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1 Introduction

1.1 Background and Introduction

The European Union aims to reduce its greenhouse gas emissions by 80-95% of 1990 levels by 2050 (European Commission, 2012). Therefore, intensified efforts are being made to favor the success of the energy transition. However, the broad term 'energy transition' does not refer to an isolated measure, but rather embodies a complex structural transformation comprising diverse individual developments. At the same time, it involves different sectors such as the electricity, industrial, heating, and transport sectors. Policy makers more and more are striving to couple these sectors in a combined effort to implement the ongoing decarbonization in a cost-effective and environmentally compatible way. At the same time, decision makers aim to ensure that security of supply is not jeopardized (BMWI, 2010).

The Federal Ministry of Economics and Technology in Germany is attempting to condense the energy transition into twelve major trends (BMWI, 2016). More specifically, the power supply system is undergoing a transition from centralized to more decentralized electricity generation (European Commission, 2013). The increasing share of renewable power plants as well as an increasing number of small-scale generation units allow for carbon dioxide emission reductions to be achieved while, at the same time, changing the requirements for the existing energy system. As regards the market organization, the implementation of an extended market coupling may allow for gains in efficiency (Parisio and Bosco (2008), Zachmann (2008)). Closely related, sufficient grid infrastructure has to be provided to enhance the system's stability as well as to ensure security of supply, even as the generation of electricity becomes more and more volatile. However, the refinancing of the respective grid expansions may be regarded as a core issue. Furthermore, in view of the demand side, energy-efficiency savings may allow for a reduction in overall energy consumption. Additional energy savings on a residential level may be attributable to the deployment of smart meters, which is one subfield of the superordinate digitalization. Finally, as the coupling of sectors is increasingly promoted, the efficient integration of combined heat and power generation is a further goal.

These identified trends challenge the power supply systems of today. In particular, the increasing share of intermittent and highly volatile electricity generation is causing an augmented need for short-term power system flexibility (Delft and Microeconomix (2016), International Energy Agency (2014), NREL et al. (2014)). Against this backdrop, flexibility means the ability of the power supply system to respond to the high volatility of electricity generation and demand in a sufficient and reliable manner. Such flexibility may especially be provided by flexible generation units, expanded interconnection capacity, storage technologies, or demand-side management (International Energy Agency, 2014).

In this thesis, three major subfields of the energy transition are addressed, all of which may be positioned within the topic of short-term power system flexibility. To leverage benefits and guarantee the successful realization of the energy transition, the individual trends should be made compatible with each other, and benefits may be leveraged by applying and interacting different flexibility options. Therefore, it is vital to deepen the economic understanding of the underlying dynamics in order to fulfill effectively and efficiently the flexibility needs which have been identified. The key findings derived within the individual chapters of this thesis are intended to form the basis for comparatively evaluating the costs and benefits of different flexibility measures.

Power system flexibility may not only be provided by suppliers. The demand side could play a key role as well. Therefore, this thesis opens with an analysis of the impact of an advanced metering infrastructure on residential electricity consumption. Smart meters, as such, are attributable to digitalization and may provide additional information with higher granularity to customers, grid operators, and retailers. Thereby, consumers may be enabled to alter their consumption behavior, whereas more efficient grid operation may be facilitated since grid operators will gain additional information on a subordinate grid level. Additionally, retailers may reduce their imbalances by forecasting electricity demand with both an increased temporal resolution and higher accuracy.

In the second part of this thesis, the impact of an intensified electrification process within the transport sector is explored using a simulation method. In the coming years the number of electric vehicles is expected to increase significantly(The Federal Government of Germany (2009), The White House (2011)). As a consequence, two aspects are of particular relevance. First, the charging behavior of electric vehicle drivers impacts the time-dependent rate of electricity consumption as well as the respective extremes. Second, electrical vehicle storage may be harnessed in the context of grid services. Electric vehicle storage could thus provide short-term flexibility to the power supply system (see, e.g., Kahlen and Ketter (2015), Kahlen et al. (2017)). Especially in the case of bidirectional charging, grid-relieving consumption behavior and demand-side management may become feasible.

Finally, this thesis includes three chapters dealing with the economics of sequential short-term electricity markets. In this context, the limited predictability and high volatility of renewable electricity generation has caused an augmented need to trade products with shorter contract duration closer to physical delivery. As a consequence, sequential short-term electricity market designs were established in Germany that face both strongly increasing relevance and trade volumes, especially on an intraday level (Hagemann and Weber, 2013). The functioning of short-term electricity markets is regarded as a crucial prerequisite for integrating huge amounts of renewable energy sources into the power supply systems of today (Scharff et al. (2013), Simon (2013)). In this thesis, focus is placed on the impact of restricted participation in markets with sub-hourly products.

In the following section, the individual chapters of this thesis will be outlined in detail. Each of the five chapters is based on a single paper. The articles presented in Chapter 2, Chapter 4 and Chapter 5 were developed in collaboration with researchers who are also affiliated with the Institute of Energy Economics at the University of Cologne. These articles are co-authored with one researcher each. As regards the collaboration, within each paper the authors contributed in equal shares.

1.2 Research Outline

1.2.1 The Impact of Advanced Metering Infrastructure on Residential Electricity Consumption - Evidence from California

Chapter 2 contains an analysis of the impact of an advanced metering infrastructure on residential electricity consumption. The article presented is co-authored by Simon Paulus and has not yet been published.

In the context of policy makers aiming to achieve heightened carbon dioxide emission reduction targets, discussions surrounding energy saving measures have recently become increasingly relevant. On a residential level, energy-saving measures depend heavily on the bounded rationality of consumers. Implementing an advanced metering infrastructure addresses this issue by allowing for real-time feedback on electricity consumption and thereby enabling a bidirectional communication between the consumer and the respective service utility. We analyze the effect of the policy-induced deployment of advanced metering infrastructure in California in order to derive quantitative estimates for the respective aggregate impact on residential electricity consumption. Since states exhibit significant heterogeneity as far as energy-related consumption characteristics are concerned, we apply synthetic control methods and derive a weighted combination of New Mexico and New York as the control group. We isolate the effect of smart meters by filtering out distorting effects and empirically compare the Californian trend in residential electricity consumption over time with the respective one in the control group.

Based on the empirical results, we find a significant reduction of the average monthly residential electricity consumption in California of approximately 6%, induced through the deployment of the advanced metering infrastructure. Furthermore, we find a clear seasonal pattern of electricity savings. The reduction of electricity consumption is only significant in non-heating periods. Finally, the results indicate a continuous effect, at least during our period of observation. Our results may provide crucial information for policy makers to assess the effectiveness of a policy-driven deployment of advanced metering infrastructures to achieve electricity savings at the residential level.

1.2.2 Leveraging the Benefits of Integrating and Interacting Electric Vehicles and Distributed Energy Resources

Chapter 3 focuses on a beneficial interaction of photovoltaic generation units and electric vehicles in the light-weight transport sector. The article has not yet been published. I am the sole contributor.

The essay considers two parallel trends, both of which are expected to impact the existing power system significantly. First, a rapidly increasing number of renewable power plants can be identified. High numbers of small-scale generation units are changing the requirements for the existing energy system. At the same time, an electrification of the transport sector is underway. In this chapter, potentials from using photovoltaic generation units together with electric vehicles are analyzed. The main purpose is to fill a current research gap by adopting two perspectives. First, light is shed on the cost-saving potential of electric vehicles on a residential level where households may achieve a higher share of self-consumption. Second, a system-oriented perspective is taken and the peak load impact as well as the respective peak-load reduction potential of electric vehicles is analyzed.

To address the research issues in question, a bottom-up simulation approach has been developed to model the driving behavior of electric vehicles as well as the resulting charging demand. The simulation results show that, on a household level, smart charging strategies oriented to renewable energy sources (RES) may allow for a share of self-consumption that is about 59% higher compared to uncontrolled charging. On a system level, the results suggest that uncontrolled and RES-orientated charging may drive the average peak load of electricity purchased from the grid to increase significantly by 69% to 84% of the available charging capacity. In contrast, by implementing tariff schemes which incentivize a peak-load minimizing charging behavior, the peak-load impact under analysis may be reduced to 27% on average. However, there is only limited potential to counteract reverse power flows from photovoltaic electricity generation in peak hours.

1.2.3 Price Volatility in Commodity Markets with Restricted Participation

In Chapter 4, an article is presented which is published within the Working Paper Series of the Institute of Energy Economics at the University of Cologne (Knaut and Paschmann, 2017b). The work is co-authored by Andreas Knaut. We analyze the underlying drivers of the high price volatility observed in German electricity markets with sub-hourly contract duration.

The analysis is motivated through the identification of an apparently systematic but puzzling price pattern in two sequential short-term electricity markets, namely the day-ahead and intraday auction. In these markets, electricity is first traded via hourly contracts, and three hours later a subsequent auction with quarter-hourly contract duration is settled. We observe huge price variations between the respective contract prices. In more detail, the 15-minute contract prices tend to fluctuate around the previously settled day-ahead prices, which reveals high price volatility.

We develop a stylized theoretical model depicting the price formation in both markets under analysis. We account for the interaction of sequential markets with differing product granularities. Based on the model, we find that the high volatility is mainly driven by two influencing factors. First are the sub-hourly variations of renewable generation and electricity demand. Second, restricted participation in the intraday auction compared to the market with hourly contracts triggers an increase of the respective supply curve gradient. Building on that model, we conduct an empirical validation using historical price data. We are thereby able to link restricted participation in the intraday auction to welfare losses of EUR 108 million in 2015 and EUR 55 million in 2016.

1.2.4 Decoding Restricted Participation in Sequential Electricity Markets

In the chapter previously discussed, the assumption of restricted participation in the intraday auction is crucial, but yet the underlying drivers remain undetected. We hence pose the research question of how to decode these drivers in Chapter 5. The underlying article is co-authored by Andreas Knaut and is published within the Working Paper Series of the Institute of Energy Economics at the University of Cologne (Knaut and Paschmann, 2017a).

Restricted participation may trigger both high price volatility and welfare losses. Therefore, it may be beneficial to identify the underlying drivers in order to derive countermeasures with the purpose to increase efficiency. In this chapter, we consider four potential drivers of restricted participation: i) the state of not knowing and inertia, ii) costs of market entry, iii) flexibility constraints of generation units, and iv) a lack of cross-border market coupling. We present empirical evidence that the role of inertia is essentially negligible. Conducting exemplary profitability analyses, we then find an indication that costs resulting from market entry should not prevent agents from extending their trading activities to markets with sub-hourly contracts.

In order to address the remaining potential explanatory approaches, we set up a fundamental electricity market model with quarter-hourly temporal resolution. Hereby, we are able to replicate the price pattern observed in real-world data. Disentangling the individual drivers under analysis by analyzing different sets of constraints, we finally identify the lack of sub-hourly market coupling as being the most relevant driver of restricted participation in the German intraday auction. As a consequence, it may be beneficial for policy makers to urge the implementation of market coupling on a sub-hourly level. Finally, we simulate the impact of introducing full market coupling on a 15-minute level and suggest that the price volatility of quarter-hourly prices may, as a result, decrease by a factor close to four.

1.2.5 Economic Analysis of Price Premiums in the Presence of Non-convexities - Evidence from German Electricity Markets

Chapter 6 focuses on the economic analysis of price premiums in German short-term electricity markets where the underlying merit order exhibits a discontinuous shape. It has not yet been published as an article, and I am the sole contributor.

Economic theory suggests that the limited storability of electricity may pose limits to arbitrage. The widespread explanatory approach for price premiums in electricity markets developed by Bessembinder and Lemmon (2002) may yield positive as well as negative differences between forward and real-time prices, depending on the volatility and skewness of spot prices. In Longstaff and Wang (2004), the authors analyze historical prices from US electricity markets and find the general model to be applicable to their real-world data. However, even though a similar pattern of price premiums can be found in two sequential German short-term electricity markets, namely the day-ahead and intraday auction, there is empirical evidence that the idea of price premiums being solely explicable through statistic key figures of spot prices is not transferable to the market dynamics under analysis. This in itself is not surprising, as there is no informational update between the two market settlements and since both markets are cleared in rapid succession. Based on these relations, an alternative explanatory approach is developed. A theoretical analysis is presented which depicts the price formation in sequential markets with increasing product granularity and a differing supplier structure. The model allows to analyze the impact of non-convexities on price premiums in sequential market designs.

The model suggests that non-convexities in only a subset of sequential markets may lead to price differences at equilibrium. These price premiums can be either negative or positive, depending on whether the non-convexities are more pronounced in the first or second market. As a consequence, the direction of price premiums directly depends on the market settlement being in particular sections of the underlying supply curves. To support this hypothesis, historical real-world data reveal a high correlation of load and the direction and value of price premiums. Therefore, price premiums between the day-ahead and intraday auction reflect a value for additional short-term power system flexibility rather than incorporating a value of risk-bearing. A proxy is derived which yields a value of additional national power system flexibility equal to EUR 10.2 million in 2015. In contrast, the respective value for flexibility provided by neighboring countries is EUR 6.4 million in 2015. Even though these are rather small numbers, it may be worth thinking about further applications of the general model framework, such as in the case of sequential block and single unit auctions.

1.3 Methodological Remarks

From a methodological point of view, the analyses conducted within this thesis essentially build upon three different types of approaches. First, the essays presented in Chapter 2 and Chapter 4 heavily build on an empirical analysis applying regression techniques. A completely different approach is adopted in Chapter 3. More precisely, numeric simulation processes are applied, which, at least partially, are based on an underlying optimization problem. Similarly, Chapter 5 depicts findings that were derived with the use of a fundamental electricity market model. Finally, this thesis also presents theoretical economic models and analyses, such as those presented in Chapter 4 and Chapter 6.

The methodological diversity allows for shedding light on the research issues in question by adopting a multi-perspective view. Hereby, it is accounted for the complexity as well as the variety of these research questions, and the choice of each approach is directly motivated by the question of what may fit the problem structure the best. Additionally, the combination of different methodological approaches may bring significant value added. By way of illustration, in Chapter 4 we complement a theoretical model with an additional empirical analysis. We break down the complex problem structure into a simplified theoretical model framework, solve the model, and then directly feed the respective results into a subsequent empirical analysis. As a consequence, the results are expected to be both more compelling and convincing.

Yet, a profound knowledge of the limits and assumptions related to each of the approaches applied is crucial in order to interpret and categorize the respective results. Thus, a detailed discussion of the underlying methodological approaches is presented within each chapter.

2 The Impact of Advanced Metering Infrastructure on Residential Electricity Consumption - Evidence from California

One important pillar in the debate about energy-saving measures addresses energy conservation. In this paper, we focus on the deployment of advanced metering infrastructure to reduce the impact of limited information and bounded rationality of consumers. For California, we empirically analyze the influence of a statewide and policy-driven installation of advanced metering infrastructure. We apply synthetic control methods to derive a suitable control group. We then conduct a Difference-in-Differences estimation and find a significant negative impact of smart meters on monthly residential electricity consumption that ranges from 6.1 to 6.4%. Second, such an impact only occurs in non-heating periods and does not fade out over the analyzed time period.

2.1 Introduction

In the light of exacerbated discussions on climate targets and emission reduction goals, energy-saving measures have become increasingly important. In the residential sector, such measures have to account for specific characteristics such as limited information and bounded rationality. Although there should be a natural interest in reducing electricity consumption, it is common knowledge that the savings potential is yet to be leveraged. In this paper, we analyze the impact of advanced metering infrastructure (AMI) on residential electricity consumption. The AMI feeds back real-time information on electricity consumption and enables bidirectional communication between the consumer and the respective service utility.

Since, from a consumer‘s perspective, cost recovery after installing AMI is at least questionable, pilot tests and policy-induced measures are the prevalent ways of evaluating smart-meter deployment. The respective impact of smart meters on electricity consumption may differ in both frameworks. In pilot tests, a loss of generality resulting from small samples and the Hawthorne effect, whereby individuals alter their behavior in response to their awareness of being observed, may be relevant. Therefore, we focus on a statewide policy measure and identify a lack of empirical evidence in the existing literature. On the basis of our analyses, decision makers may assess the effectiveness of a policy-driven deployment of smart meters.

We analyze the impact of AMI based on empirical evidence from California. Following the Californian Energy Crisis in 2001, the government issued a decision regarding statewide deployment of smart meters in the Energy Action Plan II of 2005. As a consequence, the three major service utilities committed themselves to installing AMI right across their service areas beginning in 2008. As such, smart meters provide consumers and utilities with more detailed consumption information[1]. We compare the Californian development of residential electricity consumption over time with the respective one in a synthetic control group named 'Synthetic California'. We construct this control group using synthetic control methods in order to resemble Californian characteristics (Abadie et al., 2010). Furthermore, we isolate the effect of advanced metering infrastructure by filtering out distorting effects such as energy savings related to energy-efficiency measures.

We find a significant reduction of the average monthly residential electricity consumption in California that effectively ranges between 6.1 and 6.4% during our period of observation. However, we identify a clear seasonal pattern of electricity savings, showing significant reductions of electricity consumption only in non-heating periods. We suggest that this may be due to the fact that some household appliances are more likely to be substitutable in non-heating periods and thus provide higher saving potentials. On the contrary, heating represents a more basic need and therefore electricity consumption patterns may be less likely to change during heating periods[2]. Finally, our results suggest that the impact of additional informational feedback on electricity consumption is continuous during our period of observation.

We reckon that, at least within the seven years under analysis, smart-meter deployment is a suitable way to achieve overall electricity savings in the residential sector. However, for service utilities, an ongoing assessment of the respective impact on electricity consumption may be beneficial to foster persistent effects. Finally, seasonal fluctuations with respect to the impact of AMI suggest that energy-conservation measures should be complemented by other energy-saving measures in order to achieve a general and continuous reduction in electricity consumption.

[1]The smart meters may provide data with higher temporal resolution and device-specific information.

[2]In the US, up to 65% of households have electric space heating and thus a significant impact on electricity consumption is expected.

The remainder of the paper is organized as follows. Section 2.2 provides the main literature background. In Section 2.3, we depict the identification strategy for measuring the impact of smart meters on residential electricity consumption. We then present the most relevant characteristics of residential electricity consumption in Section 2.4 and furthermore provide a broad overview on energy-saving measures that are relevant for the analysis. Our applied empirical approach and the data are described in Section 2.5, and the respective results are discussed in Section 2.6. Finally, we draw conclusions in Section 2.7.

2.2 Literature Background

When analyzing the impact of AMI on residential electricity consumption, we essentially expect the respective influence to be triggered by additional informational feedback. The paper at hand in a broader context is hence positioned in behavioral economics. One important pillar for such literature deals with aspects surrounding bounded rationality, which may serve as an explanatory approach for the actual behavior of consumers. As the provision of informational feedback directly addresses the limited information of consumers, we first focus on some basic principles in the literature. According to Simon (1957), the term 'bounded rationality' refers to the rationality that is exhibited by the economic behavior of humans. More precisely, rationality is assumed to be bounded due to the limited information that individuals have at certain reference points in time. Naturally, how decisions are taken, assuming that individuals first face a lack of perfect information and second are not even capable of processing all the information they encounter, remains an open question. The joint answer given by behavioral economists and psychologists has directed researchers to the aspect of time itself. Over time, decisions of individuals are influenced by new information that, after being 'fed back' to the individuals, triggers adjustments in their decisions. Such an informational feedback (or 'learning') re-aligns initial thinking, punishes deviant behavior, and leads to the amelioration of decisions (Arthur, 1991, 1994, North, 1994). Arthur (1994) labels this behavioral 'process' as inductive reasoning, implying that the individual initially assumes a variety of working hypotheses, acts upon the most credible ones, and then replaces them by new ones if they fail to work. Thus, the interplay between economic and psychological research evidently can not be neglected (Rabin, 1998, Simon, 1986).

The essence of bounded rationality and informational feedback has inspired a vast body of prior research, not only in the field of energy (e.g. DiClemente et al.

(2001)). Above all, the impact of providing feedback on consumption is of particular interest. In the related literature, such an effect has most often been measured with the help of empirical work that is constrained by data and/or the experimental design itself. Therefore, the setting of experimental studies and the selection of variables are crucial.[3] This paper addresses the relevance of bounded rationality in the energy sector. In this context, informational feedback incorporates a measure that is supposed to effect an overall reduction of electricity consumption based on additional information. A summary of experimental energy-related studies has been published by Faruqui et al. (2010). The authors conducted their survey based on pilot programs in the United States, investigating the effect of in-home displays on consumer behavior, and found that reductions in consumption from such programs reached 7% on average. More recent research has been conducted by Gans et al. (2013) dealing with the effect of informational feedback on residential electricity consumption. In that study, the authors analyze the impact of smart meters in a large-scale natural experiment in Northern Ireland. They find that the decline in residential electricity consumption induced through smart meters ranges between 11 and 17%.

Targeting an overall reduction of electricity demand, the literature distinguishes between three different types of energy-saving measures. Despite the energy-conserving impact of informational feedback, electricity consumption can also be influenced by energy-efficiency programs and demand response. Whereas informational feedback induces a behavioral change so that 'using less electricity' results as the outcome, energy efficiency aims at a reduced energy usage while maintaining a comparable level of service (Boshell and Veloza, 2008, Gillingham et al., 2006, McKinsey and Company, 2009). Efficiency is thus closely linked to the installation of energy-efficient technologies within households such as freezers, refrigerators, dishwashers, light bulbs, and other appliances. In contrast to these direct measures, demand response is related to the electricity market itself. Despite a reduction of peak demand that was observed in field experiments on dynamic pricing (Faruqui and Sergici, 2010), Joskow and Wolfram (2012) stress that the overall penetration of demand response measures in the US has been low so far. For California, the impact of demand response programs is still negligible today. In this paper, we focus on the isolated impact of deploying AMI and thus position this article in the literature analyzing energy-conservation measures.

Recently, behavioral literature has focused on the growing appreciation of how

[3]A review of such features from experimental studies can be found in Selten (1998).

non-price interventions can affect consumer behavior. As such, informational feedback provided to the consumer is pivotal in order to increase the household‘s responsiveness and likewise influence its electricity consumption. Among others, Allcott (2011) reports that providing social norm information induces consumers to conserve electricity. Allcott and Rogers (2014) expand the analysis on social norms by using data from the Opower program, in which home energy reports based on social comparison are repeatedly provided to residential electricity consumers.

Supplementing prior research, we focus on the impact of AMI in a large-scale framework rather than analyzing short-term pilot programs. Moreover, the literature so far gives a long list of issues related to the explanatory power of pilot tests. Such aspects cover, inter alia, the representative nature of the sample, the time horizon, additional and distorting monetary incentives, and measurement errors. Furthermore, a Hawthorne effect may be identified, reflecting the fact that people may alter their behavior when they know that they are participating in an experimental study (Adair, 1984). Thus, the transferability of results from pilot tests to a larger and more general context is at least questionable. We intend to fill this gap by deriving an empirical approach that will allow us to draw conclusions from an energy-conservation measure induced by statewide policy. Complementing prior research, we are thus able to assess the effectiveness of a policy-driven deployment of smart meters in the context of energy-conservation measures.

2.3 Identification Strategy

In the US, smart-meter[4] deployment in several states is fostered by legislation. While some states have not passed any smart-meter legislation yet, others have already fully adopted smart-meter plans. Figure 2.1 depicts the status of smart-metering legislation across the US states.

We use the dichotomy of states with significant impact of smart-metering legislation and states with negligible smart-meter penetration rates in order to derive an experimental setting. On the one hand, we identify the statewide and policy-induced smart-meter deployment in California as a treatment that allows us to analyze the impact of smart meters on consumption. On the other hand, states that do not yet have any smart-meter penetration may serve as a control group.

[4]Such smart meters are part of the Advanced Metering Infrastructure (AMI). For more details on AMI see 2.8.1.

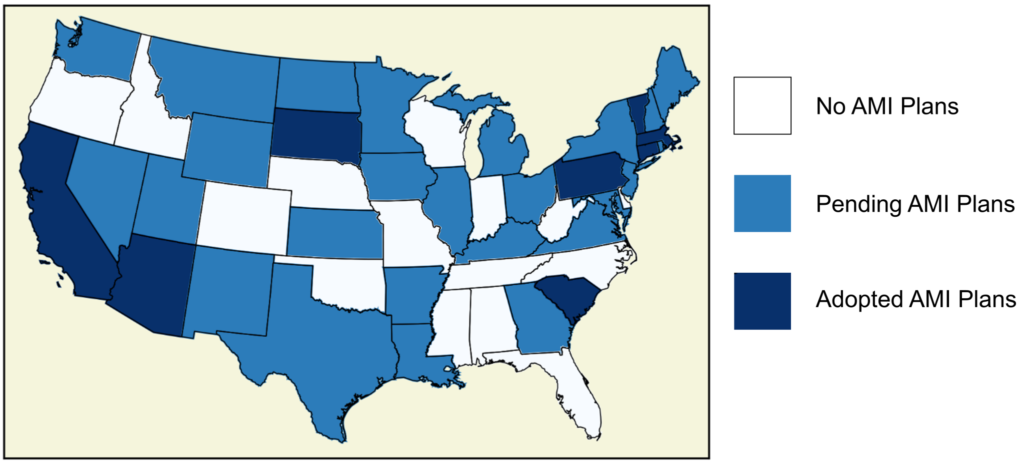


Figure 2.1: Smart-metering legislation across the US states (EIA 2011)

The installation of smart meters refers to a short and precisely controllable period, essentially ranging from 2009 to 2011. Being a statewide measure, all residential customers are affected in the same manner. By analyzing the development of electricity consumption before, during, and after the deployment of smart meters, we are thus able to clearly relate back possible changes to the trigger event. We furthermore isolate the respective impact in question by controlling for the other electricity saving impacts (i.e. energy efficiency and self-consumption from renewable energies).

We would like to observe the development of residential electricity consumption in a population that faces the introduction of informational feedback over time (treatment group) and the respective control group. The control group should ideally reproduce the characteristics of the population that experiences the treatment. Since the characteristics influencing residential electricity consumption are heterogeneous across the US states, we do not expect a single state to resemble Californian consumption characteristics appropriately. In this paper, we therefore apply synthetic control methods in order to evaluate what might be a control group that meets the above outlined requirements. We thereby aim to guarantee quasi-randomness. In a next step, we then conduct a Difference-in-Differences estimation to test for causality as well as to quantify the reduction effect in scope.

2.4 The Californian Case

In order to evaluate the impact of deploying smart meters in California, it is first necessary to understand the most relevant drivers of residential electricity consumption and its development over time. This is crucial since, besides the deployment of smart-meter infrastructure, further political measures were adopted that tackle issues related to energy conservation, energy efficiency, and demand response. When it comes to energy savings, California is one of the most ambitious states, with various measures having been adopted to achieve an overall decrease of electricity consumption and thus greenhouse gas emissions. Beginning with the energy crisis in California in 2001, policy makers decided to foster an increase of energy efficiency with a particular focus on the residential sector.

In this regard, there were repeatedly updated energy action plans, all of which defined goals for energy consumption (CPUC and CPA, 2003). These action plans mainly aimed at:

- meeting energy growth needs as well as optimizing resource efficiency and energy conservation;
- reducing electricity demand;
- ensuring security of gas and electricity supply including the provision of an appropriate infrastructure;
- achieving goals with respect to renewable energies and distributed electricity generation.

In order to tackle the above aims, the Energy Action Plan considered measures fostering voluntary dynamic pricing, explicit incentives for demand reduction, rewards for demand response, energy-efficiency investments, energy-conservation measures, energy-efficiency programs, and programs that support improvements of energy efficiency when it comes to buildings and devices. Furthermore, within the scope of the Energy Action Plan 2 in 2005, the government issued a decision for a large-scale deployment of smart meters (CPUC and CPA, 2005). As a consequence, the three major investor-owned utilities (IOUs), namely Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E), started programs that deployed AMI within their service areas. As depicted in Figure 2.2, these IOUs cover more than 75% of all customer accounts[5] in California (2015).

[5] These numbered 13,845,610 in December 2015 and the respective energy consumption is related to a share greater than 70%.

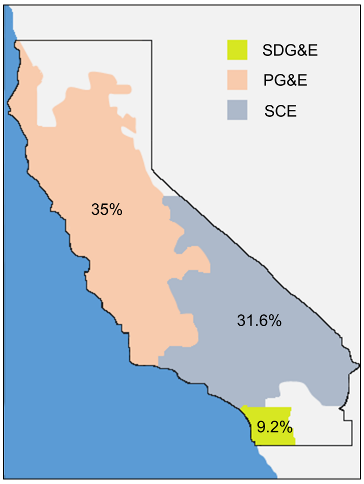


Figure 2.2: Investor-Owned Utilities (IOUs) and the respective share of Californian customer accounts (2015, Dec.)

Below, we explain the most relevant types of measures and their impact on residential electricity consumption in more detail. We distinguish between measures related to energy efficiency of buildings and devices, demand response triggered by electricity price schemes, and energy conservation including, among others, the deployment of AMI.

Demand Response Through Electricity Tariff Design

'Load shifting' is a typical demand response from electricity consumers. It occurs if consumers are able to react to price signals from the electricity market. Technically, a consumer reduces load in response to a signal from a service provider or grid operator. Today, electricity consumers in the residential sector in California face either a tiered tariff scheme or a time-of-use pricing scheme. In tiered tariff schemes, electricity prices are relative to a 'baseline' consumption of electricity within a defined territory. As such, the tariff scheme follows a typical quantity-dependent pricing that varies across predefined blocks of usage. The number of tiers offered and temporal definitions with respect to peak, semi-peak, and off-peak vary among IOUs, and peak prices can be more than twice the off-peak ones.[6] In general, consumers receive their electricity and gas bills at the end of each month, following a standardized 30-days billing cycle. Billing contains information on daily gas and electricity usage gathered by smart meters throughout the cycle. Consumers are thus able to identify monthly variations of gas and electricity usage on daily and monthly levels.[7]

[6] We provide two simplified versions of residential tiered and time-of-use schedules in Section 2.8.7.
[7] Sample bills from PG&E, SDG&E and SCE can be found under the service portal from each IOU.

A two-tiered tariff had already been implemented in California prior to the energy crisis in 2000. However, with the energy crisis and the inconvenience caused by blackouts that were induced by supply shortages, regulators enhanced the tier structure by introducing five tiers. These were removed again in 2013 due to ongoing discussions on tier design and, as of today, Californian tariff design relies on time-of-use pricing that distinguishes between peak and off-peak times. Additionally, the implementation of real-time pricing has so far been ruled out as an option in California.

A change in tiered electricity tariff design could potentially provoke slight changes in overall consumption levels. This may, for example, be the case if load shifting causes a decrease in electricity consumption in peak periods which is even higher than the respective increase in off-peak periods. Within this paper, we assume that there is no significant impact of implementing more or less tiers on the absolute electricity consumption. To support this hypothesis, we test the assumption of parallel trends within our empirical analysis. We would expect potential distorting effects related to a change in the electricity tariff design, if any, to be uncovered within this procedure since the introduction of five tiers in California was in the pre-treatment periods.

Energy Efficiency

Besides regulatory efforts to ensure security of supply through tier design, numerous energy-efficiency policy measures which are directed towards a reduction of energy consumption exist for California (Office of Energy Efficiency and Renewable Energy, 2016). The majority of energy-efficiency measures are so-called rebate programs.[8] The three major IOUs, PG&E, SDG&E, and SCE, have all offered energy-efficiency rebate programs for energy-efficient technologies since 2006. Within these programs, consumers willing to replace equipment with energy star labelled devices receive a per unit rebate.[9] Such incentives are particularly designed to reduce load through state-of-the-art devices. While the utility level remains constant with the same service offered (i.e., for example, cooling in the fridge), less electricity is needed to ensure this service. Empirical evidence reveals a need to distinguish between different devices. Light bulbs, refrigerators, and freezers provide rather robust empirical evidence for electricity reduction if replaced within households. Thus, we

[8]Additionally, appliance standards on a national level have been implemented in the Appliance Efficiency Regulations for California in 2006 as well as the Public Benefits Funds for Renewables and Efficiency launched in 1998.

[9]Further details on the applicable residential equipment are provided at the website 'http://programs.dsireusa.org/system/program/'.

expect a significant impact of energy-efficiency measures on electricity consumption (Gillingham et al., 2006). We therefore account for energy savings related to energy efficiency by adjusting electricity consumption data so that the impact of informational feedback can be studied independently.[10]

Energy Conservation

Finally, a change of consumption behavior is another way to achieve a reduction of electricity consumption. Through behavioral changes, 'consuming less electricity' with a given technology portfolio is feasible. However, information on the consumption must be revealed in such a way that consumers are able to make informed decisions. As bounded as these decisions may be, decisions change and, in most cases, may improve if such information is provided to consumers. In this paper, we focus on the three major IOUs in California, which are adopting plans to distribute smart meters to all households in their respective service areas. In fact, these plans were transformed into physical deployment of smart meters, as depicted in Figure 2.3. The deployment of AMI began in 2008, and first achieved a penetration rate above 10% in 2009.

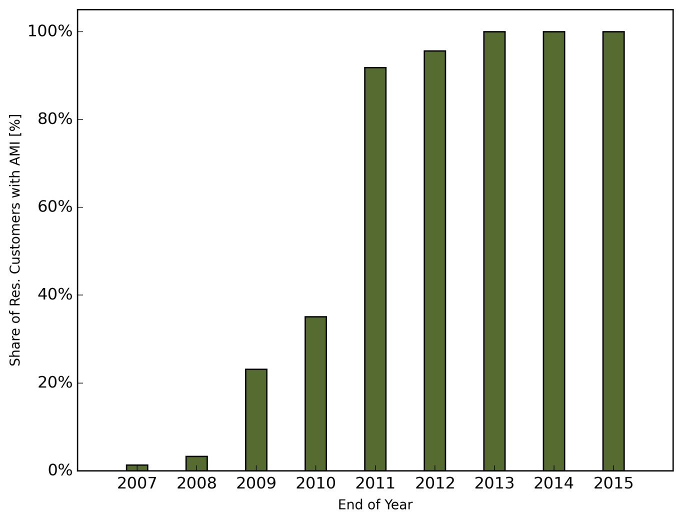


Figure 2.3: Share of Californian (three major IOUs) households with AMI (smart meters) over time

As of 2011 the share of Californian households with AMI corresponds to the share

[10]For more details, see Section 2.5.

of customer accounts covered by the three major IOUs.[11]

Households having installed AMI with the respective smart meters are now able to track their daily electricity consumption via a meter on the device. Additionally, consumption data are processed by the utility and, as in the case of SDG&E, for instance, are provided to the customer via on online tool. With the help of the customer tool, households are able to check their gas and electric usage on a daily basis. By connecting a home area network to the smart meter, households are able to track energy consumption information and more details on their energy-usage profile. Most commonly, thermostats and in-home displays are state of the art in such technical setups (SDG&E, 2016).

2.5 Data

We base our empirical analysis on variables that may have information on both fluctuations of residential electricity consumption over time and the respective differences between the states. We use monthly state-specific data, and in the following we briefly depict the variables we use as well as the respective sources.

2.5.1 Dependent Variable: Residential Electricity Consumption

We define the dependent variable in order to make it possible to isolate the impact of AMI on residential electricity consumption from other policy measures that coincide with the deployment of smart meters and that may also influence residential electricity consumption. We therefore correct data on residential electricity consumption provided by the IOUs for both own consumption related to residential photovoltaic (PV) electricity generation and electricity savings achieved through energy-efficiency programs. That is to say, we mimic the development of residential electricity consumption as if there was no treatment besides smart meters. The respective formula is depicted in Equation 2.1.

$$Demand_{m,s}^{res,adj} = Demand_{m,s}^{res,billed} + Self\,Consumption_{m,s}^{res,PV} + Savings_{m,s}^{res,ee} \tag{2.1}$$

[11] The share of Californian households in services areas that are covered by the three major IOUs may vary over time.

Our initial data on residential electricity consumption consists of monthly (m) state-specific (s) electricity sales in the residential sector, which we label $Sales^{res}_{m,s}$. As far as California is concerned, we only include data for the three major IOUs, PG&E, SCE, and SDG&E, in line with our identification strategy. Since the IOUs cover the major share (i.e. $> 75\%$) of residential customers in California, we assume that there is no loss of representative nature. In the next step, we divide $Sales^{res}_{m,s}$ by the respective number of customer accounts in order to get the average monthly electricity consumption per household for which consumers are billed ($Demand^{res,billed}_{m,s}$). We use this relative measure in order to compare residential electricity consumption in different states independently of the total level of consumption, which may differ. As outlined above, we now account for the average electricity generation from PV systems, which replaces electricity purchased from the grid. In general, California uses a billing system that is called net metering. The essence of this procedure refers to households being directly billed for their total electricity purchase minus the amount of energy that they feed back into the grid. Thus, there is a direct incentive for self-consumption of electricity generated from renewable energy sources. This self-consumed energy ($SelfConsumption^{PV,residential}_{m,s}$) has to be added to the basic electricity consumption data in order to get unbiased values.[12]

Second, we adjust our data for residential electricity savings that result from energy efficiency (ee) programs ($Savings^{res,ee}_{m,s}$). The respective data are collected from the individual service utilities in the US states and are listed in Table 2.1.[13] Such data are based on the technical savings potential, which is the number of residential devices that face a specific efficiency upgrade multiplied by the respective electricity consumption.[14] However, it is not clear whether or not the data are equal to the actual reduction in electricity consumption. First, rebound effects may not be ruled out. The existing literature, however, provides little support for such an increase in energy use, which is known as backfire (Gillingham et al., 2015). Second, Fowlie et al. (2015) found that projected savings from energy-efficiency programs may exceed actual reductions many times over. We therefore aim to control whether measurement errors with regard to energy efficiency savings may bias our empirical results. In the context of our identification strategy, we explicitly guarantee that smart meters are accessible at the time of the defined treatment period starting in

[12]For more details on the calculation methodology, see Section 2.8.5.

[13]We restrict our analysis to residential efficiency programs in California, New York, and New Mexico since those are the relevant states resulting from the synthetic control methods according to Section 2.6.1.

[14]In the example of New York, the data are furthermore corrected for free-rider and spillover effects (New York State Department of Public Service, 2016).

2009. As there is a time lag between significant energy-efficiency savings beginning in 2006[15] and the treatment, we are able to control for the accuracy of the methodology in filtering out the impact of energy-efficiency measures by testing for the assumption of parallel trends before the treatment.

As regards the data references for California, we rely on the California Energy Efficiency Statistics for the three major IOUs of interest (CPUC, 2016), for New York we take state-wide Energy Efficiency Portfolio Standard (EEPS) Program Electricity Savings Data (New York Office of ITS, 2016), and for New Mexico we review annual efficiency reports published by the major service utility[16] (PNM, 2016). An overview on the respective data is provided in Table 2.1. Whenever only a subset of utilities provides energy savings data, we restrict our empirical analysis to the average residential electricity consumption within the respective service area. However, the corresponding utilities that provide data cover the majority of households in their states and thus we assume their representative nature. By now adding $Savings_{m,s}^{res,ee}$, we finally get the average adjusted residential electricity consumption per household ($Demand_{m,s}^{res,adj}$), which we use as the dependent variable within our empirical framework.

Table 2.1: Energy efficiency savings data

State	Utilities	Period of time	Resolution
California	PG&E, SCE, SDG&E	2006-2015	Monthly
New York	Statewide	2008-2015	Monthly
New Mexico	PNM	2008-2015	Monthly

2.5.2 Explanatory Variables

By using panel data, we account for both cross-sectional and cross-temporal differences within the US states. Since we encounter varying temporal and spatial resolutions among our explanatory variables, we have to adjust some of our data in order to perform our estimation approach. For instance, household survey data are only available on census region level in most cases. Thus, we first address this spatial issue by assigning federal states to the census regions where necessary. As a consequence, we face a minor loss of cross-sectional explanatory power. Second, for

[15]The development of energy-efficiency savings in California is illustrated in Figure 2.7 in Section 2.8.2.

[16]This is the Public Service Company of New Mexico, which covers more than 50% of all customer accounts in New Mexico.

the chosen period between 2002 and 2015, we need to distinguish between continuously updated data with monthly observations, yearly available data, and household survey data based on observations in 2001, 2005, and 2009. For some survey data, we are able to add data for the years 2011 and 2013. In order to obtain an overall monthly and state-specific dataset, we use previous observations if no updated data are available.

Table 2.2 gives an overview of all variables that are used in our empirical analysis. Furthermore, it provides further details such as a brief explanation of each variable and depicts the respective sources. Key to our identification strategy is the deployment status of AMI (EIA, 2016b). It reflects the treatment under analysis by measuring the progress of installation of smart meters by households over time. We furthermore include explanatory variables concerning the employment level, wages, residential electricity sales, customer accounts, and electricity prices that are published by the US Energy Information Administration (EIA) or the Bureau of Labor Statistics (BLS). It is worth mentioning that the electricity price is calculated as an average value across all tariff tiers. Furthermore, the EIA also provides data on residential electricity consumption, which are the basis for the derivation of the dependent variable. Data are provided on a monthly and state-specific level.

In addition, we include climate data. More precisely, heating degree days ($HDDs$) and cooling degree days ($CDDs$) are calculated based on per state temperature values that we obtain from the meteorological data forms of the National Oceanic and Atmospheric Administration (NOAA, 2016).[17]

Complementing these data, we add data reflecting household characteristics with a focus on electricity usage behavior and appliances. Such data are taken from the Residential Energy Consumption Survey (RECS) and the American Household Survey (AHS) for three and five reference points in time, respectively, namely 2001, 2005, 2009, 2011, and 2013. The survey data consist of different technologies and the percentage of households using specific electrical appliances. For instance, we include data on the average number of refrigerators per household, the share of households that use electric heating, and the usage intensity of heating by fuel type for census regions and states. Physical household characteristics such as the average number of rooms per household, the average number of electric ovens, and the average floor space available per household are additionally gathered on a state level. Data on the share of household members with a high-school diploma or higher as

[17] To derive HDDs, for example, the difference between daily high and low temperatures is compared to the threshold of 65°F and summed over all days of a month. The respective data are furthermore standardized to 1000.

well as the average number of 'elderly' people living in each state are taken from RECS as well. Finally, as we expect macro-economic indicators to be relevant when explaining the development of electricity consumption over time, we include data on the unemployment level and adjusted gross domestic product. Hereby, we also control for the impact of the Great Recession. Both indicators are taken from the BLS. In addition, Table 2.3 shows descriptive statistics for all variables used for our empirical estimations under Section 2.6.2.

2.6 Empirical Analysis

Following the identification strategy from Section 2.3, we use a two-stage empirical approach. First, we derive a control group by applying synthetic control methods.[19] In a second step, we conduct a Difference-in-Differences estimation to quantify the effect under analysis.

2.6.1 Derivation of the Control Group Using Synthetic Controls

States are rather heterogeneous. This implies that characteristics driving residential electricity consumption exhibit significant regional variation. Above all, these characteristics include climatic conditions such as temperature and humidity, housing, and social characteristics as well as demographic aspects. Consequently, it is questionable whether a single US state adequately resembles Californian characteristics with respect to residential electricity consumption. In order to circumvent such hindrances, we apply synthetic control methods and derive a weighted combination of US states that we use as the control group, 'Synthetic California'. The application of synthetic control methods is positioned in the context of a vast body of existing literature that gives further insights into methodological details (e.g. Abadie and Gardeazabal (2003), Abadie et al. (2010), and Abadie et al. (2015)). The individual weights for the synthetic counterfactual are determined according to the objective function expressed by Formula 2.2.

$$\min_{w}(X_1 - X_0 \cdot w)' V (X_1 - X_0 \cdot w) \tag{2.2}$$

Here w denotes a vector with positive weights for each state that has yet to be derived. The individual weights sum up to one. In order to optimize these weights,

[19]The respective procedure is described in detail in Section 2.6.1.

