4}$$

, where $\bar{a}_{it}$ and $\overline{p_t}$ are time-weighted averages. It follows easily that $\partial \bar{p}_i \left(Cov\left(a_{it}, p_t\right), \bar{p}_t, a_{it}\right) / \partial Cov\left(a_{it}, p_t\right) > 0$ and $\partial \bar{p}_i \left(Cov\left(a_{it}, p_t\right), \bar{p}_t, a_{it}\right) / \partial \bar{p}_t > 0$. As discussed in section 3.2, demand price covariance of sector i, $Cov\left(a_{it}, p_t\right)$, may increase if RTP is adopted by consumers of a different sector, such that flat priced customers of sector i may face an increase in their retail rate. Moreover, independent of the particular demand and price covariance, flat rates increase with renewable capacity entry in each sector, i.e. $d\bar{p}_i / dK_0 > 0$, since the average wholesale price $\bar{w}_t$ has to increase for reasons described in the previous section. This will basically imply that within an increasing fraction of periods, during which electricity is supplied at almost zero-marginal costs by renewables, flat rate based consumption is significantly more distorted than before renewables enter the market. Higher efficiency losses, in turn, imply that potential consumer surplus gains from switching to RTP can increase considerably in each sector with renewable supply (see section 3.3).

3. Welfare effects from exposing heterogeneous consumers to real-time retail pricing

Our analysis is based on comparing welfare changes from adopting or rejecting real-time pricing by different types of consumers (consumer sectors). Since retailers and generators make zero profits in the long-run equilibrium, total net welfare changes equal total net consumer surplus changes.[6] In each sector, total consumer surplus changes constitute of surplus changes by customers who switch from flat rate to real-time pricing, $\triangle CS_i^s = \sum_t^T \int_{p_{1t}}^{\bar{p}_{0i}} \left(\alpha_{1i} - \alpha_{0i}\right) a_{it} x^{\epsilon} dx$, by customers who remain on flat rate tariffing, $\triangle CS_i^f = \sum_t^T \int_{\bar{p}_{1i}}^{\bar{p}_{0i}} \left(1 - \alpha_{1i}\right) a_{it} x^{\epsilon} dx$, and by incumbent RTP customers, $\triangle CS_i^r = \sum_t^T \int_{p_{1t}}^{p_{0t}} \alpha_{0i} a_{it} x^{\epsilon} dx$ (Borenstein and Holland, 2005). Variable and parameter values before and after the RTP share in sector i changes are indexed by 0 and 1, respectively.[7] Total net consumer surplus changes of incumbent RTP consumers are then given by

$$\Delta CS^r \quad = \sum_i^I \sum_t^T \quad \left[\frac{\alpha_{0i} a_{it}}{\epsilon + 1}\left({p_{0t}}^{\epsilon+1} - {p_{1t}}^{\epsilon+1}\right)\right]. \tag{5}$$

[6] Hence, we basically compare the compensating variations in each sector from raising the RTP share in different sectors to different levels, ignoring the private costs of RTP such as costs for metering infrastructure or transaction and adjustment costs.

[7] Consumers adopting real-time pricing are paying $\bar{p}_{0i}$ before and p_{1t} after switching in each period t.

Total surplus changes of tariff-switching consumers read as

$$\Delta CS^s = \sum_i^I \sum_t^T \left[\frac{(\alpha_{1i} - \alpha_{0i})\, a_{it}}{\epsilon + 1} \left(\bar{p}_{0i}^{\epsilon+1} - p_{1t}^{\epsilon+1} \right) \right]. \tag{6}$$

Finally, total surplus changes of flat rate consumers as

$$\Delta CS^f = \sum_i^I \sum_t^T \left[\frac{(1 - \alpha_{1i})\, a_{it}}{\epsilon + 1} \left(\bar{p}_{0i}^{\epsilon+1} - \bar{p}_{1i}^{\epsilon+1} \right) \right]. \tag{7}$$

In previous work, Borenstein and Holland (2005) show for a representative electricity consumer (homogeneous consumers) that under standard assumptions $\Delta CS^r < 0$, $\Delta CS^f > 0$ and $\Delta CS^s > 0$, that is incumbent RTP consumers lose when the aggregate share of real-time priced consumers rises, while flat rate consumers as well as consumers switching to real-time pricing gain surplus. Total welfare changes from introducing RTP, i.e. $\Delta CS = \Delta CS^r + \Delta CS^s + \Delta CS^f$, are usually found to be positive in many applications to real electricity systems as mentioned above.

The primary purpose of modeling consumer heterogeneity is to compare the unrealized welfare gains of selective instead of comprehensive RTP adoption. This analysis is motivated by arguments found in the RTP literature, suggesting that mostly large, predominantly industrial customers could be willing to enroll in RTP or other dynamic pricing programs, since having rather low private costs, yet, potentially high benefits. In practice, many programs incentivizing demand sided response are targeted at large industrial or commercial customers (cf. Faruqui and Sergici, 2010; Faruqui et al., 2012; Blonz, 2016; FERC, 2016).[8] This raises the question about how much welfare gains might be left on the table under targeted RTP tariffing, or whether allocative inefficiencies from exposing residential and/or small commercial consumers to flat electricity pricing might actually be larger than if industrial customers are flat priced. In this regard, previous work has already demonstrated how overall welfare changes from RTP can depend on which type of consumers adopt RTP. The reasoning goes along the specific covariance of demand and price, $Cov\,(a_{it}, p_t)$, that characterizes the different consumer sectors. The more sectoral demand is skewed towards high price periods, that is the more "peaky" it is, so that $Cov\,(a_{it}, p_t)$ is relatively large, the larger are the potential total welfare gains from implementing RTP in this sector (cf. Borenstein, 2005; Holland and Mansur, 2006). This follows the reasoning that "overconsumption" during high- or peak-price periods is the main source of allocative inefficiency arising from flat retail pricing. Put differently, efficiency gains from RTP are considered to

[8] For example, PG&E, a large Californian utility deploys a critical peak-pricing program which is mainly tailored to large industrial or commercial customers.

consist mainly of cost savings in expensive peak-load generation capacity, which stands idle most of the time. Hence, the amount of unrealized efficiency gains would be comparatively large, if mainly "peaky" consumer types, such as residential or commercial consumers, would remain on their flat tariffs.

However, this intuition mainly suffices to explain the benefits of RTP in a conventional market, where mostly dispatchable technologies supply energy so that prices are high when demand is high and vice versa. Yet, as will be explained in section 3.3 in a system with large-scale variable renewable energy supply, prices may occasionally be very low (high) during high (low) demand periods. In other words, demand and price likely covary less for many consumers, and due to the rising incidence of low- to zero price periods, inefficiencies from flat retail pricing may increasingly be attributable to "underconsumption" in low price periods rather than "overconsumption" during high price periods. Hence, the differential effect on total welfare changes from selective RTP adoption could thus increasingly depend on the covariation of characteristic demand patterns and variable renewable output profiles.

Consequently, in order to analyze the changing impact of consumer heterogeneity on the benefits of RTP, we will compare the total welfare gains, ΔCS, when RTP is adopted by either relatively "peaky" or relatively "flat" consuming customers, and then check, how the differences in welfare gains change with growing variable renewable electricity supply shares in equilibrium.

Finally, modeling heterogeneous consumer sectors allows us to decompose the aggregate welfare changes from RTP into sectoral welfare effects, and thus to also look at potential cross-sectoral distributional effects. We thereby can complement previous studies, which have so far emphasized the role of intra-sectoral distributional effects or, that is, the redistribution of consumption costs from introducing RTP.[9] Hence, we can quantify the external effects from selective RTP adoption or targeted RTP implementation, as we will discuss in section 3.2 in more detail. More specifically, we will provide intuition on how selective RTP adoption may exert negative price effects on a potentially large number of flat priced customers in sectors. Thus, not only intra-sectoral, but also cross-sectoral distributional effects could pose a social acceptance barrier to the roll-out of retail real-time pricing programs.

3.1. The components of consumer surplus changes from real-time pricing

As indicated in the previous section, both sectoral and cross-sectoral consumer welfare effects from real-time pricing can be attributed to the idiosyncratic demand and

[9] Consumption costs are redistributed among consumers of the same type/sector, e.g. the residential sector, if facing the same flat rate but having differing demand patterns, so that some customers cross-finance electricity costs of other customers.

price covariation. In order to derive some basic intuition on this relationship, we use expression (6) and (7) and derive the consumer surplus gains from switching to RTP or remaining flat priced in sector i as functions of the specific price demand covariance $Cov\left(a_{it}, p_{0t}\right)$, which then read as:[10]

$$\Delta CS_i^s = T\varphi_i \left[\bar{a}_{it}\left(\bar{p}_{0i}^{\epsilon+1}\left(Cov\left(a_{it}, p_{0t}\right)\right) - \overline{p_{1t}^{\epsilon+1}}\right) - Cov\left(a_{it}, p_{1t}\right)\right], \tag{8}$$

$$\Delta CS_i^f = T\phi_i \bar{a}_{it}\left[\bar{p}_{0i}^{\epsilon+1}\left(Cov\left(a_{it}, p_{0t}\right)\right) - \bar{p}_{1i}^{\epsilon+1}\left(Cov\left(a_{it}, p_{1t}\right)\right)\right], \tag{9}$$

where $\varphi_i = \left(\alpha_{1i} - \alpha_{0i}\right)/(\epsilon+1)$, $\phi_i = \left(1 - \alpha_{1i}\right)/(\epsilon+1)$ and $\bar{p}_i\left(Cov\left(a_{it}, p_{0t}\right)\right)$ is given by equation (4) in section 2.3.

Equation (8) contains two intuitive components driving consumer surplus changes from switching to RTP, ΔCS_i^s. The first component is the "average overconsumption", represented by the spread between the particular flat rate (before switching) and the average real-time retail price (after switching), $\bar{p}_{i0}^{\epsilon+1}\left(Cov\left(a_{it}, p_{0t}\right)\right) - \overline{p_{1t}^{\epsilon+1}}$. The second component is the "system mismatching component" (cf. Lamont, 2008), represented by the specific covariance of demand and real-time retail price, $Cov\left(a_{it}, p_{1t}\right)$. The "overconsumption" component reflects that inefficiencies from flat pricing increase with the tendency to demand much electricity during periods in which it is generated rather expensively. The more this is the case, the larger is the spread between the flat rate, $\bar{p}_{0i}$, and the average wholesale price $\bar{w}_t = \bar{p}_t$, and thus $\overline{p_{1t}^{\epsilon+1}}$. Therefore, the efficiency gains from responding to high supply costs in real-time are correspondingly larger, too. In turn, the "system mismatching component" implies that individual benefits from switching to RTP increase with the tendency to have high electricity demand during low price periods, where $p_{1t} < \bar{p}_{i0}$, and vice versa.[11] Below we discuss how increasing variable renewable electricity supply can significantly decrease $Cov\left(a_{it}, p_{1t}\right)$, while $\bar{p}_{i0}$ is relatively high, such that switching to RTP becomes increasingly beneficial for all types of customers, in particular for those consumer types, whose demand covaries rather strongly with price in absence of VRE supply (i.e. in a conventional system).

Moreover, equation (9) contains another mechanism, important to consider when analyzing the distributional implications from selective RTP adoption or targeted RTP

[10] Applying the definition of the sample covariance, $Cov\left(x, y\right) = \frac{1}{N}\left[\sum_n^N \left(x_n y_n\right) - N\bar{x}\bar{y}\right]$ by adding $\left(T\bar{a}_{it}\overline{p_{1t}^{\epsilon+1}} - T\bar{a}_{it}\overline{p_{1t}^{\epsilon+1}}\right)$ in equation (6) yields

$$\Delta CS_i^s \quad = \quad T\frac{\varphi_i}{T}\left[\sum_t^T a_{it}\bar{p}_{0i}{}^{\epsilon+1} - T\bar{a}_{it}\overline{p_1^{\epsilon+1}} - \left(\sum_t^T a_{it}p_{1t}^{\epsilon+1} - T\bar{a}_{it}\overline{p_{1t}^{\epsilon+1}}\right)\right]$$

, which gives $\Delta CS_i^s = \Delta CS_i^s\left(\bar{p}_{0i}, \bar{p}_{1t}, Cov\left(x, y\right)\right)$ as in (8).

[11] Put differently, consumer surplus gains from adopting RTP, ΔCS_i^s, are the larger, the lower $Cov\left(a_{it}, p_{1t}\right)$ is relative to the "average overconsumption" component.

implementation and consumer (sector) heterogeneity. Specifically, equation (9) implies that if consumer demand of sector i covaries stronger with price subsequent to a change in the share of RTP consumers in another sector, such that $Cov\left(a_{it}, p_{1t}\right)$ increases, then customers of sector i can lose since facing a higher flat rate (cf.section 2.3), $\bar{p}_{1i}^{c+1}\left(Cov\left(a_{it}, p_{1t}\right)\right)$. Hence, while efficiency is augmented on aggregate, if customers of a particular sector adopt or are exposed to RTP, such selective adoption/implementation could entail politically problematic distributional consequences. In the following section, we provide heuristics on how RTP adoption in one sector could negatively affect flat priced consumer surplus in another sector.

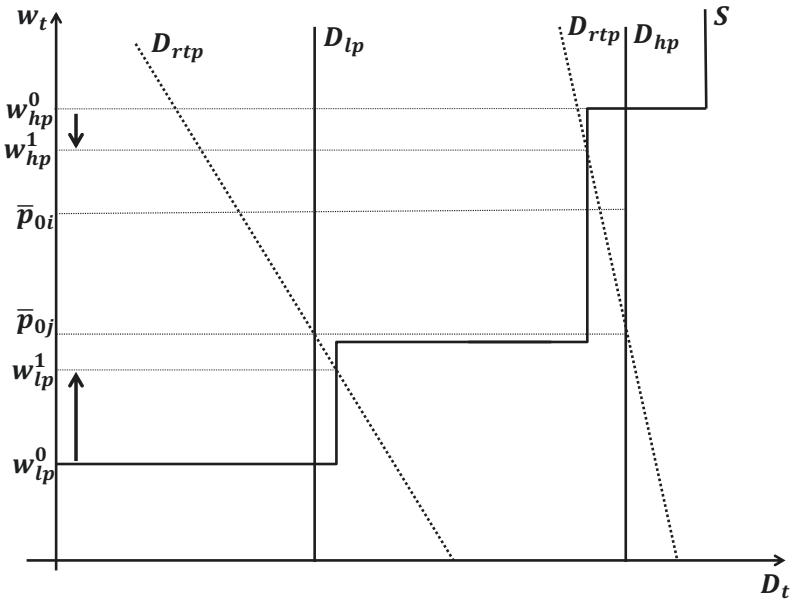
3.2. Cross-sectoral welfare effects from incomplete real-time pricing

In this section, we briefly illustrate the possible external price and cross-sectoral welfare effects of selective RTP adoption, by discussing how increments in the RTP share of sector j, α_j, could change the wholesale price distribution, and thus the flat rate paid by sector i consumers, $\bar{p}_{1i} = \bar{p}_{1i}\left(Cov\left(a_{it}, p_{1t}\right)\right)$. As we show below, given the according change in the covariation of demand and price in sector i, $Cov\left(a_{it}, p_{1t}\right)$, flat priced consumers in sector i can pay more or less than before sector j adopts RTP, and thus can either incur surplus losses or gains.[12] Here, we focus on the politically relevant case, in which RTP adoption in sector j exerts a negative pecuniary externality, that is $Cov\left(a_{it}, p_{1t}\right)$ and therefore $\bar{p}_{1i}$ increase such that consumers in sector i lose, i.e. $\Delta CS_i^f < 0$.

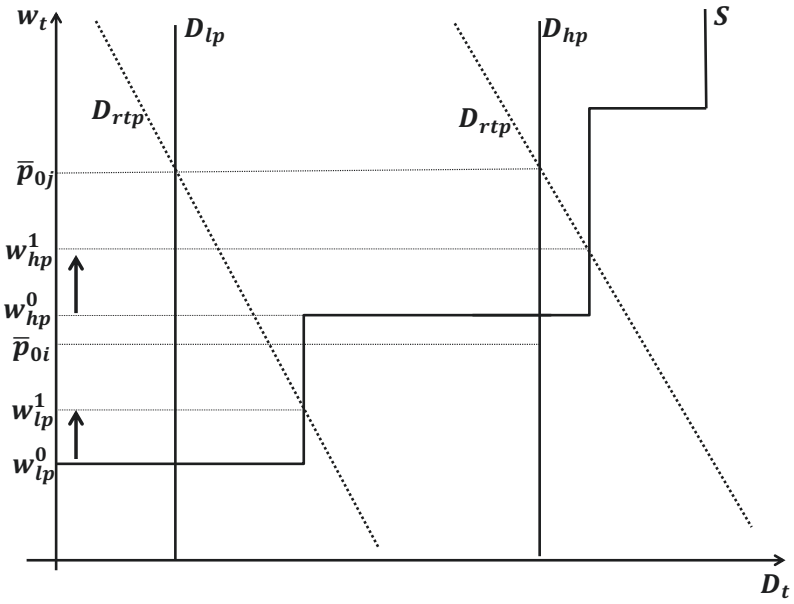
One can distinguish two cases, in which an increasing RTP share in sector j can raise the covariation of sector i demand and wholesale prices, $Cov\left(a_{it}, p_{1t}\right)$, and thus the corresponding flat retail rate, $\bar{p}_{1i}$. First, $Cov\left(a_{it}, p_{1t}\right)$ rises, if on average prices increase sufficiently stronger during low-price periods (i.e. $\bar{p}_{0i} > w_t$) than they drop during high price periods (i.e. $\bar{p}_{0i} < w_t$). Second, $Cov\left(a_{it}, p_{1t}\right)$ rises if prices increase both in low- and many high-price periods. The former case applies if sector i demand is initially "peakier" than sector j demand, whereas in the latter case it is the other way around. Each case is depicted in Panel 1a and 1b of Figure 1, respectively, which gives a stylized presentation of the short-run wholesale market equilibrium.

If $Cov\left(a_{it}, p_{0t}\right)$ is initially larger than $Cov\left(a_{jt}, p_{0t}\right)$, then $\bar{p}_{0i}$ is larger than $\bar{p}_{0j}$ before (and after) sector j adopts RTP (Panel 1a). An increase in the RTP share α_j implies that the *aggregate* demand curve rotates around the point $\left(D_{jt}\left(\bar{p}_{0j}, p_t\right), \bar{p}_{0j}\right)$ in each period (see section 2.1). This is reflected by the change from the solid to the dashed

[12] If consumers in sector i also switch to RTP, their surplus gains will of course also be affected by RTP adoption in a different sector, possibly in the same direction. For instance, if $Cov\left(a_{it}, p_{1t}\right)$ increases with α_j, then consumer surplus gains from switching to RTP in sector i, ΔCS_i^s, are comparatively lower than if α_j would not change.



(a) Sector i demand "peakier" than sector j demand.



(b) Sector j demand "peakier" than sector i demand.

Figure 1 Wholesale market equilibrium with and without RTP consumers.

Note. - D_{lp} and D_{hp} represents the aggregate demand curve during low- and high-price periods, respectively, when all consumers are flat priced. D_{rtp} gives aggregate demand after sector j has switched to real-time pricing, and thus rotates around the point $(D_{jt}(\bar{p}_{0j}, p_t), \bar{p}_{0j})$, since sector j consumers demand more in periods, in which their previous flat rate is lower than the wholesale price, i.e. $\bar{p}_{0j} > w_t$, and less in periods where $\bar{p}_{0j} < w_t$. The original flat rate in sector i, $\bar{p}_{0i}$, is higher than $\bar{p}_{0j}$, if sector i demand covaries stronger with price (Panel 1a), and lower the other way around (Panel 1b). The wholesale price in low- and high price periods before sector j adopts RTP, w_{lp}^0 and w_{hp}^0, is defined by the intersection of the inelastic demand curve, D_{lp} and D_{hp}, with the aggregate supply curve, S, which depicts the marginal generation costs of the equilibrium generation technology portfolio. The wholesale price in low- and high price periods after sector j adopts RTP, w_{lp}^1 and w_{hp}^1, is defined by the intersection of the elastic demand curve, D_{rtp}, with the aggregate supply curve.

demand curve for an exemplary low- and high-price period in each panel, respectively. For analyzing the corresponding wholesale price changes, only the intersections along the vertical segments of the stepwise supply curve are of interest. Thus, while real-time priced consumers in sector j start to reduce consumption, when wholesale prices w_t exceed their previously paid flat rate and the flat rate paid by sector i consumers, they increase consumption when w_t is below $\bar{p}_{j0}$ and thus also below $\bar{p}_{0i}$. Wholesale prices decrease and increase correspondingly. Additionally, w_t also falls in periods where $\bar{p}_{0j} < w_t < \bar{p}_{i0}$, which is not shown. Ultimately, sector i faces a higher flat rate, $\bar{p}_{1i}$, due to RTP in sector j, if the wholesale price increases in low-price periods, where $w_t < \bar{p}_{0j} < \bar{p}_{i0}$, are sufficiently larger than the price drops in other periods. This is particularly the case, if sector j demand, a_{jt}, is relatively large in these periods, as it determines the size of the hourly consumption change (demand curve rotation) following RTP adoption and the according retail price change, $\bar{p}_{0j} - p_{1t}$. Additionally, a_{it} has to be sufficiently large in these periods, too, as this determines the demand weight of sector i in these periods, and thus the increase in $\bar{p}_{1i}$.[13]

Panel 1b of Figure 1 shows the case in which sector j demand is "peakier" than sector i demand, that is $Cov\left(a_{it}, p_{0t}\right) < Cov\left(a_{jt}, p_{0t}\right)$, so that the flat rate in sector j initially exceeds the flat rate in sector i, $\bar{p}_{0i} < \bar{p}_{0j}$. Accordingly, RTP adoption in sector j implies that tariff switching consumers start to increase consumption also in periods where $\bar{p}_{i0} < w_t < \bar{p}_{0j}$. Therefore, from sector i's perspective wholesale prices not only decrease, yet also increase during high price periods, where $\bar{p}_{i0} > w_t$. In addition, w_t increases as before during low-price periods, where $\bar{p}_{i0} < w_t$. Again, whether and to what extent flat rate consumers of sector i lose, $\Delta CS_i^f < 0$, depends on the relative demand weight, that is on how large a_{it} and a_{jt} are in these periods, respectively.

3.3. Effects of carbon tax induced variable renewable supply on welfare gains from RTP

This section roughly outlines how growing, carbon tax induced VRE supply affects the welfare gains from RTP. The aggregate welfare gains from implementing RTP can increase by a magnitude of order with growing supply from VRE (Chao, 2011; Kopsakangas Savolainen and Svento, 2012; Gambardella et al., 2016). Particularly, sectoral consumer surplus gains from switching to RTP, $\Delta CS_i^s\left(\bar{p}_{0i}, \overline{p_{1t}^{c+1}}, Cov\left(a_{it}, p_{1t}\right)\right)$, can rise for two reasons. First, if VRE supply is at a large scale, tariff switching customers face occasional, yet potentially large, positive spreads between their previous flat rate

[13] Obviously, Figure 1 does not depict the long-run equilibrium effects of RTP on installed generation capacity K. As shown by Borenstein and Holland (2005), total installed capacity decreases with the RTP share. This implies that while peak- and maximum price levels decrease, peak-prices have to occur more frequently at lower levels to allow for sufficient short-run profits that finance peak-load technology entry. Hence, all consumers face more peak-price periods, which also contributes to the increase in sectoral flat rates.

and their real-time retail rate, $\bar{p}_{i0} - p_{1t} > 0$, which is again caused by two important changes in the electricity price distribution (Gambardella et al., 2016). On the one hand, the incidence of almost zero or very low wholesale prices increases as soon as aggregate demand can be fully served by renewables at zero-marginal costs during relatively windy and/or sunny periods, i.e during periods of high resource availability, av_{nt}. On the other hand, the specific flat rate, $\bar{p}_{0i} = \bar{p}_{0i}(w_t, \tau)$, inflates with renewable entry independent of whether the sector-specific demand and price covariance, $Cov(a_{it}, p_{0t})$, is originally high or low (see section 2.2), since the average equilibrium wholesale price, $\bar{w}_t$, has to increase considerably to allow for large-scale renewable capacity entry. Both effects intensify the "average underconsumption" effect from flat tariffing, so that efficiency gains from tariff switching rise. In addition, due to the increasing variability of supply, high (low) individual demand, captured by a_{it}, can more often coincide with low- (high-) price periods, so that more demand-weight is put on the positive flat-to-real-time-price spreads, $\bar{p}_{i0} - p_{1t} > 0$. This should then also be reflected in the "system mismatching component", $Cov(a_{it}, p_{1t})$, that is, in a decrease of demand and price covariation. Consequently, as welfare gains from adopting RTP increase considerably with supply from VRE technologies, so does the amount of unrealized welfare from rejecting RTP.[14] To what extent the amount of unrealized welfare gains differs, if some consumers reject while others adopt RTP, will particularly depend on the change in the "system mismatching component".

4. Data

4.1. Residential demand data to analyze intra-sectoral redistribution of consumption costs

As laid out in the introduction, our first aim is to analyze how variable renewable electricity supply changes the potential distributional effects of RTP within a certain customer segment. More specifically, we are interested in the individual electricity bill changes from being put on RTP, reflecting the amount of redistributed consumption costs within a given pool of retail customers. Individual bill changes mainly depend on the particular covariation of consumption and real-time (wholesale) price, and thus on the individual demand variation in each hour over a representative year. In section 5.1, we compute the electricity bill changes of heterogeneous residential customers, who are assumed to be switched from flat rate to real-time pricing (cf. Borenstein, 2007).

[14] Note that, the average availability factor of renewable capacity is usually rather low, so that low price periods occur only during a small fraction of all periods even at high renewable capacity entry levels. Still, these few occasions might suffice to render RTP in every consumer sector much more welfare improving than when renewables are absent.

Table 1 Descriptive statistics of 74 quasi-synthetic residential consumption profiles

Observations	Annual consumption [MWh/a]						Peak consumption [kWh]	
N	Mean	Maximum	Minimum	Q_1	Q_2	Q_3	Maximum	Minimum
74 X 8760	4.7	8.6	1.4	3.7	4.6	5.5	8.7	2.3

Note. - This table shows descriptives on the residential demand data, where Q1, Q2 and Q3 denote the first quartile, the median and the third quartile, respectively.

For this we use a publicly available data set of 74 different quasi-synthetic residential load profiles from HTW Berlin - University of Applied Sciences Research (2015), reflecting empirical distributions of residential consumption, gathered in separate grid regions of Germany in 2010. The total consumption of the sample amounts to 346.7 MWh for the reported year, during which the median and average customer consumed 4.6 MWh and 4.7 MWh, respectively. Minimum and maximum consumption levels amount to 1.4 MWh and 8.6 MWh per year, while the upper and lower quartile consumed 3.7 MWh and 5.5 MWh per year. Individual peak demand ranges from 2.3 kWh to 8.7 kWh with an average of 4.5 kWh. In 2015, the average three- to four-person household in Germany consumed about 4 MWh and 4.7 MWh, respectively.[15] These household-types only made up about 12.5 % and 9 % of all 40.8 million households in Germany for the same year.[16] In this regard our consumption data seems slightly skewed towards two to four-person households or towards above average one- to two-person households. However, the average consumption profile provides a good fit to the standard load profile of residential customers used by distribution and transmission system operators for hourly demand projections and is discussed below. This indicates that the data set captures the main daily, weekly and seasonal variations in the consumption patterns quite adequately such that the underlying heterogeneity in consumption patterns is representative to a certain extent, which is sufficient for our analysis.

We are specifically interested in assessing the changes of electricity bill changes resulting from increasing market penetration of variable renewable supply technologies. In doing so we will simulate long-run equilibria with different wind and solar power supply shares (see subsequent chapter) and use the equilibrium wholesale price data

[15] These statistics are obtained from http://www.die-stromsparinitiative.de/fileadmin/bilder/Stromspiegel/broschuere/Stromspiegel-2016-web.pdf.

[16] 41% of German households have been reported as single-person households and 31.4% as two-person households, which consumed about 2.6 MWh and 3.2 MWh in 2015, respectively. These statistics are obtained from https://www.destatis.de/DE/ZahlenFakten/Indikatoren/LangeReihen/Bevoelkerung/lrbev05.html;jsessionid=A58F76BF99528BC720343B409CB1C5FC.cae3.

to compute the break-even flat and real-time rates a retailer would charge each out of the above set of electricity customers under perfect competition. For each of the 74 consumption profiles, we then compute the incurred consumption costs under real-time pricing and flat-rate tariffing and subtract the former from the latter to derive individual electricity bill changes.

4.2. Cost and sectoral demand data for simulating electricity market equilibria

To simulate the long-run equilibrium effects of heterogeneous demand patterns, we group consumers into residential, industrial as well as commercial customers, indexed r, in and c, respectively, and create sector-specific hourly electricity demand profiles for a representative year. More specifically, for each sector we compute the characteristic demand scale parameter, a_{it}, which determines the shift of the isoelastic demand function, $d_{it}(p, a_{it}) = a_{it}p^{\epsilon}$, in each period t. Doing so first requires to obtain data on hourly demand, d_{it}, and then solve for a_{it}. As we do not dispose of empirical sector-specific demand data, we apply the standard load profiles (SLPs) for German commercial and residential consumers "$G0$" and "$H0$", provided by the Federal Association of Energy and Water Industries (BDEW). These profiles are used by all transmission and distribution system operators in Germany to forecast the characteristic consumption behavior by the commercial and residential customer segment in their network region during different times of the day, week and year. Standard commercial and residential demand profiles for 2015 are obtained from Stromnetz Berlin, the DSO for the Berlin grid region.[17] These profiles are calibrated to fit the empirical total residential and commercial electricity consumption in 2015, which is provided by the German energy information agency AG-Energiebilanzen.[18] While the industrial demand profile is usually projected as a constant load, we derive it from subtracting commercial and residential load from hourly aggregate load to match the aggregate load profile in the German transmission region. Aggregate hourly load data for 2015 is obtained from the time series data package version 2017-03-06 by Open Power System Data (2017).

To derive a_{it}, we also draw on German wholesale electricity price data for each hour in 2015 provided by Open Power System Data (2017), that is we use day-ahead auction clearing prices for each MWh traded at the European Power Exchange spot market (EPEX Spot SE). Based on the empirical wholesale price distribution, we compute the sector-specific break-even retail flat rate, $\bar{p}_i$, assuming $\alpha_i = 0 \ \forall i$. Subsequently, we insert $\bar{p}_i$ into the demand function and solve for a_{it} for each of the 8760 hours (cf.

[17] Each SLP is available at https://www.stromnetz.berlin/en/grid-user.htm.

[18] The data on final energy consumption in Germany, on which also Eurostat draws on, is available at http://www.ag-energiebilanzen.de/10-0-Auswertungstabellen.html.

Table 2 Descriptive statistics of the synthetic demand profile data

Sectoral demand profile	Share in total annual demand	Median	Mean	Maximum	Minimum	Variance	Covariance		
$d^*_{it}(a_{it}, \bar{p}^*_i)$	[%]	[GWh]	[GWh]	[GWh]	[GWh]	$Sd(d_{it})$	$Cov(d_{it}, D_t)$	$Cov(d_{it}, av_{w,t})$	$Cov(d_{it}, av_{s,t})$
Commercial	30.8	13.6	18.3	38.1	6.7	9.3	78.7	0.01	0.80
Residential	25.3	15.7	15.1	34.9	4.9	6.4	34.9	0.12	0.22
Industrial	43.9	25.4	26.1	50.5	0.2	8.1	-1.5	-0.06	-0.48
Total	100.0	59.0	59.4	80.1	36.0	10.6	112.0	0.07	0.54

Note. - This table shows descriptives on the characteristic (synthetic) demand profile of the residential, commercial and industrial consumer sector, d^*_{it}, respectively, from which the characteristic demand scale parameter, a_{it}, is computed. Columns 8, 9 and 10 at the right of the table show the covariance of sectoral demand with aggregate demand D_t, with the availability of wind and solar capacity, $av_{w,t}$ and $av_{s,t}$, respectively.

Borenstein, 2005).[19] In the base case we set own-price elasticity ϵ to -0.05, which is at the low end of empirical estimates (cf. Faruqui and Sergici, 2010; Allcott, 2011).

Table (2) gives some descriptive information about the synthetic sectoral demand profiles, d_{it}. Importantly, it shows that residential and commercial demand covary stronger with aggregate demand, and, thus, likely with wholesale prices than industrial consumption in the base case (no carbon taxation, no renewables entry). The comparative welfare analysis in section 5.2 is based on the difference in these demand characteristics. Hence, we compare scenarios of incomplete RTP adoption in the industrial sector with incomplete RTP adoption in the residential and commercial sector. As explained above, this approach is motivated by two considerations. First, it follows the intuition given in previous work, suggesting that foregone welfare gains are larger, if mostly consumers with rather "volatile" consumption patterns avoid RTP instead of "evenly" consuming consumers. Second, this analysis also captures the potential aggregate and sectoral welfare consequences of selective RTP adoption or of smart-meter roll-out plans and dynamic tariffing programs targeted only at the largest, predominantly industrial customers.

The sectoral demand profiles are used in the simulations of competitive long-run equilibria for a representative year, that is for 8760 hours. To simulate market equilibira, we formulate the formal model of section 2 as a mixed complementary problem (MCP) in GAMS (Rutherford, 1995) using the PATH solver algorithm (Ferris and Munson, 2000). The model code, LORETTA Version 1.0.1, is open source (Gambardella, 2017).[20] We loosely calibrate the model to the German power system by using a stylized

[19] In contrast to Borenstein (2005) but without loss of relevant information, we do not adjust hourly price data to yield zero-profits of installed generation capacity.

[20] LORETTA is the "LOng-run Electricity market model with Time-varying retail TAriffing" and

Table 3 Technology cost assumptions

Cost parameters	Technology				
	Wind	Solar PV	Coal	CCGT	OCGT
Annualized fixed costs fc_i [k EUR/(MW*a)]	136.43	76.49	145.85	88.65	49.32
Marginal production costs c_i [EUR/MWh$_{el}$]	0.1	0.1	18.19	64.41	96.76
CO_2-efficiency $e_i\eta_i$ [tCO$_2$/MWh$_{el}$]	0	0	0.88	0.33	0.51
Thermal efficiency η_i [MWh$_{el}$/MWh$_{th}$]	1	1	0.45	0.61	0.39

Note. - Marginal production costs shown in euro per megawatt hour (MWh) for a carbon tax equating zero, i.e. c_i shown consist of fuel and variable operations and management costs only. Annualized specific fixed costs (per MW and year) comprise overnight investment as well as fixed operation and maintenance costs. Cost annuities are calculated with a risk-free interest rate of 7%, assuming lifetimes of 25 years for wind turbines solar PV, OCGT and CCGT, and 35 years for lignite and hard coal plants. While taking on a long-run perspective, prospected average fuel costs base on the "new policies scenario" for Europe, reflecting IEA's fuel price projections for 2030 (IEA, 2014).

set of supply technologies, which comprises of onshore wind and solar photovoltaic (solar PV) as VRE generation technologies, hard coal as (nonvariable) base- and midload technologies as well as combined cycle and open cycle natural gas turbines (CCGT and OCGT) as peak and superpeak technologies. Technology specific marginal generation costs are based on long-run projections on average fuel prices, f_n, and on operation and maintenance costs, c_n^{om}, taken from IEA's World Energy Outlook 2014 (IEA, 2014). Additionally, prospective thermal efficiency rates, η_i, are provided by Schröder et al. (2013). Fuel specific CO_2-efficiency factors, e_n, are obtained from Icha (2013). Annualized fixed costs, fc_n, are also taken from Schröder et al. (2013) and consist mostly of overnight construction costs. Table 3 includes all relevant cost parameters of the stylized technology portfolio used for the simulation. Hourly output profiles by solar PV and wind onshore turbines are based on empirical capacity factors, av_{0t}, for all 8760 hours and each VRE technology in 2015, provided by Open Power System Data (2017).

5. Results

5.1. Distributional effects of real-time pricing in the residential sector

In this section, we analyze how variable renewable electricity supply affects the redistribution of consumption costs among residential customers following the introduction of mandatory real-time pricing. Previous work on this issue suggests that heterogeneous retail customers on the same flat-rate pricing scheme resemble an "insurance pool" (Borenstein, 2013), where some customers, who consume rather evenly across periods, cross-subsidize customers' electricity consumption with a peakier demand. Without any changes in consumption behavior, the latter would therefore lose

is available at: https://www.pik-potsdam.de/research/sustainable-solutions/models/loretta.

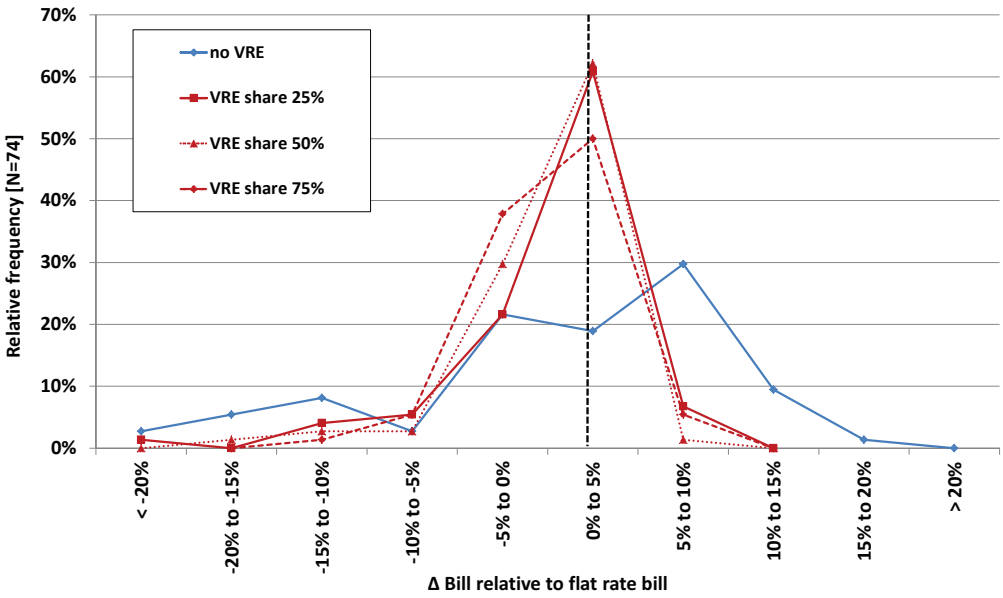


Figure 2 Distribution of relative bill changes among 74 German residential customers (median is given by black dashed line).

as soon as they would have to pay high prices when consuming much, while the former would accordingly benefit from paying less on average.

