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Chapter 1

Introduction

This cumulative PhD thesis comprises four articles. Three of them are published in peer-reviewed international academic journals and one is submitted to such a journal (see Sections 1.1, 1.2, 1.3, 1.4 for additional details on where the papers are published respectively submitted to). The aim of this introduction is to reveal the common denominator of all including papers and connect it to the overall research question. Except for the last paper in this cumulative dissertation (the fourth paper in Chapter 5), all remaining papers are interwoven in many respects, i.e., topical, methodological, and in their reference to the strategic behaviour of firms in electricity markets.

The research question of this dissertation is twofold. The first topic is on strategic behavior of firms in electricity markets. The second one is about how the electricity production from intermittent renewable sources affect the wholesale electricity price variance – a highly relevant topic for investors in flexible generation and policy makers alike. A necessary condition to analyze these points is to have free markets instead of monopolized industries. Indeed, the industry has changed tremendously in the last decades initiated by the liberalization process which took place in most industrial countries and also in Germany and Austria which are the geographical scope of the first and second paper.

The first paper of this dissertation in Chapter 2 concerns the competitiveness of one of the largest electricity exchanges in Europe which covers the German/Austrian market for electricity. The issue of competitiveness is strongly connected with strategic behavior of firms in this market, i.e., in a perfectly competitive market there is no room for strategic behavior at least not in the short-run. By using statistical methods from the field of *new empirical industrial organization*, we estimate the degree of market power in this market with the result that there is no evidence for anticompetitive behavior for the years 2007 to 2010. This result also forms the basis for the second paper of the thesis. The scope of the analysis, however, focuses *only* on short-term bidding behavior of companies on the day-ahead spot market. Nevertheless, strategic behavior of firms in this market for the timespan analyzed is not found.

The second paper in Chapter 3 which is also of empirical nature, analyzes the effect of intermittent renewable electricity production on the wholesale electricity price variance in the German/Austrian market. The theoretical foundations of this analysis make use of the result of the first paper, i.e., that the day-ahead spot market is working efficiently. We are able to show that the two pivotal factors influencing price variance are the shape of the industry supply function and the distribution of the residual demand which is the demand reduced by the in-

intermittent infeed of renewables. In the empirical part, we quantify by using *statistical methods* the effects of intermittent renewable infeed on the spot price variance of the German/Austrian market for the years 2007 to 2012. We find that the aggregated supply function in the German/Austrian market is inverse S-shaped. This leads to non-monotonic effects on the price variance, i.e., the first few Gigawatt of intermittent renewable production tends to decrease the price variance while larger amounts tends to increase the variance.

In the third paper (see Chapter 4) the focus is not explicitly on electricity markets. Within a standard *industrial organization* framework, we analyze the profitability of entry deterrence by means of corporate social responsibility (CSR). We manage to show that under some circumstances entry deterrence via CSR can be a profitable strategy. In the paper we did not build a bridge to the electricity industry to keep the results more general. However, since the deregulation of electricity markets has affected also the retailing sector, the results can be easily associated with this market. In particular, if some final electricity consumers have preferences for electricity generated from “green” sources, the introduction of CSR measures could be a profitable strategy for the incumbent in order to deter entry.

The fourth paper in Chapter 5 deals with the effect of additional information on the quality of decisions by making use of *simulation methods*. We find a way of constantly increase information by systematically limiting the ranges of probabilities which serve to calculate expected utilities. We simulate these probabilities and compare the decisions stemming from the constantly increasing better information to a reference scenario where we assume complete information about these probabilities. The mayor result is that the returns to scale on information decrease.

Concerning the overall research question I conclude that strategic behavior on the German/Austrian wholesale electricity market in the short-run is hardly possible due to the competitiveness of the day-ahead spot market. However, for energy companies operating also in the retailing business, CSR could be an option to behave strategically. Moreover, there could be the possibility for medium and long-run strategic behavior like, e.g., investment decisions of new plants. The profitability of such investment decisions is also connected with the tremendous increase in intermittent renewable generation, which leads to lower average wholesale prices and tends to have at first a dampening effect on the wholesale electricity variance in Germany.

In the following subsections I give additional information on the four papers. In particular, where these papers are published or where they have been submitted to. Furthermore, I discuss my own contribution to each of these papers. According to the cumulative dissertation guidelines of the PhD Management program at the University of Vienna of June 26, 2008 the three published papers of this dissertation sum up to 4.75 points where three points are necessary.¹

1.1 Chapter 2: Measuring Competitiveness of the EPEX Spot Market for Electricity (published)

This paper is joint work with one of my supervisors David Wozabal. It is published in *Energy Policy*, Vol. 62, November 2013, pages 948–958. According to the latest *VHB-JOURQUAL* 2.1 (2011) ranking, Energy Policy is ranked B.

¹An A-ranked journal accounts for three points, a B-ranked for two, and a C-ranked for one point. The points are weighted with $3(N + 2)^{-1}$, where N is the number of authors except supervisor.

I contributed to all parts of this paper. These are the review of the relevant literature, the way we estimated market power in the empirical part, and the setup of the fundamental electricity market model. I acknowledge close guidance by my supervisor, in writing up the results and having many fruitful discussions about the statistical techniques we used.

1.2 Chapter 3: The effect of intermittent renewables on the electricity price variance (submitted)

This paper is joint work with one of my supervisors David Wozabal and my PhD colleague David Hirschmann. The paper was submitted to the *Journal of Industrial Economics* on Dec 13, 2013. According to the latest *VHB-JOURQUAL* 2.1 (2011) ranking, the Journal of Industrial Economics is ranked A.

I mostly contributed to the empirical part of the paper. In particular, I was responsible for the estimation of the effects of renewable infeed on the Austrian/German wholesale price variance and for writing these chapters.

1.3 Chapter 4: Corporate Social Responsibility – A Strategic and Profitable Response to Entry? (accepted)

This paper is a joint work with one of my supervisors Franz Wirl. It was accepted for publication in the *Journal of Business Economics* on Nov 8, 2013. According to the latest *VHB-JOURQUAL* 2.1 (2011) ranking, the Journal of Business Economics is ranked B.

I contributed to all parts of this paper. I acknowledge close supervision in writing up the results by my supervisor and furthermore, on handling mathematical issues in the theoretical model.

1.4 Chapter 5: The Effect of Information on the Quality of Decisions (accepted)

This paper is a joint work with my PhD colleague Magdalena Six. It was accepted for publication in the *Central European Journal of Operations Research* on March 18, 2013. According to the latest *VHB-JOURQUAL* 2.1 (2011) ranking, the Central European Journal of Operations Research is ranked C.

I contributed to all parts of the paper except for the implementation of the iterative improvement of the information set.

Chapter 2

Measuring Competitiveness of the EPEX Spot Market for Electricity (published)

The issue of market concentration in electricity markets and resulting possible anti-competitive behavior of producers is a much discussed topic in many countries. We investigate the day-ahead market for electricity at the EPEX, the largest central European market for electricity. To analyze whether generating companies use their market power to influence prices, we use a conjectural variations approach as well as a direct approach to construct marginal costs of electricity production. Given the available data, we cannot reject the hypothesis that there was no systematic abuse of market power by the suppliers of electricity on the EPEX day-ahead spot market for the years 2007–2010. These results are essentially robust when restricting the sample to high load hours, which are generally considered to be the most prone to market manipulation.

2.1 Introduction

In the last decades most industrialized countries all over the world have seen a trend towards liberalization of electricity markets. This process was accompanied by discussions on optimal market design and mechanisms to ensure transparency and efficiency of the markets. In the process, in a range of countries doubts were raised on whether the pricing is free of market manipulation by large producers (for example Green and Newbery, 1992; Wolfram, 1999; Borenstein et al., 2002; Fabra and Toro, 2005; Weigt and von Hirschhausen, 2008).

In this paper, we investigate whether the electricity producers use their market power to influence prices to their favor at the European Power Exchange (EPEX), the German/Austrian spot market for electricity. To analyze this issue, we use two independent methods: A conjectural variations approach proposed by Bresnahan (1982), which, to the best knowledge of the authors, has not been applied to the German market before, and a fundamental model to compute the marginal prices of electricity generation.

The conjectural variations approach is based on a theoretical model in which firms make their decisions based on conjectures on the reaction of their competitors. From the analysis of the conjectures the degree of market power can be directly deduced. The advantage of this approach is that it lends itself to statistical estimation and the relevant parameters can be identified by using data on prices and quantities. Since our analysis is on an industry level, plant level data is not required. Instead, we use publicly available high frequency data on prices and aggregate demand as well as prices for primary energy for our study. On the basis of this analysis, we find no evidence of the systematic exercise of market power during the observation period 2007–2010. For each of the four years, the parameters estimated from the conjectural variations model correspond to conjectures that fit to a perfectly competitive market. The results are essentially robust when restricting the sample to high load hours, where the incentives for market manipulation are the highest.

To complement the above analysis, we propose a fundamental approach, mimicking the mechanics of an efficient market by modeling the marginal costs of production of nuclear, coal, gas, and oil plants and intersecting the resulting merit order with electricity demand minus the production from intermittent sources of electricity. The result serves as an input for the calculation of the optimal operation of storage plants, whose marginal costs are pure opportunity costs. This yields a fictitious competitive price that is compared to the actual market price. To the best knowledge of the authors, this paper is the first that explicitly considers the operations of storages in a fundamental approach to measure market power. Because of scarce data, we apply the fundamental approach only for the year 2010, for which it yields results that are consistent with the conjectural variations approach in the sense that prices are only slightly above the hypothetical marginal costs calculated in the fundamental approach.

Both of the approaches used to detect market power are of statistical nature. We therefore are not able to detect instances of market manipulation that occur very infrequently and have only a negligible effect on average prices. However, we believe that the misuse of market power only becomes a policy problem, if it significantly influences the cost of electricity for the end consumers. For this to happen, prices have to be distorted upwards in a large number of hours or there have to be hours with extremely high prices. Such a deviation from competitive behavior would be detected by the methods applied in this paper. Moreover, an in-depth analysis of single hours would require very detailed data on plant dispatch, bids, and detailed technical specifications of single plants. Unfortunately, this data is not publicly available for the German market.

We start our exposition with a short history of the joint German/Austrian electricity market and the ongoing debate about the alleged anti-competitive behavior of generation companies. In Germany, deregulation of the electricity market was introduced in 1998. In 2000, the Leipzig Power Exchange and the European Energy Exchange (EEX) were founded. Two years later the two German power exchanges merged under the name EEX. In 2009, the EEX spot market joined with the French exchange PowerNext to form the EPEX. The Austrian market was fully liberalized in 2001. Although there exists an Austrian power exchange, the relevant day-ahead spot market for electricity in Austria is the EPEX. In the remainder of the paper, we disregard the history of name changes and will refer to the spot market as the EPEX.

The founding of the German power exchanges clearly was a success in terms of traded quantities as Figure 2.1, Panel (a) shows. While in 2005 only 10% of the demand for electricity was traded on the EPEX day-ahead markets (see Growitsch and Nepal, 2009), the importance

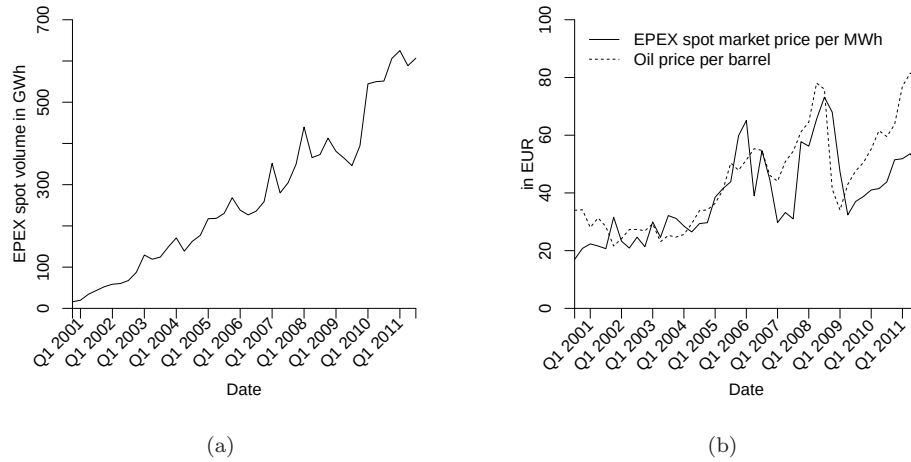


Figure 2.1: The evolution of EPEX traded quantities (a), as well as average prices on the EPEX day-ahead spot market from 2007–2010 (b).

of the exchange increased in the recent years. In 2011, there were 174 EPEX spot market participants listed and registered for auctions in the German/Austrian market, about half of which are from Germany/Austria. The price for electricity is determined in a single price, closed bid auction for every hour of the next day which takes place at 12 p.m., seven days a week, year-round, including statutory holidays. Allowed prices range between $-3,000$ EUR/MWh and $3,000$ EUR/MWh. Since the interconnection between the different areas of the EPEX market zone are usually sufficient to avoid congestion, there is no need for zonal or nodal pricing and the prices found in the day-ahead auctions are valid for the whole market zone. This even holds in the rare case of congestion where the resulting costs of re-dispatch are charged via network fees.

In the first year after liberalization, electricity prices on the exchange were rather low and it seemed that the liberalization was a success also from a consumer's perspective (see Bower et al., 2001). However, in the subsequent years EPEX spot prices rose sharply (see Figure 2.1, Panel (b)), triggering a public and political debate which was further boosted by an increasing market concentration as 30 small electricity producers merged into four large producers within a short period (see Lise et al., 2006). In 2009, the four biggest German energy producers Energie Baden-Württemberg AG (EnBW), E.ON AG (E.ON), Rheinisch-Westfälisches Elektrizitätswerk AG (RWE), and Vattenfall Europe AG (Vattenfall) owned 80% of production capacities and supplied 82% of electricity into the German power grid (Bundeskartellamt, 2011). Power producers counter accusations of price manipulations by claiming that higher electricity prices are caused by higher prices for primary energy. The development of the oil prices depicted in Figure 2.1, Panel (b) partially supports this statement.

The debate on whether high wholesale electricity prices are connected to higher input prices or to strategic withholding of capacities by the four big players is not resolved up to this day and is still discussed in academia, politics, and in the public. The European Commission (EC) and the German federal cartel office (GFCO) picked up the topic and, based on the sector inquiry issued by the EC and London Economics, concluded that at least in some hours the market outcomes were poor in the years 2003 to 2005 (European Commission, 2007; London Economics,

2007). As a result and to address the EC's concern about profitable withholding of generation capacity by E.ON, one of the leading German electricity producers, the company had to divest about 5,000 MW generation capacity. In contrast to E.ON, RWE and Vattenfall did not make any commitments (Bundeskartellamt, 2011). The legal proceedings against E.ON, RWE, and Vattenfall were suspended in 2008 due to lack of conclusive evidence. In the year 2009, the GFCO initiated another sector inquiry, analyzing wholesale electricity prices for the years 2007 and 2008. Although, the GFCO concluded that the situation of competition is unsatisfactory, they were not able to prove significant withholding of capacities by the electricity producers (Bundeskartellamt, 2011).

With the launch of a transparency platform, the legislative authorities tried to increase transparency in the electricity market. The platform for the German/Austrian market is maintained by the EEX since the end of October, 2009. The issue of transparency is deeply connected with efficiency, since it eliminates information asymmetries within the actors in the market. Ockenfels (2007) argues that market monitoring can lead to an increased transparency level and moreover can establish trust in the market. However, market monitoring can also have the opposite effect, providing data about power plant availability that can be used by competitors to assess whether unilateral withholding of generation capacity is profitable (Grimm et al., 2008). The EEX transparency platform publishes only aggregated data about plant availabilities and the reporting is obligatory only for plants with more than 100 megawatt (MW) installed capacity. Hence, the policies represent a compromise between reducing information asymmetries and not revealing too much information, which may in turn foster market inefficiencies.

The remainder of the paper is structured as follows: In Section 2.2, we review the existing literature on empirical methods for measuring market power in energy markets and discuss the conjectural variations approach and its limitations. In Section 2.3, we detail the conjectural variations approach used in this paper. We also discuss how to resolve the technical issues of model identification and endogeneity bias, making consistent estimation of the model possible. In Section 2.4, we discuss the fundamental approach of measuring marginal costs. Section 2.5 discusses the results of the econometric model and the fundamental approach. Section 2.6 concludes the paper and gives an outlook onto future research.

2.2 Literature Review

The issue of market power was controversially discussed in many countries after the liberalization of electricity markets. Especially after the California energy crisis in 2001 and 2002, an intense academic debate concerning the wholesale electricity market in California started, see for example Borenstein et al. (2002); Joskow and Kahn (2002); Kim and Knittel (2006); Puller (2007); Bushnell et al. (2008). Most of these papers are empirical studies and find indications for the abuse of market power during the crisis. Other liberalized markets in the US have also been analyzed. For example, Mansur (2007) studies the effect of vertical integration of generators and retailers on market competitiveness in the Pennsylvania, New Jersey, and Maryland market (PJM) finding that integration increases competition and that the restructuring of PJM's electricity market lead to an increase in anti-competitive behavior by large net sellers. Biggar (2011) found noncompetitive behavior of certain generating firms by identifying the pivotal suppliers and analyzing their bidding strategies in the Australian market.

The abuse of market power is also an issue in Europe. In UK, which was one of the

first countries to liberalize its markets, Wolfram (1999) finds indications that wholesale prices were higher than marginal cost, but not as high as standard oligopoly models would predict. Sweeting (2007) detects considerable inefficiencies in the British electricity markets during the late 1990s despite falling market concentration. In the Spanish electricity market, Kühn and Machado (2004) find that market power has had little impact on spot prices. However, the results from Fabra and Toro (2005) suggest that the Spanish electricity producers might have been alternating between episodes of collusion and price wars.

The existing academic literature analyzes the issue of market power in the German market either using descriptive statistics in combination with concentration indices or by fundamental approaches trying to recover the true marginal costs from the technical specifications of the production technology in combination with the input prices. While the former method is rather ad-hoc and often does not yield conclusive results the latter is dependent on the availability of detailed plant level data.

Müsgens (2006) concludes that prices were competitive from June, 2000 until August, 2001, but there is a strong evidence for anti-competitive practices in the period from September, 2001 to June, 2003. Weigt and von Hirschhausen (2008) find that EPEX prices are mostly above competitive levels from 2002 to 2006. The empirical findings which indicate an abuse of market power in the German wholesale electricity market are not without controversy: Möst and Genoese (2009) conclude that based on the Lerner Index they cannot confirm the exercise of market power. Swider et al. (2007) argue that calculations of short-run marginal costs are often flawed and criticize empirical studies that use the markup on these costs as indicator for abuse of market power. The fundamental analysis on a plant level requires the knowledge of plant specific costs and restrictions such as ramping constraints and minimum production levels, which make an hourly analysis of the price setting mechanism nearly impossible (see also Ockenfels, 2007).

In a perfectly transparent wholesale electricity market, the most intuitive way of analyzing its competitiveness would be to look at the changes of market participant's bidding curves over time. A systematic deviation of bids from marginal costs, especially in peak-demand hours when prices are high, would be an indicator for an abuse of market power. However, due to the lack of such in-depth data for the German market, methods which do not necessarily rely on firm level data are needed. These methods can be broadly divided into four categories: methods based on concentration indices, fundamental approaches, residual demand or supply analysis, and strategic models.

Concentration indices, like the Herfindahl-Hirschman index, can be easily computed but rely on the strong assumptions that high market shares always lead to abuse of market power. Fundamental approaches on the other hand heavily rely on firm level data of generation plants, since the aim is to calculate the true marginal costs of each firm. Based on these estimates a hypothetical price under perfect competition is calculated and compared with market outcomes. Although the approach is appealing as no economic modeling of firm behavior is necessary, it is hard to implement because detailed data on the operational characteristics of generation units is required. Besides numerous contributions on fundamental modeling in the engineering literature, Mansur (2008) provides an econometric model incorporating non-convexities of costs like unit commitment of generating units. By including these intertemporal constraints, the author estimates plant output on price-cost markups using fixed effect panel data regressions.

The third approach comprises the pivot supplier index (PSI), the residual supplier index

(RSI), and the residual demand analysis. While the latter identifies market power depending on the residual demand curve of each firm in the market (see Wolak, 2003), the former account for the importance of specific generators in fulfilling the market demand. The fourth approach includes supply function equilibria, and the conjectural variation method. The analysis of supply function equilibria, is the theoretically soundest way of modeling wholesale electricity markets, however, it has the disadvantage that it leads to rather hard optimization problems. See Bolle (1992); Green and Newbery (1992); Willems et al. (2009); Genc and Reynolds (2011) for applications of this approach. Apart from models trying to explain an abuse of market power via prices and costs, and/or quantities, Harvey et al. (2004) analyze outage rates of power plants as indicator for strategic behavior of the generating companies.

Like supply function equilibrium models, conjectural variations models are also market equilibrium models. The firms in the market are assumed to engage in a Cournot competition and have conjectures about other players' reaction to output expansions and contractions. As the model lends itself to efficient estimation of the conduct parameters determining the conjectures held by firms, it is widely used to identify competition in various industries, see Bresnahan (1989) for a general overview and e.g., Wolfram (1999); Puller (2007); Bask et al. (2011) for applications to energy markets.

The theoretical foundation of conjectural variations models is disputed in the literature. Corts (1999) criticized the empirical application of the conjectural variations model proposed by Bresnahan (1989). He shows that the asymptotic estimates for a simplified model only depend on the demand and are, thus, completely determined by how equilibrium quantities respond to demand, i.e., the equilibrium variation. However, to accurately measure the conduct parameters one has to also include the equilibrium quantity, i.e., the absolute value of the output. The estimates may, therefore, be misleading. However, it can be directly deduced from Proposition 1 in Corts (1999) that for the case of perfect competition the estimates are correct. Since our estimates suggest the absence of market power in the German market for the years 2007–2010, the aforementioned methodological pitfalls should not pose a problem for the paper at hand. Another point of criticism against the conjectural variations approach is that it is static in the sense that market in consecutive periods are treated as independent. The model therefore neglects possible intertemporal links between the periods.

2.3 The conjectural variations model and its empirical identification

In this section, we describe the empirical setup for estimating the degree of market power in the German/Austrian electricity market. Although we focus exclusively on the spot market, the results are relevant also for other markets, since the spot market price for electricity determines the opportunity costs of bidding on other markets such as the futures market or the intra-day market. Hence, higher prices on the spot market, caused by the misuse of market power, may also drive prices in other markets up.

The approach closely follows the framework outlined in Bresnahan (1982). We first describe the conjectural variations model in Section 2.3.1 and address the issue of parameter identification by the use of exogenous variables that shift demand and supply in Section 2.3.2. We proceed to argue our choice of shifters in Section 2.3.3 and wrap up in Section 2.3.4 with

a discussion on how to estimate the degree of market power and how to deal with possible endogeneity biases.

