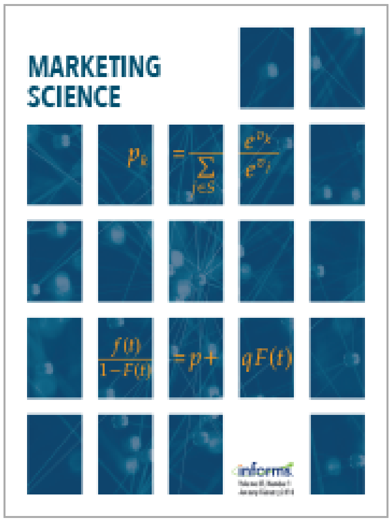

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Practice Prize Winner

ECO: Entega's Profitable New Customer Acquisition on Online Price Comparison Sites

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Market liberalization of the German household electricity market has led to an excessive number of competitors (1,150 electricity providers) and volatile price dynamics on price comparison sites. To date, providers that are struggling to achieve a top ranking on price comparison sites do not appear to implement a consistent or elaborate strategy for attracting customers. We developed a pricing tool, *E*lectricity *C*ontract *O*ptimization (ECO), that addresses this highly competitive market situation by integrating various available data sources, such as data from price comparison sites, demographic data, and regional sales or cost data. ECO sets regionally varying one-time bonuses to attract new customers on price comparison sites with the goal of optimizing sales and profit targets or optimally allocating sales budgets. Based on two field experiments, we demonstrate that ECO's optimization procedure reduces ENTEGA yearly sales costs for new customer business, on average, by 35% relative to previously used pricing heuristics. ENTEGA uses ECO monthly to analyze different scenarios or to set prices and one-time bonuses on price comparison sites.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mksc.2015.0943.

Keywords: pricing; price comparison sites; price optimization; field experiments
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1. Introduction

1.1. Market Situation

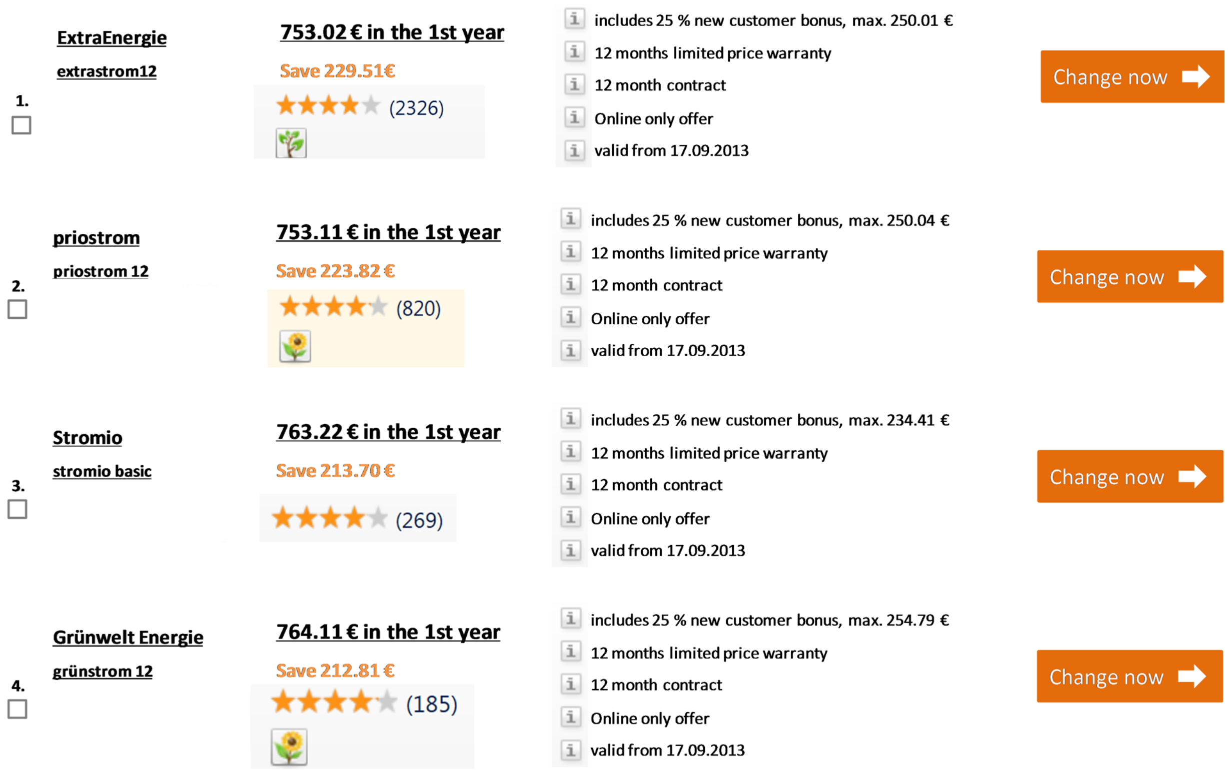
The repeal of the monopolies of state-regulated energy providers in 1998 has led to an increasingly competitive energy market in Germany. Market liberalization permits all customers to freely choose their electricity provider by allowing all (new) providers to use the grids of other providers (Lohse and Künzel 2011). In January 2013, the Federal Association of Energy and Water Industry (BDEW) observed that 1,150 different electricity providers offer electricity at a supra-regional or national level. In addition to heavy competition, several mergers and acquisitions, as well as substantial tax increases, have led to volatile price dynamics. Driven by the large price differences in the market, increasing provider switching has been observed. From 2010 to 2011, the market experienced a +27% increase (2.81 million versus 3.57 million new contracts) in provider switching (Verivox 2013). A.T. Kearney (2012) predicts that in 2016, approximately 12 million households, representing approximately 30% of the total market, will switch electricity contracts.