Yet, for the same reasons as before but now related to intra-sectoral demand heterogeneity, individual demand of many customers may start to covary less with real-time electricity prices, when variable renewable supply shares rise (see section 3.3). Hence, previous losers from introducing mandatory real-time pricing may become winners even without adjusting their consumption habits. If this applies to a critical mass of customers within each "insurance pool", then this effect would render the distributional effects less of a social acceptance barrier to real-time pricing. Computing the average covariance of individual demand and real-time price over all 74 consumption profiles gives that it indeed decreases from 0.002 to -0.4 or 0.0006 when the equilibrium supply share by renewables increases from zero to 75%.[21]

Accordingly and, thus, supporting our intuition, Figure 2 shows that the distribution of bill changes contracts as renewable supply shares increase from zero (blue graph) to 75% (red dashed graph), implying both lower relative bill increases (losses) and decreases (gains). Each graph depicts the relative frequency distribution of individual bill changes due to real-time pricing relative to the original bill under flat rate pricing

[21] Although the sample demand profiles covary little with simulated equilibrium prices, they covary strongly with aggregate demand. Demand and equilibrium prices covary little because of the stylized technology portfolio, which we are using. Due to this, marginal supply costs remain on the same level for large variation in demand and thus over extended periods over the day.

(negative values indicate bill increases). Hence, without renewable supply, roughly 19% of the consumers would pay at least 5% more than under flat-rate pricing. If the renewable supply share increases to 25% and 75% (red solid and dashed graphs), the portion of consumers paying at least 5% more than before drops to 11% and 7%, respectively. In all renewable scenarios, the largest part of consumers are winners, that is between 50% and 62% of them pay less than under flat rate pricing, and only between 1% and 7% of the customers pay at least 5% less. In absence of variable renewable supply, in turn, about 39% of consumers pay at least 5% less on real-time pricing than when on the flat-rate tariff, so that the distribution of winners is also more spread out than in the scenarios with renewables.

The shrinking proportion of significant bill changes indicates that intra-sectoral distributional effects of real-time pricing could actually become less of a policy concern in a variable renewable based system, and therefore less of a hurdle to its widespread adoption. We think that similar findings could apply to samples of the industrial and commercial customer sector, since the main driver of this outcome is the "randomness" of renewable output reducing the average covariation of demand and wholesale electricity prices.

Nonetheless, the consumption data used in this analysis are limitedly representative of the whole residential consumer population. As mentioned in section 3.1, annual average consumption levels are more in the range of two- to four-person household levels, and therefore possibly above the population mean consumption level. We can only guess to what extent the observed annual mean consumption indicates household size or composition and, thus, consumption habits. However, multi-person households, who could be overrepresented in our sample, possibly tend to consume more evenly than smaller households. This could then explain why we find that in our sample the median customer would actually pay less under real-time pricing than under flat-pricing across all of the considered scenarios. Therefore, while electricity bill increases from real-time pricing concern relatively few customers in this set of profiles, with or without variable renewable supply, they still might be a concern for the median residential consumer.

More generally, our results crucially hinge on both the variable renewable technology portfolio in equilibrium and the market-specific demand fluctuations, that is, on the covariance of the renewable output and demand profiles. For instance, in a solar power based market, solar energy may cover daily demand peaks during noon, yet, not during evening periods after the sun has set. Additionally, annual demand peaks usually occur usually during winter time in Germany, when solar energy output is at its minimum as opposed to (onshore) wind energy output. As a result, wholesale prices and residential demand patterns could covary more strongly on average than in the scenarios analyzed above, where wind energy supply occasionally lowers prices during

evening and/or winter peak periods. In this case, changes in the distribution of winners and losers from RTP due to variable renewable entry could actually be less pronounced or even inverted.[22]

Furthermore, the above results are based on the assumption of stationary consumption patterns. However, changes in the long-run consumption patterns, due to increased use of electrified heating and/or transportation means, for instance, imply that the distribution of bill changes could be even more skewed towards bill reductions in the high renewable supply scenarios. This would be the case, if electric vehicles are, for example, mostly charged during midday hours, when solar output peaks, or during night hours, when wind output usually peaks.

5.2. Unrealized welfare gains from incomplete RTP adoption

In this section, we compare the annually unrealized welfare gains from rejecting real-time pricing either in the industrial or in the residential and commercial consumer sector. We do so for different levels of variable renewable capacity entry. The aim is to analyze the differential effects of heterogeneous demand patterns on the welfare gains from RTP and how these effects might change at high renewable supply shares. This comparative welfare analysis follows the common assumption outlined in the introduction, arguing that large fractions of the residential and commercial consumer sector could actually prefer to stick with flat rate tariffing, since being prone to overestimate potential losses from adopting RTP. Additionally, the analysis sheds light on the possible distributional consequences across customer sectors, resulting from targeted time-varying tariffing programs or a selective roll-out of advanced metering infrastructure.

We therefore compare two types of scenarios, the "less residential and commercial RTP"-scenario and the "less industrial RTP"-scenario given in Table 4. In the "less residential and commercial RTP"-scenarios, both the residential and commercial RTP share are simultaneously raised from 1% to 33% and 66%, keeping the industrial RTP share fixed at 99%, i.e. $\alpha_r < 99\%$, $\alpha_c < 99\%$ and $\alpha_{in} = 99\%$. To control for demand size, we fix the respective *aggregate* RTP share $\alpha = \sum_i^I \gamma_i \alpha_i$ and determine the industrial RTP share $\alpha_{in} < 99\%$ to get an equivalent "less industrial RTP"-scenario, now fixing α_r and α_c at 99%. In the $\alpha = 44\%$ scenarios we compare the extreme case, in which either the residential and commercial sectors remain fully flat priced, while the industrial sector fully adopts RTP, or the other way around. These scenarios serve to partial out

[22] While annual demand peaks usually occur during summer time in California, daily demand peaks particularly of residential customers also occur during evening hours. Hence, our findings might also apply to the residential sector in the CAISO region.

Table 4 Sectoral RTP share scenarios

Scenario	Sectoral RTP share [%]		
Aggregate RTP share [%]	"less residential and commercial RTP" ($\alpha_{in} = 99\%$)		"less industrial RTP" ($\alpha_r = \alpha_c = 99\%$)
α	α_r	α_c	α_{in}
44	1	1	1
62	33	33	15
81	66	66	57

Note. - This table shows the exogenous share of real-time priced consumers for each sector and on aggregate. Note that if $\alpha_r < 99\%$ and$\alpha_c < 99\%$, then $\alpha_{in} = 99\%$ ("less residential and commercial RTP"-scenario). If $\alpha_{in} < 99\%$, then $\alpha_r = 99\%$ and$\alpha_c = 99\%$ ("less industrial RTP"-scenario), except when $\alpha = 44\%$, where $\alpha_r = 51\%$ and $\alpha_c = 99\%$. Hence, the "less residential and commercial RTP"-scenarios reflect different levels of incomprehensive RTP adoption by residential and commercial customers. The share of real-time priced customers either remains unchanged ($\alpha_{r,c} = 1\%$) is raised to 33% and 66%, while the share of industrial real-time priced consumers equals 99% (full adoption). Accordingly, in the "less industrial RTP"-scenarios the residential and commercial sector is fully real-time priced ($\alpha_{r,c} = 99\%$), whereas the industrial share of real-time priced customers is increased below 99%, such that the resulting aggregate share of real-time priced customers α matches those obtained in the "less residential and commercial RTP"-scenarios. Scenarios are then compared along the respective aggregate share of real-time priced consumers α.

overlapping welfare effects.[23]

The annually unrealized consumer surplus gains L, which accrue if a consumer sector adopts RTP only partially ($\alpha_i < 99\%$), are defined by $L = \Delta CS \mid_{\alpha=0.99} - \Delta CS \mid_{\alpha_i<0.99}$. In the following we analyze the difference in L between the two scenarios, $\Delta L = L \mid_{\alpha_{r,c}<0.99} - L \mid_{\alpha_{in}<0.99}$, which is equal to the difference in annual consumer surplus gains:

$$\Delta L = \Delta CS \mid_{\alpha_{in}<0.99} - \Delta CS \mid_{\alpha_{r,c}<0.99} . \tag{10}$$

Each bar in Figure 3 gives the difference in unrealized welfare gains, ΔL, for different renewable supply shares and carbon taxes. As ΔL is positive across all scenarios, our results support the intuition that unrealized welfare gains are comparatively high, if mainly residential and commercial customers reject real-time retail pricing.[24] Additionally, both L and ΔL increase significantly with growing supply from variable renewables. More specifically, if residential and commercial customers remain on flat prices in absence of renewable energy supply (dark-blue bar at $\alpha = 44\%$ in Figure 3),

[23] In difference to Table 4, in the "less industrial RTP"-scenario with $\alpha = 44\%$ only the commercial RTP share amounts to 99%, while the residential RTP share amounts to 51%. Further simulation and welfare outcomes based on other combinations of α_r, α_c and α_{in} are given in Table C.10 of Appendix C.

[24] As is shown by Figure B.4b in the Appendix B, we find only slight differences in the quantitative outcomes, if VRE supply is induced by a VRE capacity subsidy. Further, as Table C.12 in Appendix C shows, the above results do not change qualitatively, if we increase the own-price elasticity to $\epsilon = -0.1$ in all consumer sectors. However, if industrial consumers react twice as sensitive to price changes than commercial and residential consumers, then L is larger if industrial consumers reject RTP than if residential and commercial do.

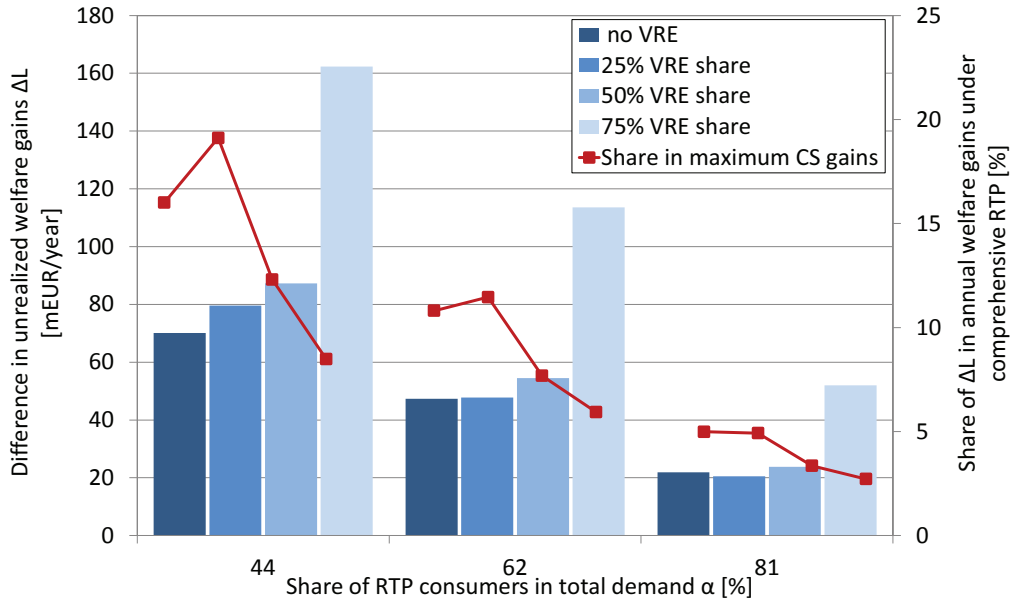


Figure 3 Differences in annually unrealized welfare gains from incomprehensive RTP adoption in the residential and commercial or industrial consumer sector (ΔL).

about 70 million EUR or 57% more in surplus gains would be lost per year than if the industrial sector remained on flat pricing. When 75% of electricity is supplied by renewables, unrealized consumer surplus gains more than double and are about 162.2 million EUR per year or 18% larger (light-blue bar at $\alpha = 44\%$ in Figure 3). Although rather moderate, these numbers suggest that implementing RTP in the residential and commercial sector could become relatively more important, particularly at high renewable supply shares, ceteris paribus.

However, while the difference in unrealized welfare gains increases in absolute terms with renewable supply, ΔL decreases relative to the total consumer surplus gains from comprehensive real-time pricing, $\Delta CS \mid_{\alpha=0.99}$. This is indicated by the falling red markers in Figure 3, which are plotted against the secondary y-axis and show the ratio $\Delta L / \Delta CS \mid_{\alpha=0.99}$. So, again in the $\alpha = 44\%$ comparison, $\Delta L / \Delta CS \mid_{\alpha=0.99}$ decreases from 16.0% to 8.5%. In this regard, heterogeneous consumption habits appear to have less differential welfare effects at high renewable supply shares.

Importantly, the annual amount of unrealized welfare gains L increases much stronger with variable renewable electricity supply. Again, in the "less residential and commercial RTP"-scenario at $\alpha = 44\%$, we find that L roughly quintuples from 0.23 to 1.08 billion EUR per year, if the renewable supply share increases from zero to 75%.[25]

[25]Note that L can be derived by deducting ΔCS at $\alpha = 44\%$, given in column 2 and 3 of Table 5, from $\Delta CS \mid_{\alpha=0.99}$, i.e. the annual consumer surplus gains from comprehensive RTP. Table 5 gives that $\Delta CS \mid_{\alpha=0.99}$ equals 0.44 and 1.91 billion EUR per year without and with 75% of renewable electricity

Table 5 Annual welfare gains from RTP with and without carbon tax induced VRE supply

Scenario		Annual consumer surplus change [EUR million/year]						
		ΔL	Total		RTP adopting consumers		Flat rate consumers	
VRE supply share [%]	Aggregate RTP consumer share α [%]	Differential welfare loss	less residential and commercial RTP consumers	less industrial RTP consumers	less residential and commercial RTP consumers	less industrial RTP consumers	less residential and commercial RTP consumers	less industrial RTP consumers
0	44	70.1	210.2	280.3	553.7	82.8	-337.3	204.1
	62	47.4	293.3	340.6	500.0	82.5	-200.2	264.7
	81	21.9	368.8	390.6	462.9	249.5	-87.5	147.8
	99	-	438.1		443.4		1.4	
75	44	162.3	830.0	992.3	912.9	952.1	-81.0	43.0
	62	113.6	1210.4	1324.0	1226.1	1250.4	-12.7	76.8
	81	52.0	1570.9	1622.9	1556.9	1571.6	17.4	54.7
	99	-	1912.0		1912.9		2.6	

Note. - This table shows the total annual consumer surplus gains from raising the share of real-time priced consumers from 1% in the residential, commercial and industrial consumer sector (in millions of 2016 Euro) for low and high VRE supply shares in total supply. Note that if $\alpha = 44\%$, then $\alpha_{in} = 99\%$ and $\alpha_c = \alpha_r < 1\%$ ("less residential and commercial RTP"-scenario), while $\alpha_{in} = 1\%$ and$\alpha_c = 99\%$ and $\alpha_r = 51\%$ in the "less industrial RTP"-scenario.

The foregone welfare gains also increase relative to the potential welfare gains from comprehensive real-time pricing, $\Delta CS\mid_{\alpha=0.99}$. In per capita terms, however, these values seem quite moderate as each customer would lose between 5 and 22 EUR per year, using the number of registered meters in Germany. Yet, as explained in section 6, per capita losses (benefits) might rise substantially with the future utilization of electrified heating, cooling and transportation.

Interestingly, at low renewable supply shares much of the difference in unrealized welfare gains from rejecting RTP (i.e. $\Delta L > 0$) results from surplus losses incurred by residential and commercial flat rate consumers. In sum, these range from 87.5 to 337.3 million EUR per year in the "less residential and commercial RTP"-scenario when renewable supply is absent, as column 8 of Table 5 shows. As is explained in more detail in the subsequent section, losses are borne almost in equal parts by the commercial and residential sector at low renewable supply shares, but mostly by residential customers at high renewable supply shares. The reason for these losses is the negative pecuniary externality that RTP adoption by industrial consumers causes so that rates of residential and commercial flat rate consumers rise.[26] Hence, even if

supply, respectively, while$\Delta CS\mid_{\alpha=0.44}$ equals 0.21 and 0.83 billion EUR per year.

[26]Table C.10 in Appendix C additionally gives the results for equilibria in which residential consumers remain flat priced, while consumers in the commercial and industrial sectors are fully (compare values at $\alpha = 74\%$). Depending on the share of renewable energy, this scenario would imply that between 17% (i.e. 82 out of 438 million EUR per year) and 23% (0.5 out of 1.9 bn EUR per year) of the potential annual welfare gains would remain unrealized. Residential flat rate consumers' surplus losses amount to between 103 and 202 million EUR per year. Welfare losses L do not exceed those

the intra-sectoral redistribution of consumption costs was not a problem, a majority of customers could find themselves opposing the implementation of real-time pricing in general. Put differently, regulators and retailers should consider the potentially negative distributional effects from implementing dynamic tariffing programs targeted at large consumers.[27]

However, at high (75%) renewable supply shares, flat rate consumers' surplus losses drop to a fraction of those obtained without renewable supply. Instead, consumer surplus gains from switching to real-time pricing increase significantly in all sectors (see columns 6 and 7 of Table 5). Hence, ΔL increasingly consists of unrealized switching gains by residential and commercial customers. In the "less industrial RTP"-scenario, residential and commercial surplus gains from switching amount to between 0.95 and 1.57 billion EUR per year and thus are 6 to 15 times larger than when renewable supply is absent. In the corresponding "less residential and commercial RTP"-scenario, industrial consumer surplus gains from tariff switching roughly quadruple to slightly lower levels of about 0.91 and 1.56 billion EUR per year. While we showed in 5.1 that potential bill changes from RTP are diminished for most (residential) customers at high renewable shares, these results show that the direct incentives to choose the RTP tariff increase simultaneously, given, of course, any private costs of adopting RTP.

5.3. Sectoral consumer surplus changes from RTP

To better understand the above results, we now decompose the aggregate welfare changes into the sectoral consumer surplus changes and analyze their main drivers at low and high renewable supply shares.

We showed that foregone welfare gains, L, are larger when only industrial consumers are fully real-time priced ("less residential and commercial RTP"-scenario), since residential and commercial flat rate consumers incur surplus losses. Columns 4 and 6 of Table 6 show that residential flat rate customers (third number in each block) lose between 65.2 and 185.3 million EUR per year in absence of renewable supply, while commercial customers lose between 26.2 and 156.2 million EUR per year.[28] Corre-

obtained from incomprehensive RTP adoption in the commercial sector, but exceed those from low RTP adoption in the industrial sector.

[27]Again, these welfare impacts are quite moderate, if broken down to the benefits or losses per capita. The residential sector in Germany consists of roughly 48 million customers (meters), so that losses as well as benefits from RTP are highly dispersed. Thus, it is questionable whether these highly dispersed welfare changes raise the opposition to RTP at current electricity demand volumes in the German market. In other power markets, such as CAISO and most U.S. power markets, for instance, residential demand volumes are much larger (see section 6), so that negative cross-sectoral distributional effects from targeted RTP programs or selective RTP adoption might be more pronounced also at current electricity demand levels.

[28]Note again that these losses do not result from redistributed consumption costs (adverse selection effect), since each sector faces its specific break-even flat rate, such that industrial consumers do not

Table 6 Sectoral annual consumer surplus gains from RTP

VRE supply Share	Total RTP shareα	Consumer by tariff	Residential [EUR million/year]		Commercial [EUR million/year]		Industrial [EUR million/year]	
[%]	[%]		$\alpha_r < 99\%$	$\alpha_r = 99\%$	$\alpha_c < 99\%$	$\alpha_c = 99\%$	$\alpha_i = 99\%$	$\alpha_i < 99\%$
	44	All	-188.4	-137.6	-160.5	125.3	559.0	292.6
		RTP	0.0	-45.7	0.0	128.5	553.7	0.0
		Flat	-185.3	-88.7	-156.2	-3.1	4.2	292.8
0	62	All	-161.8	-97.5	-70.1	110.5	525.2	327.7
		RTP	-30.9	-92.5	10.6	113.9	520.3	61.1
		Flat	-127.6	-1.8	-76.6	-3.2	4.1	266.7
	81	All	-137.1	-106.3	5.6	86.7	500.3	410.2
		RTP	-68.6	-101.1	35.7	90.5	495.9	260.1
		Flat	-65.2	-1.9	-26.2	-3.5	3.9	150.0
	99	All		-111.4		69.1		480.4
		RTP		-106.1		73.2		476.3
		Flat		1.4		-3.6		3.8
	44	All	-110.6	174.7	26.1	741.0	914.5	76.7
		RTP	0.0	211.9	0.0	740.2	912.9	0.0
		Flat	-109.1	-35.7	26.7	-0.5	1.4	77.4
75	62	All	66.8	395.6	272.0	739.4	871.6	189.1
		RTP	129.4	397.9	226.3	738.3	870.3	114.2
		Flat	-60.9	-0.6	46.6	-0.5	1.5	75.9
	81	All	225.5	381.7	505.9	727.1	839.5	514.2
		RTP	253.5	384.2	464.9	726.1	838.5	461.3
		Flat	-26.1	-0.7	41.9	-0.7	1.6	53.7
	99	All		374.2		724.6		813.3
		RTP		376.7		723.5		812.6
		Flat		-0.6		-0.7		1.5

Note. - This table shows the total annual consumer surplus gains from raising the share of real-time priced consumers from 1% in the residential, commercial and industrial consumer sector (in millions of 2016 Euro). Results are given for equilibria without renewable supply (at a zero carbon tax) and with a renewable supply share of 75% in total supply at a EUR 400/tCO_2. Cells in each column are divided into three rows giving the annual consumer surplus changes in total, of consumers who switch the tariff and of consumers who remain on the flat tariff. Surplus changes of incumbent real-time priced consumers are marginal and are given by the difference between the total and the surplus changes from switching and from being on the flat price.

spondingly, Table 7 shows that the residential and commercial flat rates, $\bar{p}_r$ and $\bar{p}_c$, increase from 50.7 to 52.1 EUR per MWh, and from 58.1 to 59.1 EUR per MWh, respectively. Further, column 6 and 7 of Table 7 show that the respective covariance of demand and real-time price, $Cov\,(a_{it}, p_t)$, increases with α_{in}. This result is in line with the intuition discussed in section 3.2, suggesting that an increase in $\alpha_{j\neq i}$ (industrial RTP share) raises the covariance of demand and price in sector i (residential and commercial), if basic demand in sector j covaries comparatively less with price, as is the case here (compare top row of column 6, 7 and 8 of Table). Therefore, implementing RTP mainly in the industrial sector exerts a negative pecuniary externality on residential and commercial flat rate consumers. As a result, the residential sector always net loses and the commercial sector net loses as long as the flat rate consumer share is sufficiently large, i.e. unless α_c exceeds 33% ($\alpha > 62\%$).[29] Since residential customers constitute the majority of electricity consumers (see section 6), this result implies that most customers would reject RTP, even if they are not directly affected. However, these losses appear too low in per capita terms to really bother residential customers, at least at current demand levels. Nonetheless, this aspect has not been highlighted so far, and although dynamic pricing schemes targeted at large commercial and industrial customers, such as the PG&E's critical peak pricing program in CAISO, are efficiency augmenting on aggregate, their potentially negative distributional effects should nonetheless be considered by regulators and utilities.

However, the negative externality caused by RTP in the industrial sector is mitigated through growing renewable electricity supply. Comparing the top and bottom rows of Table 7 shows that variable renewable supply reduces the demand and price covariation in the residential and commercial sector, $Cov\,(a_{i,t}, av_{n,t})$, and thereby counteracts the flat rate inflation effect. The decrease in price and demand covariation is particularly due to the slight positive covariation of residential and commercial demand with wind and solar availability, as is given by $Cov\,(a_{i,t}, av_{n,t})$ in Table 2. Thus, residential and commercial consumers tend to have higher demand during low price periods and lower demand during high price periods.[30] Accordingly, the bottom rows of Table 6) show that

cross-subsidize consumption in other sectors (cf. Borenstein and Holland, 2005; Borenstein, 2013).

[29] Of course, the sectoral welfare changes are rather sensitive to the assumed own-price elasticities. Thus, if changing ϵ from -0.05 to -0.1 only in the residential sector, we find that residential flat rate consumer losses from RTP in the industrial sector increase by about 16% to 215.2 million EUR per year, while commercial flat rate consumer losses remain almost unchanged (cf. Table C.12 in Appendix C). Interestingly, raising only industrial consumers' elasticity to price yields that residential flat rate customers gain when industrial consumers are fully real-time priced, while commercial flat rate customers incur even higher losses. If the own-price elasticity equals -0.1 in all sectors, both residential and commercial flat rate customers' losses are larger than in the base case, where $\epsilon = -0.05$.

[30] This is different for the industrial sector, whose demand pattern covaries negatively with wind and particular with solar availability. Therefore, as $a_{in,t}$ covaries more with wholesale prices than before

Table 7 Sectoral flat retail rates as well as characteristic covariances of demand and real-time price for selected scenarios.

VRE supply share	Aggregate RTP share α	Flat rate $\bar{p}_i$ [EUR/MWh]			Covariance of demand scale a_{it} and real-time price p_t		
[%]	[%]	$\bar{p}_c$	$\bar{p}_r$	$\bar{p}_{in}$	$Cov\,(a_{ct}, p_t)$	$Cov\,(a_{rt}, p_t)$	$Cov\,(a_{int}, p_t)$
	1	58.1	50.7	49.2	154.4	33.3	24.3
0	44	59.1	52.2	47.3	170.1	51.7	-17.3
	44*	58.2	52.1	47.9	155.3	51.3	-4.7
	99	58.4	52.2	47.5	159.1	51.9	-12.5
	1	137.3	133.0	142.1	30.8	-28.8	150.6
75	44	137.1	133.9	141.5	28.8	-16.7	137.3
	44*	136.4	133.6	141.8	20.4	-19.2	145.9
	99	136.1	133.5	141.4	17.8	-17.9	142.3

Note. - This table shows the equilibrium flat rates in the residential, commercial and industrial consumer sector and the corresponding covariance of the demand scale parameter, a_{it}, and real-time retail price, p_t, for selected scenarios. The $\alpha = 44^*\%$ marks the "less industrial RTP"-scenario as defined in Table 4.

surplus losses of residential flat rate customers decrease by up to 58%, when industrial consumers are on RTP and renewables supply about 75% of electricity. Commercial flat rate consumers actually gain in surplus.

Simultaneously, consumer surplus gains from switching to real-time pricing increase sharply, especially in the residential and commercial sector. The "RTP"-rows in column 7 of Table 6 yield that surplus gains by tariff switching commercial consumers can roughly tenfold from 73 to 723 million EUR per year (cf. "comprehensive RTP scenario", $\alpha = 99\%$). While in fact losing from adopting RTP, when renewable supply is absent, residential consumers switching to real-time pricing gain up to 397.9 million EUR per year (cf. column 5). Industrial consumers' switching gains less than double and amount to as much as 912.9 million EUR per year (column 9).The substantial rise in tariff switching gains due to large-scale renewable energy supply is in line with the intuition given in 3.3. Switchers face larger positive price spreads ($\bar{p}_{0i} - p_{1t} > 0$), since flat retail rates inflate[31] substantially in all sectors, i.e. more than double if VRE supply

renewable market entry, industrial consumers tend to demand more during high price periods. This change in the covariance of industrial demand and wholesale price may, of course, not arise or could be much less pronounced, if the actual demand pattern is flatter than the synthetic profile used here.

[31]The flat rate inflation primarily mirrors the high average wholesale price (135 EUR/MWh, see Table A.8), which has to materialize to allow for a 70% to 75% renewable supply share in equilibrium (see subsection 2.2). The corresponding carbon tax level thus has to be raised to EUR 400/tCO_2, and amounts to EUR 50 or EUR 100/tCO_2 to achieve ~25% and ~50% of renewable electricity in total supply. The fossil-fueled technology portfolio changes accordingly towards high-marginal cost, gas fired (low carbon) technologies (CCGT and OCGT), as Table A.8 in Appendix A shows. The low average wind and solar capacity factor requires that total capacity entry roughly quintuples from 78

75% of electricity, and since real-time prices, p_t, drop to zero or very low levels in about 36% of all hours.

6. Robustness and limitations

Our analysis of time-varying pricing with heterogeneous consumers relies on synthetic demand data and is based on necessary simplifications in modeling a German low-carbon electricity market. This section aims at identifying the most important limitations of our methodological approach.

First, our findings on consumer-specific welfare changes crucially hinge on the characteristic, sectoral demand profiles. Besides the limitation that our synthetic demand data reflect sectoral demand characteristics specific to the German system and similar markets, empirical hourly demand data would improve the validity of our numerical analysis.[32] The main disadvantage of using synthetic load profiles instead of real sectoral demand data is the possible mismatch with the empirical variation in the total load profile. Thus, although residential and commercial demand covary with real aggregate demand as intuition would suggest, the synthetic industrial demand profile represents probably only a decent approximation. That is, since we derive the industrial demand scale parameter, $a_{in,t}$, from the hourly difference between total and commercial as well as residential demand, our synthetic industrial profile might be less "flat" than the real profile. Thus, $a_{in,t}$ varies rather strongly, as is indicated by the high standard deviation in Table 2. Apparently, $a_{in,t}$ covaries negatively with aggregate demand. Consequently, industrial demand changes and the corresponding wholesale price changes subsequent to adopting RTP may actually be more (less) pronounced in high (low) price with a more even profile. Therefore, also the pecuniary externality in the residential and commercial sector could actually be smaller than found above. To check the robustness of the pecuniary externality, we fix $a_{in,t} = c$ for each period t to match the mean of real industrial demand[33] in Germany in 2015, and then simulate the same scenarios. We find that commercial flat rate customers lose even more, while residential flat rate customers do not lose Annual welfare losses are still higher if mainly residential commercial customers remain flat priced, yet, on aggregate there are no surplus losses by residential and commercial flat rate consumers (see Table C.11 in Appendix C). Hence,

GW at zero carbon taxation, to 362 GW at EUR 400/tCO_2.

[32]This also applies to using empirically sound estimates of own-price elasticity for each sector, instead of assuming symmetric elasticities to price as done in our analysis. Industrial, yet, also commercial customers may actually be more responsive to price variations than in our base case scenarios, and therefore benefit more from adopting RTP. This implies, in turn, that selective RTP adoption may also cause stronger negative external price effects on flat priced customers in other sectors.

[33]Total annual demand shares thus remain unchanged.

we think that the main welfare outcomes still prevail, if applying a more realistic, i.e. more even industrial demand profile.

Further, our analysis abstracts from possible long-run changes in the characteristic demand patterns and volumes. Particularly residential demand volumes could increase with growing utilization of electrified heating, cooling and/or transportation. Combined with distributed generation and/or storage facilities (e.g. rooftop solar PV systems) as well as smart-appliances, residential demand patterns may adapt more efficiently to supply patterns even without time-varying (and locational) price signals. Given this is not the case, smart-appliances, which reduce the individual transaction costs of reacting to real-time prices, may increase the own- and cross price elasticity of residential demand. Hence, foregone welfare gains from "too little" enrollment in real-time pricing programs by residential consumers may be even higher than we find above. Larger demand volumes, on the other hand, could also imply larger surplus losses experience by flat rate customers, if only specific consumer groups adopt RTP. The negative welfare impacts could therefore already be more significant in most U.S. power markets such as CAISO in California, for instance, than those we find for the German power market. Whereas residential consumption roughly accounted for only 25% of total electricity consumption in Germany in 2015, although 94% out of the 50.3 million electricity meters belong to residential customers,[34] average residential electricity consumption made up 44% of total U.S. electricity consumption in 2016.[35]

Aside from these limitations, our approach omits several other factors, due to which our welfare results may be positively and negatively biased. Since these factors have already been discussed in previous, similar studies, we only mention them briefly (cf. Borenstein and Holland, 2005; Holland and Mansur, 2006; Leautier, 2014). As we ignore electricity storage technologies ("in front of" and "behind" the meter) or cross-border trade to adjacent markets, hourly price spreads could actually be lower than those in the simulations above, implying that aggregate and sectoral welfare gains from adopting RTP could be overestimated. In turn, assuming zero cross-price elasticities of demand (i.e. no demand shifting), no transmission constraints and locational pricing or any costs of transmission capacity expansion, we may also underestimate the welfare gains from RTP.

[34]Numbers are provided by the Bundesnetzagentur (Federal Network Agency for Electricity, Gas, Telecommunications, Post and Railway of Germany), and are taken from its "Monitoring Report 2016" available at: https://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/Sachgebiete/Energie/Unternehmen_Institutionen/DatenaustauschUndMonitoring/Monitoring/Monitoringbericht2016.pdf?__blob=publicationFile&v=2

[35]Data provided by the U.S. Energy Information Administration at: https://www.eia.gov/electricity/data/browser

7. Conclusion

This paper addresses the relevance and welfare implications of barriers to adopt time-varying retail pricing in electricity markets with heterogeneous consumers and growing shares of variable renewable electricity supply. In particular, we analyze how variable renewable electricity supply affects the distributional effects of substituting typical flat- for real-time retail pricing (RTP) within a certain consumer sector, using residential consumption data from Germany. Additionally, we investigate the effect of consumer heterogeneity on the unrealized consumer welfare gains from selective RTP adoption, by simulating long-run electricity market equilibria and applying synthetic residential, commercial and industrial demand profiles.

Our results suggest that variable renewable electricity supply reduces demand and wholesale price covariance, and thereby mitigates the distributional effects of introducing real-time pricing among the residential customers in our sample. Since facing only slight changes in their electricity bills, most residential consumers thus should have less reason to expect significant losses from adopting RTP and to reject it at high deployment rates of renewables. However, if residential and commercial consumers prefer nonetheless to remain flat priced, the amount of unrealized welfare gains is comparatively large and increases with variable renewable electricity supply. Thus, introducing RTP comprehensively instead of targeting, for instance, large industrial consumers, as is done in practice, becomes increasingly important with growing supply from wind and solar power. Targeting certain customer groups may also reveal as problematic at low renewable supply shares, due to negative pecuniary externalities arising from RTP adoption. Specifically, we find that implementing RTP in the industrial consumer sector only can imply rate increases for residential and commercial flat rate consumers, since changes in industrial consumption behavior can increase the covariation of demand and price in these sectors. The resulting consumer surplus losses are particularly large at low renewable deployment and rather sensitive to assumptions about own-price elasticity and sectoral demand patterns.

These results shed light on economic mechanisms relevant to assessing both the feasibility of time-varying retail rates and the welfare implications of unlocking price responsive demand by heterogeneous consumers in low carbon power markets. In particular, our research illustrates the possible cross-sectoral distributional impacts of targeted dynamic retail pricing programs, which have so far not been addressed in the RTP literature. Although we apply a stylized model of the German electricity market, the above welfare and distributional results could also be observed in other markets with a similar consumer structure as well as generation technology portfolio. Further research should particularly account for possible changes in sectoral demand volumes, patterns

and elasticities to price, resulting from increased utilization of electrified heating and transportation combined with storage technologies or smart appliances. Importantly, tariff choices should be modeled explicitly, in order to understand how other barriers such as privacy concerns, transaction costs or cognitive bias, could impede a widespread adoption of time-varying retail pricing, necessary to accommodate the growing shares of variable supply from wind and solar power in many markets.

Appendix A. Market simulation outcomes

Table A.8 Selected simulation results.

VRE supply share	RTP share	Capacity [GW]						Total annual consumption (Mean)	Mean wholesale price (Peak price)	Total annual supply costs (Fixed cost share in %)	Peak price duration (Zero price duration)
[%]	[%]	Coal	OCGT	CCGT	WIND	PV	Total	[TWh]	[EUR/MWh]	[bn EUR/a]	[% of year]
0	1	70.4	7.5	-	-	-	78.0	509.0 (58.1)	48.1 (49.4×10^3)	26.6 (35)	0.0 (-)
0	44	70.2	4.0	-	-	-	74.1	511.0 (58.3)	48.1 (1.3×10^3)	26.4 (34)	2.8 (-)
0	44*	70.3	2.6	-	-	-	72.9	511.6 (58.4)	48.1 (1.1×10^3)	26.4 (34)	4.9 (-)
0	99	70.0	0.7	-	-	-	70.6	513.8 (58.7)	48.1 (0.9×10^3)	26.2 (34)	7.6 (-)
70	1	-	21.4	49.8	176.9	114.2	362.3	485.4 (55.4)	135.3 (49.6×10^3)	67.0 (56)	1.2 (36.2)
73	44	-	16.6	48.9	180.3	115.2	361.1	509.8 (58.2)	135.2 (23.8×10^3)	66.2 (57)	1.6 (31.6)
73	44*	-	14.5	48.9	179.7	116.4	359.4	512.8 (58.5)	135.2 (14.8×10^3)	66.1 (57)	1.8 (30.9)
75	99	-	11.6	47.6	183.9	117.7	360.8	537.0 (61.3)	134.9 (5.2×10^3)	65.2 (59)	1.5 (25.1)

Note. - This table shows selected equilibrium results with regard to capacity entry K, wholesale prices and annual total supply costs. Results are shown for scenarios, in which the carbon tax τ and VRE entry are zero, and where τ amounts to 400 EUR/tCO_2, yielding a VRE supply share of between 70% and 75% (column1). Additionally, scenarios shown differ with regard to the aggregate RTP share (column 2), ranging between 1%, 44% and 99%. To compare the effect of demand characteristics, in the $\alpha = 44\%$ scenario only industrial customers fully adopt RTP, while in the alternative scenario, marked by an asterisk, RTP is adopted by residential ($\alpha_r = 51\%$) and commercial customers ($\alpha_c = 99\%$) only. Importantly, the VRE supply share rises by 5 percentage points at full RTP adoption, due to the demand increases during low price hours. Full RTP adoption reduces total capacity entry by between 1.5 (with VRE entry) and 7.4 GW (without VRE entry), in particular peak-load capacity entry (OCGT) is reduced by about 90% (without VRE entry) and 50% (with VRE entry). Renewable capacity entry increases with the RTP share, i.e. wind and solar generation capacity increase by about 7GW and 3 GW, respectively, and thus compensates much of the reduced peaker capacity entry. Again, this is due to the demand increases during low or zero price hours, causing higher short run profits for VRE technologies. Total capacity entry is about five times larger in the equilibria with high VRE supply shares, resulting mainly from the low average capacity factors of wind and solar power (VRE capacity constitutes 80% to 85% of total capacity). As a consequence, total annual supply costs (column 14) increase by about 150% in the equilibria with VRE entry, of which 56% to 59% represent fixed investment costs. Accordingly, the mean wholesale electricity price roughly triples in the the VRE equilibria. Total annual and mean consumption (column 9) is thus about 5% lower than without VRE entry (compare $\alpha = 1\%$ scenarios), but becomes larger the larger the RTP share. The frequency of zero- or almost zero wholesale prices decreases with (column 12). Peak price levels decrease, while peak-price frequency increases with the RTP share, either with or without VRE entry.