2.3.1 The model of competition

We consider n firms i , with $1 \leq i \leq n$, maximizing profits π_i by choosing their output q_i such that marginal revenues equal marginal costs. Defining

$$Q = \sum_i q_i = q_i + \sum_{j \neq i} q_j = q_i + q_{-i} \quad (2.1)$$

to be the total production and c_i to be the marginal cost function of firm i , the resulting first order condition of the firms' profit maximization problem is

$$\frac{\partial \pi_i(q_i, q_{-i})}{\partial q_i} = P'(Q(q_i, q_{-i}))Q'(q_i, q_{-i})q_i + P(Q(q_i, q_{-i})) - c_i(q_i) = 0. \quad (2.2)$$

where P is the inverse demand function.

The above equation, (2.2), cannot be solved for q_i without further knowledge on the strategic interaction of the companies, i.e., the function $Q'(q_i, q_{-i})$ which indicates how the overall quantity would change in dependence of the production of company i . In case of perfect competition or a monopoly producer, the problem becomes trivial: For perfect competition we have $Q' \equiv 0$ and all companies would sell at marginal costs whereas for a monopoly producer $Q(q_M) = q_M$, i.e., $Q' \equiv 1$. However, for all levels of competition *in between* these two extremes, solutions cannot be obtained without any further assumptions. We therefore assume that companies decide on their outputs according to their beliefs about the reaction function, R_{-i} , of their rivals, which corresponds to a *conjectural variations* model of competition. In specific, we have $Q(q_i) = R_{-i}(q_i) + q_i$ and if we assume $R'_{-i} = r_{-i} \in \mathbb{R}$, (2.2) can be rewritten as¹

$$P(Q(q_i)) = c_i(q_i) - P'(Q(q_i))(1 + r_{-i})q_i. \quad (2.3)$$

We define $\lambda_i = 1 + r_{-i}$ and note that $\lambda_i = 0$ for the case of perfect competition and $\lambda_i = 1$ for the case of a monopoly. Hence, λ_i parameterizes the policy of company i by identifying the *conjectures* the company has about the effects of its output changes on the overall produced quantities. The parameters λ_i therefore serve as a measure of competitiveness of the industry with higher values being an indication of less competition, i.e., the market being closer to joint profit maximization, and smaller values being an indication of a more competitive industry.

For our analysis, we consider an aggregate approach, i.e., we are not trying to find the parameters λ_i for individual firms i , but rather analyze the following expression (assuming symmetric conduct parameters, i.e., $\lambda_i = \lambda^0$, $\forall 1 \leq i \leq n$)

$$P(Q) = n^{-1} \sum_{i=1}^n c_i(q_i) - n^{-1} \sum_{i=1}^n \lambda^0 P'(Q) q_i = c(Q) - \lambda P'(Q) Q \quad (2.4)$$

obtained from (3) by summing over i and dividing by n . Here, $\lambda = n^{-1} \lambda^0$ can be interpreted as the aggregate industry wide conjectural variation parameter while $c(Q) = n^{-1} \sum_{i=1}^n c_i(q_i)$

¹Linearity of the reaction function follows from a linear specification of marginal costs together with linear demand as shown in Lindh (1992) for the case of consistent conjectural variations. In this paper, we assume linearity of both the marginal cost function and the demand, see Section 2.3.2.

are the average marginal costs of production.

Goal of this analysis is to estimate the parameter λ as a proxy for the degree of market power in the EPEX day-ahead spot market for electricity. There are two technical difficulties connected to the statistical analysis of this problem. First, the price is influenced by the marginal costs as well as the *conjectures* held by the companies, both depending on the output Q . Hence, without knowledge of the marginal costs, it is impossible to estimate the parameter λ as any shift in prices could either be caused by a shift in the marginal costs or by output adjustments. Thus, there is an identification problem in estimating the degree of market power from equation (2.4). We will deal with this problem in the next subsection by introducing demand and cost shifters that will help to estimate a linear specification of the marginal costs and resolve the identification issue. The second technical difficulty stems from the fact that in the course of estimating the marginal costs and equation (2.4), we are confronted with the classical endogeneity problem arising from estimating prices dependent on output. We use an instrumental variable approach, to deal with this problem as will be discussed in Section 2.3.4.

2.3.2 Empirical identification of the model

To make (2.4) accessible to statistical inference, we first estimate $P'(Q)$. To this end, we model the demand function $Q(P)$ as dependent on exogenous demand shifters Y as well as parameters α , i.e., $Q(P) = Q(P, Y, \alpha)$. Specifically, we assume the following linear specification of the demand function

$$Q = \alpha_0 + \alpha_1 P + \alpha_2 Y_1 + \alpha_3 Y_2 + \alpha_4 Y_2 P + \epsilon_1. \quad (2.5)$$

where ϵ_1 is a random exogenous shock to the system and $\alpha = (\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4)^\top$. In the above equation the demand shifters $Y = (Y_1, Y_2)$ enter in two ways: Y_1 and Y_2 both contain variables that shift the demand function vertically, while Y_2 , additional to a vertical shift, changes the slope of the function $P \mapsto Q(P, Y, \alpha)$, i.e., is additionally a *rotator*. Note that while Y_2 is a random variable, Y_1 can contain more than one shifter and therefore is a random vector. Correspondingly, α_2 is a parameter vector while the other coefficients are scalars. From (2.5), we conclude that $P'(Q) = (\alpha_1 + \alpha_4 Y_2)^{-1}$ and define

$$Q^* = -P'(Q)Q = -\frac{Q}{\alpha_1 + \alpha_4 Y_2}. \quad (2.6)$$

We can thus rewrite (2.4) as

$$P = \lambda Q^* + c(Q), \quad (2.7)$$

where the marginal costs are a function of a set of exogenous cost shifters W and a parameter vector β , i.e., $c(Q) = c(Q, W, \beta)$.

To estimate λ , we additionally need estimates for the marginal costs $c(Q, W, \beta)$ which we assume to follow the linear specification

$$c(Q, W, \beta) = \beta_0 + \beta_1 Q + \beta_2 W + \epsilon_2, \quad (2.8)$$

where $\beta = (\beta_0, \beta_1, \beta_2)^\top$. $\beta_0 \in \mathbb{R}$ is the marginal cost of the cheapest technology and β_2 are the coefficients of the cost shifters. From the linearity of the marginal costs it follows that the costs of production are quadratic in the produced quantity and linear in the demand shifters. Looking at Figure 2.2 depicting a marginal cost function for the German/Austrian market, the

	Variable name	Type	Unit	Frequency
Cost shifters	Emission rights price	Metric	EUR	Daily
	Coal price	Metric	USD	Daily
	Gas price	Metric	USD	Daily
	Oil price	Metric	USD	Daily
	Wind	Metric	MWh	Hourly
Demand shifters	Daylight hours	Metric		Daily
	Hour	Categorical		Hourly
	National holidays	Categorical		Hourly
	Temperature index	Metric	Centigrade	Daily
	Weekday	Categorical		Hourly
Rotator	Temperature index	Metric	Centigrade	Daily

Table 2.1: Cost and demand shifters.

first statement seems plausible. Since we use mainly fuel prices as cost shifters, the assumption of linear dependence of the cost on the demand shifters is justified as well. Consequently, (2.7) becomes

$$P = \lambda Q^* + \beta_0 + \beta_1 Q + \beta_2 W + \epsilon_3. \quad (2.9)$$

Note that λ is identified because of the inclusion of the term $\alpha_4 Y_2$ in (2.5). Without this term, i.e., with $\alpha_4 = 0$, variables in Y would only cause vertical shifts of the demand function (2.5) and correspondingly (2.9) would change to

$$P = \frac{\lambda}{\alpha_1} Q + \beta_0 + \beta_1 Q + \beta_2 W + \epsilon_3 = \left(\frac{\lambda}{\alpha_1} + \beta_1 \right) Q + \beta_0 + W \beta_2 + \epsilon_3. \quad (2.10)$$

While the parameter $(\lambda/\alpha_1 + \beta_1)$ is identified, it is not possible to deduce the value of λ from knowledge of $(\lambda/\alpha_1 + \beta_1)$. Loosely speaking, we cannot disentangle the influence of marginal costs, β_1 , and market power, λ , with model (2.10). The additional exogenous variable Y_2 in (2.6) mitigates this problem (see Bresnahan, 1982).

2.3.3 Empirical setup

In this section, we discuss our choice for the variables W and Y , i.e., the demand and cost shifters summarized in Table 2.1.

As demand we use hourly load data for Germany and Austria provided by the European Network of Transmission System Operators for Electricity (ENTSO-E). Demand is influenced by deterministic seasonal factors such as the hour of the day, the weekday, daylight hours, dummies for national holidays in Germany and Austria as well as average daily temperatures, which we use as demand shifters. Extreme temperature affect electricity prices by increasing the demand for electricity due to higher demand for heating and cooling causing a non-linear effect of temperatures on demand. By including squared temperatures in the set of demand shifters, the structure of the model is complex enough to capture this effect. As a proxy for temperatures, we construct a daily temperature index for Austria and Germany as the population weighted mean of all the Austrian and German cities with more than 10,000 inhabitants. The index is constructed using the two Mathematica 7.0 functions *CityData* and *WeatherData*.

We use prices for primary energy such as oil, gas, and coal; prices for emission rights, and

production quantities from intermittent technologies such as wind turbines as cost shifters. As proxy for the production from wind turbines, we use the 24 hour ahead forecasts for wind energy production in the four German grid regions as published by the grid operators 50hertz, Amprion, TransnetBW GmbH, and Tennet. For Austria there is no publicly available high frequency data on produced wind energy in this period. However, since most of the wind energy in the EPEX area is produced in Germany, and since the yields in Austria are highly correlated with German yields, we expect the sum of forecast wind energy production in Germany to be a good proxy for the overall production. We use 24 hour ahead predictions instead of the produced values since the prices on the spot market are fixed on the previous day and therefore forecasts have a greater explanatory power than actual production data. Clearly, it can be expected that higher production from wind turbines drives the market price for electricity down, since the owners of wind plants are paid a fixed market independent price for their production. Hence, high wind energy production tends to lower the deployment of other, more expensive, technologies.

Crude oil prices are a major determinant of electricity production prices, since oil prices are highly correlated with prices of other primary sources of energy, as for example with prices of natural gas from long term supply contracts, which are usually based on a mix of the current and lagged oil prices (see Table 2.3 for an exact parametrization of oil-indexed gas prices). Furthermore, crude oil prices are instrumental in explaining the long term variations of electricity prices and the observed structural breaks due to changes in the macroeconomic climate (see also Figure 2.1, Panel (b)). We use daily Brent prices (see Table 2.3) in our analysis.

A large portion of the electricity base-load in Europe is generated by coal fired plants. In Germany and Austria 38.6 percent of the total production in 2010 was generated in plants running on lignite and hard coal. Since coal prices are not as closely tied to oil prices as gas prices, we include the price of hard coal (CIF ARA 6000k) as a cost shifter in our analysis. Prices for lignite are not publicly available, since it is not traded on public exchanges. However, as the two types of coal are close substitutes, it is reasonable to assume a strong correlation in prices.

Since the electricity sector is covered by the European Emission Trading system, i.e., electricity producers have to pay for their carbon dioxide emissions, the price of emission rights is a relevant cost driver for electricity production from fossil fuels. We therefore include daily prices for emission certificates as quoted at the EEX (Carbix) in the set of cost shifters.

As can be seen from Table 2.1, the data on prices for primary energy and the prices for emission rights is available in daily resolution. However, the prices of electricity do not react to daily changes on the corresponding commodity markets, but rather to long term trends. To eliminate noise introduced by daily fluctuations, we apply exponential smoothing to the time series of all cost shifters (except wind) considering the last 30 days with smoothing factor 0.1.

2.3.4 Estimation of the conduct parameter λ

Having resolved the identification problem, the system of equations (2.5) and (2.9) are still subject to an endogeneity bias caused by the simultaneity of the two equations. We deal with this issue by an instrumental variable approach as is standard in econometric literature. Specifically, we apply two stage least squares regression (2SLS) to construct valid instruments for equations (2.5) and (2.9).

To estimate (2.5), we use temperatures as Y_2 and the remainder of the demand shifters

as Y_1 . Clearly, P and PY_2 are endogenous in (2.5), since they are affected by the produced quantities Q . We instrument for these variables using the cost shifters W , i.e., the prices for primary energy and the prices for emission rights. These seem to be reasonable instruments, since the input prices can be expected to influence the demand for electricity only indirectly via the electricity price. It turns out that the chosen instruments are strong in the sense that they explain a significant part of the variation of the price process. Correspondingly, we are able to reject the hypothesis of weak instruments with an F-test on the coefficients of the first stage regression. The results of the regression (2.5) for the years 2007 to 2010 can be found in Table 2.5 in the Appendix. Since the adjusted R^2 is around 80% in nearly all the regressions, we conclude that there is little room for omitted variable bias and the estimated coefficients can be trusted to be accurate. We apply a heteroskedasticity and autocorrelation consistent estimation of the covariance matrix of the coefficient estimates in all regressions in this paper using the *R* package *sandwich* (see Zeileis, 2004).

To estimate equation (2.9), we construct Q^* as described in (2.6) from the coefficients of P and PY_2 estimated from equation (2.5). Furthermore, we construct two dummy variables D_1 and D_2 , which are set to 1 in the 10% of the hours with the highest and the lowest loads respectively. We include the interaction of D_1 and D_2 with Q^* as well as the dummies themselves in the regression (2.9). The interactions enable us to quantify the strategic bidding behavior separately for high load and low load hours. The resulting regression (2.9) suffers from the problem of endogeneity because of the variables Q , Q^* , and Q^*D_i . We again use a 2SLS approach to construct valid instruments for these variables. Specifically, we use the demand shifters Y , the interaction between $-P'(Q)$ and Y , and the interaction between D_i and Y as instruments in the first stage regression. Intuitively, the number of daylight hours, temperatures, hour, weekdays, and holidays affect the price only via their effect on quantities and therefore are a good choice for instrumenting Q , Q^* , and Q^*D_i . We again are able to rule out the possibility of weak instruments by testing whether the coefficients of the instruments in the first stage regression are jointly zero. The results of the corresponding regressions and the estimates for λ as coefficient of Q^* are discussed in Section 2.5.

2.4 A Fundamental Approach for Estimating Marginal Costs

In this section, we discuss a direct method to estimate the hourly short-run marginal cost of electricity production. Although we try to capture the main aspects of price formation, the proposed model is rather basic and relies on many simplifying assumptions. For more complete fundamental models of the German market, we refer to Müsgens (2006); Schwarz and Lang (2006); Weigt and von Hirschhausen (2008); Möst and Genoese (2009).

We adopt a bottom-up approach: We model the marginal cost of each available generation unit to construct a merit order of electricity production and use the demand for electricity to determine the *marginal production unit*, i.e., the most expensive plant that has to be switched on in every hour. If the producers bid at their marginal costs, i.e., the market is competitive, then the marginal cost of the marginal plant equals the market price of electricity.

As mentioned in the introduction, the fundamental model is rather challenging owing to problems of data availability: Besides detailed technical plant level information, it has to be

	Efficiency	Size	Number	Capacities in GW	
				Installed	Available
Gas	0.45	130	212	27.53	20.56
Coal	0.38	261	101	26.31	21.85
Lignite	0.37	329	60	19.76	16.18
Oil	0.39	90	36	3.23	2.62
Uranium	0.33	1,138	18	20.48	15.88
Sum			427	97.31	77.09

Table 2.2: Size-weighted average efficiency levels, average plant size (installed capacity in MW), number of plants, installed, and average available capacities of non-regenerative electricity generating units in Germany/Austria in 2010.

known whether a plant is available for production at a given point in time and what are the prices for inputs such as primary sources of energy and emission certificates on a plant level. Since most of this data is confidential, we use various assumptions and simplifications discussed in the following paragraphs.

Also note that pricing according to the marginal cost of production does not allow peak plants to recover their fixed costs. However, at the overall capacity bound prices might be higher than the short run marginal costs of production even if the market is competitive and producers have no market power (see also the discussion on peak load pricing, for example Crew et al., 1995).

For Germany, the Bundesnetzagentur (2011) published a list of German power plants with an installed capacity larger than 20 MW in October 2011 containing information on 643 plants with an installed total capacity of 108 GW. The list specifies gross production capacities as well as the type of the plant. For Austria we use plant level data on 144 plants with a total capacity of 13 GW provided by the EEX transparency platform. Note that the aforementioned source is incomplete, since firms have to report the available capacity only for plants which have installed more than 100 MW of capacity. However, the share of the Austrian electricity production in the total German/Austrian market is rather small and a large fraction of the total Austrian electricity production is generated by run-of-river hydro plants for which hourly production is known.

Table 2.2 shows the distribution of installed and average available capacities differentiated by primary energy carrier (PEC). It can be seen that coal and lignite fired plants together account for the largest share in the power plant portfolio. Furthermore, Table 2.2 shows efficiency levels, average plant sizes, and the number of plants in our sample.

Not all installed capacities are available at all times owing to maintenance, outages, and other (un)foreseeable events. The EEX transparency platform publishes data on available capacities for the German/Austrian market in daily resolution. This service is based on voluntary commitments of energy producers and therefore does not cover all providers and the data is available only on PEC-level for the two countries separately and not on generating unit-level. To resolve this problem, we calculate the relative available capacities for each PEC and use these to uniformly decrease the available capacity for all plants using a specific PEC.

For our analysis, we partition the plants in two categories: intermittent sources of electricity such as wind turbines, run-of-river hydro plants, solar panels and controllable plants such as all types of coal and gas plants, nuclear plants, and storage plants. Demand is constructed by

adding grid losses and rescaling hourly load data from ENTSO-E in order to fit with production data. We treat intermittent sources of energy as effectively reducing the demand for electricity, i.e., we construct a residual demand profile by subtracting the electricity produced from intermittent sources from the overall demand. Additionally, we adjust the residual demand for the positive net export out of the area of Germany and Austria which is publicly available in hourly resolution at the website of ENTSO-E.

The resulting residual demand is intersected with the merit order which consists of controllable plants, which we further partition into two subcategories: Plants whose marginal costs are mainly fuel and emission costs, and plants whose marginal costs are determined by opportunity costs. The first category consists of coal, gas, and nuclear plants while the second category consists of storage plants. The marginal cost of storage plants is the expected future revenue that can be generated with the stored electricity. A storage plant produces electricity only if the price exceeds the opportunity cost, complicating the dispatch decisions of these plants.

We deal with this complication by first dispatching the plants that are driven by fuel cost for the whole year of 2010 and then use the resulting prices to plan the dispatch of the storage plants. In a further step, we adjust the residual demand profile by the net production/consumption of the storage plants. Based on the new profile, we redo the dispatch planning for the fuel cost driven plants and calculate the competitive price as the marginal costs of the limiting plant. Of course, in reality, the dispatch decisions of all plants are made simultaneously and therefore sequential planning potentially introduces errors. We try to mitigate this problem by incorporating a linear price response function in the dispatch planning of the storage plants, i.e., storage plants are aware of how much the price changes as a result of their decisions. If the linear price response is specified correctly, then the decisions do not change in another round of sequential dispatch planning.

We start by describing the fuel cost driven plants in detail: the marginal cost of plant j using PEC i in hour h is given by

$$MC_j^i(h) = \frac{1}{\eta_j}(I_i(h) + \tau_i E(h)), \quad (2.11)$$

where $I(h)$ are prices for primary energy, $E(h)$ are prices for emission rights, η_j is the generating unit specific efficiency factor, and τ_i the emission factor which depends on the PEC. We use a constant price of USD 9.33 for uranium (see Table 2.3) and the cost shifters discussed in Section 2.3.3 as prices for primary energy, which we assume to be the same for all producers. For gas we use the price provided by the German Federal Office of Economics and Export Control (BAFA), which represents the value of gas at the German border. We believe that this price best captures the right mix between oil-indexed gas contracts and gas from the exchange.² Since there is no market for lignite, we assume its price to be 80 % of the price for coal. The reason for this assumption is that lignite mines are usually close to power plants, reducing transportation costs and thus the price. The efficiency factor for plant j , η_j , takes values between zero and one and describes the relation between energy input in terms of primary energy and energy output in terms of electricity. We calculate efficiencies for each generating unit using PEC specific linear functions of the date of construction (see Schröter, 2004, for the exact parameterization of the functions). In Table 2.3, we show the average PEC prices including the price for emission rights,

²Unfortunately, this data is only available in monthly resolution, which is the reason, why we do not use it in the econometric model.

PEC	Type	$\overline{MC}(\eta = 1)$	τ
Coal	CIF ARA 6000k	12.94	2.59
Gas	Oil-indexed ¹	29.93	0.18
Gas	Border ²	23.24	0.18
Lignite	Assumption ³	11.50	2.73
Oil	Europe Brent Spot Price FOB	40.06	0.25
Uranium	Assumption ⁴	7.05	0.00

¹ We calculated the daily gas price, I_{Gas} , with the following formula $I_{\text{Gas}}(t) = 26.2 + 1.69I_{\text{Oil}}(t) + 3.57I_{\text{Oil}}(t - 270)$, as suggested by Yegorov and Wirl (2009).

² In the fundamental model, we use the gas price provided by BAFA.

³ Since there exists no liquid market for lignite, we use 0.8 times the coal price.

⁴ Fuel costs for German nuclear power plants are 9.33 USD/MWh (see International Energy Agency and OECD, 2010).

Table 2.3: Average marginal cost of production in EUR/MWh for the year 2010 and emission factors of the different PECs.

and levels for τ_i .

Although, the marginal cost of production is mainly driven by the energy conversion efficiency, fuel costs, and emission rights, we are aware that our specification of the marginal cost function does not perfectly reflect reality, since we do not consider ramping costs, minimum production levels, and start up costs of plants. We do not directly model these facts on a plant level, since we do not have the required plant specific data. Instead, we deal with these issues in an approximate way by specifying so called must-run plants for every day. In particular, we assume that if a nuclear, coal, lignite, or a combined cycle gas plant is switched on at some point of time on a given day, then it has to remain switched on for the whole day, producing at least its minimum output. The minimum output of the plants classified as must-run on any given day is subtracted from the demand in the same way as is done for intermittent sources of electricity. The rationale for this is that must-run generating units will bid at low prices, since they need to produce anyway owing to technical reasons.

In accordance with Nicolosi et al. (2010), we use 30%, 80%, 60%, and 85% of the capacity as minimum production levels for coal-, lignite-, combined cycle gas-, and nuclear-plants respectively. Note that these figures are not technically motivated but observed in a certain period of time in Germany. Moreover, we adjust the demand by taking combined heat and power plants (CHP) into account which produce electricity as a by-product when producing heat. Using data from a typical CHP plant, we estimate hourly temperature dependent must-run levels via fractional logit regressions. More specifically, we regress electricity output against temperatures and electricity prices and obtain the temperature dependent must-run levels as forecast from the estimated model setting the electricity price to the marginal production cost of a nuclear plant.