Consumers currently purchase approximately 50% of their electricity contracts online (A.T. Kearney 2012), primarily via price comparison sites (see Verivox, uSwitch, and Confused). Furthermore, 80% of consumers use price comparison sites to gather new information before switching electricity providers (A.T. Kearney 2012).

1.2. Price Comparison Sites

Consumers who visit price comparison sites (see Figure 1) to find a new household electricity contract are asked to enter the estimated consumption level of their household, their zip code, and their current provider. The price comparison site then ranks electricity providers according to the savings that could be achieved relative to the current provider costs (Figure 1). These price comparison sites further intensify the competitive pressure in the market. In particular, electricity

Figure 1 (Color online) Example Ranking on a Price Comparison Site Showing Rank, Provider, Yearly Price, Savings, Provider Rating, and Contract Details (e.g., Bonus Size and Minimum Contract Duration)



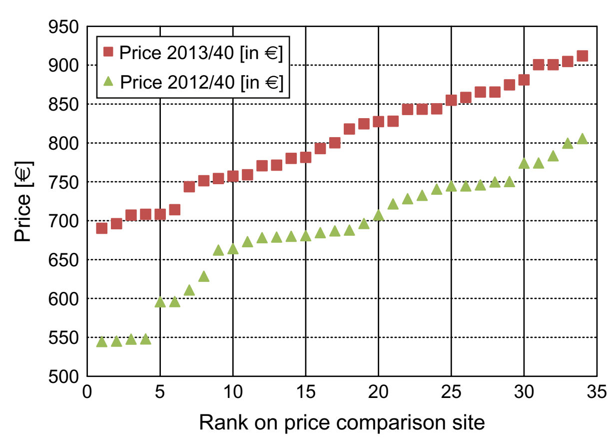
providers pursue new customers by offering one-time bonuses, a price reduction that new customers receive for the first contractual year. These one-time bonuses reduce the total cost of the first year of service, affecting providers' ranking on price comparison sites. Thus, one-time bonuses are critical price instruments for new customer acquisition.

For a seemingly homogeneous product such as electricity, one would expect extreme price competition with low price differences. However, we observe significant price dispersion consistent with the consensus that wide dispersion exists among Internet retailers on price comparison sites (Chevalier and Goolsbee 2003). In addition to the significant price differences at the same time, prices in the household electricity contract market also vary substantially from one year to the next. This makes it difficult for managers of electricity providers to successfully follow a "learning by experimenting" approach that could help translate current prices into sales. Figure 2 illustrates typical changes in prices and respective ranks within one zip code region for the years 2012 (week 40) and 2013 (week 40). Figure 2 also demonstrates that price differences between the top and bottom ranks in this market can reach 50% or higher.

Providers that are struggling to achieve a top ranking do not appear to implement a consistent or elaborate strategy for determining bonuses and prices: Some providers link the amount of bonuses to customers' consumption levels (e.g., 25%), whereas others allocate fixed bonuses. Furthermore, some providers also offer very low prices and sell against prepayments for a whole year.

Consistent with Arbatskaya (2007), Baye et al. (2004), Chevalier and Goolsbee (2003), and Smith and Brynjolfsson (2001), we find that providers' ranking on price comparison sites is highly effective in

Figure 2 (Color online) Prices and Respective Ranks for 3,000-kWh Contracts of One Zip Code Region on a Price Comparison Site in Week 40 of 2012 and 2013 Indicating Large Price Increases and Price Dispersion



predicting sales, as consumers tend to switch to electricity providers that appear at the top of the rankings. Indeed, the top two ranked providers in our sales data accounted for 69% of all of the 2012 contracts. Baye et al. (2004) also report similar rates for leaders in other product categories (approximately 70% for the top two ranked companies). Although the projected sales for the top-ranked companies are attractive, the typically negative profit margins associated with reaching these ranks prohibit most companies from targeting the absolute top ranks; otherwise, companies may face bankruptcy, as did FlexStrom and Teldafax. Both companies previously lured customers with extremely low prices, resulting in top rankings on price comparison sites. With this strategy, FlexStrom gathered up to 835,000 customers, and Teldafax amassed up to 700,000 new customers. However, their strategy proved to be unsuccessful as they both declared bankruptcy. Thus, providers often face a trade-off between choosing a profitable rank and choosing a rank that leads to a high number of new customers.

Depending on the region (i.e., zip code), the price level and dispersion may differ; different prices may be required to reach the same ranking in different regions. Furthermore, depending on the region and consumption level, costs for providers (e.g., network charges or dues to local providers) and thus profit margins differ considerably. Consequently, providers need to carefully study rank-demand patterns and regional differences to identify profitable ranking positions, given their cost structure, budget, and loyalty rate. There are approximately 8,200 different regions (i.e., zip code regions) in Germany and several[1] kWh-usage groups. Thus, electricity providers must manage more than 10 million rank, provider, and price combinations for a specific day for the regional top 30 providers alone. The associated planning effort and time requirements for regularly analyzing such a large amount of data (approximately 3 GB of new data from price comparison sites several times per week) are enormous. Because a thorough analysis of this large amount of data on a daily basis is not feasible without a tool, most providers use simple heuristics, such as targeting a certain rank for an average kWh-usage group. This approach, however, often results in negative profit margins.