Table 2.2: List of variables and references

Label	Explanation	Resolution	Region[18]	Measure	Ref(2016)
$AMI_{m,s}$	Share of households with AMI	Yearly	State-specific	%	EIA
$CDD_{m,s}$, $HDD_{m,s}$	Cooling degree days, Heating degree days	Monthly	State-specific	1000°F	NOAA
$Clothesdryer_{m,s}$	Avg. share of electric clothesdryers	'01,'05,'09	Census regions	Relative share	RECS
$Customers^{res}_{m,s}$	Total residential customer counts	Monthly	State-specific	Total	EIA
$Demand^{res,billed}_{m,s}$	Avg. electricity sales per household	Monthly	State-specific	MWh	EIA
$Education_{m,s}$	Share of household members with a high school degree or higher	'01,'05,'09, '11,'13	Census regions	Relative share	RECS
$ElderlyPeople_{m,s}$	Avg. number of old people living in a household	'01,'05,'09, '11,'13	Census regions	Total	RECS
$Feedback^{PV}_{m,s}$	Total residential feed-back (grid) from PV	Monthly	State-specific	MWh	EIA
$Floorspace_{m,s}$	Avg. floorspace per household	'01,'05,09	Census regions	m^2	RECS
$GDP_{m,s}$	Total real GPD per employee	Yearly	State-specific	mil. USD	BLS
$Heating$ $Equipment_{m,s}$	Share of households using electric heating	'01,'05,'09	Census regions	Percent	RECS
$Irradiation_{m,s}$	Avg. (1998-2009) solar irradiation	Monthly	State-specific	kWh/ m^2/day	NREL
$MainHeating_{m,s}$	Share of households with electricity as main heating fuel	'01,'05,'09	Census regions	Relative share	RECS
$Oven_{m,s}$	Avg. number of electric ovens per household	'01,'05,'09	Census regions	Total	RECS
$Price^{res}_{m,s}$	Avg. electricity price for residential customers	Monthly	State-specific	Euro/ kWh	EIA
$Refrigerators_{m,s}$	Avg. number of refrigerators per household	'01,'05,'09	Census regions	Total	RECS
$Rooms_{m,s}$	Avg. number of rooms per household	'01,'05,'09	Census regions	Total	RECS
$Unemployment_{m,s}$	Unemployment level	Yearly	State-specific	Relative share	RECS
$Wage_{m,s}$	Avg. weekly wage	Monthly	State-specific	1000 USD	BLS

Notes to Table 2.2: The exact references are: NOAA (NOAA, 2016), RECS (EIA, 2016a), EIA (EIA, 2016b), BLS (BLS, 2016), NREL (NREL, 2016)

Table 2.3: Descriptive statistics

Variable	N	Mean	SD	Min	25%	Median	75%	Max
$CDD_{m,s}$	2352	0.07	0.10	0.0	0.0	0.003	0.10	0.58
$Clothesdryer_{m,s}$	2352	0.77	0.14	0.47	0.54	0.84	0.90	0.97
$Demand^{res,adj}_{m,s}$	2352	0.81	0.27	0.41	0.60	0.73	0.95	1.97
$Education_{m,s}$	2352	0.59	0.03	0.54	0.56	0.59	0.62	0.64
$Elderlypeople_{m,s}$	2352	0.33	0.03	0.28	0.31	0.33	0.34	0.37
$Floorspace_{m,s}$	2352	2049	250	1568	1895	2080	2289	2405
$GDP_{m,s}$	2352	0.006	0.001	0.004	0.005	0.006	0.007	0.009
$HDD_{m,s}$	2352	0.47	0.42	0.00	0.06	0.38	0.80	1.92
$HeatingEquipment_{m,s}$	2352	0.25	0.17	.06	0.13	0.23	0.29	0.65
$MainHeating_{m,s}$	2352	0.22	0.16	0.06	0.09	0.18	0.24	0.62
$Oven_{m,s}$	2352	1.02	.02	1.00	1.01	1.01	1.03	1.09
$Price^{res}_{m,s}$	2352	0.111	0.038	0.048	0.082	0.100	0.141	0.241
$Refrigerators_{m,s}$	2352	1.24	0.05	1.14	1.20	1.23	1.28	1.30
$Rooms_{m,s}$	2352	5.81	.32	5.19	5.65	5.93	6.13	6.21
$Unemployment_{m,s}$	2352	0.06	0.02	0.02	0.05	0.06	0.08	0.12
$Wage_{m,s}$	2352	0.85	0.18	0.52	0.52	0.80	0.96	1.46
$AMI_{m,s}$	2352	0.03	0.16	0.00	0.00	0.00	0.00	0.99

we rely on a procedure that minimizes the distance vector between Californian pre-treatment characteristics (X_1) and the respective characteristics of the resulting control group ($X_0 w$). These characteristics include all variables that are depicted in Section 2.5. We divide the pre-treatment period into two sub-periods. In more detail, we consider a first pre-treatment period (1) that starts in 2002 and ends in 2005. Based on this first period, we calculate the weights for the synthetic control group according to the above mentioned methodology. Additionally, we define a second pre-treatment period beginning when the Energy Action Plan in California was adopted (2006) and continuing until the beginning of the treatment period in 2009 (c.f. Figure 2.5). The second pre-treatment period allows the assumption of parallel trends to be tested.

With regard to the data, the varying temporal resolution does not distort the derivation of a synthetic control group since the respective methodology is based on averages over time. More precisely, neglecting temporal variability, the chosen approach aims to determine weights such that average values of the explanatory variables during the first pre-treatment periods are resembled. We then account for the relative importance of the individual explanatory variables X by introducing a weight vector V. Following standard synthetic control methods (see, e.g., Abadie and Gardeazabal (2003)), we rely on a regression-based technique in order to derive V.[20] Naturally, the set of time periods for determining V is also restricted to the first set of pre-treatment periods.

The set of states that are considered to be control group candidates is restricted. Suitable candidate states should exhibit no significant impact of AMI during the entire period of observation. Thus, we use a subset of states with a smart meter penetration lower than 10% as possible control group candidates. The respective threshold exactly matches the definition of our treatment as we consider the treatment period beginning in the first year with a Californian share of AMI higher than 10%. The remaining candidate states are depicted in Figure 2.4.

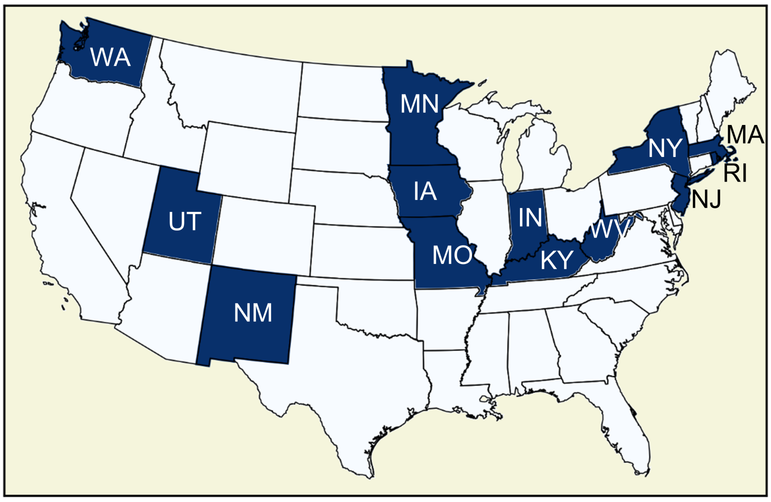


Figure 2.4: Candidate states with low AMI penetration

As a result, we obtain Synthetic California, which combines the states of New York and New Mexico, which are given weights of 62.5 and 37.5% respectively. A deeper analysis of the underlying causal relations reveals that New York adequately resembles Californian housing characteristics, whereas New Mexico is particularly characterized by similar climate conditions.

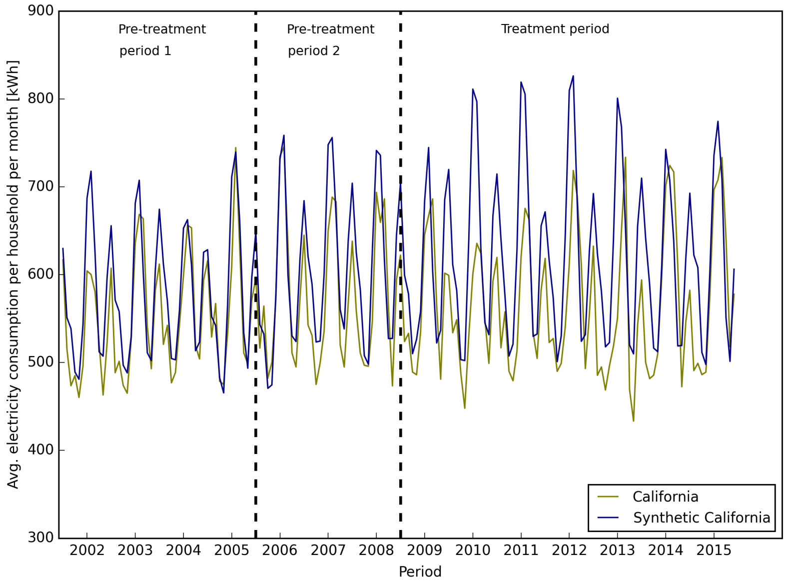
We now reduce our initial dataset by considering just the two sections, California and Synthetic California. The variables for Synthetic California are calculated as the weighted combination $X_0 w$. The resulting development of residential electricity consumption is depicted in Figure 2.5i, where we highlight the three periods that we differentiate. For illustration purposes, Figure 2.5ii depicts the respective difference plot. In order to support the claim of a suitable control group, it is crucial that the pattern of residential electricity consumption in Synthetic California before

[20]Details on weights are listed in Section 2.8.4.

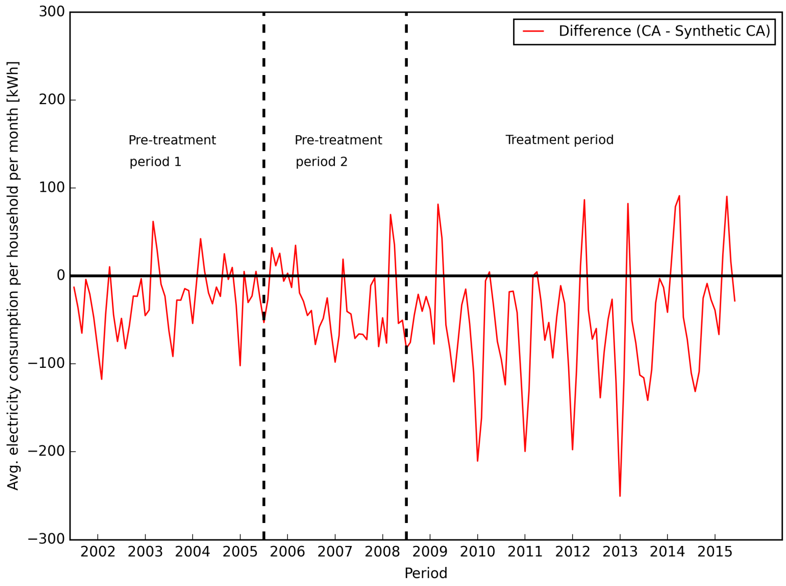
the treatment resembles the respective real Californian one. We therefore compare the differences in residential electricity consumption between the two sections in both pre-treatment periods. In general, the consumption pattern in the upper figure is characterized by seasonal trends. More precisely, the development of residential electricity consumption exhibits recurrent upwards and downwards movements in a range between 430 and 830 kWh/month. The figures show that the seasonal component, in particular, is reproduced accurately. As regards the differences in levels, the respective values in California and Synthetic California differ only slightly between the two pre-treatment periods. In more detail, whereas the residential electricity consumption in the first pre-treatment period is 11 kWh lower on average in California compared to Synthetic California, the respective average difference is -15 kWh in the second pre-treatment period. Even though there is no perfect pre-treatment match in both periods, the respective difference is rather constant until the treatment period. Additionally, the average difference in residential electricity consumption amounts to -36 kWh in the post treatment periods, which already indicates a significant treatment effect. We therefore assume that residential electricity consumption would have developed identically in California and Synthetic California if there had not been any additional treatment. Simply put, the assumption of parallel trends is valid. We now focus on the development of residential electricity consumption after the treatment. Essentially beginning in 2010, we observe a clear excess of negative differences, indicating a significant impact of AMI on electricity consumption. Furthermore, the absolute value of peak differences is doubled compared to the pre-treatment periods. To sum up, our descriptive results already indicate a negative influence of smart meters on residential electricity consumption. However, we address the question of causality and quantify the impact under analysis within the next section.

2.6.2 Difference-in-Differences Estimation Results

We define the yearly share of AMI as the treatment variable and thereby account for the respective deployment process. In more detail, there is a time lag between the decision for the smart-meter deployment and the ability of every household to use AMI which is directly reflected by the treatment variable. We apply a linear Difference-in-Differences estimation in levels according to Formula (2.3). We aim to estimate the coefficient γ to shed light on whether or not a significant decrease of residential electricity consumption due to smart-meter deployment has been achieved. For our estimation, we rely on monthly data gathered over 14 consecutive years



i Synthetic controls: Descriptive comparison



ii Synthetic controls: Difference plot

Figure 2.5: Descriptive comparison and differences between the development of residential electricity consumption in California and 'Synthetic California'

(2002-2015). According to the estimation approach, we directly use the differences between the respective values for California and Synthetic California.[21] Besides the treatment variable, we control for other potential impacting factors. We use the subset of variables that provide monthly observations, because data with a temporal variability different from that exhibited by the dependent variable would lead to distorted results and issues of collinearity. First, we include monthly average electricity prices ($Price_m^{res}$). Furthermore, we consider data for HDD_m and CDD_m to account for weather conditions. Finally, we account for macro-economic impact factors comprising wage data ($Wage_m$) and the development of the unemployment level ($Unemploymentlvl_m$). In addition to the explanatory variables, we estimate the error term μ_m using robust standard errors to account for heteroscedasticity. It is worth mentioning that we do not estimate an aggregate constant term but control for different periods.

$$\begin{aligned}\Delta Demand_m^{res,adj} = {} & \alpha_1 Dummy_{Pre-Treatment1} + \alpha_2 Dummy_{Pre-Treatment2} \\ & + \gamma \Delta AMI_m \\ & + \beta_1 \Delta Price_m^{res} \\ & + \beta_2 \Delta CDD_m + \beta_3 \Delta HDD_m \\ & + \beta_4 \Delta Unemploymentlvl_m + \beta_5 \Delta Wage_m \\ & + \mu_m \end{aligned} \tag{2.3}$$

We conduct a two-stage least squares regression analysis to address issues related to endogeneity of electricity prices. In more detail, one may expect simultaneity of residential electricity consumption and the respective prices due to mutual bidirectional dependencies. We therefore use the lagged electricity price as an instrument[22] for the original explanatory variable. We argue that the electricity prices from past months affect the current prices ($cov[Price_{m-1}^{res}, Price_m^{res}] \neq 0$) since, for example, fixed price components do not change on a monthly basis. We identify a high first-order autocorrelation of 96% in California and 76% in Synthetic California.[23] At the same time, we do not expect the electricity price from the previous month to impact the current electricity consumption as it does not reflect the price that households are actually charged. Thus, there should be no direct impact on the decision ra-

[21] We provide an overview of the respective descriptive statistics in Section 2.8.3.
[22] A Kleiberger-Paap test indicates that the hypothesis of weak instruments may be rejected.
[23] Lower values compared to California may be traced back to the use of a weighted combination of electricity prices.

tionale of households other than through its impact on the current electricity price and thus we assume that the exclusion restriction is valid ($cov[Price^{res}_{m-1}, \mu] = 0$). As well as the electricity price, it is relevant to comment on the other explanatory variables included. By default, weather conditions are a factor given exogenously and the economic variables such as wage data are most commonly assumed to have a unidirectional impact on electricity consumption as well. Moreover, we do not expect our estimation to be biased by omitted variables, since we include the most relevant variables that, according to prior literature, are assumed to have an impact on residential electricity consumption. Finally, we isolated the impact of AMI such that we do not expect any other policy measures to influence the artificial electricity consumption we use.

To investigate the impact of the treatment in question and to break down the respective temporal development, we depict estimates for three specifications, namely IV (1), IV (2), and IV (3). Put simply, IV (1) measures the aggregate impact of deploying AMI in California on the state-wide residential electricity consumption. Results for IV (1) are displayed in Table 2.4, where we find the treatment effect to be significant at the 1% level. A 100% diffusion rate of AMI triggers an average monthly residential electricity reduction of 31 kWh per household, which is equivalent to a relative reduction of 5.1%. These estimation results provide the first evidence of causality and both estimates which are controlling for significant differences in the pre-treatment periods are insignificant. However, additional insights and further evidence for causality are provided in Section 2.8.6. Thus, we claim that there is no systematic difference between the Californian and the Synthetic Californian development of residential electricity consumption other than that induced through the AMI.

All in all, the p-value of the model suggests significance. With regard to the additional explanatory variables included, both CDD and HDD reveal highly significant coefficients, and reduced regressions show that they constitute the major share of explanatory power. This is plausible as both variables reflect the need for electricity through, for example, air conditioning in non-heating periods and heating in colder months. In addition, we see a slightly significant negative impact of the unemployment level. An increasing unemployment rate tends to be accompanied by decreasing wages, which reduces the available budget for the electricity bill. Finally, we observe a negative coefficient for the electricity price, as increasing prices are expected to create incentives for reducing electricity consumption. However, the respective estimate is insignificant, which may be traced back to the data availabil-

Table 2.4: IV Estimates for DiD estimation

		Dependent variable: $\Delta Demand_m^{res,adj}$			
Explanatory variable	IV (1)	IV (2)		IV (3)	
Pre-Treatment1	-0.07	-0.002		-0.003	
	(0.007)	(0.007)		(0.007)	
Pre-Treatment2	-0.10	-0.006		-0.004	
	(0.008)	(0.008)		(0.008)	
		Non-heating	*Heating*		
ΔShare $AMI_{total,m}$	-0.031***	-0.042***	-0.01		
	(0.01)	(0.01)	(0.01)		
				Non-heating	*Heating*
ΔShare $AMI_{2009-2011,m}$				-0.020	0.024
				(0.025)	(0.02)
				Non-heating	*Heating*
ΔShare $AMI_{2012-2014,m}$				-0.041***	-0.008
				(0.013)	(0.016)
				Non-heating	*Heating*
ΔShare $AMI_{2015,m}$				-0.039**	-0.031
				(0.016)	(0.022)
$\Delta Price_m^{elec,res}$	-0.46	-0.48		-0.36	
	(0.51)	(0.49)		(0.57)	
ΔCDD_m	0.66***	0.67***		0.68***	
	(0.08)	(0.08)		(0.081)	
ΔHDD_m	0.04**	0.06***		0.05***	
	(0.02)	(0.02)		(0.02)	
$\Delta Unemploymentlvl_m$	-0.53*	-0.46		-0.88**	
	(0.20)	(0.24)		(0.36)	
$\Delta Wage_m$	0.05	0.04		(0.07)	
	(0.06)	(0.06)		(0.06)	
$observations$	167	167		167	
R^2	0.45	0.47		0.48	
F	23.8	22.91		17.17	
p-value	0.00	0.00		0.00	

Notes to Table 2.4: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. We use data from January 2002 until December 2015.

ity. Furthermore, we do not directly use the electricity prices that households are actually charged; instead we use averages across all tariff periods and service areas.

In addition to IV (1), we specify IV (2) in order to investigate seasonal variations of the treatment effect under analysis. We differentiate between heating and non-heating periods, all of which are defined within the same year. We define heating periods to cover the months from January to March and from October to December. We observe a significant impact of AMI in non-heating periods, whereas there is no significant influence in colder months. The respective reduction in non-heating periods amounts to 42 kWh per household per month (6.7%). We expect some devices to be more likely to be substitutable in summer periods (such as air conditioning, dryers etc.), whereas electric heating in the heating period is a more basic need. As one main finding, we thus conclude that the potential for energy conservation can basically be leveraged by households in non-heating periods. At the same time, the average residential electricity consumption in the states under consideration tends to be higher in the non-heating periods. Thus, policy makers may achieve a slight reduction of the electricity consumption in peak months by deploying AMI. Such a finding is especially important in the light of the Californian energy crisis, which was the event triggering the deployment of smart meters. However, we are well aware that we do not control for the one-time peak load but focus on the overall electricity consumption.

In addition to IV (2), we specify IV (3) in order to analyze the temporal structure of the impact of smart meters on residential electricity consumption and to address the question of continuous effects. More precisely, we split up the post-treatment periods into three sub-periods and differentiate between heating and non-heating periods. Overall, we get similar results with respect to the influence of the climate factors CDD and HDD. Furthermore, the macroeconomic indicator is now significant at the 2% level and the respective estimate is slightly higher than in IV (1). As regards the treatment effect, we identify additional evidence for seasonality. The impact of AMI on residential electricity consumption is significant in non-heating periods only. Analyzing differences between the non-heating periods in all three post-treatment periods, we first find that the impact of AMI is insignificant in the first post-treatment period. We argue that this finding may be traced back to the introductory phase of deploying smart meters. In the first period, there are no observations available that reflect a state in which all households are able to access AMI. The aggregate effect in which we are interested may thus be derived instead from the last two post-treatment periods with AMI being fully deployed. From 2012 to 2015, we observe a relative reduction of residential electricity consumption that ranges from 6.1% to 6.4%. Compared to the literature, this is a little lower than the reductions gained from field experiments, as mentioned in Section 2.2. In addition, we find that this reduction potential related to AMI is rather continuous over time. We find no evidence that the impact under analysis comes to an abrupt end after some years. However, it may be worth considering an extended period of observation in future research. Finally, the temporal structure identified supports the hypothesis of causality. One may, in particular, assume that the methodology to isolate the impact of AMI from energy efficiency savings is imprecise. However, if that were the case, we would expect significant differences in electricity consumption before the deployment of smart meters was completed, as rather constant energy-efficiency savings were achieved from 2007 onwards (Figure 2.7 in Section 2.8.2). Rather to the contrary, we identify coefficients that strongly comply with the temporal development of the share of AMI.

2.7 Conclusion

One topic worth stressing in the light of climate targets and emission reduction goals focuses on energy conservation. Within the residential sector, the design of energy-saving programs has to account for unique behavioral aspects such as limited information and bounded rationality. Against this backdrop, we investigate how AMI is impacting on residential electricity consumption at the state level over time. Our identification strategy is based on a decision for statewide smart-meter deployment by the government of the state of California in 2005. As such, the treatment on which we are focusing is policy-driven and not based on a natural experiment or pilot program as predominantly studied in prior research. We are thus able to circumvent hindrances stemming from a lack of generality or Hawthorne effects. We aim at assessing the overall effectiveness of policy measures related to energy conservation. To the best of our knowledge, such a framework has not been studied so far.

We apply a two-stage empirical approach. First, we derive a control group as a weighted combination of US states using synthetic control methods. We find a combination of New York and New Mexico that reproduces the characteristics of California appropriately. We then descriptively depict the development of residential electricity consumption in California and its counterfactual, 'Synthetic California', and find an indication for a change in consumption after 2009 when introducing smart meters. In order to draw inferences regarding causality and significance, we apply a Difference-in-Differences estimation in a second step. Our results comprise two major findings, all of which contribute to the existing literature on energy conservation. First, we observe a significant reduction in electricity consumption induced through AMI in non-heating periods that essentially ranges from 6.1 to 6.4%. In contrast, there is no significant reduction in heating periods. Thereby we infer that reductions in electricity consumption induced by smart-meter deployment are linked to seasonality. Second, based on our empirical results, we find an indication that the impact of additional informational feedback on residential electricity consumption is continuous during the period analyzed. However, we are not able to draw a unique conclusion on persistence due to a lack of further periods of observation.

Summarizing our findings, we suggest that the Californian smart-meter deployment is effective in leveraging energy-saving potentials. We expect this finding to be mainly attributable to the additional informational feedback that smart meters provide. In essence, this information may be the cornerstone for altering consumption decisions that have been taken previously. Theory suggests that breaking the rationality boundaries improves decisions with respect to electricity savings. We find an indication that the impact of smart meters on consumption is continuous. However, for service utilities it may be worth implementing monitoring procedures in order to assess the long-term impact of smart meters. Furthermore, it may be worth considering supplementary informational feedback such as programs that focus on social comparisons. Finally, we find that the influence of AMI exhibits strong seasonal variations. Thus, it may be beneficial to consider complementary energy-saving measures.

2.8 Appendices

2.8.1 The General Functioning of the Advanced Metering Infrastructure

Figure 2.6 shows the simplified functioning of the AMI. As depicted, the AMI first enables the collection of consumption data differentiated by energy source. The consumption data are collected by a smart meter device that then processes and transmits the data via an electronic network to the end user. As such, the AMI could provide real-time consumption data with electricity price information, allowing users to curb electricity consumption if electricity prices are increasing. As information flows iteratively between the meter and the end user, we stress that such a system is a closed informational system allowing (potentially) for correction of consumption in a continuous manner (c.f. 'inductive process' from Section 2.2).

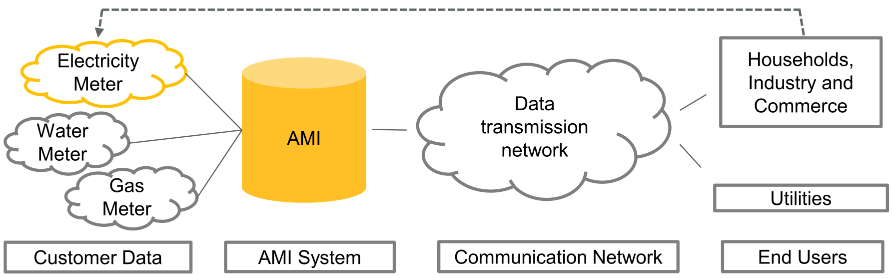


Figure 2.6: Simplified illustration of Advanced Meter Infrastructure (AMI) and its informational feedback

2.8.2 Development of Energy-Efficiency Savings in California

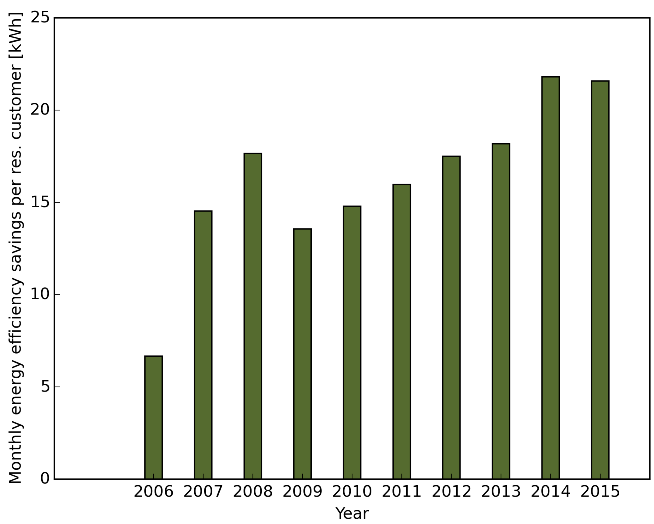


Figure 2.7: Development of energy-efficiency savings in California over time

Depicting the development of energy-efficiency saving estimates for California in Figure 2.7, we identify a significant and rather continuous impact of energy-saving measures beginning in 2007.

Table 2.5: Descriptive statistics: Differences in levels (California minus Synthetic California)

Variable	N	Mean	SD	Min	25%	Median	75%	Max
ΔCDD_m	168	0.01	0.05	-0.12	0.00	0.005	0.002	0.18
$\Delta Demand_m^{res,adj}$	168	-0.02	0.05	-0.20	-0.05	-0.02	0.00	0.11
ΔHDD_m	168	-0.22	0.22	-0.83	-0.41	-0.18	-0.01	0.09
$\Delta Price_m^{res}$	168	0.005	0.015	-0.079	-0.003	0.006	0.014	0.039
$\Delta Unemployment_m$	168	0.016	0.012	0.00	0.00	0.01	0.027	0.04
$\Delta Wage_m$	168	0.03	0.05	-0.14	0.01	0.04	0.06	0.10
ΔAMI_m	168	0.393	0.444	0.000	0.000	0.131	0.954	0.997

2.8.3 Descriptive Statistics: Difference-in-Differences Variables

2.8.4 Empirical Results: Weight Vector V for the Exogenous Variables

The weight vector V is presented in Table 2.6.

Table 2.6: Weights of the exogenous variables

Label	Weight
$CDD_{m,s}$	0.109
$Clothesdryer_{m,s}$	0.091
$Education_{m,s}$	0.008
$Elderlypeople_{m,s}$	0.010
$Floorspace_{m,s}$	0.071
$GDP_{m,s}$	0.119
$HDD_{m,s}$	0.263
$HeatingEquipment_{m,s}$	0.090
$MainHeating_{m,s}$	0.040
$Oven_{m,s}$	0.000
$Price_{m,s}^{res}$	0.042
$Refrigerators_{m,s}$	0.009
$Rooms_{m,s}$	0.083
$Unemployment_{m,s}$	0.000
$Wage_{m,s}$	0.149

2.8.5 PV Self-Consumption

In general, we calculate the quantity of self-consumed electricity generation as the difference between the total electricity generation by PV systems and the amount that is fed back into the grid. Monthly data with respect to the total electricity generation from renewable energy plants in the residential sector that is fed back into the grid are provided by the U.S. Energy Information Administration (EIA) (EIA, 2016b). Furthermore, the EIA provides data on the total capacity of PV systems installed on a residential level. However, there are no publicly available monthly data on the total PV electricity generation in households. This is due to the concept of net metering. Thus, we use a heuristic approach in order to derive PV electricity generation data. More precisely, our approach is based on the monthly average global horizontal irradiance, which is given in $\frac{kWh}{m^2 d}$ for each state by the National Renewable Energy Laboratory (NREL, 2016). The respective averages were derived from observations between 1998 and 2009 and do not vary across the years during our period of observation. We assume a typical efficiency of 13.2% for PV systems and a power density of $9m^2/kWp$. For illustration purposes, our calculation methodology is expressed in Equation 2.4.

$$\begin{aligned} SelfConsumption_{m,s}^{res,PV} = {} & InstalledCapacity_{m,s}^{res,PV} \cdot \overline{Irradiation}_{m,s}^{GHI} \\ & \cdot Days^{month} \cdot Efficiency^{PV} \cdot Area^{kWp} \\ & - FeedBack_{m,s}^{res,PV} \end{aligned} \tag{2.4}$$

2.8.6 Difference-in-Differences Estimation: Additional Evidence for Causality

By controlling for differences in electricity consumption apart from those related to AMI, we provide additional evidence for causality. In more detail, we include yearly time dummies in addition to the share of AMI to control for other impacting factors. All the respective time dummies yield insignificant coefficients as depicted in Table 2.7. One may claim, therefore, that we identify no impact on residential electricity consumption other than that induced through the deployment of smart meters.

2.8.7 Simplified Residential Schedules

Residential schedules from PG&E and SCE, as shown in Figure 2.8, may not fully reflect the wide range of tariff designs provided by the IOUs. As one example, we do not consider schedules from the CARE program where customers are eligible for reduced tariffs. Moreover, rate structures may be subject to changes over time. Our data were collected in the first quarter of 2016. However, the samples below illustrate tier and time-of-use schedules in a simplified way.

Table 2.7: IV Estimates for DiD estimation when controlling for yearly time dummies

	Dependent variable: $\Delta Demand_m^{res,adj}$
Explanatory variable	IV (1)
2003	-0.003
	(0.008)
2004	-0.009
	(0.009)
2005	0.009
	(0.021)
2006	0.011
	(0.011)
2007	-0.006
	(0.01)
2008	0.022
	(0.028)
2009	0.049
	(0.034)
2010	0.056
	(0.050)
2011	0.078
	(0.052)
2012	0.041
	(0.037)
2013	0.035
	(0.029)
2014	0.002
	(0.034)
ΔShare $AMI_{total,m}$	-0.035***
	(0.015)
$\Delta Price_m^{elec,res}$	-0.42
	(1.08)
ΔCDD_m	0.70***
	(0.09)
ΔHDD_m	0.03***
	(0.02)
$\Delta Unemploymentlvl_m$	-0.22
	(0.13)
$\Delta Wage_m$	0.07
	(0.06)
$observations$	167
R^2	0.45
F	23.8
p-value	0.00

Notes to Table 2.7: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. We use data from January 2002 until December 2015.

PG&E

Residential Schedule E-1

	Tier 1 Baseline	Tier 2 101-200% Baseline	Tier 3 >200% Baseline
$/kWh	0,18	0,24	0,40

Residential Time-of-Use Rate Schedule E-7

$/kWh Summer (Winter)	Tier 1 Baseline	Tier 2 101-200% Baseline	Tier 3 >200% Baseline
Peak	0,38 (0,16)	0,44 (0,22)	0,60 (0,38)
Off-Peak	0,13 (0,13)	0,19 (0,19)	0,35 (0,35)

SCE

Domestic Schedule D

	Tier 1 Baseline	Tier 2 101-200% Baseline	Tier 3 >200% Baseline
$/kWh	0,16	0,23	0,29

Domestic Time-of-Use Schedule D

$/kWh	Summer (Winter)
Peak	0,44 (0,33)
Off-Peak	0,28 (0,28)
Super-Off-Peak	0,13 (0,14)

Figure 2.8: Simplified schedules for tier and time-of-use in the residential sector

Generally, tiers may be subject to change in terms of numbers, territory, and pricing as well. Significant differences in the tariff structure for time-of-use schedules stem from the definitions of peak and off-peak. In the above example, PG&E defines peak hours as ranging from 12 am to 6 pm, whereas all other hours are declared off-peak. For SCE, peak hours are defined as ranging from 2 pm to 8 pm. The off-peak period begins at 8 am and lasts until 2 pm. Additionally, the period from 8 pm to 10 pm is considered as off-peak. The 'super off-peak' period comprises the hours between 10 pm and 8 am, while peak is replaced by off-peak at weekends.

3 Leveraging the Benefits of Integrating and Interacting Electric Vehicles and Distributed Energy Resources

In this paper, benefits resulting from the interaction of electric vehicles and photovoltaic generation units are analyzed. In doing so, a bottom-up approach is developed to simulate the driving and charging behavior of electric vehicles. An economic analysis is then performed to determine key findings for households with photovoltaic systems and electric vehicles: First, smart electric vehicle charging concepts may allow households to achieve higher cost-saving potentials by increasing their share of self-consumption by 59% compared to the case of uncontrolled charging. Second, adopting more of a system-oriented perspective, smart electric vehicle charging concepts could react to times of peak load and thereby reduce the average peak-load increase due to electric vehicles to 27%. According to these findings, it may be beneficial for policy makers to encourage peak-load minimizing charging behavior by introducing, e.g., load-sensitive tariff schemes. Technical challenges arising from the peak-load impact of electric vehicles may be regarded as being a coordination problem. Finally, the analysis shows that the potential of electric vehicles to counteract extremes of reverse power flows due to high photovoltaic electricity generation is limited.

3.1 Introduction

The power supply system is facing an ongoing transition from centralized to more decentralized electricity generation. The increasing share of renewable power plants as well as an increasing number of small-scale generation units change the requirements for the existing energy system. At the same time, an electrification of the transport sector is underway, meaning that in the coming years the number of electric vehicles will increase significantly(see ,e.g., The Federal Government of Germany (2009), The White House (2011)).

As more and more vehicles begin to run on electricity instead of gasoline and diesel, the absolute electricity consumption as well as the temporal load structure will be increasingly affected by vehicle charging behavior. Yet battery storage in electrical vehicles may be harnessed for additional storage applications and grid services. Put simply, electric vehicle storage may be used to smooth out the highly volatile feed-in profiles from distributed energy sources. Imagine, for example, an electric vehicle storage that is used in combination with a photovoltaic (PV) system. On the one hand, the vehicle may be directly charged using renewable energy generation. Smart charging could help to reduce or even avoid the need for electricity to be purchased from the grid and thereby allow for cost-saving potential to be leveraged, depending on the underlying regulatory framework. On the other hand, electric vehicle storage could provide additional flexibility to the power supply system (see, e.g., Kahlen and Ketter (2015), Kahlen et al. (2017)) or even be used in the context of demand-side management and grid-relieving consumption behavior given, e.g., bidirectional charging.

Yet the rapidly growing share of photovoltaics in the energy mix has resulted in an electricity generation profile that is increasingly dichotomous. In other words, there may potentially be a few hours with very high electricity generation followed by hours with zero electricity generation if the sun suddenly stops shining. A high simultaneity of photovoltaic systems feeding-in electricity at the same time stresses the grid. However, as demand and renewable electricity generation do not perfectly coincide, the application of storage technologies may be beneficial in alleviating such grid issues. Research has yet to be conducted as to whether electric vehicles could serve as sufficient buffer storage. Heterogeneity in driving profiles, for example, makes it harder to determine to what extent electric vehicles could be charged using photovoltaic systems. Therefore, the concurrence of photovoltaic electricity generation and electric vehicle charging demand should be simulated via modeling techniques that account for differences in, e.g., the individual driving behavior.

In this paper, the interaction between photovoltaic generation and electric vehicle charging behavior is analyzed extensively. More specifically, two key aspects are investigated: First, the cost-saving potential of electric vehicles in helping to achieve a high share of self-consumption on an individual household level is simulated. Second, a system-oriented perspective is assumed and the peak-load impact of electric vehicles is analyzed. Consequently, the peak-load reduction potential of electric vehicles is determined relative to different charging concepts and incentive schemes.

In order to investigate the concurrence of photovoltaic electricity generation and electric vehicle charging demand, a bottom-up approach is developed. The model simulates electric vehicle driving and charging behavior in power supply systems with high penetration rates of electric vehicles. In quantifying the potential of electric vehicles to increase the self-consumption of photovoltaic electricity generation, it can be found that uncontrolled electric vehicle charging would result in a share of self-consumption that is rather comparable to a case without any storage. Here, the charging demand and photovoltaic electricity generation would only partially coincide. However, smart charging strategies designed to follow the generation from renewable energy sources (RES) may allow for a share of self-consumption of about 59%, 57% more than in the case of uncontrolled charging. This share of self-consumption is even higher than in the case of a stationary battery storage, as charging demand triggers an increase in the overall residential electricity demand. By analyzing the impact of socio-demographic characteristics of potential electric vehicle owners, the most relevant drivers of the simulation results can be identified. The share of self-consumption tends to be especially high if the vehicle is used less often and for comparitively shorter trips. Above all, being connected to the residential power socket during midday hours yields higher shares of self-consumption. As a consequence, unemployed and retired electric vehicle owners tend to exhibit high shares of self-consumption.

On a system level, uncontrolled and RES-oriented charging may trigger a significant increase in the peak load of the household in terms of the electricity purchased from the grid. The results show that the electric charging behavior in these two cases increases the household's peak load on average by between 69% and 84% of the available charging capacity. However, tariff schemes that incentivize peak-load minimizing charging behavior, such as those with peak-load pricing, may be beneficial in reducing the maximum charging demand of electric vehicles. In fact, load-sensitive tariffs could encourage electric vehicle charging to shift away from times of peak load, thereby reducing the average peak-load increase due to electric vehicles to 27%. Nevertheless, the simulation indicates that only limited potential exists to counteract the peak of reverse power flows from photovoltaic electricity generation. Therefore, complementary measures such as charging opportunities in addition to residential charging and efficient congestion management, especially on a distribution grid level, should be considered.

The results presented in this article enable a better understanding regarding the impact of increasing shares of electric vehicles on the power supply systems of today. As such, it may be beneficial for policy makers to implement load-sensitive tariff schemes to avoid technical issues linked to a strongly increasing peak load in local distribution grids. On a household level, there may be a business case to couple photovoltaic electricity generation with electric vehicle charging demand.

The remainder of this paper is structured as follows: The main literature background is depicted in Section 3.2. The modeling approach developed to simulate the charging behavior of electric vehicles is then presented in Section 3.3. In Section 3.4, the main model results are shown and discussed in detail. Finally, Section 3.5 concludes.

3.2 Literature Background

The European Union has committed to reducing greenhouse gas emissions by 80-95% by 2050 compared to 1990 levels (European Commission, 2012). In order to achieve these targets, strong efforts have been made to support investments into distributed renewable electricity generation (European Commission, 2013). In Germany, the share of renewable electricity generation accounted for 27.8% of the overall gross electricity production in 2015 (German Federal Government, 2015). Yet high shares of highly volatile distributed electricity generation, such as wind and solar power, may challenge the power supply systems of today. Especially if distributed generation units are operated in an uncontrolled manner without reactive power management, the voltage stability may be jeopardized and an increasing voltage level may be identified (Lopes et al., 2007). Furthermore, as stated in Lopes et al. (2007), the power quality may be affected by harmonic distortions and variations of the transient voltage. In order to alleviate these challenges, smart grid infrastructure has been rolled out (Blumsack and Fernandez, 2012). Nevertheless, there is an increasing need for grid services in order to guarantee the balance of demand and supply at each point in time. From a rather market-oriented perspective, forecast uncertainty triggers an additional need for short-term trading opportunities with preferably short contract duration (see, e.g., Borggrefe and Neuhoff (2011), Knaut and Obermüller (2016), Knaut and Paschmann (2017b), von Roon and Wagner (2009)).

As the electricity generation from photovoltaic power plants only partially coincides with demand, storage technologies may be beneficial in order to shift the volatile electricity generation into periods with high demand (Toledo et al., 2010). Otherwise, the photovoltaic electricity generation may exceed demand in individual hours (Denholm and Margolis, 2007). The utilization of energy storage may therefore allow households to reduce or even avoid purchasing electricity from the grid.

As a consequence, cost savings potentials could be leveraged as the share of residential self-consumption increases (Kousksou et al., 2014). From a system point of view, one major issue regarding increased distributed generation is the high simultaneity of photovoltaic electricity generation being fed into local distribution grids. As a consequence, costly grid reinforcement may become necessary (dena, 2012). However, small-scale energy storage on a residential level may help to reduce these grid expansion needs (Zeh and Witzmann, 2014). Depending on the underlying regulatory framework, residential energy storage could be harnessed for grid services and thus may facilitate the large-scale integration of distributed generation units (Kousksou et al., 2014).

Although it is well known that small-scale electricity storage may facilitate the integration of residential photovoltaic generation units, a respective business case may be hard to find. High initial investment costs pose hindrances to investing into the respective energy storage systems (Nair and Garimella, 2010), especially for existing plants (Hoppmann et al., 2014). However, opportunities for electrification in the transportation sector have recently become more plentiful, with electric vehicles leading the path for decarbonization in the passenger vehicle segment. With a large-scale diffusion of electric vehicles to be expected within the next years, it is necessary to analyze whether vehicle storage may be harnessed for additional applications coupled with photovoltaic generation units. The literature so far provides detailed insights into the interaction of electric vehicles and smart grids as well as the major challenges that arise(see, e.g., Mwasilu et al. (2014), San Roman et al. (2011), Galus et al. (2013) and Garcia-Valle and Pecas Lopes (2013)). Yet, Richardson (2013) identifies a research gap surrounding the interaction of solar power and electric vehicles. More precisely, it is found that previous articles mainly focus on individual business cases lacking representativeness and generality. In Birnie (2009) and Li et al. (2009), for example, the authors analyze benefits from combining parking lots with solar photovoltaic panels. Furthermore, the respective business models for charging electric vehicles with photovoltaic electricity generation are discussed in Letendre (2009) and the technical feasibility of such concepts is the major topic in Gibson and Kelly (2010) and Kelly and Gibson (2011).

Complementing the existing literature, three major pillars surrounding the interaction of photovoltaic electricity generation and electric vehicles are addressed, all of which could support a beneficial integration of high numbers of electric vehicles into the power supply systems of today: First, the heterogeneity exhibited by electric vehicle users is analyzed with respect to its impact on the potential to couple phovotoltaic generation units and electric vehicle storage. The respective procedure allows to circumvent hindrances resulting from small samples and specific configurations. Second, detailed insights on major factors affecting the electric vehicle storage potential are developed. In doing so, the role of user characteristics is analyzed in more detail. Finally, adopting a system-oriented perspective, the peak-load impact of electric vehicles can be evaluated. Within the analyses, special focus is placed on the role of different charging concepts[1].

3.3 Methodology

A bottom-up simulation approach is applied to model the electric vehicle driving behavior and the resulting charging demand. The driving profiles that can be observed today[2] may differ significantly from those to be expected with an increasing penetration rate of electric vehicles. The modeling approach developed especially allows driving profiles to be mimiced in a world with high diffusion rates of electric vehicles.

In a first step, the driving behavior of lightweight electric vehicles in the private transportation sector is modeled by the use of statistical information. Based on the simulated driving characteristics, the resulting charging behavior can then be derived. In the following, the individual steps are explained in more detail.

3.3.1 Modeling the Driving Behavior of Electric Vehicle Owners

Simulating Electric Vehicle Owner Characteristics

The derivation of weekly driving profiles is based on a preceding simulation of electric vehicle driver characteristics, and it is assumed that the owner is the only user of the electric vehicle. Interactions with secondary vehicles are not considered. The general program sequence is depicted in Figure 3.1. Initially, the age and gender of the vehicle owner are simulated based on general demographic data combined with information on car owners in Germany (Endlein et al., 2015). Depending on both

[1] More details on charging procedures and the respective impact on the grid integration of electric vehicles are presented in Müller et al. (2017). However, the authors adopt a grid operator's perspective and lack scalability as well as representativeness of their results.