Although biogas plants are controllable, we treat them as producing a constant power output throughout the year. This assumption can be justified by the data provided by the German grid company 50 Hertz for the output of biogas plants in its grid. The reason for the constant pattern is the fact that biogas is considered a renewable source of energy and thus receives fixed, market independent rates for its production. The producers therefore aim at minimizing their production cost by producing at a constant rate.

Figure 2.2 shows an example of the merit order ignoring must-run power plants and supplied electricity from renewable energy sources. In this particular example, the cheapest technology

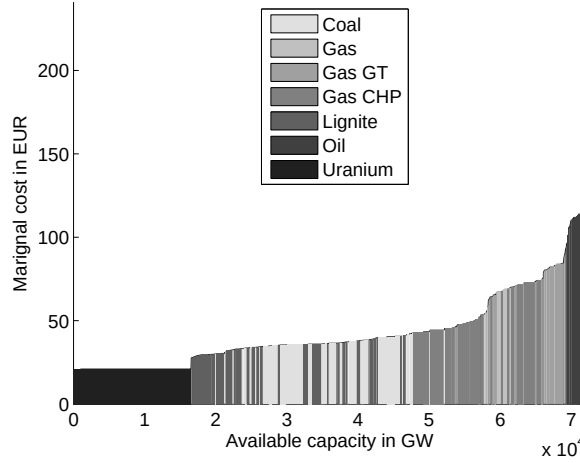


Figure 2.2: Constructed merit order (only plants fueled by non-regenerative PEC and without must-run plants), November 17, 2010.

to produce electricity was uranium followed by lignite, coal, gas, and oil. All the nuclear power plants in our sample are assumed to have an efficiency factor of one third (Schröter, 2004). Therefore, there is no variation between the marginal costs in this segment of the merit order. The very high marginal costs to the right of the merit order are due inefficient generating units mostly running on diesel.

Next, we incorporate the storage plants. These plants have a maximum pumping capacity of 8 GW and a generation capacity of 13 GW in the transnational market. Storage plants act strategically in the sense that they pump if the price of electricity is low and generate if the price of electricity is high. In order to capture this behavior, we include an optimization problem in our analysis.

First, we estimate a linear price response function for every hour h by defining the vectors $r_h = (r_{h,-k}, \dots, r_{h,0}, \dots, r_{h,k})$, where $r_{h,0}$ is the residual demand as described above and $r_{h,i} = r_{h,0} + if$, $-k \leq i \leq k$ and $f \in \mathbb{R}$ as well as $k \in \mathbb{N}$ are fixed. We then determine the merit order based prices $p_{h,i}$ for all the demands $r_{h,i}$ using the merit order containing only the controllable plants. Based on the pairs $(p_{h,i}, r_{h,i})_{-k \leq i \leq k}$, we estimate an OLS regression for every hour with the quantities as independent variable. We hence obtain coefficients $\hat{a}_h$ and $\hat{b}_h$ parameterizing the linear relationship

$$p_h(r_h) = \hat{a}_h + \hat{b}_h r_h \quad (2.12)$$

between demand and price in hour h . The assumption of local linearity of the price response seems realistic, considering the shape of the marginal cost curve in Figure 2.2. We choose f to be 10 MW and k such that $[r_{h,-k}, r_{h,k}]$ covers the whole range of residual demands that could result from shifts caused by the operation of storage plants.

Based on these price responses, we model the decision problem of the storage plants jointly as deterministic optimization problem for the year 2010, i.e., for 8760 hours. The joint modeling is a simplification that makes it possible to incorporate the price response to the entire industry, which is necessary to obtain realistic results as discussed above.

Each plant $i \in \{1, \dots, n\}$ maximizes profits by deciding about the amount of electricity used

for pumping, $x_i^p(h)$, and the amount generated, $x_i^g(h)$, in hour h . We thus solve the problems

$$\max_{x_i^p, x_i^g} \sum_{h=1}^{8760} \left[p_h \left(\sum_{i=1}^N x_i^p(h) - x_i^g(h) \right) \cdot (x_i^p(h) - x_i^g(h)) \right], \quad (2.13)$$

keeping track of the storage balance, and constraining the operations of pumps and generators as well as the amount of stored capacity using detailed data on plant characteristics such as inflows, capacities, and reservoir topology (see Brenner, 2012). We model $p_h(\cdot)$ using the estimated linear price responses (2.12), i.e., the price is an affine function of the quantities. The resulting convex quadratic optimization problem is solved using *GUROBI* 5.02. Although, we use several simplifications to model the storage plants, the outcomes can still be assumed to be significantly better than if storage plants were ignored altogether, or only modeled by simple heuristics, as it was done in previous studies (e.g., London Economics, 2007; Bundeskartellamt, 2011).

2.5 Results

We start by discussing the results of the conjectural variations model and then proceed with the results of the fundamental approach. While the former method is applied to the period 2007 till 2010 the latter is restricted to the year 2010 due to restricted data availability. For the computations we use *R* (see R Development Core Team, 2011) and the 2SLS regressions were estimated with the help of the package *AER* by Kleiber and Zeileis (2008).

The aim of the conjectural variations approach is to estimate parameter λ , which serves as a proxy for the degree of competitiveness in the EPEX day-ahead spot market. We use a linear demand and marginal cost structure with various demand and cost shifters as described in Section 2.3. Table 2.4 shows the results of the regressions for each year. We see that the estimated conjectural variation parameter λ , i.e., the coefficient of Q^* , is not significantly different from zero in the years 2007 to 2010. This means that there is no evidence for anti-competitive behavior in the EPEX day-ahead spot market in the analyzed period.

Most studies that found evidence for the misuse of market power identified these inefficiencies in high load hours. To analyze those hours separately, we include the interaction terms of Q^* with the dummy variables D_1 and D_2 introduced in Section 3. The estimated coefficients of these interactions terms can be interpreted as changes in the coefficient for Q^* in the hours with extreme loads. For example in the year 2010 the estimated λ for the high load hours is $0.0001 + 0$ while the coefficient for the low load hours is $0.0001 + 0.0014$. Note that all estimated values are very small and all but two of them are statistically not significantly different from 0 as can be seen from the p-values. Hence, we can conclude that even in the restricted sample corresponding to extreme load scenarios the chosen approach shows no indication of strategic bidding by the generation companies.

The estimated coefficients of the other variables seem reasonable, i.e., the market price of electricity increases with rising demand, emission rights prices, and prices for primary energy, while it decreases with wind production. Except in the years 2008 and 2009, almost all explanatory variables behave in this way. The significantly negative coefficients of some of the input prices in these years are somewhat counterintuitive. We do not have a convincing explanation for these patterns, but note that the year 2009 was a very heterogeneous period in terms of energy prices: While in the first half of the year the oil prices were low and the economy

	2007	2008	2009	2010
Intercept	-115.3329 0.0000	-90.9173 0.0000	-20.6278 0.1036	-80.0342 0.0000
Low-Load-Dummy	2.3561 0.0131	-3.4530 0.0019	-1.6518 0.1315	-4.1175 0.0001
High-Load-Dummy	22.2126 0.0000	-1.7960 0.2293	2.4702 0.0788	3.5543 0.0000
Coal price	1.9463 0.0268	4.1416 0.0000	1.4853 0.0987	0.3914 0.2396
Emission rights	1.1590 0.0776	-0.5159 0.0000	1.3647 0.0004	2.8009 0.0000
Gas price	0.5961 0.3169	-0.3971 0.4407	-0.3312 0.0008	0.1219 0.4000
Oil price	0.6130 0.0000	-0.2598 0.0000	-0.4546 0.0000	0.2560 0.0000
Wind	-2.5794 0.0000	-2.2144 0.0000	-1.8591 0.0000	-1.2039 0.0000
Load	1.3630 0.0000	2.2228 0.0000	1.1964 0.0000	0.9798 0.0000
Q^*	0.0000 0.8564	0.0000 0.2674	-0.0001 0.2078	0.0001 0.3857
$Q^* \cdot \text{Low-Load-Dummy}$	-0.0013 0.0000	0.0000 0.2450	0.0031 0.3969	0.0014 0.7220
$Q^* \cdot \text{High-Load-Dummy}$	-0.0008 0.2108	0.0000 0.0004	0.0001 0.8012	0.0000 0.8282
Adjusted R^2 N	0.5383 8,729	0.7436 8,729	0.6253 8,729	0.7657 8,760

Table 2.4: Coefficients and p-values (heteroskedasticity and autocorrelation consistent estimation of the variance-covariance matrix) for the regression (2.9) for the years 2007–2010.

was in recession, the second half of the year was characterized by a significant improvement of the macroeconomic climate and sharp price rises on the energy markets. We conclude that these structural breaks cause the counterintuitive results observed for this year. The adjusted R-squared, and thereby the fraction of explained variation, is high in all the models limiting the possibility of wrongly estimated coefficients due to omitted variables and furthermore is an indication that our specification of the cost function captures the real cost structures reasonably well.

Next, we compare the market prices of 2010 to hypothetical *efficient* prices using the merit order approach discussed in Section 2.4. Figure 2.3, Panel (a) shows average, hourly, realized day-ahead spot market prices in the EPEX and the average, hourly prices based on our merit order approach. The structure and the level of the two average cost curves are reasonably close. This finding is an indication that the prices in the year 2010 roughly follow the hypothetical prices calculated by intersecting demand and marginal costs, i.e., that the market worked efficiently. Figure 2.3, Panel (b), which shows a plot of the ordered prices from the fundamental model as well as the ordered realized prices, confirms this finding and shows that except for the very low and the very high prices the fundamental model seems to provide a reasonable fit to the data. Running an OLS regression without intercept of the prices from the merit order approach on actual prices yield a coefficient of 0.98, suggesting that the marginal costs calculated with the merit order approach are slightly below the actual prices, i.e., that the producers charge a small markup. However, the average price difference is rather small and the marginal cost do not include load changing costs and the cost of switching plants on and off and thus are a

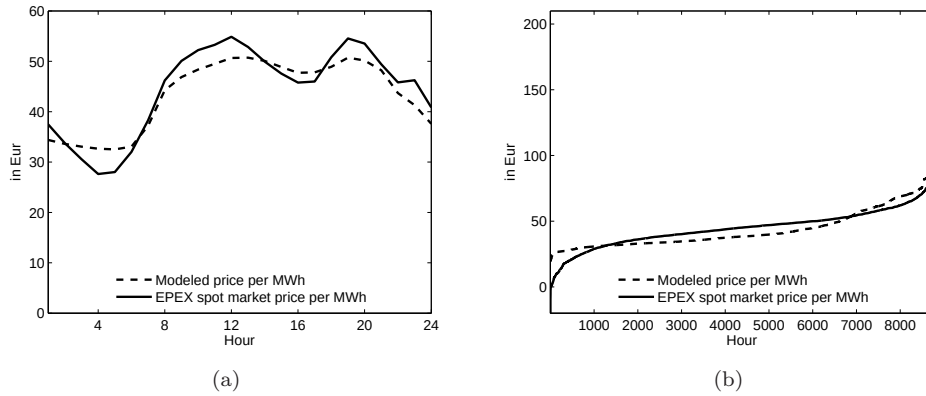


Figure 2.3: Hourly average price profile (a) and (b) ordered EPEX prices in 2010 and ordered prices constructed with the merit order approach

lower bound on the real short-run marginal costs. Thus, in line with the conjectural variations approach, the results are an indication for an efficiently working EPEX spot market.

Based on the analysis above, we conclude that on average there is no evidence of market manipulation in the EPEX spot market for the time period 2007–2010. The results are robust, even when restricting the analysis to subsets of the data. Furthermore, we performed the conjectural variations analysis with a quadratic marginal cost function and found essentially identical results, indicating that the model is also robust with respect to changes in the parametric form of the marginal cost function.³

The fundamental analysis for the year 2010 methodologically complements the conjectural variations approach and also shows no significant deviations of the prices on the EPEX from the competitive prices. We note that both of the chosen approaches can only detect systematic deviations from competitive behavior, that lead to *average* prices being different than competitive prices. We cannot, therefore, make any statements regarding individual hours based on the presented results.

2.6 Conclusion and Further Research

In this paper, we analyzed the efficiency of the EPEX spot market for electricity in the years 2007–2010. The topic of abuse of market power on the EPEX is controversially discussed in academics as well as in public. We contribute to the discussion by proposing a conjectural variations model to analyze whether the players on the market interact strategically or bid their capacities at marginal prices. Our analysis showed that the market worked efficiently during the aforementioned time period. This result was confirmed by the results of a fundamental approach, which compares the marginal cost of the limit power plant to the actual price of electricity. The latter approach was only applied for the year 2010, since it requires detailed data on a plant level which is difficult to obtain.

The findings of this paper are surprising to a certain extent, considering the ongoing public debate in Germany and that the market is highly concentrated with only four big players, a fact that some authors take as an indication of the abuse of market power. Our analysis leads

³The results of this analysis are available upon request.

us to conclude that simple, ad-hoc measures of market concentration, such as the Herfindahl Hirschman index are not adequate to assess the competitiveness of a market, since these measures, at best, measure a *potential* for the abuse of market power but are unable to distinguish an inefficient market from an efficient market with only a few major players.

It has to be noted that all our results are based on averages, i.e., we show that *on average* there was no abuse of market power in the analyzed years. This, of course, does not exclude the possibility of the existence of single hours for which market outcomes were poor. However, our analysis suggests that market manipulation and withholding of capacities does not seem to be a structural problem on the EPEX. This can be seen as an indication that the policies put in place by the regulator to ensure transparency of the market are sufficient to guarantee an efficient spot market.

Further support for the hypothesis of the competitiveness of the EPEX spot market is provided by the research on the connection between spot markets and other markets: According to Bushnell et al. (2008), firms which have committed a portion of their output to other markets than the spot market, have a lower incentive to raise prices on the spot market. This holds true for futures contracts as well as for the case of vertical integration and arrangements between wholesalers and retailers. The unifying factor for both applications is price commitment which takes place before the production commitment on the spot market. Wolak (2000) analyzed the positive linkage between the quantity of hedge contract levels and the competitiveness of prices on the Australian market. These results also apply to the German market, since the EEX, where German power derivatives are traded, is among the most active exchanges in Europe (see Wilkens and Wimschulte, 2007). Moreover, due to historical reasons many generating firms in Germany and Austria are engaged in the retailing business. However, Biggar (2011) points out that also the expectation of the development of futures and retail contracts plays a role, i.e., if higher spot market prices drive up futures prices (retail prices) it might still be profitable to misuse market power to raise spot market prices.

In this paper, we analyzed the short term bidding behavior of companies on the EPEX. However, medium and long term decisions of companies, such as maintenance and expansion planning are also potentially strategic decisions, which could be used for collusive behavior of companies and cannot be detected by analyzing the short term behavior of companies on spot markets. Collusive or strategic behavior on this level is an interesting topic for further research.

Another interesting direction of research would be to extend the analysis to a firm level, i.e., to estimate one conjectural parameter per firm. This of course, requires the availability of firm level production data, which at the moment is not freely available.

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2.7 Appendix

2.7.1 2SLS regression of the demand equation

	2007	2008	2009	2010
Intercept	69.7866 0.0000	57.3537 0.0000	64.1149 0.0000	59.7576 0.0000
Price	-0.0720 0.0723	0.1211 0.2246	-0.0148 0.8207	0.1087 0.0792
Wind	0.4243 0.0000	0.3934 0.0016	0.4659 0.0010	0.4399 0.0000
Temperature	-1.4482 0.0000	0.6413 0.0917	-1.3900 0.0003	-1.0852 0.0002
Temperature ²	0.0201 0.0000	-0.0052 0.6168	0.0080 0.0084	0.0101 0.0000
Daylight hours	-0.0076 0.0016	-0.0085 0.0021	-0.0082 0.0644	-0.0066 0.0023
Hour 2	-1.9284 0.0000	-2.1780 0.0000	-0.9911 0.1122	-0.8428 0.0000
⋮				
Hour 24	4.2415 0.0000	3.7874 0.0000	3.0304 0.0000	2.3322 0.0000
Wednesday	0.8449 0.1404	0.0136 0.9702	-0.0311 0.9422	0.2567 0.3455
Thursday	0.6519 0.3186	0.5593 0.1575	-0.5551 0.3805	0.0472 0.9062
Friday	-0.0777 0.8979	-0.7824 0.1390	-1.3450 0.0185	-1.3823 0.0242
Saturday	-7.5907 0.0000	-9.9521 0.0000	-8.9959 0.0000	-8.9622 0.0000
Sunday	-11.8091 0.0000	-15.0886 0.0000	-11.6750 0.0000	-12.0236 0.0000
Monday	-1.1670 0.0500	-1.2927 0.0000	-1.1572 0.0072	-1.3582 0.0000
Holiday DE	-11.5762 0.0000	-10.4376 0.0000	-10.1239 0.0000	-10.4635 0.0000
Holiday AT	-4.3264 0.0036	-5.6000 0.0018	-3.3234 0.0686	-3.6643 0.0255
Price · Temperature	0.0215 0.0022	-0.0110 0.1066	0.0243 0.0043	0.0145 0.0237
Adjusted R^2	0.7986	0.8156	0.8159	0.8806
N	8,729	8,729	8,729	8,760

Table 2.5: Coefficients and p-values (heteroskedasticity and autocorrelation consistent estimation of the variance-covariance matrix) of regression (2.5) for the years 2007–2010.

Chapter 3

The effect of intermittent renewables on the electricity price variance (submitted)

In this paper, we analyze the effect of intermittent electricity production from renewables on the electricity spot price variance. Using a static market model, we identify the variance of the infeed from intermittent electricity sources (IES) and the shape of the industry supply curve as two pivotal factors influencing the electricity price variance. The model predicts that the overall effect of IES infeed on the variance depends on the produced amount: while small to moderate quantities of IES tend to decrease the price variance, larger quantities have the opposite effect. In the second part of the paper, we test these predictions using data from Germany, where investments in IES have been massive in the recent years. The results of this econometric analysis largely conform with the prediction from the theoretical model. This has implications for policy makers coordinating subsidy schemes for renewables, flexible production capacities, and electricity storages.

3.1 Introduction

In the last decades electricity markets were liberalized in many countries, most of which established electricity exchanges where electricity is traded on an hourly basis. Since the possibilities of storing electricity are limited and demand is highly inelastic, electricity prices exhibit strong daily, weekly, and yearly seasonalities which are mainly driven by fluctuating demand. This peculiar property of electricity is shared by no other commodity and prompted active research investigating the competitiveness of the markets, the statistical properties of the price process, and the determinants of price formation.

In the last years the debate centered on the transformation of electricity production driven by the goal to decrease the carbon footprint of the industry. From the perspective of understanding electricity prices, the most interesting aspect of this transition is the interplay of large intermittent production capacities with the above mentioned characteristics of electricity de-

mand and insufficient storage capacities. The massive build-up of wind energy in Germany, for example, caused turmoils on the electricity market and with grid operators alike.

There exists extensive literature on the impact of intermittent electricity sources (IES) on electricity prices. Most of the studies focus on the price level and it is widely agreed on that an increase in IES reduces the average spot prices (see, e.g., Sensfuß et al., 2008; Green and Vasilakos, 2010; Jacobsen and Zvingilaite, 2010; Woo et al., 2011). In this study, we want to assess the impact of intermittent production on the variance of electricity prices.

Clearly, the evolution of the price variance is a major determinant when investing in plants, for which the return is directly connected to the variation of prices (see Muche, 2009; Dunne and Mu, 2010). Likewise the returns on investments in smart grid infrastructure depend heavily on the variance of prices. The higher the price variance, the higher the incentive to invest in smart grid and metering technology that smoothens the demand. Since these technologies are necessary to deal with the challenges induced by an increased share of IES production, understanding the mechanisms that drive price variance on electricity exchanges is of importance to academics, policy makers, and investors alike.

However, the extant literature is not clear on the issue of price variance: First, many studies refer to price variability for which there are many possible definitions, including the range of observable prices, the frequency of price spikes, the price variance, or the volatility. Second, findings are contradictory. While most authors predict an increase in price variability due to IES, some empirical works find a reduced price variability of power prices as the amount of intermittent production increases. In this paper, we introduce a theoretical framework that reconciles both findings and is consistent with the data observed on the German electricity market.

Among the theoretical works predicting an increased price variability is Milstein and Tishler (2011) who consider a two stage game for electricity producers. In the first stage, energy producers decide which share of their production portfolio will be intermittent. In the second stage, energy is produced accordingly, but with some probability the IES cannot be exploited. If the IES cannot produce energy, prices spike due to inelastic demand. This implies that IES can increase price volatility. Green and Vasilakos (2010) simulate the impact of wind generation on the spot market prices in the UK for the year 2020. They rely on real world wind data, information on existing and planned wind farms, and demand data. Assuming a competitive market, they simulate monthly price distributions. The results imply that volatility of prices increases in future and that the magnitude of the increase depends on the competitiveness of the market. In Chao (2011) a central planner chooses a production portfolio and sets prices as to maximize expected social welfare. Stochastic demand depends on prices, and supply is subject to random outages or intermittence. For two different pricing schemes, scenarios with and without IES are compared. While average prices decrease, the load-weighted standard deviations increase mildly.

Other papers focus on historical data and find that price variance has increased due to IES. Woo et al. (2011) examine the effect of wind generation upon spot prices in Texas by means of a (partial-adjusted) linear regression model. They show that rising wind generation reduces the spot prices. By extrapolation of the data they argue that price variance tends to increase if wind generation is raised. More recently, Ketterer (2012) analyzed the German electricity market by using a GARCH model. She finds that an increased production from wind reduces the mean price but increases the variance while an increased load shows the opposite effects.

The conclusions concerning price variability are ambiguous in Jónsson et al. (2010) who study the effects of wind energy forecasts on prices in Denmark. They consider different levels of wind penetration, that is, the percentage of electricity produced by wind turbines. Their findings suggest that higher predicted wind penetration lowers the mean spot price and reduces the intra-day variance of the prices. Still, they conclude that price volatility will increase in future, due to the varying price patterns induced by different wind penetration scenarios. Jacobsen and Zvingilaite (2010) also study the current market situation in Denmark on a broad level and focus on the large share of IES. With respect to prices, they conclude that prices fluctuate more but that the frequency of peak prices is reduced.

Tveten et al. (2013) report that solar infeeds in Germany have decreased price variance substantially from 2009–2011. They compare days with similar electricity demand and different levels of solar energy production and find that on days with high solar infeeds the price variance is lower. This is attributed to the merit order effect: under high solar power penetration, the production mix is changed, i.e., peak power plants with high short-run marginal costs are used less. Therefore, prices stay at a lower level and do not jump up to peak-load prices, which reduces fluctuations.