ENTEGA, our cooperation partner, knew that this situation was not desirable in such a dynamic environment and was searching for academic support to handle this increasingly challenging market.

[1] Price comparison sites sometimes sell their ranking data to providers. Because usage levels are metric, price comparison sites provide the ranking data at kWh-usage group intervals. The number of intervals used varies from site to site.

1.3. Cooperation Partner and Aim of the Project

ENTEGA (entega.de) is the sales company of one of Germany's largest energy suppliers, HSE AG. HSE has 2,600 employees, and the company generated revenues of approximately €2 billion in 2012. With more than one million customers, of which approximately 600,000 purchase green electricity, ENTEGA is currently the second largest green electricity provider in Germany.

Two of the most relevant strategic objectives of the ENTEGA sales department relate to size and growth targets, whereas the main focus of ENTEGA's top management is profitability. To fully capitalize on the available data and to better link marketing activities to outcomes, we developed a sales and profit optimization tool: ECO (*E*lectricity *C*ontract *O*ptimization). ECO considers the relationships among rankings, sales, profit margins, and regional demand-side (market size and consumption levels) and supply-side (costs and competition) differences. ECO provides accurate and timely predictions for sales, profits, and budget consequences for alternative market scenarios. ECO further supports the provider's decision to optimally set one-time bonuses to reach a certain rank that (1) maximizes the total profit for a planning period, (2) maximizes the profit subject to new customer targets for a planning period or (3) maximizes the profit subject to budget restrictions, depending on the electricity provider's requirements.

2. Related Literature on Pricing Strategies Aimed at Price Comparison Sites

As research on price comparison sites for the household electricity market is scarce, we discuss interesting findings from the retail pricing literature and relate these findings to our market context. Previous research has demonstrated that prices on price comparison sites are dynamic (Kannan and Kopalle 2001, Koçaş 2005) and that they increase pressure among competitors, thereby leading to continuous price adjustments and thus price dispersion (Iyer and Pazgal 2003, Pan et al. 2004). From an information theory standpoint, price comparison sites should lead to lower price dispersion because they lower search costs by providing an overview of all alternative offerings. However, significant price dispersion has been observed on price comparison sites (Baye et al. 2004, 2006; Brown and Goolsbee 2002; Chevalier and Goolsbee 2003; Clemons et al. 2002; Ratchford et al. 2003; Smith and Brynjolfsson 2001). Although retailers at the top of the rankings receive most of the clicks (Arbatskaya 2007, Baye et al. 2004, Chevalier and Goolsbee 2003), researchers have demonstrated that retailers with prices greater than the minimum price also receive a considerable number of clicks (Iyer and Pazgal 2003, Lal and Sarvary 1999, Smith and Brynjolfsson 2001).

Smith and Brynjolfsson (2001) provide one explanation for why retailers do not need to strive for a top ranking on price comparison sites. By analyzing panel data from book consumers, they find that consumers place special emphasis on well known retailer brands (the biggest three: Amazon, Barnes and Noble, and Borders) by using the brand as a proxy for retailer credibility, thereby enabling these familiar brands to charge a premium price. Koçaş (2002) and Chen and Hitt (2004) support this finding. Koçaş (2002) suggests that online retailers invest in information technology (IT) and marketing to create buyer lock-in, buyer preferences or both. Furthermore, Ellison and Ellison (2009) find that retailers apply obfuscation strategies (e.g., increasing search costs) leading to lower consumer price sensitivity. Additionally, Pan et al. (2001) observe that retailers that charge higher prices tend to provide less information to obfuscate consumer searches and to render comparisons of alternatives more difficult. However, a considerable amount of the variance in price dispersion remains unexplained (Pan et al. 2001). Baye and Morgan's (2001) model indicates that even if all consumers purchase from the lowest price retailer identified by a price comparison site, dispersion in prices remains in equilibrium.

Although electricity is a homogenous product, we also observe significant price dispersion in our data, which is consistent with the existing literature. Brand preferences may exist among customers; however, there are a large number of well known brands that vary from region to region (i.e., the former default providers). Furthermore, because of market liberalization, consumers switch instead from the well known regional provider (i.e., the former default provider) to a more favorable provider in terms of price. Thus, consumers may attach minor importance to well known brands. The relevance of brands may also be lower in this context compared with other contexts because price comparison sites tend to delist providers with low customer evaluations. We also do not expect to find an effect of obfuscation strategies, as all information for all brands is standardized and transparent on price comparison sites such as Verivox or Confused. To hinder obfuscation strategies and to protect customers, Verivox, for instance (in their default search settings), only considers providers that are recommended by more than 70% of customers and that do not require prepayments or deposits.

Based on game theory approaches, Koçaş (2005) and Iyer and Pazgal (2003) expect retailers to apply mixed pricing strategies. Iyer and Pazgal (2003) expect that retailers trade off between taking advantage of loyal consumers, and thus charging the reservation price, and charging lower prices to attract new consumers. Offering one-time bonuses to new customers in the first year is one way to implement such a mixed strategy.

In our energy context, providers do not seem to follow a deliberate strategy but rather seem to use simple heuristics, such as targeting a certain rank for an average kWh-usage group. This sometimes results in negative profit margins. To our knowledge, no research on price comparison sites has focused on the optimization of prices based on different marketing targets. We developed a pricing approach that sets regionally varying one-time bonuses to reach a certain rank on price comparison sites so as to optimize profit while considering sales targets or budget restrictions.