[2] For more details on early adopters, see, e.g., Rogers (2003) and Santini and Vyas (2012).

parameters, the respective employment status can be derived[3] (DESTATIS, 2017). If the simulated vehicle owner is employed, a random draw is conducted to derive the daily working time as well as to simulate whether the person works on weekends. Based on the previous characteristics, conclusions on the respective earnings may be drawn(DESTATIS, 2015).

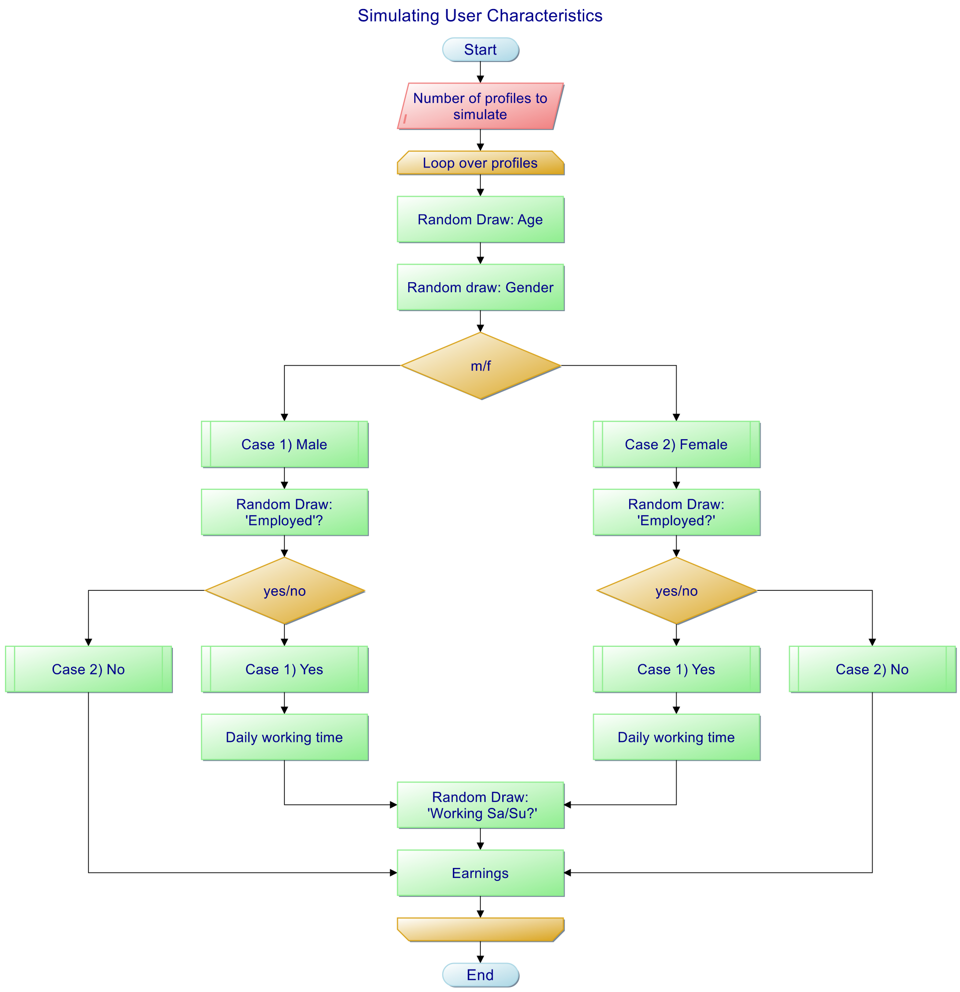


Figure 3.1: Program sequence simulating user characteristics

[3]Being employed may have a significant impact on the driving behavior if the electric vehicle is used to commute to work.

Simulating Weekly Driving Profiles

The simulation seeks to replicate recurrent typical driving patterns rather than considering one-time occasions such as holiday trips. General driver characteristics are linked to the resulting driving requirements based on statistical information referring to the usage of lightweight vehicles in the private transportation sector in Germany (Follmer et al., 2008). Unfortunately, the data does not differentiate between the driving behavior of electric vehicles and conventional cars. Yet, since this article considers rather high diffusion rates of electric vehicles, it is to be expected that electric vehicles will replace the driving patterns that are nowadays served by conventional cars. By linking driver characteristics and driving requirements, it is facilitated to account for a wide range of heterogeneity. The underlying driver characteristics are transferred into driving profiles that are, so to say, customized as statistical data is broken down into specific user groups such as students, unemployed and employed persons. Further differentiation is made with respect to the age and gender.

The program sequence is illustrated in Figure 3.2. First, the employment status is transferred into the overall driving schedule. In doing so, a probability-weighted draw is conducted to check whether the car is used to go to work. In order to link specific trips to general employment characteristics, an additional random draw is applied referring to the period in which the daily working day beings. The procedure is based on a probability density function for the start of the work day.

Having dealt with possible commutes to work, focus is now placed on residual daily trips apart from working purposes. In a first step, the average number of trips per day is derived depending on the underlying user characteristics. In doing so, the corresponding driving distances can be extracted from statistical data. Within a loop, these trips are then iteratively transferred into the overall driving schedule. There is an initial probability-weighted draw with respect to a particular purpose for each trip under consideration. In general, ten types of purposes are differentiated which are, inter alia, related to leisure activities such as doing sports, honorary positions and cultural activities. Furthermore, shopping, personal dealings and accompaniment are considered. It is accounted for the fact that the probability of specific purposes may vary depending on the day of the week. For each trip it is then simulated whether the electric vehicle is used in the context of the purpose under evaluation. A criterion is applied which is based on statistics referring to the total number of days on which a car is used per week as well as to the general share of trips that are performed using passenger cars. Both data sets are extracted from Follmer et al. (2008). If the current trip presupposes the use of the electric vehicle, it is to be simulated at which time the activity starts. In Follmer et al. (2008), a rich set of data is provided with respect to the starting times for the purposes considered. However, as the temporal resolution (hourly) does not fit the purpose of modeling quarter-hourly profiles, probability density functions were derived from discrete statistical values using least-squares methods. Thereby, a continuous representation of probabilities for each point in time was achieved. Finally, based on the starting point, the average activity duration, and the respective driving time, the trip is transferred into the weekly driving schedule.

Within the iterative procedure, previous trips are always accounted for to avoid overlaps. The iterative procedure is repeated until there are no residual trips left. As a result, a weekly driving schedule with 15-minute temporal resolution is finally acquired. The schedule provides information on the purposes of all trips, the driving duration, and distances.

3.3.2 Modeling the Charging Behavior of Electric Vehicles

The charging concepts considered within this paper comprise uncontrolled charging as well as charging strategies oriented to smart renewable energy sources (RES). Within the system analysis, a third charging concept is simulated to minimize the residential peak load. The individual concepts will be outlined in more detail below. The analysis is restricted to assuming that the only charging opportunity is provided by a residential power outlet or wallbox.

Individual households are considered which possess both a photovoltaic generation unit as well as an electric vehicle. The respective investment costs are neglected within the analysis and sunk costs are assumed as the focus of this article is placed on the interaction and the beneficial operation of both devices rather than on the general investment decision.[4] It is assumed that the installed capacity of the photovoltaic power plant equals 10 kW_{inst}, which is a typical parameterization for a residential consumer in Germany (BNetzA, 2017). The absolute value as well as the temporal structure of the photovoltaic electricity generation are derived from solar irradiation data for Germany. More precisely, the respective data refers to the test reference year provided by the German meteorological service[5] (DWD, 2011).

[4]Furthermore, the opportunity to increase the photovoltaic generation capacity is neglected. As residential customers today are rather less charged relative to their system capacity, peak-load reduction potentials do not result in additional photovoltaic generation capacity becoming more economic.

[5]The data refers to *'Region 5'* in Germany, which is, for example, close to Cologne.

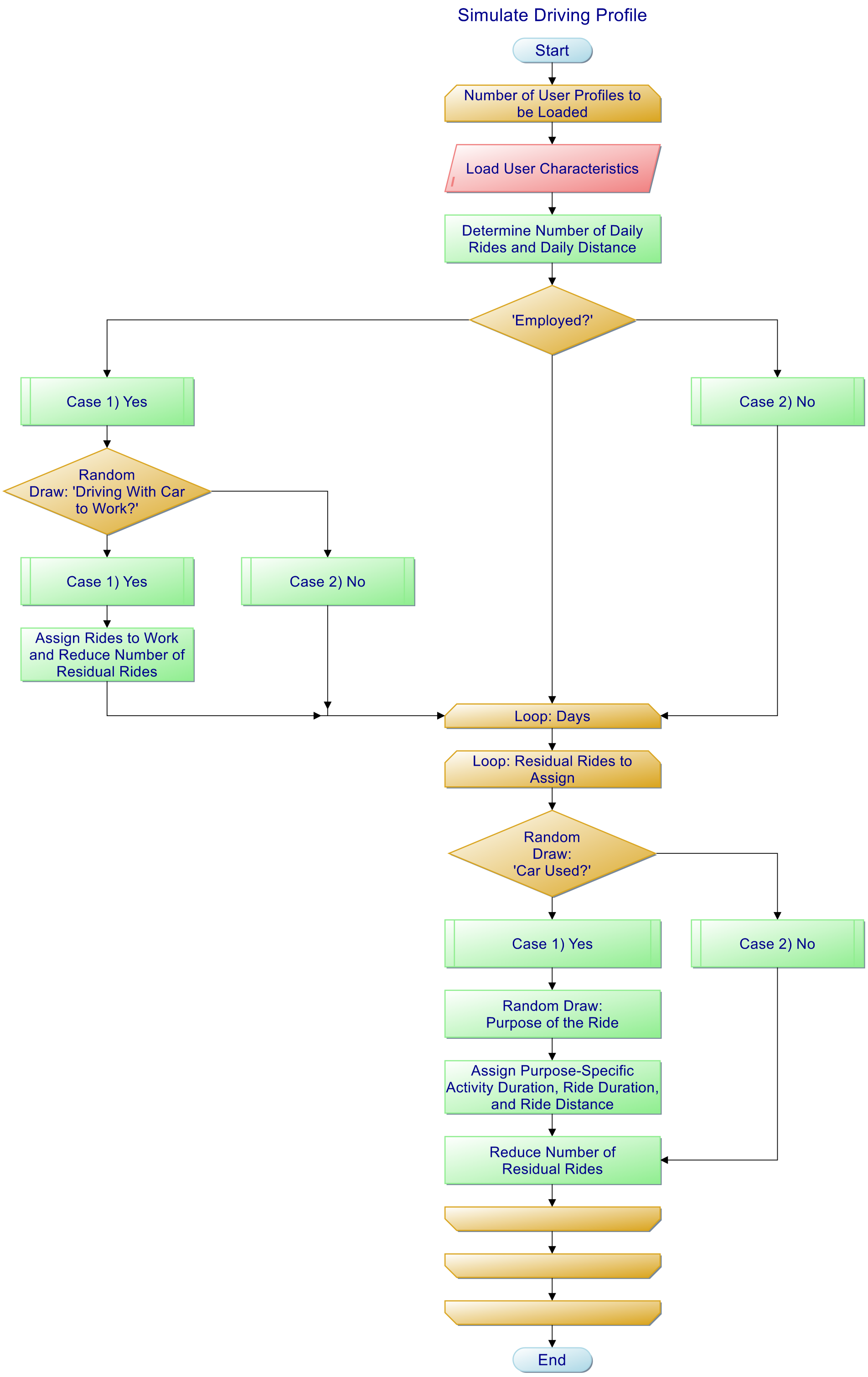


Figure 3.2: Program sequence simulating driving profile

The hourly data may be interpolated in order to obtain a time series with 15-minute temporal resolution. With respect to the conventional residential load, it is initially assumed that the yearly electricity consumption equals 4,500 kWh per household. The respective load structure is derived from reference load profiles for a four-person household(VDI, 2008). Within the scope of this paper, several sensitivity analyses are conducted considering different load profiles, which are attributable to specific socio-economic characteristics.

Households aim to minimize the overall costs of their electricity purchase from the grid. A constant residential electricity tariff is assumed equal to 31.5 ct/kWh. Photovoltaic electricity generation that is not used for residential appliances (self-consumption) but rather fed back into the grid is remunerated with a constant feed-in premium of 11.1 ct/kWh. As total costs are not within the scope of the analysis, the absolute values of the assumptions made do not impact the results. Only the relative cost structure plays a crucial role. More specifically, the assumptions refer to a case in which self-consumption is always preferred compared to electricity purchased from the grid. Regarding the electric vehicles, a storage capacity of 25 kWh and a specific energy usage of 20 kWh/100km are considered. Finally, perfect foresight with respect to load, driving needs and electricity generation of the photovoltaic generation unit is assumed.

Charging Concepts

The most relevant characteristics of the three charging concepts considered should be briefly discussed. First, the classification 'uncontrolled charging' refers to the case in which smart charging algorithms which allow to react to a selective load at specific points in time are not available. Instead, the vehicle is charged with the maximum available charging capacity until the storage limit is reached, whenever connected to a charging station. In the context of this paper, this is the single-phase maximum residential charging load available, equal to 3.7 kW.

In a second step, households are able to apply smart charging algorithms which support the cost optimization problem by enabling a profitable interaction of photovoltaic electricity generation and electric vehicle charging demand ('RES-oriented charging'). Simply put, the electric vehicle is primarily charged if the sun is shining. This concepts yields a linear optimization problem for each residential decision maker considered. A detailed overview on the optimization problem is presented in Section 3.6.1.

Assuming a system-oriented perspective, it is finally seeked to analyze the theoretical peak-load reduction potential without explicitly implementing the underlying charging procedure. The peak load ($peak\_load$) which is stressing the grid is therefore endogeneized and embodies the objective function which is to be minimized. In doing so, it is accounted for both the peak of electricity purchased from the grid as well as reverse power flows resulting from high amounts of photovoltaic electricity generation that are fed back into the grid. Therefore, the target function (3.1) is included:

$$\begin{aligned} &minimize\, z = peak\_load \\ &\qquad with\ \ 1)\ peak\_load \geq ev\_charging\_load\_grid_t + residential\_load_t \\ &\qquad\qquad\quad 2)\ peak\_load \geq pv\_to\_grid_t, \end{aligned} \tag{3.1}$$

where electricity purchased from the grid comprises both conventional residential load ($residential\_load_t$) as well as the electric vehicle charging load (ev_charging_ load_grid$_t$). Photovoltaic electricity generation that is fed back into the grid is embodied by the term $pv\_to\_grid_t$.

3.4 Results

In this section, benefits resulting from the interaction of electric vehicles and photovoltaic generation units are analyzed to determine key findings for households with photovoltaic systems and electric vehicles: First, the economic analysis addresses the research question whether smart electric vehicle charging concepts may allow households to achieve higher cost-saving potentials by increasing their share of self-consumption. Second, adopting more of a system-oriented perspective, the peak-load impact of electric vehicles as well as the capability of electric vehicles to contribute to a peak-load reduction is simulated. It is abstained from grid calculations due to the individual character of grid configurations. Yet, the economic results may form the basis for further technical analyses.

3.4.1 Self-Consumption

Reference Case

In analyzing the self-consumption potential of individual households, two benchmark cases are initially derived to provide a comparative basis for the further results. In this analysis, the first benchmark is considered as a household without any storage device. As a second benchmark, a stationary battery storage device with a 3 kW load limit and a loading capacity equal to 6.6 kWh is considered. The efficiency of the storage device is assumed to amount to 95%. The optimization results are depicted in Table 3.1.

Table 3.1: PV usage characteristics

Reference case simulation results

	Case a: No storage	Case b: Stationary storage
Self-Consumption (Mean)	27.5%	52.0%
Share Demand Provided by PV (Mean)	39.6%	55.3%

Supporting the general applicability of the modeling approach as well as the validity of the data, these results are well in line with those presented in the existing literature. In Luthander et al. (2015), the authors present an overview on simulation-based analyses with focus on the share of self-consumption. The respective results range between 25% and 38%. Furthermore, the authors state that households may achieve an even larger share of self-consumption, ranging between 45% and 65%, if the photovoltaic power plant is combined with a stationary battery storage.

The Impact of Electric Vehicles on the Residential Share of Self-Consumption

Uncontrolled Charging

To begin with, the impact of uncontrolled charging concepts is simulated for 1,000 different driving profiles. In doing so, the influence of electric vehicle charging processes on the general residential load structure can be evaluated. Figure 3.3[6] presents a boxplot for the average hourly residential electricity demand across all simulated profiles. The red marker shows the mean overall residential load including the charging load. The green boxes bound the 25% and 75% quantile thresholds. Additionally, the dashed lines mark the 10% and 90% thresholds. Finally, the lowest

[6] These are averages across all 15-minute time intervals within each hour over the whole year simulated.

line reflects the conventional residential electricity demand without electric vehicles. In order to offer an intuition for times of higher shares of self-consumption, the photovoltaic electricity generation in representative summer and winter weeks are also given[7].

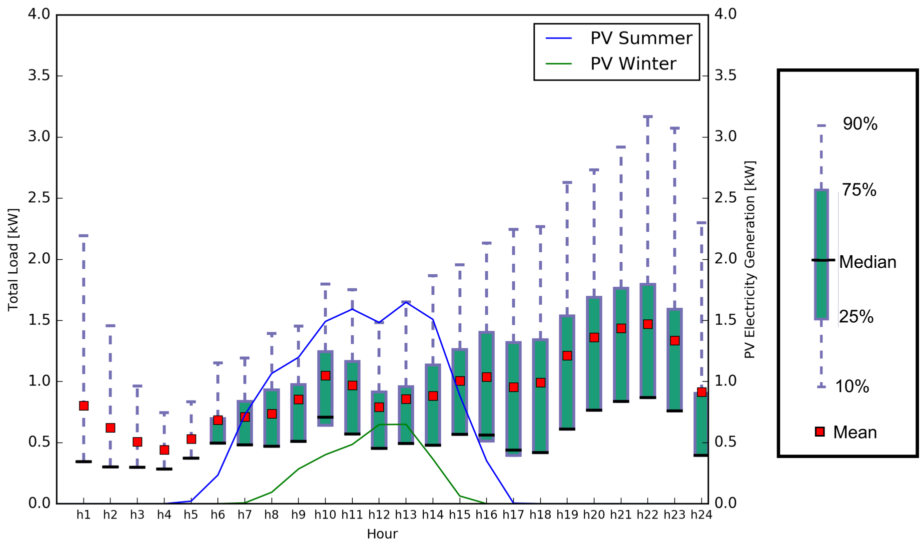


Figure 3.3: Impact of uncontrolled ev charging demand on residential load profiles compared to the pv generation (3.7 kW)

Uncontrolled charging concepts tend to trigger higher residential loads in the early evening hours. These results may be traced back to typical working times: When people get home from work, they plug in their electric vehicle and charge their storage device. As indicated in Figure 3.3, the charging load tends to coincide with high conventional residual loads, which could lead to an increased peak-load level (analyzed in more detail in Section 3.4.2). Furthermore, with regards to the self-consumption potentials, photovoltaic electricity generation and the electric vehicle charging load only partially coincide and therefore limit the amount of photovoltaic electricity that can be directly used to charge the vehicle.

To provide quantitative support for the previous observations, the numeric simulation results referring to both the share of self-consumption and the share of residential electricity demand that may be covered by photovoltaic electricity generation are shown in Table 3.2. The findings reveal that the average share of self-consumption only slightly increases (+30% relative increase; +8.7% absolute) compared to the benchmark without any storage device (Section 3.4.1). This is due to two reasons:

[7]These weeks are determined by a least-mean-squares procedure applied to the difference of residential load and photovoltaic electricity generation in each week of the year.

First, the electric vehicle storage is characterized by limited availability. Second, uncontrolled charging concepts allow for self-consumption potentials being leveraged solely coincidentally. However, the value distribution of the simulation results also reveals that, in individual cases, households may achieve a share of self-consumption that is even higher than in the case of the second benchmark with a stationary battery storage. Such a finding may be due to the fact that electric vehicles cause an overall increase in the residential electricity demand as a result of their charging needs. As such, the share of demand that is covered by photovoltaic electricity generation significantly decreases compared to the benchmark case without electric vehicles, even though self-consumption increases. In addition, it is worth stressing that there are also driving profiles which exhibit hardly any additional self-consumption potential. These driving profiles reveal a higher probability of vehicles not being located at the place of residence in the midday hours, e.g., due to work requirements.

Table 3.2: Results in the case of uncontrolled charging on a household level

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Self-Consumption	27.5%	28.1%	34.8%	50.2%	69.7%	36.2%	6.9%
Share Demand PV	12.4%	17.3%	29.4%	32.7%	40.3%	27.1%	5.3%

RES-Oriented Charging

Prior findings suggest that the application of smart charging algorithms that seek to interact charging processes and photovoltaic electricity generation may allow for additional cost-saving potentials to be leveraged. By achieving higher shares of self-consumption, households may be able to save on their electricity costs. Figure 3.4 depicts the impact of RES-oriented charging on the resulting residential demand profiles. It is observed that, compared to uncontrolled charging, the charging load tends to be shifted into midday periods in order to benefit from the interaction of photovoltaic electricity generation and charging demand. As a consequence, the average share of self-consumption, especially in the midday hours with high solar power availability, may increase significantly[8].

[8]As the objective function is meant to target high shares of self-consumption, households are indifferent when to charge their vehicle whenever the sun is not shining. Thus, an arbitrary prevalence of charging processes in night periods may be identified. In the real-world, however, residential customers may prefer charging their vehicle as early as possible due to range anxiety. Nonetheless, the temporal structure of charging processes in periods without photovoltaic electricity generation does not impact the following results. Detailed insights into the concurrence of photovoltaic electricity demand and electric vehicle charging demand in individual hours may be found in Section 3.6.4.

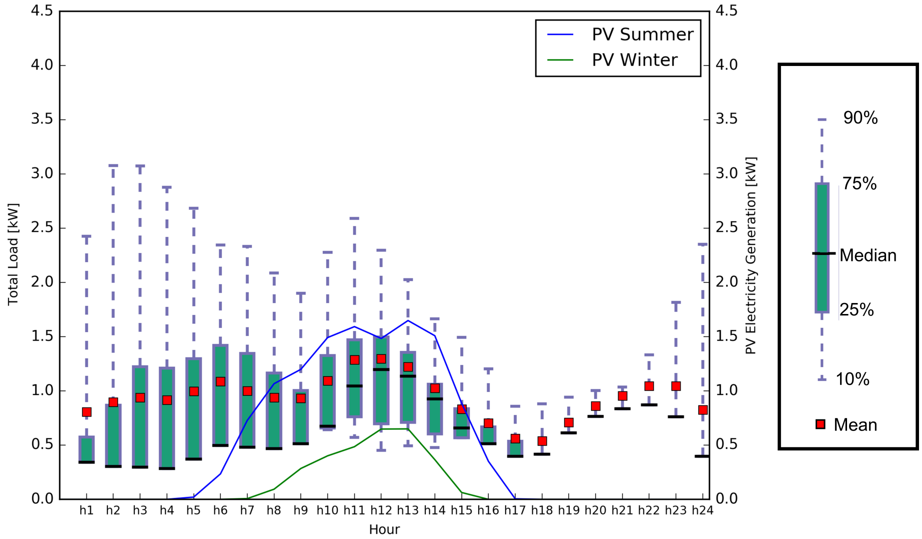


Figure 3.4: Impact of RES-oriented ev charging demand on residential load profiles compared to pv generation (3.7 kW)

The optimization model from Section 3.6.1 is applied yielding the results in Table 3.3. The mean share of self-consumption increases by 59% compared to the case of uncontrolled charging. Therefore, the share of self-consumption is on average about 11% higher than in the benchmark case with a stationary storage device but no electric vehicle. Overall, the mean self-consumption potential now amounts to 57.6%, which is at least double the achievable level without any storage device. Additional residential load that stems from charging processes may be scheduled such that directly charging the vehicle with photovoltaic electricity generation becomes feasible. At the same time the targeted driving behavior is not impacted. The results clearly emphasize the importance of appropriate charging algorithms to support the interaction of electric vehicles and photovoltaic generation units.

Table 3.3: Results in the case of RES-oriented charging on a household level

Simulation Results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Self-Consumption	29.9%	39.5%	59.3%	70.3%	79.0%	57.6%	9.5%
Share Demand PV	16.2%	22.2%	50.8%	59.1%	60.2%	44.8%	13.5%

Apart from the average values, the cost-saving potential of smart charging algorithms is found to strongly depend on the underlying driving behavior. If an individual driving profile is rather restrictive, the share of self-consumption may even correspond to the benchmark case without any storage device, i.e., a minimum share of self-consumption equal to 29.9%. Therefore, the impact of particular socio-demographic characteristics on the achievable share of self-consumption is analyzed in detail within the next subsection.

Decoding Socio-Demographic Impact Factors

Six different types of households are considered, each of which exhibits different socio-demographic characteristics. The analysis focuses on RES-oriented charging in order to analyze what types of households are more likely to benefit from shifting their charging demand relative to the feed-in profiles from photovoltaic power plants. The simulation procedure is based on the use of synthetic load profiles which are customized depending on the individual socio-economic characteristics. The profiles were generated with a load profile generator (Pflugradt, 2017) and taken from Feridarova (2015)[9]. The driving profiles which are assigned to the individual households furthermore comply with the underlying socio-economic characteristics. Details on the exact specifications are presented in Table 3.4.

Table 3.4: Socio-demographic characteristics

Case specification

Case	Household Characteristics	Electric Vehicle Driver	Consumption/a
Case 1	Couple (no child), age: both 38, with work	Male (38), employed	3,281 kWh
Case 2	Family (child), age: both parents 45, with work	Male (45), employed	3,455 kWh
Case 3	Family (child), age: both parents 42, unemployed	Female (42), unemployed	3,977 kWh
Case 4	Single (child), with work	Female (31), employed	2,616 kWh
Case 5	Couple, both retired	Male (72), retired	3,856 kWh
Case 6	Multigenerational home, working couple, 2 children, 2 seniors	Male (68), retired	8,475 kWh

Table 3.5: Results in the case of RES-oriented charging on a household level for different socio-economic specifications

Simulation results

Case	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Case 1	22.1%	30.1%	44.4%	59.0%	67.5%	43.6%	9.2%
Case 2	28.9%	34.3%	49.6%	63.6%	73.5%	49.7%	9.6%
Case 3	32.7%	37.5%	52.3%	67.9%	75.1%	52.7%	9.0%
Case 4	20.2%	29.6%	41.9%	59.4%	67.2%	42.7%	9.7%
Case 5	45.1%	49.2%	52.9%	65.0%	74.6%	54.3%	5.3%
Case 6	68.2%	73.1%	81.1%	84.0%	85.8%	79.9%	3.6%

Analyzing the share of self-consumption for the individual socio-demographic cases considered, as presented in Table 3.5, conclusions on the most relevant impact factors can be derived. For example, a relatively high share of self-consumption can

[9]The exact data is accessible via Waffenschmidt (2015).

be identified if the electric vehicle driver is retired (*Case 5* and *Case 6*). A retired couple, on average, may achieve a share of self-consumption of about 54.3%. The corresponding value distribution, what means the range between the minimum and maximum target figure in all simulated cases, is flat. The underlying reason for this result is most likely that retired drivers tend to exhibit relatively short mean daily driving distances. Statistics reveal that the group of retired people examined in this study has an average daily driving distance of 23 km, which is approximately a third of the driving distance for employed persons between 30 and 50 years old. In addition, the driving purposes of retired people tend to be related to activities with shorter duration. Within this analysis, shopping activities with an average residence time of 15 minutes constitute a significant share of all trips. As a consequence, the vehicle may be assumed being connected to the residential power outlet a large part of the midday hours if the sun is shining.

Apart from being connected to the residential power outlet during the midday hours, the corresponding charging demand is a further core issue. With respect to the retired drivers, for example, a rather small charging demand limits the potential to charge the electric vehicle with photovoltaic electricity generation. Overall, the highest share of self-consumption may be achieved if the vehicle is assigned to a multi-generational household since the conventional electricity demand in midday hours is rather high. In contrast, employed persons with long working hours exhibit a significantly lower self-consumption potential. Oftentimes, in this case, the vehicle is not connected to the residential charging station when the sun is shining. The socio-demographic groups that fall under this category are, for example, a family in which both parents work (*Case 1* and *Case 2*) as well as the employed single (*Case 4*). Here, the self-consumption potential is on average between 9% and 45% lower than for the retired group considered. On the other hand, there are households with barely any additional cost-saving potential related to electric vehicles, illustrated by the 5% quantile thresholds shown in the tables. These findings may be traced back to the concurrence of trips and photovoltaic electricity generation along each day. Finally, the average self-consumption potential of an unemployed family (*Case 3*) is similar to the one of the retired drivers considered. However, a wider distribution of the simulated share of self-consumption is observed. As a family on average exhibits a higher number of daily trips, the temporal structure is crucial.

3.4.2 Peak-Load Impact and Peak-Load Reduction Potential

The Impact of Different Charging Concepts

Uncontrolled Charging

In a first step, the peak load impact of electric vehicles is analyzed in the case of uncontrolled charging concepts. It is account for both the peak of residential load that is met by electricity purchased from the grid and the minimum of the residual load, equal to the total residential load minus the photovoltaic electricity generation. The simulation procedure is repeated iteratively for 1,000 driving profiles. The numeric results are illustrated in Table 3.6. As a benchmark, the values for the case without an electric vehicle ('No EV') are listed as well.

Table 3.6: Peak-load impact in the case of uncontrolled charging

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Load [kW]	4.47	4.47	5.42	5.96	5.96	5.34	0.46
Peak Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Load [kW]	-5.69	-5.69	-5.69	-5.62	-5.26	-5.67	0.04
Minimum Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

Uncontrolled charging on average drives the peak load to increase by 3.08 kW or 136%. Relative to the charging load, it may be concluded that electric vehicle charging processes under uncontrolled charging can yield a peak load increase amounting to 83% of the available vehicle charging capacity. The relative increase is robust to alternative charging capacities. In the case of 2.3 kW, for example, the average peak load increases by 78% of the charging capacity (see Section 3.6.2). Due to a frequency of charging processes in the early evening, when the conventional load tends to be very high, the peak load of residential appliances and electric vehicle charging tend to coincide. Even the minimum peak-load increase is equal to 60% of the vehicle charging capacity. However, the maximum amount of electricity fed back into the grid is only reduced to a negligible extent. There appears to be a need to analyze whether differing charging concepts may be suitable to reduce the peak-load impact identified as well as to reduce the peak of electricity fed back into the grid.

RES-Oriented Charging

As self-consumption of electricity directly reduces the amount of electricity fed back into the grid, is is now analyzed whether RES-oriented charging may help to avoid additional stress posed to the distribution grid. Detailed descriptive statistics on the simulation results are listed in Table 3.7.

Table 3.7: Results in the case of RES-oriented charging on a household level

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Load [kW]	2.26	2.26	5.19	5.85	5.96	4.80	1.23
Peak Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Load [kW]	-5.68	-5.68	-5.68	-5.42	-5.21	-5.64	0.09
Minimum Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

Although leveraging cost-saving potentials on an individual household level may be possible, applying RES-oriented charging algorithms on average may not significantly reduce the peak load of reverse power flows. On the other hand, the average peak load related to electricity purchased from the grid increases by 69% of the available charging capacity what is, in the case of 3.7 kW, 2.5 kW. Such peak-load impact is only slightly lower than in the case of uncontrolled charging. The question arises as to whether incentive schemes such as dynamic pricing and peak-load pricing may be suitable to leverage peak-load reduction potentials that are not encouraged by flat tariff schemes.

Peak-Load Minimizing Electricity Charging Behavior

The theoretical peak-load reduction potential that may be achieved when supporting peak-load minimizing behavior is now examined. In doing so, the peak load is endogenized within the target function, analogous to Section 3.3.2. The results are illustrated in Table 3.8.

Table 3.8: Results in the case of peak-load minimizing charging behavior

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Load [kW]	2.26	2.26	2.81	4.47	5.96	2.88	0.71
Peak Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Load [kW]	-5.69	-5.69	-5.62	-2.60	-1.68	-5.07	1.0
Minimum Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

It can be observed that the impact of electric vehicle charging processes on the resulting peak load of electricity purchased from the grid may be reduced to a large extent if incentivized in an appropriate way. In this case, the average peak load only increases by 0.62 kW or 27.4%. As the peak load in our simulation results occurs in the early evening hours, the vehicle tends to be connected to the domestic power outlet for a longer time in these periods. A driver may, for example, think about coming home from work and using the vehicle the next morning again. Therefore, significant load-shifting potential can be identified. The charging demand may be distributed along a certain time period such that the peak-load impact is rather small. Simply put, the impact of electric vehicle charging processes on the electricity load is a coordination problem.

Yet, the residential peak of negative power flows caused by photovoltaic electricity generation may only be reduced to a limited extent. The absolute peak load on average is merely reduced from 5.7 kW to approximately 5.1 kW, which is about 17% of the available charging load. Only 5% of all households are essentially able to significantly counteract the maximum of photovoltaic electricity generation which is fed back into the grid. Thus, our results yield an indication that, under the analyzed framework, the stress posed to the grid by simultaneous photovoltaic electricity generation may not be reduced by interacting electric vehicles with distributed energy sources. This result may be due to the fact that a significant share of vehicles tends to be parked away from the place of residence at noon when the solar power availability reaches its maximum, e.g., when people are at work. The results emphasize the importance of alternative charging opportunities, such as public charging stations, in order to leverage peak-load reduction potentials on a distribution grid level.

To deepen the understanding of these results, additional sensitivity analyses provide further insights. Regarding the impact of alternative charging capacities, the potential to minimize the peak-load impact of electric vehicles only slightly ($\leq$ 10%) changes under the assumption of a charging load equal to 2.3 kW or 11 kW (Section 3.6.3). This finding indicates significant load-shifting potential. Households are subject to a lack of coordination as well as zero incentives to alter their charging behavior. On the other hand, charging with high loads to meet the driving requirements is only a minor issue.

Furthermore, conclusions can be drawn regarding the potential impact of range anxiety. A scenario is considered in which electric vehicle drivers target a minimum storage level of 50% in each period (see Section 3.6.5). The results depict that the average peak load impact increases from 27% to 38%. However, it is imaginable that in a worst case scenario range anxiety may trigger a charging behavior that is comparable to uncontrolled charging. Thus, it may be beneficial to reduce hindrances that favor range anxiety such as providing sufficient charging infrastructure. Finally, the peak-load reduction potential is analyzed in terms of different socio-economic groups (see Section 3.6.6). The results reveal that the average peak-load increase due to electric vehicle charging demand ranges from 0% in the case of the retired group to 48% for the working couple. In the case of the retired group, the vehicle tends to sit at home for longer periods such that the load-shifting potential is significant. In the case of working people, the driver may wish to charge the vehicle in the early evening hours shortly after coming home from work in order to drive to a leisure activity directly afterwards. Consequently, the respective load-shifting potential may be limited.

3.5 Conclusion

In this paper, the interaction of electric vehicles and photovoltaic generation units is analyzed. Two key aspects are examined in detail: First, emphasis is placed on the cost-saving potential of electric vehicles which results from helping individual households to achieve a significantly higher share of self-consumption. Second, a system perspective is adopted and the impact of electric vehicles on the residential peak load is analyzed. Within the analyses, special focus is placed on the influence of different charging concepts.

From a methodological point of view, a bottom-up simulation approach is developed to model the electric vehicle driving and charging behavior. The model allows for scalability such that the charging behavior in future power supply systems with high diffusion rates of electric vehicles can be mimiced.

Regarding the simulation results, in the case of uncontrolled charging, there are limited opportunities to increase the share of self-consumption by charging the vehicle with photovoltaic electricity generation. The share of self-consumption is rather comparable to a case without any storage device and photovoltaic electricity generation and charging demand would only partially coincide. In contrast, smart charging strategies designed to shift charging demand into periods with high solar power availability may allow to achieve an average share of self-consumption which is about 59% higher than in the case of uncontrolled charging. Sophisticated charging concepts may hence allow for significant cost-saving potentials to be leveraged on an individual household level.

In a second part of the analysis, a system perspective is taken and the peak-load impact of electric vehicles is simulated in detail. Uncontrolled charging concepts as well as charging designs which support the concurrence of photovoltaic electricity generation and electric vehicle charging demand may cause an increase in the residential peak load ranging from 69% to 84% of the available charging capacity. In order to avoid the resulting technical issues, tariff schemes incentivizing peak-load minimizing charging behavior may be beneficial. In fact, such load-sensitive tariff schemes could encourage electric vehicle drivers to shift their charging demand away from peak-load times. Thereby, the average peak-load impact of electric vehicles could be decreased to 27%. These results are robust with respect to alternative charging capacities. However, the simulation results yield an indication that the potential to counteract the peak of reverse power flows from photovoltaic electricity generation is limited. Consequently, complementary charging opportunities, such as public charging stations, and an efficient congestion management could be crucial prerequisites to efficiently integrate electric vehicles into the power supply systems of today.

In future research it may be worth analyzing selected model assumptions in more detail. First, it could be expected that households exhibit a specific price elasticity with respect to their driving and charging behavior. However, such data has yet to be collected and evaluated. Second, only residential charging opportunities are considered within the scope of this article. Broadening the scope of the analyses to additional charging opportunities, such as charging at work, may provide valuable insights. Finally, the model could be extended to account for uncertainty.

3.6 Appendices

3.6.1 Model Description: Renewable Energy Resources (RES-)Oriented Charging

Table 3.9: Parameters of the optimization model

Model parameters	Dimension	Description
$binary\_connected_t$	$\in \{1,0\}$	Binary whether car is connected to charging station
$distance_t$	100km	Distance driven with the electric vehicle in a certain time period
$domestic\_charging\_limit$	kW	Maximum load for domestic charging
$efficiency\_charging$	%	Storage efficiency when charging and discharging
ev_energy_usage	kWh/100km	Specific energy usage of electric vehicles
$feed\_in\_premium$	EUR/kWh	Feed-in premium for photovoltaic electricity generation
min_load	%	Minimum load of electric vehicle storage
$pv\_instcap$	kW_{inst}	Installed capacity of the pv generation unit
$pv\_availability_t$	kW/kW_{inst}	Relative available pv electricity generation
$residential\_demand_t$	kW	Overall residential demand for domestic appliances
$storage\_capacity$	kWh	Storage capacity

The decision maker faces a cost minimization problem. Electricity purchased from the grid either for residential appliances or charging the vehicle is brought to account

Table 3.10: Variables of the optimization model

Model variables		
Abbreviation	Dimension	Description
$dummy\_charging_t$	kW	Dummy reflecting charging needs apart from residential charging
$ev\_charging\_load\_grid_t$	kW	Quarter-hourly vehicle charging load (grid)
$ev\_discharging_t$	kW	Discharging the electric vehicle for residential electricity consumption
$pv\_to\_grid_t$	kW	PV electricity generation fed back into the grid
$pv\_to\_consumption_t$	kW	PV electricity generation used for conventional residential load apart from charging
$pv\_to\_vehicle_t$	kW	PV electricity generation used for electric vehicle charging
$residential\_load\_gridt$	kW	Residential load besides vehicle charging that is served by electricity purchased from the grid

with the residential electricity price. Furthermore, photovoltaic electricity generation could be fed back into the grid being remunerated with a fixed feed-in premium (3.2).

$$\begin{aligned} minimize\, z = & el\_price_{res} \cdot \frac{1}{4} \cdot \left[ev\_charging\_load\_grid_t + residential\_load\_grid_t \right] \\ & - feed\_in\_premium \cdot \frac{1}{4} \cdot pv\_to\_grid_t \\ & + 1000 \cdot dummy\_charging_t \end{aligned} \tag{3.2}$$

Since only residential charging opportunities are considered, a dummy variable $dummy\_charging_t$ is included reflecting that if there are periods in which residential charging is not sufficient to meet the driving requirements, alternative charging stations are expected to be available. The respective costs are assumed to be very high.

In general, perfect foresight with respect to the photovoltaic electricity generation is assumed. The respective generation is non-dispatchable. However, three possible applications are considered which comprise directly charging the vehicle ($pv\_to\_vehicle$), serving residential electricity consumption ($pv\_to\_consumption$) and feeding back into the grid (pv_to_grid) (3.3).

$$pv\_to\_grid_t + pv\_to\_vehicle_t + pv\_to\_consumption_t = pv\_instcap \cdot pv\_availability_t \tag{3.3}$$

The electric vehicle is incorporated by implementing a respective vehicle storage equation. The storage level in each time period directly depends on its preceding level. Whenever the vehicle is used for driving purposes, the storage level is furthermore reduced by the respective energy usage which is depending on the specific energy consumption ev_energy_usage as well as the distance driven (3.4). Whenever the vehicle is located at home, it may be charged by the use of the domestic charging station ($ev\_charging\_load\_grid$) or directly from photovoltaic electricity generation (pv_to). In both cases, efficiency losses (95% efficiency) are considered. Finally, the vehicle storage may also be discharged in order to supply residential electricity consumption (discharging_load_ev_grid).

$$
\begin{aligned}
storage\_level_t = & storage\_level_{t-1} - ev\_energy\_usage \cdot distance_t \\
& + efficiency\_charging \cdot pv\_to\_vehicle_t \\
& + efficiency\_charging \cdot ev\_charging\_load\_grid_t \\
& - \frac{discharging\_ev_t}{efficiency\_charging}
\end{aligned}
\tag{3.4}
$$

The storage level may not exceed a certain threshold which is determined by the storage capacity (3.5)

$$storage\_level_t \leq storage\_capacity \tag{3.5}$$

The constraint (3.6) refers to a minimum storage level .

$$storage\_level_t \geq storage\_capacity \cdot min\_load \tag{3.6}$$

In the first time period the storage is assumed to be half-full. Furthermore, a restriction is included such that the storage level is at least half-full in the last period under consideration.

As outlined in the previous section, all charging and discharging opportunities are finally restricted by charging bounds which are illustrated in Equation (3.7), Equation (3.8) and Equation (3.9).

$$0 \leq ev\_charging\_load\_grid_t \leq domestic\_charging\_limit \cdot binary\_connected_t \tag{3.7}$$

$$0 \leq discharging\_ev_t \leq domestic\_charging\_limit \cdot binary\_connected_t \tag{3.8}$$

$$0 \leq pv\_to\_vehicle_t \leq domestic\_charging\_limit \cdot binary\_connected_t \tag{3.9}$$

The parameter $binary\_connected_t$ determines whether the vehicle is connected to the domestic power outlet in a specific period. Thus, it controls for whether the electric vehicle may be charged. The parameter is assigned in an upstream process depending on the position of the vehicle which is directly resulting from the underlying driving profile. It is assumed that the vehicle is connected to the charging opportunity whenever the vehicle is located at home.

Finally, each household faces a given demand profile. Demand may be supplied by electricity purchase from the grid, self-consumption of photovoltaic electricity generation or discharging the electric vehicle (3.10).

$$\begin{aligned} residential\_demand_t = & pv\_to\_consumption_t \\ & + residential\_load\_grid_t \\ & + ev\_discharging_t \cdot binary\_connected_t \end{aligned} \tag{3.10}$$

3.6.2 Sensitivity Analyses: The Impact of Charging Capacity in the Case of Uncontrolled Charging

The simulation results for the case of a charging capacity equal to 2.3 kW are presented in Table 3.11.

Table 3.11: Simulation results (2.3 kW)

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Residual Load [kW]	3.07	3.09	4.03	4.56	4.56	4.05	0.44
Peak Residual Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Residual Load [kW]	-5.69	-5.69	-5.69	-5.45	-5.24	-5.67	0.06
Minimum Residual Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

3.6.3 Sensitivity Analyses: The Impact of Charging Capacity in the Case of Peak-Load Minimizing Charging Behavior

The simulation results for a charging capacity of 2.3 kW are presented in Table 3.12 and in Table 3.13 in terms of a charging capacity equal to 11 kW.

Table 3.12: Simulation results (2.3 kW)

Simulation Results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Residual Load [kW]	2.26	2.26	2.81	3.33	4.56	2.67	0.37
Peak Residual Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Residual Load [kW]	-5.69	-5.69	-5.62	-2.6	-1.67	-5.06	1.0
Minimum Residual Load No EV [kW]	-5.67	-5.67	-5.67	-5.67	-5.67	-5.67	0.0

Table 3.13: Simulation results (11 kW)

Simulation Results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Residual Load [kW]	2.26	2.26	2.81	6.18	11.77	3.06	1.73
Peak Residual Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Residual Load [kW]	-5.69	-5.69	-5.62	-2.6	-1.67	-5.06	1.0
Minimum Residual Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

3.6.4 Analyzing the Temporal Structure of the Impact of Different Charging Concepts on the Share of Self-Consumption

Figure 3.5 and Figure 3.6 illustrate the coincidence index of photovoltaic electricity generation and the electric vehicle charging demand for each hour in a representative summer week. The coincidence index is determined as the hourly average share of self-consumption that is achieved accounting for conventional load as well as electric vehicle charging load.