The merit order effect also forms the base of this paper, but we study it more systematically and in a broader context for wind and PV energy. We contribute to the discussion by showing that IES can either increase or decrease price variance. For our theoretical investigations, we consider daily price variances, using a static market model with random residual demand influenced by IES infeed. We identify two factors driving the price variance: (1) the curvature of the supply function (merit order), and (2) the distribution of the random IES supply. To test our theoretical findings, we perform statistical analysis on data from Germany and are able to verify the existence of the two effects. Furthermore, our statistical analysis provides evidence that the merit order in the German market is “inverse S-shaped.”

The remainder of this paper is structured as follows. In Section 2, we detail the theoretical approach, identifying the effects which influence the price variance. In Section 3, we analyze the effects of increased intermittent electricity production on the variance of electricity prices in an econometric model. Section 4 is devoted to the policy implications of our findings, while Section 5 concludes the paper.

3.2 Theory

In the following, we provide a theoretical framework explaining how IES infeeds affect the price variance. We first explain the market model and then give an intuitive idea of two opposing effects that intermittent production has on the distribution of the electricity prices. We conclude with a formal analysis, which identifies the relevant factors influencing the price.

Our investigations are based on a standard static market model with inelastic, random aggregate demand for electricity Q . As common in the literature, we start our investigation with the assumption of a convex market supply curve S (see e.g., Barlow, 2002; Kim and Knittel, 2006; Redl et al., 2009; Arocena et al., 2012). This assumption will be relaxed later on. The market price is obtained as $S(Q)$, i.e., by intersecting the inelastic demand with the supply curve. We therefore implicitly assume that no player is able to exercise market power.

In the setting outlined above, the most natural way to include intermittent production would be to change the supply function. However, for the purpose of our model, we find it

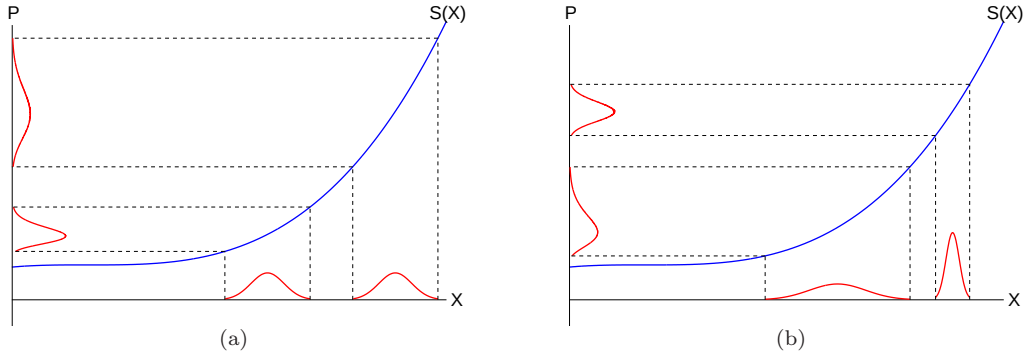


Figure 3.1: Panel (a): Shift of the residual demand with otherwise constant distribution. Panel (b): Shift of the residual demand with broadened distribution.

more convenient to subtract the intermittent production I from the demand. In this way we obtain the so called *residual demand* $Q - I$, which is the demand that has to be covered by conventional plants. The obvious advantage of this kind of modeling is that all the stochastic quantities, i.e., the demand and the intermittent infeed, enter the residual demand while the supply curve remains deterministic. Incorporating IES via a change in the supply function or via the residual demand is equivalent, if intermittent production is always fed-in regardless of the price, i.e., if it merely shifts the demand curve to the left. Indeed, typically intermittent sources of electricity have marginal costs close to zero and therefore supply all the energy they produce into the grid as long as prices are positive. Additionally many countries subsidize intermittent renewable production by guaranteed feed-in tariffs which also include preferential access to the market. Therefore it is quite standard to model renewable production via residual demand (see e.g., Sensfuß et al., 2008; Nicolosi, 2010; Graf and Wozabal, 2013; Hirth, 2013).

Figure 3.1 intuitively explains how an increase in IES infeed affects the market price in our model. The x -axis indicates the quantity of electricity and the y -axis the price. The densities on the x -axis represent the stochastically varying residual demands $X = Q - I$, which are mapped to the stochastic prices $P = S(X)$ whose densities are drawn over the y -axis. In Figure 3.1(a), the increased amount of IES shifts the residual demand to the left to a region where the supply curve is flatter. If the shape of the residual demand distribution remains unchanged, the variance of the prices decreases. If, however, an increased share of intermittent production changes the shape of the distribution of X , then the situation is ambiguous. For example, if the density of the residual demands *broadens* by an increase in intermittent production, then the variance could increase even though the residual demand is pushed into the flat area of the supply function, see Figure 3.1(b). Hence, the effect of intermittent production depends crucially on the shape of the distribution of the residual demand and on the slope of the supply function.

We state the intuitive results in a more rigorous way: Let the supply function $S : \mathbb{R} \rightarrow \mathbb{R}$ be increasing, convex, and differentiable. We compare two scenarios with different shares of intermittent energy sources. In the first scenario the residual demand is given by X with price $S(X)$. In the second scenario, we assume a larger share of IES and denote the additional random IES infeed by $I' \geq 0$ and the resulting residual demand by $Y := X - I'$. We start by investigating the case where the distribution of Y is not broader than the distribution of X ,

which we formalize as

$$F_Y^{-1}(\beta) - F_Y^{-1}(\alpha) \leq F_X^{-1}(\beta) - F_X^{-1}(\alpha), \quad \forall \alpha, \beta : 0 \leq \alpha < \beta \leq 1, \quad (3.1)$$

i.e., that the interquantile ranges of X are at least as wide as that of Y . It is shown in Lemma 3 (see Appendix 3.6) that (3.1) implies $\text{Var}(Y) \leq \text{Var}(X)$ (while the opposite is not necessarily true). We modify a theorem of See and Chen (2008) and obtain the following result, which we prove in the appendix.

Proposition 1. *Let X and Y be non-negative random variables with inverse distribution functions F_X^{-1}, F_Y^{-1} respectively, and let $S : \mathbb{R}^+ \rightarrow \mathbb{R}$ be a convex increasing function which is twice differentiable. If (3.1) holds and $Y \leq X$, then*

$$\text{Var}(S(Y)) \leq \text{Var}(S(X)). \quad (3.2)$$

Looking at the two conditions, we see that $Y \leq X$ holds by definition, but (3.1) need not hold in practice. However, the special case depicted in Figure 3.1(a) where $Y = X - c$ for some constant $c > 0$ is covered by the above result. A thorough study of the proof of the above proposition shows that, depending on the interaction between the shape of the supply function and the distributions of the residual demand, the variance may still decrease, even if (3.1) is violated. However, this analysis involves tedious algebraic manipulation and leads to conditions that do not lend themselves to economic interpretation.

To disentangle the effect of the shape of the supply function and the distribution of residual demand on the price variance, we therefore employ a first-order approximation of the supply function. The first-order Taylor approximation of S around $\mathbb{E}(X) = \mu$ reads

$$S(X) \approx S(\mu) + S'(\mu)(X - \mu). \quad (3.3)$$

Taking variances on both sides using the fact that $\text{Var}(aX + b) = a^2 \text{Var}(X)$ and $\text{Var}(b) = 0$ for $a, b \in \mathbb{R}$, we find

$$\text{Var}(S(X)) \approx S'(\mu)^2 \text{Var}(X). \quad (3.4)$$

Hence, the variance of the prices is approximated by the squared slope of S evaluated at the mean of the residual demand times the variance of the residual demand. Analogously, the first-order approximation for $\text{Var}(S(Y))$ can be found and we see that $\text{Var}(S(Y)) \leq \text{Var}(S(X))$ is *approximately* true if

$$S'(\mathbb{E}(Y))^2 \text{Var}(Y) \leq S'(\mathbb{E}(X))^2 \text{Var}(X). \quad (3.5)$$

Of course the above condition is no strict criterion, since it is based on an approximation which tends to get worse as the values of the random variables move away from their respective means. Still we can use it to explain what happens in Figure 3.1(b): From $Y \leq X$, it follows that $\mathbb{E}(Y) \leq \mathbb{E}(X)$ and therefore, since S is convex, that $S'(\mathbb{E}(Y)) \leq S'(\mathbb{E}(X))$. Hence, to outweigh the effect that Y is shifted to the flatter part of the supply curve, the variance of Y has to be correspondingly bigger so that (3.5) is violated and the variance of $S(Y)$ is larger than the variance of $S(X)$. Conversely, if Y is shifted far enough to the left, the convex shape of the supply function can outweigh a possible positive effect of $\text{Var}(Y)$ on the price variance.

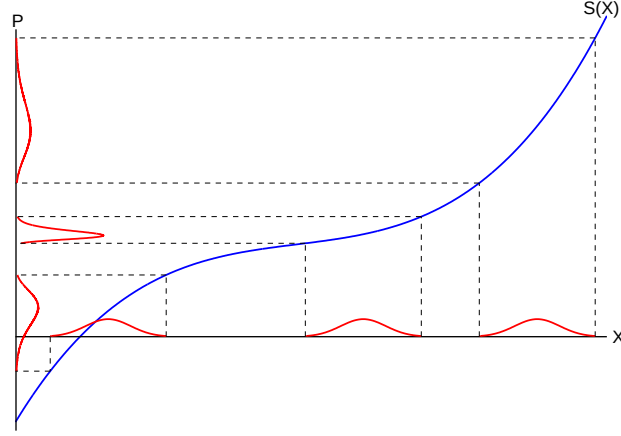


Figure 3.2: Price effects with concave-convex supply function.

Until now we have assumed a monotonically increasing, convex supply curve. However, some authors argue that inflexible, slow base-load producers cause a dramatic decrease in prices near to the left end of the supply function. Such plants would rather accept producing at a loss for a few hours than switching off, which would induce longer down times and considerable fuel costs for restarting the plant (see e.g., Fanone et al., 2013). This corresponds to the observations made in Germany in times of low demand and high intermittent infeed, where prices frequently are close to zero and sometimes even drop to negative values. He et al. (2013) adopt a dual-exponential model to capture this effect. In their paper they show that a model with a supply curve that consists of a concave part followed by a convex part fits the merit order curve on the German spot market better than a purely convex supply function. We call a function of this type *inverse S-shaped*.

Clearly, the arguments in this section can be easily adapted to this setting as is demonstrated in Figure 3.2: If the demand is shifted into the concave part of the supply function then the variance tends to increase because of the higher slope of the function in this region. Hence, in this setting, the variance as a function of the location of the mean of the residual demand, keeping all other characteristics of the distribution fixed, is U-shaped, i.e., high for very high and very low demand and smaller in the middle section.

3.3 Empirical analysis

In Section 3.2, we identified the shape of the supply function and the distribution of the residual demand as the two pivotal influences on the electricity wholesale price variance. In this section, we put these theoretical considerations to the test. For this purpose we conduct a statistical investigation of the price variances currently observed in the German day-ahead spot market of electricity. More specifically, we set up regression models, aiming to explain spot price variance by the variances and means of demand and renewable infeed, while controlling for other factors that also potentially affect electricity price variation.

We start with an overview of the German market design with a focus on the day-ahead spot market and the marketing of renewable electricity and then discuss the variables we use in the regressions. In the main part of this section, we discuss the setup of the regressions as well as the results of our study of the price data from 2007 until 2012.

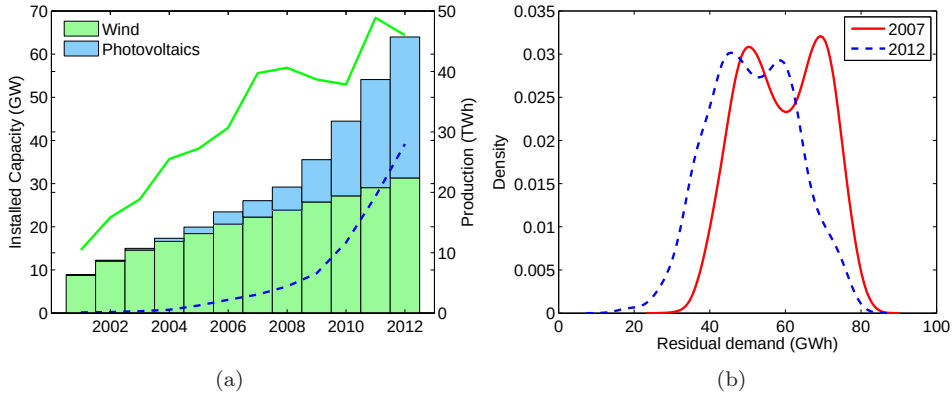


Figure 3.3: Panel (a): Installed capacity (bars) and production (lines) of wind power (solid) and PV (dotted) in Germany. Source: Wozabal et al. (2013); Panel (b): Residual demand distributions (load reduced by forecast wind power and PV production).

3.3.1 The German day-ahead Market

We pick Germany as a showcase because investment in renewable sources has been considerable in the last decade. Figure 3.3 documents this, showing the installed capacity of wind power and photovoltaics (PV): installed capacity of wind plants was growing steadily between 2001 and 2012 with an average compound annual growth rate of about 12% and installed capacity of PV more than tripled between 2009 and 2012 (see also Wozabal et al., 2013).

For Germany the relevant market places to trade electricity are the European Energy Exchange (EEX) and the European Power Exchange (EPEX). While on the EEX options and futures on power can be traded, the EPEX hosts the day-ahead and intra-day market. The hourly prices on the day-ahead market are determined in sealed bid, uniform price auctions at 12 p.m. for every hour of the next day. On the intra-day market electricity can be traded continuously for delivery in single hours on the same or the following day until 75 minutes before delivery begins.

The legal framework for subsidizing renewable power production in Germany is regulated in the German Renewable Energy Sources Act (EEG, see Federal Ministry for the Environment, Nature Conservation, and Nuclear Safety, 2013) and its amendments, which requires the grid operators to buy all the power produced by renewable sources in their grid area for a regulated tariff and sell it further on the day-ahead and intra-day market. The grid operators have to publish forecasts of renewable production for the next day. The forecast quantities are sold on the day-ahead market and the differences between the day-ahead forecasts and actual volume are traded on the intra-day market.

The difference of the revenues on the spot markets and the payments to the producers of renewable energy are typically negative and are charged along with the grid fees to the final consumers. Hence, although producers receive a fixed feed-in tariff, renewable power is traded on the wholesale markets as if producers themselves would be active in these markets. In a recent modification of the EEG, producers of renewables can also opt for a market premium system instead of a feed-in tariff. In the market premium regime, producers directly sell their quantities without any support from the grid operators (see e.g., Gawel and Purkus, 2013). The modification of the EEG is in place since 2012 and aims to incentivize market-orientated

Variable	Description	Source
Price	Hourly day-ahead spot price for Germany/Austria	EPEX (2013)
Demand	Hourly load for Germany/Austria	ENTSO-E (2013)
Wind	Hourly day-ahead wind forecast for Germany/Austria	TSOs (2013)
Photovoltaic (PV)	Hourly day-ahead PV forecast for Germany	TSOs (2013)
Temperature	Daily temperature index	Mathematica
Oil	Daily Europe Brent Spot Price FOB	EIA (2013)
Daylight minutes	Daily daylight minutes	

Table 3.1: Overview of used variables and data sources.

behavior of the suppliers of renewables. However, since most of the renewable production is sold on the day-ahead market, we focus on the day-ahead prices at the EPEX, where Germany and Austria are treated as one market zone.¹

To guarantee transparency, the EEG requires grid operators to provide data on renewable production to the public. In particular, data about production and day-ahead forecasts of renewables is available in an hourly resolution. The good data availability adds to the fact that the EPEX is an ideal showcase. Furthermore, Graf and Wozabal (2013) showed that the EPEX works efficiently, which means that the day-ahead market complies with the theoretical framework in Section 3.2.

3.3.2 Data

In this section, we discuss all the variables we use in our econometric analysis. An overview of these variables along with their descriptions and sources is provided in Table 3.1.

In order to estimate the effect of the residual demand characteristics on the price variance, we require hourly price data, hourly data on electricity demand, and hourly data on infeed from renewable sources of power. We obtain the data on prices directly from the EPEX website, the data on demand from the European Network of Transmission System Operators for Electricity (ENTSO-E) and the data on renewable infeed from the main grid operators (TSOs) in Germany/Austria.²

In this study, we define renewables as wind power and PV and do not consider other technologies. We do this for two reasons: First, because the bulk of intermittent production comes from these two technologies and second, because infeed from other relevant renewables, as for example biomass or hydro plants, can be controlled and therefore does not contribute much to the variance of the residual demand.

Since until 2012 most of the renewable energy was sold by the grid operators on the day-ahead market, we use the day-ahead forecasts for renewable production instead of actual infeeds. Prior to 2010, German PV data is not available and for 2010 we use actual production as a proxy for the day-ahead forecasts. Austrian PV production is negligible and data is not publicly available, while forecasts for Austrian wind production are available only since 2011.

¹In principle, suppliers of renewables under the market premium regime are free in electing a marketplace. However, the day-ahead spot market is much more liquid than the intra-day market: the traded volume in 2012 at the day-ahead market was 245 TWh (225 TWh in 2011) versus 15.8 TWh on the intra-day market (15.9 TWh in 2011), see EPEX (2013). Therefore, we assume that most of the produced quantities are sold on the day-ahead market.

²Germany: EnBW Transportnetze, Tennet TSO, Amprion, and 50Hertz Transmission; Austria: Austrian Power Grid.

Figure 3.3(b) shows the results of a kernel density estimation of residual demand for the first and the last year in our sample. Comparing the two years yields the following observations: (i) the mean decreased between 2007 and 2012, (ii) the shape of the distribution changed, in particular the two peaks are less pronounced in 2012 than in 2007, (iii) the maximum residual demand stayed almost constant while the minimum residual demand reduced drastically. The descriptive statistics of our sample in Table 3.2 shows that the yearly average demand decreased slightly between 2007 and 2012 but the supplied renewables increased considerably. The changing shapes of the distributions can be explained by PV production – a technology which supplies most electricity during the midday peak hours. Therefore, an increase in solar production eliminates the traditional noon peak which has an effect on the shape of the residual demand distribution (see e.g., Gawel and Purkus, 2013; Tveten et al., 2013).

Of course, the characteristics of demand and infeed of renewable power are not the only factors driving price variance. To control for influences that originate from the supply side of the market, we include oil prices and three month lagged oil prices to capture the influence of the price of primary energy. Furthermore, we include the number of daylight minutes to capture seasonal trends, and an index of daily average temperatures. To construct the daily temperature index for Austria and Germany we use a population weighted mean of all the Austrian and German cities with more than 10,000 inhabitants. The index is constructed using the Mathematica 7.0 functions `CityData` and `WeatherData` (see Graf and Wozabal, 2013). For the oil price, we use the daily Europe Brent spot price provided by EIA (2013).

3.3.3 Statistical analysis

To test the influence of residual demand, wind power, and PV infeed on the variance of German wholesale electricity prices, we estimate the following regression models with the price variance as dependent variable: A model that uses residual demand as an explanatory variable (model 1), a model in which the components that make up residual demand, i.e., demand and IES infeed, are treated as separate regressors (model 2), and a third model where we further disentangle the infeed from renewable sources into their two constituting elements, i.e., wind power and PV (model 3).

We measure daily price variances, i.e., using 24 hourly observations. The time frame to calculate the variance is chosen for the following reasons: On the one hand, it should be long enough such that the renewables can cause price variance, e.g., due to changed weather conditions. Thus, a resolution level higher than daily, e.g., half-daily, would be meaningless. On the other hand, the time frame should not be too long, since in this case one would lose important information due to aggregation and furthermore, we would end up with too few observations for a profound empirical analysis.

All models include the other factors discussed in the last section in daily resolution. We perform all regressions using heteroskedasticity and autocorrelation robust standard errors, since both the Durbin-Watson test and the Breusch-Pagan test reject the hypothesis of i.i.d. residuals for our models.

Since variance is a quadratic expression and we are performing least square regressions, i.e., minimizing the sum of squared residuals, our analysis is extremely sensitive to outliers. Therefore, we calculate the daily sample means and variances after removing the observations which deviate from the average price by more than three standard deviations for every year

	2007	2008	2009	2010	2011	2012	Total
Average price	35.85	64.83	38.93	44.51	51.50	42.51	46.37
Variance price	430.04	672.55	252.16	174.68	158.01	202.90	406.80
Average wind infeed	4.25	4.48	4.16	4.30	5.29	5.69	4.70
Variance wind infeed	13.06	13.79	11.60	12.55	18.65	18.89	15.10
Average PV infeed				0.96	2.27	3.18	1.07
Variance PV infeed				2.38	11.08	22.86	7.62
Average renewable infeed	4.25	4.48	4.16	5.26	7.56	8.87	5.77
Variance renewable infeed	13.06	13.79	11.60	13.69	25.98	36.57	22.40
Average demand	63.15	63.03	58.92	62.44	62.78	60.12	61.74
Variance demand	117.50	109.15	122.93	109.44	125.34	132.11	122.04
Average residual demand	58.90	58.55	54.75	57.18	55.22	51.26	55.97
Variance residual demand	113.14	103.24	119.03	103.55	112.98	127.36	120.04
# Outliers ⁺	114	80	56	35	17	66	368
# Outliers ⁻	0	5	28	46	89	25	193

Table 3.2: Descriptive statistics. Prices are reported in EUR/MWh while quantities are in GWh.

(see Ketterer (2012); Mugele et al. (2005) for a similar approach). Moreover, we remove days where we have less than 13 price observations left.

Table 3.2 displays the descriptive statistics of our sample. We first clean the hourly raw data by removing the outliers and then calculate the empirical mean and variance for each year separately as well as for the whole sample. Having a first glimpse on the raw data reveals several peculiarities: The yearly price variances of the years 2009 to 2012 are significantly lower than in the years 2007 and 2008, although the yearly average production of renewables increased drastically in the same time. The yearly empirical variance of the renewables has increased with the massive build-up of photovoltaics (2011 and 2012). Wind production obviously exhibits long-term variability, since e.g., average yearly production is lower in 2009 than in 2007 although installed capacity is significantly higher in 2009. We also note that the number of negative outliers peaks in 2011 while the number of positive outliers decreased between 2007 and 2011.

When studying the influence of IES on the variance of residual demand, the covariances between demand and renewable infeed obviously play an important role. In Figure 3.4, we depict the daily development of the variances of demand and renewables as well as their covariances. While the daily demand variance changes only slightly between the years (Panel a), the introduction of PV in 2010 has a significant impact on the intra-day variance of renewable infeed (Panel b). PV also affected the covariance between demand and renewables (Panel c), since this technology supplies the most power during the noon hours, a time of the day which usually coincides with high demand.

We first discuss the results from model 1, where we use the distribution of the residual demand to explain price variance. In particular, we are interested in the effects of shifts in the demand and in changes in the shape of the distribution. In the regressions, we capture the former by average daily demand and model the latter by daily variances of demand. To include the possibility of an inverse S-shaped supply function, we also include the squared average daily demand as a regressor. It turns out that both the AIC and the BIC favor the corresponding model over the model without the squared term.