3. ECO: Energy Contract Optimization Tool

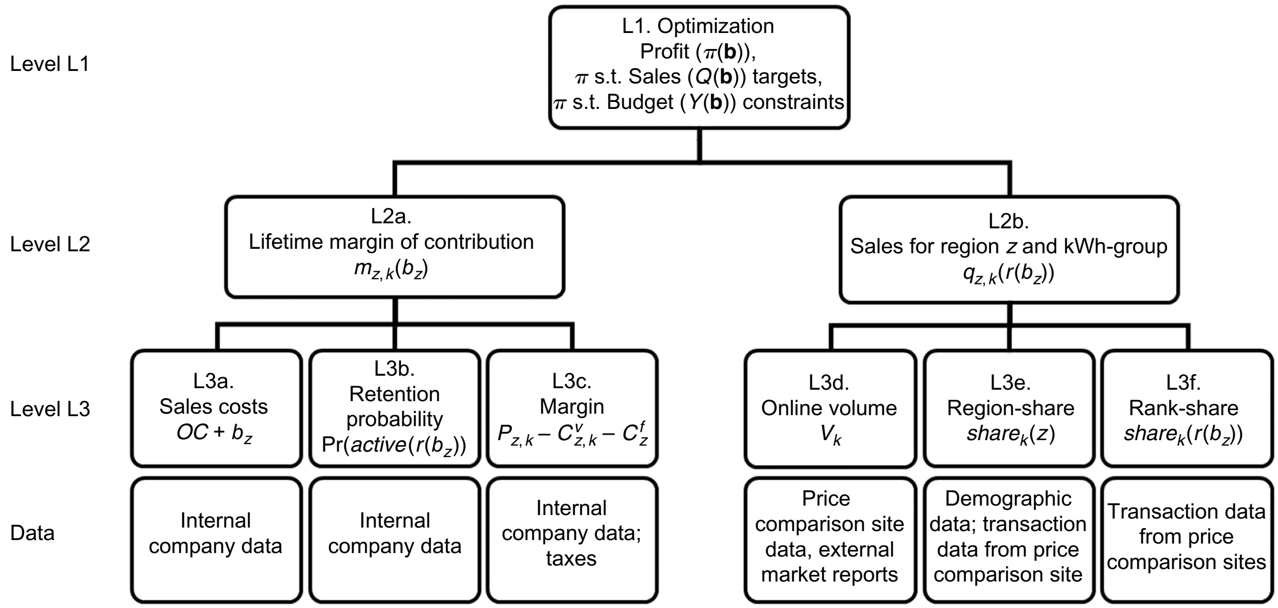
Our model aims to support the providers' decision process in optimally setting one-time bonuses and hence the total price of the first year necessary to reach a certain rank that would, in turn, optimize sales and profit targets. The market differs on a regional level with respect to competitors that offer contracts and with respect to basic utility providers and their cost structures, prices, and purchasing power. Thus, the model must address this heterogeneity in regional demand and supply. Optimization and demand modeling must operate at the regional level. This requirement is reflected in both the calculation of the margins of contribution and the sales models. In this section, we describe the different building blocks of ECO (depicted in Figure 3) for setting optimal one-time bonuses in this specific context. At level 1, the key objective (see box L1 in Figure 3), i.e., profit (unconstrained or subject to sales or budget restrictions), is calculated as the product of the level 2 variables, i.e., customers' lifetime margin of contribution (L2a) and sales (L2b). Lifetime margins of contribution are calculated by combining sales and acquisition costs (L3a), retention probability (L3b), and discounted margins of contribution (L3c). All variables used in Figure 3 are described in Table 1.

Regional sales at level 2 are modeled by decomposing the online sales volume V (L3d) of a planning period into the share that each region (L3e) and each provider receives at each price rank of a kWh-usage group k (L3f). Figure 3 shows that the one-time bonus b influences several outcomes, i.e., those of L1, L2a, L2b, L3a, L3b, and L3f.

3.1. Modeling Regional Lifetime Margins of Contribution (L2a)

For a customer, the long-term price per year, $P_{z,k,y}$, consists of two parts, costs per year y (base fee) and costs per kWh k. In our setting, $P_{z,k,y}$ is fixed by the provider before contract optimization. We therefore write the lifetime margin of contribution only as a

Figure 3 **Structure of ECO for Calculating Profits, Sales, and Required Budgets for New Customers**



Note. See notation in Table 1.

function of the one-time bonus $b_{z,t}$, our key marketing instrument to influence a customer's total price for the first year ($P_{z,k,y} - b_{z,t}$). Equation (1) shows that for an electricity provider, the discounted net lifetime margin of contribution m for a new contract closed in period t and zip code region z for a certain level of kWh usage k can be calculated based on three major components, i.e., sales (acquisition) costs, retention probability, and discounted margins.

$$m_{z,k,t}(b_{z,t}) = \overbrace{\frac{-b_{z,t}}{(1+i)} - OC}^{\text{sales costs}} + \sum_{y=1}^{Y} \overbrace{\Pr(active_y(r(b_{z,t})))}^{\text{retention probability}} \cdot \overbrace{\frac{P_{z,k,y} - C^v_{z,k,y} - C^f_{z,y}}{(1+i)^y}}^{\text{discounted margin}}. \quad (1)$$

1. Sales costs (see L3a in Figure 3) consist of the one-time bonus ($b_{z,t}$), which the customer receives at the end of the first year (hence, the bonus costs are discounted), and the online commission (OC), which the price comparison site receives at the beginning of a new contract. While some providers offer bonuses that also vary with kWh usage ($b_{z,k,t}$), ENTEGA bonuses currently do not vary by kWh usage owing to technical restrictions. Hence, we omit the kWh-usage index for the bonus levels ($b_{z,t}$).