First, Figure 3.5 refers to weekdays (Mo-Fr). The green line marks the photovoltaic electricity generation in a representative summer week.

On the other hand, Figure 3.6 depicts the respective results for the weekend.

3.6.5 The Impact of Range Anxiety on the Peak-Load Impact and the Peak-Load Reduction Potential of Electric Vehicles

Table 3.14: Results peak load minimizing charging behavior with 50% minimum load

Simulation Results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Load [kW]	2.26	2.26	2.81	4.60	5.96	3.12	0.94
Peak Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Load [kW]	-5.69	-5.69	-5.62	-2.60	-1.68	-5.07	1.0
Minimum Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

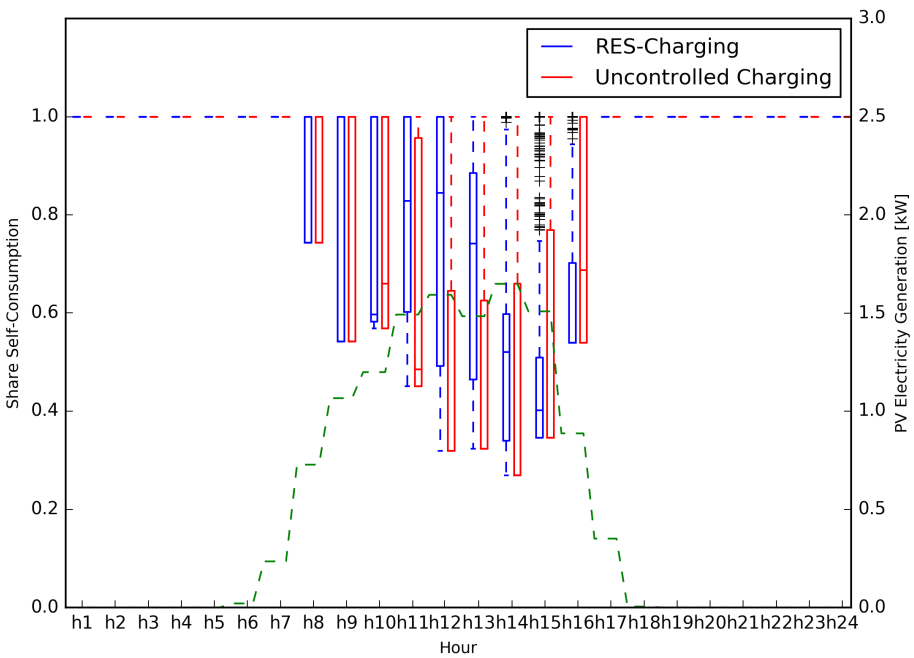


Figure 3.5: Coincidence index of photovoltaic electricity generation and electric vehicle charging demand in an exemplary summer week (weekdays)

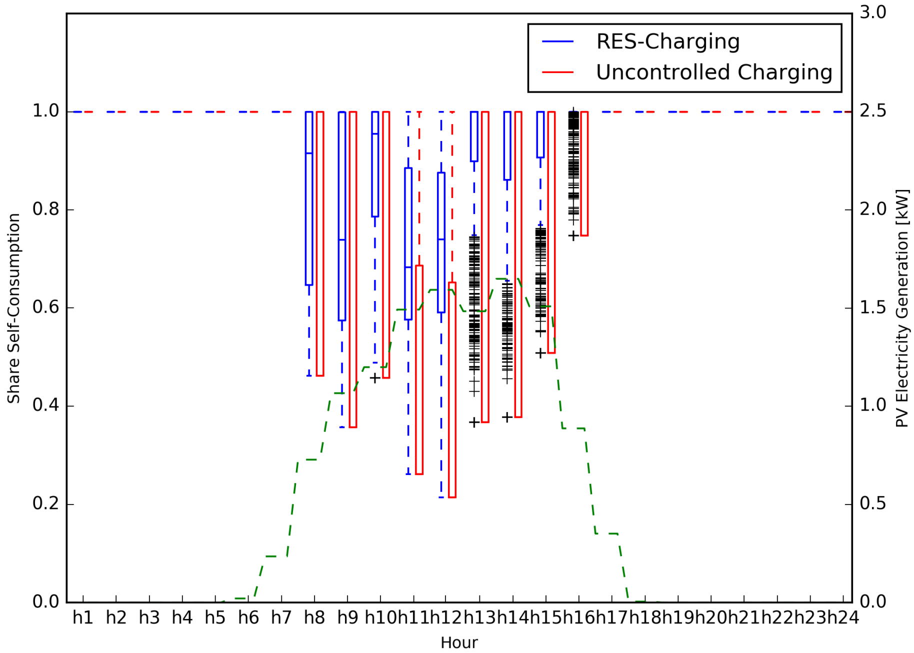


Figure 3.6: Coincidence index of photovoltaic electricity generation and electric vehicle charging demand in an exemplary summer week (weekend)

3.6.6 The Impact of Socio-Demographic Characteristics on the Peak-Load Impact and the Peak-Load Reduction Potential of Electric Vehicles

Table 3.15: Results peak load reduction potential for different socio-economic Specifications

Simulation Results								
Case	No EV	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Case1	8.31	8.31	8.31	8.31	9.6	11.2	8.5	0.58
Case2	4.99	5.85	7.2	7.4	7.4	8.6	7.4	0.3
Case3	5.2	5.3	5.75	7.3	7.4	7.4	6.97	.64
Case4	6.53	6.53	6.82	7.37	8.73	9.21	7.44	0.48
Case5	7.71	7.71	7.71	7.71	7.71	7.71	7.71	0.0
Case6	8.87	8.87	8.87	8.87	8.87	8.87	8.87	0.0

4 Price Volatility in Commodity Markets with Restricted Participation

In commodity markets, price volatility may increase significantly if the contract duration decreases. To gain insights into the underlying drivers, we analyze price volatility based on the example of German electricity markets. In doing so, we develop a theoretical model to reproduce the price formation in two markets with increasing product granularity and differing market participation. The model is then transferred into an empirical analysis revealing that the high price volatility in German short-term electricity markets is essentially triggered by restricted participation in the market with shorter contracts and by the high volatility of renewable supply and demand. We find yearly efficiency losses ranging from EUR 55 million to EUR 108 million that may be reduced if markets are coupled.

4.1 Introduction

Prices in commodity markets mostly reveal high price volatility, especially when contracts are settled close to physical delivery. This is particularly applicable to energy commodities such as oil, gas or electricity (Regnier, 2006). Price volatility embodies a crucial indicator of price uncertainty. As such, it directly impacts the decision rationale of market participants, for example, with respect to investment decisions and risk management. It is hence relevant to understand the fundamental drivers of price volatility. In this paper, we analyze price volatility based on the example of German electricity markets.

Electricity markets exhibit characteristics that favor high price volatility. First, demand and supply have to be balanced at each point in time. Second, there is only limited potential to store large quantities of energy, especially in the short run. The increasing intermittent electricity generation from renewable energies, which are prone to forecast uncertainty and highly fluctuating feed-in profiles, has increased the need of short-term trading opportunities. This lead to the establishment of new trading opportunities on the exchange where market participants are granted the option to trade products with shorter contract duration close to the point of physical delivery. In these markets, electricity is traded first with hourly and afterwards with quarter-hourly contract duration. Price variations between the respective products can be huge. Figure 4.1 illustrates the price volatility observed in the German day-ahead auction with hourly products and the intraday auction with quarter-hourly contracts on an exemplary day[1]. The Figure is puzzling as we observe an apparently systematic price pattern. Prices for quarter-hourly products fluctuate around the previously settled prices in the day-ahead auction and are much more volatile. This is especially surprising as there is essentially no informational update between both market settlements (3 hours time lag). In this article, we derive a fundamental explanatory approach to shed light on the underlying drivers of the price pattern identified. Thereby, valuable insights are provided on whether these price signals reflect an additional need for electricity market flexibility or even indicate an inefficient market design.

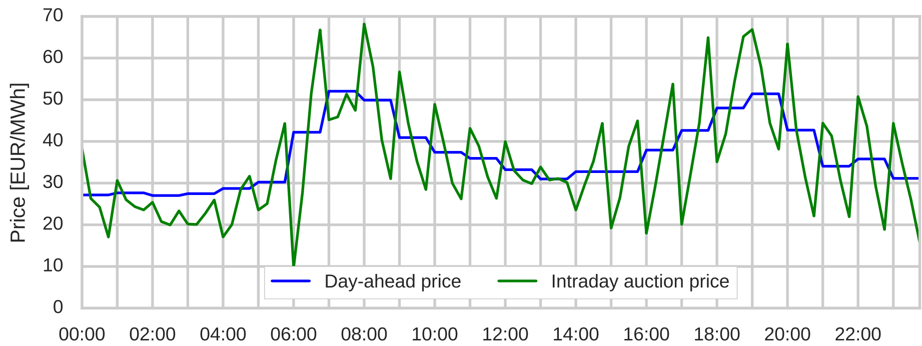


Figure 4.1: Exemplary price time series of German short-term electricity markets (2015-03-15)

The article at hand builds on the literature in the field of sequence economies which has emphasized the importance of sequential market organization in order to allocate commodities efficiently. A large and growing body of literature has investigated the interaction of sequential markets such as Green (1973) and Veit et al. (2006). Pindyck (2001) analyzes the short-term dynamics of commodity markets and Pindyck (2004) seeks to evaluate the impact of volatility on commodity prices. Closely related, Kawai (1983) derives a model in order to analyze the impact of future trading on spot market dynamics. Electricity markets represent a special subset of commodity markets and previous research into sequential electricity markets has focused on short-term trading opportunities on the exchange. In von Roon and

[1] This is the 13th of March 2015.

Wagner (2009) as well as Borggrefe and Neuhoff (2011), the authors outline the importance of functioning short-term markets in order to deal with the increasing share of renewable energies in the German power supply system and the corresponding forecast uncertainty. Ito and Reguant (2016) and Knaut and Obermüller (2016) focus on strategic behavior in sequential short-term electricity markets. Their main findings are that, under restricted market entry and imperfect competition, a systematic price premium analogous to Bernhardt and Scoones (1994) may occur in earlier market stages. Furthermore, there is a vast body of literature investigating the price formation in short-term electricity markets based on forecasting techniques such as time series analysis or artificial neural networks (Hagemann (2013), Karakatsani and Bunn (2008), Kiesel and Paraschiv (2015), Weron (2014)).

We analyze the price formation in sequential short-term electricity markets based on a fundamental approach. To the best of our knowledge, there is no prior literature with focus on the fundamental interaction of sequential markets with increasing product granularity and a differing supplier structure. It has to be stressed that we neglect the influence of uncertainty due to the rapid succession of both investigated markets. Quite the opposite: we derive a theoretical model illustrating that the high volatility of quarter-hourly intraday prices is mainly driven by two aspects. First, the main purpose of trading in the intraday auction is to balance sub-hourly variations of demand and renewable generation. Second, the gradient of the intraday auction supply curve is significantly higher than the respective gradient in the day-ahead auction. This is due to the finding of restricted market participation in the intraday auction. Consequently, we identify welfare losses (see also Hortaçsu and Puller (2008)). We conduct an empirical analysis of historical price data and validate our theoretical considerations. Furthermore, we quantify the relative increase of the supply curve gradients. Based on the respective estimates, we relate restricted participation in the intraday auction to welfare losses of EUR 108 million in 2015 and EUR 55 million in 2016. We expect these inefficiencies to increase with an augmented share of renewable energies, as they raise the need for sub-hourly trade. These losses could be reduced by the implementation of sub-hourly market coupling or by additional short-term electricity market flexibility, such as provided by storage technologies.

The article is structured as follows. First, we briefly depict the price formation in the markets of interest (Section 4.2). We then address our main research questions by conducting empirical analyses which are outlined in detail in Section 4.3. Finally, conclusions are drawn in Section 4.4.

4.2 Price Formation in the Day-Ahead and Intraday Auction

Electricity is traded sequentially at various points in time. Trading opportunities increase closer to the time of physical delivery and the contract duration for different products decreases. Figure 4.2 depicts the time line of trading for the German wholesale electricity markets. Trading on the exchange begins with futures which are traded for yearly, quarterly, monthly or weekly time intervals. These markets, in particular, address risk hedging purposes and financial trading. In contrast, in the day-ahead auction contracts for the physical delivery of electricity in specific hours are traded. The respective auction is held at noon (12:00), one day before physical delivery. Historically, the day-ahead price has been the most important reference price for all electricity market participants. The intraday auction was implemented at the end of 2014. It is settled at 3pm and first allows to trade 15-minute contracts. Market participants may hereby balance sub-hourly variations of supply and demand. Subsequently, trading is organized in a continuous intraday market. Here trade takes place on a first-come-first-serve basis via an open order book. Gate closure is 30 minutes before physical delivery and the respective products include hourly as well as 15-minute contracts. The continuous intraday market is mainly used to balance forecast errors based on updated information until delivery (Garnier and Madlener, 2014). The end of the intraday trading period marks the end of electricity trading in the wholesale markets.

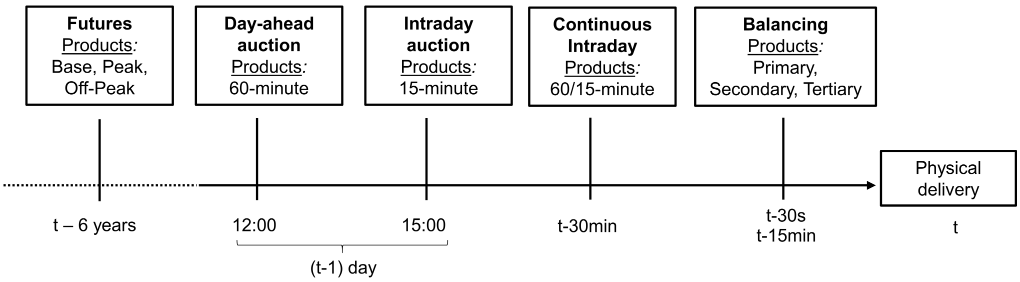


Figure 4.2: Sequence of trading in German wholesale electricity markets

In this article, we focus on the interaction of the day-ahead and intraday auction. Both markets are settled in rapid succession and differ in terms of product granularity (hourly/quarter-hourly). As the intraday auction is settled three hours after the day-ahead auction, we consider new information to be negligible between both market stages. We find empirical evidence for this hypothesis. In contrast, we suggest that the price relations under consideration are mainly driven by restricted participation in the intraday auction. As such, market participation in the intraday auction is restricted to a national level and cross-border trade is not permitted. Further details on the individual drivers of restricted participation in the intraday auction are presented in Knaut and Paschmann (2017a). Unlinke the intraday auction, the day-ahead auctions for hourly products are coupled within the internal European electricity market.

4.2.1 Theoretical Model

We use a stylized theoretical model in order to depict the market interaction as well as the price formation in the day-ahead and intraday auction. In general, we consider two types of suppliers (restricted and unrestricted) which interact in two markets (day-ahead and intraday auction) that differ in terms of product granularity and participation. Both types of suppliers participate in the market for hourly products, which embodies the day-ahead auction. In the second market (intraday auction), products are traded with shorter contract duration and only unrestricted suppliers are able to participate. More precisely, the common product that can be supplied by both types of suppliers is further split into n different sub-products in the second market which are identified by $\tau \in 1, 2, ...n$.

Consumers may demand a different quantity D_τ in each time interval τ. The demand is satisfied under perfect competition by restricted and unrestricted suppliers. Both types of suppliers operate generation plants with increasing marginal costs of generation. The unrestricted suppliers offer the quantity q_τ^u reflecting the production level in τ that results from supply in both markets. The respective total costs are $C_u(q_\tau^u)$. In contrast, the restricted players are not able to participate in the market with sub-hourly contracts. Their production level is fixed at a level of q^r along the n time intervals τ. The total production costs of the restricted players in time interval τ amount to $C_r(q^r)$. We assume simultaneous market settlement and consider information in both markets to be identical [2]. As the quantities of both types of suppliers are chosen under perfect competition, we formulate the following optimization problem. We minimize the total costs of electricity generation such that

[2]Supporting this assumption, several energy trading companies confirmed that there is no informational update between both market settlements.

supply meets demand:

$$\min z = \sum_{\tau} \left[C_u(q^u_\tau) + C_r(q^r) \right] \tag{4.1}$$

$$\text{s.t.} \qquad D_\tau = q^u_\tau + q^r \qquad \forall \tau. \tag{4.2}$$

In order to derive the optimal solution, we transform the problem into its Lagrangian representation by introducing the shadow prices p_τ:

$$\mathbb{L} = \sum_{\tau} \left[C_u(q^u_\tau) + C_r(q^r) + p_\tau (D_\tau - q^u_\tau - q^r) \right]. \tag{4.3}$$

We apply the corresponding Karush-Kuhn-Tucker conditions to derive necessary conditions which characterize the cost minimal solution. This procedure yields the optimal quantities q^u_τ and q^r as well as the respective shadow prices p_τ.

$$\frac{\partial \mathbb{L}}{\partial q^r} = \sum_{\tau} \left[C'_r(q^r) - p^*_\tau \right] = 0 \qquad \rightarrow C'_r(q^r) = \frac{\sum_\tau p^*_\tau}{n} \tag{4.4}$$

$$\frac{\partial \mathbb{L}}{\partial q^u_\tau} = C'_u(q^u_\tau) - p^*_\tau = 0 \qquad \rightarrow p^*_\tau = C'_u(q^u_\tau) \tag{4.5}$$

Due to illustration purposes, we apply the general model to a framework in which we assume linear marginal cost functions for both restricted and unrestricted suppliers. However, the following considerations could analogically be applied to different shapes of supply functions. Exemplary linear marginal cost functions are displayed in Figure 4.3. We formulate the respective marginal cost functions for both suppliers as

$$\text{Restricted suppliers:} \qquad C'_r(q^r) = a_0 + a^r_1 q^r \tag{4.6}$$

$$\text{Unrestricted suppliers:} \qquad C'_u(q^u_\tau) = a_0 + a^u_1 q^u_\tau, \tag{4.7}$$

where a_0 is the offset, a^r_1 is the gradient of the restricted supply curve and a^u_1 is the gradient of the unrestricted supply curve.[3] Adding both functions horizontally, the aggregate supply function is expressed by

$$C'(q) = a_0 + \frac{a^r_1 a^u_1}{a^r_1 + a^u_1} q = a_0 + a_1 q, \tag{4.8}$$

with $a_1 = \frac{a^r_1 a^u_1}{a^r_1 + a^u_1}$ being the gradient of the aggregate supply function. We solve the

[3] We assume the offset (a_0) of both marginal cost functions to be identical.

linear model to derive optimal quantities and prices.

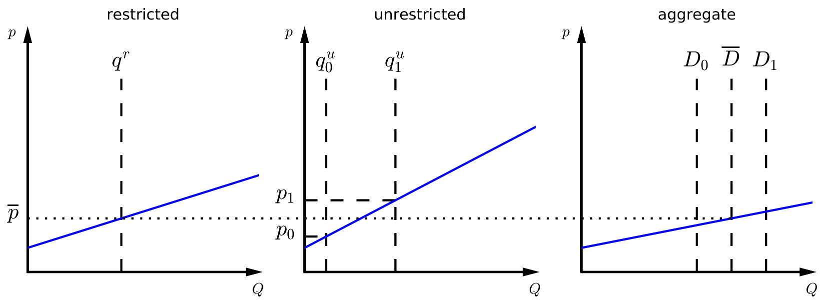


Figure 4.3: Marginal cost functions of restricted and unrestricted suppliers and the resulting aggregate marginal cost function

Proposition 4.1. *The average price ($\overline{p}$) is determined by the intersection of the aggregate supply function (including restricted as well as unrestricted suppliers) and the average demand ($\overline{D}$):*

$$\overline{p} = a_0 + a_1\overline{D}. \tag{4.9}$$

Proof. Based on the linear marginal cost functions, we plug in (4.5) and (4.2) into (4.4). As a result, we derive

$$a_0 + a_1^r q^{r*} = \frac{1}{n}\sum_{\tau} a_0 + a_1^u(D_\tau - q^{r*}). \tag{4.10}$$

Defining the average demand over n periods as $\overline{D} = \frac{\sum_\tau D_\tau}{n}$ and solving for q^{r*}, we obtain the quantity which is produced by the restricted suppliers according to Equation (4.11).

$$q^{r*} = \frac{\overline{D}a_1^u}{a_1^r + a_1^u} \tag{4.11}$$

Furthermore, based on (4.4), the average price $\overline{p} = \frac{\sum_\tau p_\tau}{n}$ is determined by the marginal generation costs of the restricted suppliers. If we plug in q^{r*}, this yields the average price which is the value of the aggregate marginal cost function in terms of the average demand ($\overline{D}$) in (4.9). $\square$

The average price $\overline{p}$ may be regarded as the settlement price in the first market where both types of suppliers are able to participate. In a next step, we derive the prices for each time period τ in the second market with unrestricted suppliers being exclusively permitted to participate.

Proposition 4.2. *The price in each time period τ depends on the difference between the average demand and the demand in each time period τ (D_τ) as well as the gradient of the unrestricted supply curve:*

$$p_\tau^* = a_0 + a_1\overline{D} + (D_\tau - \overline{D})a_1^u = \overline{p} + (D_\tau - \overline{D})a_1^u. \tag{4.12}$$

Proof. Based on the previously derived quantity q_r (Equation (4.11) and by the use of (4.2) and (4.5), we may define

$$p_\tau^* = a_0 - \frac{(a_1^u)^2}{a_1^r + a_1^u}\overline{D} + a_1^u D_\tau. \tag{4.13}$$

Here the first term is the offset of the aggregate supply function (a_0). Furthermore, we make use of the following equation

$$\frac{(a_1^u)^2}{a_1^r + a_1^u} = a_1^u - \frac{a_1^u a_1^r}{a_1^r + a_1^u} = a_1^u - a_1 \tag{4.14}$$

and introduce the gradient of the aggregate supply function (a_1). By inserting this term into (4.13) and reformulating, we obtain (4.12).

□

The optimal prices and quantities reflect the second-best market outcome, given that restricted suppliers are not able to change their production level across the time periods τ. If the restricted suppliers could adjust their production level in an unrestricted manner, the overall efficiency would increase.

Proposition 4.3. *The welfare loss due to restricted participation is expressed by*

$$\Delta W_\tau = W_\tau^{eff} - W_\tau^{ineff} = \frac{1}{2}(a_1^u - a_1)(\overline{D} - D_\tau)^2 \geq 0. \tag{4.15}$$

Proof. Adopting a rather theoretical perspective, one market with full market participation and a product granularity that complies with the actual variability of demand and renewable generation would yield the efficient market outcome. However, focusing on the role of market participation, we consider a state in which all market agents would participate in both markets as the efficiency benchmark. For comparative issues, we also derive the respective market outcome under restricted participation. This scenario is regarded as the inefficient case. Since the lack of sub-hourly market coupling may be considered being the most relevant driver of restricted participation in the German intraday auction (Knaut and Paschmann, 2017a), we assume the major share of the inefficiencies which result from restricted market participation to be avoidable by implementing full market coupling. Nevertheless, we are well aware that rather inevitable inefficiencies may not be ruled out entirely.[4]

As we assume a perfectly inelastic demand, we derive welfare implications based on cost considerations. Assuming restricted participation of some suppliers (inefficient case), the total costs to satisfy demand in period τ are expressed by

$$\begin{aligned} C^{ineff}(D_\tau) &= C_u(q^u_\tau) + C_r(q^r) \\ &= a_0(D_\tau - q^{r*}) + \frac{a^u_1}{2}(D_\tau - q^{r*})^2 + a_0 q^{r*} + \frac{a^r_1}{2}(q^{r*})^2. \end{aligned} \tag{4.16}$$

In contrast, the efficient market outcome would lead to costs that are determined by plugging in D_τ into the aggregate supply function (4.8).

$$C^{eff}(D_\tau) = a_0 D_\tau + \frac{a^r_1 a^u_1}{(a^r_1 + a^u_1)2}(D_\tau)^2. \tag{4.17}$$

Analyzing the difference between the costs in the efficient and inefficient cases and inserting the result extracted from Equation (4.11), we define the total deadweight loss according to Equation (4.18).

$$\begin{aligned} \Delta W_\tau &= C^{ineff}(D_\tau) - C^{eff}(D_\tau) \\ &= \frac{1}{2a^r_1 + 2a^u_1}\left(\overline{D}^2(a^u_1)^2 - 2\overline{D}(a^u_1)^2 D_\tau + (a^u_1)^2 D^2_\tau\right) \end{aligned} \tag{4.18}$$

By rewriting and simplifying, we finally obtain (4.15). □

Welfare losses from restricted participation essentially depend on (1) the difference between the gradient of the supply curve of unrestricted suppliers and the aggregate supply function($a^u_1 - a_1$), and (2) the volatility of demand ($\overline{D} - D_\tau$). We thus identify two major drivers of welfare losses and derive the following relations. First, if fewer suppliers participate in both markets, the gradient a^u_1 will increase causing higher welfare losses. Second, the higher the volatility of demand in the time periods τ, the higher the overall welfare losses.

[4]Introducing the intraday auction, albeit being inefficiently designed, yet may allow for an overall efficiency increase compared to a situation in which quarter-hourly trade on the exchange would not be possible at all (Neuhoff et al., 2016).

Consumers and suppliers are affected differently.

Proposition 4.4. *Compared to the case of unrestricted participation, restricted participation may trigger losses in consumer surplus and producer surplus of restricted suppliers. The producer surplus of unrestricted suppliers may increase.*

Proof. See Section 4.5.1. □

We find that consumer surplus is significantly reduced compared to the efficient outcome. The respective consumer losses are twice as high as the total welfare losses ($2\Delta W = 2\sum_{\tau=1}^{n} \Delta W_{\tau}$). In contrast, suppliers in total benefit from the inefficiencies under analysis. Taking a closer look at the distributional effects between restricted and unrestricted suppliers, we find that only unrestricted suppliers may gain a higher surplus if market participation is restricted. The surplus of restricted suppliers tends to be lower compared to the efficiency benchmark.

4.2.2 Application to Intraday Auction Prices

To apply the previous model to real-world electricity markets, it is first necessary to comment on crucial assumptions made within the stylized theoretical framework. In the context of electricity markets, demand is most commonly modeled in terms of the residual demand. Following this approach, we define the residual demand as total demand minus the electricity generation from wind and solar power ($D_t^{res} = D_t - Wind_t - Solar_t$). The electricity generation from renewable energies is subtracted from demand as it is characterized by short-term marginal costs close to zero. Consequently, the respective electricity generation corresponds to the availability of wind and solar power at each point in time. Furthermore, trade in electricity markets is performed by balancing responsible parties which are obliged to balance supply and demand within their balancing group in each time interval. Therefore, the residual demand is expected to drive the actual trade volumes in electricity spot markets. In addition, the existing literature provides evidence that demand in electricity markets can be assumed to be price inelastic, especially in the short run (Knaut and Paulus, 2016, Lijesen, 2007).

The residual demand is supplied by conventional generation units with increasing marginal costs depending on the underlying energy carrier. In our model, we assume the marginal cost functions to be linear. As far as the day-ahead auction is concerned, we clearly observe a rather linear relation of residual demand and the respective prices in historical data (for more details see Section 4.5.2). In contrast, the structure of the intraday auction supply curve may vary in individual hours as the underlying market dynamics are crucially depending on the day-ahead market clearing point. However, within the scope of this article, we use an aggregate explanatory approach that focuses on general price relations. We find empirical evidence that these relations can appropriately be modeled based on the assumption of linear relations. Further details are given in the empirical part of this article.

In general, the assumption of perfect competition may be regarded being valid in the context of the German day-ahead and intraday auction[5]. We additionally assume mean price equivalence between both markets following general economic theory (see, e.g., Delbaen and Schachermayer (1994), Harrison and Kreps (1979)). More precisely, necessary conditions to assume identical average price levels in the day-ahead and intraday auction, in particular, comprise the following aspects(Mercadal, 2015):

1. Both markets should be characterized by free market entry and perfect competition.
2. There are no transaction costs.
3. Prices should be transparent, unambiguous and accessible to each market participant.
4. Prices should refer to identical products and the respective products should be perfect substitutes.
5. Prices should be based on the same and latest available information.
6. The assumption of convexity is satisfied.

We comment on the latter four conditions in more detail. First, trade in both auctions is processed on the exchange and information transparency is given at each point in time. Sequential settlement implies that day-ahead prices embody reference prices for bids in the subsequent intraday auction. Furthermore, there is no discrimination of individual players. As a consequence, we claim that condition (3.) is met. Second, intraday auction products combined are a perfect substitute for day-ahead contracts. Additionally, contracts in both auctions refer to the physical delivery of electricity. As a consequence, we consider condition (4.) to be valid as well. As regards condition (5.), the day-ahead and intraday auction are settled in

[5] More details are presented within the findings of the Monitoring Report by the German regulator (BNetzA, 2015).

rapid succession and we have already commented on the assumption of identical information.

The assumption of convexity is subjected to a deeper examination in Paschmann (2017). As long as we are interested in aggregate price relations rather than modeling prices in individual hours, the simplification adopted within the scope of this paper is sufficient and suitable. To support this hypothesis, a descriptive analysis of historical price data reveals that the average difference between day-ahead and intraday auction prices is close to zero[6] within our period of observation (see Section 4.3.1). Consequently, we equate the hourly average price in Equation (4.12) and the hourly day-ahead auction price.

4.2.3 Illustrative Insights Derived From the Theoretical Model

Based on the theoretical model, we gain insights on price relations in sequential markets with differing product granularity and restricted market participation. In the context of the day-ahead and intraday auction, hourly products are traded simultaneously with quarter-hourly contracts ($\tau \in 1, 2, 3, 4$). The model suggests that the price formation in these markets may be illustrated according to Figure 4.4. The day-ahead supply curve reflects the aggregate marginal cost function ($C'(q)$) as market participation is considered to be unrestricted in the first market. Additionally, the gradient of the intraday auction supply curve equals the gradient of the supply curve of unrestricted producers (a_1^u). As we model intraday auction prices in terms of deviations from the corresponding day-ahead prices, we project the respective supply curve gradient on the day-ahead market clearing point as expressed by Equation (4.12). Differences between the quarter-hourly and hourly mean of the residual demand ($D_\tau - \overline{D}$) are now transferred into movements along the 15-minute supply curve and directly yield quarter-hourly intraday auction prices.

When we transfer these relations to subsequent hours as depicted in Figure 4.5, one can observe a distinct pattern of prices. Prices for quarter-hourly products fluctuate around the respective prices for hourly contracts as illustrated by the green price time series. If the market participation in the intraday auction was not restricted, the gradients of the supply curves would be equal in both markets and prices would follow the curve of the fictitious quarter-hourly residual demand level as marked in blue.

Following the illustration in Figure 4.5, we observe three typical price movements:

[6] In more detail, it is below transaction costs.

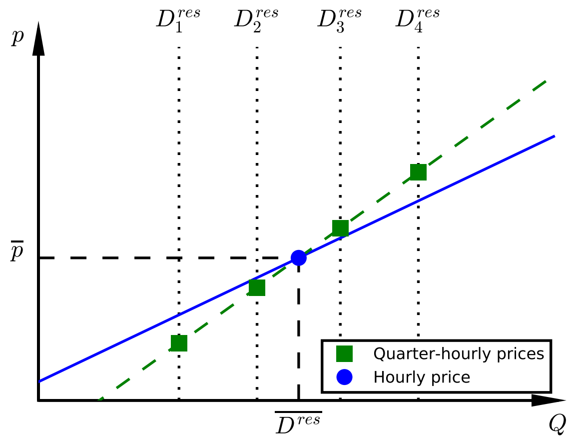


Figure 4.4: Supply and demand in the hourly and quarter-hourly market

First, for an increasing residual demand, prices in the first quarter-hour are significantly lower compared to the respective prices in the last 15-minute time interval of the hour. Second, with a decreasing demand profile, we identify reverse relations. Third, a flat demand profile leads to low price variation.

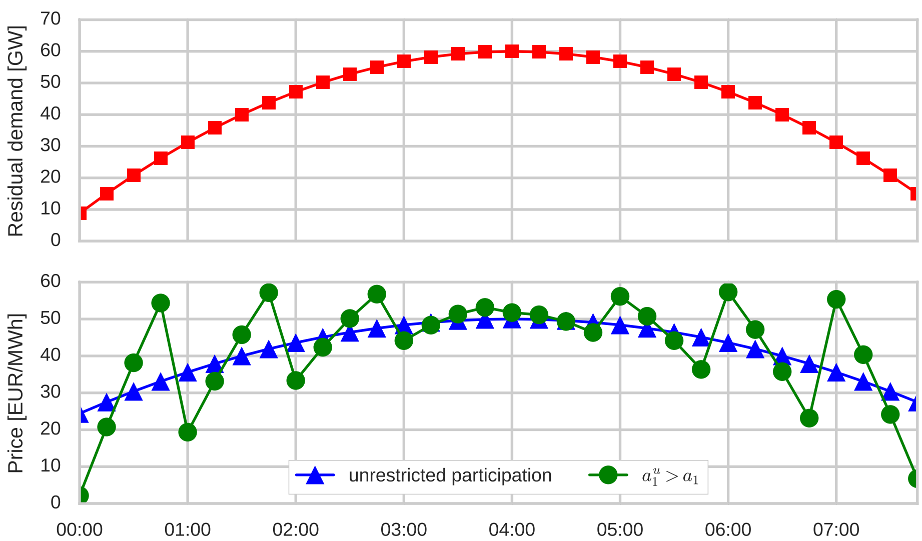


Figure 4.5: Exemplary residual demand profile and the resulting pattern for quarter-hourly product prices

So far, the model suggests that the high price volatility in sequential electricity markets is mainly driven by two aspects. First, quarter-hourly trade volumes are driven by sub-hourly deviations of the residual demand from the respective hourly means. Second, the high volatility of prices may stem from restricted participation. As a result, the gradient of the quarter-hourly supply curve increases compared to the respective hourly one ($a_1^u > a_1$).

4.3 Empirical Analysis

We first seek to test the applicability of the theoretical model with respect to historical data. We compare alternative specifications and conduct sensitivity analyses in order to support the hypothesis of robust and meaningful results. Second, we set up an empirical approach to quantify the impact of restricted participation on the price relations under analysis. Based on the respective results, we derive welfare implications. We choose an empirical approach rather than analyzing historical bid data due to two reasons. First, effects on the demand and supply side may be hard to aggregate when processing raw bid curve data. We target to account for both restricted participation on the supply side as well as a varying elasticity of wholesale demand (Knaut and Paulus, 2016). The approach adopted within this paper allows for estimating an aggregated coefficient. Second, the transformation of intraday auction bid data, which exhibits a pronounced stepped shape, into linear relations is a complex issue.

We analyze the time period from January 2015 until the end of April 2017. In the following, we first give a short overview on the respective data. We then describe our estimation approach and, finally, we depict and evaluate the empirical results.

4.3.1 Data

Due to the implementation of the intraday auction on December 9, 2014, the empirical analysis is based on data from January 2015 until the end of April 2017. A detailed list of all variables that are used is presented in Table 4.1. The table includes a brief explanation for each variable and the symbols which are used. Additionally, Table 4.2 provides information on the most relevant descriptive statistics.

Price data for German electricity markets was gathered from the European Power Exchange (EPEX SPOT SE, 2017b). In addition, we refer to the residual demand as a crucial expalantory variable which comprises two elements. First, we use forecasts

Table 4.1: List of variables and references

Symbol	Label	Variable	Measure	Reference
p_t^{ida}	id auction price	Uniform settlement price for a 15-minute product in the German intraday auction	EUR/MWh	EPEX SPOT SE (2017b)
p_t^{da}	day-ahead price	Hourly German day-ahead auction price	EUR/MWh	EPEX SPOT SE (2017b)
D_t^{res}; $\overline{D^{res}}_t$	residual demand 15; residual demand 60	Residual demand in a 15-minute period and the respective hourly mean	GW	EEX (2017a) , ENTSO-E (2017)
ΔD_t^{res}	residual demand deviation	Difference of the 15-minute residual demand and the respective hourly mean	GW	EEX (2017a) , ENTSO-E (2017)
$Solar_t$; $\overline{Solar}_t$	solar power 15 solar power 60	Day-ahead forecast for the 15-minute solar power and the respective hourly mean (ex-ante value)	GW	EEX (2017a)
$\Delta Solar_t$	solar power deviation	Difference of the 15-minute solar power and the respective hourly mean	GW	EEX (2017a)
$Wind_t$; $\overline{Wind}_t$	wind power 15 wind power 60	Day-ahead forecast for the 15-minute wind power and the respective hourly mean (ex-ante value)	GW	EEX (2017a)
$\Delta Wind_t$	wind power deviation	Difference of the 15-minute wind power and the respective hourly mean	GW	EEX (2017a)
D_t; $\overline{D}_t$	load 15; load 60	Realization of the 15-minute load and the respective hourly mean	GW	ENTSO-E (2017)
ΔD_t	load deviation	Difference of the 15-minute load and the respective hourly mean	GW	ENTSO-E (2017)

for the renewable generation which are provided by the four German transmission system operators (TSOs) who are in charge of the reliable operation of the power system (EEX, 2017a). We refer to forecasted values as trades in the day-ahead and intraday auction take place one day before physical delivery and are therefore based on expectations with regard to the electricity generation from wind and solar power plants.

Table 4.2: Descriptive Statistics (Units according to Table 4.1, N refers to the number of observations)

Variable	N	Mean	Std.Dev.	Min	25%	Median	75%	Max
id auction price	81,663	31.49	15.89	-164.48	22.62	30.57	39.92	464.37
day-ahead price	81,663	31.42	14.12	-130.09	23.94	30.29	38.11	163.52
residual demand 15	81,663	41.67	11.09	0.95	34.36	41.59	49.58	73.00
residual demand 60	81,663	41.67	11.06	1.86	34.39	41.60	49.56	72.39
residual demand deviation	81,663	0.00	0.81	-12.27	-0.39	0.00	0.38	8.82
solar power 15	81,663	3.92	6.06	0.00	0.00	0.07	6.19	27.18
solar power deviation	81,663	0.00	0.51	-5.97	-0.04	0.00	0.03	4.48
wind power 15	81,663	9.58	7.47	0.30	3.83	7.43	13.23	39.56
wind power deviation	81,663	0.00	0.18	-1.60	-0.07	0.00	0.07	1.50
load 15	81,663	55.17	10.00	25.04	46.81	54.85	64.09	78.09
load deviation	81,663	0.00	0.76	-13.29	-0.35	0.00	0.35	9.39

Second, the residual demand depends on the electricity demand. We use data on the system load since load is commonly considered as the best proxy for electricity demand[7]. We use data on the realized[8] load which is published on the transparency platform of the European Network of Transmission System Operators for Electricity (ENTSO-E, 2017).

4.3.2 Empirical Estimations

Empirical Framework

The general estimation procedure is expressed by Equation (4.19):

$$\begin{aligned} p_t &= X'_{i,t}\beta_i + \nu + \epsilon_t \\ \text{with } \epsilon_t &\sim N(0,\sigma^2), \end{aligned} \tag{4.19}$$

[7] More information on load can be found in Schumacher and Hirth (2015).

[8] Here we use the realization of load instead of forecasted values since our empirical analyses suggest that ex post data matches the day-ahead and intraday market dynamics with higher accuracy. In more detail, a descriptive analysis of forecasted load data reveals systematic forecast errors (see Figure 4.7 in Section 4.5.2). There is an indication that the available data does not reflect the actual level of information which market participants have. A frequency of forecast errors into one specific direction is not to be expected. Furthermore, the t-tests yield better results when using realized values indicating higher accuracy of data.

where p_t denotes the quarter-hourly price in period $t = 1, 2, ..., T$. $X'_{i,t}$ includes the exogenous variables of the model, namely the hourly day-ahead price as well as the quarter-hourly deviation of the residual demand from its respective hourly mean. We estimate the intercept ν assuming that the underlying supply function is time-invariant. The expression ϵ_t denotes the error term. In order to choose a suitable estimation methodology, we first test for basic assumptions that would be required if applying Ordinary Least Squares Regression techniques. These are standard assumptions such as predetermination or exogeneity of regressors and $p_t, X_{i,t}$ being ergodic and jointly stationary. Furthermore, ϵ should be independent and identically distributed.

Beginning with stationarity, we apply two different statistical tests for unit roots. The respective results of an Augmented Dickey Fuller test and a Phillips-Perron test are depicted in detail in Section 4.5.2. The statistics clearly reject the assumption of non-stationary processes. This is especially plausible because we only include data for a limited period of observation. The underlying drivers of demand and supply as well as prices in the markets of interest only changed slightly. These are, e.g., fuel prices and the share of renewable power plants. As such, a significant time trend is not identified.

We assume exogeneity of the residual demand due to two reasons. First, by using forecasted data for the electricity generation from wind and solar power, we guarantee exogeneity of two of the individual components by construction. Second, the realized load is a proxy for the overall electricity demand and does not reflect actual trade volumes in individual markets. We furthermore conduct a Durbin-Wu-Hausman test in order to control for the exogeneity of the day-ahead auction price. The test results reject the assumption of exogeneity [9] and we thus apply a Two-Stage Least Squares (2SLS) Regression Analysis including the hourly average of the residual demand as an instrument for the day-ahead price. The hourly residual demand is the main driver of demand in the day-ahead auction and thus is highly correlated with the respective prices ($Cov(X_{i,t}, Z_{i,t}) \neq 0$, where $Z_{i,t}$ is the instrument). This assumption is supported by the first stage regression results giving clear empirical evidence for a strong instrument. Additionally, we argue that our underlying estimation approach directly accounts for the exclusion restriction ($Cov(Z_{i,t}, \epsilon_t) = 0$). All information from the first market that can be expected to influence quarter-hourly product prices in the second market is incorporated by the inclusion of the day-ahead price. Finally, we use robust standard errors in order to account for heteroscedastic-

[9] In more detail, the test suggests that $Cov(X'_{i,t}, \epsilon_t) \neq 0$.

ity.

Empirical Validation

Based on Equation (4.12) and according to Section 4.3.2, we apply Equation (4.20) using a Two-Stage Least Squares Regression:

$$\begin{aligned} p_t^{ida} &= \beta_1 \cdot p_t^{da} + \beta_2 \cdot (D_t^{res} - \overline{D^{res}}_t) + \nu + \epsilon_t \\ &= \beta_1 \cdot p_t^{da} + a_1^u \cdot \Delta D_t^{res} + \nu + \epsilon_t. \end{aligned} \tag{4.20}$$

The difference between the residual demand on a quarter-hourly and hourly level (*residual demand deviation* (ΔD_t^{res})) is included as the main explanatory variable. Besides, the day-ahead auction price for hourly products (*day-ahead price* (p_t^{da})) is used. The coefficient β_2 can be interpreted as the gradient of the unrestricted supply curve (a_1^u).

The resulting estimates are depicted in column (1) of Table 4.3. As regards the regression technique, a comparison of the respective IV and OLS estimates is provided in Table 4.6 in Section 4.5.2. Furthermore, we show selected results for additional sensitivity analyses in columns (2) - (3). Besides these explicitly outlined results, additional insights and further sensitivity analyses are presented in Section 4.5.2.

The estimates in column (1) of Table 4.3 yield a first indication that our theoretical model is applicable to actual price relations observed in the intraday and day-ahead auction. The t-values of the coefficients validate that the difference in prices is influenced significantly by the deviation of the residual demand on a quarter-hourly level from its hourly mean. Furthermore, we observe an adjusted R^2 which is approximately 87% and thus a large part of the variance of intraday auction prices can be explained by the model. We identify sufficient explanatory power. Additionally, the estimated coefficient with respect to the day-ahead auction price is highly significant on a 1% level and close to one, as suggested by the model. Thus, the regression results confirm the validity of day-ahead auction prices as reference prices for intraday auction prices.