The results of the regression are depicted in Table 3.3 in the column marked with (1). The

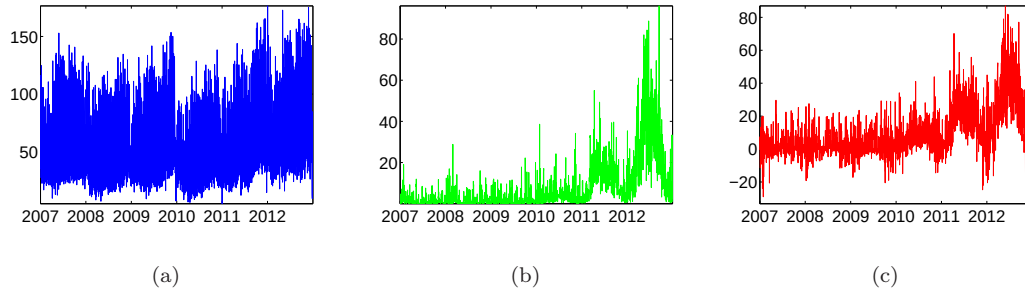


Figure 3.4: Panel (a): Variance of demand; Panel (b): Variance of renewable infeed; Panel (c): Covariance between demand and renewable infeed.

average residual demand has a convex quadratic influence on the price variance, which leads to higher variances for very low and very high levels of residual demand. This can be seen as an indication of an inverse S-shaped supply function. The variance of the residual demands has a strong positive influence on the variance of the prices. Both empirical findings support the theoretical considerations in Section 3.2, which state that changes in the price variance are driven by shifts into areas with different slope of the supply curve and by changes in the dispersion of the residual demand distribution.

To capture the influence of renewables on the variance, we estimate model 2, i.e., break up the residual demand and repeat the analysis. Motivated by the results about the quadratic relationship of the price variance on the average residual demand, we also include all the terms of the expansion

$$X^2 = (Q - I)^2 = Q^2 - 2QI + I^2, \quad (3.6)$$

i.e., the squared demand, the squared amount of intermittent production, and the interaction of the two. Following a similar logic, we split up the variance of the residual demand as

$$\text{Var}(X) = \text{Var}(Q - I) = \text{Var}(Q) - 2\text{Cov}(Q, I) + \text{Var}(I) \quad (3.7)$$

and include all the terms on the right hand side of the above equation as regressors.

Table 3.3, Column 2, shows the results of the regression for model 2. The coefficients of the covariance between demand and renewables and the interaction term of these two variables have the anticipated negative signs. Figure 3.5(a) illustrates how the predicted variance is influenced by the average amount of renewable production. The results suggest that a higher demand generally leads to a higher price variance than a lower demand, except if the low demand occurs in combination with high infeed from renewables. The co-occurrence of low demand and high infeed of renewables often result in extremely low prices and therefore higher price variance. This corresponds to the phenomenon of negative prices for electricity on the day-ahead spot market that are sometimes observed in the German market (see e.g., Fanone et al., 2013).

With regard to the variance of demand and renewables, the coefficients of model 2 show that the price variance increases with an increase in the variance of demand and renewables while the covariance between those has a negative effect. Figure 3.5(b) depicts these effects. The upper plane characterizes a situation with low covariance between demand and renewable infeed while the lower plane represents the situation with high covariance. The interpretation

	(1)	(2)	(3)
Intercept	1,013.20 (0.002)	314.79 (0.490)	214.97 (0.589)
Residual Demand Mean	-44.75 (0.000)		
(Residual Demand Mean) ²	0.47 (0.000)		
Demand Mean		-23.33 (0.110)	-23.45 (0.071)
(Demand Mean) ²		0.28 (0.034)	0.28 (0.017)
Renewables Mean		20.94 (0.122)	
(Renewables Mean) ²		1.31 (0.000)	
(Renewables Mean) * (Demand Mean)		-0.76 (0.004)	
Wind Mean			35.50 (0.008)
(Wind Mean) ²			0.68 (0.004)
Solar Mean			-47.10 (0.001)
(Solar Mean) ²			11.81 (0.000)
(Wind Mean) * (Demand Mean)			-0.86 (0.001)
(Solar Mean) * (Demand Mean)			-1.43 (0.013)
(Solar Mean) * (Wind Mean)			1.92 (0.058)
Residual Demand Var	1.84 (0.000)		
Demand Var		1.42 (0.000)	1.33 (0.000)
Renewables Var		1.29 (0.064)	3.41 (0.002)
Demand, Renewables Cov		-6.79 (0.000)	-3.87 (0.000)
Daylight Hours Mean	-0.06 (0.607)	0.05 (0.673)	0.07 (0.459)
Temperature Mean	3.42 (0.062)	3.32 (0.042)	3.38 (0.019)
Oil Price Mean	-1.13 (0.332)	-0.85 (0.367)	-0.05 (0.955)
Oil Price 3M Mean	2.32 (0.047)	3.21 (0.001)	3.66 (0.000)
Adjusted R^2	0.25	0.32	0.39
N	2,188	2,188	2,188

Table 3.3: Coefficients (p-values below) of the OLS regressions for the years 2007 to 2012 (heteroskedasticity and autocorrelation consistent estimation of the variance-covariance matrix).

of this effect is straightforward: an increased variance of demand and renewables leads to a higher price variance. However, this effect is less pronounced for a high covariance between these two variables than for a low covariance.

Finally, we discuss the results of model 3, where we split up the renewables into their composing elements, i.e., wind power and PV. However, due to the almost perfect correlation (0.95) between the variance and the mean of PV, we do not include both terms in the regression.

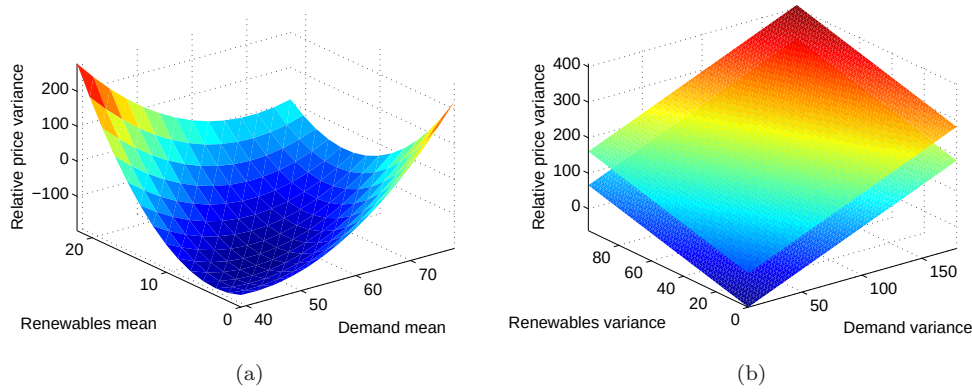


Figure 3.5: Panel (a): Marginal effects of average renewable infeed and demand (in GW) on relative price variance; Panel (b): Marginal effects of renewable infeed and demand variance on relative price variance.

The high correlation is caused by the peculiarity of PV, i.e., it supplies only during daylight hours and a higher variance is observed when more electricity from PV (higher average) is supplied. Thus, a full decomposition into the sample mean and variance of wind and PV is not possible. Instead, we only decompose the mean of the renewable production. We present the results in Table 3.3, Column 3. The marginal effects of the average wind and PV production on the relative price variance are depicted in Figure 3.6. Notice that the relative price variance is evaluated at the average demand of 62 GW (see Table 3.2). The coefficients of PV infeed and especially the high coefficient of the interaction effect between PV and demand is reflected in the sharp decrease of price variance when average intra-day PV infeed increases. Wind infeed also reduces the price variance, but not as drastically.

The coefficients of the variables which are not related to the residual demand are of similar magnitude in all three models: Price variance is increasing with average temperature, leading to higher price variance in summer than in winter. Since Germany and Austria are traditionally winter-peaking countries this seems counterintuitive at first glance. An explanation is that high PV production in summer coupled with lower demand pushes the residual demand in the concave area of the merit order resulting in a higher variance. As expected, the average three month lagged oil price which serves as a proxy for the gas price has a positive influence on the price variance. The coefficients of the average daylight minutes and the oil price are not significant. The explained variation in the data of all three regression is between 25 and 39 percent and therefore can be considered as reasonable.

As an additional exercise, we performed yearly regressions in order to identify anomalies between the different years. With one exception all relevant coefficients have the same sign as in the full sample. The results of these regressions are available on request.

3.4 Policy Implications

In this paper, we argue that the effect of IES infeed on the spot price variance depends crucially on the amount and the type of installed capacity. First, the higher the correlation of the infeed with stochastic demand the higher the variance dampening effect brought about by a decrease of the variance of residual demand. In this sense, the installation of PV capacities tends to

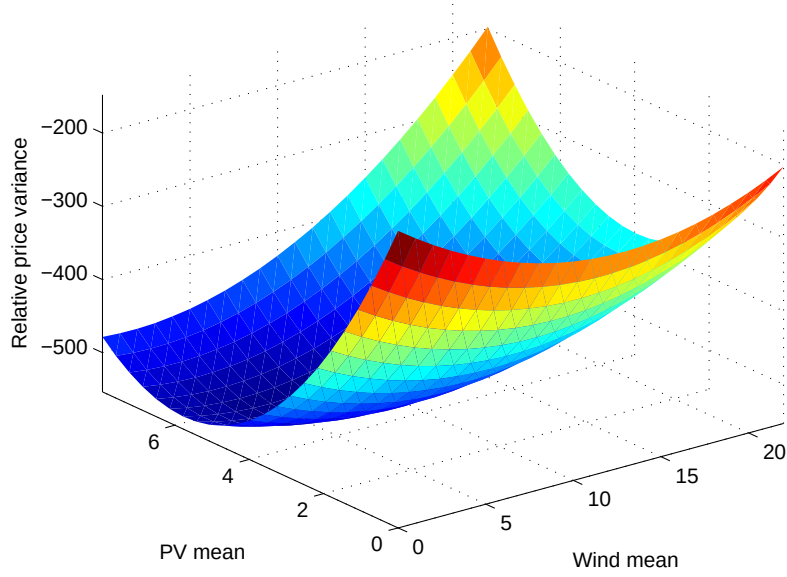


Figure 3.6: Marginal effects of average PV and wind infeed (in GW) on relative price variance evaluated at the average demand level of 62 GW.

decrease price variance more than the installation of wind turbines, since the infeed from the former has a pronounced positive correlation with demand, while the infeed from the latter shows no such clear correlation pattern. Political assessments of the desirability of wind power versus PV should take this aspect into account.

Second, according to our analysis in markets with inverse S-shaped supply functions the introduction of the first few GW of IES is likely to have a variance damping effect while a larger increase may lead to an increased price variances on the electricity exchanges, as the residual demand is pushed into the concave part of the merit order.

In fact, we can quantify this effect for the German market using the models estimated in Section 3.3. Given the estimated coefficients of model 2, we can find the daily demand and the renewable infeed that minimize the predicted variance in prices. Carrying out this exercise yields an *optimal* demand of 50 GW and an *optimal* renewables infeed of about 6.5 GW. Fixing the demand at its average of about 62 GW, the minimal variance can be reached at a level of renewable infeed of around 10 GW. Notice that these numbers are daily mean and variance levels, i.e., the daily price variance is minimized given a daily infeed of renewables and a fixed demand. Although these calculations give only a rough picture, it becomes clear that in the first years of our analysis, the IES infeed will have had a variance dampening effect on most days, while in the later years, with increased capacity and an large number of high infeed days, IES will have increased the variance on many days.

For policy makers this has wide ranging implications. Clearly, the structural changes in electricity markets, triggered by the build-up of intermittent renewable electricity production, require increased flexibility of production and consumption. This flexibility may either be provided by electricity storage plants, by a demand response via for example smart grids, or by flexible production technologies such as gas turbines (see Denholm and Hand, 2011).

Policies to promote renewable electricity production typically directly target the building

of corresponding production capacities, tacitly assuming that the demand for increased flexibility will result in market conditions that act as incentives to invest in demand side response technologies and storage facilities. However, all these solutions require substantial investments whose returns are mainly driven by price variance, i.e., if price variance goes down in the first phase of renewable expansion, then these projects become less profitable and correspondingly less capacities will be build or projects will be delayed.

Since construction of the corresponding infrastructure takes time, this in turn might result in a situation where the overall system is left with too little flexibility to handle increased IES infeed which may lead to network problems and, in the worst case, blackouts. Examples of near grid failures in Germany could be observed in the year 2011 (see Bundesnetzagentur, 2012).

In conclusion one can say that policies that subsidize the build-up of renewable intermittent capacities should also incentivize the expansion of storage capacity, some means of demand response, or transmission capacities to neighboring grid areas. A large scale demand response by consumers could for example be facilitated by a smart electricity grid in combinations with flexible pricing schemes for electric power, (see e.g., Strbac, 2008). Flexibility in the production and storage capacity can either be directly subsidized or ensured by capacity markets (see e.g., Crampton et al., 2013, for a discussion on the importance of capacity markets). The promotion of electric cars whose combined battery capacity can act as a storage device might be another option if combined with a smart grid (see e.g., Guille and Gross, 2009).

3.5 Conclusion

While the negative effect on average prices is beyond controversy in the literature, research on price variance is still rather scarce. In this paper we showed that the build-up of IES can increase as well as decrease electricity price variance. The latter effect is expected to occur for rather small amounts of IES capacity, while the former is expected, once a significant amount of IES capacity is installed. We argue this point theoretically using a simple market model and identify the slope of the supply function as well as the variance of the IES infeed as crucial factors affecting price variance. In Section 3.3, we test our theoretical considerations and quantify the opposing effects using data from the German spot market. As we argue in the last section, the findings in this paper have significant policy implications, since they show that market based incentives for investments in flexibility alone might not result in sufficient capacities to ensure network stability. Hence, policies that require producers to provide flexibility, the build-up of infrastructure such as a smart grid, or direct subsidies for flexible generation and storage facilities are called for.

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3.6 Appendix

The proof of Proposition 1 requires the following proposition:

Proposition 2. *Let X be a positive random variable which takes values on an interval $[a, b]$. Let $h : \mathbb{R}^+ \times \mathbb{R} \rightarrow \mathbb{R}$ be a function such that the following hold:*

1. $h(X, \cdot)$ is twice differentiable
2. $h(\cdot, \epsilon)$ is increasing $\forall \epsilon \in [a, b]$, and
3. $\frac{\partial}{\partial \epsilon} h(\cdot, \epsilon)$ is decreasing $\forall \epsilon \in [a, b]$.

Then for $\epsilon_1, \epsilon_2 \in [a, b]$ with $\epsilon_1 < \epsilon_2$ it holds true that $\text{Var}[h(X, \epsilon_2)] \leq \text{Var}[h(X, \epsilon_1)]$.

Proof. The proof is analogue to the proof of (See and Chen, 2008, Theorem 3.1). It suffices to show that $\text{Var}[h(X, \epsilon)]$ is a decreasing function of ϵ . We have

$$\begin{aligned} \frac{\partial}{\partial \epsilon} \text{Var}(h(X, \epsilon)) &= \frac{\partial}{\partial \epsilon} \mathbb{E}(h(X, \epsilon)^2) - \frac{\partial}{\partial \epsilon} (\mathbb{E}(h(X, \epsilon)))^2 \\ &= \mathbb{E} \left[\frac{\partial}{\partial \epsilon} h(X, \epsilon)^2 \right] - 2\mathbb{E}(h(X, \epsilon)) \frac{\partial}{\partial \epsilon} (\mathbb{E}(h(X, \epsilon))) \\ &= \mathbb{E} \left[2h(X, \epsilon) \frac{\partial}{\partial \epsilon} h(X, \epsilon) \right] - 2\mathbb{E}(h(X, \epsilon)) \left(\mathbb{E} \left(\frac{\partial}{\partial \epsilon} h(X, \epsilon) \right) \right) \\ &\leq 0. \end{aligned}$$

The last inequality follows from the fact that for a random variable X , and for continuous functions f, g on $\mathbb{R}$, $\mathbb{E}[f(X)g(X)] \leq \mathbb{E}[f(X)]\mathbb{E}[g(X)]$ if f is monotonically increasing and g is monotonically decreasing (see e.g., Gurland, 1967). The interchange of the differential operator and the expectation is clearly justified by the assumptions we have made. $\square$

Proof of Proposition 1. The proof is analogue to (See and Chen, 2008, Theorem 3.3). We sketch the important steps.

Define $h(u, \epsilon) = g(F_X^{-1}(u) + \epsilon[F_Y^{-1}(u) - F_X^{-1}(u)])$, with $\epsilon \in [0, 1]$. First, note that $h(\cdot, \epsilon)$ is an increasing function $\forall \epsilon \in [0, 1]$. Secondly, note that $\frac{\partial}{\partial \epsilon} h(\cdot, \epsilon)$ is an decreasing function since

$$\begin{aligned} \frac{\partial}{\partial u} \frac{\partial}{\partial \epsilon} h(\cdot, \epsilon) &= \frac{\partial}{\partial u} \{ [F_Y^{-1}(u) - F_X^{-1}(u)] g'(F_X^{-1}(u) + \epsilon[F_Y^{-1}(u) - F_X^{-1}(u)]) \} \\ &= [(F_Y^{-1})' - (F_X^{-1})'] g'(F_X^{-1}(u) + \epsilon[F_Y^{-1}(u) - F_X^{-1}(u)]) \\ &\quad + \epsilon(F_X^{-1})' [F_Y^{-1} - F_X^{-1}] g''(F_X^{-1}(u) + \epsilon[F_Y^{-1}(u) - F_X^{-1}(u)]) \\ &\quad + (1 - \epsilon)(F_X^{-1})' [F_Y^{-1} - F_X^{-1}] g''(F_X^{-1}(u) + \epsilon[F_Y^{-1}(u) - F_X^{-1}(u)]) \\ &\leq 0 \end{aligned}$$

For the last inequality note that the first term is negative due to condition (2) and g being increasing ($g' > 0$), while the second and third term are negative due to condition (1), convexity of g ($g'' > 0$) and properties of distribution functions, $(F_X^{-1})' \geq 0$ and $(F_Y^{-1})' \geq 0$.

Now one can apply Proposition 2 and finds

$$\text{Var}[g(Y)] = \text{Var}[h(u, 1)] \leq \text{Var}[h(u, 0)] = \text{Var}[g(X)].$$

$\square$

The following lemma links inequality (3.1) to the variance of the random variables.

Lemma 3. *If for two random variables X and Y*

$$F_Y^{-1}(\alpha) - F_X^{-1}(\alpha)$$

is monotonically decreasing, then $\text{Var}(Y) \leq \text{Var}(X)$.

Proof. Notice that for $\alpha > \alpha'$, we have

$$F_Y^{-1}(\alpha) - F_X^{-1}(\alpha) \leq F_Y^{-1}(\alpha') - F_X^{-1}(\alpha')$$

and therefore

$$F_Y^{-1}(\alpha) - F_Y^{-1}(\alpha') \leq F_X^{-1}(\alpha) - F_X^{-1}(\alpha'),$$

i.e., the inter-quantile range of Y is smaller than that of X for all quantiles α, α' .

Setting $\alpha_1 = F_X(\mathbb{E}(X))$ and $\alpha_2 = F_Y(\mathbb{E}(Y))$, yields

$$\begin{aligned} \text{Var}(X) &= \int_{-\infty}^{\infty} (x - \mathbb{E}(X))^2 f_X(x) dx = \int_0^1 (F_X^{-1}(\alpha) - F_X^{-1}(\alpha_1))^2 d\alpha \\ &\geq \int_0^1 (F_Y^{-1}(\alpha) - F_Y^{-1}(\alpha_1))^2 d\alpha \geq \int_0^1 (F_Y^{-1}(\alpha) - F_Y^{-1}(\alpha_2))^2 d\alpha \\ &= \text{Var}(Y), \end{aligned}$$

where the last inequality follows from

$$\mathbb{E}(Y) = F_Y^{-1}(\alpha_2) = \arg \min \{a : \mathbb{E}[(Y - a)^2]\}.$$

□

Chapter 4

Corporate Social Responsibility – A Strategic and Profitable Response to Entry? (accepted)

This paper investigates whether an incumbent has an incentive to introduce corporate social responsibility (CSR) activities only as a response to entry by a competitor, i.e., the incumbent would eschew CSR if left uncontested. We assume that the entrant cannot provide CSR at least at the outset for two reasons: (i) it would not be credible due to its lack of recognition and (ii) due to high fixed cost to pay e.g., for licensing. More precisely, this paper shows that monopolistic firms can have indeed the incentive to introduce CSR activities only as a response to entry. Therefore, increased competition can turn a firm “green,” providing a “win-win” for business as well as for the environment.

4.1 Introduction

Without doubt, *Corporate Social Responsibility* (CSR) is the most visible aspect of firms’ attempts to include ethical aspects in their decisions and is currently one of the hottest management issues. This topic is covered widely and extensively in many academic journal articles, in the public media in serious papers (e.g., several special issues in *The Economist*) as well as in tabloids, on TV, online blogs etc. Many consultants, among them most prominently Michael Porter, have been praising the profitability (“win-win”) of socially and in particular environmentally responsible behavior for quite a long time, e.g., already in Porter and Van Der Linde (1995).

A survey of the academic literature, which is huge and mostly empirical, is here eschewed. Bénabou and Tirole (2010) give an overview of the recent developments in the economics of prosocial behavior and link it to CSR. Kitzmüller and Shimshack (2012) explore why CSR exists. We review here only the few related papers that address strategic aspects, which gets short shrift in the CSR literature. Kopel (2009) is one of the few papers accounting for firms’ strategic interactions in the context of CSR (allowing for first mover advantages). Another

one is Lambertini and Tampieri (2011) that considers a static duopoly game where firms can choose between profit seeking or CSR and their emphasis is to characterize a mixed outcome (one profit seeking, the other CSR), which is stable for low impact of pollution and CSR sensitivity. Another way of exploiting CSR strategically is to use it as product differentiation device. Rodríguez-Ibeas (2006) sets up a model of standard vertical product differentiation where some consumers have preferences towards the environmental quality of a product. He then analyzes welfare and environmental effects when the population of environmental conscious consumers increase. Manasakis et al. (2007) also consider a duopoly market where each firm produces one brand of a differentiated good and consumers have identical preferences regarding the physical characteristics of the good but are heterogeneous in valuing the firms' CSR activities. They then analyze the incentives of firms' owners to hire social responsible managers. Becchetti et al. (2005) examine the case of a horizontal product differentiation model where consumers differ in their degree of social responsibility. To the best knowledge of the authors', the current literature on strategic CSR has not yet tackled CSR as a device for an incumbent to respond to entry.