Appendix B. Welfare and distributional effects under renewable subsidization

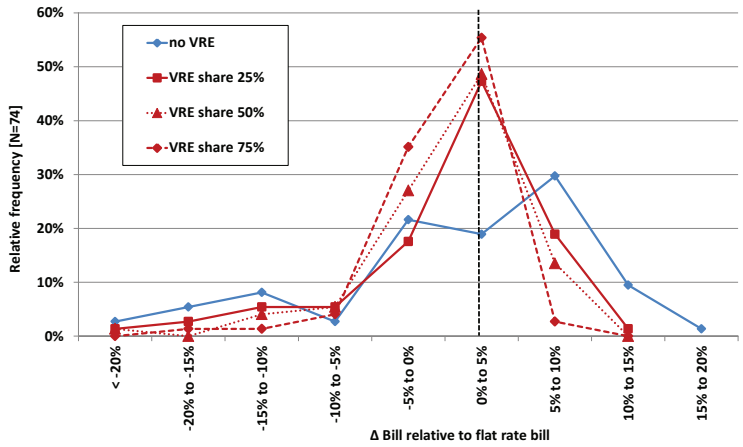
Currently, market entry of VRE technologies is typically subsidy rather than carbon tax induced. Germany and other EU power markets have so far relied on renewable

feed-in-tariffs, while a range of U.S. states have implemented some form of renewable portfolio standard (RPS). In comparison to the carbon tax regime, the long run generation portfolio can consist of both low-marginal cost, carbon emitting generation technologies (i.e. coal) and VRE technologies. Additionally, consumers usually pay for VRE entry via a constant unit charge or levy, creating a dead-weight loss (DWL) in all periods, that is also in low/zero wholesale price periods, whereas a carbon tax causes a DWL only when carbon emitting technologies produce (high price periods). To check whether this has any influence on our basic results, we apply a simple model of a renewable portfolio standard, requiring a certain renewable output share of $\beta \in [0, 1]$ per MWh of *conventional output* over T periods. Retailers thus have to procure $\beta \sum_t^T D_t(\mathbf{p}, \tau)$ units of electricity at the constant price s, which can be interpreted as the clearing price of a centralized market auction for renewable certificates (RECs), where each MWh of renewable output yields one certificate. Demand for certificates has to equal certificate supply $\bar{S}_0$, which is simply given by the total annual electricity supply from VRE technologies deployed in equilibrium, i.e. $\bar{S}_0 = \sum_t^T q_{0t}$. Retail firms recover their expenses for renewable electricity, $s\beta \sum_t^T D_t(\mathbf{p}, \tau)$, through the uniform tax τ, which each consumer has to pay per unit of consumed electricity.[36] Hence, also RTP consumers face a constant adder on top of their RTP rate, which is the main difference to the carbon tax. Each unit of renewable output, q_{0t}, receives the subsidy s, but, taking advantage of the perfect foresight assumption, we model aggregate hourly payments as a forward payment per unit of installed renewable capacity. Thereby, the subsidy only affects the decision to invest in renewable technologies, yet not hourly output decisions.[37] Denoting the dispatch rate of available renewable capacity in t, $av_{0t}^v k_0^v$, as $u_{0t} \in [0, 1]$ the first order condition w.r.t. investment in the renewable technology then changes to $\sum_t^T av_{0t}[(w_t - c_0) + u_{0t}s] = fc_0$.

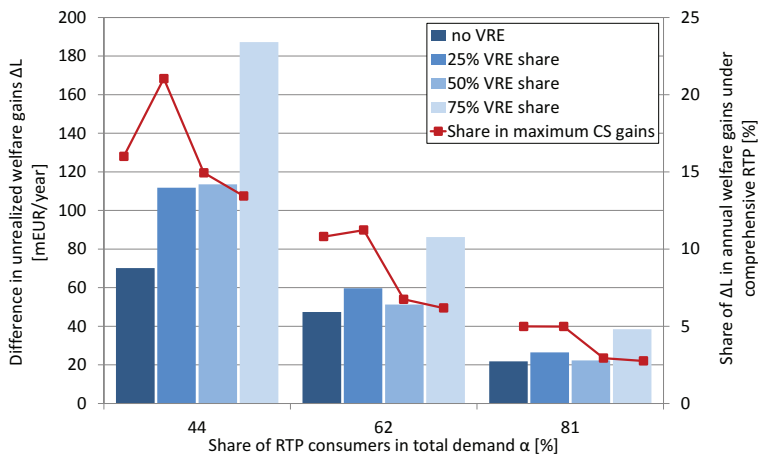
Figure B.4a and B.4b present the distributional effects of RTP and the differences in unrealized welfare gains from rejecting RTP under subsidy induced VRE entry. The only major difference in the welfare results can be found in the scenario where 75% of electricity is supplied by renewable technologies. Aggregate welfare gains from comprehensive RTP adoption are almost one third lower when VRE entry is subsidy induced (1.3 versus 1.9 billion EUR per year). This can mainly be explained by the tax wedge, τ, in zero- and low-price periods, which increases from 9 to 63 EUR per MWh, as the VRE supply share increases from 25% to 75%. Due to this, RTP adopters face lower

[36] Under the zero-retail-profit condition this implies that in equilibrium $\tau = s\beta$, since it has to hold that $\tau \sum_t^T D_t(\mathbf{p}, \tau) = s\beta \sum_t^T D_t(\mathbf{p}, \tau)$.

[37] The actual output subsidy would imply the possibility of negative prices, since renewable producers would then be indifferent to produce at a negative wholesale price up to the subsidy level, i.e. $w_t = -s$ in each period. This would add unnecessary complexity in our analysis.



(a) Distribution of relative bill changes among 74 German residential customers under VRE subsidies (median is given by black dashed line).



(b) Differences in annually unrealized welfare gains from incomprehensive RTP adoption in the residential and commercial or industrial consumer sector (ΔL).

Figure B.4 Distribution of relative bill changes and differences in unrealized welfare gains from incomprehensive sectoral RTP adoption under VRE subsidies.

price spreads in low *wholesale* price periods than under carbon taxation, and therefore make less surplus gains from switching to RTP.

Appendix C. Alternative RTP share combinations, higher price elasticity, flat industrial demand profile

Table C.9 Sectoral RTP share scenarios

Scenario	Sectoral RTP share [%]		
Aggregate RTP share [%]	"less residential and commercial RTP" ($\alpha_{in} = 99\%$)		"less industrial RTP" ($\alpha_r = \alpha_c = 99\%$)
α	α_r	α_c	α_{in}
61	66	1	11
64	1	66	19
74	1	99	-

Note. - This table shows alternative RTP share scenarios to Table 4, based on which welfare results are given in Table C.10. In difference to the base scenarios, either the residential or the commercial RTP share is raised to 66% in the "less residential and commercial RTP"-scenario. Additionally, we also consider a scenario, where only residential consumers remain flat priced, while the commercial and industrial sector are fully real-time priced, so that the aggregate RTP share amounts to 74%.

Table C.10 Annual welfare changes from RTP with and without carbon tax induced VRE supply

			Annual consumer surplus change [EUR million/year]					
Scenario		ΔL	Total		RTP adopting consumers		Flat rate consumers	
VRE supply share [%]	Aggregate RTP consumer share α [%]	Differential welfare loss	less residential and commercial RTP consumers	less industrial RTP consumers	less residential and commercial RTP consumers	less industrial RTP consumers	less residential and commercial RTP consumers	less industrial RTP consumers
0	61	59.3	276.4	335.7	476.7	68.6	-193.9	273.7
	64	34.38	311.2	345.5	542.2	96.8	-224.5	255.4
	74	-	355.9	-	561.8	-	-199.3	-
75	61	126.82	1168.1	1294.9	1146.9	1222.1	24.0	75.9
	64	92.63	1260.4	1353.0	1335.9	1279.4	-72.5	76.8
	74	-	1460.6	-	1564.7	-	-100.8	-

Note. - This table shows the total annual consumer surplus gains (in millions of 2016 Euro) from raising the sectoral share of real-time priced consumers, α_i, from 1% to the levels given in the scenarios of Table C.9. Comparing the flat rate consumer surplus changes at $\alpha = 61\%$ and $\alpha = 64\%$ yields that losses incurred are larger, if mainly residential customers remain flat priced. If only residential consumers remain flat priced ($\alpha = 74\%$), their surplus losses are the largest in all scenarios. Interestingly, when VRE supply equals 75%, residential surplus losses increase (from 72.5 to 100.8 million EUR per year) with the RTP share in the other sectors (compare $\alpha = 64\%$ and $\alpha = 74\%$ scenario).

Table C.11 Annual welfare changes from RTP with flat industrial demand profile.

Scenario		ΔL	Annual consumer surplus change [EUR million/year]					
			Total		RTP adopting consumers		Flat rate consumers	
VRE supply share [%]	Aggregate RTP consumer share α [%]	Differential welfare loss	less residential and commercial RTP consumers	less industrial RTP consumers	less residential and commercial RTP consumers	less industrial RTP consumers	less residential and commercial RTP consumers	less industrial RTP consumers
0	44	75.9	211.7	287.5	153.4	154.97	63.2	137.9
	62	52.6	299.8	352.3	242.4	356.68	62.8	1.1
	81	24.2	379.9	404.1	346.9	408.37	38.5	1.2
	99	-	454.4		458.6		1.3	
75	44	126.5	858.2	984.8	822.8	843.6	37.7	144.2
	62	91.9	1236.2	1328.1	1184.9	1268.7	62.8	62.8
	81	41.4	1597.8	1639.2	1559.2	1607.9	34.8	34.8
	99	-	1942.3		1943.5		2.5	

Note. - This table shows the total annual consumer surplus gains (in millions of 2016 Euro) from raising the share of real-time priced consumers, α_i, from 1% to the levels given in Table 4. The RTP share scenarios are equivalent to those shown in Table 5, however, the industrial demand scale parameter, $a_{in,t}$, is constant and equals the hourly mean of industrial demand of 26.1 GWh. This corresponds to how German TSOs project large industrial customers. As industrial demand is thus constant it does, of course, not covary with aggregate demand or wholesale prices. The negative externality from industrial RTP adoption ("less residential and commercial RTP consumers") is much smaller than in the base case (cf. Table 5), such that flat rate consumers obtain surplus gains (second but last column). This is due to the fact that only commercial flat rate customers lose from RTP adoption by industrial consumers, as discussed in the main text. Additionally, in absence of VRE supply (top rows), aggregate residential and commercial surplus gains from adopting RTP ("less industrial RTP consumers"-scenario) are notably larger than if applying the original industrial demand pattern. Apart from that, the difference in unrealized welfare gains, ΔL, is slightly larger in absence of large-scale VRE supply and roughly 20% smaller in presence of VRE supply, if compared to the corresponding values for ΔL in Table 5.

Table C.12 Annual welfare changes from RTP with higher own-price elasticity of demand

Scenario		ΔL	Annual consumer surplus change [EUR million/year]					
			Total		RTP adopting consumers		Flat rate consumers	
VRE supply share [%]	Aggregate RTP consumer share α	Differential Welfare Losses	less residential and commercial RTP consumers	less industrial RTP consumers	less residential and commercial RTP consumers	less industrial RTP consumers	less residential and commercial RTP consumers	less industrial RTP consumers
higher residential own-price elasticity $\epsilon = -0.1$								
0	44	134.4	169.8	304.2	553.5	116.9	-366.7	195.3
	99	-	492.8		509.3		1.4	
75	44	481.6	805.4	1287.0	911.8	1227.2	-91.4	63.8
	99	-	2431.5		2445.9		3.3	
higher industrial own-price elasticity $\epsilon = -0.1$								
0	44	-95.7	381.4	285.7	284.4	154.7	104.1	138.0
	99	-	596.4		602.2		1.6	
75	44	-819.4	1808.2	988.8	1683.0	848.9	130.3	144.0
	99	-	2807.7		2809.9		3.8	
higher own-price elasticity $\epsilon = -0.1$								
0	44	122.1	380.6	502.8	780.5	371.3	-386.4	145.5
	99		782.6		793.9		3.6	
75	44	270.5	1740.6	2011.2	1756.1	2046.5	-8.1	-26.7
	99	-	3903.2		3907.5		5.9	

Note. - This table shows the total annual consumer surplus gains (in millions of 2016 Euro) from raising the sectoral share of real-time priced consumers, α_i, from 1%, assuming a doubling in sectoral own-price elasticity, ϵ, from -0.05 to -0.1. When either the residential or industrial price elasticity amounts to -0.1, ϵ remains unchanged in the other sectors at the base case level of -0.05. Table C.12 shows that our main findings are sensitive to the assumption about heterogeneity in price elasticity. However, it is important to note that to our knowledge clear empirical evidence is lacking for systematic differences in the own-price elasticities between different electricity consumer sectors. Assuming that residential demand is more price elastic yields higher surplus losses by flat rate consumers in the "less residential and commercial RTP consumers"- scenario ($\alpha = 44\%$), equalling 366.7 and 91.4 million EUR per year, which is roughly 9% and 12% larger than in the corresponding base scenarios (cf.Table 5). As residential consumers now react more sensitive to price changes, intuitively, they also incur higher surplus losses when their flat rates increase due to RTP implementation in the industrial sector. In turn, they also benefit significantly more from switching to RTP, particularly at high renewable supply shares, where residential surplus gains from switching (not shown) roughly double to 483.5 million EUR per year (cf.Table 6). Accordingly, the aggregate surplus gains from switching are about 40% to 29% larger than those shown in Table 5, amounting to about 116 and 1227 million EUR per year. Comparatively higher surplus losses at low VRE supply and larger switching gains at high VRE supply imply larger unrealized welfare gains from rejecting RTP, L, such that ΔL almost doubles or triples, respectively, if compared to the base scenario. A qualitative change in our findings results if industrial consumers react more sensitive to price, since foregone welfare gains are now larger, if these consumers remain flat priced instead of consumers in the other two sectors. The difference in unrealized welfare gains, ΔL, thus amounts to -95.7 and -819.4 million EUR per year. This results mainly from larger industrial consumer surplus gains from switching, which are almost twice as high as under base assumptions (compare with "less residential and commercial RTP"-scenario in Table 5). Interestingly, flat rate consumers do not lose on aggregate, if only industrial consumers are real-time priced. Specifically, residential flat rate consumers do not lose but gain, while commercial customers do not lose as much as in the base case (not shown). Finally, if all sectors are more price elastic (last four rows), residential and commercial flat rate consumers incur comparatively larger losses at low VRE supply shares (386.4 versus 337.3 EUR million per year), yet, much lower losses at high VRE supply (8.1 versus 81 EUR million per year), if industrial consumers adopt RTP. Surplus gains from switching to RTP less than double in the industrial sector, and more than doubles in the residential and commercial sector. The difference in unrealized welfare gains, ΔL, is roughly 74% and 66% if compared to the equivalent base scenarios.

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Chapter 4

Renewable Energy Support, Negative Prices and Real-Time Pricing[1]

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Renewable Energy Support, Negative Prices, and Real-time Pricing

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ABSTRACT

We analyze the welfare effects of two different renewable support schemes designed to achieve a given target for the share of fluctuating renewable electricity generation: a feed-in premium (FiP), which can induce negative wholesale prices, and a capacity premium (CP), which does not. For doing so we use a stylized economic model that differentiates between real-time and flat-rate pricing and is loosely calibrated on German market data. Counter-intuitively, we find that distortions through induced negative prices do not reduce the net consumer surplus of the FiP relative to the CP. Rather, the FiP performs better under all assumptions considered. The reason is that increased use of renewables under the FiP, particularly in periods of negative prices, leads to a reduction of required renewable capacity and respective costs. This effect dominates larger deadweight losses of consumer surplus generated by the FiP compared to the CP. Furthermore, surplus gains experienced by consumers who switch from flat-rate to real-time pricing are markedly higher under the FiP, which might be interpreted as greater incentives to enable such switching. While our findings are primarily of theoretical nature and the full range of implications of negative prices needs to be carefully considered, we hope that our analysis makes policy-makers more considerate of their potential benefits.

Keywords: RES support schemes, Induced negative prices, Real-time pricing

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1. INTRODUCTION

Many countries around the world strive for high shares of renewable energy sources (RES) in their electricity systems, and fluctuating RES, such as wind power and solar photovoltaics, are likely to make up a major share of most of them. Increasing the share of fluctuating RES, however, confronts policy-makers with various economical, technological and institutional challenges (see Edenhofer et al., 2013). One particular question in this regard, is which support instrument can achieve a given RES target most efficiently.

A major concern is that RES support instruments have a distortionary impact on prices. This impact differs between instruments, and thus also generates different effects on efficiency. One aspect being increasingly debated is the point at which such instruments induce negative prices; see for example Nicolosi (2010), De Vos (2015), and Perrez-Arriga and Battle (2012) and on this issue. The latter make clear that more careful scientific examination is needed. This inspires the

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focus of our analysis, which compares the following two instruments: a subsidy on production, often called a market premium on energy or feed-in premium (FiP), and a subsidy on investment, often called a market premium on capacity or capacity premium (CP). The former can give rise to negatives prices up to the (negative) level of the premium, while the latter does not. Common wisdom thus suggests that the FiP would be generally less efficient than the CP due to the deviation from marginal cost pricing. However, as we shall show later, the contrary may hold when targets are defined as relative production shares.

This finding complements previous work by Green and Léautier (2015), who compare the welfare impacts of a production subsidy with either physical or financial dispatch insurance. Importantly, like the FiP the physical dispatch insurance induces negative prices while the financial insurance avoids this by compensating RES supply curtailment with out-of-market payments. They find that when RES targets are defined in terms of absolute capacity, and when consumers are taxed to pay for RES subsidies, then a production subsidy with physical dispatch insurance is inferior to financial dispatch insurance. This is precisely because negative prices occur more often in the case of the former, which reduce the marginal value of RES (market value), and thus require a higher RES subsidy. Consequently the tax to finance the subsidy also increases, which gives rise to additional dead weight losses.

Our work differs from Green and Léautier (2015) in two respects: we define RES targets as relative production shares rather than absolute capacity, and we consider two widely used instruments (FiP and CP) instead of different types of insurances. In particular, the choice of relative production targets is prompted by common policy practice, at least in the EU[1]. Within this setting, we find that in contrast to their results, a FiP can actually be more efficient than a CP despite the presence of negative wholesale prices. This is because respective dead weight losses from a higher levy are outweighed by reduced overall supply cost from lower RES capacity entry. This is possible if targets are defined in relative production terms, such that a higher utilization of installed RES capacities reduces the costs of achieving the targets. We also find that the greater the response of the demand to price, the lower the additional dead weight loss of the FiP in comparison to its positive capacity effect. That is, the higher the share of price responsive consumers, the higher the utilization of RES during hours of high RES supply, resulting in a reduction of required RES capacity. In contrast, Fell and Linn (2013) find for renewable portfolio standards (RPS) that different degrees of demand responsiveness do not substantially affect cost effectiveness. This however may be related to the relatively low proportions of RES examined.

In contrast to the model presented here, Green and Léautier (2015) also consider flexibility restrictions of thermal base load plants and find that financial dispatch insurance is more efficient than physical insurance as it is associated with a lower number of hours with negative prices. Likewise, Rosnes (2014) comes to the same conclusion, comparing a non-price-distortionary investment subsidy (resembling the CP) with a production subsidy that distorts prices (resembling the FiP). In this paper we do not consider such inflexibilities, mainly because we take a long-term perspective over which it can be assumed that the flexibility of thermal generators will increase substantially. This issue is further discussed at the end of the paper.

Our analysis is based on a long-run partial equilibrium model of the electricity sector. We employ the framework developed by Borenstein and Holland (2005) and later used *inter alia* by Allcott (2012) and Gambardella et al. (2016), specifically to analyze the efficiency gains and dis-

1. See EU Directive 2009/28/EC, which sets relative renewable energy targets for each member state for 2020. Several European countries, including Germany, have also set longer-term national renewable energy targets in relative terms.

tributional implications of raising price responsiveness. We draw extensively on the work of Gambardella et al., which analyzes the benefits of real-time retail pricing under carbon taxation and variable renewable energy supply. We loosely calibrate our model to the German market, which is characterized by high shares of fluctuating renewables. We further adopt a long-term perspective, assuming a RES share of 50% in total consumption as a target. Choosing this case is also driven by the fact that the two instruments we analyze are currently prominently debated in Germany in the context of ongoing reform of the support scheme in place (*EEG*); see Enervis and BET (2013) and Agora Energiewende (2014) for exemplary proposals.

While we focus on a particular aspect of FiPs and CPs, investment incentives should also be considered to assess the relative performance of these two instruments in a broader context. Recent work by Aldy et al. (2015) analyzes a natural experiment using data of U.S. wind energy subsidies. They find that where output determines the social benefits of a policy, production subsidies outperform investment subsidies. Capacity payments have been criticized on the basis that investors had just focused on putting "steel-in-the-ground" rather than on optimizing output (Boute 2012). Another important difference between the instruments relates to risk exposure for RES generators; see for example Pahle and Schweizerhof (2016) on this.

The remainder of this paper is structured as follows. In section 2 we describe the general approach, the model and the parameters used. In section 3 we present the results of the base case and sensitivity analyses. In section 4 we discuss potential distortions due to model limitations. The final section concludes.

2. METHODOLOGY

2.1 General approach

We use a stylized electricity market model with endogenous investments assuming profit-maximizing generators and utility-maximizing consumers. The model includes the two market-based RES support instruments discussed above, i.e. premiums on energy or capacity. These are set to induce a RES share of 50% in the base case. We compute the respective long-term equilibria for different shares of consumers with real-time pricing (RTP) tariffs. In the base case, we assume an RTP share of 10%; we also investigate other exogenously set RTP shares of 1%, 20%, 30%, 40% and 50%, resembling "what-if" policy scenarios. Such an approach—which only considers benefits and not the costs of RTP related to metering infrastructure—is widespread in the literature and has been used for example by Allcott (2012) in the context of demand-side flexibility and capacity markets. In other words, we do not determine the endogenous equilibrium RTP share, but only analyze the effects of exogenously increasing the share of RTP consumers.

We further compare welfare outcomes between the two RES support instruments as well as the benefits of increased RTP for different types of consumers under each of the two instruments. This is done by calculating overall welfare changes between scenarios with different RTP shares. We also study the distribution of welfare effects between different consumer groups. This is done by separating the rents of consumers with RTP tariffs, flat-rate pricing (FRP) tariffs, and those consumers who switch between the two tariffs. In doing so, we are able to determine under which instruments implied incentives to switch to RTP are higher.

2.2 Model description

Building on Gambardella et al. (2016) we use a long-run equilibrium model of a perfectly competitive wholesale and retail electricity market, including endogenous investment in generation

capacity. We further pursue a greenfield approach and do not consider existing plant capacities. This is because the main focus of our analysis does not rest on transitional effects of policy induced RES entry but on its long-run welfare effects. Importantly, in the long-run both approaches lead to identical results: if existing capacities are considered then the market would over time adapt to the new regulatory environment—new profitable capacities are built and existing unprofitable capacities are decommissioned—until it attains the very equilibrium computed through the greenfield approach. That is, for any given RES supply share, the thermal technology portfolio would adapt and converge to the equilibrium portfolio as obtained in our simulations regardless of the initial conditions. Of course, the higher the targeted RES share, the more "drastic" are the changes from today's perspective. But it must be taken into account that respective change would only unfold over decades.

The model further covers a full year on an hourly basis, assumes perfect foresight of all decision makers and is formulated as a Mixed Complementarity Problem (MCP). This MCP constitutes the lower level problem of a Mathematical Program with Equilibrium Constraints (MPEC), the upper level of which is represented by the regulator's problem of setting instrument levels so that in equilibrium a certain RES share (50% in the base case) is achieved. The MPEC is implemented in GAMS and solved with the commercial solver NLPEC.[2]

2.2.1 Supply side

Generators maximize annual profits Π as shown in equation (1) by choosing capacity K_i for each technology i and output $q_{i,t}$ for each hour t and technology i, taking into account each technology's capacity constraint as given by (2). Aside from the revenues from energy sales $\sum_{i,t} p_t \cdot q_{i,t}$, profits also include an additional payment for renewables j in the form of either a feed-in-premium (FiP) mp^q on renewable output $q_{j,t}$ or a capacity premium (CP) mp_j^c per unit of installed renewable capacity K_j.

$$\Pi = \sum_{i,t}(p_t - mc_i) \cdot q_{i,t} - \sum_i fc_i \cdot K_i + \begin{cases} \sum_{j,t} mp^q \cdot q_{j,t} \text{(FIP)} \\ \sum_j mp_j^c \cdot K_j \text{ (CP)} \end{cases} \tag{1}$$

$$q_{i,t} \leq K_i \cdot av_{i,t} \qquad \forall i,t \tag{2}$$

The Lagrange function of the problem is thus

$$L = \Pi + \sum_{i,t} \lambda_{i,t} \cdot (K_i \cdot av_{i,t} - q_{i,t}) \tag{3}$$

where $\lambda_{i,t}$ denotes the hourly shadow price of capacity of technology i. From (3) the Karush-Kuhn-Tucker (KKT) conditions can be derived, which describe optimal firm behavior. The corresponding KKT condition regarding the dual variable $\lambda_{i,t}$ reads as follows:[3]

$$0 \leq K_i \cdot av_{i,t} - q_{i,t} \perp \lambda_{i,t} \geq 0 \qquad \forall i,t \tag{4}$$

2. The GAMS code and all input parameters are available from the first author's homepage under an open-source license.

3. The symbol $\perp$ implies orthogonality, i.e., $0 \leq x \perp f(x) \geq 0$ is equivalent to $x, f(x) \geq 0$ and $x \cdot f(x) = 0$. That is, if $x > 0$ then $f(x) = 0$, and if $f(x) > 0$ then $x = 0$.

Table 1: Sets, indices, parameter and variables.

Symbol	Description	Unit
Sets and indices		
$\mathbf{t} \in \mathbf{T}$	Time periods	Hours
$\mathbf{i} \in \mathbf{I}$	All generation technologies	
$\mathbf{j} \in \mathbf{J}, \mathbf{k} \in \mathbf{K}, \mathbf{J} \cup \mathbf{K} = \mathbf{I}$	Renewable (j) and fossil (k) generation technologies	
Parameters		
$\boldsymbol{\alpha}$	Share of RTP consumers	[0,1]
$\mathbf{av_{i,t}}$	Hourly availability of installed capacity	[0,1]
$\boldsymbol{\eta}$	Price elasticity of demand at reference point	[0,1]
$\mathbf{fc_i}$	Fixed generation costs	€/(MW*a)
$\mathbf{m}$	Slope of inverse linear demand curve	€/(MWh)^2
$\mathbf{mc_i}$	Marginal generation costs	€/MWh
$\mathbf{p0_t}$	Interception of linear demand curve	€/MWh
$\mathbf{rt}$	Targeted renewable share	[0,1]
Variables		
$\boldsymbol{\Pi}$	Generator profits	€/a
$\mathbf{K_i}$	Generation capacity	MW
$\boldsymbol{\lambda_{i,t}}$	Shadow price of capacity constraint	€/MW
$\boldsymbol{\lambda^{rt}}$	Shadow price of RES target constraint	€/MWh
$\mathbf{l}$	Levy to finance RES support	€/MWh
$\mathbf{cf_{j,t}}$	Hourly RES capacity factor	[0,1]
$\mathbf{mp_j^c}$	Market premium on capacity (CP)	€/MW
$\mathbf{mp^q}$	Market premium on energy (FiP)	€/MWh
$\bar{\mathbf{p}}$	Flat-rate retail price	€/MWh
$\mathbf{p_t}$	Wholesale price	€/MWh
$\mathbf{R_t}$	Retail price	€/MWh
$\mathbf{q_{i,t}}$	Hourly generation	MWh
$\mathbf{Q_t}$	Overall hourly demand	MWh
$\mathbf{Q_t^{RTP}}$	Hourly demand RTP consumers	MWh
$\mathbf{Q_t^{FRP}}$	Hourly demand FRP consumers	MWh
$\mathbf{CS^{gross}}$	Total gross consumer surplus	€/a
$\mathbf{CS^{net}}$	Total net consumer surplus (welfare)	€/a
$\mathbf{CS^{FRP}}$	Net consumer surplus FRP consumers	€/a
$\mathbf{CS^{RTP}}$	Net consumer surplus RTP consumers	€/a
$\mathbf{CS^{SWITCH}}$	Net consumer surplus switching consumers	€/a

The other KKT conditions depend on the chosen instrument. Under the FiP, the first order conditions with respect to hourly output $q_{j,t}$ of renewables and fossil technologies $q_{k,t}$ are as follows:

$$0 \leq mc_j - mp^q + \lambda_{j,t} - p_t \perp q_{j,t} \geq 0 \qquad \forall j,t \tag{5a}$$

$$0 \leq mc_k + \lambda_{k,t} - p_t \perp q_{k,t} \geq 0 \qquad \forall k,t \tag{5b}$$

From (5a) it follows that the premium on output mp^q incentivizes generators to supply renewable energy $q_{j,t}$ even at negative prices up to the point where p_t equals the negative value of mp^q—given that renewables have zero short-run marginal costs and the capacity constraint is not binding ($mc_j = \lambda_{j,t} = 0$). The first order condition for investment in capacity reads as:

$$0 \leq fc_i - \sum_t \lambda_{i,t} \cdot av_{i,t} \perp K_i \geq 0 \qquad \forall i,t \tag{6}$$

Table 2: Fixed and variable costs of generation technologies.

	Annuitized fixed costs ($\mathbf{fc_i}$) [€/(kW*a)]	Variable costs ($\mathbf{mc_i}$) [€/MWh]
Wind	136	0
PV	76	0
Base (hard coal)	125	34
Mid (CCGT)	89	64
Peak (OCGT oil)	40	174

That is, firms invest in capacity $K_i \geq 0$ until the marginal capacity value[4] $\sum_t \lambda_{i,t} \cdot av_{i,t}$ is equal to the marginal investment costs fc_i, resulting in zero-profits as implied by the assumption of perfect competition. In other words, if $fc_i > \sum_t \lambda_{i,t} \cdot av_{i,t}$, there is no capacity entry of the respective technology ($K_i = 0$).

In contrast under the CP, the premium on capacity mp_j^c enters the first order condition regarding investment in renewables as shown in equation (7a). The respective first order condition for fossils (7b) remains as under the FiP.

$$0 \leq fc_j - mp_j^c - \sum_t \lambda_{j,t} \cdot av_{j,t} \perp K_j \geq 0 \qquad \forall j \tag{7a}$$

$$0 \leq fc_k - \sum_t \lambda_{k,t} \cdot av_{k,t} \perp K_k \geq 0 \qquad \forall k \tag{7b}$$

Further, first order conditions for energy output are independent of technology:

$$0 \leq mc_i + \lambda_{i,t} - p_t \perp q_{i,t} \geq 0 \qquad \forall i,t \tag{8}$$

Thus, in contrast to the FiP, generators only supply renewable energy $q_{j,t}$ when wholesale prices are non-negative ($p_t \geq 0$).

Regarding parameterization, we consider three representative thermal technologies (base, mid, peak) and two variable renewable technologies (onshore wind, solar PV). The thermal technologies are loosely calibrated to hard coal (base), natural gas combined cycle gas turbines (CCGT, mid), and oil-fired open cycle gas turbines (OCGT, peak), respectively. While this selection is certainly stylized, it covers the relevant spectrum of technology options with respect to the relationship between fixed and variable costs (Table 2). The cost parameters have been calculated drawing on techno-economic parameters provided in Schröder et al. (2013) and fuel price scenarios of the 2014 IEA World Energy Outlook.

On the RES side, we focus on the two most prominent fluctuating technologies, as these are very likely to contribute most to renewable targets in many countries. In particular, we leave out offshore wind and biomass because of their higher costs and restricted potentials.[5] Hourly RES availability factors are calculated from 2013 German market data. Annual average capacity factors are 18% for onshore wind and 10% for solar PV.

4. Note that $\lambda_{i,t} \cdot av_{i,t}$ equals hourly net producer surplus per unit of energy sold, that is either $av_{j,t}(p_t - (mc_j - mp^q))\forall j$ or $av_{k,t}\,(p_t - mc_k)\forall k$.

5. Explorative model runs that include these technologies indicate that the computation time increases substantially without changing qualitative results.

2.2.2 Demand side

Based on the framework developed by Borenstein and Holland (2005), we split consumers into two segments as shown in equation (9): consumers on flat-rate pricing (FRP) having a share of $1-\alpha$ and facing a time-invariant price, which in equilibrium equals the demand-weighted average of hourly wholesale prices $\bar{p}$; and consumers on real-time pricing (RTP) having a share of α and facing a time-variant price, which in equilibrium equals the hourly wholesale price p_t. Additionally, we assume that total RES subsidies are spread evenly across all consumers in the form of a levy l per unit of electricity consumed. Therefore, the final retail price faced by each consumer comprises two components: the costs of energy and the costs of RES supports. Total demand Q_t equals the sum of hourly FRP and RTP consumer demand:

$$Q_t(p_t,\bar{p},l,t) = \alpha \cdot Q_t^{RTP}(p_t,l) + (1-\alpha)\cdot Q_t^{FRP}(\bar{p},l) \qquad \forall t \tag{9}$$

We further assume that demand is a linear function of the respective price for both consumer types, and takes the following form:

$$Q_t^{RTP}(p_t,l,t) = \frac{1}{m}\cdot(p0_t-(p_t+l)) \qquad \forall t \tag{10a}$$

$$Q_t^{FRP}(\bar{p},l,t) = \frac{1}{m}\cdot(p0_t-(\bar{p}+l)) \qquad \forall t \tag{10b}$$

where $p0_t$ is the hourly prohibitive price which shifts the demand curve from hour to hour to capture structural demand variations. Retail prices are determined under the assumption that homogenous retail firms maximize profits under perfect competition. That is, retailers buy electricity from generators on the wholesale market and sell it on to consumers making zero-profits. In addition, retailers are obliged by the regulator to collect the levy l from consumers to finance the RES subsidies. Assuming that retailers do not cross-finance their respective expenses, levies are set so that total premiums paid to RES generators equal total levies paid by consumers. Rewriting corresponding zero-profit condition gives the premium on generation (11) and capacity (12) respectively as:

$$0 = l - \frac{\sum_{j,t} q_{j,t}\cdot mp^q}{\sum_{i,t} q_{i,t}},\ l\ free \tag{11}$$

$$0 = l - \frac{\sum_{j,t} K_j\cdot mp_j^c}{\sum_{i,t} q_{i,t}},\ l\ free \tag{12}$$

Noting that retailers procure energy for both consumer types at the hourly equilibrium wholesale price p_t determined by the market clearing condition (13), perfect retail competition implies that p_t has to equal the hourly retail price. Likewise, retailers' zero-profit condition (14) gives that FRP consumers' flat energy price $\bar{p}$ equals the demand-weighted average of p_t.

$$0 = \sum_i q_{i,t} - \alpha\cdot\frac{p0_t-(p_t+l)}{m} - (1-\alpha)\cdot\frac{p0_t-(\bar{p}+l)}{m}\ ,\ p_t\ free \qquad \forall t \tag{13}$$

$$0 = \sum_t \left((\bar{p} - p_t) \cdot (1-\alpha) \cdot \frac{p0_t - (\bar{p} + l)}{m} \right), \ \bar{p} \ free \tag{14}$$

Regarding the share of RTP consumers α there is no data available for the German market, but there is evidence that it is larger than zero. Namely Agora Energiewende (2015) uses an exemplary bid curve to illustrate that a certain proportion of demand is already responsive to prices (around 3 GW in the particular hour analyzed). Due to this lack of data we assume $\alpha = 10\%$ in the base case, which approximates mid-run projections in other markets such as PJM (cf., Allcott 2012).

Regarding demand parameters, we calculate the slope m and the hourly prohibitive price $p0_t$ using a price elasticity of -0.05 in the base case, and demand-weighted annual average prices and quantities drawing on German market data for 2013. While both the functional form and the value of price elasticity are conventions supported by the literature, there is little evidence for the shape of demand functions for any consumer type. Green and Vasilakos (2010) also use a linear function, but Bushnell (2011), for example, uses a partial log-function and Borenstein and Holland (2005) use an iso-elastic function. Likewise, parameters for own-price elasticity also vary. Both Bushnell (2011) and Borenstein and Holland (2005) use the same value as we do, whereas Green and Vasilakos (2010) apply higher values (-0.2 and -0.3). Other work, such as Pineau and Murto (2003), uses even higher values (-0.4). Given that modeled prices very much depend on the parameterization of demand, we discuss the effect of alternative price elasticities (-0.01 and -0.1) as part of a sensitivity analysis.

2.2.3 The regulator's problem

The regulator needs to set the levels of the FiP (mp^q) and the CP (mp_j^c) respectively so that the RES production target $rt \in [0,1]$ as defined in equation (15) is achieved in equilibrium; the asterisk denotes that all prices and quantities are equilibrium levels, and mp is used as a general form for both premiums.

$$\frac{\sum_{j,t} q_{j,t}^*(mp)}{\sum_t Q_t^*(p_t^*, \bar{p}^*, l, t)} = rt \tag{15}$$

To determine the premium levels, one would need to solve equation (15) for mp, but this cannot be done in closed form because price and quantities are equilibrium levels. In face of this, we need to determine the levels numerically, which we do by formulating the regulator's problem as a mathematical program with equilibrium constraints (MPEC). The mathematical program simply consists of an equality constraint (15), but for technical reasons a dummy function to be maximized is required, for which we chose gross consumer surplus as given in equation (16) for convenience reasons. The MPEC thus consists of equations (15)–(16) entailing the upper level "optimization" by the regulator and the following equilibrium constraints entailing producer and consumer behavior: supply side equations (4)–(6) in case of the FiP and (4),(7a)–(8) in case of the CP, and demand side equations (9)–(14).

$$CS^{gross} = \sum_t \left[\alpha \cdot \left(\frac{p0_t^2 - (p_t + l)^2}{2 \cdot m} \right) + (1-\alpha) \cdot \left(\frac{p0_t^2 - (\bar{p} + l)^2}{2 \cdot m} \right) \right] \tag{16}$$

Even though we determine levels numerically, basic economic reasoning already allows some inferences about how the premiums are set. To begin with, the implicit shadow price λ^{rt} of

the RES target constraint (16) reflects the marginal social value of each unit of RES production for achieving the target. Intuitively, the level of both instruments depends on λ^{rt}. More specifically, efficiency requires that λ^{rt} is identical for all RES technologies per unit of production under both instruments.

For the FiP this implies that mp^q is equal for all technologies and identical to λ^{rt}, which simply follows from the relation of social value to production. This does not mean though that only a single RES technology enters the market, i.e. the one with the highest capacity factor to cost ratio. The reason is that market revenues differ for all technologies because of different availability patterns, e.g. PV produces more in high price hours during noon than wind. On this also see Lamont (2008), who derives the long-run marginal value of RES.

In contrast, under the CP capacity is subsidized and hence control is indirect in the sense that even though capacity is subsidized, it is production that creates value. The hourly production of one unit of capacity of technology j can be expressed using an hourly capacity factor $cf_{j,t} \in [0,1]$ defined as the ratio of the actual output to the maximal output (capacity) in hour t, i.e. $cf_{j,t} = \frac{q^*_{j,t}}{K_j}$. Note that here again $q^*_{j,t}$ denotes the hourly equilibrium output and thus constitutes the actual utilization of capacity in contrast to its technical availability ($av_{j,t}K_j$). Since the capacity factor is identical to the marginal production of each unit of capacity, efficiency requires that $mp^c_j = \sum_t cf_{j,t} \cdot \lambda^{rt}$. That is the capacity premium mp^c_j must equal annual production per unit of capacity $\sum_t cf_{j,t}$ times the uniform social marginal value of RES output λ^{rt}.

From the above it also follows that the capacity premium must differ for technologies if their average availability and thus capacity factors differ, too. More precisely, in our model each unit of wind capacity is more valuable than PV capacity for achieving a given RES production target, that is $\sum_t cf_{wind,t} \cdot \lambda^{rt} > \sum_t cf_{PV,t} \cdot \lambda^{rt}$, if wind is relatively more available for production ($\sum_t av_{wind,t} > \sum_t av_{pv,t}$) and thus has a higher output per unit of capacity (capacity factor). Accordingly, a single technology-neutral premium would overpay technologies with low capacity factors (PV) leading to an inefficient outcome.