On closer examination, the estimated coefficient for *residual demand deviation* reveals a positive sign and embodies the gradient of the supply curve in the intraday auction. The positive coefficient implies that a positive deviation of the residual demand leads to an increase of quarter-hourly prices compared to the respective hourly day-ahead price. This is exactly what we would expect based on the theo-

Table 4.3: Regression estimates for intraday auction price data

	Dependent variable: id auction price ($p_{q,t}^{ida}$)		
Explanatory variable	IV (1)	IV (2)	IV (3)
day-ahead price (p_t^{da})	0.96***	0.96***	0.96***
	(0.002)	(0.002)	(0.002)
residual demand deviation (ΔD_t^{res})	7.65***		
	(0.08)		
positive residual demand deviation		7.69***	
		(0.17)	
negative residual demand deviation		7.60***	
		(0.14)	
wind power deviation ($\Delta Wind_t$)			-8.54***
			(0.14)
solar power deviation ($\Delta Solar_t$)			-9.64***
			(0.13)
load deviation (ΔD_t)			6.96***
			(0.07)
intercept (ν)	1.26***	1.24***	1.26***
	(0.08)	(0.10)	(0.08)
$observations$	81,663	81,663	81,663
adj. R^2	0.87	0.87	0.88
F	80,094	53,961	41,459

Notes to Table 4.3: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. The term *positive residual demand deviation* in column (2) is constructed using a dummy variable that equals one if the residual demand deviation is positive. The term *negative residual demand deviation* is constructed using a dummy variable that equals one if the residual demand deviation is negative. Due to the indication of endogeneity with respect to the variable *day-ahead price*, we use *residual demand deviation 60* as the instrumental variable and apply a 2SLS Regression. In general, we use data from January 2015 until the end of April 2017.

retical model. 15-minute excess demand requires additional electricity generation what means moving right on the merit order. The average absolute value for *residual demand deviation* amounts to 0.58 GW and can be transferred into an absolute price difference of 4.36 EUR/MWh. To sum up, we find evidence that restricted participation in combination with highly variable demand indeed triggers the high volatility of intraday auction prices observed.

In a next step, we aim at providing additional evidence for the applicability of the model to real-world data by conducting further sensitivity analyses and robustness tests. We follow the general idea of deriving hypotheses based on the underlying model and testing them empirically. First, the assumption of a linear supply curve would imply that linear relations are applicable to both positive as well as negative deviations of the residual demand. Distinguishing between positive and negative differences of the residual demand (*positive residual demand deviation* and *negative residual demand deviation*) in column (2) of Table 4.3, both coefficients differ only slightly on a 2% level. The coefficients are furthermore both significant on a 1% level. The overall picture hence strongly supports the hypothesis of a continuous linear relation between supply and prices in the intraday auction[10].

Second, we decompose the residual demand deviation into its three elements *wind power deviation*, *solar power deviation*, and *load deviation*. The respective estimates in column (3) reveal some variations (40%) as controlling for the isolated impact of solar power, for example, must be seen as referring to only a subset of hours. Since the individual drivers are only partially correlated, the respective subset is different for each driver and thus the estimated coefficients may vary. Besides absolute values, it is far more relevant to evaluate whether the signs of the coefficients match the underlying causal relations. A positive deviation of the renewable energy generation implies oversupply which in turn causes lower prices in the intraday auction. As to be expected, the respective coefficients are negative, whereas the coefficient for load is positive. Analyzing the value distribution of solar and wind power as well as load, it is revealed that the volatility of intraday auction prices is mainly driven by the quarter-hourly variation of load. However, very high differences in prices may also result from a high gradient of solar power generation. To sum up, the results presented in this section suggest model validity and robustness of our findings.

[10]In addition, we tested for alternative specifications such as assuming quadratic relations but found no empirical evidence for higher accuracy.

Econometric Analysis of the Supply Curve Gradients

As a further part of the empirical analysis, we conduct a comparative analysis for the gradients of the supply curves in the day-ahead and intraday auction. We aim at approximating welfare implications. Against this backdrop, the day-ahead spot market price in Equation (4.20) is substituted by the hourly residual demand according to Equation (4.9). The purpose is to estimate a_1 as a proxy for the gradient of the aggregate supply curve. We thus obtain Equation (4.21):

$$p_t^{ida} = a_1 \cdot \overline{D^{res}}_t + a_1^u \cdot \Delta D_t^{res} + \xi + \epsilon_t, \tag{4.21}$$

where the constant intercept of the hourly supply curve is shifted into the constant ξ and the error-term of the estimation equation. The argument for assuming exogeneity is analogous to the reasoning in Section 4.3.2. Based on these considerations and as the day-ahead price is no longer included, we apply an Ordinary Least Squares Regression using robust standard errors. The empirical results indicate explanatory power and a significant impact of the respective explanatory variables. We observe a slight decrease of the adjusted R^2 due to a loss of information by using a less informative variable ($\overline{D^{res}}_t$ instead of p_t^{da}). Furthermore, we are now able to comment on the average difference of the aggregate and unrestricted supply curve by comparing the coefficients a_1 and a_1^u. The estimation results are depicted in Table 4.4. According to the results presented in column (1), the estimated coefficient for the impact of the quarter-hourly residual demand deviation (*residual demand deviation*) on intraday auction prices is more than seven times higher than the influence of the hourly residual demand (*residual demand 60*) on the proxy for day-ahead spot prices. We find clear evidence for restricted participation. Furthermore, we evaluate the structural development of the respective relations in column (2). One could assume that the impact of restricted participation may fade out after the introductory phase of the intraday auction. Even though the difference between the estimated proxies for the gradients of the day-ahead and intraday supply curves decreases from factor 8.5 in 2015 to factor 6.5 in 2016, the first four months of 2017 yield an indication that the impact of restricted participation on the intraday auction price volatility is again exacerbated in 2017 (Knaut and Paschmann, 2017a). Thus, our results suggest that the welfare losses identified are persistent rather than exhibiting a short-term nature. Finally, we aim at shedding light on seasonal aspects. The estimates in column (3) depict that the impact of restricted participation in the intraday auction on the resulting price volatility is slightly more pronounced (+13%)

in winter periods. This result may be traced back to a slightly steeper supply curve in winter periods, at least on average.

Table 4.4: Regression estimates for intraday auction price data (2)

	Dependent variable: id auction price ($p_{q,t}^{ida}$)		
Explanatory variable	OLS (1)	OLS (2)	OLS (3)
hourly residual demand ($D_{h,t}^{res}$)	1.03***		
	(0.005)		
residual demand deviation ($\Delta D_{q-h,t}^{res}$)	7.65***		
	(0.08)		
hourly residual demand (2015)		1.03***	
		(0.004)	
residual demand deviation (2015)		8.75***	
		(0.14)	
hourly residual demand (2016)		0.95***	
		(0.004)	
residual demand deviation (2016)		6.21***	
		(0.10)	
hourly residual demand (2017)		1.16***	
		(0.006)	
residual demand deviation (2017)		8.49***	
		(0.22)	
hourly residual demand (Summer)			0.99***
			(0.004)
residual demand deviation (Summer)			6.95***
			(0.09)
hourly residual demand (Winter)			1.03***
			(0.005)
residual demand deviation (Winter)			8.20***
			(0.13)
intercept (ξ)	-10.26 ***	-10.68***	-10.58***
	(0.19)	(0.18)	(0.18)
$observations$	81,663	81,663	81,663
adj. R^2	0.64	0.70	0.66
F	26,273	11,366	13,710

Notes to Table 4.4: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. In OLS (2) we interact the explanatory variables with yearly time dummies. In OLS (3) we determine summer periods ranging from April until the end of September. We use data from January 2015 until the end of April 2017.

Based on the estimates for the gradients of the aggregate and unrestricted supply curve (a_1 and a_1^u), we are now able to derive a proxy for the welfare losses. The respective procedure is expressed by Equation (4.15). The total welfare losses from restricted participation decreased from EUR 108 million in 2015 to EUR 55 million in 2016. This reduction may be traced back to a decreasing difference between the gradients of the supply curves. However, the respective results for the first four months in 2017 indicate a renewed rise of the welfare losses. When analyzing the distributional effects in detail, the reduction of the consumer surplus ranges from EUR 110 million in 2016 to EUR 216 million in 2015. On the supply side, the surplus of unrestricted producers is increased by EUR 120 million in 2015 and EUR 64 million in 2016 and surplus of restricted suppliers is reduced by EUR 12 million in 2015 and EUR 9 million in 2016 compared to the efficiency benchmark.

We note that these calculations do not include actual costs of market entry and thus have to be regarded as an upper bound for the welfare and distributional effects linked to restricted participation. As the lack of market coupling is considered as the most relevant driver of restricted participation (Knaut and Paschmann, 2017a), we may regard German power plant operators as the unrestricted suppliers. In this case, the German suppliers profit from non-coupled markets. In contrast, power plant operators in neighboring countries and German consumers suffer from the lack of market coupling. As the implementation of cross-border trade of 15-minute and even shorter contracts is planned for 2017 (Cross-Border Intraday Market Project $XBID$), welfare losses may decrease in the future. However, ensuring sufficient cross-border intraday capacities as well as an efficient coupling mechanism are crucial pillars that should be urged by policy makers.

4.4 Conclusion

This article is motivated through the identification of strongly increasing price volatility in German electricity markets with quarter-hourly products. To shed light on the underlying drivers, we develop a theoretical model illustrating the price formation in sequential commodity markets based on a fundamental approach. In doing so, we consider two markets which are characterized by increasing product granularity and a change in the set of suppliers along the sequential market settlements. The model is then applied to the German day-ahead and intraday auction which allow for trading hourly and quarter-hourly products respectively. We find that the high quarter-hourly price volatility in real-world data is essentially triggered by two factors. First are the high variability of demand and renewable electricity generation. Second, we identify that the supply curve in the intraday auction inclines compared to the day-ahead auction. Market participation in the intraday auction is restricted. Based on our estimates, we relate restricted participation to welfare losses that approximated EUR 108 million in 2015 and EUR 55 million in 2016.

The main findings presented within the scope of this article provide a better understanding of sequential markets with both a differing product granularity and a change in the underlying supplier structure. The identification of inefficiencies is indispensable to derive appropriate countermeasures in order to improve the current electricity spot market design. This is especially relevant as the increasing share of renewable energies will trigger an increasing relevance of sub-hourly short-term trade. Thus, efficiency losses may even increase if the short-term power system flexibility is not increasing accordingly. Based on our findings, policy makers should tackle issues related to intraday market participation. Above all, the implementation of market coupling on a sub-hourly level may be a first step towards a more efficient market outcome. Since this is, at least partially, addressed by the Cross-Border Intraday Market Project, which is supposed to be implemented within the course of this year, the respective go live should be promoted. Furthermore, the provision of sufficient cross-border intraday capacity as well as the implementation of an efficient coupling mechanism should be urged.

On a more micro-economic level, a fundamental understanding of price relations within the scope of the day-ahead and intraday auction can be transferred into price forecasts and may support the evaluation of future market developments. Market participants need to understand long-term drivers of price spreads in short-term electricity markets in order to assess investment decisions with respect to more flexible generation units. However, as of today, an exemplary profitability calculation for a battery storage unit reveals that the current price volatility does not allow for profitable operation.

Finally, as we observe the respective price patterns not only in electricity markets, it would be worthwhile to transfer the model to further market settings, e.g., with respect to other commodities such as gas, coal or oil. However, since the respective market characteristics are fundamentally different, we leave scope for future research.

4.5 Appendices

4.5.1 Proof of Proposition 4.4 on Distributional Effects

Proof. Before taking a closer look into the distributional effects which are attributable to restricted participation, we first derive the respective surplus of consumers and producers. We consider consumers to be price inelastic, at least up to a certain threshold where the electricity price exceeds the value of lost load (VOLL). We link the VOLL to the price p^{VOLL} which marks the upper limit of the willingness-to-pay regarding electricity consumption (this definition is analogous to Knaut and Obermüller (2016)). On the supply side, the producer surplus is determined by the difference of the uniform market price and the marginal costs of electricity generation of each producer.

In the case of restricted participation ($ineff$), the consumer (CS) and producer surplus (PS) in each period τ are calculated as

$$CS_\tau^{ineff} = p^{VOLL} D_\tau - \overline{p}\overline{D} - p_\tau (D_\tau - \overline{D}) \tag{4.22}$$

$$PS_\tau^{ineff} = \overline{D}\overline{p} + (D_\tau - \overline{D}) p_\tau - C^{ineff}(D_\tau). \tag{4.23}$$

If all suppliers were able to vary their production level according to the temporal resolution τ, the efficient outcome (eff) would lead to the consumer and producer surplus which is expressed in the following two equations:

$$CS_\tau^{eff} = (p^{VOLL} - p_\tau^{eff}) D_\tau \tag{4.24}$$

$$PS_\tau^{eff} = p_t^{eff} D_t - C(D_\tau). \tag{4.25}$$

The price in the efficient case ($p_\tau^{eff} = a_0 + a_1 D_\tau$) directly depends on the aggregate marginal cost function. The difference in consumer and producer surplus can therefore be formulated as

$$\begin{aligned} \Delta CS_t &= CS_\tau^{eff} - CS_\tau^{ineff} \\ &= (a_1^u - a_1)(\overline{D} - D_\tau)^2 + a_1 \overline{D}(\overline{D} - D_\tau) \\ &= 2\Delta W_\tau + a_1 \overline{D}(\overline{D} - D_\tau) \end{aligned} \tag{4.26}$$

$$\begin{aligned}\Delta PS_\tau =&PS_\tau^{eff} - PS_\tau^{ineff}\\ =&-\frac{1}{2}(a_1^u - a_1)(\overline{D} - D_\tau)^2 - a_1\overline{D}(\overline{D} - D_\tau)\\ =&-\Delta W_\tau - a_1\overline{D}(\overline{D} - D_\tau).\end{aligned} \tag{4.27}$$

We insert the previously derived welfare losses ΔW_τ for both the change in consumer and producer surplus. Summing up over the n time periods yields

$$\Delta CS = \sum_{t=1}^{n} \Delta CS_\tau = 2\sum_{\tau=1}^{n} \Delta W_\tau + a_1\overline{D}\underbrace{\sum_{\tau=1}^{n}(\overline{D} - D_\tau)}_{=0} = 2\sum_{\tau=1}^{n} \Delta W_\tau \geq 0 \tag{4.28}$$

$$\Delta PS = \sum_{\tau=1}^{n} \Delta PS_\tau = -\sum_{\tau=1}^{n} \Delta W_\tau - a_1\overline{D}\underbrace{\sum_{\tau=1}^{n}(\overline{D} - D_\tau)}_{=0} = -\sum_{\tau=1}^{n} \Delta W_\tau \leq 0. \tag{4.29}$$

The consumer surplus decreases due to restricted participation in the second market. It is twice as high as the overall welfare losses. In contrast, the producers face an increasing surplus. The respective increase is expressed by the total sum of welfare losses along all time periods. As these considerations differ across restricted and unrestricted suppliers, we now analyze the respective surplus in more detail. In the inefficient case, we derive the following relations

$$PS_\tau^{r,ineff} = \overline{p}q^r - C^r(q^r) \tag{4.30}$$

$$PS_\tau^{u,ineff} = \overline{p}(q_\tau^u) + p_\tau(D_\tau - \overline{D}) - C^u(q_\tau^u). \tag{4.31}$$

In the efficient case, the respective surplus would be as follows

$$PS_\tau^{r,eff} = p_\tau^{eff} q_\tau^{r,eff} - C^r(q_\tau^{r,eff}) \tag{4.32}$$

$$PS_\tau^{u,eff} = p_\tau^{eff} q_\tau^{u,eff} - C^u(q_\tau^{u,eff}). \tag{4.33}$$

We derive the optimal quantities which are supplied by restricted and unrestricted suppliers (efficiency benchmark) with the use of the aggregate supply function:

$$q_\tau^{r,eff} = \frac{a_1^u}{a_1^r + a_1^u} D_\tau \tag{4.34}$$

$$q_\tau^{u,eff} = \frac{a_1^r}{a_1^r + a_1^u} D_\tau. \tag{4.35}$$

As regards the restricted suppliers, we derive the difference in surplus:

$$\Delta PS_\tau^r = PS_\tau^{r,eff} - PS_\tau^{r,ineff} \tag{4.36}$$

$$= \frac{1}{2} a_1 (1 - \frac{a_1}{a_1^u})(D_\tau^2 - \overline{D}^2). \tag{4.37}$$

Summing up over all time periods, we can furthermore simplify the respective expression according to

$$\Delta PS^r = \sum_{\tau=1}^{n} \Delta PS_\tau^r = \frac{1}{2} a_1 \underbrace{(1 - \frac{a_1}{a_1^u})}_{\geq 0} \underbrace{\sum_{\tau=1}^{n} (D_\tau^2 - \overline{D}^2)}_{Var(D_\tau) \geq 0} \geq 0. \tag{4.38}$$

As the variance of demand is always positive, we conclude that restricted suppliers are characterized by a lower surplus in the inefficient case compared to the efficiency benchmark. In a next step, we derive the difference in surplus for unrestricted suppliers. As we have already derived the difference in surplus for both all suppliers as well as the restricted set of suppliers, we present the following expression:

$$\Delta PS^u = \underbrace{\Delta PS}_{\leq 0} - \underbrace{\Delta PS^r}_{\geq 0} \leq 0. \tag{4.39}$$

To sum up, we find that restricted participation leads to a reduction in consumer surplus. In contrast, unrestricted suppliers may achieve a higher surplus in the inefficient case, whereas restricted suppliers suffer from restricted participation. □

4.5.2 Supplementary Information on the Econometric Approach

The Relation of Quantities and Prices in the Day-Ahead Auction

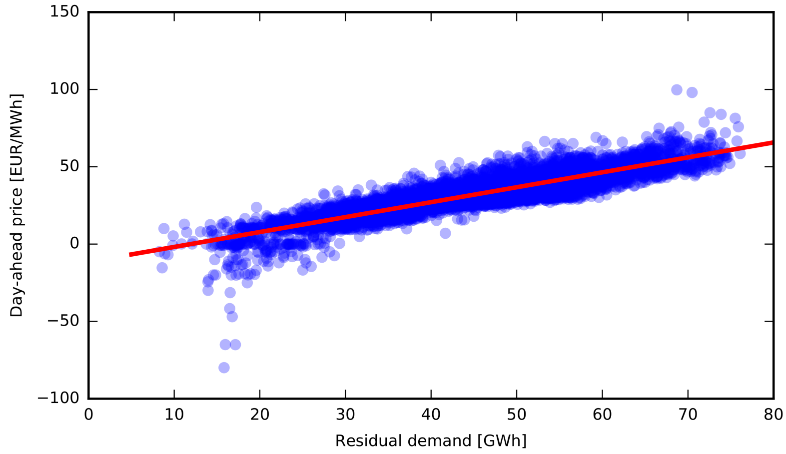


Figure 4.6: Relation of German day-ahead quantities and prices in 2015 (trend line with linear shape marked in red)

Distribution of load forecast errors

The distribution of load forecast errors during our period of observation is illustrated in Figure 4.7.

Unit Root Tests

We apply both an Augmented Dickey Fuller test and a Phillips-Perron test for unit roots. The respective test results are displayed in Table 4.5 (Dickey and Fuller, 1979, Phillips and Perron, 1979). The Phillips-Perron test uses Newey-West standard errors in order to account for serial correlation. The null hypothesis of both tests is that there is a unit root in the periods of observation. We tested the Akaike Information Criterion (AIC) in order to determine the optimal lag lengths. As the AIC results are ambiguous for the variables considered and tend to indicate using as many lags as tested for, we use the Schwert rule of thumb and consider a leg length of 65 (Schwert, 1989). We prefer making a slight error due to including too many lags since Monte Carlo experiments suggest that this procedure is preferable to including too few lags. In order to give evidence for the robustness of our results, we repeated the tests for

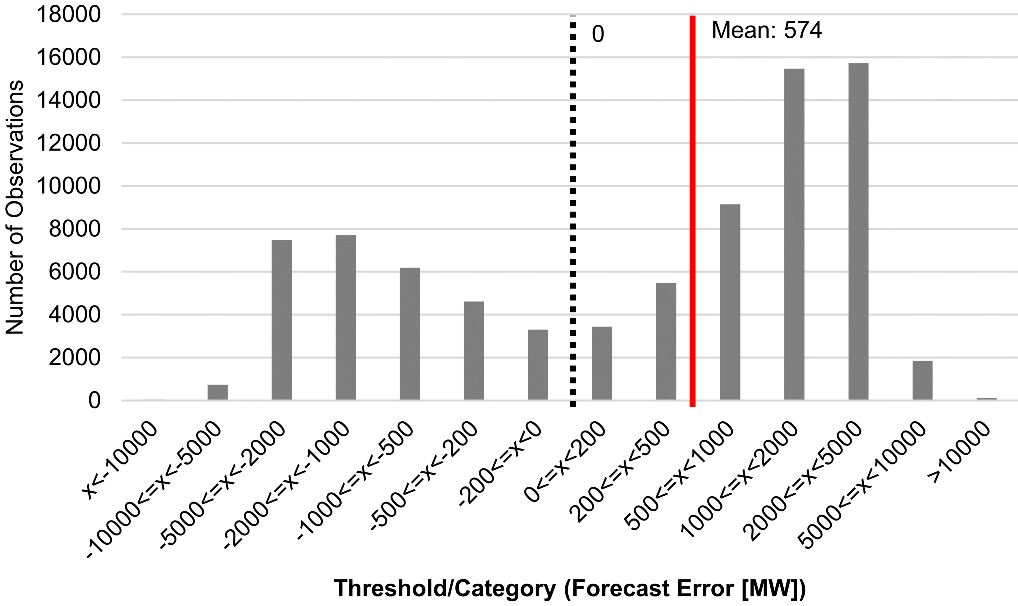


Figure 4.7: Distribution of load forecast errors during the period of observation

different lag lengths. Within the scope of the Augmented Dickey Fuller test, we extend the basic test of a random walk against a stationary autoregressive process by including a drift and a trend term. As far as the listed results are concerned, we decide whether to include a trend or constant by checking the significance of the trend/constant parameters at a 5% significance threshold. The parameter *residuals* refers to the estimation results for Equation 4.20 using a 2SLS regression.

Table 4.5: Unit root tests

	Augmented Dickey Fuller (Levels)			Philipps-Perron Test (Levels)		
Variable	statistic	p-value	lags	statistic	p-value	lags
id auction price	-18.34	0.00	65	-188.27	0.00	65
day ahead price	-16.32	0.00	65	-24.04	0.00	65
residual demand 60	-12.36	0.00	65	-21.71	0.00	65
residual demand deviation 15	-47.20	0.00	65	-683.70	0.00	65
residuals (ϵ)	-26.09	0.00	65	-310.22	0.00	65

Table 4.6: Comparison of IV and OLS

	Dependent variable: id auction price ($p_{q,t}^{ida}$)	
Explanatory variable	IV	OLS
day-ahead price (p_t^{da})	0.95***	0.95***
	(0.002)	(0.003)
residual demand deviation (ΔD_t^{res})	7.65***	7.65***
	(0.08)	(0.08)
intercept (ν)	1.26***	1.55***
	(0.08)	(0.11)
observations	81,663	81,663
adj. R^2	0.87	0.87
F	80,094	43,979

Notes to Table 4.6: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. For the IV estimates *day-ahead price* we use *residual demand deviation 60* as the instrumental variable and apply a 2SLS Regression. In general, we use data from January 2015 until the end of April 2017.

IV and OLS Estimates

Additional Information with Respect to Robustness, Alternative Hypotheses, and Methodological Variation

We evaluate further variations of the basic estimation procedure and conduct additional tests for alternative specifications to provide evidence for the assumption of the general applicability of our theoretical model to historical data. Based on the model, one may also think about directly estimating the difference between the day-ahead and intraday auction price without explicitly including the day-ahead price as an explanatory variable. The respective estimation results are depicted in Table 4.7. As to be expected, the 15-minute deviation of the residual demand is a significant (1% level) driver of differences between day-ahead and intraday auction prices. Additionally, the respective estimate equals the coefficients which are presented in Table 4.3 and Table 4.4. Even though we identify a minor loss of explanatory power due to not directly including the day-ahead price, these results support the robustness of our findings.

In a next step, we address the four specific 15-minute intervals of each hour via a dummy variable in order to analyze whether the estimated coefficients for the quarter-hourly deviation of the residual demand from its hourly mean differ significantly across the 15-minute time intervals of each hour. The estimation results in column (2) of Table 4.3 depict that the respective coefficients differ slightly at a level

Table 4.7: Regression Estimates Sensitivity Analyses (1)

	Dependent variable:	
	(p_t^{da} - p_t^{ida})	(p_t^{ida})
Explanatory variable	OLS (1)	OLS (2)
residual demand deviation (ΔD_t^{res})	7.65 ***	
	(0.08)	
day-ahead price (p_t^{da})		0.96***
		(0.002)
residual demand deviation (Q1)		7.85***
		(0.14)
residual demand deviation (Q2)		6.75***
		(0.17)
residual demand deviation (Q3)		6.64***
		(0.24)
residual demand deviation (Q4)		7.72***
		(0.10)
intercept (ξ)	0.08***	1.23***
	(0.02)	(0.08)
$observations$	81,663	81,663
adj. R^2	0.54	0.87
F	9,825	32,802

Notes to Table 4.7: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. We use data from January 2015 until the end of April 2017.

of approximately 18%. These differences suggest that the underlying intraday auction supply curve is slightly steeper in the edge regions which are far more likely to be relevant in the first and last quarter-hourly period of each hour. Such finding is plausible since the deviation of the residual demand from its hourly mean tends to be higher in these time periods. However, we still find the overall model being applicable.

5 Decoding Restricted Participation in Sequential Electricity Markets

Restricted participation in sequential markets may cause high price volatility and welfare losses. In this paper, we therefore analyze the drivers of restricted participation in the German intraday auction which is a short-term electricity market with quarter-hourly products. Applying a fundamental electricity market model with 15-minute temporal resolution, we identify the lack of sub-hourly market coupling being the most relevant driver of restricted participation. We derive a proxy for price volatility and find that full market coupling may trigger quarter-hourly price volatility to decrease by a factor close to four.

5.1 Introduction

The increasing share of renewable energies has caused an exacerbated need of short-term trading opportunities for electricity. Forecast uncertainty and highly volatile feed-in profiles of renewable energies favor the trade of shorter contracts closer to the time of physical delivery (see, e.g., Garnier and Madlener (2014), Karanfil and Li (2017), Weber (2010)). In this paper, we focus on the interaction of two sequential short-term electricity markets in Germany. The first market is the day-ahead auction with hourly products which is settled at noon one day before physical delivery. Second, we consider the intraday auction which allows the trade of quarter-hourly contracts three hours after the day-ahead market settlement.

This article is especially motivated through Knaut and Paschmann (2017b) analyzing the impact of restricted participation in the day-ahead and intraday auction. The authors find that restricted participation may trigger both high price volatility as well as welfare losses. Based on these findings, we target to identify the underlying drivers of restricted participation in the German intraday auction. Our results are supposed to form the basis for evaluating countermeasures in order to reduce the respective inefficiencies.

In general, we consider four potential drivers of restricted participation: i) inertia as the state of not knowing[1]; ii) costs of market entry; iii) inflexibility of power plants; and iv) a lack of cross-border market coupling. In this article, we focus our attention on the latter three drivers as there is empirical evidence that the role of inertia is of minor relevance for the intraday auction. We conduct exemplary profitability analyses and find an indication that costs of market entry are not expected to prevent profit maximizing traders from participating in the intraday auction. In a next step, we set up a fundamental electricity market model with 15-minute temporal resolution which is essentially capable of replicating the price pattern observed in real-world data. We then disentangle the effects of power plant flexibility and market coupling on sub-hourly price volatility. Our analysis is motivated by the fact that cross-border trade may cause convergence of prices if sufficient transmission capacity is available (see, e.g., Parisio and Bosco (2008), Zachmann (2008)) and thus the overall efficiency may increase. Indeed, our results suggest that the lack of cross-border trade is the major fundamental driver of restricted participation in the intraday auction.

Having identified the lack of sub-hourly market coupling as the most important driver, it may be beneficial for policy makers to urge the realization of the 'XBID' project aiming to implement cross-border intraday trade on a 15-minute level in the internal European electricity market (EPEX SPOT SE, 2017d). Furthermore, additional market coupling on sub-hourly levels such as proposed for Germany, the Netherlands, and France may be worth considering (EPEX SPOT SE, 2017a). To derive a proxy for the effectiveness of such measures, we evaluate the influence of sub-hourly market coupling on the price volatility within our modeling framework. Our results suggest that full market coupling on a quarter-hourly level may trigger the sub-hourly price volatility to decrease by a factor close to four.

Besides providing insights for policy makers, our results are also important for firms participating in the day-ahead and intraday auction as we are able to depict the most relevant drivers of the high price volatility observed. At first sight, the high price volatility may seem to be favorable for investments into power plant flexibility. Based on our findings, however, this may be a false conclusion. Therefore, investment decisions regarding flexible generation units should account for the impact of the targeted quarter-hourly market coupling on prices.

Finally, the methodological approach extends research so far as the temporal resolution of the model, to the best of our knowledge, is a unique feature compared to dispatch models that are most commonly applied in the existing literature. We

[1] For more details on inertia of market participants see Doraszelski et al. (2016).

clearly point out that simulating the power supply system with sub-hourly temporal resolution will become increasingly important. This is especially relevant to simulate investment decisions of flexible generation units with higher accuracy. At the same time, we are able to simulate the impact of different types of market coupling on the respective sequential market dynamics.

The remainder of this paper is organized as follows. We first briefly depict the main literature background. In Section 5.3 we then present our strategy, i.e., how to decode the drivers of restricted participation in the German intraday auction. The respective analysis of the individual drivers considered is presented in detail within the following sections. Finally, we conclude in Section 5.6.

5.2 Literature Background

Focusing on the interaction of sequential markets, this paper is positioned in research surrounding market equilibria and the respective market outcome in sequential market configurations (see, e.g., Green (1973), Pindyck (2001), Veit et al. (2006)). In the context of the power sector, Borggrefe and Neuhoff (2011) and von Roon and Wagner (2009) comment on the important role of sequential short-term electricity markets due to a strongly increasing share of renewable energies in Germany. In addition, Knaut and Obermüller (2016) and Ito and Reguant (2016) investigate the optimal strategy choices of renewable producers in sequential markets. The authors find incentives to withhold production capacity in the first market which may cause systematic price premiums in subsequent market stages. Additionally, Mezzetti et al. (2007) suggest a lowballing effect that may lead to a comparably lower price in the first market.

Supporting the findings of Knaut and Paschmann (2017b), the idea of high price volatility due to restricted participation has also been studied in Allen and Gale (1994). Furthermore, in Polemarchakis and Siconolfi (1997) the authors point out that limits to market participation may result in incomplete markets and consequently competitive equilibria may not exist. Finally, restricted market participation may lead to limited arbitrage (Hens et al., 2006). We aim at contributing to the existing literature by developing a strategic approach to analyze the underlying drivers of restricted participation in real-world electricity markets.

5.3 Identifying the Drivers of Restricted Participation

Electricity markets are most commonly organized in a sequential order. Closer to physical delivery the contract duration tends to decrease and the respective markets are cleared in rapid succession. Against this backdrop, Figure 5.1 depicts the sequential market design for the wholesale electricity markets in Germany [2].

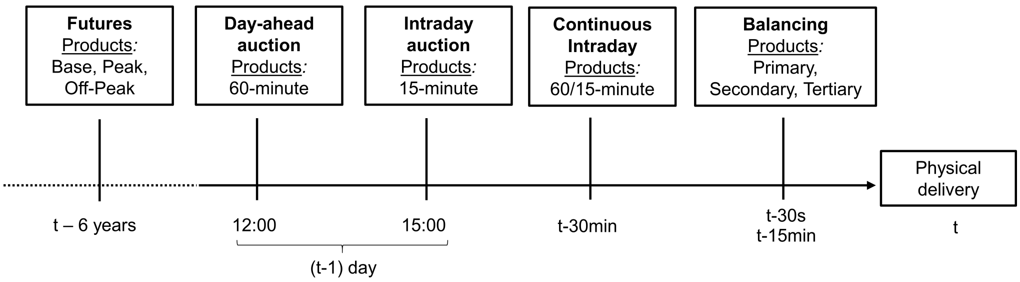


Figure 5.1: Sequence of trading in wholesale markets

In this paper, we focus on the market interaction between the German day-ahead and intraday auction. Following Knaut and Paschmann (2017b), trade in the intraday auction mainly stems from quarter-hourly deviations of the residual load from the respective hourly means. Here residual load is defined as the difference between the overall system load and the electricity generation from renewable power plants. Due to the rapid succession of both auctions, the impact of forecast errors on the trade volumes is negligible. There is no informational update between both market stages. According to Knaut and Paschmann (2017b), the gradient of the intraday auction supply curve furthermore steeply increases compared to the respective day-ahead merit order due to restricted participation. Consequently, quarter-hourly intraday auction prices are much more volatile than hourly day-ahead prices and welfare losses can be identified[3].

We consider the following four possible reasons for restricted participation in the intraday auction:

i) **Inertia as the state of not knowing**: Market participants may be used to dispatch their power plants on an hourly level according to the day-ahead auction. It is plausible that they may not directly adjust their trading behavior to newly emerging markets such as the intraday auction.

[2] For more details see Knaut and Paschmann (2017b).

[3] This is especially relevant as the increasing share of renewable electricity generation implies an augmented importance of sub-hourly trading opportunities.

ii) **Costs of market entry**: There may be additional costs for market agents to participate in a new market with a different contract design. This may, e.g., be due to market entry fees or a lack of a respective trading department that enables trading of quarter-hourly products. Furthermore, a lack of aggregation with respect to smaller generation units may be identified.

iii) **Inflexibility of power plants**: Power plant operators may not be able to adjust their production schedule on a sub-hourly level. This may be due to technical constraints or due to high costs for starting up additional capacities. Especially base load generation units such as nuclear or lignite power plants can be regarded as being less flexible.

iv) **Cross-border trade**: So far, trade of 15-minute products only takes place on a national level. Thereby, only German generation units participate in the market. In contrast, the day-ahead auction is characterized by implicit market coupling across several European countries. Obviously this leads to restricted participation in the market for quarter-hourly products compared to the day-ahead auction.

We empirically analyze the development of the day-ahead and intraday auction price relations over time in order to comment on the role of inertia (Section 5.7.1). We find an indication that effects related to restricted participation do not fade out. Rather to the contrary, they may be characterized being persistent. In this article, we therefore focus on the latter three hypothetical drivers and evaluate which of them may be a valid explanatory approach for restricted participation in the German intraday auction. First, we shed light on the costs of market entry. We compare fees that arise from trading on the exchange and profits for exemplary generation technologies that may be gained by extending trading activities to the intraday auction. Second, we introduce a modeling framework to simulate the interaction of hourly and quarter-hourly electricity markets which is able to account for the inflexibility of power plants as well as the role of cross-border trade. Based on the model framework, we disentangle both possible drivers of restricted participation iii) and iv).

5.4 Costs of Market Entry

In a first step, we provide insights on the benefits and costs for participants entering the intraday auction. We therefore focus on simulating the additional monetary benefits that would result from extending trading activities from solely participating in the day-ahead auction to trading in the intraday auction as well and put the respective results into context with trading fees. We consider two exemplary generation units which are a flexible combined cycle gas turbine (CCGT) and a rather inflexible lignite-fired power plant. In order to conduct profitability analyses for both types of power plants using historical price data, we use a mixed integer program[4]. To comment on the additional revenue potential when entering the intraday auction, we compare a scenario in which the power plant operator only participates in the day-ahead auction and a case in which trade in the intraday auction is allowed as well. We implement sequential trading decisions. That is to say, the power plant operator first decides on the hourly day-ahead supply under perfect foresight with respect to hourly prices. In a next step, the quarter-hourly schedule is optimized as a deviation from the previously settled hourly trade quantities based on quarter-hourly prices. We assume that decision makers target to maximize their profits. Furthermore, we consider ramping and start-up constraints as well as part-load losses. Additionally, we account for transaction fees on the power exchange[5]. The methodology applied is based on comparable approaches that have most commonly been applied in the existing literature[6] (see, e.g., Frangioni et al. (2009), Ostrowski et al. (2012), Richter et al. (2016)). Details on the respective parameter assumptions are presented in Table 5.1. We use exogenous day-ahead and intraday auction prices based on historical data from 2015 (EPEX SPOT SE, 2017c).

Table 5.1: Assumptions asset optimization

	Min load [%]	Max ramp rate [%/15Min]	Start-up/Shut-down rate [%/15Min]	Efficiency full-load/part-load [%]	Fuel Price (incl CO_2) EUR/MWh_{th}
CCGT (70 MW)	20	100	100/100	54/25	19.37
Lignite (300 MW)	50	37.5	12.5/12.5	30/25	3.42

In order to compare our simulation results with actual costs related to market entry, we use data that is provided by the exchange (EPEX SPOT SE, 2016b). The respective costs are summarized in Table 5.2. The costs of market entry for the day-ahead and intraday auction comprise a one-time as well as yearly fees.

Our simulation results are presented in Table 5.3. We depict yearly profits which can be achieved from trading activities in the day-ahead and intraday auction for both types of power plants. As we regard trading decisions being sequential and

[4]The model is presented in detail in Section 5.7.3

[5]Based on actual values market participants are charged for on the exchange (EPEX SPOT SE), these are 0.04 EUR/MWh for the day-ahead auction and 0.07 EUR/MWh for the intraday auction.

[6]The methodological approach is furthermore similar to Section 5.5.1

Table 5.2: Costs of market entry for the day-ahead and intraday auction

	Initial payment	Yearly fee
Day-ahead auction	EUR 25,000	EUR 10,000 /a
Intraday auction	EUR 7,000	EUR 5,000 /a

independent, the overall profit from solely participating in the day-ahead auction equals the values listed in the column *Day-ahead Profit*.

Table 5.3: Model results

	Day-ahead Trades TWh	Day-ahead Profit Mio. EUR	Intraday Auction Trades TWh	Additional Intraday Auction Profit Mio. EUR
CCGT	0.19	1.5 (7.9 EUR/MWh)	0.04	0.23 (5.7 EUR/MWh)
Lignite	2.5	54.1 (21.6 EUR/MWh)	0.05	0.3 (6 EUR/MWh)

According to the second scenario considered, participating in the intraday auction yields additional profits that are depicted in the column *Additional Intraday Auction Profit*. Based on the simplified model calculations, additional revenues that may be gained by both types of power plants in the intraday auction exceed the respective costs of market entry many times over. For example, a lignite power plant could earn an additional yearly profit of EUR 300,000 compared to an initial payment of EUR 7,000 and a yearly fee of EUR 5,000. However, we are well aware that besides fees for market entry additional costs may be relevant. These may, for example, refer to implementing a new trading department or paying wages of traders. As these cost components are difficult to quantify, we do not consider these costs explicitly within this paper. Nevertheless, our results provide an indication that costs of market entry may not hinder participation in the intraday auction. Quite the contrary, there are economic incentives to participate in this market.

5.5 Fundamental Analysis

We choose a fundamental modeling approach in order to simulate price relations under different restrictions referring to technical constraints and cross-border trade. In the following, we briefly outline the main characteristics of the chosen modeling approach.

5.5.1 Modeling Approach

The modeling approach adopted within this paper extends the electricity system optimization model DIMENSION which has been developed at the Institute of Energy Economics (EWI) at the University of Cologne (Richter, 2011) and which has been applied in numerous studies (see, e.g., Jägemann (2014), Bertsch et al. (2015) and Knaut et al. (2016)). In general, the model so far allows to simulate the hourly dispatch within the internal European electricity market. In order to address the research issues in question, we extend the model to account for a quarter-hourly temporal resolution. In more detail, we mimic the interaction of two simultaneously settled markets with first hourly and second quarter-hourly products. The objective function of the model aims at satisfying the demand at minimum total system costs. The short-term marginal costs embody a proxy for the electricity price. The model is implemented as a linear program (LP) in GAMS. We focus on simulating the quarter-hourly dispatch in 2015 in order to compare our results with historical observations.

In the following, we first depict and explain the most relevant model characteristics as well as basic equations and constraints before we then analyze the modeling results. In Section 5.7.6 the overall model is presented in a condensed way with focus on the formalization. Table 5.4, Table 5.5, and Table 5.6 give an overview on the notation applied.

Table 5.4: Sets

Model Sets

Abbreviation	Description
a ∈ A	Technologies
s ∈ S; S ⊂ A	Storage technologies
c, c_1 ∈ C	Market regions
c', c_1' ∈ C'; C' ⊂ C	Market regions with cross-border trade on a 15-minute level
q ∈ Q	Quarter-hourly time intervals
h ∈ H	Hourly time intervals
h_q ∈ H	Set of hours that belong to a specific quarter-hourly time interval

Table 5.5: Parameters of the electricity system optimization model

Model parameters

Abbreviation	Dimension	Description
ac_a	[EUR/MWh$_{el}$]	Attrition costs for ramping
$av_{q,a,c}$	[%]	Availability
$d_{q,c}$	[MW]	Total demand in 15-minute resolution to be satisfied
ef_a	[t/MWh$_{th}$]	Emissions per fuel consumption
fu_a	[EUR/MWh$_{th}$]	Fuel price (full load)
fu_a^{ml}	[EUR/MWh$_{th}$]	Fuel price (min load)
cp	[EUR/t]	CO_2 emission price
$in_{a,c}$	[MW]	Installed capacity
ml_a	[%]	Minimum part load level
rr_a	[%]	Maximum ramp rate
st_a	[h]	Start-up time from cold start
η_a	[%]	Net efficiency (generation)

Table 5.6: Variables of the electricity system optimization model

Model variables

Abbreviation	Dimension	Description
$hD_{h,c}$	[MW]	Trade quantities on an hourly level
$qD_{q,c}$	[MW]	Trade quantities on a quarter-hourly level
$CU_{q,a,c}$	[MW]	Capacity that is ramped up within one quarter-hour
$CD_{q,a,c}$	[MW]	Capacity that is ramped down within one quarter-hour
$CR_{q,a,c}$	[MW]	Capacity that is ready to operate in each quarter-hour
$hGE_{h,a,c}$	[MW$_{el}$]	Hourly electricity generation
$qGE_{q,a',c}$	[MW$_{el}$]	Quarter-hourly electricity generation
hIM_{h,c,c_1}	[MW]	Hourly net imports in c from c_1
$qIM_{q,c',c_1'}$	[MW]	Quarter-hourly net imports in c' from c_1'
$hST_{h,s,c}$	[MW]	Hourly consumption in storage operation
$qST_{q,s,c}$	[MW]	Quarter-hourly consumption in storage operation
TSC	[EUR]	Total system costs

Objective Function

The electricity system optimization program applied is based on cost minimization. In more detail, total system costs (TSC) comprise the variable costs of electricity generation ($Costs^{var}$), additional costs for part-load operation ($Costs^{part-load}$), start-up costs ($Costs^{start}$), and ramping costs ($Costs^{ramping}$).

$$TSC = \sum_{c\in C}\sum_{a\in A}\sum_{q\in Q}\left[Costs_{q,a,c}^{var} + Costs_{q,a,c}^{part-load} + Costs_{q,a,c}^{start} + Costs_{q,a,c}^{ramping}\right] \quad (5.1)$$

First, the net electricity generation that stems from dispatching on an hourly and quarter-hourly level is multiplied with fuel as well as CO_2 emission prices what yields the variable costs of electricity generation ($Costs^{var}$) (5.2).

$$\begin{aligned} Costs_{q,a,c}^{var} = & (\sum_{h_q \in H} hGE_{h_q,a,c} + qGE_{q,a,c}) \cdot (\frac{fu_a}{\eta_a}) \\ & + (\sum_{h_q \in H} hGE_{h_q,a,c} + qGE_{q,a,c}) \cdot (\frac{cp \cdot ef_a}{\eta_a}) \end{aligned} \tag{5.2}$$

Depending on the configuration, part-load losses ($Costs^{part-load}$) may be considered (5.3). They comprise linearized losses depending on the difference between the fuel costs at full load and minimal load and the share of the overall generation capacity that is operated below the totally available generation capacity.

$$Costs_{q,a,c}^{part-load} = (CR_{q,a,c} - \sum_{h_q \in H} hGE_{h_q,a,c} - qGE_{q,a,c}) \cdot (\frac{fu_a^{ml} - fu_a}{\eta_a}) \cdot (\frac{ml_a}{1 - ml_a}) \tag{5.3}$$

Furthermore, we include start-up costs ($Costs^{start}$). Based on expert opinions gained from industrial project partners, we link start-up processes to a doubling in fuel consumption (5.4). We are aware that this is a simplifying linear approach not exactly reflecting the complexity of real-world start-up processes. Nevertheless, we are thereby sufficiently capable to account for start-up costs within the analyses.

$$Costs_{q,a,c}^{start} = CU_{q,a,c} \cdot (\frac{fu_a}{\eta_a}) \tag{5.4}$$

Finally, we consider ramping costs ($Costs^{ramping}$) which reflect increasing attrition if the electricity generation deviates from the respective value in the previous period. Ramping costs are linked to wear and tear of technical components (5.5).

$$Costs_{q,a,c}^{ramping} = (CU_{q,a,c} + CD_{q,a,c}) \cdot ac_a \tag{5.5}$$

Regional Coverage and Equilibrium Constraints

We consider Germany as well as its neighboring countries in order to reduce the computational complexity[7]. The availability of processing cross-border trade is limited by exogenous historical net transfer capacities (NTC) and we account for the respective average grid losses.