This paper investigates how entry changes an incumbent's evaluation of CSR, i.e., whether an incumbent introduces CSR activities only as a response to an entering competitor. We assume that the entrant cannot provide CSR at least at the outset for two reasons: Firstly, CSR is typically associated with cleaner production, better treatment of workers, local sourcing, etc. In essence, these are all credence good attributes since a consumer is unable to verify them even after consumption. Therefore there is no rationale why consumers should believe CSR claims of a newcomer lacking consumer recognition; admittedly, the entry of a well known firm into a new market need not fit our scenario. Secondly, due to high fixed cost to pay e.g., for certifications from ISO 1400 or EU Eco-Management and Audit Scheme. Related (but different) is the idea in McWilliams and Siegel (2001) to link CSR to experience goods. The reason why these goods are more likely to be associated with CSR is that consumers view CSR activity as a signal about the attributes of the private good. Siegel and Vitaliano (2007) expand the connection by also including credence goods. They provide empirical evidence that firms offering experience or credence goods are more likely to engage in CSR activities than firms selling search goods. Also Heyes (2005) and Goyal (2006) suggests signaling as motive for CSR.

4.2 Model

Consumers have unit demand for a good at the value v that is known and normalized, $v = 1$. In addition, they exhibit unknown willingness to pay θ over and above v for a product produced by a firm with active and visible CSR contributions. The willingness to pay increment for CSR, θ , is the consumers' private information. However, the firm knows its distribution, i.e., the density f and cumulative distribution function F . For reasons of simplicity we assume a uniform distribution with support $[0, \bar{\theta}]$. CSR is a one and all feature, i.e., the firm can choose or leave it. Furthermore, CSR activities require fixed costs (φ) for set up (e.g., for certification fees and installing a reporting scheme) and the CSR produced good has higher unit costs $c > 0$, where the cost of traditional production are normalized to zero. Moreover, we assume the unit cost to be lower than the total maximum willingness to pay for the CSR version of the good, i.e., $c < 1 + \bar{\theta}$. A potential entrant produces the same good at higher costs than the incumbent, $v > k > 0$, but without the CSR option and engages in price competition.

4.2.1 Incumbent monopoly

The incumbent monopoly has two options: to use CSR or not. Assuming no CSR (identified by the superscript 0), the optimal policy is to charge the willingness to pay, i.e., $p^0 = v$, that induces the profit (using the normalization $v = 1$),

$$\pi^0 = v = 1. \quad (4.1)$$

Engaging in CSR implies for the monopoly's optimal price policy and implied profit,

$$\pi^s := \max_{p \geq v} \{(p - c)(1 - F(p - 1)) - \varphi\}. \quad (4.2)$$

For a price $p > v = 1$ only the types $\theta \geq p - v$ will buy, while the others abstain. Of course, charging below the above monopoly price, $p^0 = v$, yet to spend on CSR is clearly suboptimal. Therefore, the above maximization implies in the case of the uniform distribution and for an interior solution (not necessarily optimal and therefore the hat indicates that this solution is only a candidate since the firm can still eschew CSR and the superscript s refers to this socially responsible policy),

$$\hat{p}^s = \frac{1 + c + \bar{\theta}}{2}. \quad (4.3)$$

A first and necessary but not sufficient condition for profitable CSR is that $\hat{p}^s > 1$, because $\hat{p}^s < 1$ is clearly dominated by $p = v = 1$ and no CSR that saves costs. Assuming that the monopoly applies CSR, its profit is

$$\pi^s = \frac{(1 - c + \bar{\theta})^2}{4\bar{\theta}} - \varphi.$$

Therefore, accounting for all options, the optimal monopolistic profit (π^m) is given by, $\pi^m = \max\{\pi^0, \pi^s\}$ if supported by the correspondingly optimal strategy either to provide CSR or not. The uncontested monopoly will engage in CSR if and only if $\pi^s > \pi^0 = 1$.

Proposition 4. *The following conditions are sufficient that an incumbent monopoly eschews CSR even if that allows to raise the price, i.e., $\hat{p}^s > 1 \iff \bar{\theta} > 1 - c$ (otherwise CSR is suboptimal anyway), first for the cost parameter c ,*

$$c > c^m := 1 + \bar{\theta} - 2\sqrt{(1 + \varphi)\bar{\theta}}, \quad (4.4)$$

and then for the maximum willingness to pay for the CSR upgrade,

$$\bar{\theta} < \bar{\theta}^m := 1 + c + 2\varphi - 2\sqrt{(1 + \varphi)(c + \varphi)}. \quad (4.5)$$

Proof. See Appendix. □

Given these conditions it is very easy to find parameters where the monopoly's optimal action is to eschew CSR. Consider a simple example for the first condition about CSR costs assuming $\bar{\theta} = 1$ (i.e., the maximal willingness to pay for CSR is equal to the value of the standard product) and $\varphi = 0$, then any $c > 0$ meets the feasibility $\hat{p}^s > 1$ yet rules out CSR for an uncontested

monopoly (see Equation 4.4); similarly assume negligible costs for CSR, $c = \epsilon > 0, \varphi = 0$, then any $\bar{\theta} < 1 - \epsilon$ rules out monopolistic CSR but here because it would require to lower the price, $\hat{p}^s < 1$ (see Equation 4.3). In words, even assuming (i) that consumers are willing to pay up to twice the price for a CSR-good compared with the standard good and (ii) that the costs of CSR (fixed and variable) are negligible, CSR is unprofitable for an uncontested incumbent. Summarizing, a monopoly will introduce CSR only under very favorable conditions, i.e., for low costs and a (very) large willingness to pay. This can also be seen in Figure 4.1 which contains the feasible parameter space in terms of CSR cost c and maximum willingness to pay $\bar{\theta}$ for no fixed cost $\varphi = 0$. The dark gray area shows parameter combinations where CSR activities are profitable while the much larger light gray area defines parameter values where the uncontested monopoly does not engage in CSR.

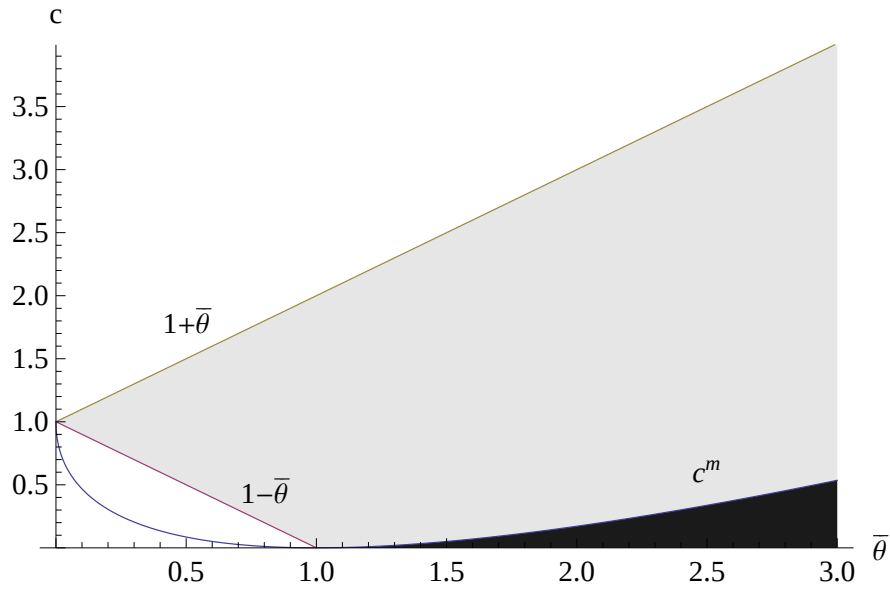


Figure 4.1: The light gray area in the $(\bar{\theta}, c)$ plane defines where CSR is unprofitable for the monopolist and the dark gray area where CSR is profitable ($\varphi = 0$)

4.2.2 Incumbent monopoly faces an entrant

Now given the incumbent monopoly's reluctance to engage in CSR – a reminder of Hicks' claim that a monopoly secures the best of all profits, a quiet life – how does that attitude change with an entrant? In this case, the incumbent, has the following options:

1. The incumbent sets its price infinitesimally below the cost of the entrant, i.e., $p = k$ and thereby deters entry by pricing.
2. The incumbent permits entry and still eschews CSR. Given Bertrand competition and the homogeneous good characteristic, the equilibrium price is infinitesimally above the cost of the entrant, i.e., $p = k$. This however, cannot be an equilibrium, because the incumbent has then to share the revenues which lowers its profit. Hence, the incumbent will strictly prefer the above option 1 of entry deterrence.
3. Entry deterrence via CSR. The incumbent offers its CSR-upgraded product coupled with a price p^i that leaves no residual demand for the entrant who charges only for his costs,

i.e., $F(p^i - k) = 0$. Given the full support of the distribution (i.e., a very small θ has positive probability, which holds of course for the assumed uniform distribution) entry deterrence requires $p^i = k$ (again infinitesimally above). That policy is again clearly dominated by standard entry deterrence as in point 1 by yielding the same revenue but saving all CSR expenditures.

4. The incumbent permits entry but introduces simultaneously CSR.

Since option 2 and 3 are dominated by option 1, we elaborate on the conditions under which option 4 dominates option 1.

The entrant, which cannot provide CSR chooses the price p^e and the incumbent p^i . Therefore, a type θ buys from the incumbent if and only if

$$v + \theta - p^i > v - p^e \geq 0 \implies \theta > p^i - p^e,$$

and for the given prices (p^i, p^e) , the demands are: for the entrant

$$x^e = \begin{cases} 0 & \text{if } p^i \leq p^e \vee p^e \geq v \\ F(p^i - p^e) & p^i > p^e \wedge p^e \leq v, \end{cases} \quad (4.6)$$

and the incumbent

$$x^i = 1 - F(p^i - p^e), \quad (4.7)$$

where $p^i \geq p^e + \bar{\theta}$ implies zero demand by the nature of the cumulative distribution function ($F = 1$).

An interior Nash equilibrium with the incumbent providing now the CSR-upgraded product and the entrant the brown no-frills product results from solving the two profit maximization problems simultaneously,

$$\max_{p^e \leq v} \{ (p^e - k) F(p^i - p^e) \}, \quad (4.8)$$

$$\max_{p^i} \{ (p^i - c) (1 - F(p^i - p^e)) - \varphi \}. \quad (4.9)$$

Focusing on interior outcomes with entry, the equilibrium prices are,

$$p^e = \frac{2k + c + \bar{\theta}}{3} \leq v, \quad (4.10)$$

$$p^i = \frac{2(c + \bar{\theta}) + k}{3}, \quad (4.11)$$

that imply for the monopoly's and entrant's profit,

$$\pi^e = \frac{(\bar{\theta} + c - k)^2}{9\bar{\theta}}, \quad (4.12)$$

$$\pi^i = \frac{(2\bar{\theta} + k - c)^2}{9\bar{\theta}} - \varphi. \quad (4.13)$$

Note, that in order to have positive demand left for the entrant and therefore to ensure an interior solution $p^e = \frac{2k + c + \bar{\theta}}{3} \leq 1 = v \iff c \leq 3 - \bar{\theta} - 2k$. Furthermore, $c < 2\bar{\theta} + k$, otherwise the per unit profit of the incumbent, $p^i - c$, would be negative (see Equation 4.11).

Therefore, the crucial conditions for CSR as response to entry is that CSR is only unprofitable in an uncontested monopoly, i.e.,

$$\pi^0 = 1 > \frac{(1 - c + \bar{\theta})^2}{4\bar{\theta}} - \varphi = \pi^s$$

but preferred to entry deterrence when facing an entrant,

$$\pi^i = \frac{(2\bar{\theta} + k - c)^2}{9\bar{\theta}} - \varphi > k = \pi^k.$$

Proposition 5. *Given the following conditions on costs,*

$$k + 2\bar{\theta} - 3\sqrt{(k + \varphi)\bar{\theta}} = \bar{c} > c > c^m, \quad (4.14)$$

or on maximum willingness to pay

$$\frac{4c + 5k + 9\varphi - 3\sqrt{(k + \varphi)(8c + k + 9\varphi)}}{8} < \bar{\theta} < \bar{\theta}^m, \quad (4.15)$$

CSR is only optimal as a response to entry and it is preferred (strictly) to entry deterrence.

Proof. See Appendix. □

Therefore intermediate costs for CSR as well as significant but not too high maximum willingness to pay for CSR render purely strategic use of CSR optimal. In Figure 4.2 we show the feasible parameter space in terms of CSR cost c and maximum willingness to pay $\bar{\theta}$ (gray areas) for no fixed cost, $\varphi = 0$, the entrant's cost $k = 0.1$, which determines also the outside option for the incumbent, i.e., the profit when deterring entry via pricing. According to Proposition 5, the light gray area displays the parameter combinations of $\bar{\theta}$ and c where CSR is a profitable answer to entry, while the gray area represents the space where entry deterrence via pricing is preferred. Parameters belonging to the dark gray area make CSR already in the monopoly case profitable.

Given the conditions in Proposition 5, it is very simple to construct examples and Figure 4.3 shows corresponding ones by varying the operating costs for CSR (c). The willingness to pay for the standard good is set to one by assumption which allows to relate this willingness to pay to the cost of CSR and the maximum willingness to pay for the CSR good relative to the willingness to pay of the normalized standard good. In this example we set the maximum willingness to pay for the CSR good equal to one, which implies a 100 % increase in maximum valuation of the CSR adjusted good compared to the standard good. Using this normalization, the CSR upgrade costs 10% (the fixed cost element φ) of the consumers' valuation of the standard good. The crucial point is the comparison of profits. Figure 4.3 shows that an incumbent monopoly will not engage in CSR, no matter how cheap its operating costs are ($\pi^0 > \pi^s$, and in this example not even for the case of no fixed costs). However, in case of entry in the industry, using CSR as a profitable response to entry dominates entry deterrence by limit pricing for even quite substantial CSR costs, up to $c < 0.76$ ($\pi^i > \pi^k = k$). The corresponding sales and prices can be seen in Figure 4.4 in the appendix.

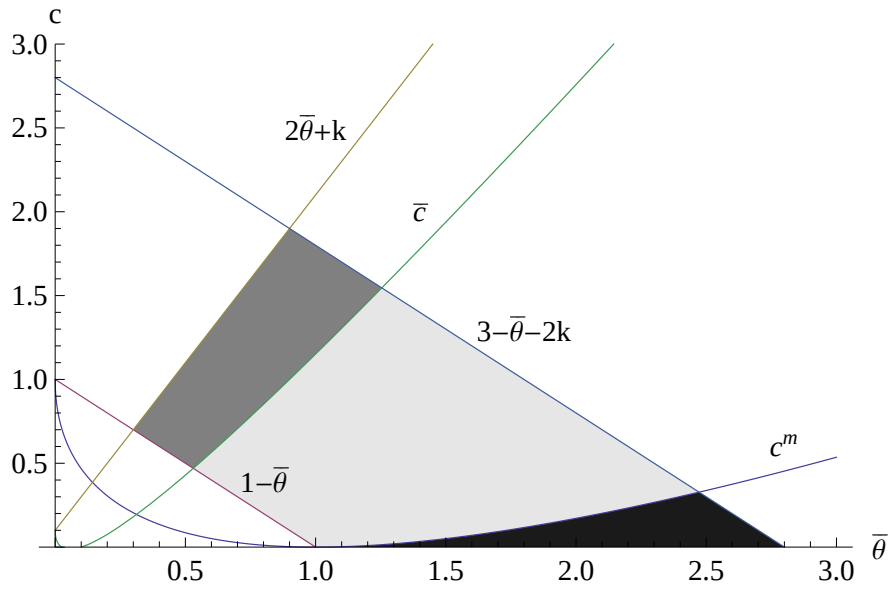


Figure 4.2: The light gray area in the $(\bar{\theta}, c)$ plane defines where CSR is a profitable answer to entry, the dark gray area where CSR is already profitable in the monopoly case, and the gray area where entry deterrence via pricing is the optimal strategy ($\varphi = 0, k = 0.1$)

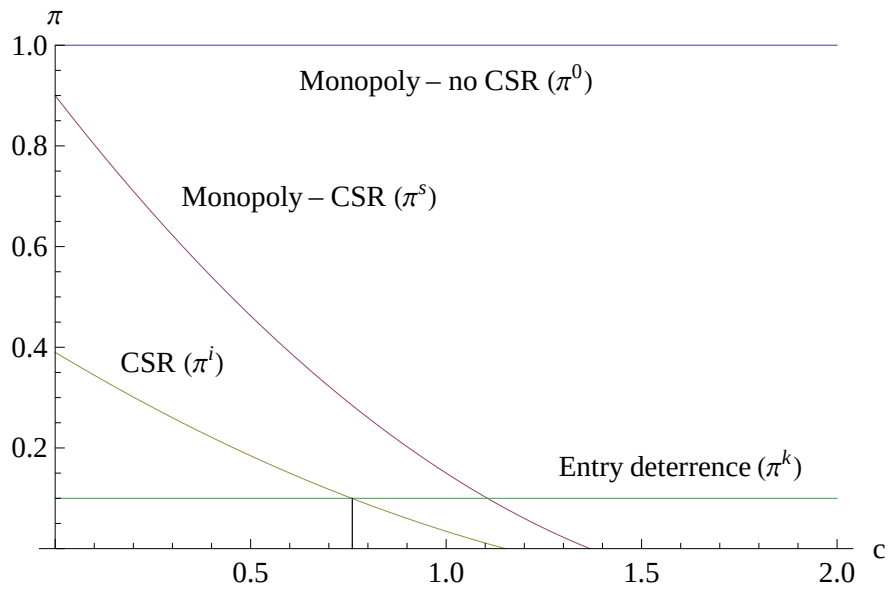


Figure 4.3: Incumbent's profit vs CSR costs ($k = 0.1, \varphi = 0.1, \bar{\theta} = 1$)

4.3 Conclusion and topics for future research

This paper has shown that entry can induce incumbents to use CSR only as strategic instrument. Therefore, the recent wave of CSR pursued primarily by incumbents can have less noble reasons than claimed (e.g., the ads of many oil companies, BP = “beyond petroleum,” and in particular, by Chevron with its claims “that oil companies should support the communities and small business”) by being a response to increased competition due to market liberalizations and globalization. However, it provides also another possibility of Porter’s claim of a “win-win” for business and environment. The difference is that it needs an increase in competition as a trigger.

Our analysis relies on the assumption that only the incumbent can provide CSR. This seems a plausible assumption in many cases, because of the credence good nature of CSR (on credence goods see the fine survey of Dulleck and Kerschbamer, 2006). The incumbent’s CSR-strategy is much more credible because of its strong incentive to stay in the market which is hard to belief for entrants. In particular, the entrant may be a ‘flight by night’ firm only skimming a profit opportunity. A recent paper, Hockerts and Wüstenhagen (2010), argues the opposite that often small “emerging Davids” initiate the diffusion of sustainable products that are only in a later stage copied by “greening Goliaths.” This alternative hypothesis is of particular interest for empirical testing. More precisely, this could be done by analyzing particular industries which have gone through a transition process induced by liberalization (e.g., the electricity industry). Our intuition is that the outcome depends on industries: Organic food may support the hypothesis of Hockerts and Wüstenhagen (2010) while most ‘big’ industries (oil, energy, automobiles) fall into the category we investigated in this paper. Of course, the assumption of a ‘monopoly’ is presumably a far-fetched description for most if not all non-competitive markets such that the actions of always existing fringe firms, the “Davids,” is ignored. Of course this suggests to investigate how far this analysis can be extended to oligopolistic markets, inside and outside, and may include also a competitive fringe. Oligopolistic CSR markets but without entry are treated in e.g., Lambertini and Tampieri (2011) and Wirl (2013) within a dynamic game. Studying the dynamics of CSR is another possible direction for extending our model (compare also Wirl et al., 2013).

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4.4 Appendix

4.4.1 Proof of Proposition 1

It suffices to show that the profit of the monopolist when engaging in CSR activities π^s is smaller than the profit eschewing CSR even if the monopolist could charge a price $\hat{p}^s > 1 \iff c > 1 - \bar{\theta}$. Calculating the threshold levels from

$$\pi^s = \frac{(1 - c + \bar{\theta})^2}{4\bar{\theta}} - \varphi = 1 = \pi^0,$$

for the critical cost parameter yields two roots

$$c_i^m = 1 + \bar{\theta} \pm 2\sqrt{(1 + \varphi)\bar{\theta}}.$$

Note that $c_1^m > 1 + \bar{\theta}$ and therefore this root is dominated by the necessary condition $c < 1 + \bar{\theta}$. It follows that the monopoly engages in CSR activities if $0 < c < c_2^m = c^m, \forall \bar{\theta}^m > 1 + 2\varphi + 2\sqrt{(1 + \varphi)\varphi}$, and eschews CSR activities if $1 + \bar{\theta} > c > \max \{1 - \bar{\theta}, c^m\}$.

Analogously, the condition for the maximum willingness to pay can be derived. $\square$

4.4.2 Proof of Proposition 2

It suffices to show that the profit of the incumbent when engaging in CSR activities π^i is larger than the profit of the incumbent deterring entry by limit pricing π^k . Furthermore, eschewing CSR in the uncontested monopoly is necessary, otherwise the introduction of CSR as a strategy would be obsolete anyway. Calculating the threshold levels from

$$\pi^i = \frac{(2\bar{\theta} - c + k)^2}{9\bar{\theta}} - \varphi = k = \pi^k,$$

for the critical cost parameter yields two roots

$$c_i = 2\bar{\theta} + k \pm 3\sqrt{\bar{\theta}(k + \varphi)}.$$

Note that $2\bar{\theta} + k < c_1, \forall k > 0$, therefore this root can be ignored. It follows that CSR is a profitable strategy to entry if $c^m < c < c_2 = \bar{c}$.

Analogously, the condition for the maximum willingness to pay can be derived. $\square$

4.4.3 Example

Figure 4.4 depicts the corresponding sales and prices from the example discussed in Section 4.2.2. In particular panel b, the one about prices shows that the entrant hits the upper price limit for very high costs, $c = 1.8$, of CSR thus $p^e = 1$ and $p^i = \hat{p}^s$ for $c > 1.8$, without covering all sales.