2. The retention probability (L3b in Figure 3), $\Pr(active_y(r(b_{z,t})))$, decreases over time ($y$) and is influenced by the rank at which a contract is closed. Based on internal churn data, ENTEGA estimated that the probability that a customer who buys at rank r is active after y years is equal to $\Pr(active_y(r)) = 1.3e^{-g(r)0.334y}$, with $g(r) = 1.75/(4.0+r)^{0.16}$ describing the increasing retention probability with increasing r. Customers who buy at the top ranks (and thus receive higher bonuses) are more likely to churn after the minimum contract duration to repeatedly benefit from new customer bonuses; hence, these customers have a higher churn probability.

3. The projected margins of year y are calculated by subtracting customers' costs that arise owing to their kWh usage, $C^v_{z,k,y}$ and yearly costs, $C^f_{z,y}$, from the net price, $P_{z,k,y}$ (see L3c in Figure 3). Costs that vary with kWh usage ($C^v_{z,k,y}$) refer to several taxes (renewable energy law EEG surcharge,[2] §19 tax,[3] electricity tax, and offshore tax), electricity sourcing costs, and net usage costs per kWh. Yearly costs ($C^f_{z,y}$) refer to net usage costs that arise per contract and that have to be paid to a customer's local utility provider in zip code region z, whereas Y denotes the planning horizon of the company.

3.2. Modeling Sales (L2b)

Most energy providers target the entire market; however, in general, large portions of a provider's customer base are regionally concentrated because of historical market structures. Consequently, few, if any, sales occur in most of the zip code regions and kWh-usage groups.

[2] The EEG surcharge was established to support subsidies provided to developers of renewable energy as part of the German Renewable Energy Act.

[3] The §19 tax was added to the consumers' electricity bills to subsidize the net usage costs of energy-intensive companies.

Table 1 Definitions, Subscripts, and Variables

Variable	Notation
b, B	Bonus in €; set of considered bonus levels
δ	Threshold for optimization heuristic
e	Latitudinal coordinate
ε	Error term
C^f	Costs of a contract that are independent from the kWh-usage
C^v	Costs of a contract that depend on the kWh-usage
$g(r)$	Function that describes at which rate the retention probability increases with the rank at which a contract was closed
h	Number of households
i	Discount rate
k	Subscript for kWh-usage group
l	Price rank class index for fitting function $share_k(r_{z,k,t}(b_{z,t}))$
m	Lifetime margin of contribution
n	Longitudinal coordinate
OC	Online commission per contract that has to be paid to price comparison site
P	Long-term price of a contract per year not including the bonus
π	Profit
ppi	Purchase power index
$\Pr(active_y(r))$	Retention probability; i.e., the probability that a customer who closed the contract at rank r is still active after y years
Ψ, Ψ^*	Budget; budget constraint
q, Q, Q^*	Sales quantity; cumulative sales for planning periods; sales target
r	Price rank of a provider at price comparison site
R_k	Number of different providers (offers) in kWh-usage group k
$share_k(z)$	The share of the overall online sales potential of kWh-usage group k that region z receives
$share_k(r_{z,k,t}(b_{z,t}))$	The sales-share of kWh-usage group k as a function of the price-rank r that is reached by setting bonus b in a specific region z and period t
t	Subscript for time period
V	Online sales volume
x	Dummy variable indicating higher-level zip code region
w	The number of new customer contracts sold in the past period
y	Subscript for year
z	Subscript for zip code region

This limits providers' ability to solely use company data for response modeling. Hence, relying on ENTEGA's internal sales data alone does not seem suitable for developing a regionally differentiated pricing approach that addresses the entire German market. We therefore design a general sales model q consisting of three submodels for online volume (L3d), region share (L3e), and rank share (L3f).

$$q_{z,k,t}(r_{z,k,t}(b_{z,t})) = \overbrace{V_{k,t}}^{\text{online-volume}} \; \overbrace{share_k(z)}^{\text{region-share}} \; \overbrace{share_k(r_{z,k,t}(b_{z,t}))}^{\text{rank-share}}. \tag{2}$$

To achieve our general sales model q, we first decompose the online sales volume $V_{k,t}$ of a period t and specific kWh-usage group k into the level of individual regions (z) per kWh-usage group k, $q_{z,k,t}$ by multiplying $V_{k,t}$ by the share of sales for each region z in the total sales for all regions of k, $share_k(z)$. Regional sales are then linked to the provider ranks on the price comparison site for each kWh-usage group by multiplying the sales of a region by the share that each rank receives, $share_k(r_{z,k,t}(b_{z,t}))$. Even for a provider with identical bonuses across kWh-usage groups in a region, the resulting ranks and the relationship between ranks and the resulting provider shares may vary for each kWh-usage group.

To estimate our more general demand model, ENTEGA purchased sales data from a price comparison site that links online sales to the ranks on the price comparison site for different consumption levels and zip code regions.[4] The sales data from the price comparison site contain information about the number of contracts sold at each rank in each zip code region for each month and differentiate between nine different kWh-usage groups.