Each market area is characterized by power balance conditions reflecting that national demand plus the demand of storage units equals the intra-zonal electricity generation plus net imports in each time step at equilibrium. To derive the national demand ($d_{q,c}$), we use historical load data from 2015 that we extracted from the ENTSO-E transparency platform (ENTSO-E, 2017) and apply the respective load structure to the overall electricity demand in 2015. Since the data does not provide a quarter-hourly temporal resolution for all countries, we interpolate the respective hourly values where necessary. As we furthermore target to mimic the interaction of two simultaneously settled markets, where the market with increased product granularity is characterized by restricted participation, we use the following three equilibrium conditions:

$$hD_{h_q,c} + qD_{q,c} = d_{q,c} \quad \forall\, q, c \tag{5.6}$$

$$\sum_{a \in A} hGE_{h,a,c} + \sum_{c_1 \in C} hIM_{h,c,c_1} - \sum_{s \in S} hST_{h,s,c} = hD_{h,c} \quad \forall\, h, c \tag{5.7}$$

$$\sum_{a \in A} qGE_{q,a,c} + \sum_{c_1' \in C'} qIM_{q,c,c_1'} - \sum_{s \in S} qST_{q,s,c} = qD_{q,c} \quad \forall\, q, c. \tag{5.8}$$

Equation (5.6) determines that the overall inelastic demand on a quarter-hourly level $d_{q,c}$ may be supplied by hourly dispatched as well as quarter-hourly dispatched generation units. The hourly supply (hGE) is a positive rational number, whereas the quarter-hourly supply (qGE) may be negative as well which accounts for negative adjustments compared to the hourly supply schedule. At the same time, all generation units have to remain net suppliers. Finally, the quarter-hourly decision variables are limited by constraints that refer to restricted participation and will be explained in more detail below.

[7] The neighboring countries comprise Austria, Belgium, the Czech Republic, Denmark, France, the Netherlands, Poland and Switzerland.

Generation units

Different types of power plants are grouped into vintage classes. We consider conventional, nuclear, thermal and storage generation units as well as renewable power plants. The renewables are essentially subdivided into generation units based on wind power (onshore and offshore), solar power, hydro power and biomass. At the same time, we distinguish whether generation units are combined heat and power plants (chp) and we include a condition reflecting that the German heat demand in the domestic as well as in the industrial sector has to be supplied by all German chp power plants. As this is not the focus in this paper, further insights can be found in Richter (2011) and Jägemann (2014).

The installed capacities of each type of generation unit are mainly based on historical values and we present the resulting generation capacity in 2015 in Table 5.7.

Table 5.7: Installed capacity in 2015

Type	Gross Capacity [GW]
Hard Coal	25.41
Lignite	19.94
Natural Gas	31.37
Oil	3.92
Nuclear	10.73
Pumped Storage	6.49
Run of River / Seasonal Storage	5.16
Wind	42.60
Wind onshore	39.32
Wind offshore	3.28
Photovoltaics	38.36
Biomass	7.29
Others	1.60

We use data on the average power plant availability in order to limit the maximum electricity generation by each type of generation unit. The net electricity generation which results from hourly and quarter-hourly dispatch may not exceed the total installed capacity multiplied with the respective availability (5.9).

$$\sum_{h_q \in H} hGE_{h_q,a,c} + qGE_{q,a,c} \leq av_{q,a,c} \cdot in_{a,c} \quad \forall q,a,c \tag{5.9}$$

At the same time, the electricity generation, if present, has to exceed the minimum load (5.10).

$$\sum_{h_q \in H} hGE_{h_q,a,c} + qGE_{q,a,c} \geq ml_a \cdot CR_{q,a,c} \quad \forall q,a,c \tag{5.10}$$

The electricity generation from wind and solar power and the respective feed-in structure is fixed to historical values from 2015[8], which are provided by the ENTSO-E and EEX transparency platforms (ENTSO-E (2017) , EEX (2017b)).

Analyzing the short-term power market flexibility in Germany, storage technologies play a crucial role. These technologies especially include pump and hydro storage generation units. The respective plants are mainly characterized by storage level restrictions, turbine as well as pump capacity, exogenous injections as well as withdrawals and efficiency parameters. We determine an arbitrary target value for the storage value implying that the storage level at the beginning of the optimization period shall equal the respective one in the last period under consideration. Besides, we consider some flexibility potential based on demand-side management. Here demand-side management includes various sources such as industrial processes (e.g., aluminium-electrolysis and cement mills), heating, aeration and ventilation in the service, municipal and domestic sector, and electric vehicle flexibility potentials. We determine a specific demand-side management potential and the overall electricity demand of the respective processes has to be balanced along the modeling period.

Technical Constraints

Three main pillars referring to technical constraints of power plants are considered. These include ramping constraints, part-load losses and start-up restrictions.

First, ramping in both directions is restricted by maximum ramp rates which were extracted from various projects in collaboration with industrial partners. The respective data is depicted in Table 5.18 in Section 5.7.4. The available generation capacity in each time step depends on the available capacity in the period before as well as the capacity that has been ramped up or down. We implement the equations listed in (5.11).

[8] In Germany these were approx. 79 TWh electricity generation from wind and 35 TWh from photovoltaic power plants.

$$\begin{aligned} CR_{q,a,c} = CR_{q-1,a,c} + CU_{q-1,a,c} - CD_{q-1,a,c} \quad & \forall q,a,c \\ CU_{q,a,c} \leq rr_a \cdot (in_{a,c} - CR_{q,a,c}) \quad & \forall q,a,c \\ CD_{q,a,c} \leq rr_a \cdot (CR_{q,a,c}) \quad & \forall q,a,c \end{aligned} \tag{5.11}$$

Finally, start-up constraints are transferred into additional limits for the capacity that may be ramped up according to (5.12).

$$CU_{q,a,c} \leq \frac{in_{a,c} - CR_{q,a,c}}{st_a} \quad \forall q,a,c \tag{5.12}$$

All of these technical constraints are linked to additional costs that are included in the objective function.

Electricity Market Prices

In this paper, we are especially interested in price relations. Therefore, we derive prices based on the fundamental modeling results. Being a linear program, we are able to interpret the marginals on the power balance constraints as the marginal costs of electricity generation. The marginal on Equation (5.7) may thus be regarded as reflecting the electricity price in the market with hourly products, whereas we consider the marginal on (5.8) allowing to draw conclusions on the respective quarter-hourly electricity prices. As we are not interested in absolute price levels, but in the comparison of price relations, the application of marginals is assumed to be suitable.

5.5.2 Results

We address the fundamental impact of technical constraints and a lack of cross-border trade on electricity prices by gradually implementing or relaxing additional constraints in the model in order to analyze the respective impact on prices. We compare the specific results based on descriptive key figures. These, inter alia, include the minimum as well as maximum values, the standard deviation, and percentile thresholds. We refer to prices p_h reflecting the marginals on the hourly power balance constraint and to prices p_q as marginals on the respective quarter-hourly constraint.

Reference Case and Model Validation

We aim to link our model results to the real-world market outcome by analyzing a Reference Scenario S_{ref}, in which we mimic the actual day-ahead and intraday market interaction for 2015. Such reference case is a fundamental model run including all technical constraints that refer to power plant inflexibility as outlined above. Furthermore, we assume that there is no quarter-hourly market coupling. We expect this setup to represent the current status of the electricity markets in Germany and the neighboring countries.

In order to evaluate the model validity, we compare prices derived from the fundamental model results and real price data for 2015. Based on the comparison in Table 5.8, we suggest that the model is able to reproduce the average price level in 2015 well, but rather fails in reproducing comparably high and low price levels. This deficiency of linear fundamental models is well known and is the result of numerous model assumptions. First, the aggregation of generation units into vintage classes causes a lack of accuracy regarding the actual diversity of power plants. As a result, we expect the prices simulated in the model framework not to represent the actual variability of electricity prices. As a second aspect, the assumption of perfect foresight does not comply with the real-world problem. We therefore expect that our results may be downward-biased with regard to restricted participation since our assumptions can be regarded being rather optimistic as far as the participation in markets with sub-hourly contract duration is concerned. However, as we do not aim at forecasting as well as interpreting absolute price levels, but rather intend to derive conclusions on the fundamental impact of restricted participation on price relations, our simulation approach still appears suitable. Nonetheless, we are well aware of the limited generalizability of our results regarding actual electricity prices.

According to Knaut and Paschmann (2017b), restricted participation causes a distinct price pattern that is characterized by quarter-hourly prices fluctuating around the respective hourly ones. The sub-hourly price volatility is much higher than the hourly one. The model applied in this article is basically able to reproduce such characteristic price pattern as shown in Figure 5.2. In order to characterize the extent of the quarter-hourly price deviations from hourly means, we use two indicators for sub-hourly price volatility in the following. These are *mean absolute price difference (p_h - p_q)* and *standard deviation price difference (p_h - p_q)*. Even though the levels of both indicators signify less pronounced price fluctuations in our model runs compared to historical data (by up to factor seven) (see Table 5.8), we are yet confident that relative comparisons of different scenarios yield meaningful indicators for our

Table 5.8: Summary statistics for the reference case and historical prices

	S_{ref} [EUR/MWh]	Historical [EUR/MWh]
Mean (p_q)	30.25	31.66
Mean (p_h)	30.25	31.63
Min (p_q)	8.56	-164.48
Min (p_h)	10.49	-79.94
10% Percentile (p_q)	23.59	14.52
10% Percentile (p_h)	23.47	16.26
90% Percentile (p_h)	36.89	47.44
90% Percentile (p_q)	37.52	49.64
Max (p_q)	83.41	464.37
Max (p_h)	52.82	99.77
Mean absolute price difference (p_h - p_q)	0.87	6.57
Standard deviation price difference (p_h - p_q)	1.60	9.28

further analysis.

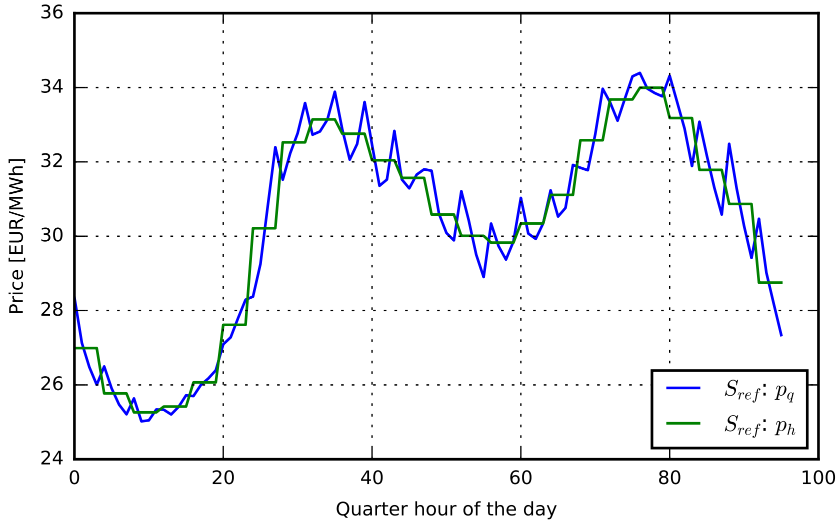


Figure 5.2: Daily pattern of average hourly and quarter-hourly price levels in the reference model run

The role of power plant flexibility

We are first interested in whether power plant inflexibility may serve as a sufficient explanatory approach for restricted participation in the intraday auction. Whereas, as a reflection of reality, all types of model restrictions related to technical constraints of generation units are considered in the Reference Scenario S_{ref}, we now aim at analyzing whether neglecting power plant flexibility constraints may trigger restricted participation and the resulting characteristic price pattern to disappear. Thus, we set up the 'No-Ramping Scenario' (S_{noramp}) without technical constraints. Again cross-border trade on a quarter-hourly level is not permitted. We choose a comparative illustration and depict the fundamental model results for both scenarios in Figure 5.3. In the graph, we present average price relations for each quarter-hour of the day along the modeling period. Further details including descriptive statistics on the hourly as well as quarter-hourly price levels can be found in Table 5.23 in Section 5.7.8.

In order to comment on whether the quarter-hourly price volatility observed in historical data may stem from technical constraints, we compare the two target figures *mean absolute price difference* and *standard deviation of price differences* between both scenarios (Table 5.9).

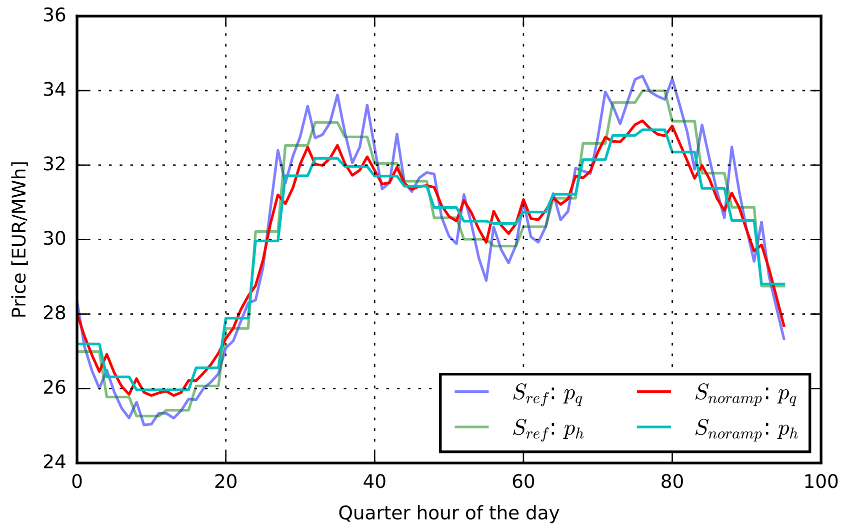


Figure 5.3: Daily pattern of average hourly and quarter-hourly price levels in the reference model run (S_{ref}) and the model run without ramping restrictions (S_{noramp})

Table 5.9: Evaluation of price differences: The role of power plant flexibility

Target Figure	S_{noramp} [EUR/MWh]	S_{ref} [EUR/MWh]
Mean absolute price difference (p_h - p_q)	0.51	0.87
Standard deviation price difference (p_h - p_q)	0.99	1.6

Our modeling results suggest that neglecting technical constraints causes a decreasing price volatility in the market with quarter-hourly contract duration[9]. More precisely, we find that the standard deviation of price differences decreases by 60% if we do not account for technical constraints. However, we still observe that the 15-minute electricity price proxies are significantly fluctuating around the respective hourly ones. The characteristic price pattern, which we trace back to restricted participation, is still applicable. Therefore, we find an indication that additional influencing factors may trigger the pattern observed. In the next section, we hence aim at assessing the relative impact of power plant inflexibility in comparison to a lack of market coupling on a quarter-hourly level.

The Role of Market Coupling

We compare fundamental model results for both a scenario without any cross-border trade on a sub-hourly level and a scenario with full market coupling. At the same time, we include all technical constraints referring to power plant flexibility. Simply put, we compare the Reference Case (S_{ref}) with a scenario in which quarter-hourly cross-border trade is permitted (S_{fullcb}). We use target figures analogous to the previous sections. The respective results are illustrated in Figure 5.4.

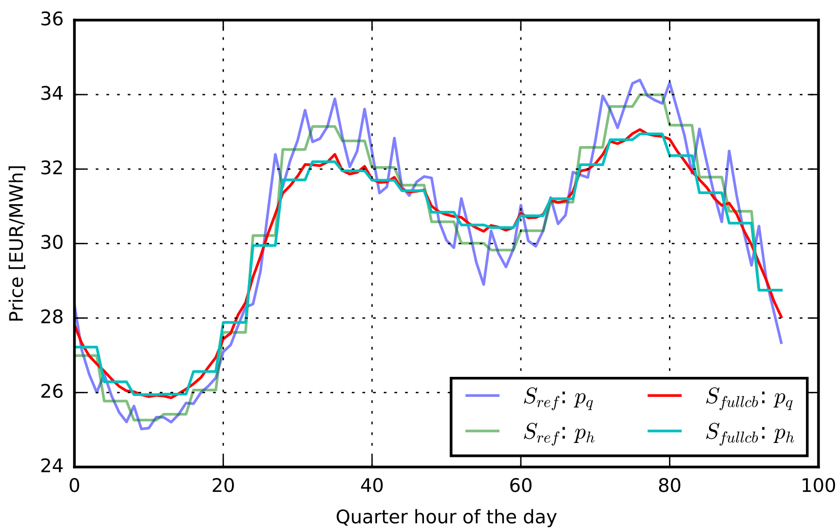


Figure 5.4: Daily pattern of average hourly and quarter-hourly price levels in the reference model run (S_{ref}) and model run with cross border trade on a quarter-hourly level (S_{fullcb})

[9]We analyze the individual impact of all types of technical constraints considered in more detail in Section 5.7.7.

Table 5.10: Evaluation of price differences: The role of market coupling

Target Figure	S_{ref} [EUR/MWh]	S_{fullcb} [EUR/MWh]
Mean absolute price difference (p_h - p_q)	0.87	0.24
Standard deviation price difference (p_h - p_q)	1.6	0.55

The permission of cross-border trade on a 15-minute level clearly induces a convergence of hourly and 15-minute prices which can be traced back to increased market participation. Furthermore, the Reference Case's price pattern in which quarter-hourly prices are fluctuating around the respective hourly ones tends to disappear if quarter-hourly market coupling is implemented. Additionally, according to Table 5.10, the mean absolute price difference as a proxy for restricted participation and price volatility decreases by a factor close to four. All in all, we find an indication that the lack of sub-hourly market coupling is the main driver of restricted participation in the market with quarter-hourly contracts. We furthermore derive the welfare impact of implementing sub-hourly market coupling based on our modeling results. The total system costs (5.1) would decrease by EUR 55 million if 15-minute cross-border trade was permitted. These numbers are similar to the estimates derived in Knaut and Paschmann (2017b).

5.6 Conclusion

In this paper, we analyze three plausible drivers of restricted participation in the German intraday auction with 15-minute contract duration in detail. As the overall efficiency of sequential market designs decreases with limited market participation, it is crucial to identify the underlying drivers in order to take countermeasures.

First, we are interested in whether costs of market entry may represent an economic driver of not participating in the intraday auction while, in contrast, participating in the day-ahead auction. Based on economic calculations for different types of generation units, we find an indication that this may not be consistent with the individual economic decision rationales.

Second, we apply a fundamental electricity market model in order to evaluate the impact of both power plant inflexibility as well as a lack of sub-hourly market coupling on the quarter-hourly price volatility. Our results indicate that the lack of market coupling on a quarter-hourly level is the most relevant driver of restricted participation in the German intraday auction. Based on our results, we finally suggest that additional market coupling may cause the 15-minute price volatility to decrease by a factor close to four.

Our results may serve as a basis for deriving countermeasures in order to reduce inefficiencies that result from restricted participation in electricity markets with sub-hourly products. It may be beneficial for policy makers to urge the implementation of quarter-hourly market coupling across the internal European electricity market as, at least partially, addressed by the 'XBID' project. At the same time, understanding the most relevant drivers of restricted participation in the intraday auction may help power plant operators to forecast the impact of policy measures such as introducing sub-hourly market coupling on the resulting prices. This is crucial in order to evaluate long-term business strategies. Finally, our methodological approach points out that energy system models may benefit from a quarter-hourly temporal resolution, especially when seeking to model the investment decisions of flexible generation units. The model allows to simulate sequential market dynamics with differing product granularity and different types of market coupling.

5.7 Appendices

5.7.1 Empirical Analysis

In order to assess the impact of introducing a new trading opportunity on the resulting price relations, we empirically analyze the development of the respective market dynamics over time. We thereby get an indication for the maturity of the market. The empirical results help shedding light on the role of inertia and the state of not knowing of market participants. Our estimation approach heavily builds on the approach applied in Knaut and Paschmann (2017b). In the following, we first depict the data used. We then present our estimation procedure and evaluate the respective results.

Data

Our empirical analysis is based on data from January 1, 2015 until April 30, 2017. We conduct the empirical estimation on a quarter-hourly level. Table 5.11 gives an overview on all relevant data included. We furthermore provide a brief explanation regarding each parameter. Supplementary, the respective descriptive statistics are presented in Table 5.12.

We include general price data for the day-ahead and intraday auction which is provided by the European Power Exchange (EPEX SPOT SE, 2017c). As regards the main explanatory variables, we first gathered the day-ahead forecasts for the electricity generation from wind and solar power since trade in the spot markets under consideration is based on forecasted values. The respective data is available on the transparency platform of the European Energy Exchange (EEX, 2017b). Second, we use the realizations of the actual system load[10]. The respective load values, as a proxy for the overall electricity demand[11], are accessible via data provided by the Transmission System Operators (TSOs) on the transparency platform of the European Network of Transmission System Operators for Electricity (ENTSO-E, 2017).

Table 5.11: List of variables and references

Symbol	Label	Variable	Measure	Reference
p_t^{ida}	id auction price	Uniform settlement price for a 15-minute product in the German intraday auction	EUR/MWh	EPEX SPOT SE (2017c)
p_t^{da}	day-ahead price	Hourly German day-ahead auction price	EUR/MWh	EPEX SPOT SE (2017c)
D_t^{res}; $\overline{D^{res}}_t$	residual demand 15 residual demand 60	Residual demand in a 15-minute period and the respective hourly mean	GW	EEX (2017b) , ENTSO-E (2017)
ΔD_t^{res}	residual demand deviation	Difference of the 15-minute residual demand and the respective hourly mean (Forecasts)	GW	EEX (2017b) , ENTSO-E (2017)
$Solar_t$; $\overline{Solar}_t$	solar power 15 solar power 60	Day-ahead forecast for the 15-minute solar power and the respective hourly mean (ex-ante value)	GW	EEX (2017b)
$Wind_t$; $\overline{Wind}_t$	wind power 15 wind power 60	Day-ahead forecast for the 15-minute wind power and the respective hourly mean (ex-ante value)	GW	EEX (2017b)
D_t; $\overline{D}_t$	load 15; load 60	Realization of the 15-minute load and the respective hourly mean	GW	ENTSO-E (2017)

[10]Here we use ex post instead of ex ante values as we find the respective data matching the causal relations under analysis with higher accuracy. The forecasted values available exhibit systematic deviations which are not consistent with the economic rationales of the market participants considered. Therefore, we expect the realizations of the system load to match the actual level of information more accurately.

[11]For more details on load see Schumacher and Hirth (2015).

Table 5.12: Descriptive Statistics (Units according to 5.11, N refers to the number of observations)

Variable	N	Mean	Std.Dev.	Min	25%	Median	75%	Max
id auction price	81,663	31.49	15.89	-164.48	22.62	30.57	39.92	464.37
day-ahead price	81,663	31.42	14.12	-130.09	23.94	30.29	38.11	163.52
residual demand 15	81,663	41.67	11.09	0.95	34.36	41.59	49.58	73.00
residual demand 60	81,663	41.67	11.06	1.86	34.39	41.60	49.56	72.39
residual demand deviation	81,663	0.00	0.81	-12.27	-0.39	0.00	0.38	8.82
solar power 15	81,663	3.92	6.06	0.00	0.00	0.07	6.19	27.18
wind power 15	81,663	9.58	7.47	0.30	3.83	7.43	13.23	39.56
load 15	81,663	55.17	10.00	25.04	46.81	54.85	64.09	78.09

Empirical Estimation

We use Ordinary Least Squares (OLS) regression techniques and apply estimation equation (5.13) with the intraday auction price being the dependent variable.

$$\begin{aligned} p_t^{ida} &= \beta_1 \cdot \overline{D^{res}}_t + \beta_2 \cdot (D_t^{res} - \overline{D^{res}}_t) + \nu + \epsilon_t \\ &\text{with } \epsilon_t \sim \; N(0, \sigma^2), \end{aligned} \tag{5.13}$$

Here the intraday auction price is modeled as a deviation from the respective day-ahead price which was settled before. Simply put, we use a reference price approach in which the increased product granularity induces imbalances that cause new market equilibria in the second market stage, the intraday auction. However, since we aim at comparing the estimates that reflect the impact of trade quantities on prices, we replace the day-ahead price with the hourly residual demand ($\overline{D^{res}}$). We base our procedure on the fact that the hourly residual demand is the main driver of trade in the day-ahead auction. At the same time, we are well aware that not directly including the day-ahead price causes a minor loss of explanatory power.

According to Section 5.3, we additionally include the deviation of the quarter-hourly residual load from its hourly mean ($D_t^{res} - \overline{D^{res}}_t$) as the main driver of additional trade needs on a quarter-hourly level in the intraday auction. We furthermore estimate a constant intercept in order to be able to interpret the R^2. Finally, we use robust standard errors to account for heteroscedasticity.

Based on both an Augmented Dickey Fuller as well as a Phillips-Perron test (see 5.7.2), we reject the hypothesis of non-stationary processes. We additionally expect our estimation approach not to be biased by endogeneity since our explanatory variables are based on forecasted values that have been generated before the day-ahead market settlement. We do not include actual trade volumes but a proxy for the total electricity demand. Thus, the market outcome is assumed not to have a direct impact on the variables used. Additionally, the solar and wind power depend on weather conditions that are exogenously given. Overall, we hence assume a unidirectional impact of the explanatory variables on the dependent variable. It is worth considering issues related to omitted variables. In Knaut and Paschmann (2017b), the authors show that forecast errors do not have a significant impact on the intraday auction price as they tend to reveal closer to physical delivery and are far more likely to be balanced within continuous intraday trade. Furthermore, we got several expert opinions of energy trading companies giving evidence that there is no informational update between both market settlements. Since cross-border trade is furthermore not permitted within the intraday auction, imports and exports, which are typical variables with potential influence on the price formation, are not worth considering.

We apply two OLS specifications (OLS (1) and OLS (2)). Whereas in OLS (1) we aim at measuring the average increase of the gradient of the supply curve in the intraday auction compared to the day ahead auction, OLS (2) focuses on structural changes over time. In more detail, in OLS (2) we separately estimate the coefficients for the years 2015, 2016, and 2017 by interacting the explanatory variables with the respective time dummies. Thereby, we are able to comment on effects related to the introduction of the intraday auction and inertia.

Similar to the analysis presented in Knaut and Paschmann (2017b), we identify a significant increase of the gradient of the intraday auction supply curve by a factor higher than seven compared to the respective one in the day-ahead auction. Our estimates exhibit sufficient explanatory power with the R^2 being above 66%. Based on OLS (2), we furthermore infer that the respective relation of the coefficients slightly decreases from factor 8.5 in 2015 to factor 6.5 in 2016. However, the impact of restricted participation is again exacerbated in the first four months of 2017 and we identify a factor of 7.3. It has to be taken into account that the findings for 2017 are solely based on four months of observations. It may be worth analyzing a prolonged period in future research. Nevertheless, we find an indication that inertia as the state of not knowing is only a minor driver of restricted participation in the intraday auction. A high difference between the hourly and quarter-hourly gradients is persistent over time. To sum up, our estimation results suggest that effects related to introducing a new trading opportunity and inertia do not trigger the major share of restricted participation in the intraday auction.

Table 5.13: Regression estimates for intraday auction price data

	Dependent variable: id auction price ($p^{ida}_{q,t}$)			
Explanatory variable	OLS (1)	OLS (2)		
residual demand 60 ($D^{res}_{h,t}$)	1.03^{***}			
	(0.005)			
		2015	*2016*	*2017*
		1.03^{***}	0.95^{***}	1.16^{***}
		(0.004)	(0.004)	(0.006)
residual demand deviation (ΔD^{res}_{t})	7.65^{***}			
	(0.08)			
		2015	*2016*	*2017*
		8.75^{***}	6.21^{***}	8.49^{***}
		(0.14)	(0.10)	(0.22)
intercept (ν)	-11.26^{***} (0.19)	-10.84^{***} (0.17)		
observations	81,663	81,663		
adj. R^2	0.66	0.70		
F	26,273	11,366		

Notes to Table 5.13: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. In OLS (2) we interact the explanatory variables with yearly time dummies. We use data from January 2015 until the end of April 2017.

5.7.2 Unit Root Tests

We apply both an Augmented Dickey Fuller test and a Phillips-Perron test for unit roots. The respective test results are displayed in Table 5.14 (Dickey and Fuller, 1979, Phillips and Perron, 1979). The Phillips-Perron test uses Newey-West standard errors in order to account for serial correlation. The null hypothesis of both tests is that there is a unit root in the periods of observation. We tested the Akaike Information Criterion (AIC) in order to determine the optimal lag lengths. As the AIC results are ambiguous for the variables considered and tend to indicate using as many lags as tested for, we use the Schwert rule of thumb and consider a leg length of 65 (Schwert, 1989). We prefer making a slight error due to including too many lags since Monte Carlo experiments suggest that this procedure is preferable to including too few lags. In order to give evidence for the robustness of our results, we repeated the tests for different lag lengths. Within the scope of the Augmented Dickey Fuller test, we extend the basic test of a random walk against a stationary autoregressive process by including a drift and a trend term. As far as the listed results are concerned, we decide whether to include a trend or constant by checking the significance of the trend/constant parameters at a 5% significance threshold.

Table 5.14: Unit root tests

	Augmented Dickey Fuller (Levels)			Philipps-Perron Test (Levels)		
Variable	statistic	p-value	lags	statistic	p-value	lags
id auction price	-18.34	0.00	65	-188.27	0.00	65
day ahead price	-16.32	0.00	65	-24.04	0.00	65
residual demand 60	-12.36	0.00	65	-21.71	0.00	65
residual demand deviation 15	-47.20	0.00	65	-683.70	0.00	65

5.7.3 Profitability Analysis Model Description

Table 5.15: Sets of the model applied for profitability analyses

Sets

Abbreviation	Description
q ∈ Q	Quarter-hourly time intervals
h ∈ H	Hourly time intervals
h_q ∈ H	Set of hours that belong to a specific quarter-hourly time interval

Table 5.16: Parameters of the model applied for profitability analyses

Model parameters

Abbreviation	Dimension	Description
η	[%]	Net efficiency (generation)
fu	[EUR/MWh$_{th}$]	Fuel price incl CO_2 (full load)
fu^{ml}	[EUR/MWh$_{th}$]	Fuel price incl CO_2 (min load)
in	[MW]	Installed capacity
ml	[%]	Minimum part load level
rr	[%]	Maximum ramp rate
$p_{DA,h}$	[EUR/MWh$_{el}$]	Day-ahead auction price
$p_{ID,q}$	[EUR/MWh$_{el}$]	Intraday auction price
st	[h]	Start-up time from cold start

Table 5.17: Variables of the model applied for profitability analyses

Model variables

Abbreviation	Dimension	Description
GE_h	[MW$_{el}$]	Day-ahead electricity generation
ΔGE_q	[MW$_{el}$]	Quarter-hourly production schedule as deviation from day-ahead supply
O_q	[MW]	Bool whether plant is in Operation
$Start_q$	[MW]	Bool whether start-up process is initiated
Profit	[EUR]	Profit of power plant

We apply profit maximization.

$$
\begin{aligned}
\underset{GE_h, \Delta GE_q}{\text{maximize}}\, Profit = \sum_q \Big[\big(\sum_{h_q} \frac{1}{4} \cdot Revenue_{DA,h_q} \big) \\
+ Revenue_{ID,q} - Costs_{Production,q} - Costs_{Startup,q} \Big] \\
whith \\
Revenue_{DA,h} &= GE_h \cdot (p_{DA,h} - 0.04) \\
Revenue_{ID,q} &= \Delta GE_q \cdot \frac{1}{4} \cdot (p_{ID,q} - 0.07) \\
Costs_{Production,q} &= \frac{\sum_{h_q} GE_{h_q} + \Delta GE_q}{\eta} \cdot fu \\
&+ (O_q \cdot in - \sum_{h_q} GE_{h_q} - \Delta GE_q) \cdot \frac{fu^{ml} - fu}{\eta} \cdot \frac{ml}{1 - ml} \\
Costs_{Startup,q} &= Start_q \cdot ml \cdot in \cdot \frac{fu}{\eta}
\end{aligned}
\tag{5.14}
$$

The revenue terms include transaction costs which depend on the specific market place. These are actual fees charged on the exchange. Based on expert opinions, we assume start-up procedures to cause doubled fuel costs.

We consider the following constraints:

$$\sum_{h_q} GE_{h_q} + \Delta GE_q \leq in \cdot O_q \quad \forall q \tag{5.15}$$

$$\sum_{h_q} GE_{h_q} + \Delta GE_q \geq ml \cdot O_q \quad \forall q \tag{5.16}$$

$$\sum_{h_q} GE_{h_q} + \Delta GE_q \geq 0 \quad \forall q \tag{5.17}$$

$$\sum_{h_q} GE_{h_q} + \Delta GE_q - \sum_{h_{q-1}} GE_{h_{q-1}} + \Delta GE_{q-1} \leq rr \quad \forall q \tag{5.18}$$

$$\sum_{h_{q-1}} GE_{h_{q-1}} + \Delta GE_{q-1} - \sum_{h_q} GE_{h_q} + \Delta GE_q \leq rr \quad \forall q \tag{5.19}$$

Without going into detail with respect to the exact formula, we furthermore account for the fact that a generation unit may only be in operating mode ($O_q = 1$) if a start-process ($Start_q$=1) has been initiated several period before, according to *Start-up time from cold start*.

5.7.4 Techno-economic parameters

Table 5.18: Techno-economic parameters for conventional power plants. Note: We consider several vintage classes for each type of generation unit. Depending on the construction year, we thus depict ranges for specific parameters.

	Net efficiency [%]	Max ramp rate [%/Min]	Availability [%]	Start-up time [h]	Minimum part-load [%]
Coal	37 - 46	0.02-0.033	84	5 - 7	27 -40
Coal (innovative)	50	0.4	84	4	27
Lignite	32 - 43	0.02-0.025	86	10 - 11	35 - 60
Lignite (innovative)	47	0.04-0.05	86	7	30
CCGT	40 - 60	0.05-0.08	86	2 - 3	40 - 70
OCGT	28 - 40	0.1-0.25	86	0.25	40 - 50
Nuclear	33	0.04	92	24	45
Biomass (solid)	30	1	85	1	30

5.7.5 Fuel and carbon dioxide emission costs

Table 5.19: Fuel costs and CO_2 emission costs 2015

Type	Costs [EUR/MWh_{th}]
Nuclear	3.5
Lignite	3.5
Oil	27.7
Coal	8.9
Gas	18.4

CO_2 emission price [EUR/tCO_2]	2015
CO_2	4.8

5.7.6 Model Overview

Minimize

$$TSC = \sum_{c\in C}\sum_{a\in A}\sum_{q\in Q}\left[Costs^{var}_{q,a,c} + Costs^{part-load}_{q,a,c} + Costs^{start}_{q,a,c} + Costs^{ramping}_{q,a,c}\right] \tag{5.20}$$

with

$$\begin{aligned} Costs^{var}_{q,a,c} = &(\sum_{h_q\in H} hGE_{h_q,a,c} + qGE_{q,a,c}) \cdot (\frac{fu_a}{\eta_a}) \\ &+ (\sum_{h_q\in H} hGE_{h_q,a,c} + qGE_{q,a,c}) \cdot (\frac{cp \cdot ef_a}{\eta_a}) \end{aligned} \tag{5.21}$$

$$Costs^{part-load}_{q,a,c} = (CR_{q,a,c} - \sum_{h_q\in H} hGE_{h_q,a,c} - qGE_{q,a,c}) \cdot \frac{fu^{ml}_a - fu_a}{\eta_a} \cdot \frac{ml_a}{1-ml_a} \tag{5.22}$$

$$Costs^{start}_{q,a,c} = CU_{q,a,c} \cdot (\frac{fu_a}{\eta_a}) \tag{5.23}$$

$$Costs^{ramping}_{q,a,c} = (CU_{q,a,c} + CD_{q,a,c}) \cdot ac_a \tag{5.24}$$

such that

$$hD_{h_q,c} + qD_{q,c} = d_{q,c} \quad \forall\, q,c \tag{5.25}$$

$$\sum_{a\in A} hGE_{h,a,c} + \sum_{c_1\in C} hIM_{h,c,c_1} - \sum_{s\in S} hST_{h,s,c} = hD_{h,c} \quad \forall\, h,c \tag{5.26}$$

$$\sum_{a\in A} qGE_{q,a,c} + \sum_{c_1'\in C'} qIM_{q,c,c_1'} - \sum_{s\in S} qST_{q,s,c} = qD_{q,c} \quad \forall\, q,c \tag{5.27}$$

$$\sum_{h_q \in H} hGE_{h_q,a,c} + qGE_{q,a,c} \leq av_{q,a,c} \cdot in_{a,c} \quad \forall q,a,c \tag{5.28}$$

$$\sum_{h_q \in H} hGE_{h_q,a,c} + qGE_{q,a,c} \geq ml_a \cdot CR_{q,a,c} \quad \forall q,a,c \tag{5.29}$$

$$CR_{q,a,c} = CR_{q-1,a,c} + CU_{q-1,a,c} - CD_{q-1,a,c} \quad \forall q,a,c \tag{5.30}$$

$$CU_{q,a,c} \leq rr_a \cdot (in_{a,c} - CR_{q,a,c}) \quad \forall q,a,c \tag{5.31}$$

$$CD_{q,a,c} \leq rr_a \cdot (CR_{q,a,c}) \quad \forall q,a,c \tag{5.32}$$

$$CU_{q,a,c} \leq \frac{in_{a,c} - CR_{q,a,c}}{st_a} \quad \forall q,a,c \tag{5.33}$$

5.7.7 Details on the Impact of Individual Technical Constraints

In the following, we shed light on the individual impact of all types of technical constraints considered. Therefore, we add further model restrictions in a step-wise manner while assuming that cross-border trade on a quarter-hourly level is not permitted. Starting without any constraints referring to ramping and start-up characteristics (S_1), we consider limits to ramp rates in S_2 and compare the respective model results. In the left graph of Figure 5.7.7, we illustrate average price relations in each quarter-hour of the day along the modeling period. In the right table, we present the respective descriptive statistics for the hourly as well as quarter-hourly price levels. In order to comment on whether the quarter-hourly price volatility observed in historical data may stem from technical constraints, we compare the mean absolute price differences and the standard deviation of price differences as indicators for price volatility.

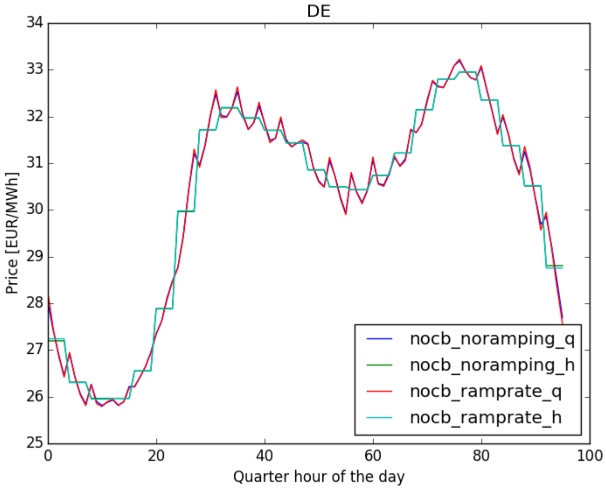


Figure 5.5: No ramping vs raming rate

	S_{noramp}	S_2
Min	10.3/10.1	10.3/10.1
10%	23.6/24.0	23.7/24.0
Mean	30.1/30.1	30.1/30.1
90%	36.9/36.9	36.9/36.9
Max	44.1/44.1	44.1/44.1
STD	5.9/6.0	5.9/6.0

Table 5.20: No ramping vs raming rate

Table 5.21: Evaluation of price differences [EUR/MWh]

Target Figure	S_{noramp}	S_2
Mean absolute price difference (p_h - p_q)	0.51	0.54
Standard deviation price difference (p_h - p_q)	0.99	1.05

We identify that power plant inflexibility, which is incorporated by ramp rates, only has very small impact on the quarter-hourly price volatility. Moreover, comparing the price lines in the graph, we find an indication that both scenarios are quite similar with regard to price volatility. More details are presented in Table 5.21. Based on the target figures *Mean absolute price difference* and *Standard deviation price difference*, we find that adding ramping constraints only causes a slight increase of the price volatility. The average absolute price difference increases by approximately 6%.

In a second step, we aim at analyzing the impact of further technical constraints by including part-load losses and start-up constraints. Again we refer to the target figures from above and present the respective modeling results in Table 5.22. For the sake of simplicity, we focus on the resulting price differences. The expression S_2 means the inclusion of ramp rates, whereas in S_3 we additionally consider part-load losses. Finally, S_4 extends the previous model runs and start-up constraints as well as the related costs are implemented.

The results suggest a progressively increasing quarter-hourly price volatility. Finally, adding attrition costs resulting from ramping processes, we obtain the Reference Scenario (S_{ref}) which is evaluated in detail within the article. Overall, our modeling results suggest that the most significant change regarding the quarter-

Table 5.22: Evaluation of price differences [EUR/MWh]

Target Figure	S_2	S_3	S_4
Mean absolute price difference (p_h - p_q)	0.54	0.61	0.65
Standard deviation price difference (p_h - p_q)	1.05	1.14	1.21

hourly price volatility is induced by considering ramping and start-up costs.

5.7.8 Descriptive Statistics on Model Results

Table 5.23: Descriptive statistics on model results (electricity prices [EUR/MWh]) evaluating the impact of technical constraints

	S_{noramp}	S_{ref}
Min	10.3/10.1	10.5/8.6
10%	23.6/24.0	23.5/23.6
Mean	30.1/30.1	30.3/30.3
90%	36.9/36.9	37.5/36.9
Max	44.1/44.1	52.8/83.4
STD	5.9/6.0	6.2/ 6.4

Table 5.24: Descriptive statistics on model results (electricity prices [EUR/MWh]) evaluating the impact of sub-hourly market coupling

	S_{ref}	S_{fullcb}
Min	10.5/8.6	10.3/10.3
10%	23.5/23.6	23.8/23.8
Mean	30.3/30.3	30.1/30.1
90%	37.5/36.9	36.9/36.9
Max	52.8/83.4	44.1/44.1
STD	6.2/ 6.4	5.9/5.9

6 Economic Analysis of Price Premiums in the Presence of Non-convexities - Evidence from German Electricity Markets

Analyzing price data from sequential German electricity markets, namely the day-ahead and intraday auction, a puzzling but apparently systematic pattern of price premiums can be identified. The price premiums are highly correlated with the underlying demand profile. As there is evidence that widespread models for electricity forward premiums are not applicable to the market dynamics under analysis, a theoretical model is developed within this article which reveals that non-convexities in only a subset of sequential markets with differing product granularity may cause systematic price premiums at equilibrium. These price premiums may be bidirectional and reflect a value for additional short-term power supply system flexibility.

6.1 Introduction and Research Question

Economic theory suggests that the limited storability of electricity may pose limits to arbitrage. Price levels in sequential markets may hence differ significantly and sudden changes in prices may be identified. At the same time, recent developments are characterized by the establishment of sequential short-term electricity markets in Germany to deal with the increasing share of highly volatile intermittent renewable electricity generation. A trend of trading shorter contracts closer to the physical delivery may be identified. These markets face an ongoing increase in trade volumes, but the economic understanding of the respective market dynamics has yet to be deepened.

In this paper, an analysis of price premiums in the context of two sequential German short-term electricity markets is conducted. The day-ahead auction is cleared at noon one day ahead delivery and offers hourly products. It is regarded as providing the most relevant reference price for subsequent trade. Second, the intraday auction is considered which is settled three hours afterwards and allows for trading quarter-hourly contracts.

In the research area of electricity markets, the model presented in Bessembinder and Lemmon (2002) embodies a widespread explanatory approach for price premiums between forward and real-time electricity markets. However, there is evidence that the model is not applicable to price premiums between the day-ahead and intraday auction. The rapid succession of both market settlements without updated information requires the derivation of an alternative approach to decode the puzzling pattern of price premiums identified. Therefore, a theoretical model is developed to analyze price premiums in the presence of non-convexities in sequential markets with differing product granularity.

The model uncovers that non-convexities being more pronounced in only a subset of sequential markets may lead to both negative or positive price premiums. The direction of price premiums depends on the market settlement being in particular sections of the underlying merit order. Indeed, the real-world data reveals a high correlation of load and the direction as well as the value of price premiums. It may be stressed that the price premiums under analysis incorporate a value of additional short-term power system flexibility rather than reflecting a value of risk. Analyzing the cost-saving potential from smoothing these non-convexities, a proxy for the value of additional power system flexibility could be derived. On a national level, this is approximately EUR 10.2 million in 2015. The corresponding value for flexibility which is provided by neighboring countries is EUR 6.4 million in 2015. These are rather small numbers, but yet the general model framework may easily be transferred to other applications such as sequential block and single unit auctions.