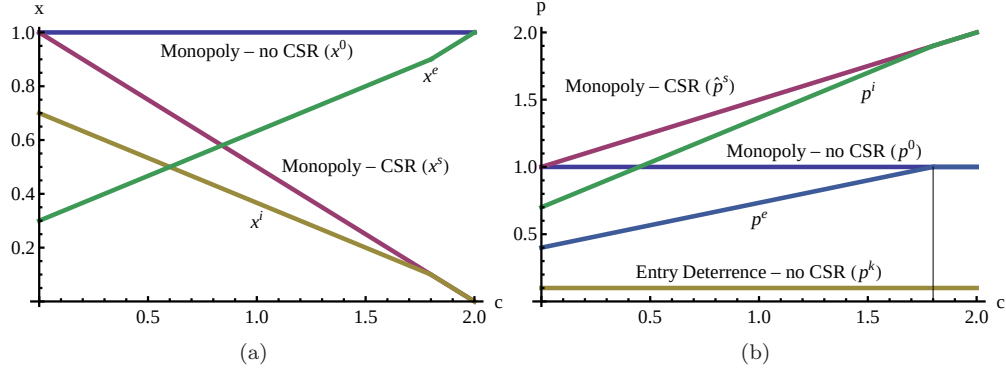


Figure 4.4: Strategies vs CSR costs ($k = 0.1, \varphi = 0.1, \bar{\theta} = 1$)

Chapter 5

The Effect of Information on the Quality of Decisions (accepted)

We study the effect of additional information on the quality of decisions. We define the extreme case of complete information about probabilities as our reference scenario. There, decision makers (DMs) can use expected utility theory to evaluate the best alternative. Starting from the worst case – where DMs have no information at all about probabilities – we find a method of constantly increasing the information by systematically limiting the ranges of the probabilities. In our simulation-based study, we measure the effects of the constant increase in information by using different forms of relative volumes. We define these as the relative volumes of the gradually narrowing areas which lead to the same (or a similar) decision as with the probability in the reference scenario. Thus, the relative volumes account for the quality of information. Combining the quantity and quality of information, we find decreasing returns to scale on information, or in other words, the costs of gathering additional information increase with the level of information. Moreover, we show that more available alternatives influence the decision process negatively. Finally, we analyze the quality of decisions in processes where more states of nature are considered. We find that this degree of complexity in the decision process also has a negative influence on the quality of decisions.

5.1 Introduction

In decision making under uncertainty, decision makers (DMs) are confronted with several alternatives with different outcomes in various states of nature. What they do not know are the precise probabilities of the states of nature. For example, DMs may know only the intervals, in which the true probabilities lie, or they might have information about the rank order of the true probabilities. In order to incorporate the aforementioned kinds of information, we consider the case in which the available information about the true probabilities is represented by linear inequalities. We define the area in the probability space, which consists only of probability-

vectors (p-vectors) fulfilling the inequalities, as an *information set*. Therefore, an information set represents the given level of information.

A vast amount of literature deals with the issue of incomplete information on probability distributions, or, conceptually equivalent, with incomplete information on attribute weights in multicriteria decision problems. Our work distinguishes itself from the existing literature in a crucial point. Instead of working with static incomplete information, we develop a method to systematically include additional information. Building on the work of Fishburn (1965), many studies concentrated on the DM's difficulties to find the best alternative in case of incomplete information. One of these static approaches is presented in Charnetski and Soland (1978), who opt to decide for the alternative maximizing a measure called *comparative hypervolume*. Essentially, we avail ourselves of the same measure, but use it under a dynamic setting. By the help of an exogenous mechanism, we analyze the outcomes of decisions when information about the probabilities becomes more precise. Thereby, we can examine the effect of additional information on the quality of decisions, i.e., does better information lead to better decisions? Do we need a disproportional increase in information in order to obtain an increase in decision quality at higher information levels? Moreover, we are interested in the impact of more complex decision processes on the quality of decisions. This can either be the case when DMs face more alternatives to choose from or when a decision under uncertainty consists of more potential outcomes.

The area of sensitivity analysis is based on the theory of uncertain probabilities in decision making. Its key objective is to study the sensitivity of an optimal decision subject to changes in the probabilities of the states of nature. Evans (1984) and Schneller and Sphicas (1985) determined the optimal alternative for a selected p-vector. On the basis of the selected vector, the authors analyzed the maximal distances one can travel in the probability space without a change in the optimal alternative. Furthermore, the authors built confidence spheres with maximal radius around the chosen p-vector. As opposed to the mentioned distance-based approach, the discussion of Starr's domain criteria (cf. Starr, 1962, 1966) in Schneller and Sphicas (1983) is a volume-based analysis. The volume-based approach specifies that in a decision under uncertainty, DMs should decide for the alternative whose area of optimality has the largest volume. The paper also describes how to incorporate beliefs about the probabilities in the form of linear inequalities in Starr's domain criteria.

In the related field of multicriteria decision analysis, weights that specify the DMs' trade-offs between the individual criteria are analyzed instead of probabilities. Dias and Clímaco developed a decision support tool dealing with incomplete information on attribute weights (Dias and Clímaco, 2000, 2005). Eiselt and Laporte (1992) extended Starr's domain criteria and applied it in the weight space of multicriteria decision problems. In-depth and additional research was undertaken in the field of multicriteria decision aid methods (c.f. Bana e Costa, 1986) and in the field of stochastic multicriteria acceptability analysis (c.f. Lahdelma et al., 1998; Lahdelma and Salminen, 2001; Lahdelma et al., 2003; Tervonen and Lahdelma, 2007).

Vetschera (2009) uses the volume of an area in weight space as a measure for the information of DMs in a negotiation process. Information refers to a DM's ability to assess the opponent's preferences, represented by constraints in the weight space. The approach described in Sarabando et al. (2012) resembles Vetschera (2009), but argues from a mediator's view. In a methodological setting similar to ours, Vetschera et al. (2010) studied the impact of the amount of case information on the results of a case-based multiple criteria sorting problem.

Studies working with specific areas in the probability or in the weight space usually choose between two approaches: The distance-based approach (e.g., Evans, 1984; Schneller and Sphicas, 1985) or the volume-based approach (e.g., Schneller and Sphicas, 1983). In our simulation, we make use of the latter in two senses. First, the measure of the given level of information is defined as the volume of the respective information set. Second, also the measure of the quality of decisions refers to the volume of a specific area in the probability space. Such an area is defined by the property that it consists only of $\mathbf{p}$ -vectors inducing the “right” decision. When a DM without knowledge of the precise probabilities ranks a number of alternatives in the same way as if he knew the precise probabilities, we call this a right decision. Later on, we relax this rule and allow also for similar rankings.

The remainder we organize as follows. Section 5.2 explains the concept in detail and deals with certain hypotheses. In Section 5.3, we introduce the measure for the quality of information, the method to systematically generate a sequence of information sets of increasing quality, and a measure for the quality of decisions. Section 5.4 describes the framework of the simulation and Section 5.5 states the results. Finally, we conclude the study and give an outlook onto future research.

5.2 Concept and hypotheses

5.2.1 Concept

Figure 5.1 illustrates the aforementioned method of increasing information. We always start on the left side, where we have no information about the precise probabilities, besides the usual assumptions¹. We call the respective information set *starting information set*. On the right side we have the situation of complete information about the precise probabilities. This case is equivalent to the situation of decision making under risk, where DMs can apply expected utility theory to decide for an alternative. The $\mathbf{p}$ -vector under complete information is our “reference” $\mathbf{p}$ -vector, denoted as *true $\mathbf{p}$ -vector* $\mathbf{p}^*$.

Beginning from the starting information set, we gradually improve the information sets, i.e., the DM is given more precise information about $\mathbf{p}^*$ in each step. This leads to a sequence of information sets. The stepwise improvement of information is implemented by gradually limiting the ranges for the probabilities. When looking at the respective information sets, this means that the information sets contract around $\mathbf{p}^*$.

In order to measure the implications of better quality of information, the sequence of information sets has to fulfill an important condition. The relative increase in quality of information from one information set to the next has to be constant for the whole sequence of information sets.

A smaller area of an information set is equivalent to more precise information about the ranges of probabilities. Therefore, we define the measure for the quality of information as the volume of the respective information set.

Our concept to measure the quality of decisions given a certain level of information can be described as follows. First, we have to specify what we mean by making a right decision: a DM makes the right decision given a certain level of information, when he ranks a number of alternatives in the same way as if he knew $\mathbf{p}^*$. This is the reason why we first have to determine

¹Probabilities are between zero and one and also sum up to one.

the expected utility ranking of alternatives induced by $\mathbf{p}^*$. The given level of information is represented by the respective information set. Therefore, we determine the area within an information set consisting only of p-vectors which lead to the same or a predefined ranking as $\mathbf{p}^*$. The quantitative measurement of the quality of decisions is then defined as the volume of the aforementioned area within an information set, divided by the volume of the respective information set. We call this measure the *relative volume* (rv). The rv can be interpreted as the probability to make the right decision with a given level of information.

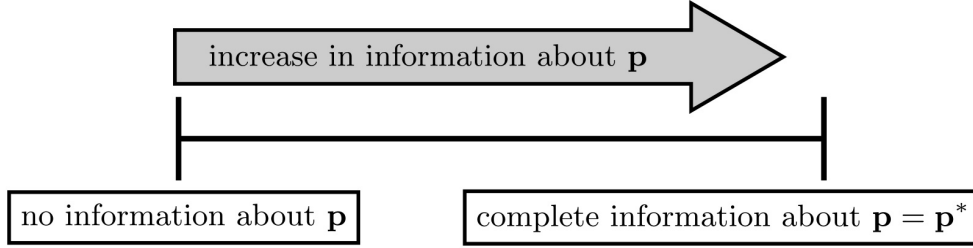


Figure 5.1: A dynamic approach of increasing information

5.2.2 Hypotheses

With the help of four hypotheses, we formulate the main research questions of this paper.

Since the information set's volume appears in the denominator of the rv, a smaller information set leads automatically to a higher rv – unless the nominator, the volume of the area of p-vectors inducing correct choices, does not decrease overproportionally. Our construction of the rv allows for such an overproportional decrease only in exceptional cases, and thus on average, the rv has to increase. Although this increase has its origin in our methodology, we state it as Hypothesis 1, since it serves as the basis for Hypothesis 2.

- **H1:** *The rv rises if the quality of information increases.*
In average, the quality of decisions increases if the information about $\mathbf{p}^*$ becomes more precise.
- **H2:** *There are decreasing returns to scale on information.*
With the improvement of information at a constant rate, we also expect the rv to increase, but at a decreasing rate. We argue that on a high level of information the marginal return of information will be smaller than on a lower information level.
- **H3:** *More alternatives induce lower rvs.*
We postulate that a setup with more alternatives leads to lower rvs. The argument for this is simply combinatorial, i.e., more alternatives lead to more ranking possibilities. Thus, the area in which all p-vectors lead to the same or predefined ranking as $\mathbf{p}^*$ becomes smaller.
- **H4:** *A higher number of states leads to lower rvs.*
In a more complex decision process, i.e., more states of nature, we conjecture lower rvs.

5.3 Method

In Section 5.3.1 we describe the method of generating a sequence of information sets, where the relative increase in information from one information set to the next is constant. The sequence of information sets represents the increasing quality of information. We make use of the sequences in Section 5.3.2, when we measure the influence of better information on the quality of decisions with the help of the rvs.

5.3.1 The iterative improvement of the information set

We consider decisions under risk where the outcome is uncertain and alternatives lead to different outcomes in different states of nature. In the following, we consider decision problems with a finite set of alternatives $A = \{A_1, \dots, A_N\}$ and a finite number of K states. Let p_k be the probability that state k occurs for $k = 1, \dots, K$, then $\mathbf{p} = (p_1, p_2, \dots, p_K)$ is the p-vector of all states. We assume that the utilities of the alternatives in different states are known, but we do not know the precise probabilities, p_k .

The information about the probabilities is given in the form of linear inequalities. These inequalities define the information set P of possible p-vectors $\mathbf{p}$. If no other information about probabilities is available, P is at least characterized by the conditions that $\sum_{k=1}^K p_k = 1$ and $p_k \geq 0, \forall k$. We call this *information set* starting information set and label it as P_0 . Moreover, let $\mathbf{p}^*$ denote the true p-vector. Throughout the paper, $\mathbf{p}^*$ is not known to the DMs. However, we generate values for $\mathbf{p}^*$ so that we have a reference for measuring the improvement of an information set.

The currently available information of a DM is represented through an information set. We start with no available information, i.e., in the information set P_0 . Starting from P_0 , our method iteratively generates the information sets $P_j, j > 0$. Depending on the number of states K , P_0 corresponds to the standard- $(K-1)$ -simplex lying in the affine hyperplane defined by $\{(p_1, \dots, p_K) \in \mathbb{R}^K \mid \sum_{k=1}^K p_k = 1\}$. P_0 also corresponds to the convex hull of its vertices $\{v_1, v_2, \dots, v_K\}$, where $v_1 = (1, 0, \dots, 0, 0), v_2 = (0, 1, \dots, 0, 0), \dots, v_K = (0, 0, \dots, 0, 1)$.

Improving the quality of an information set is equivalent to finding linear inequalities, which cut away regions not containing the true p-vector $\mathbf{p}^*$. By iteratively adding new inequalities, we obtain a sequence of improving information sets, $\langle P_j \rangle_{j \geq 0}$. Thus, we know that P_{j+1} is always a part of P_j .

We measure the quality of an information set by its *volume* $V(P_j)$. Consequently, the sequence of volumes of improving information sets, $\langle V(P_j) \rangle_{j \geq 0}$, has to be decreasing, i.e., $V(P_{j+1}) \leq V(P_j)$.

Working towards hypotheses **H1** and **H2**, we develop an algorithm which generates – depending on P_j – in each iteration an information set P_{j+1} , so that the ratio of $V(P_{j+1})$ and $V(P_j)$ equals a constant rate for all $j \geq 0$. An important property of this method is that as j tends to infinity, the resulting information set P_∞ contains only the true parameter $\mathbf{p}^*$.

We use two different, but similar, algorithms which fulfill the above described properties – the *barycentric subdivision* (cf. Munkres, 1984) and a similar method defined by us, which we call the *alternative barycentric subdivision*. For both subdivisions, the steps to generate P_{j+1} out of P_j are the same for all j . Hence, we use P_1 and P_0 in illustrating the algorithms in order to simplify the notation. Let V_K equal the set of vertices $\{v_1, \dots, v_K\}$ of P_0 as defined before and let $\mathcal{P}(V_K)$ be the powerset of V_K without the empty set. Further, we define the *barycenter*

B of a set of vertices $\{v_1, \dots, v_m\}$ with $1 \leq m \leq K$ as

$$B(\{v_1, \dots, v_m\}) = \frac{1}{m} \sum_{i=1}^m v_i.$$

The *barycentric subdivision* (bsd) of P_0 is a function defined on the set of vertices V_K , whose output is a set of $K!$ sets of vectors. The vectors of each set correspond to the vertices of a subpart of P_0 , all subparts have the same volume, and the union of these subparts is P_0 . To give a formal definition of the bsd, we first have to order the powerset $\mathcal{P}(V_K)$ by inclusion. Second, we have to find the $K!$ maximal chains $C_i = \{c_{i1}, \dots, c_{iK}\}$, in the partial order of $\mathcal{P}(V_K)$. Third, we apply the barycenter function $\mathcal{B}(\cdot)$, defined as $\mathcal{B}(C_i) = \{B(c_{i1}), \dots, B(c_{iK})\}$, to each maximal chain C_i . Then, the bsd is defined as the following set,

$$\text{bsd}(V_K) = \{\mathcal{B}(C_i), i = 1, \dots, K!\},$$

(cf. Munkres, 1984). The subpart containing the true p-vector $\mathbf{p}^*$ becomes P_1 .

By iteratively applying this procedure, we yield a sequence of information sets $\langle P_j \rangle_{j \geq 0}$ which fulfills that

$$V(P_{j+1}) = \frac{1}{K!} V(P_j). \quad (5.1)$$

The barycentric subdivision has the disadvantage that the volumes of the subparts become very small, even when working only with a small number of states K .

The *alternative barycentric subdivision* (a-bsd) of P_0 yields K subparts of equal volume. Let $B(V_K)$ be the barycenter of P_0 and let W_K^h be the set of vertices V_K without the h^{th} vertex v_h , $1 \leq h \leq K$. Then, the a-bsd is defined as

$$\text{a-bsd}(V_K) = \{\{W_K^h\} \cup \{B(V_K)\}, \quad h = 1, \dots, K\}.$$

Each of these sets corresponds to the vertices of a subpart of P_0 , the union of these subparts yields again P_0 . As before, we declare the subpart which contains the true p-vector $\mathbf{p}^*$ as information set P_1 .

The iterative application of the a-bsd yields a sequence of information sets $\langle P_j \rangle_{j \geq 0}$ which fulfills that

$$V(P_{j+1}) = \frac{1}{K} V(P_j). \quad (5.2)$$

The a-bsd results in a sequence of information sets that does not contract as regularly as the ones of the bsd. This follows from the property that a-bsd, in contrast to bsd, does not necessarily shrink the largest edge of an information set in each iteration step. For our purposes, however, the a-bsd is more appropriate since the volumes decrease also for a larger number of states only by the factor K^{-1} . The a-bsd implies a further advantage over the bsd when it comes to implementing the idea of information sets. In order to find the vertices of the next information set, the only necessary calculation using a-bsd is the determination of the barycenter of the current vertices. Whereas in case of the bsd, the calculation of the vertices of the next information set entails the systematical intersection of (hyper-)planes, which becomes very cumbersome in higher dimensions. Figure 5.2 shows the difference between the bsd and the a-bsd of P_0 for the case that $K = 3$.

Figure 5.3 shows the sequence of information sets $\langle P_j \rangle_{j=0, \dots, 4}$ depending on a fixed $\mathbf{p}^*$ (shown

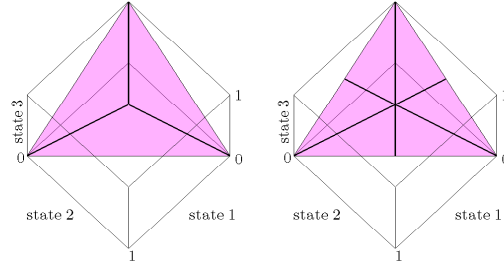


Figure 5.2: Alternative barycentric subdivision (left) versus barycentric subdivision (right) for $K = 3$

as the black point) for $K = 3$ in case of the a-bsd.

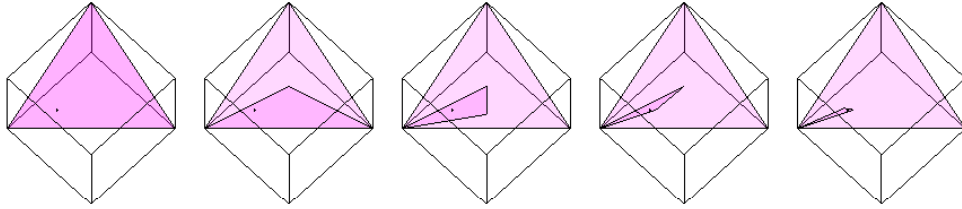


Figure 5.3: A sequence of information sets in case of the alternative barycentric subdivision

5.3.2 The (averaged) relative volume

We can now develop a measure for the quality of decision depending on the quality of information. We take the same true $\mathbf{p}^*$, which was used to generate a sequence of information sets $\langle P_j \rangle_{j \geq 0}$. We generate a utility matrix for a set of N alternatives and K states of nature. For each alternative A_i , $i = 1, \dots, N$, $\mathbf{p}^*$ is used to calculate the expected utility value, $\mathbb{E}_{\mathbf{p}^*}[A_i]$. Arranging the expected utilities $\mathbb{E}_{\mathbf{p}^*}[A_i]$ according to their value gives the “true” ranking of the alternatives.

So as to compare the actual ranking with the true ranking we distinguish between two methods. First, we consider only $\mathbf{p}$ -vectors in an information set which lead to exactly the same ranking as induced by $\mathbf{p}^*$. Second, we suggest a weaker matching of rankings. We pay attention only to the top-ranked alternatives induced by $\mathbf{p}^*$. In particular, we want an identical ranking for these top-level alternatives, while the remaining alternatives might be ranked differently. We call the thereby resulting measures rv^{exact} and $rv^{\text{top}T}$, where T specifies the number of alternatives in the top-level. We will discuss the exact definitions of the measures below.

We denote by M_j either an area which consists only of $\mathbf{p}$ -vectors inducing the same ranking as $\mathbf{p}^*$ or an area consisting only of $\mathbf{p}$ -vectors which lead at the top-level to the same ranking of the alternatives as $\mathbf{p}^*$ does. The rv of M_j is given by

$$rv(M_j) = \frac{V(M_j)}{V(P_j)}, \quad (5.3)$$

and can thus be interpreted as the probability of making the right decision. The rv depends on the specific position of $\mathbf{p}^*$ and on the specific values of the generated utility matrix. That

is why we perform several runs with a different $\mathbf{p}^*$ and a different utility matrix in each run, and average over the rv of each run, so as to wipe out this effect.

Making use of Equation 5.1 in case of the bsd and Equation 5.2 in case of the a-bsd, we know the volume $V(P_j)$ of the j -th information set.

As described above, we work with two different methods to compare the induced rankings of alternatives. The procedure to calculate the volume of M_j , described below, is similar with both methods. The difference, arising in the top-ranked matching method, is that only the first T alternatives in the ranking are considered.

The area M_j is defined by several inequalities. First, the K inequalities defining the information set P_j are also valid for M_j . Second, the requirement that all the p-vectors in M_j have to induce the same ranking as $\mathbf{p}^*$, can also be expressed with the help of inequalities.

We first address the case of the exact matching. Let A'_i be the alternative on the i^{th} place in the ranking induced by $\mathbf{p}^*$, $i = 1, \dots, N$. More formal, this means that $\mathbb{E}_{\mathbf{p}^*}[A'_1] \geq \mathbb{E}_{\mathbf{p}^*}[A'_2] \geq \dots \geq \mathbb{E}_{\mathbf{p}^*}[A'_N]$. Then, $a'_{i,k}$ is the value of the alternative ranked on the i^{th} place, in state k , $k = 1, \dots, K$. Thus, all p-vectors element of M_j fulfill

$$\sum_{k=1}^K a'_{i,k} p_k \geq \sum_{k=1}^K a'_{i+1,k} p_k, \quad \forall i = 1, \dots, N-1.$$

Plugging in $1 - \sum_{k=1}^{K-1} p_k$ for p_K and rearranging the inequalities, gives for all $i = 1, \dots, N-1$

$$\sum_{k=1}^{K-1} (a'_{i,k} - a'_{i+1,k} - a'_{i,K} + a'_{i+1,K}) p_k \geq a'_{i+1,K} - a'_{i,K}.$$

Together with the inequalities $p_k \geq 0, \forall k = 1, \dots, K-1$, we obtain a system of $(K) + (N-1) + (K-1) = N + 2K - 2$ inequalities defining the area M_j within P_j in dimension $K-1$.

In case of the top-level matching, only the first T alternatives in the ranking have to be equal to the true ranking. The ranking of the alternatives on rank $T+1, \dots, N$ need not be equal to the true ranking. Formally, this translates to the inequalities $\mathbb{E}_{\mathbf{p}^*}[A'_1] \geq \mathbb{E}_{\mathbf{p}^*}[A'_2] \geq \dots \geq \mathbb{E}_{\mathbf{p}^*}[A'_T]$. Moreover, an implied requirement is that $\mathbb{E}_{\mathbf{p}^*}[A'_{T+i}] \leq \mathbb{E}_{\mathbf{p}^*}[A'_T]$, $i = 1, \dots, N-T$, which ensures that the expected values of the alternatives on ranks $T+1, \dots, N$ are actually smaller than the ones of the top-ranked.