3.2.1. Sales Submodel 1: Sales Volume V (L3d). The first sales submodel is an aggregate for online demand V_t (L3d in Figure 3). Seasonal patterns, trends, and specific events (e.g., tax increases and related media coverage increase the traffic on price comparison site) can strongly influence overall demand in the online market. Therefore, we model the overall online demand for electricity contracts as a separate function. The demand on the price comparison site from which we received sales data is projected to the overall demand for electricity contracts by dividing the forecast by the market share of the price comparison site. The forecast for the online market volume V_t for a period t is based on two model components: The first component captures the increasing trend ($\ln(V_t) = b_0 + b_1 t + \varepsilon_t$) of log volume sales, $\ln(V_t)$; the second model component fits an autoregressive (AR) model to the residuals (ε_t) of the trend model. AR models seemed suitable since about 60% of customers are multiple contract switchers who tend to seek the next new customer bonus as soon as the minimum contract duration of typically 12 months expires. Based on analyses of the (partial) autocorrelation function of the residuals of the trend model and the stability of the predictive sales pattern for the next 12 periods, we used volume lags of periods 1, 10, and 11 to fit the estimation sample. To calibrate the aggregate volume model ($r^2 = 0.63$), we used monthly periods 1 to 48 (see the triangles in Figure 4). We determined the hold-out predictive accuracy ($r^2 = 0.43$) based on periods 49 to 67 (see the squares in Figure 4).

[4] For confidentiality, these data do not contain seller identities and hence do not allow for an analysis of brand effects (see Baye and Morgan 2009).

Figure 4 (Color online) Aggregate Online Market Demand (V): Data, Model Fit, and Forecasts

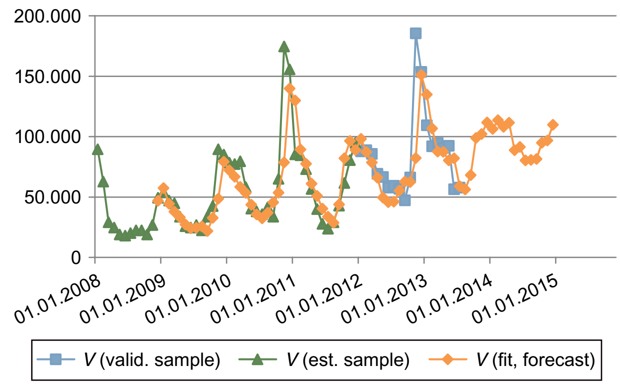


Figure 4 also contains the fitted volumes (diamonds) and model forecasts. As new sales data become available, the model estimates are updated. In yearly revisions, the model (lag) structure should be updated because the time-series length is still short. For model implementation, all available volume data (estimation and validation periods) are used to fit model parameters while maintaining the lag structure as determined in the model selection phase. The following equation presents the combined trend and AR model with the parameters determined by using the estimation sample

$$V_t = e^{\overbrace{(10.411+0.0119t)}^{\text{trend-part}}+\overbrace{(0.62\varepsilon_{t-1}+0.035\varepsilon_{t-10}+0.396\varepsilon_{t-11})}^{\text{AR-part}}}. \quad (3)$$

Estimated total online sales volume V_t is then broken down to the level of kWh-usage groups ($V_{k,t}$, see Equation (2)) by multiplying V_t with the average sales share of each kWh-usage group in previous periods ($V_{k,t} = V_t(\bar{V}_k/\bar{V})$).

3.2.2. Sales Submodel 2: Share-of-Region Model (L3e). The second sales submodel determines distribution of the online sales potential of a period across all regions. We predict the share of the sales potential that every region receives in the overall online demand of the respective kWh-usage group k as a function of the purchasing power index (ppi) of zip code region z, the number of households in the zip code region (h), the number of new customer contracts sold in the past period (w), and the longitudinal (n) and latitudinal coordinates (e) of the zip code region center as follows:

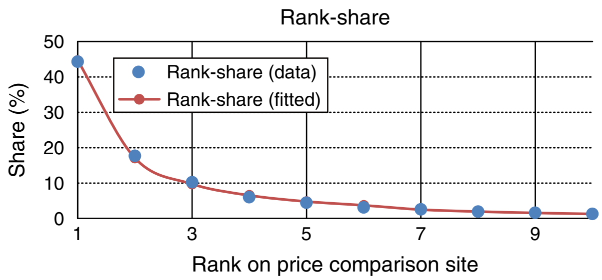
$$\begin{aligned} share_k(z) = \exp\Bigg(& a_{1,k}ppi_z + a_{2,k}h_z + a_{3,k}w_z \\ & + a_{4,k}n_z + a_{5,k}e_z + \sum_j a_{5+j,k}x_{z,j}\Bigg) \\ & \cdot \Bigg(\sum_z \exp\Bigg(a_{1,k}ppi_z + a_{2,k}h_z + a_{3,k}w_z \\ & + a_{4,k}n_z + a_{5,k}e_z + \sum_j a_{5+j,k}x_{z,j}\Bigg)\Bigg)^{-1}, \end{aligned} \quad (4)$$

First, we tested geographically weighted regression (GWR) models (LeSage and Pace 2009) to account for regional differences. We then substituted these models using a set of dummy variables (x) indicating higher-level zip code regions. The dummy variables captured further regional differences that might be caused, for example, by differences in regional utility providers or price levels. Furthermore, the dummy variables were computationally less demanding than the GWR models. Again, the models were tested based on the hold-out sample predictive performance by using 70% of the data for estimation and 30% of the data for validation. The average hold-out performance across the nine kWh-usage groups was $r^2 = 0.731$ (worst fit: $r^2 = 0.64$, best fit: $r^2 = 0.88$). To assess the relevance of the individual variables used in Equation (4) we estimated individual models for an average kWh-usage group that only used the respective variable (type) as an independent variable. This test confirmed that all variable types significantly improve variance accounted for. Past sales showed the highest individual predictive power, followed by the number of households of a region, the purchase power index, the regional zip code dummies, and the longitudinal and latitudinal information.