It is crucial to understand the fundamental properties of the price premiums identified as they may reflect market needs or even indicate inefficiencies. As regards the day-ahead and intraday auction, the price premiums are, at least partially, triggered by restricted participation in the intraday auction. The introduction of cross-border market coupling on a sub-hourly level may be beneficial to reduce the resulting welfare losses. From a business perspective, the findings and the systematology uncovered are relevant to evaluate business strategies building on the price differences observed.

The article is organized as follows. In Section 6.2 the paper is positioned in the existing literature and a broad overview on possible limits to arbitrage is provided. In a next step, an empirical analysis of price premiums in the German day-ahead and intraday auction is presented in Section 6.3. To gain insights into the drivers of the price premiums under consideration, a theoretical analysis is conducted within Section 6.4. The respective results are then contextualized in Section 6.5. Finally, conclusions are drawn.

6.2 Literature Background

The Fundamental Theorem of Asset Pricing depicts conditions for arbitrage-free and complete markets (Dybvig and Ross, 1987). In particular, the coincide of stochastic processes and equivalent martingales causes markets not to exhibit unexploited arbitrage opportunities. Based on this theory, in Weber (1981) the author states that prices in sequential auctions epitomize a martingale where, on average, prices neither go systematically up nor down over time. The Law of One Price furthermore clarifies that in perfect financial markets goods should have an identical price across all locations (Isard (1977) and Richardson (1978)). However, real-world markets may require a more differentiated view.

The general impact of sequential market designs on prices has extensively been studied (see, e.g., Allaz and Vila (1993), Juvenal and Petrella (2015), Kilian and Murphy (2014), Knittel and Pindyck (2013)). In Mezzetti et al. (2007), the authors suggest a lowballing effect reducing the first stage market price. As regards the application to real markets, in Ardeni (1989) it is stressed that the Law of One Price does not hold true for sequential commodity markets, at least in the long run. Based on the example of electricity markets, empirical evidence for this hypothesis is provided in Ito and Reguant (2016). The authors identify systematic price premiums in forward markets. Taking up on the general idea of non-convergence of sequential markets' prices, a concept of equilibrium models with a certain degree of disequilibrium is developed in Grossman and Stiglitz (1980).

Economic theory suggests that prices in sequential markets may particularly differ in the case of limited arbitrage. In Grossman and Stiglitz (1980), the authors identify transaction costs as a first plausible driver of systematic price differences in sequential markets (see, e.g., Ardeni (1989), Jha and Wolak (2015)). Second, market power abuse may trigger price spreads since dominant firms may not benefit from exploiting arbitrage opportunities (Ito and Reguant, 2016). As a third factor, risk aversion may drive the Law of One Price to fail (McAfee and Vincent, 1993). For illustration purposes, in Ashenfelter (1989) the author analyzes wine auctions and observes significant differences in prices for identical goods. The respective explanatory approach is based on risk aversion, quantity constraints, and asymmetric information. Such asymmetries regarding market participants may also refer to an asymmetric valuation of goods and different preferences (Bernhardt and Scoones

(1994), Salant (2010)).

One further category of explanatory approaches for limited arbitrage refers to institutional and regulatory schemes. In Borenstein et al. (2008), the authors point out that uncertainty about a regulatory change may trigger prices in sequential markets to differ and empirical evidence from Californian electricity markets is presented. Finally, newly emerging markets may trigger learning processes leading to price differences shortly after introducing a new trading opportunity (Doraszelski et al., 2016).

In this paper, focus is placed on price relations within sequential electricity markets. Following economic theory, electricity exhibits unique features that cause a need for a differentiated analysis compared to other commodities such as oil and gas. First, the limited potential to store huge amounts of electricity poses limits to arbitrage opportunities. Furthermore, limited access to capital and strict regulation for financial players may be relevant (Birge et al., 2014). In Bessembinder and Lemmon (2002), the authors develop an equilibrium model that is supposed to be tailored for sequential electricity markets. In doing so, the authors suggest that forward premiums are negatively affected by high price volatility. At the same time, they identify a positive correlation of forward premiums and the skewness of prices in the real-time market. Complementary to Bessembinder and Lemmon (2002), in Longstaff and Wang (2004) the authors present empirical evidence from US electricity markets that the theoretical model is actually applicable to real-world data. In contrast to their scope, the analysis conducted within this article focuses on electricity markets with fundamentally different market characteristics. Above all, there is essentially no informational update between both market settlements. Nevertheless, a similar pattern of price premiums is observed yielding a puzzle which is yet to be solved.

6.3 Empirical Analysis of Price Premiums in the German Day-ahead and Intraday Auction

An empirical analysis of price premiums between the German day-ahead and intraday auction provides first insights on the topic under analysis. The day-ahead auction is settled at noon one day ahead physical delivery. The respective products are hourly contracts for the physical delivery of electricity. Following the day-ahead auction, the intraday auction with 15-minute contract duration is settled one day ahead delivery at 3pm[1]. Both markets exhibit a uniform market price. Additionally, both market stages are settled in rapid succession such that there is no significant informational update that impacts trade (Knaut and Paschmann, 2017b)[2]. Since trade in both markets refers to physically binding contracts without pure financial clearing, the main purpose is matching supply and demand according to the contract duration offered, rather than speculation and risk hedging. More precisely, in Knaut and Paschmann (2017b) the authors show that the interaction of the day-ahead and intraday auction is essentially driven by increasing product granularity (hourly vs. quarter-hourly) and restricted participation in the intraday auction. In Knaut and Paschmann (2017a), the authors furthermore clarify that the lack of sub-hourly market coupling may be regarded as the most relevant driver of restricted participation in the German intraday auction.

Since the product granularity increases from the day-ahead to the intraday auction, arbitrage refers to bundles of goods. Four evenly distributed contracts which are traded in the intraday auction may act as a perfect substitute for the respective day-ahead contract. Arbitrage is even facilitated by the rapid succession of the market settlements. As the market characteristics hence basically comply with the no-arbitrage argument, it could be expected to find mean price equivalence. Nevertheless, systematic price premiums in individual hours of the day can be identified when analyzing historical price data. For illustration purposes, the distribution of price premiums for the individual hours of the day is presented in Figure 6.1. The figure is based on price premiums which are defined as the difference between the day-ahead auction price and the mean price level of the corresponding four intraday auction contracts. The target figure is derived according to Equation (6.1). The analysis is based on historical day-ahead and intraday auction price data from January 16, 2015 until November 2, 2016 (EPEX SPOT SE, 2016a) and the respective descriptive statistics are presented in detail in Table 6.2 in Section 6.7.1.

$$\Delta p = p^{day-ahead} - \frac{\sum_{t=t1}^{t4} p_t^{intraday}}{4} \tag{6.1}$$

In Figure 6.1 mean values are marked in red and the black lines give the median values. The green boxes range from the second to the third quartiles, whereas the dashed lines illustrate the 10 % and 90 % percentiles. Furthermore, the dashed hor-

[1]For more details on the purpose of implementing the intraday auction complementary to continuous intraday trade see Neuhoff et al. (2016). As regards the market depth, an illustration of average trade volumes is presented in Section 6.7.7.

[2]The influence of forecast errors on the resulting market prices is negligible.

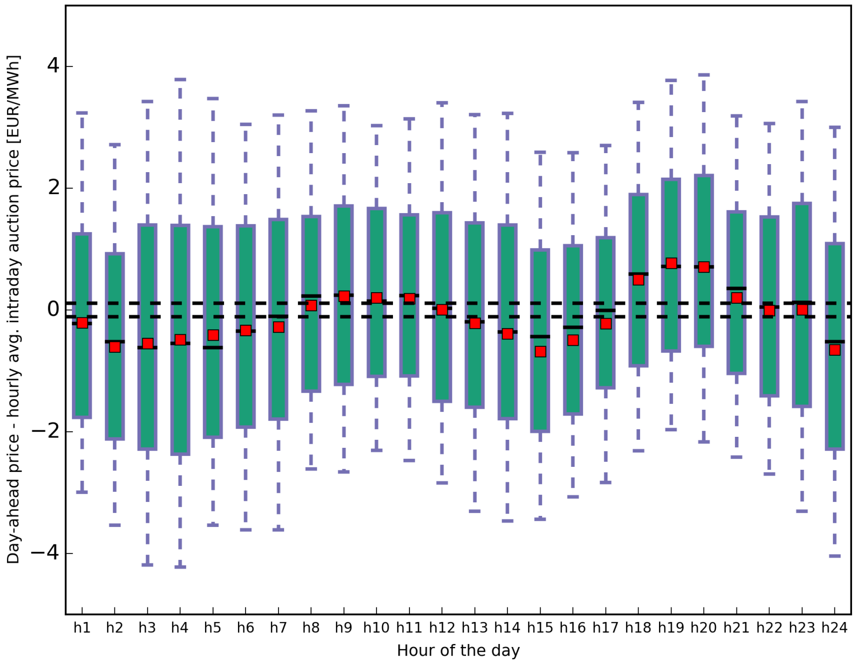


Figure 6.1: Distribution of differences between day-ahead and intraday auction prices compared to the respective transaction costs (January 16, 2015 - November 2, 2016)

izontal lines highlight the transaction costs. Based on the exact numbers which are presented in column *Mean* of Table 6.2, the conclusion can be drawn that in individual hours (i.e., e.g., *h2* and *h15*) positive price premiums clearly outweigh negative ones. However, in other hours (such as in *h19*) reverse relations can be identified. The direction of price differences hence varies during the course of the day. In the majority of hours these price differences even exceed the direct transaction costs for trading, which are demanded by the exchange[3]. More specifically, positive price premiums, for example, range between 0 ct/MWh and 77 ct/MWh and the respective average is 29 ct/MWh. Nevertheless, the aggregate net price premium across all hours of the day approximately equals the transaction costs.

Based on the empirical findings, it could be expected that market participants may anticipate the direction of price differences and exploit additional arbitrage opportunities. As this is not reflected by the real-world data, it is relevant to deepen the understanding of the underlying drivers.

[3]These are 0.04 EUR/MWh in the day-ahead and 0.07 EUR/MWh in the intraday auction (EPEX SPOT SE, 2016b).

The pattern of price premiums identified, albeit less pronounced, is comparable to the findings of prior literature dealing with price differences between electricity forward and real-time markets (see, e.g., Longstaff and Wang (2004) and Viehmann (2011)). This is rather counterintuitive since some basic characteristics of the market configurations under analysis differ crucially. In particular, there is no informational update between the day-ahead and intraday auction. The lack of risk reduction between both market settlements does not comply with the assumption of risk premiums. Additionally, whereas in Longstaff and Wang (2004) the authors give empirical evidence for the applicability of the equilibrium pricing model presented in Bessembinder and Lemmon (2002), an analogous procedure is essentially not transferable to price differences between the day-ahead and intraday auction. More precisely, building on the empirical approach adopted in Longstaff and Wang (2004), a simple empirical analysis may be conducted to test for the correlation of price premiums and the variance as well as the skewness of the day-ahead spot prices. Detailed results are presented in Section 6.7.2. In short, there is empirical evidence that this explanatory approach is not applicable to the price premiums under analysis.

The analyses presented within this article follow the general idea presented in Knaut and Paschmann (2017b) and seek to analyze the impact of restricted participation on sequential commodity market prices. Whereas the respective modeling approach in Knaut and Paschmann (2017b) appears suitable to analyze general price relations on an aggregate level, a need for extending the model may be identified when analyzing the price formation in individual hours. More precisely, the analysis conducted within this paper is especially motivated through the observation of pronounced stepped shapes in real-world bid curve data as examplified in Section 6.7.3. Therefore, a theoretical framework is developed within this essay to analyze the influence of non-convexities in only a subset of sequential markets on the resulting price relations.

6.4 Theoretical Analysis

Two classes of suppliers (restricted and unrestricted) are distinguished, both of which interact in two simultaneously[4] settled markets that differ in terms of product granularity and market participation. Both types of suppliers participate in the first mar-

[4]Due to the rapid succession of both market settlements, information in both markets is considered to be identical. This assumption is furthermore supported by energy trading companies confirming that there is no relevant informational update between both market settlements.

ket, whereas in the second market only unrestricted suppliers are able to participate. The first stage product is split up into two identical sub-contracts for the periods t ($t \in t1, t2$) that can be traded in the second market. The sub-contracts may combined act as a perfect substitute for the first stage product.

Consumers may demand a different positive quantity D_t in each time interval t[5]. Demand is satisfied under perfect competition by both restricted and unrestricted suppliers. Both suppliers operate production units with increasing marginal costs of production.

As the quantities of both types of suppliers are chosen under perfect competition, the following optimization problem can be formulated. Simply put, the total production costs are minimized such that supply meets demand.

$$\min z = C_r(q^r) + \sum_t \left[C_{u,t}(q^u_t) \right] \tag{6.2}$$

$$\text{s.t.} \qquad D_t = q^r + q^u_t \qquad \forall t. \tag{6.3}$$

Here $C_r(q^r)$ marks the overall costs for the production level q^r of all restricted suppliers. The costs are determined by the first market's outcome as restricted suppliers are not permitted to participate in the second market with shorter contracts. In contrast, $C_{u,t}(q^u_t)$ refers to the respective production costs for unrestricted suppliers in period t. The quantity q^u_t may vary in each time period and results from the first and second markets' settlements.

The set of restricted suppliers is characterized by an aggregate marginal cost curve. In more detail, Equation (6.4) depicts that a linear shape is assumed. The parameter a_0 determines a fixed offset, whereas a^r_1 is the gradient of the restricted supply curve.

$$C'_r(q^r) = a_0 + a^r_1 q^r \quad | \; a_0 > 0, a^r_1 > 0 \tag{6.4}$$

With respect to unrestricted suppliers, a stepped discontinuity within their marginal cost function is considered. Hereby, it is accounted for a case in which unrestricted participation is somehow systematic and its impact on the resulting market dynamics may vary depending on the market settlement being in particular sections of the merit order (Equation (6.5)). For the sake of simplicity, the offset (a_0) is the same as in the case of restricted suppliers.

[5]Demand in electricity markets is characterized as being rather price inelastic. This is especially valid for short-term markets as considered in this paper (see, e.g., Lijesen (2007) and Knaut and Paulus (2016)).

$$C'_{u,t}(q_t^u) = \begin{cases} a_0 + a_1^u q_t^u & q_t^u \leq Q_{disc} \quad | \, a_0 > 0, a_1^u > 0 \\ a_0 + \Delta_{disc} + a_1^u q_t^u & q_t^u > Q_{disc} \quad | \, a_0 > 0, a_1^u > 0 \end{cases} \tag{6.5}$$

The parameter Q_{disc} (> 0) may be regarded as the threshold which determines the discontinuous section of the merit order. Furthermore, a respective step height of Δ_{disc} is considered. For illustration purposes, Figure 6.2 depicts the respective relations. The lack of unrestricted suppliers within a particular section of the merit order is transformed into a marginal cost function with a stepped shape. Thereby, the aggregated merit order of both restricted and unrestricted suppliers is dynamic and depends on the demand quantities.

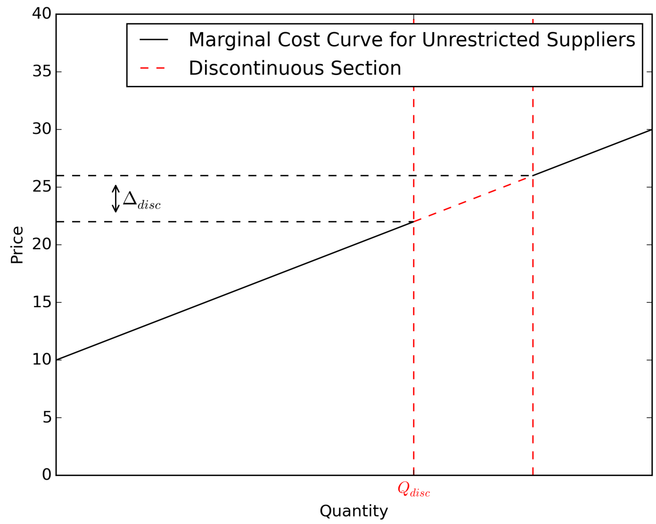


Figure 6.2: Illustration of the market configuration under analysis

The analysis is based on the assumption of an increasing demand profile ($D_{t2} > D_{t1}$) and hence the resulting mixed complementarity problem can be solved on the basis of the corresponding Karush-Kuhn-Tucker (KKT) conditions.

Proposition 6.1. *If demand exceeds a certain threshold such that the optimal production level of unrestricted suppliers under continuous relations would exceed the non-convexity, it is cost-optimal to fix the production of unrestricted suppliers and satisfy additional demand exclusively by restricted suppliers. Thereby, excess supply by restricted suppliers compared to the case of continuous relations can be identified. This quantity choice is optimal as long as the additional costs due to exclusive supply by* *restricted suppliers are outweighted by avoided costs due to the discontinuous step.*

Proof. The detailed mathematical proof is outlined in Section 6.7.4. The optimal production level of restricted suppliers depending on the respective demand level may be defined according to Equation (6.6). The corresponding production level of unrestricted suppliers may be directly derived by the use of Equation (6.3).

$$q^{r*} = \begin{cases} \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} & (a1) D_{t2} \leq \frac{2\cdot Q_{disc}\cdot(a_1^r+a_1^u)+D_{t1}\cdot a_1^u}{2\cdot a_1^r+a_1^u} \\ D_{t2}-Q_{disc} & (a2) \frac{2\cdot Q_{disc}\cdot(a_1^r+a_1^u)+D_{t1}\cdot a_1^u}{2\cdot a_1^r+a_1^u} < D_{t2} \leq \frac{2\cdot Q_{disc}\cdot(a_1^r+a_1^u)+D_{t1}\cdot a_1^u+\Delta_{disc}}{2\cdot a_1^r+a_1^u} \\ \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} + \frac{\Delta_{disc}}{2\cdot(a_1^r+a_1^u)} & (a3) \frac{2\cdot Q_{disc}\cdot(a_1^r+a_1^u)+D_{t1}\cdot a_1^u+\Delta_{disc}}{2\cdot a_1^r+a_1^u} < D_{t2}, D_{t1} \leq \frac{2\cdot Q_{disc}\cdot(a_1^r+a_1^u)+D_{t2}\cdot a_1^u+\Delta_{disc}}{2\cdot a_1^r+a_1^u} \\ D_{t1}-Q_{disc} & (a4) \frac{2\cdot Q_{disc}\cdot(a_1^r+a_1^u)+D_{t2}\cdot a_1^u+\Delta_{disc}}{2\cdot a_1^r+a_1^u} < D_{t1} \leq \frac{2\cdot Q_{disc}\cdot(a_1^r+a_1^u)+D_{t2}\cdot a_1^u+2\cdot\Delta_{disc}}{2\cdot a_1^r+a_1^u} \\ \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} + \frac{\Delta_{disc}}{a_1^r+a_1^u} & (a5) D_{t1} > \frac{2\cdot Q_{disc}\cdot(a_1^r+a_1^u)+D_{t2}\cdot a_1^u+2\cdot\Delta_{disc}}{2\cdot a_1^r+a_1^u} \end{cases} \tag{6.6}$$

□

Furthermore, this essay aims to shed light on the respective price implications.

Proposition 6.2. *In the presence of non-convexities, mean price equivalence is not a necessary condition at equilibrium. Rather to the contrary, positive price premiums may be identified that range between 0 and* $0.5 \cdot \Delta_{disc}$.

Proof. As the market outcome is determined under perfect competition, the respective inverse demand functions could directly be applied to draw conclusions on prices. The equations derived in (6.7) have to be satisfied at equilibrium. Here m^1 refers to the first market where both restricted and unrestricted suppliers are permitted to participate. The second market with restricted participation and increased product granularity is named m_t^2. It is worth mentioning that the first market's price is directly determined by the marginal costs of restricted suppliers as the respective production may only be traded within the first market. Furthermore, $C_r'(q^r) \geq \frac{(C_{u,t1}'(q^r)+C_{u,t2}'(q^r))}{2}$ is valid.

$$\begin{aligned} p(m^1) &= C_r'(q^r) \\ p(m_t^2) &= C_{u,t}'(q^r) \end{aligned} \tag{6.7}$$

These price relations provide the basis to analyze whether the discontinuity may trigger price differences between the sequential markets at equilibrium[6]. Equation (6.8) can be used to calculate the respective price differences.

[6]To bridge the gap to the mathematical proof in 6.7.4, it is assumed that $\epsilon \to 0$.

$$\Delta p = p(m^1) - \overline{p(m_t^2)} = \begin{cases} 0 & (a1) \\ (D_{t2} - Q_{disc}) \cdot a_1^r - \frac{(D_{t1} - D_{t2} + 2 \cdot Q_{disc}) \cdot a_1^u}{2} & (a2) \\ 0 & (a3) \\ (D_{t1} - Q_{disc}) \cdot a_1^r + \frac{(D_{t1} - D_{t2} - 2 \cdot Q_{disc}) \cdot a_1^u}{2} - \frac{\Delta_{disc}}{2} & (a4) \\ 0 & (a5) \end{cases} \quad (6.8)$$

Inserting the respective thresholds for D_{t2} according to (6.6) into the second term of (6.8) yields a price difference that ranges between 0 and $0.5 \cdot \Delta_{disc}$. Inserting the respective thresholds for D_{t1} into the fourth term (a4) yields analogous relations.

□

Since there are positive and negative price differences in the real-world price data, it may be worth analyzing the impact of non-convexities not only in the framework of unrestricted suppliers, but also extending the previous considerations to restricted suppliers.

The idea of considering non-convexities in the supply curve of either unrestricted or restricted suppliers may be motivated through a simplified illustration of the merit order for the German power plant fleet and its neighboring countries[7] assuming unlimited cross-border transmission capacity. The simplifying classification that unrestricted suppliers embody German power plants, whereas restricted suppliers are, in particular, located in the neighboring countries, is derived from Knaut and Paschmann (2017a). The authors stress that the lack of sub-hourly market coupling is the most relevant driver of restricted participation in the intraday auction. Figure 6.3 depicts the respective marginal costs depending on the underlying fuel costs as well as the CO_2 emission costs. Non-dispatchable renewable electricity generation is neglected. In addition, Figure 6.4 illustrates the aggregate supply curve of both types of suppliers. Hereby, it is facilitated to derive conclusions on the impact of non-convexities in either the restricted or unrestricted supply curve depending on the overall demand level. The underlying data is extracted from the fundamental electricity market model DIMENSION which is presented in more detail in Knaut and Paschmann (2017a) and (Richter, 2011). For simplification purposes and as the bidding behavior of flexible pumped storage generation units is a complex issue which is not in the focus of this paper, the respective generation capacities are illus-

[7] Denmark, the Netherlands, Belgium, France, Switzerland, Austria, Poland and the Czech Republic

trated in both edge regions of the merit order. Depending on the operational mode, pumped storage power plants may buy cheap electricity and produce electricity in periods with comparably higher prices.

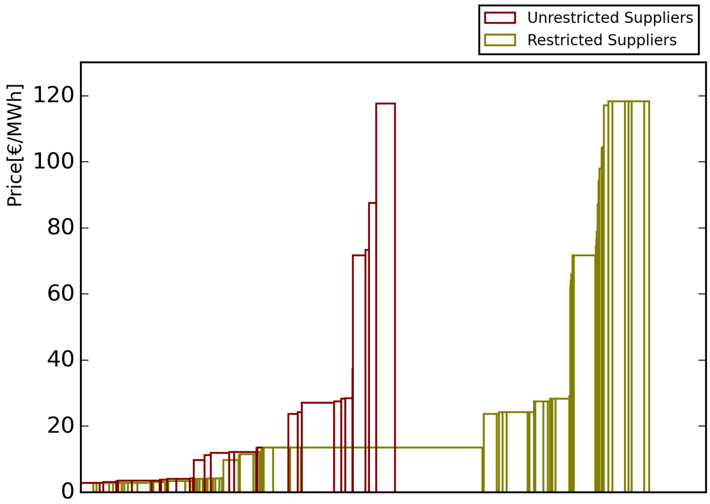


Figure 6.3: Stylized illustration of the unrestricted and restricted supply curves

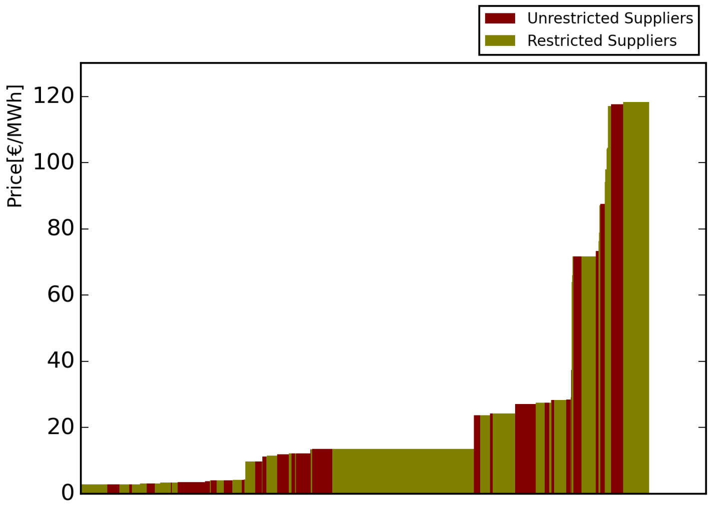


Figure 6.4: Stylized aggregate merit order for Germany and its neighboring countries

The figures already convey the idea that there are significant non-convexities in particular sections of the merit order. These considerations are also reflected and observable in real-world bid curve data from the German day-ahead and intraday auction (Section 6.7.3). The prevalence of non-convexities being more pronounced in either the restricted or unrestricted supply curve may vary depending on the overall demand level. Non-convexities within the German merit order tend to be especially relevant if demand is rather high.

Proposition 6.3. *Negative price premiums may stem from discontinuities in the marginal cost curve of restricted suppliers. The maximum price difference is bounded by $-\Delta_{disc'}$, which is the step height of the respective discontinuity. Overall, the frequency of positive and negative price differences depends on the market clearing being in particular sections of the merit order where non-convexities in either the unrestricted or restricted supply curve are more pronounced.*

Proof. The detailed proof is similar to the previous one and outlined in Section 6.7.6. As a result, if the merit order of restricted suppliers exhibits a non-convex section, Equation (6.9) depicts the optimal production level.

$$q^{r*} = \begin{cases} \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} & (b1) D_{t2} + D_{t1} \leq \frac{2\cdot(Q_{disc'}+\epsilon)\cdot(a_1^r+a_1^u)}{a_1^u} \\ Q_{disc'} + \epsilon & (b2) \frac{2\cdot(Q_{disc'}+\epsilon)\cdot(a_1^r+a_1^u)}{a_1^u} < D_{t1} + D_{t2} \leq \frac{2\cdot(Q_{disc'}+\epsilon)\cdot(a_1^r+a_1^u)+2\cdot\Delta_{disc'}}{a_1^u} \\ \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} - \frac{\Delta_{disc}}{a_1^r+a_1^u} & (b3) D_{t1} + D_{t2} > \frac{2\cdot(Q_{disc'}+\epsilon)\cdot(a_1^r+a_1^u)+2\cdot\Delta_{disc'}}{a_1^u} \end{cases} \tag{6.9}$$

Price implications can be derived analogous to the procedure applied in Equation 6.8 in Proposition 6.2. The relation $p(m^1) = C_r'(q^r)$, however, is no longer a necessary condition as the average marginal costs of unrestricted suppliers now exceed the respective marginal costs of restricted suppliers. Depending on the trading decision of unrestricted suppliers, the first stage market price may either be $p(m^1) = C_r'(q^r)$ or $p(m^1) = \frac{(C_{u,t1}'(q^r)+C_{u,t2}'(q^r))}{2}$. However, the arbitrage-free second market's price may exceed the respective price in the first market at equilibrium since the non-convexity eliminates additional opportunities for arbitrage[8].

$\square$

As regards the electricity markets under consideration, it may furthermore bring value added to analyze additional costs which are attributable to the non-convexities. Against this backdrop, the costs in a framework with non-convexities could be compared to a benchmark which would be a continuous merit order for both types of suppliers. Thereby, the monetary value of smoothing non-convexities is calculated. The respective difference in costs yields the value of additional flexibility from a system perspective. Once more, the classification unrestricted suppliers is linked to national generation capacity.

[8]In the real world, the strategic rationale of agents on the demand side may support this allocation as they face an incentive not to pay the higher marginal costs of unrestricted suppliers to all restricted suppliers within a uniform price auction.

Proposition 6.4. *A naive proxy for the additional costs attributable to non-convexities within the supply curve of unrestricted suppliers may be estimated as EUR 10.2 million in 2015. Furthermore, a similar proxy for the value of additional power system flexibility in neighboring countries may be derived. The respective estimate is EUR 6.4 million.*

Proof. First, the case of a non-convexity within the cost function of unrestricted suppliers is considered. It is sufficient to analyze the respective additional costs in terms of the scenario (a2) due to symmetric relations. For the sake of simplicity, the lower threshold for D_2 in the case of (a2) may be substituted with the term $\hat{D}_t$ and Equation (6.10) could be defined.

$$\begin{aligned} &\Delta Costs(D_t - \hat{D}_t) = \Delta Costs(x) \\ &= \frac{4 \cdot (a_1^r)^5 + 12 \cdot (a_1^r)^4 \cdot a_1^u + 14 \cdot (a_1^r)^3 \cdot (a_1^u)^2 + 8 \cdot (a_1^r)^2 \cdot (a_1^u)^3 + \frac{9}{4} \cdot a_1^r \cdot (a_1^u)^4 + \frac{1}{4} \cdot (a_1^u)^5}{8 \cdot (a_1^r)^4 + 24 \cdot (a_1^r)^3 \cdot a_1^u + 26 \cdot (a_1^r)^2 \cdot (a_1^u)^2 + 12 \cdot a_1^r \cdot (a_1^u)^3 + 2 \cdot (a_1^u)^4} \cdot x^2 \end{aligned} \tag{6.10}$$

The respective cost implications are mainly driven by the gradient of the restricted supply curve (see Section 6.7.5). Analogous results can be derived for the case of a discontinuous marginal cost curve of restricted suppliers.

$$\begin{aligned} &\Delta Costs(D_t - \hat{D}_t) = \Delta Costs(x) \\ &= \frac{\frac{1}{4} \cdot a_1^r \cdot (a_1^u)^2 + \frac{1}{4}(a_1^u)^3}{2 \cdot ((a_1^r)^2 + 2 \cdot a_1^r \cdot a_1^u + (a_1^u)^2)} \cdot x^2 \end{aligned} \tag{6.11}$$

Here welfare losses are mainly driven by the gradient of the unrestricted supply curve.

To derive estimates from real-world price data, as x is unobservable, the relation $D_t - \hat{D}_t = x = \frac{\Delta(p(m^1), p(m_t^2))}{a_1^r}$ may be exploited . In the case of negative price premiums, a_1^r is to be substituted by a_1^u.

To derive numbers for the gradients a_1^r and a_1^u, empirical estimates presented in Knaut and Paschmann (2017b) can be used. The aggregate day-ahead merit order exhibits a gradient of approximately 0.96 EUR/GWh and is defined by $a_1^{r,u} = \frac{a_1^r \cdot a_1^u}{a_1^r + a_1^u}$. Additionally, the aggregate gradient of the unrestricted suppliers (a_1^u) may be approximated as 7.65 EUR/GWh. This yields an estimate for a_1^r which is 1.1 EUR/GWh. Inserting these estimates into (6.10), additional costs due to non-convexities may be calculated according to Equation (6.12).

$$\Delta Costs(\Delta(p(da), p(id_t))) \begin{cases} = 1145.5 \cdot \Delta(p(da), \overline{p(id_t)})^2 & \Delta(p(da), p(id_t)) < 0 \\ = 690.94 \cdot \Delta(p(da), \overline{p(id_t)})^2 & \Delta(p(da), p(id_t)) > 0 \end{cases} \tag{6.12}$$

The term da marks the day-ahead and id the intraday auction. Applying the respective relations to all price differences observed in 2015 (EPEX SPOT SE, 2016a), the cost terms presented above can be derived.

As regards the interpretation of these estimates, the limits of this approach should be taken into account. Nevertheless, the respective numbers yield a naive indication for the magnitude of the value of additional short-term power system flexibility.

□

6.4.1 Numerical Example

For illustration purposes, this section provides a simple numerical example. More precisely, the set of parameters is defined according to Table 6.1.

Table 6.1: Numerical example: Parameter assumptions

Parameter	Value
a_1^r	1
a_1^u	2
$Q_{disc'}$	4
$\Delta_{disc'}$	5
Q_{disc}	12
Δ_{disc}	10

Motivated through empirical observations in the electricity markets under analysis, it is assumed that the gradient of the unrestricted supply curve (a_1^u) exceeds the respective gradient of the restricted supply curve (a_1^r). The increment is assumed to be twice as high as in the case of restricted producers. As regards restricted suppliers, a non-convexity ($\Delta_{disc'}$) is considered if the production level is rather low ($Q_{disc'}$). In contrast, in the case of unrestricted suppliers, there is a discontinuous step (Δ_{disc}) at a higher quantity (Q_{disc}).

Demand first increases according to a linear shape and then decreases again. The resulting hourly production level over time of both restricted and unrestricted suppliers is illustrated in Figure 6.5.

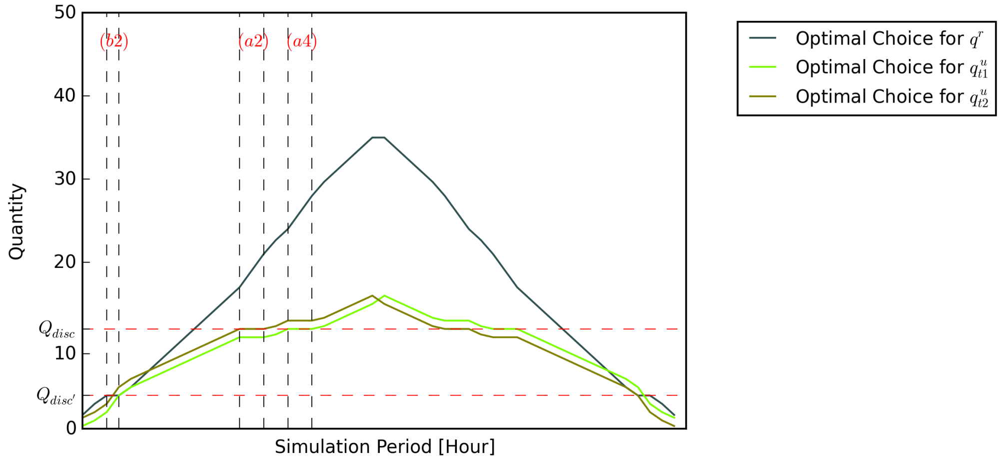


Figure 6.5: Optimal production level in the numerical example

If the production level of restricted suppliers approximates the non-convexity threshold ($Q_{disc'} = 5$), the respective supply is fixed and compensated by an increased production level of unrestricted suppliers ($b2$). Based on the gradient of the unrestricted supply curve ($a^u_1 = 2$), this allows for cost savings as long as the additional supply of unrestricted suppliers in both time periods does not exceed the quantity 2.5. If demand continues to increase, the overall production level of restricted suppliers is adjusted downward compared to the case of continuous relations. As a consequence, all thresholds for D_{t2}, which were presented in Equation (6.6), are adjusted by subtracting the term $\frac{\Delta disc'}{a^r_1 + a^u_1}$. If the optimal production level of unrestricted suppliers under continuous relations would now exceed the respective discontinuous step ($Q_{disc} = 12$), reverse relations can be identified and additional supply by unrestricted suppliers is replaced by an increased production level of restricted suppliers (($a2$) and ($a4$)).

In a next step, conclusions on the resulting price differences between both markets may be drawn. Figure 6.6 presents the simulated prices for the numerical example. For illustration purposes, the maximum feasible price difference for the case of a non-convexity within the restricted supply curve is considered.

Dependent on the demand level, the direction of price differences at equilibrium may vary. If the non-convexity in the restricted supply curve causes an unbalanced increase of production by unrestricted suppliers, the price in the market with shorter contracts is higher compared to the first market with unrestricted participation and vice versa. If the demand level exhibits a high temporal variability ($D_{t1} \neq D_{t2}$), the

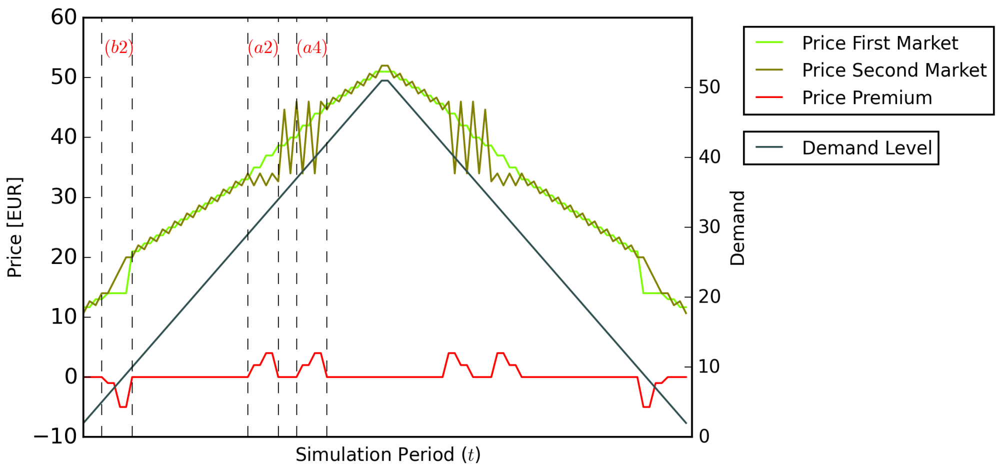


Figure 6.6: Price implications in the numerical example

impact of a non-convexity in the unrestricted supply curve on the respective price premiums is limited to half the step height (Δ_{disc}). Finally, it is worth mentioning that price volatility may temporarily increase significantly if unrestricted supply in only one period exceeds the non-convexity.

6.5 Empirical Application

Following the theoretical model, price premiums in sequential markets with differing product granularity may stem from non-convexities being more pronounced in only a subset of the sequential market stages. As a prerequesite, a differing supplier structure in the German day-ahead and intraday auction can be identified which is triggered by restricted participation in the market with sub-hourly products (Knaut and Paschmann, 2017a). The sharp stepped shape of the underlying bid curves may result in a varying frequency of non-convexities dependent on the market settlement being in particular sections of the merit order. Bearing this is mind, a systematic correlation between the individual supply curves and the resulting price differences is to be expected. An analysis of the correlation of load and price premiums by the use of historical data facilitates to test for these relations.

Based on the illustration of marginal cost curves for generation units in Germany and its neighboring countries in Figure 6.3 and Figure 6.4, the following expectations could be formulated[9]:

1. Non-convexities are more pronounced in the right area of the German merit order. The day-ahead price may hence be expected to exceed the respective intraday auction price if demand is rather high.
2. Compared to its neighboring countries, Germany has a comparably large share of low-cost generation units, for example, due to nuclear and lignite-fired power plants. Negative price premiums, if any, would rather be expected to coincide with low demand.
3. The overall stepped shape of the merit order is less pronounced within the smoother marginal cost curve of restricted suppliers. The extremes of positive price premiums may hence exceed the maximum negative price differences.

It has to be annotated that the use of a common aggregate supply curve crucially depends on the assumption of sufficient cross-border capacity. A respective lack may trigger additional non-convexities. The empirical analysis will provide insights with respect to the validity of the three hypotheses. Since in short-term electricity markets the residual load is commonly used in order to map demand, data was gathered which is provided by ENTSO-E (2017) and EEX (2017b) to derive the residual demand as the difference between the overall system load and the electricity generation from renewable energy plants. The period of observation ranges from January 16, 2015 until November 2, 2016. Figure 6.7 illustrates the average hourly deviation of the residual demand from its overall mean. Positive values hence embody hours with a comparably high residual demand. Apparently, daily profiles of the residual load exhibit distinct recurrent patterns. Furthermore, the corresponding average price premiums for each hour of the day along the period of observation are presented. The figure indicates a high correlation between the residual load and the resulting price differences. If the residual demand tends to be comparably high, the day-ahead price is on average higher than the respective intraday auction price. Reverse relations are applicable to hours with a tendency of lower demand.

The initial hypotheses are confirmed by the empirical observations. The historical data yield an indication that in peak hours the non-convexities in the German supply curve are more pronounced. A lack of national peak load generation units or pumped storage power plants may trigger additional electricity imports. There are incentives to target excess supply within the day-ahead market to avoid extremely high costs of purchasing additional quantities from unrestricted suppliers in the intraday auc-

[9] It is worth stressing that actual bidding data may not fully comply with the fundamental merit order.

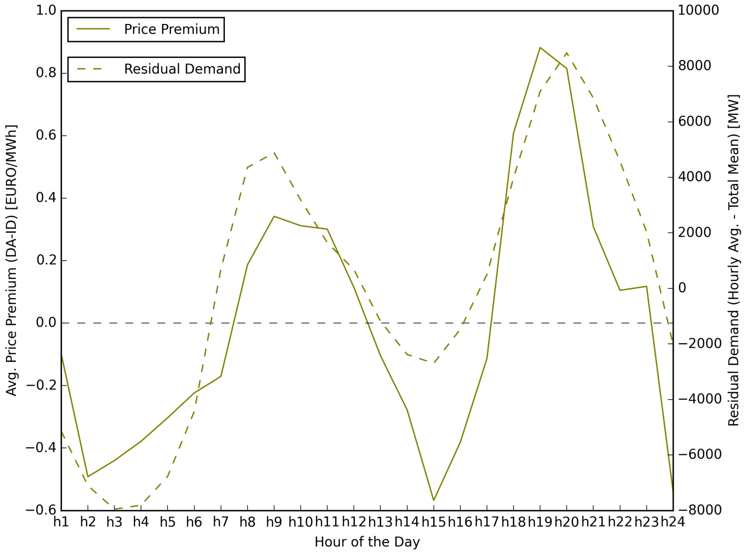


Figure 6.7: Average correlation of residual demand and price premiums (January 16, 2015 - November 2, 2016)

tion. As a result, the day-ahead price could be above the respective average intraday auction price[10] (*Hypothesis 1*).

In contrast, if the residual demand is rather low, the discontinuous shape of the supply curve of restricted producers tends to drive the resulting price premiums. A comparably large share of demand is satisfied by unrestricted suppliers. The German intraday auction price may exceed the respective day-ahead price as restricted suppliers do not face the opportunity to shift their trade quantities into the intraday auction. At the same time, the respective price difference is arbitrage-free due to the non-convexity within the restricted supply curve (*Hypothesis 2*). It is finally worth mentioning that the maximum positive price premium is higher than the maximum negative price difference (*Hypothesis 3*).

To deepen the understanding of the analysis, Figure 6.8 presents empirical results with respect to the role of seasonality. The classification of seasons is based on metereological dates. As to be expected, the difference between the average residual load and its overall mean is more pronounced in winter than in summer periods. Accordingly, the extremes of the price premiums increase by approximately 70%

[10]Both types of suppliers are expected to prefer trading in the day-ahead market. In order to meet the residual demand profile, unrestricted suppliers which committed their production capacity via hourly contracts are willing to pay a price equal to their marginal production costs to reduce their electricity generation by trading sub-hourly contracts within the intraday auction.

ranging from 0 to 130 ct/Mwh. These relations support the hypothesis that the impact of non-convexities is especially relevant in case of extreme demand values.