5.4 Simulation

In this section we examine our hypotheses defined in Section 5.2.2 using simulation-based methods. To calculate the volume of M_j from the inequalities we used the Matlab-package *multi-parametric toolbox (mpt)*, by Kvasnica et al. (2004). We summarize the framework of the simulation in Figure 5.4 and subsequently explain the simulation in more detail.

5.4.1 One simulation run

We describe each step of a simulation run in the following.

1. Generate a utility matrix for a set of N alternatives and K states of nature. The entries

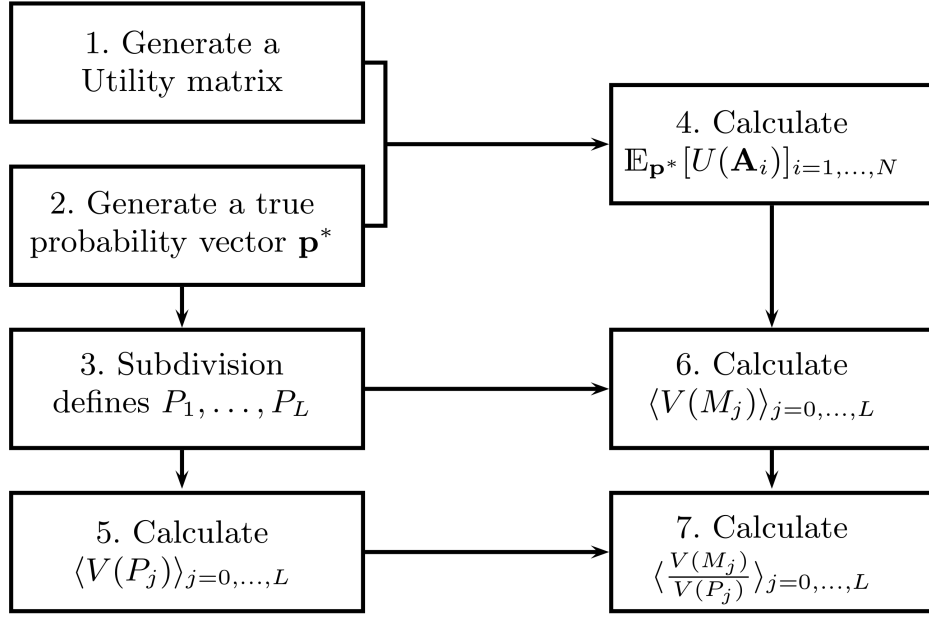


Figure 5.4: The simulation framework

of the utility matrix are randomly drawn and uniformly distributed on $[0, 1]$.

2. Generate a fixed true p-vector $\mathbf{p}^*$. We use the method developed by Rubinstein (1982) to ensure that $\mathbf{p}^*$ is randomly drawn and uniformly distributed on the simplex. There, an exponentially distributed p-vector with rate one is generated and then standardized to sum up to one.
3. Use an appropriate way of subdividing an information set, i.e., bsd or a-bsd. Depending on the true p-vector $\mathbf{p}^*$, generate, using one of these methods, the sequence of information sets $\langle P_j \rangle_{j=0,\dots,L}$, where L is an arbitrarily chosen parameter.
4. Calculate the expected utility of each alternative using the true p-vector $\mathbf{p}^*$. Rank the expected utilities of alternatives induced by $\mathbf{p}^*$.
5. Calculate the volumes of each information set P_j , $j = 0, \dots, L$ (independent of $\mathbf{p}^*$).
6. Calculate the volumes of each area M_j , within P_j , which consists only of p-vectors leading to the same (top-) ranking as $\mathbf{p}^*$.
7. Calculate the sequence of rvs $\langle V(M_j)/V(P_j) \rangle_{j=0,\dots,L}$.

Performing the simulation run several times, R , and averaging over each rv results in a sequence of *averaged relative volumes* (arv) $\langle \sum_{r=1}^R rv_r(M_j)/R \rangle_{j=0,\dots,L}$.

5.4.2 Parameter settings

Table 5.1 summarizes the parameter settings. The maximum number of six states and five information sets is given by limitations of the simulation engine. More precisely, in the case of $K > 6$ or $L > 5$, the angle between the bounding hyperplanes of an information set can

become so small that the volume of the information set is almost zero and cannot be computed anymore by *mpt*. The number of alternatives (N) we use in our simulation ranges from three to nine, with six alternatives in the standard case. This choice is justified by the following arguments. In case of very few alternatives, the probability is high that alternatives are ranked in the “true” order by chance and not due to the given information. On the other hand, if the number of alternatives is very large, it becomes very unlikely to obtain an exact matching, even with good information at hand. Thus, our chosen numbers of alternatives represent a balance between a low and a high number of alternatives.

In order to remove the effect of the generated $\mathbf{p}^*$ and the generated utility matrix, we repeat the simulation run described above 10,000 times with different utility matrices and different true $\mathbf{p}$ -vectors in each run. To test whether the repetitions were sufficient and to ensure thereby that our results are robust, we run the whole procedure again. No statistically significant differences were found between these runs. Thus, we conclude to have stable results.

Parameters	Standard	Other values
# of states (K)	3/4/5/6	–
# of alternatives (N)	6	3/9
# of information sets (L) (incl. P_0)	5	–
# of examined top-ranked alternatives (T)	3 (for $N = 6$)	–
Mode of subdivision	a-bsd	bsd (for $K = 3$)

Table 5.1: Summary of the simulation parameters

5.5 Results

Figure 5.5 shows the results for $K = 3$ and all other parameters chosen according to the standard parameter settings listed in Table 5.1. Note that on the x-axis we plot the increase of information compared to the information set P_0 . In the case of a-bsd as mode of subdivision this yields a stepwise improvement by the factor $V(P_j)(V(P_{j+1}))^{-1} = K$. Using a logarithmic scale to base K on the x-axis, gives the number j of the corresponding information set, $j = 0, \dots, 4$.

Table 5.2 shows the results of the $\text{arv}^{\text{exact}}$ and the arv^{top3} for the standard parameter settings. In the following we discuss the attributes of the rvs referring to our four hypotheses.

K	3	4	5	6	3	4	5	6
	$\text{arv}^{\text{exact}}$				arv^{top3}			
P_0	0.1039	0.0617	0.0449	0.0349	0.1875	0.1344	0.1115	0.0936
P_1	0.1985	0.1118	0.0752	0.0547	0.3117	0.2092	0.1611	0.1287
P_2	0.3117	0.1786	0.1160	0.0815	0.4405	0.2952	0.2217	0.1708
P_3	0.4310	0.2588	0.1682	0.1150	0.5562	0.3868	0.2872	0.2185
P_4	0.5416	0.3425	0.2280	0.1554	0.6572	0.4763	0.3550	0.2708

Table 5.2: Values for $\text{arv}^{\text{exact}}$ and arv^{top3} , standard parameter setting

We also analyzed the rvs using the bsd as mode of subdivision. However, a direct comparison of the results using a-bsd and bsd as mode of subdivision is not possible. In case of the bsd, the quality of information increases by the factor $(K!)^j$, compared to an increase by K^j in case

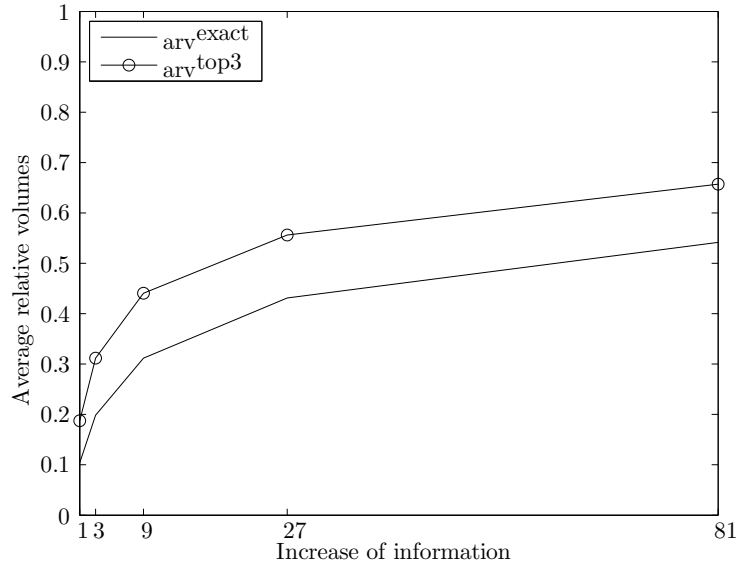


Figure 5.5: Comparison of $\text{arv}^{\text{exact}}$ and arv^{top3} for $K = 3$, all other parameters chosen according to the standard setting

of the a-bsd. Hence, we cannot test whether one mode of subdivision increases the quality of decisions faster than the other.

5.5.1 Hypothesis H1

Hypothesis **H1** postulates an increase of the rvs in additional information. Table 5.2 shows that the $\text{arv}^{\text{exact}}$ and arv^{top3} increase with the number of information sets. In Figure 5.5, we see for $K = 3$ that an increase in information lets the arvs rise. In order to test hypothesis **H1** we calculate the slopes of our piecewise linear functions and test whether the slopes are greater than zero or not. In particular, we perform one-sided t-tests. The null hypothesis states that the slopes are a random sample from a normal distribution with mean below or equal zero and unknown variance, whereas the alternative hypothesis states that the mean is larger than zero. Table 5.3 shows highly significant results, meaning that the null hypothesis can be rejected and therefore that the rvs increase with better information using the standard parameter setting. Hence, we confirm this hypothesis.

5.5.2 Hypothesis H2

Hypothesis **H2** concerns the curvature of rv^{exact} and rv^{top3} . Taking into account the improvement of information we expect the indices to increase at diminishing rates (Figure 5.5 shows this for the average values). To test the curves' shapes we compute first differences of the slopes of the piecewise linear functions. Moreover, we test whether the first differences are on average greater or equal than zero against the alternative hypothesis that they are smaller than zero. The results are stated in Table 5.4. In all cases we can reject the null hypothesis. This means rv^{exact} and rv^{top3} have decreasing slopes. Therefore, hypothesis **H2**, which states that there are decreasing returns to scale on information, is confirmed.

K		3	4	5	6	3	4	5	6
s_1		rv^{exact}				rv^{top3}			
	Mean	0.0473	0.0167	0.0076	0.0040	0.0621	0.0250	0.0124	0.0070
	t	93.5212	75.0463	65.1739	56.1527	90.227	83.9358	61.7798	54.3238
s_2	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Mean	0.0189	0.0056	0.0020	0.0009	0.0215	0.0072	0.0030	0.0014
	t	84.3525	70.4481	61.9935	55.4899	78.0223	66.6864	61.1373	54.1039
s_3	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Mean	0.0066	0.0017	0.0005	0.0002	0.0064	0.0019	0.0007	0.0003
	t	75.9681	66.6315	59.2062	53.3669	65.2112	62.2338	55.9185	51.1556
s_4	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Mean	0.0020	0.0004	0.0001	0.0000	0.0019	0.0005	0.0001	0.0000
	t	63.2037	61.9142	56.2533	51.5506	56.4932	56.5767	51.8509	48.9099
	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

$s_p, \forall p = 1, \dots, 4$: Slope of the rv between the steps of information

Table 5.3: One-sided t-tests of the slopes, standard parameter setting

K		3	4	5	6	3	4	5	6
$s_2 - s_1$		rv^{exact}				rv^{top3}			
	Mean	-0.0284	-0.0111	-0.0055	-0.0031	-0.0407	-0.0178	-0.0094	-0.0056
	t	-53.1449	-49.5250	-48.2661	-44.0482	-53.4511	-50.0147	-45.9517	-43.0954
$s_3 - s_2$	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Mean	-0.0122	-0.0039	-0.0015	-0.0007	-0.0150	-0.0053	-0.0024	-0.0011
	t	-49.8279	-47.4183	-45.8938	-44.1966	-49.1579	-46.2319	-46.4913	-43.2306
$s_4 - s_3$	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Mean	-0.0046	-0.0012	-0.0004	-0.0001	-0.0046	-0.0014	-0.0005	-0.0002
	t	-47.0844	-46.8965	-44.3933	-42.5289	-41.7030	-44.1477	-42.9052	-41.1170
	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

$s_p, \forall p = 1, \dots, 4$: Slope of the rv between the steps of information

Table 5.4: One-sided t-tests of the first differences of the slopes, standard parameter setting

5.5.3 Hypothesis H3

Table 5.5 shows the values of the arv^{exact} , running the simulation with different amounts of alternatives. We only concentrate on the rv^{exact} since the rv^{top3} is meaningless for the case $N = 3$. In order to show that the rv^{exact} decreases when we consider more available alternatives, we perform one-sided t-tests. In particular, we compare the rv^{exact} using 3 (6) alternatives versus 6 (9) alternatives. The results displayed in Table 5.6 are highly significant, meaning that the null hypothesis (the rv^{exact} using 3 (6) alternatives is lower or equal than the averages using 6 (9) alternatives) can be rejected. Hence, we also confirm hypothesis **H3**.

K	3	4	5	6	3	4	5	6
	$arv^{\text{exact}}(N = 3)$				$arv^{\text{exact}}(N = 9)$			
P_0	0.4929	0.4521	0.4208	0.4014	0.0255	0.0095	0.0045	0.0027
P_1	0.6247	0.5442	0.4954	0.4569	0.0611	0.0232	0.0104	0.0058
P_2	0.7267	0.6251	0.5609	0.5110	0.1206	0.0483	0.0217	0.0115
P_3	0.8029	0.6965	0.6235	0.5624	0.2042	0.0880	0.0398	0.0210
P_4	0.8542	0.7554	0.6766	0.6105	0.3027	0.1403	0.0670	0.0354

Table 5.5: Results of arv^{exact} for $N = 3$, and $N = 9$, all other parameters chosen according to the standard setting

K		3	4	5	6	3	4	5	6
		$\text{rv}^{\text{exact}}(N=3) - \text{rv}^{\text{exact}}(N=6)$				$\text{rv}^{\text{exact}}(N=6) - \text{rv}^{\text{exact}}(N=9)$			
P_0	Mean	0.3890	0.3904	0.3759	0.3665	0.0784	0.0522	0.0404	0.0322
	t	139.9196	152.1096	154.1671	158.1796	81.0498	81.9203	80.0287	80.2076
	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P_1	Mean	0.4262	0.4324	0.4202	0.4022	0.1374	0.0885	0.0648	0.0489
	t	129.9675	145.7406	151.4024	153.3706	78.7104	79.9712	79.9128	77.5489
	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P_2	Mean	0.4151	0.4466	0.4449	0.4295	0.1911	0.1303	0.0943	0.0700
	t	115.0061	135.7107	145.5064	150.3952	75.1169	77.449	78.8527	76.8143
	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P_3	Mean	0.3718	0.4377	0.4553	0.4474	0.2268	0.1708	0.1284	0.0940
	t	98.5106	122.3489	137.7429	145.8184	70.2775	73.4865	77.1057	76.1901
	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P_4	Mean	0.3126	0.4128	0.4486	0.4551	0.2389	0.2023	0.1609	0.1200
	t	81.7497	109.9185	127.2424	139.1587	63.4219	69.7484	74.3125	74.5458
	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5.6: One-sided t-tests of the differences of results between different amounts of alternatives. Comparison only on rv^{exact} , all other parameters chosen according to the standard setting

5.5.4 Hypothesis H4

Our last hypothesis deals with the “role of dimension”. We conjecture that more states of nature lead to lower rvs. The average values of the rvs represented in Table 5.2 suggest that this conjecture may be true. In order to clarify hypothesis **H4** – a higher number of states leads to lower rvs – we perform one-sided t-tests on the differences of results between different states of nature. Note that we can only compare the rvs of the information set P_0 because here the volumes of P_0 are equal for all dimensions. Table 5.7 reports these results. The t-tests confirm that the differences of the rvs between different states of nature decrease. Thus, we conclude that the simulation shows a “role of dimension” for the analyzed cases.

K		4 – 3	5 – 4	6 – 5	7 – 6	4 – 3	5 – 4	6 – 5	7 – 6
		rv^{exact}				rv^{top3}			
P_0	Mean	-0.0422	-0.0168	-0.0100	-0.0049	-0.0531	-0.0229	-0.0179	-0.0081
	t	-37.6538	-21.0266	-15.5985	-9.1490	-28.0639	-14.5345	-13.0242	-6.6122
	p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5.7: One-sided t-tests of the differences of results between different states of nature. Comparison only on P_0 , all other parameters chosen according to the standard setting

5.6 Conclusion and topics for future research

In our simulation-based study we found an algorithm to limit probability ranges systematically. We used this method as input for studying the relation between additional information and the quality of decisions. We started in an information set with no information on the potential probability ranges of a predefined reference p-vector. Next, we applied our algorithm to limit these probability ranges, i.e., to increase information. We analyzed the effect of this additional information on the quality of decisions.

With this framework in mind we analyzed various factors influencing the quality of decisions. The results were the following. First, the quality of decisions increased when the information

about the reference p-vector increased. Second, the quality of information increased but at diminishing rates. This means, that at higher information levels additional information is valued less than at lower information levels. Third, more complex decisions in form of more available alternatives for the DM lead to a lower quality of decisions. Fourth, we observed a certain “role of dimension”, meaning that more challenging decision processes, including more possible outcomes (higher number of states of nature), lead to a lower decision quality.

There are many possibilities to extend our work, or find an alternative setup to examine a similar problem. First, there may be other appropriate ways to limit the probability ranges in order to increase information systematically. One could use the complexer *barycentric subdivision* of a simplex instead of the *alternative barycentric subdivision* used by us. One could also think of an iterative bisection of the information set, where hyperplanes divide the information set into two parts of equal moment. Second, there are alternative measures for the quality of information. Instead of a volume-based approach, a distance-based approach comes to mind. For example, the radius of the largest (hyper-)sphere within an information set with the reference p-vector as center would also serve as an appropriate measure. And third, other measures of the quality of decision are possible. There exist many ways to compare the ranking of alternatives. For example, instead of working with an exact or a top3 ranking, one could take a predefined distance between rankings into consideration.

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Appendix A

Summaries

A.1 Summary

This cumulative PhD thesis comprises four articles. The dissertation discusses two topics: the strategic behavior of firms in the German/Austrian electricity markets and how the electricity production from intermittent renewable sources affects the electricity price variance. The latter is a highly relevant topic for investors in flexible generation and policy makers alike.

The first paper of this thesis analyzes the competitiveness of the German/Austrian day-ahead electricity market. Using a theoretical model and statistical methods from the field of new empirical industrial organization, no anti-competitive behavior is found in the short-run for the period 2007 to 2010. The results of this study serve as a basis for the second article.

In the second paper, the effect of intermittent renewable generation on the wholesale electricity price variance is analyzed. A theoretical model shows that the shape of the industry supply function and the distribution of the intermittent renewable generation are the pivotal drivers of the price variance. These effects are empirically quantified for the German/Austrian day-ahead market using data from 2007 to 2012. Furthermore, it is found that the industry supply function has an inverse S-shaped form which affects the price variance non-monotonically.

The third paper is a theoretical article dealing with corporate social responsibility (CSR). Within an industrial organization framework it is shown that applying CSR can deter entry into an industry and therefore can be a profitable strategy for the incumbent firm.

Papers one to three are directly connected to the research question which can be answered as follows: (i) no evidence for strategic behavior on short-term markets, (ii) on the retail market, however, CSR could be used strategically, i.e., in order to deter entry, (iii) intermittent renewable energy is likely to have a non-monotonic effect on the wholesale electricity price variance.

The last article of this dissertation deals with the question of how additional information affects the quality of decisions. We found a way to constantly increase information by systematically limiting the ranges of probabilities which serve to calculate expected utilities. We simulate these probabilities and compare the decisions stemming from the constantly increasing better information to a reference scenario where we assume complete information about these probabilities. The mayor result is that the returns to scale on information decrease.

A.2 German Summary

Diese kumulative Dissertation besteht aus vier Artikeln. Die beiden Hauptthemen der Arbeit sind die Untersuchung von strategischem Verhalten von Firmen im deutsch-österreichischen Strommarkt und die Frage, welche Auswirkungen eine erhöhte Einspeisung von intermittierender erneuerbarer Energie auf die Strompreisvarianz hat. Ein Thema das vor allem für Investoren, welche in flexible Kraftwerke investieren wollen, und Entscheidungsträger interessant ist.

Der erste Artikel beschäftigt sich mit der Wettbewerbsfähigkeit des deutsch-österreichischen Day-Ahead Strommarkts. Die empirische Analyse dieses Markts basiert auf einem Modell aus dem Feld der neuen empirischen Industrieökonomie. Im Rahmen dieser Studie konnte kein antikompetitives Verhalten in der kurzen Frist für den Zeitraum von 2007 bis 2010 entdeckt werden.

Im zweiten Artikel wird der Effekt von intermittierender erneuerbarer Energie auf die Strompreisvarianz analysiert. Dabei zeigt sich, dass die Preisvarianz durch hauptsächlich zwei Effekte determiniert wird: Die Form der aggregierten Angebotskurve und die Verteilung der erneuerbaren Energie-Einspeisung. Im empirischen Teil, wo wir wieder den deutsch-österreichischen Markt heranziehen, zeigt sich, dass die aggregierte Angebotskurve invers-S-geformt ist und es daher zu nicht-monotonen Preisvarianzeffekten kommt.

Der dritte Artikel dieser Dissertation ist ein theoretischer Beitrag zum Thema Corporate Social Responsibility (CSR). Im Rahmen eines theoretischen Modells aus dem Bereich der Industrieökonomie lässt sich zeigen, dass es für Firmen profitabel sein kann, CSR-Maßnahmen umzusetzen, um letztendlich Markteintritt von Konkurrenten zu verhindern.

Die ersten drei Artikel dieser Dissertation sind direkt mit der Beantwortung der Forschungsfrage assoziiert. Es wurde keine Evidenz für strategisches Verhalten von Firmen auf dem deutsch-österreichischen Großhandelsstrommarkt gefunden. Auf dem Endkundenmarkt jedoch könnte CSR strategisch eingesetzt werden, um Konkurrenten vom Markteintritt abzuhalten. Die Stromproduktion aus intermittierender erneuerbarer Energie führt zu nicht-monotonen Effekten bei der Strompreisvarianz.

Im letzten Artikel dieser Arbeit wird die Frage, wie zusätzliche Information die Qualität von Entscheidungen beeinflusst, beantwortet. Wir bewegen uns im Gebiet der Erwartungsnutzentheorie und definieren bessere Information als das Kennen präziserer Eintrittswahrscheinlichkeiten eines Events. Anhand simulierter Daten vergleichen wir die Entscheidungen bei zunehmend präziser werdenden Wahrscheinlichkeiten mit jenen des Referenzszenarios, für das wir komplette Information über die Eintrittswahrscheinlichkeiten annehmen. Das Hauptresultat dieser Studie ist, dass die Qualität der Entscheidungen durch zusätzliche Information zwar besser wird, allerdings mit abnehmender Grenzrate.

Appendix B

Curriculum Vitae

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