3.2.3. Sales Submodel 3: Share-of-Rank Model (L3f). The third sales submodel explains distribution of the regional sales of a period, region, and kWh-usage group among the provider ranks on the price comparison site. Because of cost and price dynamics, historic prices cannot be directly used for demand modeling. Ranks from price comparison sites, however, exert a more consistent influence on consumers' contract-choice probability over time. We therefore use the ranks on price comparison sites, which are closely related to sales data, to predict market shares (Chevalier and Goolsbee 2003). Our initial modeling tests confirmed the finding of Ellison and Ellison (2009) showing that the sellers ordinal ranking on a price comparison site predicts the sellers' sales better than their listed prices. Therefore, our third submodel builds on the rank-market share relationship rather than modeling the direct effect of prices. Because sales rapidly decrease below the top ranks, we aggregate sales across all competitors and zip code regions for each of the nine different kWh-usage groups to estimate a rank-market-share model. The share of contracts that a certain rank r on the price comparison site yields is modeled at the individual kWh-usage group level (see Figure 5).

Estimating the model at the individual kWh-usage group level seems appropriate, as the share-rank relationship varies with the kWh-usage group level. For instance, we find that 51.9% of customers buy at the first rank if they belong to the lowest kWh-usage group, whereas only 44.7% of customers buy at the first rank when they belong to the highest kWh-usage

Figure 5 (Color online) Price Ranks vs. Market Share (Actual Values and Fitted Curve)



group. Because the shape of the rank-market share model strongly varies with increasing rank, we capture the nonlinear shape of this relationship by using the following piecewise nonlinear model:[5]

$$share_k(r_{z,k,t}(b_{z,t})) = \sum_{l=1}^{L} \frac{\alpha_{k,l}}{\beta_{k,l} r_{z,k,t}^{\gamma_{k,l}}(b_{z,t})} x_l, \tag{5}$$

where α, β, and γ are the parameters of this model and x_l denotes dummy variables indicating whether a rank r belongs to one of four ranges l ($x_1 = 1$ if $r \in [1, \ldots, 6]$, $x_2 = 1$ if $r \in [7, \ldots, 13]$, $x_3 = 1$ *if* $r \in [14, \ldots, 20]$, $x_4 = 1$ *if* $r \in [21, \ldots, R_k]$; otherwise $x_l = 0$). R_k, denotes the maximum number of providers (and hence the highest available rank) across all regions in each kWh-usage group k. Figure 5 depicts the data and fitted curve for a sample kWh-usage group for ranks 1–10.

In the ECO development stage, the rank-share models were tested based on hold-out sample predictive performance using 70% of the data for estimation and 30% for validation. The average hold-out performance across the nine kWh-usage groups was $r^2 = 0.99$. The final model implementation uses all of the available data for estimation. The good fit without considering brand effects supports our assumption that brand preferences are negligible in this context.

3.3. Modeling Decision Support Options (L1 in Figure 3)

The following three different types of scenarios were identified as the most useful for the sales department energy provider (see the top level of Figure 3):

1. The basic scenario shows profit optimization for the planning period. Before adding other constraints, such as budget availability or new customer targets, to the optimization, the basic scenario is almost always used as a starting point before further scenarios are analyzed.
2. The second scenario that frequently occurs involves analyzing the consequence of a given sales target for a defined planning period.
3. The third scenario allows for optimal regional budget allocation. Often, only a certain budget is available. In that instance, the sales department needs to determine how to optimally spend exactly this budget within a specific planning period.

In the text that follows, these three scenarios are described in more detail.

Scenario 1: The basic profit optimization sets one-time bonuses b_z for each zip code region (z) such that they maximize the sum of the margins m per contract multiplied by the projected number of contracts $q_{z,k}$ sold per kWh-usage group (k) and planning period across all kWh-usage groups (K). Because costs typically do not vary within the planning periods (1 to 4 weeks), we multiply the margins of contribution of a zip code region $m_{z,k,t}(b_{z,t})$ by the predicted cumulative sales per kWh-usage group in the planning periods, $Q_{z,k}(b_z) = \sum_{t=1}^{T} q_{z,k,t}(r_{z,k,t}(b_{z,t}))$. The decision variables are the bonuses b_z for each zip code region. Based on our analysis of short-term competitive reactions (see the Web Appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0943)), we do not anticipate any competitive reactions in price levels during the planning periods. We therefore evaluate all bonuses at the most recent price levels in each region and kWh-usage group based on the assumption that ENTEGA sets bonuses b_z to maximize the overall profit margins across all kWh-usage groups. Hence, in the text that follows, we omit the period (and again kWh) subscripts for the bonus levels:

$$\underset{b_z}{\text{maximize}} \quad \Pi(b_z) = \sum_k Q_{z,k}(b_z) m_{z,k}(b_z) \qquad \forall z \in Z,\ k \in K \tag{6}$$