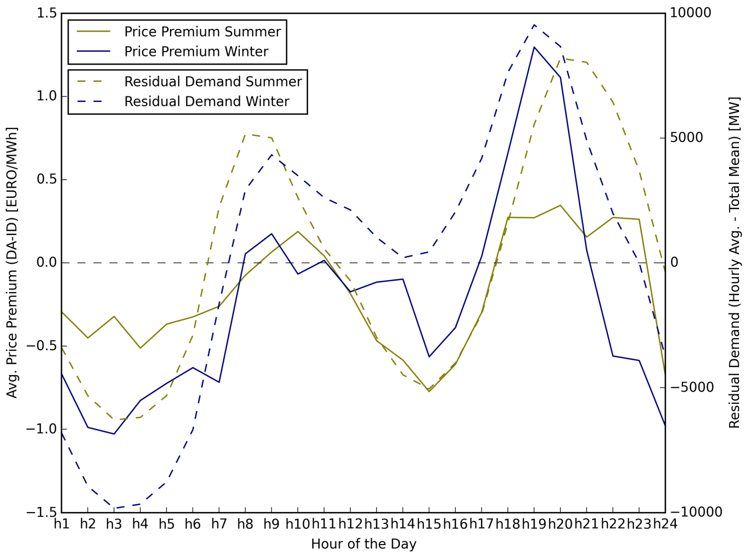


Figure 6.8: Average correlation of residual demand and price premiums in specific seasons(January 16, 2015 - November 2, 2016)

6.6 Conclusion

This article begins with an analysis of price premiums between two sequential short-term electricity markets in Germany, namely the day-ahead and intraday auction. The framework under analysis is characterized by decreasing contract duration and differing market participation. As both markets are settled in rapid succession without any relevant informational update, it is initially puzzling to identify significant price premiums in specific hours of the day. Furthermore, these price premiums can be both positive or negative.

There is empirical evidence that the explanatory approach for price premiums in electricity markets, which was developed in Bessembinder and Lemmon (2002), is not applicable to the market dynamics under analysis. To address these issues, a theoretical model is developed within this article which seeks to analyze the impact of non-convexities in sequential market designs with differing market participation. The approach is motivated through the observation of pronounced stepped shapes in real-world bid curve data. Based on the model, it can be identified that if non-convexities are more pronounced in individual sequential market stages, which is feasible due to the differing supplier structure, significant price premiums may exist. Additionally, the difference in prices may be both positive or negative depending on the relevance of non-convexities in particular sections of the underlying supply curves. This article presents an empirical analysis of real-world data from German electricity markets. The respective results reveal a correlation between load and price differences what essentially complies with the underlying model.

The empirical observations suggest that non-convexities in the supply curve of neighboring countries are especially relevant if the German residual demand is rather low. As a consequence, the average intraday auction price may be significantly higher than the respective day-ahead price. Reverse relations can be observed in peak hours indicating sharp non-convexities in the German merit order due to a lack of flexible peak load generation units. There are incentives to target excess supply in the day-ahead auction and hence the respective price may go beyond the average intraday auction price.

These findings allow to draw the conclusion that the price premiums under consideration reflect a value of additional short-term power system flexibility. In more detail, numerical proxies can be derived yielding a value for smoothing non-convexities of approximately EUR 10.2 million in 2015 in the case of additional German power system flexibility. In contrast, the respective estimate for neighboring countries is EUR 6.4 million in 2015. Even if these are relatively small numbers, the inefficiencies uncovered may be exacerbated if the share of renewable energies continues to increase and if there is a lack of investment incentives for flexible generation units. It may furthermore be beneficial to urge the implementation of cross-border trade on a sub-hourly level to align the supplier structures in the day-ahead and intraday auction.

The model developed in this article supports a better understanding of price premiums and its underlying properties in short-term sequential electricity markets. However, it may also be applicable to other frameworks, for example, sequential auctions with block and single unit bids. Finally, the findings presented in this article may favor the evaluation of business strategies targeting to exploit the price differences identified. A lack of a respective business case is to be expected, as the market depth in the intraday auction is limited and since the price premiums identified do not reflect unexploited arbitrage opportunities.

6.7 Appendices

6.7.1 Descriptive Analysis of Historical Price Premiums

Table 6.2: Descriptive statistics on price premiums between the day-ahead and intraday auction (day-ahead price - average intraday auction price) [EUR/MWh] (January 16, 2015 until November 2,2016)

Hour	Mean	Mean (abs difference)	Probability positive	Min/Max	Percentiles (10/90)
h1	-0.2	2.0	44.7%	-18.3/13.2	-3.0/3.0
h2	-0.6	2.0	39.0%	-10.9/16.1	-3.5/2.5
h3	-0.6	2.4	41.4%	-17.8/16.2	-4.2/3.1
h4	-0.5	2.5	42.6%	-13.2/17.5	-4.3/3.6
h5	-0.4	2.3	41.2%	-12.7/11.8	-3.6/3.2
h6	-0.3	2.1	44.1%	-18.6/20.2	-3.6/2.9
h7	-0.3	2.2	48.6%	-29.5/16.3	-3.6/3.0
h8	0.1	1.8	53.1%	-21.7/9.5	-2.6/3.0
h9	0.2	1.8	55.1%	-8.6/13.2	-2.7/3.1
h10	0.2	1.7	53.7%	-13.4/9.2	-2.3/2.7
h11	0.2	1.7	55.1%	-21.3/9.7	-2.5/2.9
h12	0.0	2.0	50.4%	-44.2/13.4	-2.9/3.2
h13	-0.2	2.0	46.0%	-29.5/18.6	-3.3/3.0
h14	-0.4	2.1	44.4%	-27.0/13.5	-3.5/2.9
h15	-0.7	2.1	41.9%	-41.7/17.7	-3.5/2.3
h16	-0.5	1.9	44.0%	-37.8/10.7	-3.1/2.4
h17	-0.2	1.8	49.8%	-39.5/14.3	-2.9/2.5
h18	0.5	1.9	60.3%	-8.2/18.9	-2.4/3.3
h19	0.8	1.9	63.7%	-10.6/11.9	-2.0/3.5
h20	0.7	1.9	64.5%	-7.5/11.3	-2.2/3.7
h21	0.2	1.7	57.0%	-8.0/9.1	-2.5/3.0
h22	0.0	1.8	51.2%	-7.4/8.5	-2.8/2.8
h23	0.0	2.0	52.4%	-8.5/10.6	-3.3/3.2
h24	-0.7	2.1	41.6%	-12.4/12.7	-4.1/2.7
Total	-0.1	2.0	49.4%	-44.2/20.2	-3.1/3.0

The numbers presented in column *Mean (abs difference)* reveal that the mean of the four 15-minute intraday auction prices is on average 2 EUR/MWh lower or higher respectively than the corresponding hourly day-ahead auction price. Thus, there tend to be significant differences in prices in each hour. Additionally, the probability of differences in prices being positive or negative is presented in column *Probability positive*.

6.7.2 Empirical Analysis of Price Premiums and the Underlying Drivers

Table 6.3 depicts descriptive statistics on price premiums between the day-ahead and intraday auction. Furthermore, the table shows the respective variance and skewness of the underlying day-ahead spot prices. The analysis is based on real-world data which is provided by (EPEX SPOT SE, 2016a) and ranges from January 16, 2015 until November 2,2016. The Pearson's first coefficient is used as the skewness measure which is the difference between the mean and the mode divided by the standard deviation.

Table 6.3: Descriptive statistics on price premiums between the day-ahead and intraday auction (day-ahead price - average intraday auction price) [EUR/MWh] (January 16, 2015 until November 2,2016)

Hour	Mean price difference	Variance of day-ahead prices	Skewness of day-ahead prices
h1	-0.2	88.7	-1.17
h2	-0.6	84.8	-1.13
h3	-0.6	82.4	-1.55
h4	-0.5	81.3	-1.42
h5	-0.4	84.3	-1.54
h6	-0.3	102.0	-1.50
h7	-0.3	178.2	-0.80
h8	0.1	191.7	-0.30
h9	0.2	199.1	-0.23
h10	0.2	155.7	0.01
h11	0.2	153.5	0.46
h12	0.0	214.8	2.58
h13	-0.2	129.8	-0.50
h14	-0.4	159.2	-1.65
h15	-0.7	157.1	-1.85
h16	-0.5	147.2	-0.71
h17	-0.2	149.2	-0.66
h18	0.5	176.4	0.20
h19	0.8	179.9	0.38
h20	0.7	149.6	0.54
h21	0.2	107.8	-0.08
h22	0.0	75.0	-0.26
h23	0.0	73.5	-0.16
h24	-0.7	73.4	-0.54

To analyze the correlation between the individual figures in a condensed way, a simple Ordinary Least Squares (OLS) estimation may be applied which is following the general idea adopted in Longstaff and Wang (2004). The respective results are illustrated in Table 6.4. Even if there are issues linked to the small sample size, it is yet to be expected that the results provide insights on the question of basic correlations. The respective results yield an indication that there is no significant impact of the price volatility on the respective price premiums. Furthermore, the correlation between the skewness of day-ahead prices and price premiums is at least questionable. Finally, the F test does not allow for a unique conclusion on whether the model is more accurate than basically no model at all.

Table 6.4: Regression of price premiums between the day-ahead and intraday auction (day-ahead price - average intraday auction price) [EUR/MWh]

	Dependent variable: Price Premium
Explanatory variable	OLS
day-ahead price volatility	0.0015
	(0.0013)
day-ahead price skewness	0.248
	(0.124)
intercept (ν)	-0.19
	(0.21)
observations	24
adj. R^2	0.48
F	2.97 (p-value:0.07)

Notes to Table 6.4: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. Data from January 16, 2015 until November 2,2016 is used.

6.7.3 Exemplary Historical Bid Curves

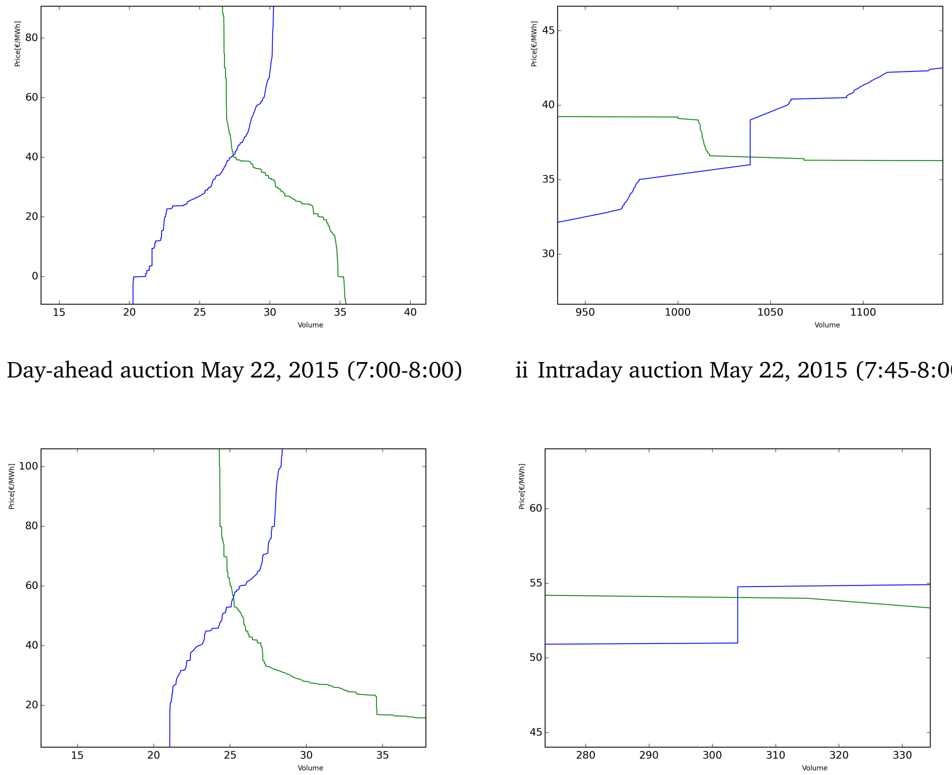
Exemplary historical bid curves are illustrated in Figure 6.9.

6.7.4 Mathematical Proof (Proposition 1)

Since the procedure is based on cost minimization, the overall production costs for restricted suppliers can be calculated with the use of Equation (6.13).

$$\begin{aligned} C_r(q^r) &= \int_0^{q^r} \left[a_0 + a_1^r \cdot q \right] dq \\ &= a_0 \cdot q^r + 0.5 \cdot a_1^r \cdot (q^r)^2 \end{aligned} \tag{6.13}$$

As regards the production level of unrestricted suppliers, the respective optimiza-



i Day-ahead auction May 22, 2015 (7:00-8:00)

ii Intraday auction May 22, 2015 (7:45-8:00)

iii Day-ahead auction October 8, 2015 (18:00-19:00)

iv Intraday auction October 8, 2015 (18:15-18:30)

Figure 6.9: Exemplary bid curves observed in the day-ahead and intraday auction

tion variables (q_{t1}^{u*} and q_{t2}^{u*}) can directly be substituted according to the equilibrium condition (6.3). Thus, the relation $q_t^{u*} = D_t - q^{r*}$ may be used so that the variable q^r remains the only decision variable as demand is assumed to be inelastic. The cost function of unrestricted suppliers in period t ($C_{u,t}(q^r)$) may hence be formulated according to Equation (6.14).

$$C_{u,t}(q^r) = 0.5 \cdot \begin{cases} |1\rangle\, 0.5 \cdot \int_0^{D_t - q^r} a_0 + a_1^u q \, dq & \\ \quad = 0.5 \cdot \left[a_0 \cdot (D_t - q^r) + 0.5 \cdot a_1^u \cdot (D_t - q^r)^2 \right] & D_t - q^r \leq Q_{disc} \\ |2\rangle\, 0.5 \cdot \left[\int_0^{Q_{disc}} a_0 + a_1^u q \, dq + \int_{Q_{Disc}+\epsilon}^{D_t - q^r} a_0 + \Delta_{disc} + a_1^u q \, dq \right] & \\ \quad = 0.5 \cdot \left[a_0 \cdot (Q_{disc}) + 0.5 \cdot a_1^u \cdot (Q_{disc})^2 \right. & \\ \quad\quad + (a_0 + (Q_{disc} + \epsilon) \cdot a_1^u + \Delta disc) \cdot (D_t - q^r - Q_{disc} - \epsilon) & \\ \quad\quad \left. + 0.5 \cdot a_1^u \cdot (D_t - q^r - Q_{disc} - \epsilon)^2 \right] & D_t - q^r \geq Q_{disc} + \epsilon \end{cases} \tag{6.14}$$

An infinitesimal small number ϵ is considered in order to formulate the optimization problem with weak inequalities only. The value of ϵ reflects the smallest tradeable increment of the production level. As the cost function to apply depends on the value of the decision variable, the respective Lagrangian can be set up depending on both cases i) $D_t - q^r \leq Q_{disc}$ and ii) $D_t - q^r \geq Q_{disc} + \epsilon$ for each of the time periods $t1$ and $t2$ to solve the optimization problem. For the sake of simplicity, is is assumed that the demand profile is increasing and consequently there is a reduced number of cases to be considered. That is to say, $D_{t2} > D_{t1} + \epsilon$ is valid. As the second derivative of the total cost function ($C^{total} = C_r(q^r) + \sum_t C_{u,t}(q^u_t)$) is always positive ($\frac{\partial^2 C^{total}}{\partial {q^r}^2} = a^r_1 + a^u_1 > 0$), all optima are local minimums.

Case1: $D_t - q^r \leq Q_{disc} \; \forall \, t$

In the first case, the discontinuity is negligible due to comparably low demand. The respective Lagrangian is presented in Equation (6.15).

$$\mathbb{L} = (-1) \cdot (C_r(q^r) + \sum_t C_{u,t}(q^r)) + \mu_{t1} \cdot (Q_{disc} - D_{t1} + q^r) + \mu_{t2} \cdot (Q_{disc} - D_{t2} + q^r) \tag{6.15}$$

Applying the respective Karush-Kuhn-Tucker (KKT) conditions, the optimal solution has to satisfy the conditions listed in (6.16).

$$\begin{aligned} (-1) \cdot \frac{\partial C_r(q^r)}{\partial q^r} + \sum_t \Big[(-1) \cdot \frac{\partial C_{u,t}(q^r)}{\partial q^r} + \mu_t \cdot (Q_{disc} - D_t + q^r) \Big] = 0 \\ D_t - q^r \leq Q_{disc} \; \forall \, t \\ \mu_t \cdot (Q_{disc} - D_t + q^r) = 0 \; \forall \, t \\ \mu_t \geq 0 \; \forall \, t \end{aligned} \tag{6.16}$$

The respective marginal cost functions are formulated in Equation (6.17).

$$\begin{aligned} \frac{\partial C_r(q^r)}{\partial q^r} &= a_0 + q^r \cdot a^r_1 \\ \frac{\partial C_{u,t}(q^r)}{\partial q^r} &= -0.5 \cdot a_0 - 0.5 \cdot a^u_1 \cdot (D_t - q^r) \end{aligned} \tag{6.17}$$

There is a need to apply a distinction of cases. More precisely, the following four scenarios have to be considered to derive the optimal solution.

1. *Scenario1:* $\mu_{t1} = 0, \mu_{t2} = 0$

2. *Scenario2:* $\mu_{t1} = 0, Q_{disc} - D_{t2} + q^r = 0$
3. *Scenario3:* $Q_{disc} - D_{t1} + q^r = 0, \mu_{t2} = 0$
4. *Scenario4:* $Q_{disc} - D_{t1} + q^r = 0, Q_{disc} - D_{t2} + q^r = 0$

Due to the assumption of an increasing demand profile ($D_{t2} > D_{t1} + \epsilon$), *Scenario4* may be ignored. Furthermore, *Scenario3* is to be neglected because of the definition of *Case1*. In the following, both relevant scenarios are analyzed in detail.

Scenario1: $\mu_{t1} = 0, \mu_{t2} = 0$

Solving the KKT conditions, the optimal choice for q_r can be formulated according to Equation (6.18). This is essentially the same solution as presented in Knaut and Paschmann (2017b) for the case of continuous relations.

$$q^{r*} = \frac{(D_{t1} + D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r + a_1^u} \tag{6.18}$$

Such quantity choice yields a valid solution ($D_{t2} - q^{r*} \leq Q_{disc}$) if condition (6.19) is met.

$$D_{t2} \leq \frac{2 \cdot Q_{disc} \cdot (a_1^r + a_1^u) + D_{t1} \cdot a_1^u}{2 \cdot a_1^r + a_1^u} \tag{6.19}$$

Scenario2: $\mu_{t1} = 0, Q_{disc} - D_{t2} + q^r = 0$

According to the scenario definition, q_r is defined as follows:

$$q^{r*} = D_{t2} - Q_{disc}. \tag{6.20}$$

Solving for μ_{t2}, Equation (6.21) can be derived.

$$\mu_{t2} = (-1) \cdot \frac{(D_{t1} + D_{t2}) \cdot a1^u}{2 \cdot (a_1^r + a_1^u)} \tag{6.21}$$

Equation (6.21) does not yield a feasible solution as the respective condition $\mu_{t2} \geq 0$ is not satisfied. This is due to the assumption of positive values for both the gradients of the supply curves as well as the demand in the periods $t1$ and $t2$ ($D_{t1}, D_{t2}, a_1^r, a_1^u > 0$).

Case2: $D_{t1} - q^r \le Q_{disc}, D_{t2} - q^r \ge Q_{disc} + \epsilon$

Based on the solution for *Case1*, a threshold for D_{t2} can be derived above which the discontinuity has to be considered (Equation (6.19)).

The resulting KKT conditions in *Case2* are depicted in (6.22).

$$\begin{aligned}
(-1) \cdot \frac{\partial C_r(q^r)}{\partial q^r} + \sum_t \left[(-1) \cdot \frac{\partial C_{u,t}(q_t^u)}{\partial q^r}\right] + \mu_{t1} - \mu_{t2} = 0 \\
D_{t1} - q^r \le Q_{disc} \\
D_{t2} - q^r \ge Q_{disc} + \epsilon \\
\mu_{t1} \cdot (Q_{disc} - D_t + q^r) = 0 \\
\mu_{t2} \cdot (Q_{disc} + \epsilon - D_t + q^r) = 0 \\
\mu_t \ge 0 \ \forall \ t
\end{aligned} \tag{6.22}$$

The respective marginal cost functions are listed in (6.23).

$$\begin{aligned}
\frac{\partial C_r(q^r)}{\partial q^r} &= a_0 + q^r \cdot a_1^r \\
\frac{\partial C_{u,t1}(q^r)}{\partial q^r} &= -0.5 \cdot a_0 - 0.5 \cdot a_1^u \cdot (D_{t1} - q^r) \\
\frac{\partial C_{u,t2}(q^r)}{\partial q^r} &= -0.5 \cdot (a_0 + (Q_{disc} + \epsilon) \cdot a_1^u + \Delta_{disc}) - 0.5 \cdot a_1^u \cdot (D_{t2} - q^r - Q_{disc} - \epsilon)
\end{aligned} \tag{6.23}$$

A distinction of cases is to be applied.

1. *Scenario1:* $\mu_{t1} = 0, \mu_{t2} = 0$
2. *Scenario2:* $\mu_{t1} = 0, Q_{disc} + \epsilon - D_{t2} + q^r = 0$
3. *Scenario3:* $Q_{disc} - D_{t1} + q^r = 0, \mu_{t2} = 0$
4. *Scenario4:* $Q_{disc} - D_{t1} + q^r = 0, Q_{disc} + \epsilon - D_{t2} + q^r = 0$

Scenario4 is irrelevant due to the assumption of an increasing demand profile. In the following, each scenario is outlined in more detail.

Scenario1: $\mu_{t1} = 0, \mu_{t2} = 0$

In the case of *Scenario1*, Equation (6.24) depicts the optimal choice with respect to the production level of restricted suppliers(q^r).

$$q^{r*} = \frac{(D_{t1} + D_{t2})}{2} \cdot \frac{a_1^u}{2 \cdot (a_1^r + a_1^u)} + \frac{\Delta_{disc}}{2 \cdot (a_1^r + a_1^u)} \tag{6.24}$$

In *Case2* the discontinuity is relevant and thus the quantity supplied by restricted suppliers is revised upwards by $\frac{\Delta_{disc}}{2 \cdot (a_1^r + a_1^u)}$ to account for the stepped shape of the merit order of unrestricted suppliers. Equation (6.18) may be regarded as a feasible solution ($D_{t2} - q^r \geq Q_{disc}$) if condition (6.25) is fulfilled.

$$q^{r*} = \frac{(D_{t1} + D_{t2}) \cdot a_1^u + \Delta_{disc}}{2 \cdot (a_1^r + a_1^u)} \leq D_{t2} - Q_{disc} - \epsilon \tag{6.25}$$

Condition (6.25) may be transferred into three possible cases:

1. $-2 \cdot D_{t2} \cdot a_1^r + 2 \cdot (Q_{disc} + \epsilon) \cdot (a_1^r + a_1^u) + D_{t1} \cdot a_1^u - D_{t2} \cdot a_1^u + \Delta_{disc} = 0, a_1^r + a_1^u \neq 0$
2. $a_1^u < -a_1^r, -2 \cdot D_{t2} \cdot a_1^r + 2 \cdot Q_{disc} \cdot a_1^r + D_{t1} \cdot a_1^u - D_{t2} \cdot a_1^u + 2 \cdot Q_{disc} \cdot a_1^u + \Delta_{disc} > 0$
3. $-a_1^r < a_1^u, 2 \cdot D_{t2} \cdot a_1^r - 2 \cdot (Q_{disc} + \epsilon) \cdot (a_1^r + a_1^u) - D_{t1} \cdot a_1^u + D_{t2} \cdot a_1^u - \Delta_{disc} > 0.$

Following the case definition, the conditions $a_1^r + a_1^u \neq 0$ as well as $-a_1^r < a_1^u$ are met. However, as both gradients of the supply curves are assumed to be positive ($a_1^u, a_1^r > 0$), the second case is not feasible. The first and third case may finally be condensed into the inequality constraint which is presented in (6.26).

$$2 \cdot D_{t2} \cdot a_1^r - 2 \cdot (Q_{disc} + \epsilon) \cdot (a_1^r + a_1^u) - a_1^u \cdot (D_{t1} - D_{t2}) - \Delta_{disc} >= 0 \tag{6.26}$$

Formulating inequality (6.26) in terms of D_{t2}, condition (6.27) can be derived.

$$D_{t2} \geq \frac{2 \cdot (Q_{disc} + \epsilon) \cdot (a_1^r + a_1^u) + D_{t1} \cdot a_1^u + \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \tag{6.27}$$

Condition (6.27) embodies a threshold which reflects the trade-off between avoiding higher costs of production by unrestricted suppliers due to the step Δ_{disc} and taking losses due to both unrestricted suppliers with comparably low production costs being forced to reduce their production level to meet D_{t1} as well as higher costs of an increased production of restricted suppliers.

Besides an upper bound for D_{t2} , inequality (6.28) is necessary to identify a valid solution ($D_{t1} - q_r \leq Q_{Disc}$).

$$D1 \leq \frac{2 \cdot Q_{disc} \cdot (a_1^r + a_1^u) + D_{t2} \cdot a_1^u + \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \tag{6.28}$$

Scenario2: $\mu_{t1} = 0, Q_{disc} - \epsilon - D_{t2} + q^r = 0$

It is to be tested whether the quantity choice in *Scenario2* (Equation (6.29)) yields a valid solution.

$$q^{r*} = D_{t2} - Q_{disc} - \epsilon \tag{6.29}$$

The resulting term for μ_{t2} is defined in Equation (6.30).

$$\mu_{t2} = -(D_{t2} - Q_{disc} - \epsilon) \cdot (a_1^r + a_1^u) + (D_{t1} + D_{t2}) \cdot 0.5 \cdot a_1^u + 0.5 \cdot \Delta_{disc} \tag{6.30}$$

As a result, a valid solution ($\mu_{t2} \geq 0$) has to satisfy the inequality constraint which is presented in (6.31).

$$D_{t2} \leq \frac{2 \cdot (Q_{disc} + \epsilon) \cdot (a_1^r + a_1^u) + D_{t1} \cdot a_1^u + \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \tag{6.31}$$

Due to the discontinuous shape of the merit order for unrestricted suppliers, the production level of unrestricted suppliers in $t2$ is held constant for a range $\Delta D_{t2} = \frac{\Delta_{disc}}{2 \cdot a_1^r + a_1^u}$ if D_{t2} increases. The lower production level is compensated by restricted suppliers that increase their production level according to the increase in D_{t2}. Due to the choice of q^{r*}, the supply of unrestricted suppliers in $t1$ never exceeds the discontinuity. Finally, as the intersection of *Scenario1* and *Scenario2* according to the inequalities (6.27) and (6.31) exactly yields the same choice of q^{r*} ($q^{r*} = D_{t2} - Q_{disc} - \epsilon$), there is no need to compare the resulting costs in both scenarios due to the steadiness in the overlap.

Scenario3: $Q_{disc} - D_{t1} + q^r = 0, \mu_{t2} = 0$

Equation (6.32) depicts the resulting term for μ_{t1}.

$$\mu_{t1} = (D_{t1} - Q_{disc}) \cdot (a_1^r + a_1^u) + (-0.5 \cdot D_{t1} - 0.5 \cdot D_{t2}) \cdot a_1^u - 0.5 \cdot \Delta_{disc} \tag{6.32}$$

For this to be a valid solution ($\mu_{t1} \geq 0$), inequality (6.33) has to be applicable.

$$D_{t1} \geq \frac{2 \cdot Q_{disc} \cdot a_1^r + (D_{t2} + 2 \cdot Q_{disc}) \cdot a_1^u + \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \tag{6.33}$$

This inequality is analogous to the respective one for D_{t2} as there are symmetric relations.

Case3: $D_{t1} - q^r \geq Q_{disc} + \epsilon, D_{t2} - q^r \geq Q_{disc} + \epsilon$

Case3 refers to a situation in which the non-convexity is relevant in both periods. The respective KKT conditions may be formulated as presented in (6.34).

$$\begin{aligned}
(-1) \cdot \frac{\partial C_r(q^r)}{\partial q^r} + \sum_t \Big[(-1) \cdot \frac{\partial C_{u,t}(q_t^u)}{\partial q^r}\Big] - \mu_{t1} - \mu_{t2} = 0 \\
D_{t1} - q^r \geq Q_{disc} + \epsilon \\
D_{t2} - q^r \geq Q_{disc} + \epsilon \\
\mu_t \cdot (Q_{disc} + \epsilon - D_t + q^r) = 0 \; \forall \, t \\
\mu_t \geq 0 \; \forall \, t
\end{aligned} \tag{6.34}$$

The respective marginal cost functions are presented in (6.35).

$$\begin{aligned}
\frac{\partial C_r(q^r)}{\partial q^r} &= a_0 + q^r \cdot a_1^r \\
\frac{\partial C_{u,t1}(q_t^u 1)}{\partial q^r} &= -0.5 \cdot (a_0 + (Q_{disc} + \epsilon) \cdot a_1^u + \Delta_{disc}) - 0.5 \cdot a_1^u \cdot (D_{t1} - q^r - Q_{disc} - \epsilon) \\
\frac{\partial C_{u,t2}(q_t^u 2)}{\partial q^r} &= -0.5 \cdot (a_0 + (Q_{disc} + \epsilon) \cdot a_1^u + \Delta_{disc}) - 0.5 \cdot a_1^u \cdot (D_{t2} - q^r - Q_{disc} - \epsilon)
\end{aligned} \tag{6.35}$$

A further distinction of cases is applied.

1. *Scenario1:* $\mu_{t1} = 0, \mu_{t2} = 0$
2. *Scenario2:* $\mu_{t1} = 0, Q_{disc} + \epsilon - D_{t2} + q^r = 0$
3. *Scenario3:* $Q_{disc} + \epsilon - D_{t1} + q^r = 0, \mu_{t2} = 0$
4. *Scenario4:* $Q_{disc} + \epsilon - D_{t1} + q^r = 0, Q_{disc} + \epsilon - D_{t2} + q^r = 0$

As has been outlined before, *Scenario4* does not play a role. Additionally, *Sce-*

nario2 does not comply with the definition of *Case3* as this would mean that the unrestricted production level in $t1$ would be below the discontinuity threshold.

Scenario1: $\mu_{t1} = 0, \mu_{t2} = 0$

Equation (6.36) characterizes the optimal quantity choice (q^{r*}).

$$q^{r*} = \frac{(D_{t1} + D_{t2}) \cdot a_1^u + 2 \cdot \Delta_{disc}}{2 \cdot (a_1^r + a_1^u)} \tag{6.36}$$

Once more, the term presented in Equation (6.36) includes an upwards adjustment ($\frac{\Delta_{disc}}{a_1^r + a_1^u}$) compared to the case of continuous relations due to the non-convexity. Inserting $D_{t1} - q^r \geq Q_{disc}$, condition (6.37) may be defined as a necessary condition with respect to the optimal solution.

$$D_{t1} \geq \frac{2 \cdot (Q_{disc} + \epsilon) \cdot (a_1^r + a_1^u) + D_{t2} \cdot a_1^u + 2 \cdot \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \tag{6.37}$$

Scenario3: $Q_{disc} + \epsilon - D_{t1} + q^r = 0, \mu_{t2} = 0$

Scenario3 yields the Lagrange multiplier which is defined in Equation (6.38).

$$\mu_{t1} = -(D_{t1} - Q_{disc}) \cdot (a_1^r + a_1^u) + 0.5 \cdot a_1^u \cdot (D_{t1} + D_{t2}) + \Delta_{disc} \tag{6.38}$$

This may be regarded as a valid solution ($\mu_{t1} \geq 0$) if condition (6.39) is fulfilled.

$$D_{t1} \leq \frac{2 \cdot (Q_{disc} + \epsilon) \cdot (a_1^r + a_1^u) + D_{t2} \cdot a_1^u + 2 \cdot \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \tag{6.39}$$

These relations are basically similar to *Case2*. There is steadiness with respect to the optimal solution (q^{r*}) in the intersection of the scenarios considered. To sum up, the optimal supply of restricted suppliers for different demand levels may be defined according to Equation (6.40).

$$q^{r*} = \begin{cases} \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} & (a1) D_{t2} \leq \frac{2 \cdot Q_{disc} \cdot (a_1^r + + a_1^u) + D_{t1} \cdot a_1^u}{2 \cdot a_1^r + a_1^u} \\ D_{t2} - Q_{disc} - \epsilon & (a2) \frac{2 \cdot (Q_{disc}+\epsilon) \cdot (a_1^r+a_1^u) + D_{t1} \cdot a_1^u}{2 \cdot a_1^r + a_1^u} < D_{t2} \leq \frac{2 \cdot (Q_{disc}+\epsilon) \cdot (a_1^r+a_1^u) + D_{t1} \cdot a_1^u + \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \\ \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} + \frac{\Delta_{disc}}{2 \cdot (a_1^r+a_1^u)} & (a3) \frac{2 \cdot (Q_{disc}+\epsilon) \cdot (a_1^r+a_1^u) + D_{t1} \cdot a_1^u + \Delta_{disc}}{2 \cdot a_1^r + a_1^u} < D_{t2}, D_{t1} \leq \frac{2 \cdot (Q_{disc}+\epsilon) \cdot (a_1^r+a_1^u) + D_{t2} \cdot a_1^u + \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \\ D_{t1} - Q_{disc} - \epsilon & (a4) \frac{2 \cdot (Q_{disc}+\epsilon) \cdot (a_1^r+a_1^u) + D_{t2} \cdot a_1^u + \Delta_{disc}}{2 \cdot a_1^r + a_1^u} < D_{t1} \leq \frac{2 \cdot (Q_{disc}+\epsilon) \cdot (a_1^r+a_1^u) + D_{t2} \cdot a_1^u + 2 \cdot \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \\ \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} + \frac{\Delta_{disc}}{a_1^r+a_1^u} & (a5) D_{t1} > \frac{2 \cdot (Q_{disc}+\epsilon) \cdot (a_1^r+a_1^u) + D_{t2} \cdot a_1^u + 2 \cdot \Delta_{disc}}{2 \cdot a_1^r + a_1^u} \end{cases} \tag{6.40}$$

6.7.5 Decoding the Impact of Both Supply Curve Gradients on the Resulting Cost Implications

The cost factor which was derived in Equation (6.10) is illustrated in Figure 6.10. Different combinations of a_1^r and a_1^u are considered.

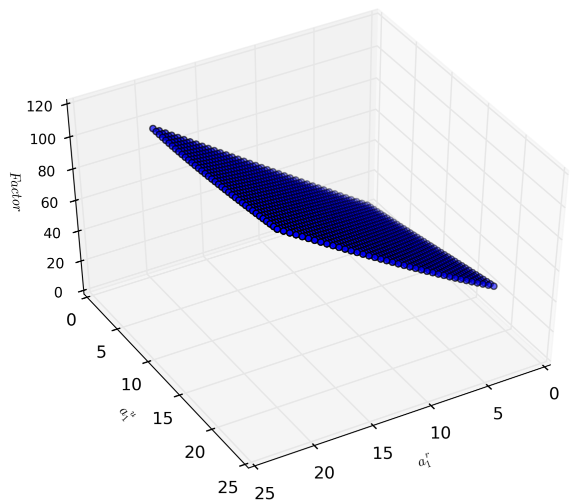


Figure 6.10: 3D plot for the resulting factor dependent on the parameterization of a_1^r and a_1^u

6.7.6 Mathematical Proof (Proposition 2)

In this section, a situation in which the merit order of restricted suppliers exhibits non-convexities is considered. The following proof is a condensed formulation as it is essentially similar to the first proof which is presented in Section 6.7.4.

As the non-convexity is exclusively relevant for restricted suppliers, there are essentially two cases which have to be differentiated. In the first case (*Case1*), the discontinuity threshold is not exceeded by the production level of restricted suppliers, whereas in the second case (*Case2*) the non-convexity has to be considered. The non-convexity is addressed by a stepped shape with height $\Delta disc'$ at the threshold quantity $Q_{disc'}$.

Case1: $q^r \leq Q_{disc}$

The previous considerations may be transferred into the Lagrangian representation of the optimization problem as presented in Equation (6.41).

$$\mathbb{L} = (-1) \cdot (C_r(q^r) + \sum_t C_{u,t}(q^r)) + \mu \cdot (Q_{disc'} - q^r) \tag{6.41}$$

The respective Karush-Kuhn-Tucker (KKT) conditions are defined in (6.42).

$$\begin{aligned}
&(-1) \cdot \frac{\partial C_r(q^r)}{\partial q^r} + \sum_t \big[(-1) \cdot \frac{\partial C_{u,t}(q_t^u)}{\partial q^r}\big] + \mu = 0 \\
&q^r \leq Q_{disc'} \\
&\mu \cdot (Q_{disc'} - q^r) = 0 \\
&\mu \geq 0
\end{aligned} \tag{6.42}$$

The relations identified within *Case1* are similar to the respective ones in the first proof. Thus, Equation (6.43) depicts the optimal solution.

$$q^{r*} = \frac{(D_{t1} + D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r + a_1^u} \tag{6.43}$$

Equation (6.43) yields a valid solution as long as the inequality constraint (6.44) is satisfied ($q^{r*} \leq Q_{disc'}$) .

$$D_{t1} + D_{t2} \leq \frac{2 \cdot Q_{disc'} \cdot (a_1^r + a_1^u)}{a_1^u} \tag{6.44}$$

Case2: $q^r \geq Q_{disc}$

In *Case2* the production level of restricted suppliers exceeds the discontinuity threshold. The according KKT conditions are defined in (6.45).

$$\begin{aligned}
(-1) \cdot \frac{\partial C_r(q^r)}{\partial q^r} + \sum_t \big[(-1) \cdot \frac{\partial C_{u,t}(q_t^u)}{\partial q^r}\big] - \mu = 0 \\
q^r \geq Q_{disc'} + \epsilon \\
\mu \cdot (Q_{disc'} + \epsilon - q^r) = 0 \\
\mu \geq 0
\end{aligned} \tag{6.45}$$

The respective marginal cost functions are listed as equations in (6.46).

$$
\begin{aligned}
\frac{\partial C_r(q^r)}{\partial q^r} &= a_0 + \Delta_{disc'} + q^r \cdot a_1^r \\
\frac{\partial C_{u,t}(q^r)}{\partial q^r} &= -0.5 \cdot a_0 - 0.5 \cdot a_1^u \cdot (D_t - q^r)
\end{aligned}
\tag{6.46}
$$

It is sufficient to consider two scenarios:

1. *Scenario1:* $\mu = 0$
2. *Scenario2:* $q^r - Q_{disc'} - \epsilon = 0$.

Scenario 1: $\mu = 0$

The optimal quantity choice with respect to q^r is derived in Equation (6.47). The quantity is adjusted downwards as additional supply of unrestricted producers compensates for the discontinuous step.

$$
q^{r*} = \frac{(D_{t1} + D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r + a_1^u} - \frac{\Delta_{disc'}}{a_1^r + a_1^u}
\tag{6.47}
$$

Condition (6.48) has to be satisfied to identify a valid solution.

$$
D_{t1} + D_{t2} \geq \frac{2 \cdot (Q_{disc'} + \epsilon) \cdot (a_1^r + a_1^u) + 2 \cdot \Delta_{disc'}}{a_1^u}
\tag{6.48}
$$

Scenario2: $q^r - Q_{disc'} - \epsilon = 0$

The scenario definition directly yields Equation (6.49).

$$
q^{r*} = Q_{disc'} + \epsilon
\tag{6.49}
$$

Condition (6.50) has to be satisfied to guarantee a valid solution ($\mu \geq 0$).

$$
D_{t1} + D_{t2} \leq \frac{2 \cdot (Q_{disc'} + \epsilon) \cdot (a_1^r + a_1^u) + 2 \cdot \Delta_{disc'}}{a_1^u}
\tag{6.50}
$$

To sum, up the optimal production level of restricted suppliers can be defined according to Equation (6.51).

$$q^{r*} = \begin{cases} \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} & (b1) D_{t2} + D_{t1} \leq \frac{2\cdot(Q_{disc'}+\epsilon)\cdot(a_1^r+a_1^u)}{a_1^u} \\ Q_{disc*} + \epsilon & (b2) \frac{2\cdot(Q_{disc'}+\epsilon)\cdot(a_1^r+a_1^u)}{a_1^u} < D_{t1} + D_{t2} \leq \frac{2\cdot(Q_{disc'}+\epsilon)\cdot(a_1^r+a_1^u)+2\cdot\Delta_{disc'}}{a_1^u} \\ \frac{(D_{t1}+D_{t2})}{2} \cdot \frac{a_1^u}{a_1^r+a_1^u} - \frac{\Delta_{disc}}{a_1^r+a_1^u} & (b3) D_{t1} + D_{t2} > \frac{2\cdot(Q_{disc'}+\epsilon)\cdot(a_1^r+a_1^u)+2\cdot\Delta_{disc'}}{a_1^u} \end{cases} \tag{6.51}$$

6.7.7 Average Intraday Auction Trade Volumes

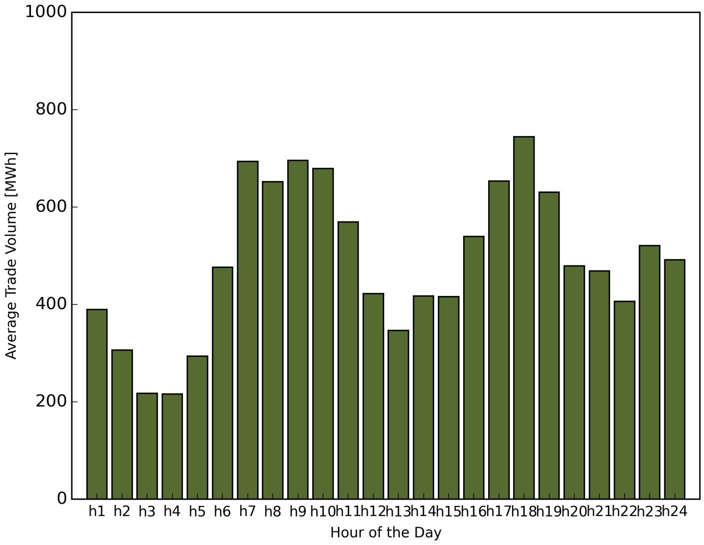


Figure 6.11: Average intraday auction trade volumes [MWh] in each hour of the day

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EDUCATION AND QUALIFICATIONS

Dec 2014 – Oct 2017	Institute of Energy Economics (EWI) at the University of Cologne, Germany **PhD in Economics** **Graduation: October 13, 2017** Title: Five Essays on the Economics of Short-term Power System Flexibility
2012 - 2014	RWTH Aachen, Germany **Master's study in Industrial Engineering** **Degree: Master of Science in Industrial Engineering (1.3)** Major: Electrical Energy Science Thesis: Development of a model to simulate scarcity prices in energy-only markets
2009 - 2012	RWTH Aachen, Germany **Bachelor study in Industrial Engineering** **Degree: Bachelor of Science in Industrial Engineering (1.8, upper 5%)** Major: Electrical Energy Science Thesis: Development of a model to estimate the costs of power supply Interruptions
2009	Collegium Augustinianum Gaesdonck, Goch (Germany) **GCE A-levels (1.0)**

EMPLOYMENT AND WORK EXPERIENCE

Since Oct 2017	Department of Information Systems for Sustainable Society **Post-Doctoral Research Fellow at the University of Cologne**
Jun 2015 – Sep 2017	ewi Energy Research & Scenarios gGmbH **Senior Research Associate** Policy and industrial consulting in energy economics

Dec 2014 – Jun 2015	Institute of Energy Economics (EWI) at the University of Cologne, Germany **Research Associate** Policy and industrial consulting in energy economics
Jul 2013 – Dec 2013	Institute of Power Systems and Power Economics (IAEW), Aachen **Research Assistant** Grid expansion planning for the transmission grid in Chile
Sep 2012 – Jun 2013	FIR e.v. at the RWTH Aachen **Research Assistant** Smart energy management, capacity markets, smart metering
Sep 2012 – Jun 2013	SWK Stadtwerke Krefeld AG (municipal utilities) **Internship** Asset management

HONORS AND AWARDS

Oct 2013 – Oct 2014	Deutschlandstipendium
2011, 2012	RWTH Dean's List (honor for academic performance)

CONFERENCES AND RESEARCH SEMINARS

Jun, 2016	39th Annual IAEE International Conference, Bergen, Norway Presentation: Short-term price volatility in commodity markets explained – Evidence from the power sector
Jun 2017	Energy Informatics & Management (EIM 2017) within the Erasmus Energy Forum 2017, Rotterdam, the Netherlands Presentation: Price Volatility in Commodity Markets with Restricted Participation
Jul 2017	1st Young Researcher Seminar at the Florence School of Regulation, Florence, Italy Presentation: Strategic Interaction in Commodity Markets with Restricted Participation

SELECTED PUBLICATIONS

Knaut, A., Paschmann, M.
Price Volatility in Commodity Markets with Restricted Participation
EWI Working Paper Series, 2, 2017

Knaut, A., Paschmann, M.
Decoding Restricted Participation in Sequential Commodity Markets
EWI Working Paper Series, 5, 2017

Bertsch, J., Lindenberger, D., Paschmann, M., Wagner, J.
Carbon dioxide emission reduction targets for the German power sector within a European context
VIK Mitteilungen, 1, 2016, pp. 23-26

Economic effects of phasing out lignite-based electricity generation on the German electricity market and the EU
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