2.3 Ex-post calculation of welfare effects

In a second step we also examine (a) welfare differences between the two instruments for given RTP shares and (b) compare the relative welfare gains from increasing the RTP consumer share α under the FiP and CP regime. Thus, on the one hand we compute the net surplus changes of RTP and FRP consumers when changing from CP to FiP. On the other hand, we analyze the relative benefits of raising the RTP share under CP and FiP induced RES entry. Accordingly, we compute the net surplus changes between equilibria where the RTP share is raised from α_0 to α_1 with $\alpha_1 > \alpha_0$. Total surplus changes can then be decomposed into incumbent RTP and FRP consumer surplus changes as well as surplus gains of consumers switching from FRP to RTP.

The starting point for calculating welfare effects is overall gross consumer surplus as defined in equation (16) above. Note that it increases strictly with decreasing prices up to the point where the retail price is zero, $p_t + l = 0$. For lower prices however, gross consumer surplus begins to decrease. This is because the price is set for consumers who have a negative willingness-to-pay. They therefore incur "damage" from additional consumption. However, consumers are compensated for this by receiving the negative retail price during these hours (see section 3.1). This is reflected in the total net consumer surplus (welfare), which equals gross consumer surplus minus the costs of electricity given by the total payments for electricity by RTP and FRP consumers:

$$CS^{net} = CS^{gross} - \sum_t [\alpha \cdot (p_t + l) \cdot Q_t^{RTP}(p_t, l) + (1-\alpha) \cdot (\bar{p} + l) \cdot Q_t^{FRP}(\bar{p}, l)] \tag{17}$$

The net surplus change of FRP consumers, i.e. consumers who face a flat-rate price for both values of α considered, is calculated as follows as

$$\begin{aligned} \Delta CS^{FRP} &= (1-\alpha_1) \cdot (CS_1^{FRP} - CS_0^{FRP}) \\ &= \sum_t (1-\alpha_1) \cdot \left[\left(\frac{(\bar{p}_0 + l_0)^2 - (\bar{p}_1 + l_1)^2}{2 \cdot m} \right) \right] \\ &\quad - \sum_t (1-\alpha_1) \cdot [Q_{t,1}^{FRP} \cdot (\bar{p}_1 + l_1) - Q_{t,0}^{FRP} \cdot (\bar{p}_0 + l_0)] \end{aligned} \tag{18}$$

with $Q_{t,1}^{FRP} = \frac{p0_t - (\bar{p}_1 + l_1)}{m}$ and $Q_{t,0}^{FRP} = \frac{p0_t - (\bar{p}_0 + l_0)}{m}$. Note that the first term reflects changes in gross consumer surplus and the second reflects changes in the costs of the electricity consumed.

The net surplus change of incumbent RTP consumers is calculated as

$$\begin{aligned} \Delta CS^{RTP} &= \alpha_0 \cdot (CS_1^{RTP} - CS_0^{RTP}) \\ &= \sum_t \alpha_0 \cdot \left[\left(\frac{(p_{t,0} + l_0)^2 - (p_{t,1} + l_1)^2}{2 \cdot m} \right) \right] \\ &\quad - \sum_t \alpha_0 \cdot [Q_{t,1}^{RTP} \cdot (p_{t,1} + l_1) - Q_{t,0}^{RTP} \cdot (p_{t,0} + l_0)] \end{aligned} \tag{19}$$

with $Q_{t,1}^{RTP} = \frac{p0_t - (p_{t,1} + l_1)}{m}$ and $Q_{t,0}^{RTP} = \frac{p0_t - (p_{t,0} + l_0)}{m}$.

Finally, the net surplus change of those consumers who switch from FRP to RTP is

$$\begin{aligned} \Delta CS^{SWITCH} &= (\alpha_1 - \alpha_0) \cdot (CS_1^{RTP} - CS_0^{FRP}) \\ &= \sum_t (\alpha_1 - \alpha_0) \cdot \left[\left(\frac{(\bar{p}_0 + l_0)^2 - (p_{t,1} + l_1)^2}{2 \cdot m} \right) \right] \\ &\quad - \sum_t (\alpha_1 - \alpha_0) \cdot [Q_{t,1}^{RTP} \cdot (p_{t,1} + l_1) - Q_{t,0}^{FRP} \cdot (\bar{p}_0 + l_0)] \end{aligned} \tag{20}$$

with $Q_{t,1}^{RTP} = \frac{p0_t - (p_{t,1} + l_1)}{m}$ and $Q_{t,0}^{FRP} = \frac{p0_t - (\bar{p}_0 + l_0)}{m}$. As can be verified, the sum of all surplus changes for the different consumer groups equals the overall change in (net) consumer surplus.

3. RESULTS

3.1 Effects on prices, quantities and welfare

Before presenting and discussing results, it is helpful to illustrate and disentangle the distortionary effects on consumer surplus of both instruments. Figure 1 shows these effects for the FiP, while Figure 2 shows them for the CP—for representative hours of high RES supply ($RE+$) and low RES supply ($RE-$). We decompose the total welfare effect into three parts, which we also refer to when discussing results in this and the following sections. The first effect holds for both instruments: due to the additional levy l on top of wholesale prices p_t, the retail price $R_t = p_t + l$ is

Figure 1: Effects of FiP on consumer surplus.

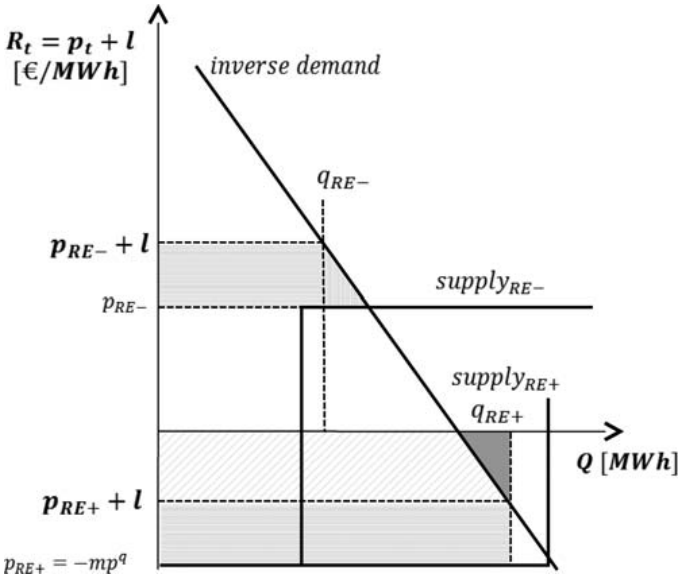
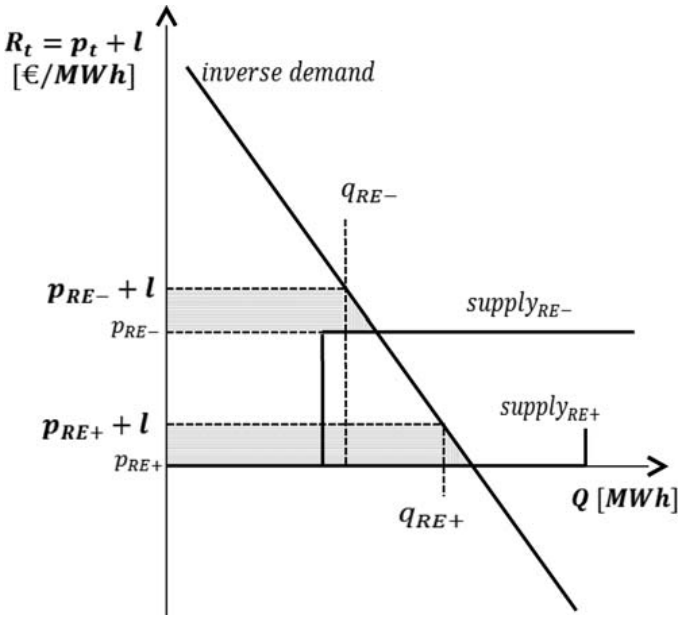


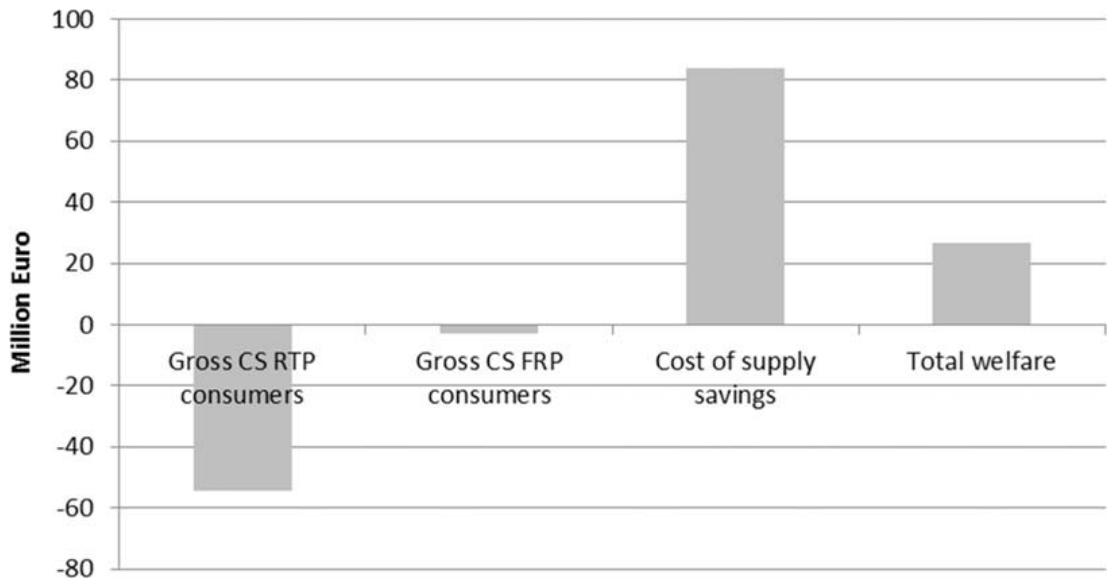
Figure 2: Effects of CP on consumer surplus.



increased, which in turn reduces consumption and respective net consumer surplus. This reduction comprises a dead weight loss (vertical hatched area), and the overall levy payments to RES generators (horizontal hatched area).

The second effect is increased net consumer surplus under the FiP in times of high RES supply. More precisely, in contrast to the CP, the FiP induces a downshift of the supply curve to the negative value of the premium ($-mp^q$). Since the levy is always lower than the premium, this means higher RES utilization and consumption. Given that consumers are saturated when R_t equals

Figure 3: Decomposed net consumer surplus (welfare) differences if changing from CP to FiP, in € million/year.



zero, they have a negative willingness-to-pay beyond this point and thus incur "damage". In turn, gross consumer surplus is reduced (solid grey triangle). However, consumers are paid the (negative) wholesale price, net of the levy, multiplied by their consumption, such that there is an overall gain in net consumer surplus (diagonal hatched area). Importantly, the overall size of these effects depends on the proportion of RTP consumers, because FRP consumers only respond to average annual prices and cannot increase consumption in periods of low prices. A third effect, not directly shown in either figure, is that less capacity is required under the FiP to meet the renewable production target. This is because renewable capacities are utilized to a greater extent under the FiP since consumption in high RES supply hours ($RE+$) is higher compared to the CP due to the negative wholesale prices under the FiP. The higher utilization of RES under the FiP therefore implies that less RES capacities are needed to meet the renewable production target.

These effects have important implications for the value of RES capacities and respective costs. Under the FiP, RES produce also at negative prices so their market value will be lower compared to the CP. In turn, in order for renewables to cover their fixed costs, total subsidies need to be higher, and thus the levy under the FiP will also be higher than under the CP. This may at first glance imply that the FiP is less efficient, since consumers have to pay a higher levy to subsidize RES, which additionally distorts consumption.

Figure 3 shows the differences between FiP and CP for all relevant welfare terms as described in section 2.2.3 for the base case, i.e. a price elasticity of -0.05 and a 10% share of RTP consumers. Results confirm that gross consumer surplus is indeed lower under the FiP. In particular, RTP consumers are worse off, because their respective price distortion is greater than under the CP. More specifically, RTP consumers under the FiP lose gross consumer rents in periods with negative prices due to additional damaging consumption (second effect, see above)—and they lose even more in all other periods because the levy is higher than in case of the CP (first effect). Yet total welfare is higher under the FiP. This stems from lower total costs of supply due to decreased capacity entry (third effect). In other words, the benefits of gross consumer surplus of the CP are outweighed

Figure 4: Equilibrium capacities under CP.

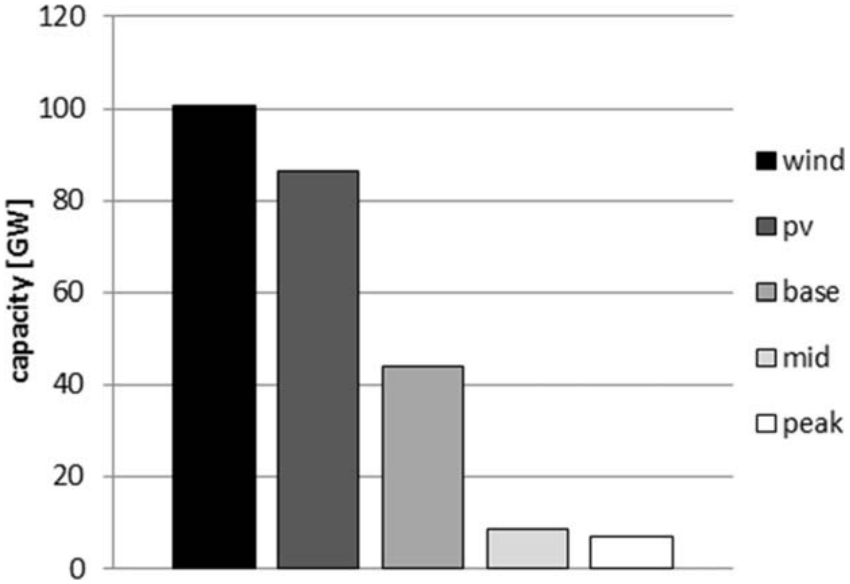
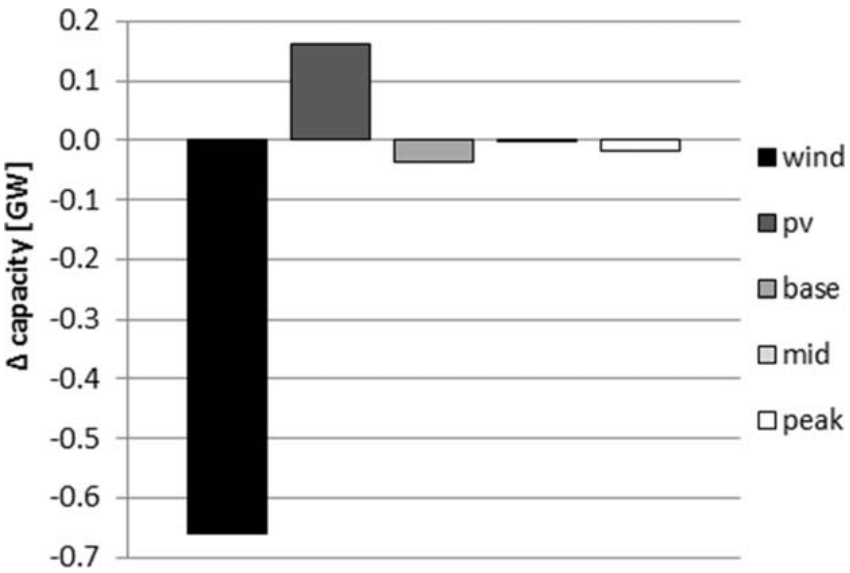


Figure 5: Capacity difference under FiP compared to CP.



by RES capacity cost advantages under the FiP. Finally, relating welfare differences to industry turnover shows that differences are only around 0.1%, and thus very small, at least for the base case we consider. Yet in this context, the size of the effect is less important than its direction. We also demonstrate below that it substantially increases for higher RES shares.

As Figure 4 and Figure 5 show in more detail, capacity differences are largest for wind, where 0.66 GW less capacity is built. Fossil capacities are also somewhat lower, but the effect is considerably smaller. This is because fossil plants do not produce when wholesale prices are negative, and are thus only affected through the change in the RES portfolio and the differences in

Table 3: Comparison of prices and market values.

	RTP wholesale price* [€/MWh]	FRP wholesale price [€/MWh]	Levy [€/MWh]	RTP retail price [€/MWh]	FRP retail price [€/MWh]	Turnover [€bil.]
FiP	27.5	37.2	43.1	70.6	80.3	34.7
CP	40.9	48.1	32.1	73.0	80.2	34.8

*demand-weighted average

consumption levels, which are lower under the FiP during times with positive retail prices due to the higher levy (first effect). Note that this also counteracts the effect of increased consumption during negative price hours under the FiP. Therefore, total consumption over the year is quite similar under the FiP and CP. In contrast, solar PV capacity is around 0.16 GW higher, which can be traced back to its specific availability pattern (increased generation during times of high demand).

When looking at prices as shown in Table 3, considerable differences come up. The average RTP wholesale price in case of the FiP is much lower ($\sim$28 €/MWh) than that of the CP ($\sim$41 €/MWh). As explained above this is because the premium on energy creates incentives to produce, even at negative prices. This happens in nearly 1200 hours and consequently lowers the average price[6]. This of course also affects the market value of RES technologies, which are likewise considerably lower under the FiP: 7.4 €/MWh compared to 29.5 €/MWh for wind, and 4.4 €/MWh compared to 27.0 €/MWh for solar PV. Likewise, overall support payments are also higher for the FiP than the CP (€18.8bn compared to €14.0bn). This is also reflected in higher levies paid by consumers (43.1 €/MWh vs. 32.1 €/MWh).

Importantly, while instruments differ considerably with respect to the wholesale price and levy levels they induce, overall retail prices are relatively similar. In particular, FRP consumers (90% of all consumers) face nearly identical prices, while there is a slight difference for RTP consumers (remaining 10% of consumers) due to the induced negative prices.

3.2 Welfare and distributional effects of increasing real-time pricing

In this section we look at welfare and distributional effects from changing the RES support scheme, for both a given and a rising share of RTP consumers (α). Table 4 shows the gross (left columns) and net (right columns) consumer surplus differences from changing from the CP to the FiP regime for *given* RTP shares. Regarding the net consumer surplus changes, FRP consumers are worse off under the FiP than under the CP (negative values), while RTP consumers are generally better off and their benefits outweigh FRP consumers' losses so that overall welfare (net consumer surplus for all consumers) increases.

Furthermore, FRP consumers lose when changing from CP to FiP because their final retail price $\bar{p} + l$ increases. More specifically, the wholesale price $\bar{p}$ becomes smaller, but the levy l rises relatively stronger, as shown in Table 3. This is mainly due to the negative wholesale prices as explained in the previous section. Additionally, by raising consumption in negative price hours in comparison to the CP, RTP consumers exert both a positive and a negative pecuniary externality affecting the levy and thus FRP consumers: the positive externality reduces the levy since less RES

6. We assume there is always sufficient demand response such that there is no administrative curtailment. This further implies that we assume that value of lost load (VoLL), which theoretically should define the price cap, is above 1449 €/MWh since this is the maximum wholesale price under both instruments in our model.

Table 4: Consumer surplus changes if changing from CP to FiP, in € million/year.

	FRP consumers		RTP consumers		All consumers	
α	Gross	Net	Gross	Net	Gross	Net
1%	−0.4	−3.3	−5.7	6.0	−6.1	2.8
10%*	−3.1	−27.6	−54.3	54.2	−57.4	26.6
20%	−5.2	−46.1	−103.1	96.7	−108.3	50.6
30%	−6.3	−56.2	−146.3	128.6	−152.6	72.4
40%	−6.5	−58.5	−181.9	150.1	−188.5	91.6
50%	−6.2	−55.0	−210.5	163.4	−216.7	108.4

*base case

entry is needed to meet the RES production target (third effect, see section 3.1). On the other side, the negative externality increases the levy through relatively higher consumption of RES in negative price hours by RTP consumers. This negative externality outweighs the positive externality, which mainly explains why all in all the levy increases more than the flat energy prices for FRP consumers falls when changing from the CP to FiP. In contrast to RTP consumers, they cannot profit from raising their consumption during periods where RTP consumers are paid to do so. Instead, FRP consumers finance the remuneration of RTP consumption in these hours.

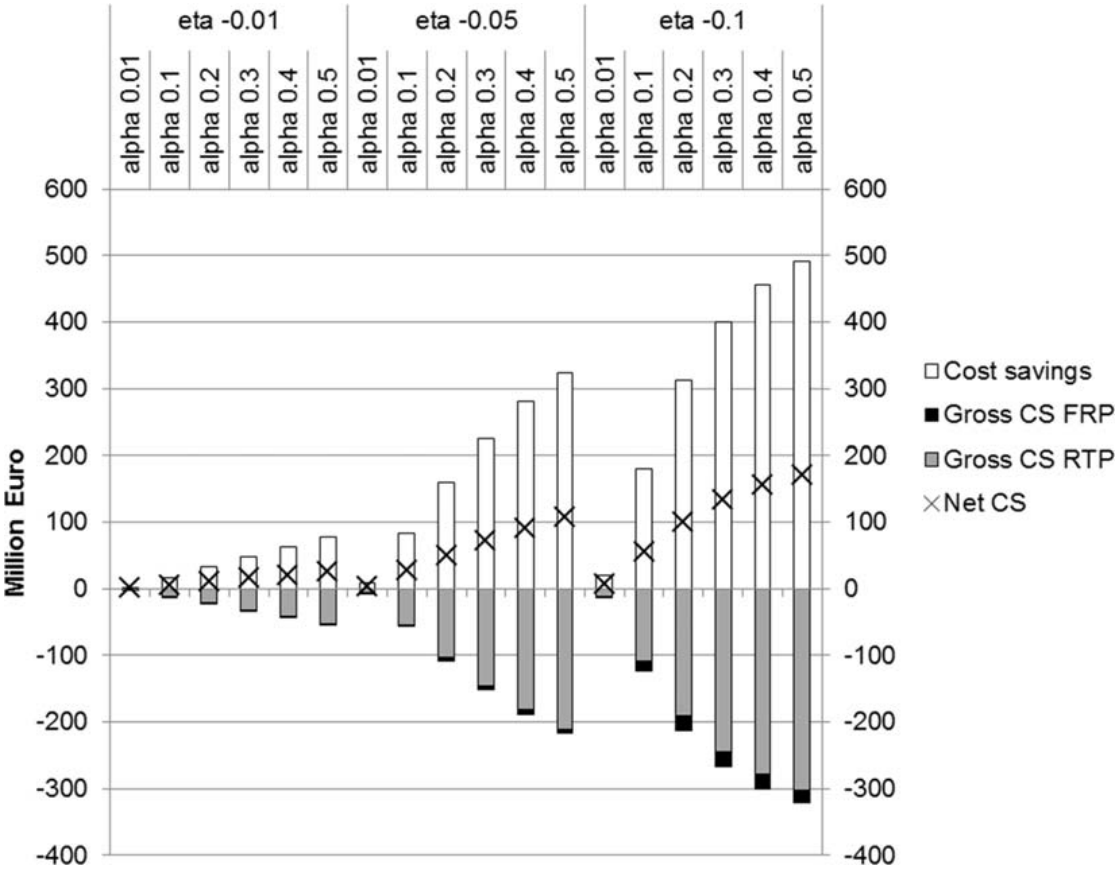
Table 4 further shows that RTP consumers also incur gross surplus losses from, firstly, paying a higher levy under the FiP which implies a higher dead weight loss (first effect, see section 3.1) and, secondly, from incurring a "damage" of consuming above their saturation level (second effect, see section 3.1). However, in contrast to the FRP consumers they overall net benefit mainly because of the payments they receive per unit of consumption when wholesale prices are negative. Put differently, they benefit from implicit cross-subsidies payed by FRP consumers for their consumption during these hours as explained in the previous paragraph.

Moreover, following the intuition given in section 3.1, the third column in Table 4 shows that total welfare gains from changing to the FiP increase with the given RTP share α. The larger the portion of consumers able to respond to the real-time retail price $p_t + l$, the relatively higher is the utilization of installed RES capacity at negative prices and thus relatively less RES capacity to achieve the RES production target is required (third effect, see section 3.1). The differences in total gross and net surplus ("All consumers") show the cost of supply savings which, as described, explain why the FiP leads to a higher welfare level than the CP.

As can be taken from comparing the total welfare gains for different RTP shares, the incremental cost savings or welfare gains respectively decrease with the RTP share α (see also Figure 6). This is mainly because the higher the share of RTP consumers, the higher is the RES capacity utilization already under the CP, so that it can only be increased to a lower extent when changing to the FiP. Therefore, also the effect of lower RES capacity entry and thus the cost of supply savings under the FiP decrease with the RTP share. On the other hand, lower relative changes in welfare gains from changing to the FiP hint towards lower relative retail price distortions induced by the levy, which are mitigated via a higher RTP share α. This is intuitive since higher RTP shares mitigate allocative inefficiencies. In fact, the difference between the levy under the CP and FiP decreases with the RTP share (not shown), while the levy shrinks under both the CP and the FiP when α rises.

Furthermore, efficiency gains from raising the RTP share decrease with higher α (Borenstein and Holland, 2005). This can be seen by comparing the total net consumer surplus changes

Figure 6: Decomposed net consumer surplus (welfare) differences if changing from CP to FiP for different elasticities and RTP shares, in € million/year.



ΔCS^{SUM} from raising the RTP share under either CP or FiP in Table 5. Moreover, Table 5 shows that by and large incumbent RTP consumers (ΔCS^{RTP}) lose[7] while FRP consumers (ΔCS^{FRP}) generally benefit from a higher RTP share for the reasons explained above. The relatively higher net surplus gains of consumers switching to RTP ΔCS^{SWITCH} under the FiP reflect the larger inefficiency from hourly flat consumption, which stems from the larger price distortion and the larger variance in wholesale prices due to the occurrence of negative prices driven by the output subsidy mp^q. That is, FRP consumers over- and under-consume relatively more under the FiP, particularly during negative price hours, implying higher allocative inefficiency. This implies higher gains from mitigating the latter via raising consumers' ability to consume optimally by putting more consumers

7. Note that while this always holds in Borenstein and Holland (2005), it is not necessarily the case in our model. Surplus gains of incumbent RTP consumers become positive when the RTP share is increased from 40% to 50% under the CP since the levy drops more than the off-peak price hours rise after the RTP share is raised: an increase of RTP implies that the utilization of RES increases since more RTP consumers increase their consumption during abundant RES supply hours. As explained above, less RES capacity entry is thus needed to achieve the RES production share target implying that the levy to finance RES capacities can be lower. While the decrease itself is relatively small (0.14 €/MWh), when multiplied with the total consumption of RTP consumers (176 TWh) it results in overall surplus gains of around €25 million.

Table 5: Net consumer surplus changes between different RTP shares, in € million/year.

$\Delta\alpha$	ΔCS^{FRP}	ΔCS^{RTP}	ΔCS^{SWITCH}	Total
Market premium on energy (FiP)				
10% → 20%	39.0	−29.5	184.6	194.1
20% → 30%	28.3	−24.7	167.4	171.0
30% → 40%	23.5	−21.8	156.0	157.7
40% → 50%	19.8	−19.4	147.3	147.7
Market premium on capacity (CP)				
10% → 20%	60.5	−23.6	133.2	170.1
20% → 30%	44.2	−13.7	118.7	149.1
30% → 40%	33.9	−5.8	110.5	138.6
40% → 50%	26.2	0.4	104.9	131.5

on RTP. Put differently, switching becomes more beneficial under FiP mostly because consumers then get payed for consuming electricity during negative price hours.

Hence, consumers may in general be more willing to switch to RTP under the FiP and thereby partially offset the welfare losses from relatively larger price distortions. Likewise, any efforts to increase RTP shares, be it infrastructure investments or institutional adjustments, are more rewarding under the FiP. But a significant part of the additional switching incentives under the FiP comes from implicit cross-subsidies during negative price hours paid by FRP consumers. That is, changing from a CP to a FiP also has important distributional consequences.

3.3 Sensitivity analyses

In order to test the robustness of the base case findings, we investigate the effects of alternative assumptions. On the one hand, we consider alternative price elasticities of demand, i.e. -0.01 and -0.1 instead of -0.05. On the other hand, we look at alternative RES shares, ranging from 0% to 75%.

Figure 6 summarizes the effects of different price elasticities, under varying RTP shares, on gross consumer surplus of RTP and FRP consumers, costs of supply, and resulting net consumer surplus. It can be seen that qualitative results do not change compared to the base case. Yet absolute differences between respective CP and FiP settings grow with increasing demand flexibility as explained in the previous section.

Figure 7 shows welfare differences between the two instruments for varying RES shares. For shares lower than 50%, there is hardly any difference between the FiP and the CP, as renewable surplus generation, and in turn negative prices, hardly play a role. Yet for RES shares beyond 50%, renewable surpluses become much more frequent, such that the relative advantage of the FiP increases substantially to around €7.6 billion in the 75% case.

Figure 8 shows energy price and levy levels for RTP and FRP consumers for different RES shares. A general observation is that wholesale prices decrease with increasing RES shares, while levies increase. This is because with rising shares RES become price-setting in increasingly many hours, which in turn reduces average wholesale prices and thus RES technologies' market value. Consequently, market premiums have to be relatively higher to compensate this effect, and at the same time more RES capacities receive the premium such that the levies also need to rise accordingly. While effects are moderate under both the CP and FiP up to a share of around 50%,

Figure 7: Decomposed net consumer surplus (welfare) differences if changing from CP to FiP for different RES shares, in € million/year.

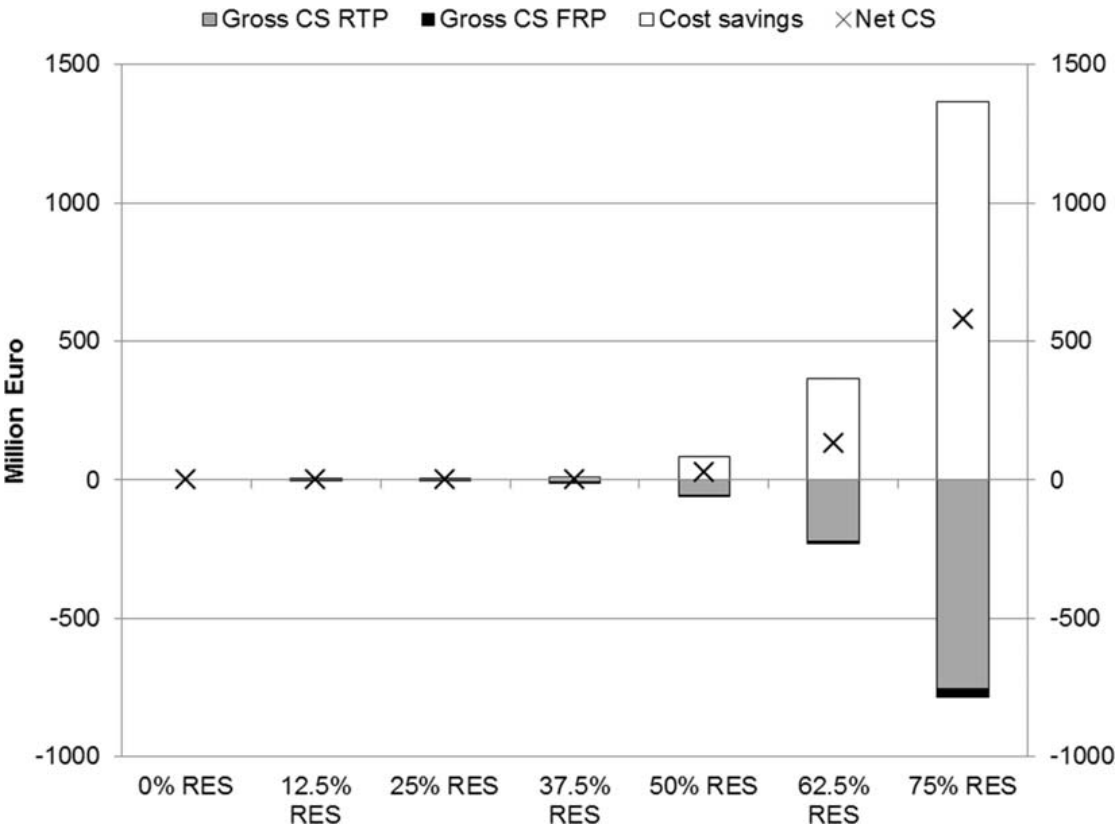
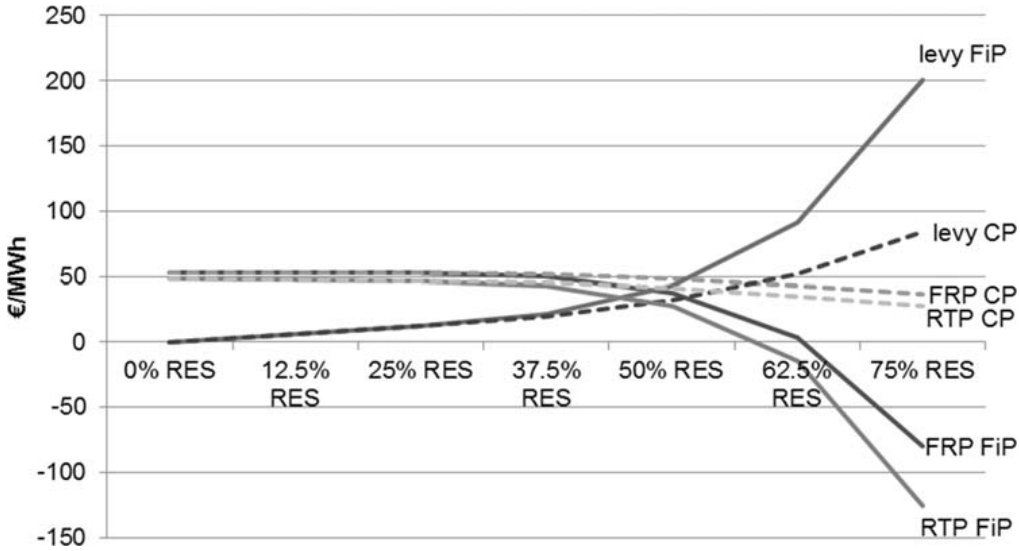


Figure 8: Demand-weighted real-time wholesale prices (RTP), flat-rate wholesale prices (FRP) and levies for varying RES shares under FiP and CP.



there are large deviations for higher shares. Very high RES targets drive a large wedge between energy prices and levies, particularly for the FiP due to the negative wholesale prices. In the 75% case, both the average RTP and FRP energy price become negative under the FiP and the levy rises to more than 200 €/MWh.

4. DISCUSSION OF LIMITATIONS

In this section, we briefly discuss some limitations of the model and indicate the direction in which these limitations may distort results.

While focusing on increased RTP, we neglect other flexibility options such as dispatchable renewable electricity sources, electricity storage, and international trade. In particular, storage and international trade will cause demand to increase in times of high RES generation and low prices, while these options increase supply in times of high residual demand. We thus tend to overestimate the fluctuations of residual load and spot prices, and the occurrence of negative prices. We accordingly also overestimate the value of increased demand-side flexibility.

A similar reasoning applies to the scaling up of historic renewable feed-in time-series. While this method is often applied in the literature, it disregards potential future smoothing effects related to changes in the design and the spatial distribution of renewable generators (see Schill 2014). This may also contribute to an overestimation of the negative prices and the value of RTP.

The opposite is true for other limitations of the model, i.e. disregarding costs and flexibility restrictions of thermal generators such as start-up and ramping costs, or restrictions related to combined heat and power generation. Ignoring such constraints substantially decreases the model's computational burden. This appears to be at least partly justified as we take a long-term perspective for which it can be assumed that the flexibility of thermal generators will not become a major issue because of technological improvements and changes in the generation portfolio; compare also Schill et al. (forthcoming). We do however acknowledge that results may be distorted because of this simplification. If such flexibility restrictions were considered in the model, negative prices under the FiP may occur even more often. At the same time, ramping-related costs of base-load plants could be higher under the FiP. Determining the net effect on welfare outcomes would require a dedicated analysis.

As for additional sensitivity analyses, it may be worthwhile assessing the robustness of welfare effects not only with respect to different elasticities, RTP shares and RES targets, but also for different functional forms of demand. For example, the general findings should also hold under an iso-elastic demand function, which would allow for negative wholesale (but not retail) prices. Overall effects may be even larger compared to the linear demand function considered here because of a greater increase in consumption during periods of negative prices. Investigating these effects is left for future research.

Our rather stylized approach of modeling electricity demand also requires discussion. Firstly, RTP not only incorporates hourly increase and reduction of demand, but also demand that shifts over hours. In engineering-oriented dispatch models with price-inelastic demand, such shifts can, in principle, be modeled by using appropriate constraints; see Zerrahn and Schill (2015). Yet in economic models with price-elastic demand, a proper representation of load shifts is more challenging (De Jonghe et al., 2014). The relevant behavioral parameter is cross-price elasticity, which is typically measured between peak, off-peak and sometimes also shoulder periods; see Faruqui and Sergici (2010) for a review of studies. However, prices in a market with high RES shares no longer exhibit such typical price patterns. Parameterizing cross-price elasticity in a future setting with high shares of RES would thus be highly speculative.

Finally, it is not clear whether actual consumers are truly as responsive to price changes as typically assumed in economic models. In particular it is doubtful whether lower prices lead to steadily increasing consumption levels. In fact, most research so far, such as Wolak (2011), focuses on RTP in times of peak prices (price spikes). Recent research by Lang and Okwelum (2015) on off-peak behavioral responses, however, confirms that consumption indeed increases in off-peak times because load is being shifted, at least partly, from peak times. Likewise, it is questionable whether the value of making consumers more responsive to real-time prices always compares favorably with the costs of equipping them to do so. Léautier (2014) for example argues that in the case of small residential customers this value might be far below the cost of installing smart meters.

5. DISCUSSION AND CONCLUSIONS

In this paper we analyze welfare effects of RES support instruments, focusing on the nexus of price responsive demand, negative electricity prices and relative RES targets in total electricity production. More specifically, we compare the total annual welfare obtained under two support instruments to achieve a RES production target: a production subsidy (FiP) which can induce negative wholesale energy prices and a capacity subsidy (CP) which does not. Since it implies stronger deviations from marginal cost pricing, common intuition suggests that the presence of negative prices lowers the relative efficiency of reaching a certain RES target, so that a CP may appear to be the more cost-efficient instrument.

Contrary to this intuition, we find that a FiP can actually lead to higher welfare than a CP despite greater wholesale price distortions. This is because a RES production target can be achieved at lower overall costs, since less RES capacity is required to obtain a given share in total production. More precisely, negative prices during hours of high RES supply incentivize RTP consumers to raise their consumption more than under the CP regime, where retail prices never drop to or below zero. Thus, RES capacities are utilized to a relatively larger extent than under the CP, implying that the same RES production target is achieved with less RES capacity entry. This finding hinges on two main assumptions: (i) a relative renewable target defined as a share in production, and (ii) a positive proportion of consumers who face real-time prices. As said above, the former allows for the capacity required to achieve the target to vary, depending on the overall level of demand and the amount of renewable output that can be sold to the market. This assumption is also of practical relevance due to the widespread implementation of production targets.

When determining welfare we do not explicitly consider the social benefits of renewable production. For a full welfare perspective though, an explicit rationale for RES subsidies (e.g. learning spillovers) would need to be included in the analysis, which we ignore for the sake of concentrating on the isolated performance in achieving a given target. There is however other literature that addresses this question. For example, if learning spillovers would indeed be the main rationale, it can be argued that the efficient subsidy is a capacity payment though (Newbery, 2012). Also Andor and Voss (2016) argue that capacity subsidies are the appropriate mean to address externalities arising from learning spillovers—but if the rationale would be to reduce GHG emissions (second best) then a subsidy on production would be justified. Accordingly, there is a rationale for both instruments, and we leave it up to the reader to decide which one is more convincing.

Another important result relates to the effect of increasing the share of RTP consumers. In particular for the FiP and its relatively stronger distortionary effect on prices, higher RTP shares mitigate respective welfare losses due to allocative inefficiencies arising from over- and under-consumption given a fixed retail price. Moreover, broken down to consumer groups, surplus gains are markedly higher for consumers who switch from FRP to RTP under the FiP. This has important

implications: On the one hand, assuming that these surplus gains will be fully internalized by the respective consumers, there are accordingly higher incentives for consumers to switch under the FiP. On the other hand, also the distributional effects need to be considered. A significant part of the additional RTP consumer surplus under the FiP is implicitly financed by the FRP consumers. That is, FRP consumers cross-subsidize RTP consumption in negative price hours, since only the latter get payed for increasing consumption during these periods. This could represent a significant social acceptance barrier to introducing RTP under a FiP. Furthermore, surplus gains roughly double when demand is assumed to be twice as elastic at the reference point. This underlines that the preferences and technological capabilities to respond to prices also play a very important role.

What definitely merits further discussion is that as prices become negative under the FiP, excessively using electricity in low-price periods appears to be a viable business model that becomes increasingly attractive with higher RES shares. In fact, in hours with negative prices energy consumption is indeed excessive in the sense that consumers receive disutility from it—and the good becomes a bad from a consumer perspective. At the same time, in such hours RES energy supply is abundant and all electricity consumed comes from RES. Since the RES production target implies that each unit of RES output has an additional social value (λ^{rt}), the private disutility per unit of excess consumption stands in a trade-off with this social value. Accordingly, while energy is wasted form a private perspective, it is put to good use from a social perspective because the implied higher per-unit production (higher capacity factors) reduces the required RES capacity and thereby the overall costs of energy supply. Further, as our findings show the net social benefits over the whole year are positive. Hence the above paradoxical situation is put into perspective when the social value of RES supply and the capacity reducing effect are taken into account.

Notwithstanding this effect, negative prices warrant caution because they could have further implications beyond the scope of this work, which may be of high practical importance. For example, we do not explicitly consider cross-price elastic behavior (load shifting), and we ignore endogenous investments to exploit negative prices. In practice though, RTP consumers might indeed exploit negative prices by investing in smart appliances, and it is unclear if this would increase their inclination for consumption in other hours as well. Thus, the structural consumption pattern could change substantially and differ rather strongly from the one we assumed. Moreover, empirical evidence for price elastic behavior at times of low or negative prices is so far rather poor, and actual effects might well deviate from our results in either direction.

In summary, this work first of all provides additional theoretical insights concerning RES support schemes and induced negative prices that have been overlooked in the literature. As for policy recommendations, the scope and limitations of our work defy a clear cut ranking of one instrument over the other. Rather we think that the primary practical added value of this work is to confront policy-makers with the widely held view that negative prices are in general inefficient. We hope that this makes them more considerate of their potential benefits and respective policy options.

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Chapter 5

Start-up Costs of Thermal Power Plants in Markets with Increasing Shares of Variable Renewable Generation[1]

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Start-up costs of thermal power plants in markets with increasing shares of variable renewable generation

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The emerging literature on power markets with high shares of variable renewable energy sources suggests that the costs of more frequent start-ups of thermal power plants may become an increasing concern. Here we investigate how this develops in Germany, where the share of variable renewables is expected to grow from 14% in 2013 to 34% in 2030. We show that the overall number of start-ups grows by 81%, while respective costs increase by 119% in this period. Related to variable renewables' production, start-up costs increase by a mere €0.70 per additional megawatt hour. While the expansion of variable renewables alone would increase start-up costs, more flexible biomass power plants and additional power storage have counteracting effects. Yet changes in reserve provision and fuel prices increase start-up costs again. The relevance of start-up costs may grow further under continued renewable expansion, but could be mitigated by increasing system flexibility.

In many countries worldwide, the shares of variable renewable energy sources are steadily increasing. One of the countries at the forefront of this development is Germany, which aims to increase the share of renewables to at least 80% of gross power consumption by 2050[1]. Because of limited hydro, biomass and geothermal resources, which would allow for dispatchable renewable power generation, the expansion focuses on variable renewable sources such as wind and solar power. Accordingly, the net load of the German power system, which has to be served by thermal power plants, power storage and potentially flexible demand-side measures, will also become more variable[2]. In consequence, the operation of remaining thermal power plants has to change compared with former base- and mid-load cycling patterns[3].

Thermal plants are assumed to start up and shut down more frequently with increasing renewable supply variability. Before a thermal plant can feed electricity to the grid, it has to be started up, that is, ramped up at least to the minimum generation level. This usually comes at a cost independent of how much output is produced[4]. The size of these quasi-fixed costs, stemming from wear and tear as well as the fuel required to heat up the steam cycle, depends on the type and size of a particular plant. Anticipating that potentially growing costs from start-ups might become an increasing concern in the context of future variable renewable energy integration, we aim to analyse how important these costs actually may become, and which factors drive their development. This aspect has received only little attention in the otherwise burgeoning literature on renewable integration—possibly because so far start-up costs have been relatively small in size.

Different market jurisdictions have established different ways to secure remuneration for these costs by allowing complex bids. In centrally dispatched pool markets such as PJM in the US, nodal spot prices computed by independent system operators have to reflect start-up costs, for example by uplift or make-whole payments[5]. In contrast, most European power markets are generally self-dispatched and bilateral, implying the use of linear (non-discriminatory) pricing, where start-up costs of thermal power plants are reflected in block bids over several consecutive hours. Under certain circumstances, complex bidding can entail inefficient market clearing results[6–8]. Consequently, an increasing number of start-ups may not only incur additional system costs, but could also come along with an increased volume of complex bidding that could affect short-run allocative market efficiency.

Quantitative research on the future development of start-up costs is scarce so far. In general, it has been shown that the demand for power system flexibility increases with growing shares of variable renewables[9,10], and that this impacts the cycling needs of thermal power plants and respective costs[11,12]. Yet previous analyses are qualitative in nature[3], do not account for longer-term changes in the generation portfolio[13], or do not report specific start-up cost outcomes[12,14–16]. Only few quantitative studies explicitly focus on start-up costs in the context of renewable integration. An NREL (National Renewable Energy Laboratory) study on wind and solar integration in the Western Interconnection evaluates cycling cost impacts with a detailed modelling approach that addresses both variability and uncertainty of renewables[17]. In five scenarios of the year 2020 with shares of wind and solar power up to 33%, cycling costs increase by $US0.14 to 0.67 per megawatt hour of additional renewable generation. An analysis of distributed wind power integration in the New England market shows that cycling needs generally increase, but results depend on wind power forecast assumptions[18]. A corresponding study on solar power integration comes to similar conclusions[19].

Here we analyse the impact of increasing shares of variable renewables on the cycling of thermal plants with an open-source numerical optimization model. With respect to cycling, we consider only start-ups and neglect costs of further upward or downward ramping, as earlier analyses have shown that ramping costs are very small compared with start-up costs[17]. We model different scenarios of the German power system for the years 2013, 2020 and 2030, and separate the effects of increasing renewable capacities

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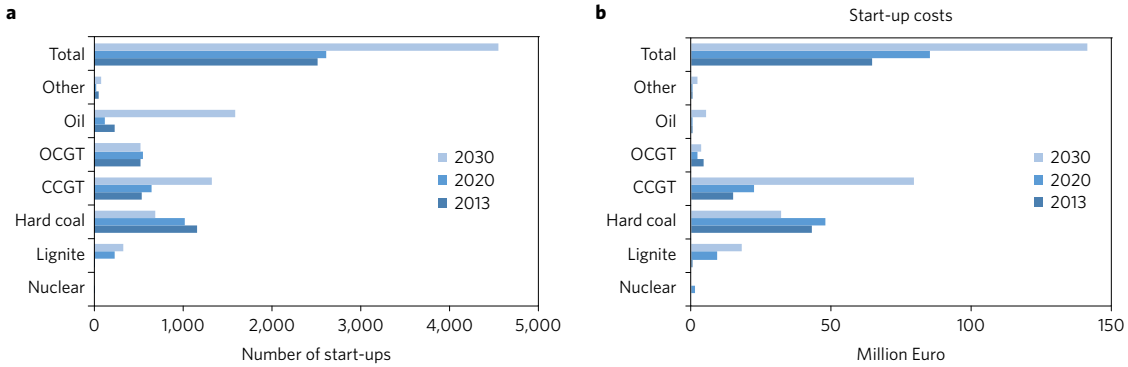

Figure 1 | Yearly numbers and costs of start-ups in baseline scenarios. a, Number of start-ups for different generation technologies. Overall start-ups of thermal power plants increase substantially between 2013 and 2030, driven by oil-fired and CCGT generators. They remain relatively low for lignite and even decline for hard coal plants. **b**, Start-up costs for different generation technologies. Start-up costs more than double between 2013 and 2030, largely driven by increasing costs of CCGT plants.

and other changes in the portfolio. We find that the overall yearly number of start-ups nearly doubles (+81%) and start-up costs more than double (+119%) between 2013 and 2030. This is driven by increasing shares of variable renewable energy sources, complementary changes of the remaining portfolio and growing fuel and carbon prices. Yet related to additional power generation by variable renewables, start-up costs increase by a mere €0.7 per additional megawatt hour of wind and solar power, and they remain low compared with total variable costs. The analysis also indicates that the relevance of start-up costs may increase further under continued growth of variable renewables beyond the levels modelled here, but could be mitigated by increasing system flexibility.

Numbers and costs of start-ups

We use an extended version of an existing unit commitment model[20] to simulate power system operations. The model minimizes total dispatch costs of the power plant fleet. Costs and restrictions related to starting up individual blocks of thermal power plants are represented with a mixed-integer formulation. The model has an hourly resolution and is solved for a full year. We apply the model to the German power system using scenarios of 2013, 2020 and 2030. We first define baseline scenarios for these years, where input parameters largely reflect the medium projections of the most recent German Grid Development Plan (in German *Netzentwicklungsplan*, NEP)[21].

While the share of variable renewables more than doubles between 2013 and 2030, the overall yearly number of start-ups of thermal power plants first increases only slightly from 2,508 in 2013 to 2,613 in 2020, and then grows to 4,544 in 2030, that is, +4% and +81% compared with 2013 (Fig. 1a). Yet the picture looks different for specific technologies. While the number of start-ups increases for lignite, combined-cycle gas turbines (CCGTs) and oil-fired plants, it stays roughly constant for open-cycle gas turbines (OCGTs) and decreases for hard coal plants.

These heterogeneous developments are driven by exogenous changes in the power plant portfolio. The NEP foresees a substantial capacity decrease of nuclear, hard coal and lignite plants between 2013 and 2030, combined with strongly increased capacities of variable renewables and CCGT plants. Because of larger supply variability due to increased renewable electricity generation, lignite plants cannot continue to run in a constant base-load mode in 2030 as was the case in 2013. Their full-load hours accordingly decrease by around 11%. Conversely, the operational pattern of hard coal plants on average changes from a mid-load position with regular daily cycles in 2013 to longer cycles in 2030. This is also driven by the fact that a larger share of the remaining hard coal fleet is operated in a flexibility-restricted combined heat and power mode in 2030. Average hard coal full-load hours accordingly increase by 9% while the number of start-ups decreases by 40%. CCGT plants have lower average full-load hours but higher overall production, and they also balance a substantial part of renewable variability in 2030. Their start-ups thus more than double (+145%). A particularly strong increase in start-ups can be observed for oil-fired plants. These peak-load generators, which have the smallest average block size of all technologies, are more frequently being used in the more volatile 2030 setting, particularly for the provision of positive (non-spinning) minute reserve. Their number of start-ups accordingly increases from 227 in 2013 to 1,590 in 2030.

While the overall number of start-ups increases by 81%, total yearly start-up costs grow more strongly from around €65 million in 2013 to €141 million (+119%) in 2030 (Fig. 1b). The growth in start-up costs is dominated by the shift toward CCGT plants (with increasing CCGT block sizes) and by fuel and carbon price increases assumed in the NEP. The latter are particularly pronounced for natural gas, translating directly into higher start-up costs. As opposed to the number of start-ups discussed above, start-up costs of oil-fired generators are negligible because of their small block sizes.

Relating this increase in start-up costs to additional power generation from variable renewables in the respective period (2013–2030) results in a value of €0.70 per additional megawatt hour of wind and solar power. To put this into perspective, values of $US0.14 to 0.67 per megawatt hour have been calculated for increasing the share of variable renewables from zero to 33% in the Western Interconnection[17]. The slightly higher values calculated here are related to higher fuel and carbon prices. It should also be noted that initial start-up costs are lower in our analysis, and the relative increase in start-up costs is thus higher compared with the US study.

Relating start-up costs to overall yearly variable costs of respective thermal generators shows that their relevance, on average, increases only slightly. This is because increasing fuel and carbon prices have an effect not only on start-up costs, but also on other variable generation costs. On average, the share of start-up costs grows from around 0.6% to 0.9% (Fig. 2). In relative terms, this appears to be a large increase, yet the overall share still remains on a low level. Accordingly, the assumed power system changes in the context of the German energy transition do not have a major impact on the relevance of start-up cost under baseline assumptions.

Yet there are again some differences between specific technologies. For lignite, the share increases from virtually zero in 2013 to 0.8% in 2030, and for CCGT plants from 0.7% to 1.2%. The relevance of start-up costs for the remaining hard coal plants

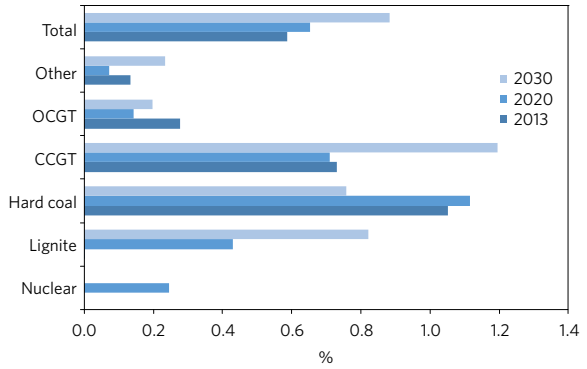

Figure 2 | Yearly start-up costs relative to yearly variable costs of main technologies. The relative relevance of start-up costs increases by 0.3 percentage points on average with the largest increase recorded for lignite (from virtually 0 cost in 2013 to 0.8% in 2030). Hard coal plants, on the contrary, experience a decrease in start-up costs.

conversely decreases from 1.1% to 0.8% because of the dispatch changes discussed above. Values for oil-fired generators are not shown in the figure, as their share of start-up costs in overall variable costs is much larger because of very low full-load hours. It decreases from around 94% in 2013 to 55% in 2030.

Results are driven by overlapping effects

An evaluation of additional model runs allows separating overlapping effects of the changing model inputs between 2013 and 2030. We start with the 2013 baseline scenario and first decompose the effects of additional variable renewables by increasing onshore and offshore wind power as well as photovoltaics capacities to 2030 levels, but holding all other input parameters constant at 2013 levels. Generation from biomass is then increased and flexibilized to 2030 assumptions in the next model run. In subsequent runs, assumptions on pumped storage, the thermal plant portfolio, the ability of renewables to provide reserves and finally fuel and carbon prices are successively changed to respective 2030 baseline levels.

Holding everything else constant, the expansion of variable renewables alone would increase the yearly number of start-ups by 1,543 (+62%, Fig. 3a). This result is intuitive given the exogenous growth in renewable variability, and it supports previous qualitative and quantitative findings in the literature[3,17]. Changes of two other assumptions, however, have countervailing effects. The assumed flexibilization of biomass power plants (in combination with a capacity expansion) and the increased pumped hydro capacity serve as additional flexibility options that together would offset most of the increase in cycling needs triggered by renewable expansion. The assumed changes in the thermal power plant portfolio, that is, the shift from nuclear, lignite and hard coal to CCGT plants, increase the number of required start-ups again. This is driven by differences in block sizes. While nuclear, lignite and hard coal plants have average block sizes of 1,339 MW, 465 MW and 316 MW in the 2013 portfolio, CCGT plants come with an average block size of only 304 MW in the 2030 scenario. Additionally assuming that renewables are eligible for the provision of balancing reserves—which is not the case in the 2013 baseline—slightly increases the number of start-ups further, as this enables a more flexible operation of some thermal generators (particularly hard coal) that were previously constrained by reserve provision. Changing fuel and carbon prices also have a small positive effect because they trigger additional non-spinning positive reserve provision by gas turbines.

Focusing on start-up costs instead of the number of start-ups, the separation shows a slightly different picture (Fig. 3b). While the effects of most parameter changes have the same direction as discussed above, the assumed change in the thermal portfolio now leads to a slight decrease of start-up costs—despite the above-mentioned increase in start-up counts. This is because decreasing block sizes matter for the number of start-ups, but not for respective costs. Instead, the shift from base-load plants to CCGT plants slightly decreases overall start-up costs because the latter have lower specific start-up costs. To mention another obvious difference between Fig. 3a and Fig. 3b, renewable expansion alone would more than double start-up costs (+114%). This increase is much larger than the corresponding effect on the number of start-ups because of strongly increased cycling of base-load plants that would incur relatively high costs under *ceteris paribus* (2013) assumptions. The share of start-up costs in overall yearly variable costs would grow to 1.6% in this setting. Growing fuel and carbon prices also have a relatively stronger positive effect, as they directly translate into higher start-up fuel costs. These effects sum up to an overall increase of start-up costs of +119%. This is nonetheless smaller than the respective growth in the share of variable renewable energy (+142%).

The separation of effects depends on the particular sequence of the decomposition analysis. Other sequences would also be possible. Supplementary Note 3 includes an alternative sequence that starts with fuel and carbon price changes, followed by changes in renewable capacity and the thermal portfolio. While the direction of effects is generally similar, the increase in start-up costs triggered by renewables alone would be even higher (+148%) compared with the sequence discussed above. Yet the share of start-up costs in overall yearly variable costs would still be lower than the one in the sequence discussed above.

Aside from more details on this alternative separation, the Supplementary Information contains additional material. This includes an analytical formulation of the model (Supplementary Note 1), a description of relevant input parameters (Supplementary Note 2), and sensitivity analyses with respect to alternative developments of renewable expansion, power storage, minimum load levels of thermal power plants, decreased renewable curtailment, smoother wind profiles, and exogenous cross-border exchange profiles (Supplementary Note 4). It also contains the description (Supplementary Note 1) and application (Supplementary Note 4) of an extended model that includes a stylized representation of neighbouring power systems and endogenous cross-border power exchange. Supplementary Note 5 concludes with a discussion of model limitations and their qualitative effects on results.

Conclusions

This study shows how start-ups of thermal power plants change in the context of a transition to larger shares of variable renewable energy sources. It complements and goes beyond previous work. For example, an analysis for the Irish system does not account for changes in the generation portfolio[13]. European analyses on thermal flexibility[12] and on the long-term effect of linear versus non-linear pricing rules[16] do not quantify specific start-up cost outcomes. The same is true for renewable integration analyses focusing on California[14] and western North America[15]. Only few quantitative studies explicitly focus on start-up costs in the context of longer-term renewable integration[17–19].

We contribute to this emerging literature with a dedicated quantitative analysis on the number and costs of start-ups in the changing German power system. Complementary to the US studies mentioned above, Germany provides a relevant international case study as a front-runner with respect to variable renewable deployment. Further, the German system is still heavily based on lignite and hard coal plants, as opposed to other systems with larger flexible gas or hydropower resources such as California[14]. We thus study the effects of renewable expansion in the context of a complementary transformation of the remaining power plant

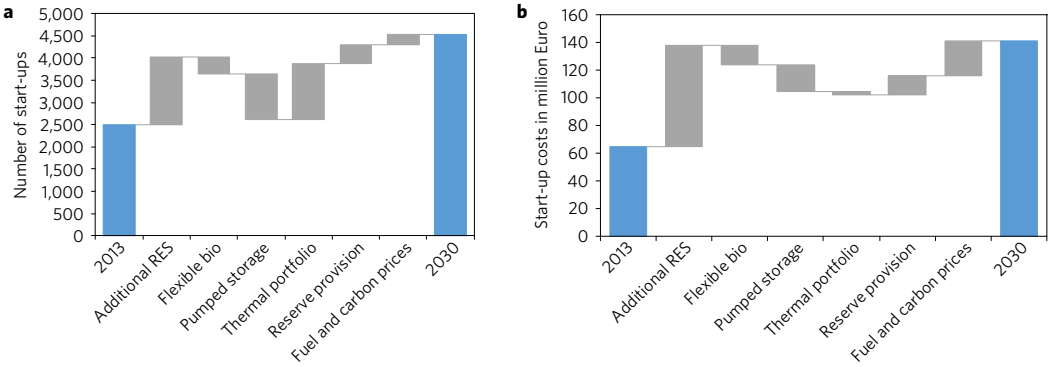

Figure 3 | Separation of effects between 2013 and 2030. a, Number of start-ups. Additional capacities of variable renewables and thermal portfolio changes substantially increase the number of start-ups, while additional pumped storage and flexible biomass have an opposite effect. **b**, Start-up costs. Renewable expansion alone would more than double start-up costs. Other factors, both negative and positive, roughly net themselves out.

portfolio. This includes a shift to more flexible plants and additional storage capacity. We also separate the effects of different portfolio changes to contrast other approaches in the literature that assume unchanged non-renewable portfolios[17–19].

Our analysis focuses on mid-term scenarios in which the share of variable renewables in Germany more than doubles from 14% in 2013 to 34% in 2030 (+142%). Under baseline assumptions, the overall number of yearly start-up procedures nearly doubles (+81%), whereas total start-up costs grow more strongly (+119%). The relative share of start-up costs in overall variable costs of thermal power plants increases from 0.6% to 0.9% and thus remains on a rather low level. Related to the growing power generation by variable renewables, start-up costs increase by €0.7 per additional megawatt hour of wind and solar power.

Several overlapping and partly countervailing effects drive these results. Isolating the effect of the expansion of variable renewables shows that this would increase start-up counts and costs to values similar to those mentioned above. Even then, start-up costs would remain at relatively low levels in absolute and relative terms and thus would be unlikely to cause major inefficiencies in the context of renewable integration. The effects of other future power system changes approximately compensate each other. Increased flexibility of biomass power plants and additional power storage capacities cause a reduction of start-up costs, whereas the assumption of renewables being able to provide reserves and growing fuel and carbon prices cause start-up costs to increase again.

While the overall relevance of start-up costs increases only moderately in the scenarios modelled here, this may change under alternative assumptions. This is also indicated by decomposition analyses and additional sensitivities (Supplementary Note 4). Start-up costs generally increase in the case of a stronger expansion of wind and solar power, lower power storage capacities, less flexible thermal power plants (including biomass) and lower cross-border exchange. In addition, our model addresses uncertainty of variable renewable feed-in not explicitly, but only implicitly by means of (deterministic) reserve provision and activation requirements. A full representation of stochastic renewable forecast errors may result in more significant impacts on start-ups. If volatility of wind and solar feed-in could be reduced, for example by a more system-friendly design of renewable plants or adjusted geographical distribution, start-up costs would not rise as much in the first place.

Our analysis may also be viewed in the context of the ongoing debate on the future design of power markets with large shares of variable renewables. On the one hand, baseline findings indicate that start-up costs do not gain central importance even if the share of variable renewables exceeds 30%. The volume of complex bids made by generators to ensure remuneration of their quasi-fixed costs in electricity auctions should thus not increase much, and market efficiency should not be significantly more affected—for instance, by paradoxically rejected blocks—than is currently the case. The transition to variable renewables would then also be unlikely to severely compromise the use of linear pricing in European power markets in the medium run.

On the other hand, under alternative assumptions, start-up costs may grow further both in absolute and relative terms. This could lead to situations in which non-convex costs of thermal power plants constitute more significant shares of total variable costs, which should then be properly addressed in future market designs. This may get increasingly important if the main options expected to provide future power system flexibility—flexible generators, storage, dispatchable renewables such as biomass, the demand side, and cross-border power exchange—developed less favourably than generally assumed, and if the shares of variable renewables increased far beyond the levels modelled here.

While the numerical analysis focuses on Germany, the transition to wind and solar power is not an exclusive German trend[22,23]. The International Energy Agency's 2016 World Energy Outlook projects global net capacity additions of wind power and photovoltaics of around 1.2 TW each between 2014 and 2040 in the 'New Policies' scenario[24]. In a scenario that is compatible with the 2 °C climate goal, capacity additions are even larger, such that wind power and photovoltaics together account for 27% of worldwide electricity generation in 2040. Our findings are thus also relevant for many other countries with thermal power systems that plan to undergo comparable transitions toward larger shares of variable renewable energy sources.

Methods

The optimization model. Exogenous model inputs include the generation portfolio, hourly load, which is assumed to be completely price-inelastic, hourly availability profiles of variable renewables, a yearly energy cap for biomass, reserve requirements and activations profiles, variable generation costs, start-up costs, minimum off-times and minimum load levels of thermal power plants. Endogenous model variables include the hourly unit commitment of all generation and storage capacities, hourly generation and reserve provision of all generators, and overall dispatch costs. The model is implemented as a mixed-integer linear program in the General Algebraic Modeling System and solved with the commercial solver CPLEX. Further information on the model is provided in Supplementary Note 1. The following paragraphs introduce the most important input parameters for baseline model runs. More details and alternative parameter assumptions for the sensitivities are provided in Supplementary Notes 2 and 4.

Generation capacity. Generation capacity is derived from the German Grid Development Plan (*Netzentwicklungsplan*, NEP). The NEP was drafted by German transmission operators and approved by the federal regulator after a series of public consultations[21]. As it serves as the basis for federal German grid

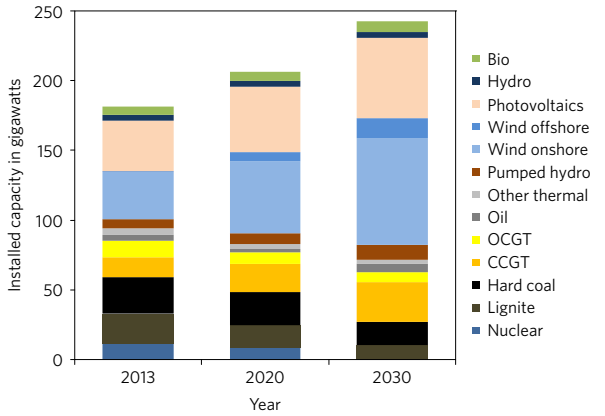

Figure 4 | Installed power generation capacities in Germany in baseline scenarios. Scenarios are derived from NEP (ref. 21). Variable renewable capacity increases substantially between 2013 and 2030, while lignite and hard coal capacity decreases, and nuclear is phased out completely. In 2020 (2030), onshore wind power reaches 51 GW (76 GW), offshore wind power 6 GW (15 GW) and photovoltaics 47 GW (57 GW). Nuclear capacity decreases from more than 12 GW in 2013 to less than 9 GW by 2020 and zero by 2030 because of the complete German nuclear phase-out by the end of 2022. Lignite and hard coal capacities decrease from 21 and 26 GW in 2013 to 11 and 16 GW in 2030, respectively. Natural gas-fired capacity conversely increases from 26 GW to 35 GW. The share of hard coal plants that operate in a combined heat and power (CHP) generation mode increases by 10% between 2013 and 2030, while the respective CHP share of CCGT plants decreases by 6%.

Table 1 | Fuel and carbon prices derived from NEP[21].

	Unit	2013	2020	2030
Lignite	$€_{2010}$ MWh_{th}^{-1}	1.5	1.5	1.5
Hard coal	$€_{2010}$ MWh_{th}^{-1}	9.6	10.0	10.3
Natural gas	$€_{2010}$ MWh_{th}^{-1}	27.0	29.9	32.8
Oil	$€_{2010}$ MWh_{th}^{-1}	54.0	56.0	60.4
CO_2 certificates	$€_{2010}$ t^{-1}	5.0	14.3	26.0

requirement legislation, it can be considered an official reference scenario, and is accordingly also used in many other studies. According to NEP, renewable capacity increases substantially by 2030 (Fig. 4), reflecting the German government's RES targets.

Fuel and carbon prices. Fuel and carbon price assumptions are also derived from NEP (Table 1). Renewables are assumed not to incur marginal costs. Yet in the case of biomass, there is a yearly energy cap, which implies a shadow price of biomass.

Time series data. Hourly profiles of variable renewables, load and power exchange with other countries are based on 2013 data, and power exchange is assumed not to change in the future in the baseline scenarios. Under these assumptions, the share of variable renewables (wind power and photovoltaics) increases from 14% (77 TWh) in 2013 to 24% (128 TWh) in 2020 and more than doubles (+142%) to 34% (187 TWh) in 2030. Including biomass and hydro power, the respective overall renewable shares are 27% in 2013 and 51% in 2030. These shares are defined as domestic renewable generation over domestic power consumption (excluding storage loading).

Data availability. The model code and all input parameters are available in Zenodo with the identifier http://dx.doi.org/10.5281/zenodo.259476[25]. The code is published under the MIT (Massachusetts Institute of Technology) open-source licence. Further, the data that support the plots within this paper and all other findings of this study are available from the corresponding author on reasonable request.

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Author contributions

All authors jointly developed the research design. W.-P.S. developed and calibrated the model, carried out the simulations, and processed the model outcomes. All authors contributed to writing the article.

Additional information

Supplementary information is available for this paper.

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Competing interests

The authors declare no competing financial interests.

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SUPPLEMENTARY INFORMATION

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Start-up costs of thermal power plants in markets with increasing shares of variable renewable generation

Supplementary Note 1. The unit commitment model

Basic model for Germany

We use a mixed-integer unit commitment model with an hourly resolution that minimizes total dispatch costs of the power plant fleet while also considering the provision of balancing reserves. In contrast to a previous model version[1], the model used here does not include electric vehicles in order not to unnecessarily complicate the analysis. The model code and all input parameters are available in a public repository under http://dx.doi.org/10.5281/zenodo.259476. The code is published under the MIT open-source license.

For numerical reasons, the model is not solved for the full year in one instance; instead, 13 consecutive sequences are solved sequentially, each covering four weeks (672 hours). For each power plant block, the operational status of the first hour of each four-week sequence is fixed to the respective value of the last hour of the previous sequence. In the very first hour, the operational status of all blocks can be freely chosen without incurring start-up costs.

The model is a deterministic mixed integer linear program. Under the assumption of perfect competition, centralized cost-minimization leads to the same dispatch decisions as a perfect decentralized market coordinated by prices in which firms maximize profits. Hence, our model mimics Pareto-efficient market allocations by minimizing overall costs of energy supply, given price-inelastic hourly demand realizations, such that overall welfare is maximized. The assumption of perfect competition in turn appears to be justified as there has been a downward trend of market concentration in Germany in recent years, which is thought to continue in the context of a further transformation to higher shares of variable renewable energy sources.[2]

In order to address some of the stochastic elements present in real-world electricity markets, the model also includes a stylized representation of reserve markets. According to current German regulation, we distinguish positive and negative as well as secondary and minute (i.e. tertiary) reserves; the smallest market segment of primary reserve is not considered. Reserves do not only have to be provided, but are also (partly) activated according to historic hourly profiles. This allows—within a deterministic framework—to make the model more realistic with respect to the effects of stochastic elements on both the supply and the demand side, including forecast errors of variable renewables.[3]

In the following, we present the analytical formulation of the model. Exogenous parameters are set in lower case letters, endogenous continuous variables have an initial upper case letter, and binary variables are completely set in upper case letters. A list of sets, parameters and variables is provided in Supplementary Table 1.

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The objective function (1) sums up all variable generation costs, including the sum of marginal generation costs and start-up costs of thermal plants as well as variable storage costs. If thermal plants provide positive (negative) reserves, their activation increases (decreases) respective variable costs because of corresponding additional (lower) fuel use. The same logic applies for variable storage costs. Renewables are assumed to be dispatched without variable costs. Curtailment of variable renewable energy sources may be penalized by assigning a positive value to $penalty_{res}$, which is not the case under baseline assumptions.

$$\begin{aligned} Cost = \sum_{i,t}\left(mc_i Q_{i,t} + sc_i ST_{i,t} + sc_i ST_{i,t}^{gt}\right) + \sum_{j,t}\left(mstc_j^{in} Stin_{j,t} + mstc_j^{out} Stout_{j,t}\right) \\ + \sum_{rsrv^{up},i,t} mc_i\, Prov_{rsrv,i,t}^{th} activ_{rsrv,t} \\ - \sum_{rsrv^{do},i,t} mc_i\, Prov_{rsrv,i,t}^{th} activ_{rsrv,t} + \sum_{i,t} mc_i\, Prov_{mr^{up},i,t}^{gt} activ_{mr^{up},t} \\ + \sum_{rsrv^{up},j,t} \left(mstc_j^{out} Prov_{rsrv,j,t}^{stout} - mstc_j^{in} Prov_{rsrv,j,t}^{stin}\right) activ_{rsrv,t} \\ - \sum_{rsrv^{do},j,t} \left(mstc_j^{out} Prov_{rsrv,j,t}^{stout} - mstc_j^{in} Prov_{rsrv,j,t}^{stin}\right) activ_{rsrv,t} \\ + \sum_{res,t} penalty_{res} Rescurt_{res,t} \end{aligned} \tag{1}$$

Equations (2a) and (2b) represent maximum and minimum generation levels of thermal blocks. The binary status variable $U_{i,t}$ is 1 if the plant is online and 0 otherwise. These equations also constrain positive and negative (spinning) reserve provision (only if generators are prequalified for reserve provision). Note that more reserves have to be provided than are actually activated in any given hour (except $activ_{rsrv,t}$ is 1). In the numerical application, the availability factor $avail_{i,t}^{th}$ is seasonally scaled with monthly average values. Equation (3) constitutes a separate restriction for non-spinning positive minute reserve provision by open cycle gas turbines. Equations (4a) to (4c) represent flexibility constraints of reserve provision. In line with the current situation in Germany, secondary reserve has to be provided within 5 minutes, minute reserve within 15 minutes.

$$Q_{i,t} + \sum_{rsrv^{up},i,t} Prov_{rsrv,i,t}^{th} \le qmax_i^{th} avail_{i,t}^{th} U_{i,t}^{th} \qquad \forall i,t \tag{2a}$$

$$Q_{i,t} + \sum_{rsrv^{do},i,t} Prov_{rsrv,i,t}^{th} \ge qmin_i^{th} avail_{i,t}^{th} U_{i,t}^{th} \qquad \forall i,t \tag{2b}$$

$$Prov_{mr^{up},i,t}^{gt} \le qmax_i^{th} avail_{i,t}^{th}\left(1 - U_{i,t}^{th}\right) \qquad \forall i^{gt},t \tag{3}$$

$$Prov_{rsrv,i,t}^{th} \le 5 * grad_i^{th} qmax_i^{th} avail_{i,t}^{th} \qquad \forall rsrv^{sr},i,t \tag{4a}$$

$$Prov_{rsrv,i,t}^{th} \le 15 * grad_i^{th} qmax_i^{th} avail_{i,t}^{th} \qquad \forall rsrv^{mr},i,t \tag{4b}$$

$$Prov_{mr^{up},i,t}^{gt} \le 15 * grad_i^{th} qmax_i^{th} avail_{i,t}^{th} \qquad \forall i^{gt},i,t \tag{4c}$$

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Equation (5a) ensures consistency between the binary status and start-up variables of thermal blocks. Equation (5b) enforces a minimum offtime. Equation (6) introduces another quasi-start-up variable related to non-spinning reserve provision by gas turbines. This is required in order to properly reflect start-up costs of these generators in the objective function.

$$ST_{i,t} \geq U_{i,t}^{th} - U_{i,t-1}^{th} \qquad \forall i,t \qquad (5a)$$

$$U_{i,t-1}^{th} - U_{i,t}^{th} \leq 1 - U_{i,tt}^{th} \qquad \forall i,t \text{ with } t \leq tt \leq t + stime_i - 1 \qquad (5b)$$

$$Prov_{mr^{up},i,t}^{gt} \leq ST_{i,t}^{gt}\,\Lambda \qquad \forall i^{gt},t \qquad (6)$$

Equations (7a) to (7c) determine hourly system integration as well as curtailment of variable renewable energy sources. These may also provide reserves in several scenarios; in this case, their reserve provision is assumed not to be flexibility-constrained. The model code includes some additional equations for special cases in which only a fraction of the installed renewable capacity is able to provide reserves.

$$Resint_{res,t} + \sum_{rsrv^{up}} Prov_{rsrv,res,t}^{res} + Rescurt_{res,t} = qmax_{res}^{res} avail_{res,t}^{res} \qquad \forall res,t \qquad (7a)$$

$$\sum_{rsrv^{do}} Prov_{rsrv,res,t}^{res} \leq Resint_{res,t} \qquad \forall res,t \qquad (7b)$$

$$Rescurt_{res,t} \leq qmax_{res}^{res} avail_{res,t}^{res} \qquad \forall res,t \qquad (7c)$$

Equation (8a) constitutes an hourly power generation capacity restriction for biomass, whereas (8b) constrains negative reserve provision. Equations (9a) and (9b) are respective flexibility restrictions for reserve provision, corresponding to (4a) and (4b). Equation (10) constrains overall biomass utilization to an overall energy cap.

$$Bio_t + \sum_{rsrv^{up}} Prov_{rsrv,t}^{bio} \leq qmax^{bio} avail_t^{bio} \qquad \forall t \qquad (8a)$$

$$\sum_{rsrv^{do}} Prov_{rsrv,t}^{bio} \leq Bio_t \qquad \forall t \qquad (8b)$$

$$Prov_{rsrv,t}^{bio} \leq 5 * grad^{bio} qmax^{bio} avail_t^{bio} \qquad \forall rsrv^{sr},t \qquad (9a)$$

$$Prov_{rsrv,t}^{bio} \leq 15 * grad^{bio} qmax^{bio} avail_t^{bio} \qquad \forall rsrv^{mr},t \qquad (9b)$$

$$\sum_t Bio_t + \sum_{rsrv^{up},t} Prov_{rsrv,t}^{bio} - \sum_{rsrv^{do},t} Prov_{rsrv,t}^{bio} \leq energy^{bio} \qquad (10)$$

Equation (11) connects the storage energy levels of subsequent periods, considering hourly charging and discharging activities, activation of positive and negative reserves, as well as respective efficiency losses. Equations (12) and (13a and b) represent upper limits on the storage level, loading capacity, and discharging capacity, respectively. A binary variable $U_{j,t}^{sto}$ ensures that storage is not loaded and

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discharged in the same period, which is relevant for scenarios with penalties on renewable curtailment. Equation (14a) ensures that loading-related positive reserve provision does not exceed scheduled storage loading in the wholesale market; equation (14b) respectively restricts the provision of discharging-related negative reserves. Equations (15a) and (15b) ensure that the storage facility has enough capacity to accommodate the additional energy of negative reserve provision, and to provide additional positive reserves, respectively. Here we assume that a full activation of the reserves provided in any given hour would have to be possible, despite $avail_{i,t}^{th}$ typically being smaller than 1.

$$Stlev_{j,t} = Stlev_{j,t-1} + Stin_{j,t}\eta_j^{in} - \frac{Stout_{j,t}}{\eta_j^{out}} + \sum_{rsrv^{do}} \left(\frac{Prov_{rsrv,j,t}^{stout}}{\eta_j^{out}} + Prov_{rsrv,j,t}^{stin}\eta_j^{in} \right) activ_{rsrv,t} - \sum_{rsrv^{up}} \left(\frac{Prov_{rsrv,j,t}^{stout}}{\eta_j^{out}} + Prov_{rsrv,j,t}^{stin}\eta_j^{in} \right) activ_{rsrv,t} \quad \forall j,t \quad (11)$$

$$Stlev_{j,t} \leq stlevmax_j \quad \forall j,t \quad (12)$$

$$Stin_{j,t} + \sum_{rsrv^{do}} Prov_{rsrv,j,t}^{stin} \leq stinmax_j(1 - U_{j,t}^{sto}) \quad \forall j,t \quad (13a)$$

$$Stout_{j,t} + \sum_{rsrv^{up}} Prov_{rsrv,j,t}^{stout} \leq stoutmax_j U_{j,t}^{sto} \quad \forall j,t \quad (13b)$$

$$\sum_{rsrv^{up}} Prov_{rsrv,j,t}^{stin} \leq Stin_{j,t} \quad \forall j,t \quad (14a)$$

$$\sum_{rsrv^{do}} Prov_{rsrv,j,t}^{stout} \leq Stout_{j,t} \quad \forall j,t \quad (14b)$$

$$\left(Stin_{j,t} + \sum_{rsrv^{do}} Prov_{rsrv,j,t}^{stin} \right) \eta_j^{in} \leq stlevmax_j - Stlev_{j,t-1} \quad \forall j,t \quad (15a)$$

$$\frac{Stout_{j,t} + \sum_{rsrv^{up}} Prov_{rsrv,j,t}^{stout}}{\eta_j^{out}} \leq Stlev_{j,t-1} \quad \forall j,t \quad (15b)$$

The wholesale market clearing condition (16) ensures that overall supply equals demand in all hours, considering cross-border exchange. Equations (17a) and (17b) are respective clearing conditions for the four reserve market segments.

$$\sum_i Q_{i,t} + \sum_{res} Resint_{res,t} + Bio_t + othergen_t + \sum_j (Stout_{j,t} - Stin_{j,t}) = dem_t^{whls} + cbex_t^{exog} \quad \forall t \quad (16)$$

$$\sum_i Prov_{rsrv,i,t}^{th} + \sum_{res} Prov_{rsrv,res,t}^{res} + Prov_{rsrv,t}^{bio} + \sum_j \left(Prov_{rsrv,j,t}^{stout} + Prov_{rsrv,j,t}^{stin} \right) = dem_{rsrv,t}^{rsrv} \quad \forall rsrv \neq mr^{up}, t \quad (17a)$$

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$$\sum_i Prov^{th}_{mr^{up},i,t} + \sum_i Prov^{gt}_{mr^{up},i,t} + \sum_{res} Prov^{res}_{mr^{up},res,t} + Prov^{bio}_{mr^{up},t} + \sum_j \left(Prov^{stout}_{mr^{up},j,t} + Prov^{stin}_{mr^{up},j,t}\right) = dem^{rsrv}_{mr^{up},t} \quad \forall t \qquad (17b)$$

It should be noted that thermal power plants (including nuclear power) are modelled as single blocks, subject to start-up costs and restrictions, while variable renewables and pumped hydro storage are represented as aggregated capacities which are assumed to be perfectly flexible. Accordingly, thermal generation $Q_{i,t}$ is flexibility-constrained, whereas variable renewable feed-in $Resint_{res,t}$ and storage output $Stout_{j,t}$ are not. Flexibility of power generation from biomass Bio_t depends on scenario assumptions. Inflexible power generation from run-of-river hydro and waste incineration $othergen_t$ are treated as constant exogenous input parameters. Hydro generation is seasonally scaled according to historic monthly average values.

Extended model with stylized neighbouring countries

In the basic model, cross-border power exchange is treated as an exogenous parameter. This parameter consists of a historic hourly pattern of net exports from Germany, and is assumed not to change in 2020 and 2030 in the basic model. In order to explore the implications of future changes in the cross-border exchange pattern, we carry out a sensitivity analysis in which power flows between Germany and its electric neighbours are modelled as endogenous variables (compare Supplementary Note 4, subsection "Endogenous cross-border exchange"). This also requires modelling neighbouring countries' power systems and making numerous additional parameter assumptions. While the analytical formulation of the extended model is explained in the following, additional input parameters are presented in Supplementary Note 2.

When modelling neighbouring countries, we do not follow a detailed unit commitment approach because of limited data availability and numerical challenges of solving large-scale unit commitment models. Instead, we use a simplified approach. We represent different generation technologies in neighbouring countries not on a block level, but as aggregate capacities, drawing on a stylized linear formulation for aggregate load change costs. Further, we abstract from modelling balancing reserves in neighbouring countries. Supplementary Table 2 shows additional sets, parameters and variables for the extended model.

The extended model requires several additional equations as well as modifications of existing ones. First, the objective function is augmented with additional terms that reflect the variable costs of dispatchable generators and storage in neighbouring countries (1'). As regards dispatchable generators, not only the sum of marginal production costs is included, but also hourly load change costs of aggregate thermal dispatchable technologies in neighbouring countries.

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$$\ldots + \sum_{dispnc,t,nc} mc_{dispnc} Qdisp_{dispnc,t,nc} + \sum_{dispnc,t,nc} \left(mc^{up}_{dispnc} Qdisp^{up}_{dispnc,t,nc} + mc^{do}_{dispnc} Qdisp^{do}_{dispnc,t,nc}\right) + \sum_{jnc,t,nc} \left(mstc^{in}_{jnc} Stin_{jnc,t,nc} + mstc^{out}_{jnc} Stout_{jnc,t,nc}\right) \quad (1')$$

Next, the German market clearing condition is modified to include endogenous cross-border exchange $\sum_l inc_{l,DE} Cbex^{endog}_{l,t}$ instead of exogenous net exports (16').

$$\sum_i Q_{i,t} + \sum_{res} Resint_{res,t} + Bio_t + othergen_t + \sum_j (Stout_{j,t} - Stin_{j,t}) = dem^{whls}_t + \sum_l inc_{l,DE} Cbex^{endog}_{l,t} \quad \forall t \quad (16')$$

An additional market clearing condition ensures that (wholesale) supply matches demand in neighbouring countries, again considering cross-border exchange (18). Here, run-of-river hydro power is treated as an exogenous parameter $ror_{t,nc}$. In contrast, hydro reservoirs are included in $Qdisp_{dispnc,t,nc}$.

$$\sum_{dispnc} Qdisp_{dispnc,t,nc} + \sum_{res} Qres_{res,t,nc} + ror_{t,nc} + \sum_{jnc} (Stout_{jnc,t,nc} - Stin_{jnc,t,nc}) = dem^{nc}_{t,nc} + \sum_l inc_{l,nc} Cbex^{endog}_{l,t} \quad \forall t, nc \quad (18)$$

Analogous to equation (2a), there is a maximum generation restriction for aggregate dispatchable capacity in neighbouring countries (19a). Equation (19b) connects the generation levels of subsequent periods and defines positive and negative load changes.

$$Qdisp_{dispnc,t,nc} \leq qmax^{dispnc}_{dispnc,nc} \quad \forall dispnc, t, nc \quad (19a)$$

$$Qdisp_{dispnc,t,nc} = Qdisp_{dispnc,t-1,nc} + Qdisp^{up}_{dispnc,t,nc} - Qdisp^{do}_{dispnc,t,nc} \quad \forall dispnc, t, nc \quad (19b)$$

Similar to equation (10) in the German basic model, equation (20) constrains overall power generation from biomass and hydro reservoirs in neighbouring countries to an overall energy cap.

$$\sum_t Qdisp_{dispnc,t,nc} \leq energy^{dispnc}_{dispnc,nc} \quad \forall dispnc = \{bio, reservoir\}, nc \quad (20)$$

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Equation (21) constrains power generation from variable renewable energy sources in neighbouring countries to installed capacity, considering variable hourly availability.

$$Qres_{res,t,nc} \leq qmax^{res}_{res,nc} avail^{res}_{res,t,nc} \qquad \forall res, t, nc \qquad (21)$$

Mirroring equations (11-14b) in the basic model, equations (22-24b) represent power storage in neighbouring countries. Equation (11) connects the storage energy levels of subsequent periods, considering hourly charging and discharging activities and respective efficiency losses. Equation (23), (24a) and (24b) constitute upper limits on the storage level, loading capacity, and discharging capacity. Again, a binary variable $U^{sto}_{jnc,t,nc}$ ensures that storage is not loaded and discharged in the same period.

$$Stlev_{jnc,t,nc} = Stlev_{jnc,t-1,nc} + Stin_{jnc,t,nc}\eta^{in}_{jnc} - \frac{Stout_{jnc,t,nc}}{\eta^{out}_{jnc}} \qquad \forall jnc, t, nc \qquad (22)$$

$$Stlev_{jnc,t,nc} \leq stlevmax_{jnc,nc} \qquad \forall jnc, t, nc \qquad (23)$$

$$Stin_{jnc,t,nc} \leq stinmax_{jnc,nc}(1 - U^{sto}_{jnc,t,nc}) \qquad \forall jnc, t, nc \qquad (24a)$$

$$Stout_{jnc,t,nc} \leq stoutmax_{jnc,nc} U^{sto}_{jnc,t,nc} \qquad \forall jnc, t, nc \qquad (24b)$$

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Supplementary Note 2. More details on input parameters

We apply the basic model to the German power system using scenarios of the years 2013, 2020, and 2030, drawing on the medium projections of the German Grid Development Plan (*Netzentwicklungsplan*, NEP). More precisely, we use the medium projection "B" of the so-called 2025 version of the Grid development plan[4] and interpolate capacities for the years 2020 and 2030. A similar methodology has been applied before.[1] All input data is available together with the open-source model under http://dx.doi.org/10.5281/zenodo.259476. The following sections contain further details on input data for the basic (German) model complementary to the information provided in the main article, and additional input parameters required for the extended model.

Generation capacities

As the power plant list of the NEP does not clearly differentiate between combined cycle gas turbines (CCGT) and open cycle gas turbines (OCGT), own assumptions are made based on various sources. CCGT plants constitute the major fraction (28 GW in 2030) and OCGT plants the minor one (7 GW in 2030). As for pumped hydro storage, a substantial capacity increase is projected from around 6 GW in 2013 to 8 GW in 2020 and 11 GW in 2030. We abstract from other storage technologies, i.e. the set J only includes pumped hydro storage.

Aggregated NEP capacities are translated into a block-sharp power plant portfolio by drawing on the official NEP power plant list and DIW Berlin's own power plant database. In order to reduce the computational burden of the program, thermal blocks smaller than 100 MW are aggregated to stylized 100 MW blocks. Shut-down dates of existing blocks and future capacity additions are derived from the NEP power plant list and are complemented with own assumptions, particularly regarding the aggregation of small power plants. For the 2030 scenario, we add 5 GW of oil-fired gas turbines as backstop peaker plants, as it turns out that additional capacity is required particularly for positive reserve provision during a few hours of the year.

Power plants that operate in a combined heat and power (CHP) mode are subject to additional operational constraints, depending on daily average ambient temperatures of the year 2013 in Germany and a respective district heating demand profile of a large German municipality. We further differentiate between public and industrial CHP plants, as well as other industrial plants. More details on respective dispatch restrictions can be found in the open-source model code. Loosely reflecting the German government's CHP targets, the overall CHP capacity increases from around 33 GW in 2013 to 37 GW in 2030. By 2030, more than 60% of the combined hard-coal, CCGT and gas-fired OCGT capacity faces some CHP restrictions. Assumptions on the flexibility of CHP generators are held constant over all scenarios in order to reduce complexity and ease comparisons between the scenarios. What is more, properly modelling future changes of CHP restrictions due to additional heat storage facilities or other flexibilisation measures would pose considerable methodological as well as data-related challenges. Accordingly, it appears reasonable not to vary CHP flexibility assumptions between scenarios.

Unit commitment parameters

As regards unit commitment modelling of thermal plants, four parameters are of particular importance: minimum load requirements, minimum offtime, start-up fuel costs and start-up depreciation costs (Supplementary Table 3). Under baseline assumptions, these unit commitment

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parameters, which draw on DIW Berlin's database and a DIW Data Documentation[5], do not change in future scenarios. In a sensitivity analysis, we use lower minimum load parameters.

Start-up costs depend on fuel and CO_2 prices as well as depreciation costs. In reality, start-up costs also depend on offtime, i.e. on a generator's temperature at the time it is started up again. As modelling offtime-dependent start-up costs is computationally demanding, we use a simplified approach: nuclear plants are generally assumed to carry out only hot starts, requiring only 30% of the cold-start fuel requirement provided in Supplementary Table 3. Lignite and hard coal plants are assumed to carry out warm starts with 50% of the typical cold-start fuel requirement. Only generators fuelled by natural gas and oil are assumed to typically carry out cold starts, incurring 100% of the start-up fuel requirements presented in the table. With 2013 cost data, this results in typical start-up costs of around €250,000 for a 1.3 GW nuclear block, €50,000 or 70,000 for 800 MW lignite or hard coal blocks, and around €70,000 for a 500 MW CCGT block.

Power generation from renewable sources

Hourly power generation from variable renewables is based on actual 2013 feed-in data provided by German TSOs. Hourly availability factors are calculated by relating hourly feed-in to respective installed capacity, properly taking into account capacity additions during the year. For 2020 and 2030, these hourly availability factors are then multiplied with installed capacities of the respective scenario.

As regards power generation from biomass, we use yearly energy caps of 41 TWh in 2013, 46 TWh in 2020, and 52 TWh in 2030. We assume generators to be completely inflexible in 2013, i.e. hourly generation from biomass is fixed to a yearly average level. This reflects actual incentives of biomass power plants in 2013 caused by a largely time-invariant feed-in tariff. In future scenarios, we assume biomass to be more flexible, also reflecting changes in the legislation. According to the current Renewable Energy Sources Act (EEG), all new biomass power plants now receive a sliding market premium instead of a feed-in tariff. Moreover, the EEG provides a so-called flexibility premium which gives incentives to design the plants for higher peak loads and lower full load hours. In 2020, half of the available energy cap is thus assumed to be used flexibly, and the other half is fixed to a yearly average value. In 2030, the biomass cap can be allocated fully flexibly among hours (within each 4-week sequence), only restricted by available generation capacity (equation 8a). Run-of-river hydro power is assumed to produce at constant hourly levels which seasonally vary between the 13 modelled 4-week sequences according to historic data.

Load, cross-border exchange, and balancing reserves

Hourly load is derived from 2013 TSO data in line with the assumptions made in the NEP scenario framework. Accordingly, the load profile is assumed not to change in 2020 or 2030 compared to 2013 levels. The total yearly net consumption is 542 TWh, including grid losses, with a peak load of 84 GW. Data on net power exchange with neighbouring countries is taken from public European TSO sources (ENTSO-E). Hourly exchange values are fixed to historic 2013 levels also in 2020 and 2030 in the basic model. Supplementary Figure 1 shows the correlation between cross-border exchange and variable renewable power generation (sum of PV, onshore and offshore wind power) in the historic German 2013 data. While there is substantial variation between single hours, which amongst other factors is caused by different load situations, there is a clear tendency of increasing exports in hours of high feed-in by variable renewable energy sources.

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Input data on the hourly provision and activation of positive and negative secondary and minute reserves is taken from German TSOs (again, using 2013 data). In every hour, an exogenously specified fraction of provided reserves is activated according to historic data. More precisely, we use the respective maxima of quarter-hourly values provided by TSOs. Importantly, all provided reserves are required to be activated with this hourly share. This prevents the model from selecting only such technologies that have low costs of reserve provision, but potentially high costs of activation. We hold reserve requirements constant between 2013 and 2030. This allows for better comparisons between scenarios. Stagnating reserve requirements also appear to be plausible despite the growth in variable renewable power sources. In recent years, reserve requirements have even decreased, triggered by various institutional and regulatory changes such as shorter lead times and commitment periods, and larger balancing areas. Moreover, future improvements are foreseeable such as the dynamic dimensioning of reserve requirements.

In contrast, scenarios differ with respect to the prequalification of different power plants to provide reserves. With the exception of nuclear plants, large thermal generators with a block size above 100 MW are generally assumed to be eligible to provide all reserve qualities, given that the respective block is online, and restricted by flexibility constraints (equations 4a and 4b). Smaller thermal plants are generally assumed not be qualified for reserve provision. Variable renewables and biomass are assumed not to provide any reserves in 2013, which largely reflects the actual situation in Germany. Anticipating institutional and technological changes, we relax this assumption by 2030 and assume variable renewables and biomass to be fully eligible to provide all types of reserves by this year. In 2020, we assume 50% of the respective renewable fleet to be able to provide reserves. This special case requires several additional model equations which are not listed above, but documented in the source code. We further assume that all open-cycle gas (or oil) turbines are able to provide non-spinning positive minute reserve. Their activation then leads to additional start-ups $ST_{i,t}^{gt}$, the costs of which are considered in the objective function.

Additional input parameters for the extended model with stylized neighbouring countries

The extended model—which is only applied to the years 2013 and 2030—requires a range of additional inputs parameters for neighbouring countries. We include the German electric neighbours Austria (AT), Belgium (BE), Switzerland (CH), Czech Republic (CZ), Denmark (DK), France (FR), Luxembourg (LU), the Netherlands (NL), Poland (PL), and Sweden (SE). In order to make country-specific parameter assumptions that are consistent across all neighbouring countries, we generally draw on the so-called Vision 3 of the most recent Ten Year Network Development Plan (TYNDP) published by European TSOs.[6] Input data for Germany does not change as compared to the basic model.

Installed generation capacities in neighbouring countries are illustrated in Supplementary Figure 2. There is a shift toward variable renewables in all countries, although generally less pronounced than in Germany. At the same time, nuclear and coal-fired capacity decreases. Entso-E[6] only provides a combined category for run-of-river hydro, hydro reservoirs and pumped storage. We accordingly separate these technologies, drawing on own assumptions and additional sources such as the Open Power System Data Platform (http://open-power-system-data.org/, Data Package National generation capacity, version 2016-10-27; primary data from ENTSOE, EUROSTAT, e-control, ELIA, UN Statistical Office, BFE, ERU, DEA, RTE 2014, RTE 2015, Tennet NL, CIRE, and Svensk Energi). Following Entso-E, we

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abstract from other storage technologies than pumped hydro, i.e. the set JNC only includes this technology.

Yearly energy budgets for run-of-river, hydro reservoirs and biomass generators are also derived from Entso-E[6]. Mirroring the German biomass assumptions, biomass generators in neighbouring countries are also assumed to be perfectly inflexible in 2013, i.e. generating on a constant average level, and perfectly flexible in 2030. Because of limited data availability, we make the simplifying assumption that run-of-river hydro power is generated on a constant average level throughout the year. For hydro reservoirs—which are relevant technologies in Austria, Switzerland, France, and Sweden—we assume a lower bound of hourly generation equal to 1/8760 of half the reservoirs' yearly energy budgets. The remaining half of the energy budget may freely be allocated within each of the 13 four-week blocks, constrained by equations (19a) and (20). This stylized approach allows representing partly flexible power generation from hydro reservoirs without engaging in—for this sensitivity, prohibitively complex—detailed reservoir modelling.

As for marginal generation costs, we use the same fuel and CO_2 price assumptions as in the German basic model. Generator efficiencies are derived from Entso-E[6]. This results in marginal generation costs as shown in Supplementary Table 4. The table also include stylized marginal load change costs of thermal power plants, which lean on an NREL study[7]. Dispatchable hydro and biomass generators are assumed not to have load change costs.

Hourly availability of onshore and offshore wind power in neighbouring countries is taken from the European Commission's EMHIRES data set (https://ec.europa.eu/jrc/en/scientific-tool/emhires). For PV, we have to resort to the German profile as a proxy because of limited data availability. Electric load profiles of neighbouring countries are derived from the Open Power System Data Platform for 2013 (http://open-power-system-data.org/, Data Package Time series, version 2016-10-28; primary data from CEPS, PSE, Amprion, BNetzA and Netztransparenz.de, Svenska Kraftnaet, TransnetBW, 50Hertz, TenneT, ENTSO-E Data Portal, Energinet.dk) and from Entso-E[6] for 2030.

Our stylized model of the interconnection of Germany and its electric neighbours includes 21 links between the 11 countries considered. The network topology is presented in Supplementary Table 5 in the form of an incidence matrix. This table also includes net transfer capacity (NTC) values. These are derived from historic TSO data for 2013 and from Entso-E[6] for 2030. We assume that NTC values are constant over all hours of the year and symmetric with respect to power flows in both directions.

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Supplementary Note 3. Separation of effects with alternative sequence

In the main article, we separate the effects of

1) additional renewables,
2) flexible (and increased) biomass capacity,
3) increased pumped storage,
4) thermal portfolio changes,
5) changing assumptions on reserve provision, and finally
6) increasing fuel and carbon prices.

The results generally depend on the particular sequence of the decomposition analysis. Other sequences would also be possible—although not all sequences would be numerically feasible.

In the following, we present the results of an alternative sequence on the separation of start-up costs. Other (meaningful) sequences may also be evaluated to raise complementary insights. We look at the following sequence:

1) Increasing fuel and carbon price prices,
2) additional renewables,
3) thermal portfolio changes
4) flexible (and increased) biomass capacity combined with increased pumped storage, and
5) changing assumptions on reserve provision.

The direction of effects is generally similar to the sequence discussed in the main article (Supplementary Figure 3). As before, growing fuel and carbon prices, increases in renewable capacity, and changing assumptions on reserve provision all have a positive influence on start-up costs, while the other factors have opposite effects. Yet the size of effects differs somewhat. The increase in start-up costs triggered by renewables alone would be even higher (+148%) than under the previous sequence. Yet the share of start-up costs in overall yearly variable costs (after first changing fuel and carbon prices) would grow to only 1.3% in this setting. Despite higher absolute start-up costs, this share would nonetheless be smaller than in the sequence presented in the main article (1.6%), as other variable costs also increase under the assumed fuel and carbon price changes. Accordingly, start-up costs should not become a major concern even under the assumption that only fuel and carbon prices as well as renewable capacities increase, but no other changes would take place in the system. It should be noted that, in order to ensure numerical feasibility, we allow for using a penalized backstop peak technology in the model run where the thermal portfolio changes are assessed. Likewise, we combine the changes of biomass pumped storage capacity in order to ensure feasibility.

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Supplementary Note 4. Sensitivity analyses

We carry out additional sensitivity analyses for the years 2020 and 2030 in order to assess the effects of alternative flexibility assumptions. These differ with respect to specific input parameters:

- **"More RES"**: Here we assume that the capacities of variable renewables, i.e. onshore wind power, offshore wind power and PV, are 10% larger compared to the baseline in 2020 and 20% larger in 2030. Accordingly, the need for flexibility in the system should increase.
- **"Less storage"**: In this sensitivity we assume that the capacity of pumped hydro storage remains constant at the 2013 level. As a consequence, storage capacity is 40% lower in 2030 compared to the baseline. This reflects the fact that pumped storage capacity expansions are currently not economic in Germany. In fact, there have not been any investment decisions worth mentioning in German pumped storage projects in recent years. While the motivation of this sensitivity is rather specific to the current German situation, results may be considered to have a rather general character with respect to the effects of changing storage capacities.
- **"Lower minload"**: The minimum load level of all thermal power plants is assumed to decrease by 25% compared to the baseline in 2020 and by 50% in 2030. Taking into account that future flexibility characteristics of the power plant portfolio are highly uncertain, this sensitivity may be considered as a rather optimistic perspective of thermal flexibility. In the future, minimum generation levels may decrease either due to retrofits of existing plants or because of new-builds that are designed for increased flexibility.
- **"Less curtailment"**: While curtailment of variable renewables does not incur any direct costs under baseline assumptions, it is penalized in the objective function in this sensitivity. Such costs can be caused by renewable support schemes, i.e. feed-in tariffs or market premiums. To fully reflect the real situation in Germany, a thorough assessment of current and future support instruments and their respective levels would be required, differentiating between technologies, age classes and plant sizes. Instead, we use a stylized, technology-invariant penalty of €100/MWh. This should serve to roughly reflect the effects of actual German renewable support schemes.
- **"Smoother wind profiles"**: Linearly scaling historic renewable feed-in patterns with future assumptions of installed capacity neglects potential smoothing effects, particularly with respect to onshore wind power. Such future smoothing may result from alternative geographic dispersion of renewable plants or generator design changes (cp. also Supplementary Note 5). We thus test the effects of three synthetically smoothed onshore wind profiles. Offshore wind and PV profiles are not changed, as both have comparatively small potentials for future smoothing.
- **"Alternative exogenous cross-border exchange"**: The future development of cross-border power exchange is highly uncertain and depends, amongst other factors, on power system developments in neighbouring countries, transmission infrastructure, and regulatory measures. In this sensitivity, we study the implications of changing cross-border exchange by linearly scaling the historic exchange profile for the year 2030. We use the scaling factors 2, 0.5, and 0. The factor 2 implies that net exchange is twice as high as in the baseline in every hour of the year. Such a development may result from future increases in interconnection capacity. Conversely, the scaling factors 0.5 and 0 imply that hourly net cross-border exchange is only half of the historic 2013 levels, or zero, respectively. This may occur if neighbouring countries also deploy additional variable renewable generators with similar generation profiles

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on a massive scale, or take measures to control load flows, such that German power exports in hours with high availability of variable renewables are less feasible.

- **"Endogenous cross-border exchange"**: Extending the previously mentioned sensitivity, we further explore the implications of alternative cross-border exchange patterns by modelling power flows between Germany and its electric neighbours as endogenous variables. This requires additional model equations (Supplementary Note 1, subsection "Extended model with stylized neighbouring countries") and additional parameter assumptions (Supplementary Note 2, subsection "Additional input parameters for the extended model with stylized neighbouring countries"). We then apply the extended model to the years 2013 and 2030, and additionally separate the effects of different power system changes in Germany and its electric neighbours. In doing so, we compare 2030 model outcomes with a 2013 simulation of the extended model, and not with the 2013 basic model. This way we avoid potential misinterpretations of artefacts arising from comparing the basic and the extended model.

To varying degrees, overall results are sensitive to deviating assumptions on renewable expansion, storage capacity deployment, changes in the minimum load level of thermal power plants, volatility of wind power profiles, and changes in cross-border power exchange. They are in contrast hardly sensitive with respect to decreased renewable curtailment. Yet effects vary substantially for different technologies. As results hardly change for the categories "Nuclear" and "Other" thermal generators, these are mostly not shown in the following figures in order to improve readability.

"More RES"

The "More RES" sensitivity assumes additional capacities of variable renewables of +10% by 2020 and +20% by 2030. The shares of variable renewables accordingly increase to 26% in 2020 and 40% in 2030, which can be interpreted as an accelerated transition from fossil to renewable power sources. Overall start-up costs increase roughly proportionally by +13% (+€11 million) in 2020 and +18% (+€26 million) in 2030, compared to respective baseline results. This is largely driven by increased cycling needs of hard coal plants and–to a smaller extent–lignite plants (Supplementary Figure 4). That is, a further expansion of variable renewables—ceteris paribus—predominantly increases cycling needs of former base- and mid-load generators with low variable costs. This reconfirms earlier findings in other power systems.[8]

"Less storage"

Assuming "Less storage", i.e. abstracting from future storage expansion, leads in 2030 to a somewhat stronger overall increase of start-up costs compared to the one observed in the "More RES" sensitivity (Supplementary Figure 5). In 2030, the assumed decrease in storage capacity of around 40% compared to the baseline results in a 28% increase of overall start-up costs (+€40 million). That is, thermal cycling needs may not only increase because of additional, renewable-induced flexibility requirements, but also in case of supply-side flexibility losses, which are comparatively small in terms of capacity. Yet the distribution of changes among generation technologies is rather different compared to "More RES". Under the assumption of lower storage capacities, oil-fired plants show in 2030 the largest increase in cycling needs, both in absolute and relative terms, closely followed by CCGT plants (in absolute terms).

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In other words, flexible mid- and peak-load plants now have to provide a substantial part of the flexibility that is provided by additional storage in the baseline, both in wholesale and reserve markets. Storage and flexible mid- and peak-load plants may thus be considered as competing flexibility options. A study that also considers investment decisions comes to similar conclusions.[9] A comparable effect is likely to occur with respect to different assumptions on demand-side flexibility, as the power system effects of storage and load shifting are very similar. A study on the Irish system conversely finds that lower storage capacities may—in specific settings—*decrease* the cycling needs of coal-fired plants until very high wind shares are reached.[8] This finding is driven by primary reserve provision of coal plants.

"Lower minload"

Results of the "Lower minload" sensitivity show that increasing flexibility of thermal power plants has an opposite effect on cycling needs as compared to the previously discussed sensitivities (Supplementary Figure 6). Under the assumption of decreased minimum load requirements of -25% in 2020 and -50% in 2030 compared to the baseline, overall start-up costs decrease by 21% (-€18 million) and 32% (-€46 million), respectively, as more generators remain online in periods of low net load. In the 2020 model runs, the absolute effect is most pronounced for hard coal plants, while in 2030 start-up cost reductions of CCGT plants dominate. Lignite plants show the strongest relative decrease. This means that lower minimum load requirements would allow lignite plants to largely preserve their merit-order position as base-load generators even under substantial expansion of variable renewables. It should be noted that such increased flexibility of thermal plants may involve not only additional investments, but also additional variable costs due to lower thermal efficiency which we abstract from in this analysis.

"Less curtailment"

The "Less curtailment" sensitivity shows that a preference for not curtailing renewable surpluses has a comparatively small effect on model outcomes (Supplementary Figure 7). Assuming a curtailment penalty of €100/MWh in the objective function, overall start-up costs increase by less than a million Euro in 2020, and decrease very slightly in 2030 compared to the baseline. Outcomes for 2020 are driven by increased cycling of nuclear power plants, which have the lowest marginal energy costs (but high start-up costs) and are thus the last to go offline in periods of excess renewable supply. In contrast, results for 2030 are driven by changes in start-ups of oil- and lignite-fired power plants. Additional model runs not shown here indicate that results would not change much even under a rather extreme penalty of €1000/MWh. The reason is that renewable curtailment is generally low in the modelled scenarios because of steep surplus-duration curves with high hourly peak surpluses and comparatively low yearly surplus energy.[10] Another reason for low curtailment—despite limited export opportunities—is the strong increase in pumped storage capacity assumed in the NEP scenarios. In the 2030 baseline, only around 2.6 TWh of variable renewable energy has to be curtailed, corresponding to 1.4% of overall potential wind and solar power generation. This value decreases to 1.4 TWh (0.8%) under the assumption of a €100/MWh curtailment penalty. It hardly decreases further under a €1000/MWh penalty, as the remaining peak surpluses cannot be integrated with the assumed storage capacities, irrespective of thermal start-up costs.

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According to these results, the effect of the actual renewable support scheme in Germany on start-up costs should be very small. Yet our analysis only provides a general indication as we, amongst other simplifications, do not differentiate between feed-in tariffs with feed-in guarantees, which may correspond to very high penalties in the objective function, and sliding market premiums, which limit negative prices to (negative) support levels. Irrespective of future changes in German renewable support policies, both schemes will still be present to some extent in the year 2030 due to their 20-year duration. A complementary analysis also uses penalties of €100/MWh and €1000/MWh to study the effect of lower renewable curtailment on dispatch and investment decisions in Germany and shows for scenarios of 2024 and 2034 that the marginal system costs of reducing renewable curtailment increase strongly, while renewable shares hardly change.[9]

"Smoother wind profiles"

We generate synthetically smoothed onshore wind profiles as follows. We first increase historic hourly availability factors by a time-invariant value corresponding to 10%, 25% or 50% of average yearly availability. We then proportionally decrease all hourly values again with corresponding factors of 1.1^{-1}, 1.25^{-1} or 1.5^{-1}, respectively, such that the overall yearly energy delivered by onshore wind generators does not change. This causes the standard deviation of hourly onshore wind generation to decrease from 0.15 in the baseline to 0.14, 0.12 or 0.10, respectively. The smoothing effect on availability-duration curves is shown in Supplementary Figure 8.

Model outcomes show that smoother wind profiles would reduce start-up costs. In the most extreme case modelled here, where the wind profile's standard deviation is reduced from around 0.15 to 0.10, overall start-up costs would decrease by 25% (-€36 million, Supplementary Figure 9). While all thermal technologies would be required to cycle less, the absolute effect is largest for CCGT plants. This is not surprising as these plants have to balance the largest part of renewable variability in this scenario. Yet lignite plants also need to be started up much less–particularly in relative terms. This is because of lower renewable surplus generation (cp. the left-hand side of the availability-duration curve), such that base-load plants have to shut down less frequently. In the cases with less extreme smoothing, effects are qualitatively similar, but quantitatively smaller. It should be noted that the synthetic profiles used here only illustrate the general effect of smoother wind power. The question how real-world future smoothing related to different geographical distributions and alternative generator designs would exactly change wind power profiles, and in turn start-up costs, is left for future research.

"Alternative exogenous cross-border exchange"

If cross-border exchange doubles in every hour compared to the 2030 baseline, overall start-up costs in Germany decline by around €23 million, or -16% (Supplementary Figure 10). As shown above, hours of German net exports (imports) are correlated with hours of high (low) renewable availability in the historic exchange pattern. Increased cross-border exchange thus smooths German net load and the operation of thermal power plants. In contrast, start-up costs increase by €15 million (+11%) if hourly exchange is only half of the historic level, and by €35 million (+25%) in case no exchange is possible at all. These findings connect to previous literature, according to which cross-border exchange is an

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important option for providing power system flexibility for the integration of variable renewable energy sources.[11,12,13]

Linearly scaling historic exchange patterns appears to be a valid approach under the assumption that historic differences between Germany's and neighbouring countries' power systems, which have given rise to the historic exchange profile, also persist in the future. Given that overall start-up costs decrease by only -16% if hourly exchange doubles and increase by a mere +11% if exchange is halved, we conclude that the results of our basic model are robust with respect to higher or lower exchange opportunities under this basic assumption.

"Endogenous cross-border exchange"

As opposed to the sensitivity presented above, we now give up the implicit assumption that the hourly profile of cross-border exchange does not change, but model exchange as an endogenous variable. This requires to also model the dispatch of neighbouring power systems as endogenous variables. As these cannot be modelled with the same level of detail as the German one in this application, our approach to modelling cross-border flows necessarily remains stylized. We do not expect to perfectly replicate real-world 2013 outcomes, nor the results of our basic model. Yet we assume that any limitations of the extended model should largely even out when looking at the differences between 2013 and 2030 outcomes of the extended model. We thus compare results of the extended model for both 2013 and 2030 in the following (and do not look at the 2013 baseline).

We find that overall yearly start-up costs of thermal generators in Germany hardly change between 2013 and 2030 in the extended model (around €68 million in 2013 and €66 million in 2030). Yet the composition of overall start-up cost changes considerably (Supplementary Figure 11). While hard coal plants account for the largest part of start-up costs in 2013, there is a shift towards CCGT plants by 2030. A qualitatively similar development was also observed in the basic model.

On the first glance, this finding may be considered to put the outcomes of our basic model—according to which start-up costs moderately increase in the context of German RES expansion—somewhat into perspective: start-up costs may not increase if additional flexibility resources of the European interconnection could be utilized. In the following, we shed some more light on the question where this additional flexibility originates from.

To do so, we separate the effects of different parameter changes between 2013 and 2030 by means of additional model runs, methodologically comparable to the separation exercise illustrated in the main article. Departing from the 2013 model run, we first carry out a simulation in which only the German part of the model is parametrized to the baseline 2030 assumptions, while all neighbouring countries as well as NTCs are still calibrated to the year 2013 ("Changes in Germany"). We subsequently increase installed variable renewable capacity in neighbouring countries to 2030 levels ("Additional RES neighbours"). Then, the remaining generation portfolio as well as load in neighbouring countries are also updated to 2030 levels ("Other changes neighbours"). Finally, NTC values are increased to 2030 assumptions ("NTC changes").

Model results show that—all other parameters being constant—both the (cumulative) changes in Germany and the expansion of fluctuating renewable energy sources in neighbouring countries would

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substantially increase start-up costs of thermal power plants in Germany (Supplementary Figure 12). The changes in Germany alone would cause start-up costs to increase to around €108 million (+60%). Although this is a little less than in the basic model, our results may be considered fairly robust also in the extended model with endogenous cross-border exchange. Together with the expansion of variable renewables in neighbouring countries, start-up costs would nearly double from €68 million to €131 million (+93%). Other changes in neighbouring countries—i.e. increasing load and additional power storage—conversely cause start-up costs in Germany to decrease again, as these allow neighbouring countries to increase their imports from Germany in hours of high German renewable feed-in. The same is true for increased interconnection capacity, which allows for increased flexibility by means of additional power exchange.

When interpreting these outcomes, it should be considered that the overall share of variable renewable energy does not increase as strongly as in the basic model. While the share of wind and solar power increases from 14% in 2013 to 34% in 2030 in the basic model (Germany only), these shares are lower in the extended model. In the whole region considered, i.e. Germany and its electric neighbours, the share of variable renewable energy sources grows from 8% in 2013 to 24% in 2030.

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Supplementary Note 5. Discussion of limitations

General remarks

The model analysis requires a range of simplifying assumptions. For some of these, the direction in which results may be distorted is intuitive; for others, effects are less clear. To begin with, unit commitment models generally draw on stylized techno-economic parameters such as offtimes and start-up costs. These are hard to estimate bottom-up and may vary substantially between different block sizes, age classes, and manufacturers. Start-up fuel requirements in reality also depend on offtime duration, i.e. on plant temperature. Moreover, it is likely that the costs and restrictions related to thermal flexibility will change in the future. Yet how these factors may impact the respective unit commitment parameters—which are in any case stylized—and overall results is difficult to foresee.

To raise a more general point, some of the assumed technical constraints may not even exist in the real world. For example, the concept of minimum offtimes represents economic considerations (e.g. avoid unnecessary wear and tear) rather than physical realities. While unit commitment modellers who focus on the system perspective generally aim to represent such intricate and plant-specific economic considerations by means of simple parameters and restrictions, it is not straightforward to estimate the qualitative effects of such simplifications on model outcomes. Likewise, drawing on exogenous—although established and policy-relevant—future power plant portfolios inherently leads to distorted outcomes as the portfolio may in fact not resemble a long-term equilibrium. The NEP capacities used here may rather constitute a desirable development with respect to generation adequacy and system flexibility, but the actual realization of these capacities is uncertain. For example, lignite and hard coal plants may be phased out earlier because of emission concerns. In summer 2016, the German parliament passed the *Strommarktgesetz*, according to which eight existing lignite blocks are to be transferred into a new type of reserve between 2016 and 2019 and shut down permanently four years later. While this is already captured in the scenarios calculated here, similar measures may occur in the future. Accordingly, the shares of specific technologies and/or their flexibility characteristics may be either under- or overrated, with unclear consequences for start-up outcomes. In order to avoid these problems, using integrated investment and dispatch models would be desirable. Yet this requires alternative problem formulations in order to maintain computability.[14,15]

Factors contributing to an underestimation of start-up costs

Another simplification more specific to the analysis made here relates to the assumption that the flexibility of CHP generators does not change in future scenarios. In the real German situation, CHP flexibility should tend to increase by 2030, for example due to additional heat storage facilities. This may result in more flexible operation patterns, i.e. increasing start-ups of CHP plants.

Another factor that generally leads to an underestimation of cycling needs and related costs is the assumption that thermal efficiency does not decrease during part-load operation. If this were to be considered, shutting plants down completely instead of operating them in part-load mode would become more attractive.

Likewise, the hourly resolution used here underestimates sub-hourly renewable variability and related cycling requirements. An Irish case study shows that an increased temporal resolution leads to more realistic estimations of thermal cycling activities and related costs, and that increasing the temporal resolution from 60 to 5 minutes results in relative start-up cost increases of around 13%.[16]

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Factors contributing to an overestimation of start-up costs

In contrast, other limitations may lead to an overestimation of start-ups and respective costs. A very important one is the assumption of fixed imports and exports in the 2020 and 2030 scenarios of the basic model. Reasons for making this simplification in the largest part of our analysis include substantial uncertainties with respect to the future development of neighbouring power systems as well as numerical challenges in solving pan-European unit commitment models. In general, power plants in neighbouring countries are unlikely to be less flexible than German ones. In addition, the shares of variable renewables in neighbouring countries are likely to be lower than in Germany in the medium run (Denmark being a noteworthy exception). Accordingly, we should underestimate the flexibility potentials in the European interconnection and overestimate start-up costs in Germany in the basic model.

In fact, the additional sensitivity "Endogenous cross-border exchange", which draws on an extended model version with a stylized representation of neighbouring countries, shows that future start-up costs in Germany may be lower than determined by the basic model. Yet our decomposition analysis indicates that results depend on the particular developments in neighbouring countries and the expansion of cross-border transmission capacities. In order to explore these factors in more detail, complementary analyses with a dedicated pan-European modelling approach would be useful.

Likewise, we tend to overestimate flexibility requirements in Germany because of linearly scaling up feed-in patterns of variable renewables. Although this is rather common in the literature, it neglects potential future smoothing of these profiles related to alternative generator designs and different geographic distributions.[10] The sensitivity "Smoother wind profiles" illustrates this effect.

Another potential overestimation of start-up costs is caused by considering only thermal power plants and pumped storage as the main suppliers of flexibility in the wholesale market. It is reasonable to assume that other types of power storage as well as demand-side flexibility potentials could increasingly play a role with larger shares of variable renewables.[3] Yet properly modelling load shifting would not only require detailed techno-economic input data on specific consumers, but also involves intricate model formulations which increase the computational burden.[17]

In case of non-spinning positive minute reserve provision by open-cycle gas (or oil) turbines, the model my also slightly overestimate start-up cost, as the costs of respective start-up costs $sc_i ST_{i,t}^{gt}$ are summed up for each hour individually. If a respective turbine provides non-spinning positive reserves in two subsequent hours, start-up costs incur for both periods. Yet such distortions should be small as this is rarely happening in the model, and overall start-up costs of gas turbines are nonetheless low compared to other technologies.

Further factors and unclear overall effect of distortions

A study that compares different model formulations shows that start-up cost outcomes hardly differ between deterministic and stochastic programs.[18] In a stochastic setting with an expected value approach, wind power forecast errors increase start-up costs by 1.5% compared to a deterministic case, while stochastic programming with a scenario tree reduces start-up costs by less than 2.0%. The reason for the latter is that the optimal number of thermal plants operating at least in part-load mode is higher than in a deterministic setting in order to be able to respond to uncertain short-term changes in power demand. Another study makes a similar point for stochastic wind power.[19] As we use a

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deterministic model, this may contribute to a slight upward distortion of start-up cost outcomes—yet effects in the opposite direction may also be conceivable.

Further, results depend on assumed fuel and CO_2 price developments. For instance, lower natural gas prices, which may for example be caused by increased shale gas exploitation, would generally lead to lower start-up costs. Assessing the effects of higher CO_2 prices would require further analyses, as this may change the dispatch merit order of lignite, hard coal and natural gas plants. Higher specific start-up costs than assumed here should lead to higher initial (and future) absolute levels, but relatively lower growth of overall start-up costs compared to those modelled here.

In our analysis, we abstract from network constraints. Regarding the German transmission grid, this assumption appears to be justified, as the scenarios are derived from the official Grid Development Plan (NEP), which assumes nearly perfect transmission expansion. As for distribution grids as well as cross-border exchange, which is fixed to historic hourly values, it is per se not clear how model outcomes are affected by this simplifying assumption. Deviations in both directions are conceivable, but these may heavily depend on specific distribution grid and cross-border congestion settings.

Summing up, a definitive assessment on the net effect of upward and downward distortions is not possible. The overall relevance of start-up costs may accordingly be either over- or underrated in this analysis. Yet we do not see any clear indication why the qualitative findings should change substantially if these limitations could be addressed.

Limitations of the extended model

The extended model version, which includes a stylized representation of neighbouring countries' power systems, necessarily comes along with additional limitations. For example, we may overestimate power system flexibility in the extended model, and accordingly under-estimate cycling requirements in Germany, because of modelling aggregate thermal generation capacity in neighbouring countries. Abstracting from balancing reserve constraints in neighbouring countries could have similar effects. With respect to hydro reservoir modelling, it is not clear if our simplified modelling approach leads to an over- or under-estimation of flexibility. The same is true for the assumption of constant and symmetric net transfer capacity values.[20,21] Actual import or export opportunities in particular hours may well be higher or lower. Likewise, it is not clear in which way flexibility outcomes are distorted by neglecting other countries than the direct electric German neighbours considered here. For example, an inclusion of the whole hydro-based Scandinavian region or Italy, combined with more detailed hydro reservoir modelling, may lead to different outcomes when it comes to system flexibility.

Negative prices

Finally, we briefly discuss the aspect of negative prices. Negative prices currently occur in bid-based real-world day-ahead or intraday power markets, and may become a more frequent phenomenon with growing shares of variable renewables. Negative prices may be thought to have an influence on start-ups and related costs in the sense that they provide additional signals to shut down generators in respective periods. In principle, we are unable to directly address negative prices with our mixed-integer cost-minimizing framework because of the solving process: first, the binary variables are solved and fixed, and subsequently the remaining linear program is solved. Accordingly, the marginals of the market clearing condition always reflect the marginal costs of the most expensive generator running

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in the respective period. These are always nonnegative, and prices thus cannot go below zero. One exception is penalized renewable curtailment, which we consider in the sensitivity discussed above. There, prices become negative in periods of curtailment at the level of the negative penalty.

In the real world, negative prices occur in day ahead or spot markets if energy-related renewable support schemes are present, or if power generators make respective energy bids, i.e. if the losses received in periods with negative prices are smaller than the costs of shutting down and subsequently starting the plants up again. In this case, negative prices are the result of efficient dispatch behaviour (or more precisely, efficient bidding). Further, negative prices may occur because of energy-based renewable support schemes.[22] Although we are unable to simulate such price formation with our model, we nonetheless determine the same unit commitment and dispatch as in a perfect decentralized bid-based market that is coordinated by prices. Outcomes with respect to start-up counts and costs accordingly do not differ. In this sense, negative prices could have distributional consequences, but would not change the short-run equilibrium.

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Supplementary Tables

Supplementary Table 1: Sets, parameters, and variables

Sets	Description	Unit
$i \in I$	Set of thermal power plant blocks of various technologies	
$i^{gt} \in I$	Subset of open cycle gas turbines qualified to provide non-spinning positive minute reserve	
$j \in J$	Set of storage technologies	
$res \in RES$	Set of variable renewable power sources	
$rsrv \in RSRV$	Set of balancing reserves	
$rsrv^{up}, rsrv^{do} \in RSRV$	Subsets of positive and negative reserves	
$mr, sr \in RSRV$	Subsets of secondary and minute reserves	
$t, tt \in T$	Time set	Hours
Parameters		
$activ_{rsrv,t}$	Hourly share of reserves activated	[0,1]
$avail_t^{bio}$	Availability of biomass generation	[0,1]
$avail_{res,t}^{res}$	Availability of variable renewables	[0,1]
$avail_{i,t}^{th}$	Availability of thermal blocks	[0,1]
$cbex_t^{exog}$	Hourly cross-border exchange, i.e. German net exports (exogenous parameter)	MWh
dem_t^{whls}	Hourly power demand on the wholesale market	MWh
$dem_{rsrv,t}^{rsrv}$	Hourly reserve provision requirements	MW
$energy^{bio}$	Biomass energy budget	MWh
η_j^{in}	Storage loading efficiency	[0,1]
η_j^{out}	Storage discharging efficiency	[0,1]
$grad^{bio}$	Load gradient per minute of biomass power plants as a share of installed capacity	[0,1]
$grad_i^{th}$	Load gradient per minute of thermal blocks as a share of installed capacity	[0,1]
Λ	Capacity of largest gas turbine	MW
mc_i	Marginal generation costs of thermal blocks	€/MWh
$mstc_j^{in}$	Marginal costs of storage loading	€/MWh
$mstc_j^{out}$	Marginal costs of storage discharging	€/MWh
$othergen_t$	Other hourly power generation (hydro, waste)	MWh
$penalty_{res}$	Penalty for curtailment of variable renewables	€/MWh
$qmax^{bio}$	Generation capacity of biomass power plants	MW
$qmax_{res}^{res}$	Generation capacity of variable renewables	MW
$qmax_i^{th}$	Generation capacity of thermal blocks	MW
$qmin_i^{th}$	Minimum generation of thermal blocks	MW
sc_i	Start-up costs of thermal blocks	€
$stinmax_j$	Storage loading capacity	MW
$stime_i$	Start-up time of thermal blocks (minimum offtime)	Hours
$stlevmax_j$	Maximum storage level	MWh
$stoutmax_j$	Storage discharging capacity	MW

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Binary variables		
$ST_{i,t}$	Start-up variable of thermal blocks (1 if block is started up in period t, 0 otherwise)	0 or 1
$ST^{gt}_{i,t}$	Start-up variable of gas turbines for non-spinning positive MR provision (1 if activated in period t, 0 otherwise)	0 or 1
$U^{th}_{i,t}$	Status variable of thermal blocks (1 if block is generating, 0 otherwise)	0 or 1
$U^{sto}_{j,t}$	Status variable of storage plants (1 if charging, 0 if discharging)	0 or 1
Free continuous variable		
$Cost$	Total dispatch costs	€
Positive continuous variables		
Bio_t	Hourly power generation from biomass	MWh
$Prov^{bio}_{rsrv,t}$	Hourly reserve provision by biomass power plants	MW
$Prov^{gt}_{mr^{up},i,t}$	Hourly provision of positive MR provision by non-spinning gas turbines	MW
$Prov^{res}_{rsrv,res,t}$	Hourly reserve provision by variable renewables	MW
$Prov^{stin}_{rsrv,j,t}$	Hourly reserve provision by storage loading	MW
$Prov^{stout}_{rsrv,j,t}$	Hourly reserve provision by storage discharging	MW
$Prov^{th}_{rsrv,i,t}$	Hourly reserve provision by conventional power plants	MW
$Q_{i,t}$	Hourly power generation by thermal blocks	MWh
$Rescurt_{res,t}$	Hourly curtailment of variable renewables	MWh
$Resint_{res,t}$	Hourly system integration of variable renewables	MWh
$Stin_{j,t}$	Hourly storage loading	MWh
$Stlev_{j,t}$	Hourly storage level	MWh
$Stout_{j,t}$	Hourly power generation from storage	MWh

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Supplementary Table 2: Additional sets, parameters, and variables in the extended model with neighbouring countries

Sets	Description	Unit
$c \in C$	Set of countries (including Germany)	
$dispnc \in DISPNC$	Set of dispatchable technologies in neighbouring countries	
$jnc \in JNC$	Set of storage technologies in neighbouring countries	
$l \in L$	Links between countries	
$nc \in NC$	Set of neighbouring countries (not including Germany)	
Parameters		
$avail^{res}_{res,t,nc}$	Availability of variable renewables	[0,1]
$dem^{nc}_{t,nc}$	Hourly power demand	MWh
$energy^{dispnc}_{dispnc,nc}$	Energy budget of dispatchable technologies (only applies for hydro reservoirs and biomass)	MWh
η^{in}_{jnc}	Storage loading efficiency	[0,1]
η^{out}_{jnc}	Storage discharging efficiency	[0,1]
$inc_{l,c}$	Incidence matrix of links and countries	-1, 0, +1
mc_{dispnc}	Marginal generation costs of dispatchable technologies	€/MWh
mc^{up}_{dispnc}	Marginal costs of upward load change	€/MWh
mc^{do}_{dispnc}	Marginal costs of downward load change	€/MWh
$mstc^{in}_{jnc}$	Marginal costs of storage loading	€/MWh
$mstc^{out}_{jnc}$	Marginal costs of storage discharging	€/MWh
ntc_l	Net transfer capacity of links	MW
$qmax^{dispnc}_{dispnc,nc}$	Aggregate generation capacity of dispatchable technologies	MW
$qmax^{res}_{res,nc}$	Aggregate generation capacity of variable renewable technologies	MW
$ror_{t,nc}$	Hourly run-of-river generation in neighbouring countries	MWh
$stinmax_{jnc,nc}$	Storage loading capacity	MW
$stlevmax_{jnc,nc}$	Maximum storage level	MWh
$stoutmax_{jnc,nc}$	Storage discharging capacity	MW
Binary variables		
$U^{sto}_{jnc,t,nc}$	Status variable of storage plants (1 if charging, 0 if discharging)	0 or 1
Free continuous variables		
$Cbex^{endog}_{l,t}$	Hourly cross-border exchange (endogenous variable)	MWh
Positive continuous variables		
$Qdisp_{dispnc,t,nc}$	Hourly power generation by dispatchable technologies (including hydro reservoirs and biomass)	MWh
$Qdisp^{up}_{dispnc,t,nc}$	Hourly upward load change of dispatchable technologies	MWh
$Qdisp^{do}_{dispnc,t,nc}$	Hourly downward load change of dispatchable technologies	MWh
$Qres_{res,t,nc}$	Hourly power generation by variable renewables	MWh
$Stin_{jnc,t,nc}$	Hourly storage loading	MWh
$Stlev_{jnc,t,nc}$	Hourly storage level	MWh
$Stout_{jnc,t,nc}$	Hourly power generation from storage	MWh

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Supplementary Table 3: Unit commitment parameters. Sources: DIW Berlin's database and ref. 5

	Minimum load (%)	Minimum offtime (hours)	Start-up fuel requirement for cold start (MWh_{th}/MW)	Start-up depreciation costs (€/MW)
Nuclear	50	10	16.7	50
Lignite / hard coal > 500 MW	40 / 38	8	5.9	49
Lignite / hard coal ≤ 500 MW	40 / 38	6	2.7	105
CCGT	45	2	2.8	60
Other steam turbines	38	2	2.8	57
Gas turbines	20	0	0.1	24

Supplementary Table 4: Marginal generation and load change costs in €/MWh

	mc_{dispnc}		mc^{up}_{dispnc}, mc^{do}_{dispnc}
	2013	2030	2013 & 2030
Nuclear	10.80	10.80	40
Lignite	10.55	31.04	60
Hard coal	34.04	49.71	60
CCGT	56.00	69.10	100
OCGT	80.00	95.01	30
Oil	167.72	192.64	40
Other thermal	49.04	63.21	50

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Supplementary Table 5: Incidence matrix for 21 country links (I) and 11 countries, and net transfer capacities (NTCs) for 2013 and 2030, derived from Entso-E (ref. 6)

	DE	AT	BE	CH	CZ	DK	FR	LU	NL	PL	SE	NTC in MW 2013	NTC in MW 2030
I1	1	-1										1850	7500
I2	1		-1									0	1000
I3	1			-1								2865	3993
I4	1				-1							1500	2300
I5	1					-1						1796	4000
I6	1						-1					2925	4800
I7	1							-1				980	2300
I8	1								-1			3688	5000
I9	1									-1		1075	2500
I10	1										-1	603	1315
I11		1		-1								803	1700
I12		1			-1							750	1100
I13			1				-1					1500	3550
I14			1					-1				0	700
I15			1						-1			2325	2400
I16				1			-1					2100	2500
I17					1					-1		1325	550
I18						1			-1			0	700
I19						1					-1	1533	2210
I20							1	-1				0	190
I21										1	-1	300	600

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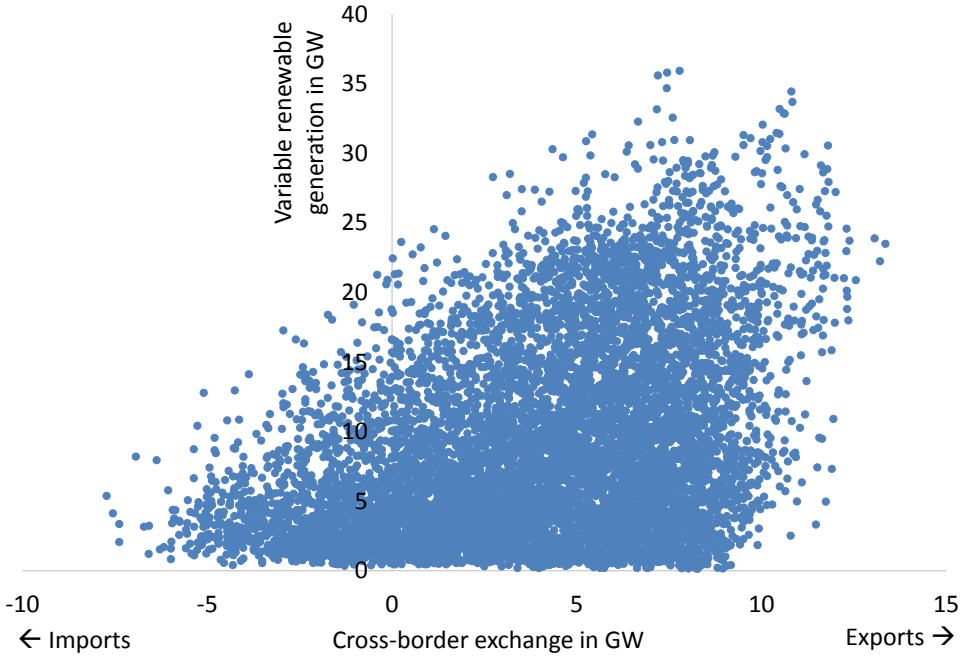
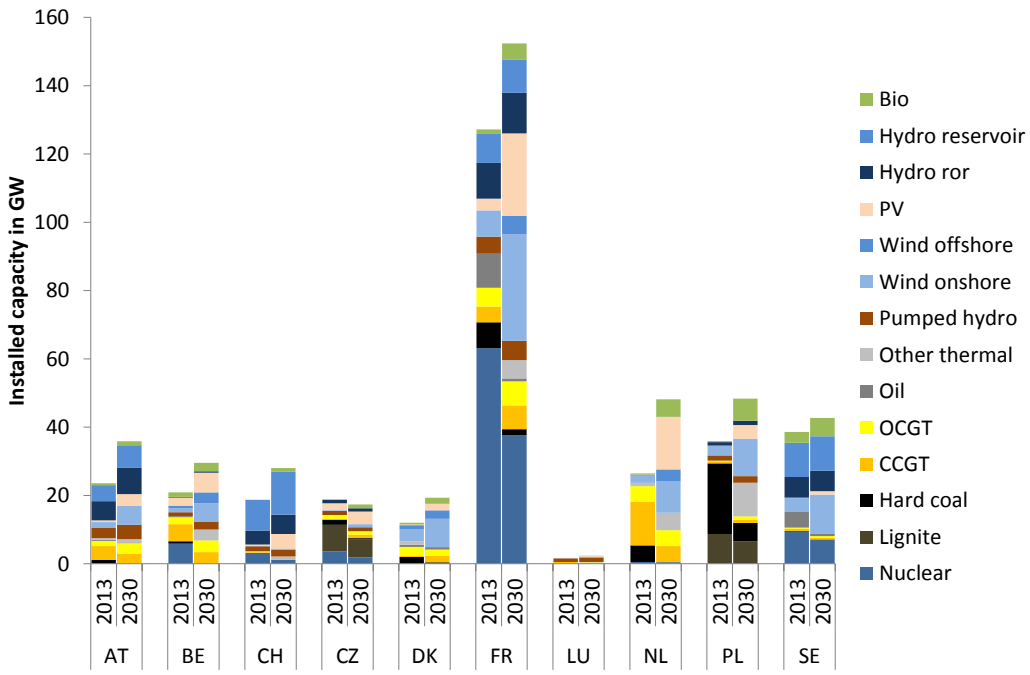
Supplementary Figures



Supplementary Figure 1: Variable renewable power generation in Germany and cross-border exchange in 2013. There is a positive correlation of net exports and the feed-in of variable renewables.



Supplementary Figure 2: Installed capacities in neighbouring countries (extended model). Data derived from Entso-E (ref. 6). Because of the deployment of variable renewables, installed capacity increases in all countries.

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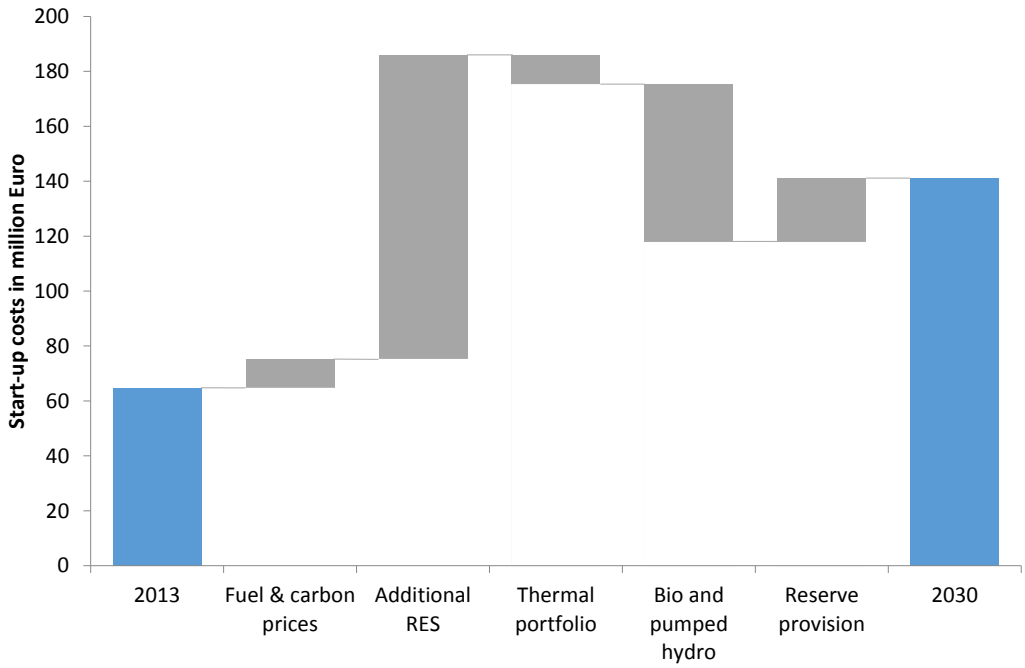
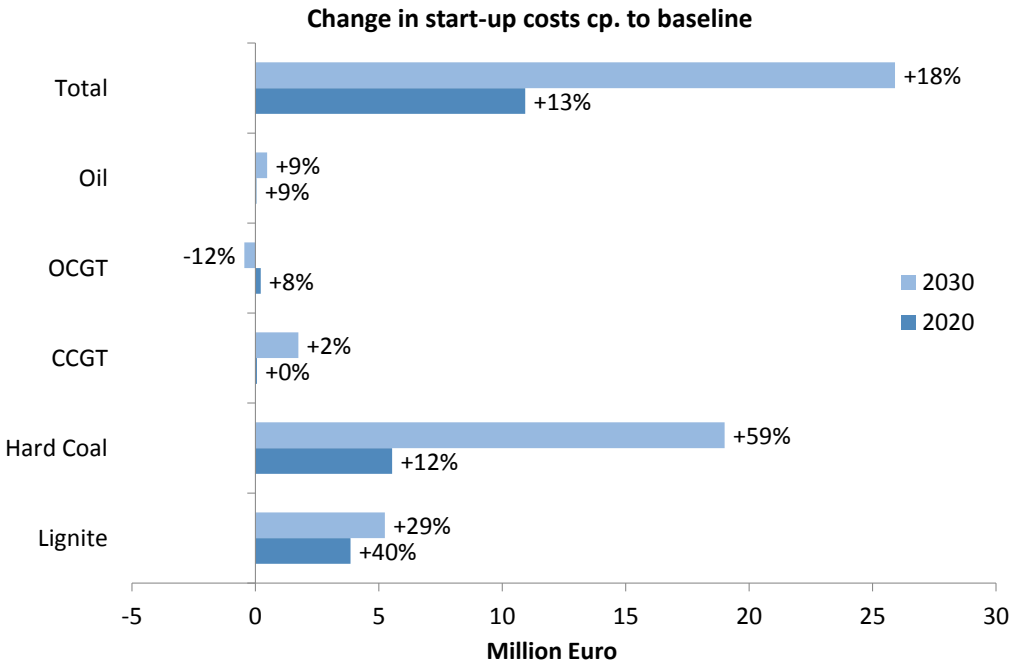


Supplementary Figure 3: Separation of effects between 2013 and 2030 baseline scenarios: start-up costs, alternative sequence. Renewable expansion has an even stronger positive effect on start-up costs as in the sequence presented in the main article.



Supplementary Figure 4: "More RES": Absolute and relative change in yearly start-up costs compared to 2020 and 2030 baseline scenarios. A further expansion of variable renewables predominantly increases cycling needs of former base- and mid-load generators.

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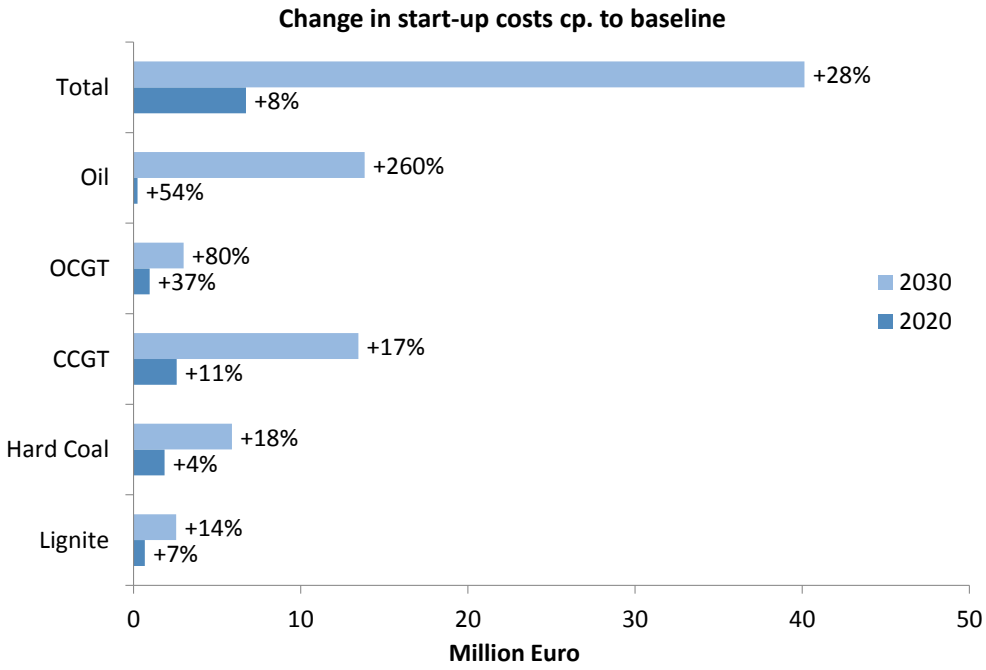
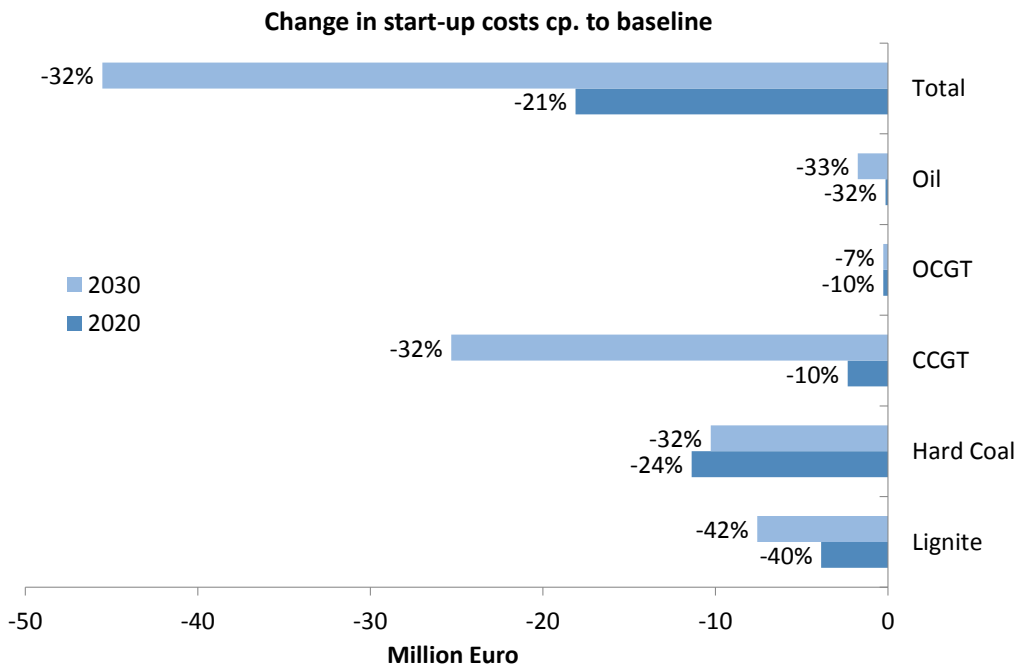
SUPPLEMENTARY INFORMATION



Supplementary Figure 5: "Less storage": Absolute and relative change in yearly start-up costs compared to 2020 and 2030 baseline scenarios. Flexible mid- and peak-load plants provide a substantial part of the flexibility that is provided by additional storage in the baseline.



Supplementary Figure 6: "Lower minload": Absolute and relative change in yearly start-up costs compared to 2020 and 2030 baseline scenarios. Lower minimum load requirements would allow thermal plants to stay online during more hours of the year and would thus substantially decrease start-up costs.

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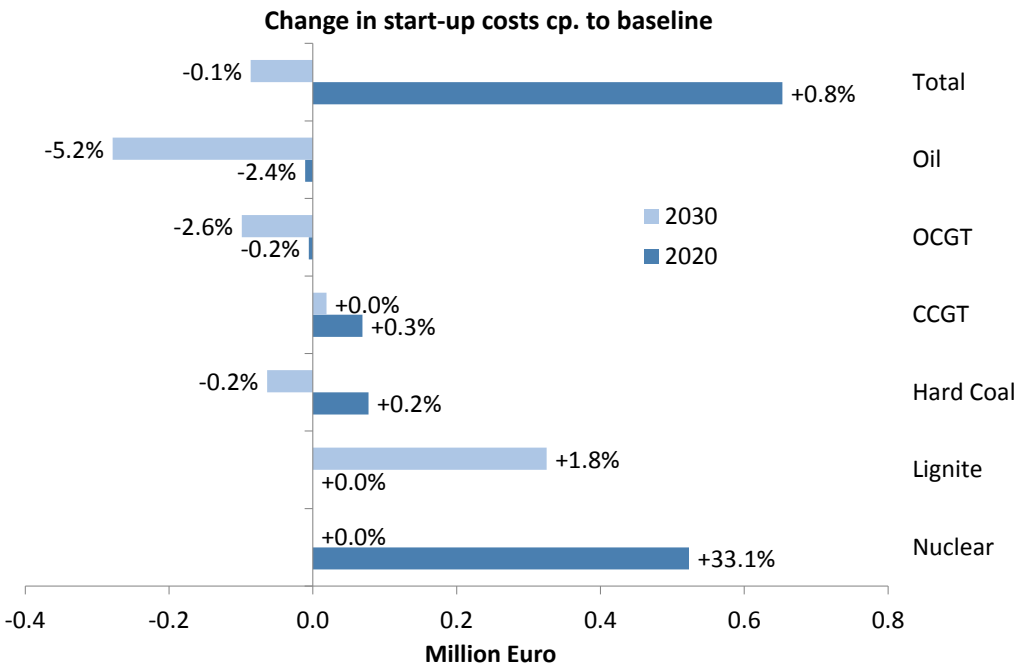
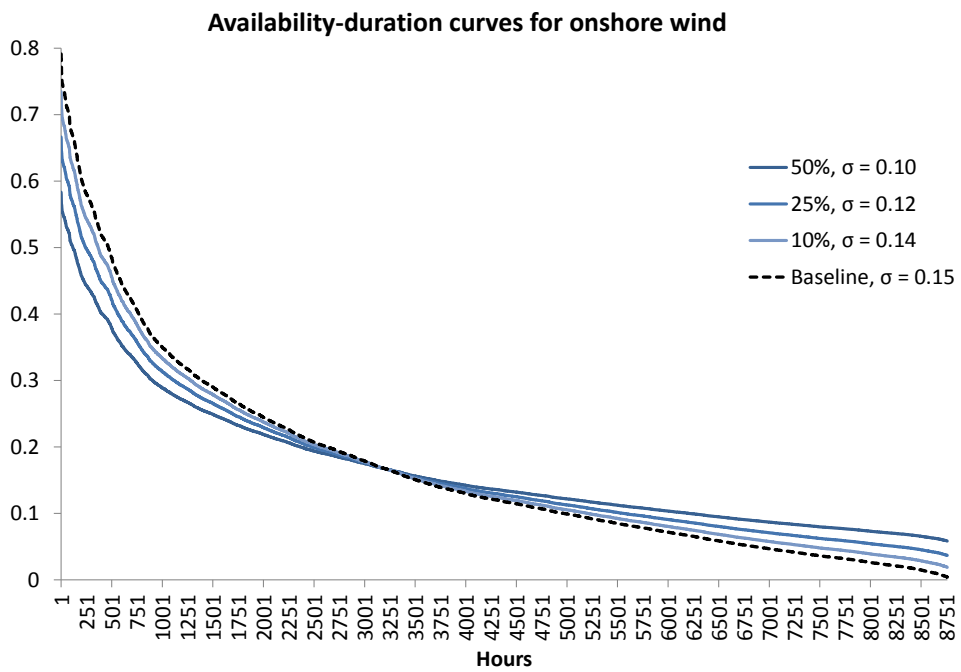


Supplementary Figure 7: "Less curtailment": Absolute and relative change in yearly start-up costs compared to 2020 and 2030 baseline scenarios. Overall effects are small compared to other sensitivities because renewable curtailment is low in the baseline.



Supplementary Figure 8: Availability-duration curves for onshore wind power. We derive three synthetically smoothed profiles such that overall yearly energy delivered by onshore wind generators does not change.

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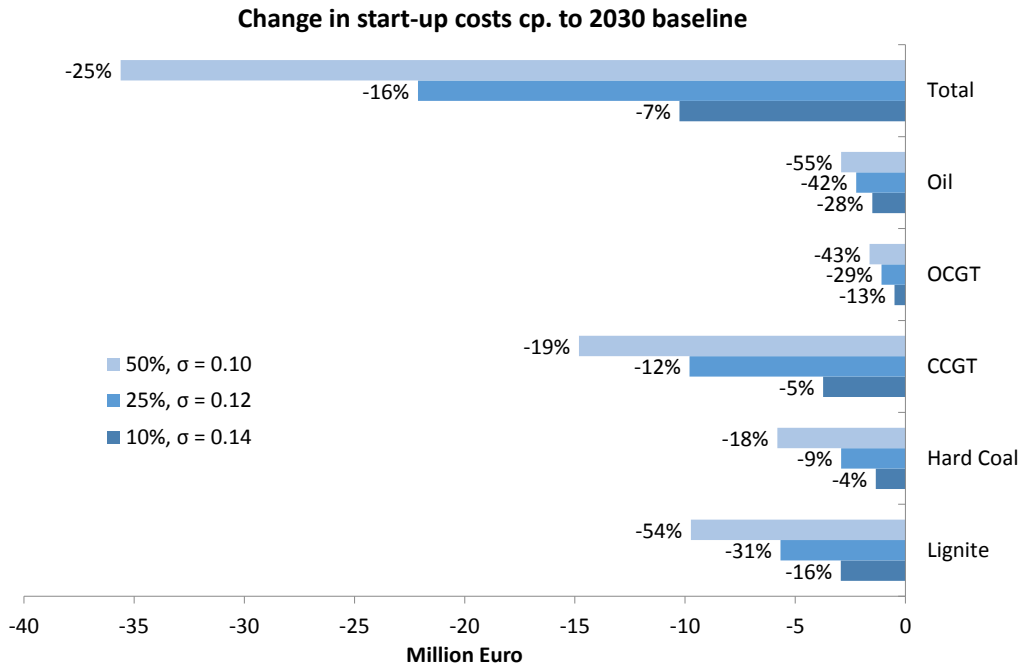
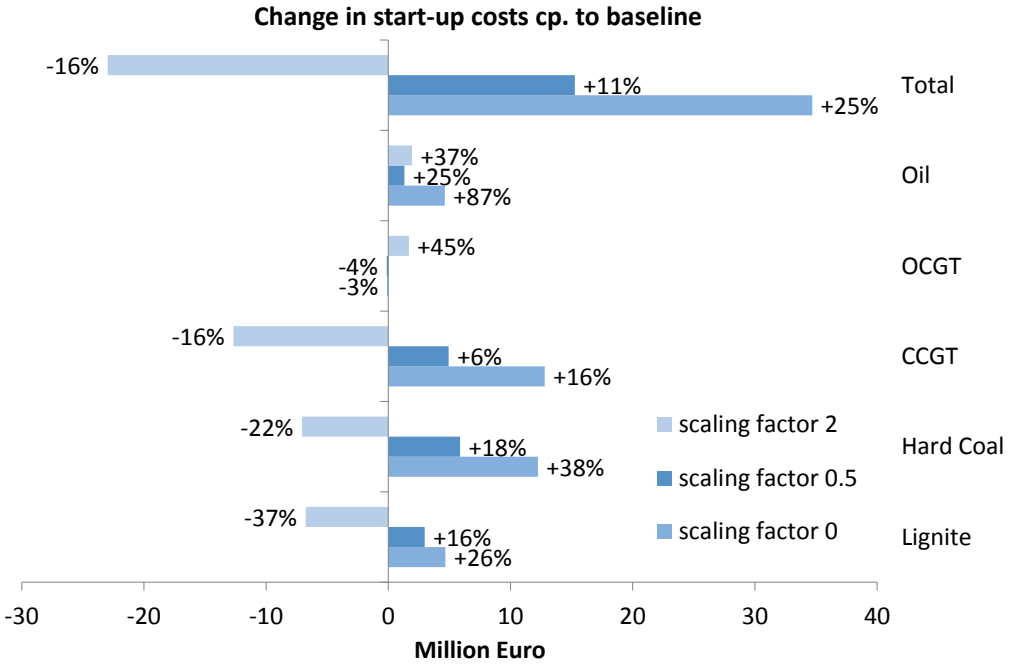
SUPPLEMENTARY INFORMATION



Supplementary Figure 9: "Smoother wind profiles": Absolute and relative change in yearly start-up costs compared to 2030 baseline scenario. Smoother wind profiles would reduce start-up costs.



Supplementary Figure 10: "Alternative exogenous cross-border exchange": Absolute and relative change in yearly start-up costs compared to 2030 baseline scenario. Higher (lower) cross-border exchange decreases (increases) start-up costs under the assumption that historic exchange patterns persists.

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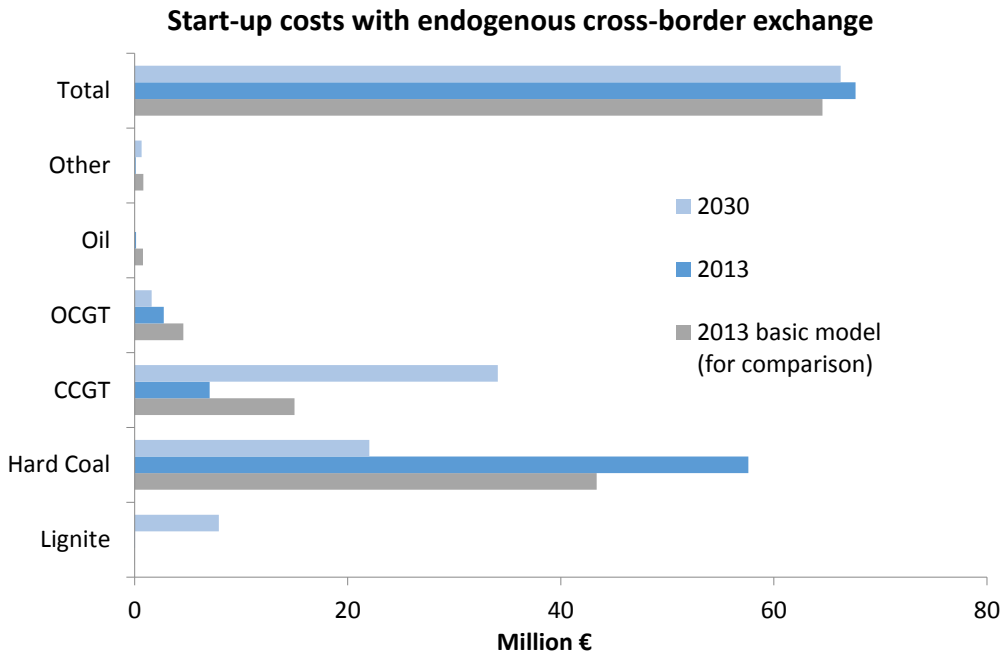
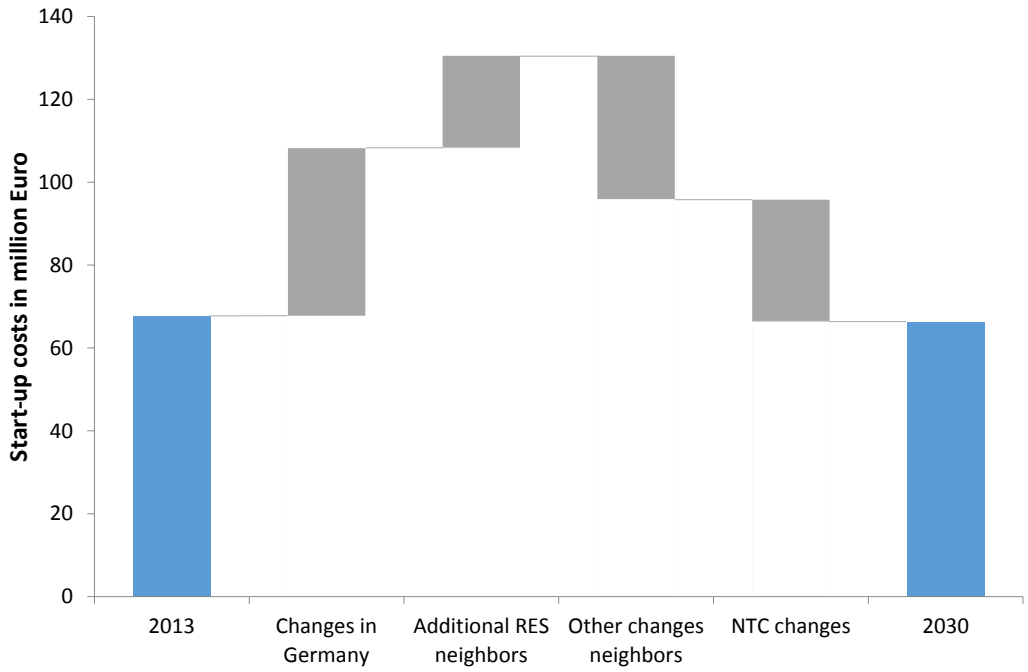


Supplementary Figure 11: Yearly start-up costs in the extended model. Start-up costs hardly change between 2013 and 2030, but their composition does.



Supplementary Figure 12: Separation of start-up cost effects between 2013 and 2030 scenarios in the extended model. Changes in Germany and the expansion of fluctuating RES in neighbouring countries would substantially increase start-up costs. Other portfolio changes in neighbour countries and increased NTCs have a counteracting effect.

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Chapter 6

Synthesis and Outlook

The usual disconnect between consumption and the time-varying costs of supply is considered a "fundamental flaw" (Stoft, 2002) in existing electricity markets. It is moreover increasingly seen as a crucial impediment to establishing efficiency and reliability in low-carbon electricity markets, deploying high shares of variable renewable generation technologies. Implementing real-time retail pricing to expose consumers to the variation in the marginal costs of electricity supply thus appears to be essential to achieving the structural transformation towards both mostly variable electricity supply and the electrification of final energy demand.

This thesis aims to contribute to the economic evaluation of introducing real-time pricing in low-carbon electricity markets, taking efficiency and feasibility into account. It does so by improving the understanding of basic mechanisms driving the long- and short-run welfare and distributional effects of real-time price responsive consumption behavior. In particular, the research in this thesis provides qualitative and quantitative insights on the interaction of climate policy instruments, variable renewable electricity generation and the introduction of real-time pricing on electricity market outcomes. In order to do so, each of the four main chapters addresses related key issues in the academic and political discourse:

Chapter 2 highlights and studies two questions relevant for decision makers: first, when to roll out real-time pricing schemes and to invest in advanced metering infrastructure as variable renewable technologies diffuse in the market, and second, which time-varying pricing scheme to implement, if accounting for feasibility constraints.

Chapter 3 studies the welfare and distributional implications of social acceptance barriers to adopting real-time pricing. Taking consumer heterogeneity into account, it sheds light on the influence of variable renewable generation on distributional impacts among residential consumers, and on the potentially adverse distributional effects across consumer sectors resulting from targeted implementations of real-time pricing.

The relative efficiency of renewable support policies is assessed in chapter 4, focusing on the complementarity of variable renewable electricity generation and real-time pricing. Specifically, the analysis compares the efficiency of renewable output and capacity subsidies in achieving a given renewable supply share target, when negative wholesale prices are accounted for.

Chapter 5 complements chapter 2 to 4, by addressing the relevance and evolution of quasi-fixed costs of thermal plant operation for growing shares of variable renewable electricity. Changes in quasi-fixed costs due to more rapid changes in plant operation are seen to cause significant price effects and represent one of several factors influencing the efficiency effects of real-time pricing, which are omitted in the analyses of the core chapters.

The remainder of this chapter is organized as follows. In Section 6.1, I will synthesize the main findings of this thesis and subsequently critically discuss the methods applied to obtain them in section 6.2. In Section 6.3, I will explain the novelty and overarching relevance of the presented research. Finally, I conclude with an outlook on the direction of further research on the economics of time-varying retail pricing.

6.1 Real-time pricing in low-carbon electricity markets: Main findings

Assessing the efficiency and feasibility of real-time retail pricing in low-carbon electricity markets is more complex than common economic wisdom would often suggest. This aspect is illustrated in several instances throughout this thesis.

First of all, implementing real-time retail pricing does not necessarily become more beneficial at high shares of variable renewable electricity supply. This finding is derived in chapter 2, which addresses the optimal timing of introducing real-time pricing and contributes to assessing the trade-off between feasibility and efficiency of real-time pricing. More specifically, it is shown that carbon-tax-induced investment in variable generation technologies can have counteracting effects on wholesale prices, which interact such that the total annual welfare gains arising from real-time pricing change in a U-shaped fashion with carbon taxation and renewable market penetration. This result complements common knowledge in the literature, suggesting that the value of real-time price responsive demand rises strictly with variable renewable deployment rates. It further challenges the timing of the ongoing advanced-meter rollout in EU and U.S. power markets, which often seems to be guided by this intuition.

In addition, chapter 2 challenges previous studies arguing in favor of second-

best time-varying pricing schemes, which are temporally less granular and thus presumably more feasible than full-fledged RTP. Comparing the relative efficiency of RTP and variable peak pricing (VPP), chapter 2 demonstrates that such second-best alternatives might become irrelevant with rising variable renewable supply shares. While they indeed could capture a significant portion of the potential efficiency gains from RTP in absence of zero-marginal cost supply from VRE, this fraction is found to become negligibly small at high renewable supply shares. The reason is that with increasing supply at zero-marginal costs from renewables, inefficiencies from flat pricing result mostly from making inefficient use of installed generation capacity, by consuming "too little" in low price periods and high VRE output. Common second-best pricing schemes such as VPP primarily aim to curb demand and reduce the inefficiency from consuming "too much" during periods of scarce generation capacity and high prices. Only RTP schemes thus appear to be adequate in providing proper signals to consumers, in order to accommodate variable (and uncertain) electricity generation.

Besides the complexity of RTP, its potential distributional implications represent another crucial acceptance barrier, which may particularly demotivate many residential and small commercial customers to adopt it. Residential or small commercial consumers are often considered to be relatively loss averse and prone to overestimate potential consumption cost increases from time-varying tariffs. Additionally, RTP rollouts are often targeted at large consumers from the industrial sector, for instance, since it is expected that these consumers net benefit even when VRE deployment is low.

In order to analyze the relevance of distributional effects of RTP and the welfare consequences of possibly too low RTP adoption rates and targeted rollouts, chapter 3 takes consumer heterogeneity regarding sector-specific demand patterns into account. It thereby complements previous research on this matter in three ways. First, it shows that residential consumers may actually have less reason to expect significant cost increases from being put on RTP at high renewable supply shares. Based on residential demand profile data, it is illustrated that variable generation reduces the covariation of price and individual demand patterns and hence the risk of facing significant changes in individual consumption costs, either positive or negative. Second, if residential and commercial consumers would nonetheless make non-optimal tariff choices by avoiding to switch from flat to real-time pricing, comparatively large amounts of welfare gains would remain unrealized, especially when renewable supply shares are high. This is mainly due to the rather favorable correlation between the sector-specific demand and empirical wind and solar output patterns. Corrective measures addressing non-optimal tariff choices could therefore become increasingly important. Third, while targeted introductions of RTP to the largest customers appear justified from a mere efficiency perspective, consumer

targeting can entail considerable adverse distributional effects on flat priced consumers in other sectors, particularly when VRE deployment is relatively low. In particular, residential consumers could be harmed and face higher flat prices due to changes in the consumption behavior of large customers, leading to corresponding changes in the wholesale price distribution and negative pecuniary externalities.

In difference to chapter 2 and 3 chapter 4 changes the focus to assessing climate and energy policy instruments in the presence of RTP, by analyzing the relative efficiency of renewable output and capacity subsidies. Renewable output subsidies are usually regarded as less cost-effective in inducing VRE capacity than capacity subsidies, since they can induce negative wholesale prices and thus an accelerated reduction in VRE market values. This, in turn, implies relatively high output subsidies and dead-weight-losses from levies to finance these subsides compared to capacity subsidies. Chapter 4 clarifies that while VRE output subsides are relatively inefficient in inducing a certain amount of VRE capacity, they can require less capacity entry to reach a certain VRE supply share target, if consumers face real-time prices, and can in this respect be more efficient than capacity subsidies. In the presence of real-time pricing negative wholesale prices would incentivize real-time priced consumers to increase consumption during instances of very high renewable generation, thereby increasing the share of renewable electricity in total consumption. As negative wholesale prices would thus ensure that VRE resources are "more efficiently used" given a certain VRE supply share target, cost savings accrue from reduced renewable capacity entry, which are sufficiently high to outweigh the higher dead-weigh-loss from higher levies under subsidies.

Importantly, these findings are obtained while omitting several factors that could significantly influence particularly the welfare outcomes described above. The research presented in chapter 5 addresses one of these omitted factors, by analyzing the quasi-fixed costs of thermal power plant operation. Thermal power plants incur quasi-fixed costs when ramping up or down generation or when starting-up and shutting down. Quasi-fixed costs are widely expected to rise significantly with VRE deployment, as thermal plants might have to change operation modes more often in response to variable renewable electricity generation. Rather inflexible generation technologies such as coal or lignite fired plants could thus become much faster unprofitable with VRE deployment than when quasi-fix costs are ignored., implying that the welfare gains from RTP could be systematically downward biased. This would challenge particularly the findings on the optimal timing of implementing RTP reported in chapter 2. The results in chapter 5 show, however, that the potential change in quasi-fixed costs from start-up processes would be negligible relative to total generation cost changes resulting from carbon taxation and fuel price dynamics. The qualitative findings in this thesis thus appear to be robust with regard

to the cost and price effects of realistic power plant operation.

6.2 Methodological discussion on model tractability, power market complexity and behavioral aspects

The core research questions of this thesis are investigated by applying comparative statics analyses in a deterministic setting. The main tool developed for this task is a stylized numerical electricity market model, different versions of which have been developed for the specific research questions addressed in chapters 2 to 4. This section critically reflects on applying a numerical model of reduced complexity.

Methodologically, the numerical modeling approach developed in this thesis contributes to the bulk of power system models in two major ways. First, it provides a consistent representation of how perfectly competitive wholesale and retail electricity markets could interact within a coherent partial equilibrium framework. Second, accounting for differently priced and heterogeneous consumers does not only serve to capture sources of allocative inefficiencies existing in real markets, but it also allows for taking a disaggregated perspective on potential welfare and distributional effects. Being able to analyze how policy interventions or pricing regimes might affect different consumer types is needed to properly assess both their efficiency implications and political feasibility.

Nevertheless, compared to many cost-minimization approaches, the electricity market model applied throughout this thesis incorporates a relatively stylized representation of actual market frameworks as well as of technological constraints and options. Deploying a stylized numerical electricity market model is, of course, useful and problematic at the same time. It is useful as it serves the main objective of this thesis well enough, which is to identify and explain basic economic mechanisms important to consider in cost-benefit analyses on real-time pricing under climate policy rather than to conduct a full-blown cost-benefit analysis. Although the focus lies on identifying basic mechanisms, applying empirical data and quantifying long-run effects in a specific market setting seems useful for conveying the relative importance of each mechanism. Finally, the simplicity of the core model is also advantageous with regard to its adaptability to different research issues, as is reflected by the modifications presented in chapters 2, 3 and 4.

Despite its usefulness in identifying robust mechanisms and the consistency it provides, the reduced model complexity has some fundamental limitations,

requiring further scrutiny. A major limitation is the abstraction from the locational variation in the value of electricity, as electricity transmission from generator to consumer is not modeled. Accounting for electricity transmission (and distribution) and the scarcity of transmission capacity could alter the above findings qualitatively and quantitatively. VRE capacities are often unevenly distributed within a certain market region, as wind and solar power availability heavily depends on location[1]. Due to this transmission constraints are seen to become more binding in specific grid areas with increasing renewable capacity (cf. Mills and Wiser, 2014; Hirth et al., 2015).[2] Remedying these constraints could, for instance, require additional investments in transmission capacity or raise the need for ancillary services such as power plant redispatch or even renewable curtailment. Introducing RTP trades off against the need for transmission capacity expansion and ancillary services, as pointed out in the introductory section 1.2.3, which affects the evolution of the efficiency gains from RTP with VRE market entry.

However, in which direction accounting for this aspect would alter the welfare results found in this thesis would crucially depend on the assumed market design, that is, on whether price signals include information about the locational value of electricity or not. In markets with locational pricing, regionally clustered VRE deployment could result in large locational price spreads, in which case efficiency gains from RTP would arise from optimally adjusting demand both over time and across regions. Locational price spreads decrease accordingly as consumers increase demand in low price regions of the grid with relatively high VRE supply, and reduce consumption in high price regions with relatively low VRE supply. The effects of introducing RTP in uniform pricing zones, such as the German electricity market, could be ambiguous, since inefficiencies arising from uniform pricing could theoretically not only decrease but also increase, if RTP would amplify regional imbalances and raise the costs of managing them. This could, for instance, be the case during low price periods, which would incentivize RTP consumers to increase demand on both sides of a congested transmission line. Costs of managing transmission congestions and the need to expand transmission grid capacity could then increase due to both VRE deployment and launching RTP at large scale. Providing insights on how introducing RTP trades off against transmission capacity or congestion man-

[1] Onshore wind power capacity in Germany is, for instance, for the largest part installed in the northern grid regions.

[2] To a certain extent this can be observed in the German power market, where the annual costs of both congestion management measures (national and cross- border redispatch) and curtailing wind and solar supply have roughly tenfolded between 2011 and 2015, while installed wind and solar capacity roughly doubled during the same period (BnetzA, 2016). The cumulative costs of planned expansions of transmission and distribution grid capacity are projected to amount to about EUR 32 billion until 2030 and EUR 9.3 billion until 2026, respectively, although these costs are probably only partially attributable to future increases in renewable electricity generation (50Hertz et al., 2017).

agement in different pricing regimes would thus clearly improve the validity of the welfare analyses conducted in this thesis.

This also applies to the inclusion of storage technologies, either grid-scale or small-scale, which can be regarded as both a substitute and complement to RTP. As discussed in section 1.2.3, accounting for the trade-off against storage technologies could imply that RTP may yield both comparatively low or high efficiency gains than those found above. Potential efficiency gains from introducing RTP could be comparatively low, since storing electricity when prices are high and discharging it when prices are low and thereby shifting supply over time would probably decrease the wholesale price spreads.Efficiency gains from RTP could in turn be comparatively high due to potential savings in usually expensive grid-scale storage capacity of pumped hydro storage or grid-connected batteries, for example. The utilization of small-scale or "behind-the-meter"-storage such as electric vehicles or walled batteries seems complementary to the implementation of RTP. Small-scale storage devices would likely affect the efficiency gains from RTP positively at every stage of VRE deployment, since giving consumers more leeway in adjusting consumption to real-time prices by shifting demand over time.

A major impediment to the validity of quantitative results is the lack of data on consumption behavior and clear empirical evidence on crucial demand parameters. This regards primarily the uncertainty about elasticity to price, which is reflected in the wide range of empirical estimates on own-price elasticities derived from a large number of field experiments on different pricing schemes and for different types of consumers (e.g. Lijesen, 2007; Faruqui and Sergici, 2010; Allcott, 2011a).[3] While assuming rather low own-price elasticity levels in the range of -0.05 seems appropriate with regard to most empirical findings, the robustness checks in chapter 2 and 3 demonstrate that the quantitative results are highly sensitive to slight changes in price elasticity. Significant increases in own-price elasticities could, for instance, result from progress in technologies enabling instantaneous, automated response to price variations, as pointed out in section1.2.4 (Faruqui and Sergici, 2010; Bollinger and Hartmann, 2015). Moreover, it seems plausible to assume that consumers' sensitivity to price is positively associated with their awareness about their consumption costs (cf. Sallee, 2014). Since consumption costs might rise with consumption levels, the electrification of final energy demand might further influence dynamics in own-price elasticities. Consequently, empirical research on elasticity dynamics would be needed, which should then be taken into account in future simulations.

Some empirical findings also show that own-price elasticities might depend on the time of the day, which has not been accounted for in the work above.

[3]The estimates on own-price elasticity found in the cited studies start from zero and can reach up to -0.4.

Specifically, consumers may only react to price variations during peak-load periods, yet not during off-peak periods (e.g. Allcott, 2011a). Given this finding has some general validity, the simulated benefits from real-time pricing may be systematically upward biased, particularly at high renewable supply shares. The benefits of RTP may in turn be systematically downward biased, since the effects of substituting electricity consumption across hours (cross-price elasticity of demand) have been ignored, as discussed in chapter 2 and 3. Heterogeneity in own-price elasticities, of which there is some empirical evidence (cf. Faruqui et al., 2012), has also been excluded from the analysis, but may actually alter some of the cross-sectoral effects of targeted RTP rollouts found in chapter 3, where only demand pattern and size differences have been included. Residential consumers could, for instance, face higher surplus losses from a targeted RTP implementation in the industrial consumer sector, if they are also more sensitive to price than other consumer groups (see also the sensitivity analysis in chapter 3).

Besides the assumptions on price elasticity, the demand patterns applied in the simulations represent another crucial driver of the welfare results presented above. Although the scenarios analyzed in chapters 2, 3 and 4 concern the mid- to long-term in a low-carbon market, systematic changes in electricity demand patterns and volumes, which might parallel the transition towards low-carbon power markets, are not considered. As with all of the aforementioned limitations, the above simulation results may therefore not capture all mechanisms relevant to describe the dynamics of efficiency gains from real-time retail pricing. Changes particularly in residential demand patterns and volumes might stem from the increased utilization of electricity for transportation, space heating or cooling (cf. Boßmann and Staffell, 2015). To what extent or in which direction results would change due to structural changes in electricity demand patterns is, however, difficult to assess. As discussed in chapter 3, efficiency gains from time-varying pricing would significantly increase in markets with mostly variable renewable electricity supply, if demand profiles covary stronger with the output profiles of wind and solar power. Hence, further research should particularly consider the effect of electrified final energy demand on electricity price and demand covariations for different consumer types.

6.3 Relevance and novelty of this work

While the economic effects of real-time pricing have been the subject of numerous theoretical and quantitative work, this section points out that the relevance of this thesis lies in its comprehensiveness, as it addresses both the efficiency and feasibility of introducing RTP. Moreover, by advancing the knowledge on the interaction of RTP and policy induced variable renewable electricity supply, this thesis provides a new perspective on what has been held as common

wisdom in the field.

In particular, this work fills an important gap in the literature, by analyzing the welfare effects of RTP at different stages of the low-carbon transformation of electricity systems. While research on RTP has so far focused on analyzing these effects in markets with either no (e.g. Borenstein, 2005; Holland and Mansur, 2006; Allcott, 2012; Leautier, 2014; Blonz, 2016) or high shares of renewable deployment (e.g. Chao, 2011; Kopsakangas Savolainen and Svento, 2012; Fell and Linn, 2013; Connect Energy Economics, 2015; Bertsch et al., 2016; Brouwer et al., 2016), chapter 2, 3 and 4 account for the gradual changes in between these states. This allows for assessing the potential timing issues of introducing RTP in more detail and for clarifying why and when targeted roll-outs of RTP might harm certain customer groups, and at which diffusion stage of VRE technologies consumer acceptance problems might become urgent.

Furthermore, by combining the welfare and distributional analysis of RTP, this thesis contributes to the bulk of numerical and theoretical analyses, which do not address efficiency and feasibility issues within a coherent framework. Studies on RTP as an VRE integration option have so far focused on cost-effectiveness or efficiency effects (Chao, 2011; Kopsakangas Savolainen and Svento, 2012; Fell and Linn, 2013; Connect Energy Economics, 2015; Brouwer et al., 2016; Bertsch et al., 2016). Analyses of the distributional effects of RTP have been limited to conventional markets, where generation is mainly based on non-renewable and non-variable technologies, and thus have ignored the important influence of supply variability (Borenstein, 2007b, 2013). Moreover, these studies have focused on intra-sectoral, yet not cross-sectoral distributional effects. Chapter 3 closes these gaps as it addresses how intra-sectoral, that is residential distributional effects of RTP are influenced by variable generation, how RTP adoption in a particular sector could affect non-adopting consumers in other sectors and whether such cross-sectoral distributional effects are altered by variable electricity supply.

Besides its contributions to the energy economic literature, the above research also has practical merit. By simulating welfare and distributional effects based on empirical data and various climate policy scenarios, this thesis provides regulators, utilities and retail firms with quantitative and qualitative insights on the proper assessment of introducing RTP and for making economically sound decisions on required infrastructure investments.

6.4 Directions for future research

How to further improve the understanding of the economics of time-varying pricing in low-carbon electricity markets? Based on the work presented in this thesis, three promising avenues for further research can be identified: *i)*

the impact of the locational variation in the value of electricity, *ii)* the role of behavioral changes and *iii)* the determinants of tariff choice.

Section 6.2 clarified that accounting for the locational variation in the value of electricity could yield further qualitative and quantitative insights on the dynamics of the efficiency gains from exposing consumers to real-time prices. Specifically, including locational variation would allow to capture the system-specific trade-off between real-time price responsive demand and transmission grid capacity or the need for costly measures to manage transmission bottlenecks. More importantly, addressing this issue would raise awareness not only about the inefficiency of time-invariant retail pricing but also of uniform retail pricing, and thus about whether real-time priced consumers do indeed face the social marginal costs of electricity supply or if they actually do not. While uniform pricing is prevalent in most European electricity markets, many markets in the U.S. deploy some from of locational pricing. As indicated in section 6.2, implementing RTP under each pricing regime might have quite different welfare implications as is usually conveyed. Economic assessments of market designs where transmission scarcity is or is not reflected in wholesale and real-time retail prices hence close an important research gap in several respects.

Section 6.2 further pointed towards the relevance of behavioral changes resulting from the diffusion of smart-appliances and the electrification of final energy demand. In order to be able to assess which behavioral changes might parallel the diffusion of variable renewable technologies and how these co-developments could interact on the efficiency gains from real-time pricing, further numerical approaches should take the dynamics in consumers' sensitivity to price, demand pattern and volumes into account.

The most important future research avenue, and simultaneously the most important caveat of the research on real-time pricing so far, is the analysis of tariff choice and the factors influencing it. Throughout this thesis and in most of the related work the decision to enroll in time-varying pricing programs is ignored. It is however fundamentally unclear what determines consumers decisions to switch tariffs and, thus, whether the potential efficiency gains from RTP quantified above can actually be realized and whether the costly advanced metering infrastructure installed in many electricity markets will actually be used. Low take-up rates of time-varying pricing schemes may simply result from the *"hassle"* involved with adopting and adjusting behavior to varying prices. Moreover, many consumers may actually be *unable to understand* or *inattentive* to both their consumption related costs and their benefits from switching to time-varying pricing. Insights on these issues would not only augment the economic analysis of time-varying pricing, but could also be of practical value, by helping to design consumer targeted policy interventions and guide tariff design aimed at unlocking its efficiency potential.

Understanding the role of individual transaction costs regarding time-varying tariffing schemes in tariff choices would present a first step in this direction. Several aspects of time-varying tariffs may be perceived as a hassle by customers such as their complexity compared to flat pricing, for instance, or the related risk of rising consumption costs (Faruqui et al., 2012; Duetschke and Paetz, 2013). While chapter 3 showed that the risk of consumption cost increases could become negligible under large-scale variable renewable generation,[4] chapter 2 demonstrated that schemes that are less complex than RTP might become inadequate in markets with growing variable renewable deployment. Further research should thus explore the technological options to minimize the hassle from "too complex" real-time pricing programs. Automated response could be one of these technological option. Home automation devices or smart appliances such as smart-thermostats, for instance, communicating with advanced meters are already available and can be expected to become affordable to many consumers. To properly assess the potential value of such "enabling" technologies, more empirical research on the effectiveness of such devices in field experimental settings is required, as done by Bollinger and Hartmann (2015), for example.

Providing such an advanced metering infrastructure could also be in the interest of distribution grid operators (DSOs) and utilities, facing an increasing need to manage network congestions due to growing shares of variable generation.[5] Combining home automation and advanced meters with new contractual arrangements with their customers would allow DSOs and utilities to create real-time price responsive pools of consumers, which could help to save in costly grid expansion or congestion management measures, as discussed above. Moreover, demand response resources may represent an interesting business case for utilities in markets for ancillary services, where they can sell these resources as balancing power and energy, for instance (Pollitt and Anaya, 2016). Further research and modeling approaches should therefore take account of the future role of DSOs and utilities as investors in smart-grid infrastructure, including the resulting influence on consumers' tariff choice.[6]

Aside from the transaction costs which agents may consider when rationally deciding upon enrolling in new pricing programs, individual retail tariff choice,

[4]The problem of bill volatility and risk could additionally be addressed by two-part tariffs, which basically imply a hedge for most of the upward price risks, while maintaining marginal incentives (Borenstein, 2007a).

[5]For instance, the costs for congestion management measures (renewable curtailment) particularly by German DSOs operating in grid regions, which have experienced high wind capacity expansion (northern Germany), have increased by fifty times to about EUR 315 million per year between 2009 and 2015 BnetzA (2016).

[6]This new role is captured in the concept of "Transactive Energy", which is developed and extensively discussed in a recent report commissioned by the U.S. Department of energy. For further details, please refer to `http://www.gridwiseac.org/pdfs/te_framework_report_pnnl-22946.pdf`

like most economic decision making, may be subject to psychological factors, potentially leading to non-optimal or biased decisions. Developing and testing behavioral economic models of discrete choice capturing this may thus prove essential to the validity of analyses about the diffusion of price responsive demand and time-varying pricing schemes. This view is supported by an increasing body of empirical, that is, experimental evidence of behavioral biased decision making about energy consumption and energy consuming durable goods. For instance, some of this evidence suggests that consumers could be rationally or irrationally inattentive to their actual consumption costs and therefore also to their potential savings from tariff switching, given that observing and reconciling price schedules with individual consumption comes at an effort (Ito, 2014; Sallee, 2014). How information about prices and consumption costs is communicated is quite crucial in this regard. In fact, rather than solely facing prices per kWh consumed, electricity consumers seem to require preprocessed, i.e. easy digestible information, such as real-time feedback on consumption costs, to make optimal consumption decisions (Jessoe and Rapson, 2014; Bollinger and Hartmann, 2015). Consumers' attention to the benefits from adopting a new pricing scheme may also depend endogenously on the potential savings arising from tariff switching (Sallee, 2014). Moreover, the aforementioned transaction costs of time-varying pricing may be more salient than the potential but "opaque" benefits involved with a tariff switch (DellaVigna, 2009). Estimating and modeling such psychological influences in tariff choice hence appear necessary to most economic evaluations of implementing time-varying pricing schemes.

Including behavioral elements in models about energy related decision making opens up new opportunities for assessing and designing corrective measures and policy interventions. Non-optimal tariff choices may, for instance, justify corrective pecuniary measures such as subsidies (taxes) to misoptimizing customers (Allcott et al., 2014). Subsidies might be based on the internalities, which misoptimizing consumers impose on themselves, by unintentionally missing out on individual benefits from tariff switching (Herrnstein et al., 1993). Importantly, internalities, just like externalities, can be heterogeneous, since some consumers might be more prone to make non-optimal decisions than others, for instance. Accounting for such heterogeneity is important for designing optimal interventions as it raises the question as to whether such interventions should be targeted or not, which also depends on the degree to which corrective taxes or subsidies could distort decisions of optimizing consumers compared to non-optimizing consumers (Allcott et al., 2014, 2015). The unrealized welfare gains from avoiding RTP in chapter 3 give some indication about the potential extent and heterogeneity in internalities. Accurate guidance on corrective measures can, however, only be based on empirical estimates of internalities and their distribution, which would require behavioral discrete choice models as their theoretical underpinning.

Such models should additionally account for the observation that electricity consumers may not only be susceptible to monetary but also to non-pecuniary incentives provided by "shadow billing" or nudges, which appeal to energy conservation norms or trigger considerations about the external health costs of individual energy consumption, for instance (Allcott, 2011b; Borenstein, 2013; Asensio and Delmas, 2015). The persistence of non-pecuniary instruments on consumer choice might be limited, however, and thus may have to be complemented by pecuniary measures (Ferraro and Price, 2013). As with empirical estimates of internalities from tariff choice, empirical evidence on the effects of non-pecuniary interventions on electricity consumer behavior are lacking.

Against this non-exhaustive overview, it becomes clear that behavioral economics can provide fruitful and perhaps also necessary approaches for future economic analyses of time-varying retail pricing. Overall, empirical and theoretical research on retail tariff choice appears to be crucial for actually unlocking the potential of price responsive demand in low-carbon electricity markets, and therefore represents the next important step for advancing the economics of real-time pricing.

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Statement of Contribution

Chapters **2** to **5** of this dissertation base on separate research papers. They are the result of collaborations between the author of the dissertation, his Post-Doc supervisor Michael Pahle, and other colleagues as indicated. The author of the dissertation has made extensive contributions to the contents of all four papers, from conceptual design and technical development to writing. This section explains how the author contributed to the four papers and acknowledges the main contributions of others.

Chapter 2 *Do Benefits from Dynamic Tariffing Rise? Welfare Effects of Real-Time Retail Pricing under Carbon Taxation and Variable Renewable Electricity Supply.* Preprint. The final version is published under a CC-BY 4.0 license in Environmental and Resource Economics (2019), Volume 75, Issue 1, Pages 183-213, DOI: `https://doi.org/10.1007/s10640-019-00393-0`.

The author of this thesis has defined the research question and design of the study in this chapter with refinements by Michael Pahle and Wolf-Peter Schill. The theoretical and numerical model on which the study is based has been developed by the author with refinements by Michael Pahle and Wolf-Peter Schill. The author preprocessed the empirical data and carried out the simulations based on this data. Analyzing, processing and the visualization of simulation results has been conducted by the author. The text of the chapter was written by the author of this thesis. The discussions of and conclusions from the study results were written in close collaboration with Michael Pahle and Wolf-Peter Schill.

Chapter 3 *Time-Varying Electricity Pricing and Consumer Heterogeneity: Welfare and Distributional Effects with Variable Renewable Supply.* Preprint. The final version is published in Energy Economics (2018), Vol. 76, Pages 257-273, DOI: `https://doi.org/10.1016/j.eneco.2018.08.020`.

The author of this thesis has defined the research question and design of the study presented in this chapter. The numerical model has been modified by the author of this thesis based the model developed in chapter **2**. The author of this thesis also conducted the theoretical analysis, preprocessed the applied empirical data and carried out the simulations. Analyzing, processing and the visualization of simulation results has been conducted by the author. The text

of the study was written by the author. Discussions and conclusions from the study results were written in close collaboration with Michael Pahle.

Chapter 4 *Renewable Energy Support, Negative Prices, and Real-time Pricing.* Published under a CC-BY 4.0 license in The Energy Journal. This article first appeared in The Energy Journal, Vol. 37, Special Issue 3, Pages 147-169, 2016, DOI: `https://doi.org/10.5547/01956574.37.SI3.mpah` - Reproduced by permission of the International Association for Energy Economics (IAEE).

Michael Pahle developed the research design and research question of the study in this chapter in close collaboration with all other authors. The numerical model on which the study in this chapter relies is based on the model developed in chapter 2 by the author of this thesis, which Michael Pahle and Wolf-Peter Schill modified to include endogenously determined renewable output and capacity subsidies via a social planner approach, using an MPEC-formulation. Wolf-Peter Schill and Michael Pahle processed and visualized the simulation results in close collaboration with Oliver Tietjen and the author of this thesis. Wolf-Peter Schill and Michael Pahle carried out the simulations. The analysis and discussion of the simulation results has been conducted by all authors. The text of the study has mainly been written by Michael Pahle. Oliver Tietjen and the author of this thesis have contributed to writing the explanation of the model mechanism, particularly section 4.2.2, the interpretation of the results, particularly section 4.3.1 to 4.3.2, and the discussion and conclusion section 4.5. Research question and design have been developed by Michael Pahle, with further refinement by all co-authors.

Chapter 5 *Start-up costs of thermal power plants in markets with increasing shares of variable renewable generation.* Published in Nature Energy 2, 17050 (2017), Pages 1-6, DOI: `https://doi.org/10.1038/nenergy.2017.50`.

Wolf-Peter Schill developed the research design and question of the study in this chapter, with refinements by Michael Pahle and the author of this thesis, who particularly developed the argument on the effect of variable renewable generation on quasi-fixed costs and the resulting effect on market efficiency. Wolf-Peter Schill developed and calibrated the numerical model, carried out the simulations, processed and visualized the simulation results. The latter was done in close collaboration with Michael Pahle and the author of this thesis. All authors contributed to writing the article. The author of this thesis contributed particularly to the discussion on the decomposition of start-up cost effects in section 5.3 as well as the conclusion 5.4 and introduction 5.1 of the article.

Tools and Resources

Different numerical models have been applied to obtain the quantitative results reported in chapter 2 to 5. This section lists the software tools used to create and run these models, and to process, analyze and visualize the empirical data and results.

Modeling The simulations in chapter 2 to 4 are based on different versions the numerical electricity market model LORETTA[7] (Gambardella, 2017). The model code is open source and available at The simulations and results in chapter 4 are based on a customized version of the open source unit commitment model DIETER[8] (Zerrahn and Schill, 2017). All numerical model simulations are performed with the General Algebraic Modeling System (GAMS) (Brooke et al., 1988), distribution 24.3.3. The model LORETTA uses the PATH 4.7 solver algorithm (Ferris and Munson, 2000) for mixed complementary optimization problems (Rutherford, 1995), which is documented at. The model DIETER uses the CPLEX solver. For further details regarding the software used, please refer to:

- LORETTA:

  `https://www.pik-potsdam.de/research/sustainable-solutions/models/loretta`

- DIETER:

  `https://zenodo.org/record/259476`

- GAMS:

  `https://www.gams.com/latest/docs/RN_243.html#RN_2433`

[7]LORETTA is the "LOng-run Electricity market model with Time-varying retail TAriffing"

[8]DIETER is the "Dispatch and Investment Evaluation Tool with Endogenous Renewables".

- PATH:

  https://www.gams.com/latest/docs/S_PATH.html

- CPLEX:

  https://www.gams.com/latest/docs/S_CPLEX.html

Data Processing Model output data was processed with GAMS and Microsoft Excel 2010. Input data were preprocessed with the free GNU source code editor Notepad++ v6 and Microsoft Excel 2010. Data was visualized using Microsoft Excel 2010, explanatory figures were created with Microsoft Powerpoint 2010, result tables were created with LyX table editor. For further details regarding the software used, please refer to:

- Microsoft Office:

  https://www.office.com/

- Notepad++:

  https://notepad-plus-plus.org/

Typesetting This thesis has been prepared with LyX 2.2, which is based on the document preparation system LaTeX, using MiKTeX 2.9. Chapter 4 and 5 have been prepared with Microsoft Word 2010 and included via the pdfpages package. For further details regarding the software used, please refer to:

- LyX:

  https://www.lyx.org/

- MiKTeX:

  https://miktex.org/

Reference Management JabRef 2.10 and BibTex were used for reference management. For further details regarding the software used, please refer to:

- JabRef:

  http://www.jabref.org/

- BibTex:

  http://www.bibtex.org/

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