$$\text{subject to:} \quad 0 \le b_z \le 0.25 P_{z,k}, \quad b_z \in B.$$

In scenario 1, the search for the optimal bonus in one zip code region is independent of the search for the optimal bonuses in other zip code regions. The objective function indicates that the number of new contracts and the margin are functions of the selected bonus level. To protect customers, the price comparison site restricts the bonus to less than 25% of the price. Furthermore, ENTEGA uses a price grid[6] of permitted bonus levels (B) to avoid an excessive number of different bonuses, which generates menu costs when uploading the results to different price comparison sites. An advantage of the discrete number of bonuses is that it is feasible to calculate projected profits for each bonus on the price grid B and then to choose the solution that maximizes the sum (across all kWh-usage

[5] Alternative local linear Gaussian kernel regression models that we tested performed similarly well. Future research could also test the usefulness of other methods such as using monotone splines to improve our simple model.

[6] For example, the price grid may include a predefined subset of bonuses with €0 as well as bonuses defined by a starting bonus, a step-size bonus, and a maximum bonus, e.g., $B = \{$€0, starting bonus = €50, step-size = €10, maximum bonus = €150$\}$.

groups) of the expected profit for each zip code region. Aggregating the regional results yields the overall profit (Π), budget (Ψ), and sales (Q) predictions.

Scenario 2: Optimization of a sales target Q^* (i.e., the number of new customers for a planning period) is more complicated because the overall profit optimization must consider trade-offs among zip code regions to reach the overall sales target. This limitation is reflected by an additional constraint on the difference between the forecasted sales contracts and the target sales number. Furthermore, the objective function aims to maximize the overall profit subject to the sales target across all zip code regions

$$\begin{aligned} &\underset{\mathbf{b}}{\text{maximize}} \quad \Pi(\mathbf{b}) = \sum_z \sum_k Q_{z,k}(b_z) m_{z,k}(b_z) \\ &\qquad\qquad\qquad\qquad\qquad \forall z \in Z,\ k \in K \\ &\text{subject to:} \quad |Q - Q^*| \le \delta \\ &\qquad\qquad\qquad 0 \le b_z \le 0.25 P_{z,k}, \quad b_z \in B, \end{aligned} \tag{7}$$

where δ denotes the threshold that this difference is not permitted to exceed and $\mathbf{b}$ denotes the vector of bonuses for all zip code regions.

Scenario 3: The profit-optimal plan, subject to spending a specific target budget Ψ^* within a planning period, is of equal complexity to that in scenario 2. This plan searches for an overall (i.e., for all zip code regions) solution to maximize profit while constraining the difference between forecasted spending and the target budget Ψ^*

$$\begin{aligned} &\underset{\mathbf{b}}{\text{maximize}} \quad \Pi(\mathbf{b}) = \sum_z \sum_k Q_{z,k}(b_z) m_{z,k}(b_z) \\ &\qquad\qquad\qquad\qquad\qquad \forall z \in Z,\ k \in K \\ &\text{subject to:} \quad |\Psi - \Psi^*| \le \delta \\ &\qquad\qquad\qquad 0 \le b_z \le 0.25 P_{z,k}, \quad b_z \in B. \end{aligned} \tag{8}$$

The required acquisitions budget is determined by the overall bonus costs and the OC that arise for each new contract, i.e., $\Psi = \sum_z (b_z + OC) Q_z$.

3.3.1. Search Heuristic for Scenario 2 and Scenario 3. The problem space for scenarios 2 and 3, in which a target sales number (Q^*) or budget (Ψ^*) must be reached, is much more complicated than that for scenario 1 because restrictions are set based on aggregate measures (i.e., the number of new customers or the budget). A typical optimization task that, for example, is comprised of 8,200 regions and 16 different bonus levels results in an intractable problem space of size $16^{8{,}200}$. To address this large problem size, we use an iterative heuristic. The search heuristic proceeds as follows:

1. *Boundaries*: In the first step, we calculate the minimum and maximum levels of Q^* and Ψ^* by setting the bonuses of all zip code regions to zero and the maximum bonus, respectively. The sales and bonus costs associated with these two solutions define the upper and lower limits for Q^* and Ψ^*, respectively. Targets with higher (lower) sales or budgets cannot be reached; thus, these targets require a reformulation of the objectives.

2. *Initialization*: Scenarios 2 and 3 are initialized by the solution ($\mathbf{b_0}$) provided by the basic profit maximization procedure (scenario 1). The optimization aims to reach the targets (sales and budget) by deviating as little as possible from the profit-optimal solution. If the current solution is within the defined boundary (δ), then the optimization terminates. Otherwise the following steps are repeated until the current solution is within the defined boundary.

3. *Iteration*:

a. If the current total number of new customers Q (scenario 2) or the required budget Ψ (scenario 3) is above (below) Q^* or Ψ^*, respectively, then the neighboring solution with the next lower (higher) bonus (if available) is calculated for all regions. We denote the bonus before the hypothetical change (iteration $i-1$) by $b_{z(i-1)}$ and the bonus level after the hypothetical change by b_{zi}.

b. We sort the zip code regions according to their decrease in normalized average (across all kWh-usage groups) profits[7]

$$(\pi_z(b_{zi}) - \pi_z(b_{z(i-1)}))/|b_{zi} - b_{z(i-1)}|. \tag{9}$$

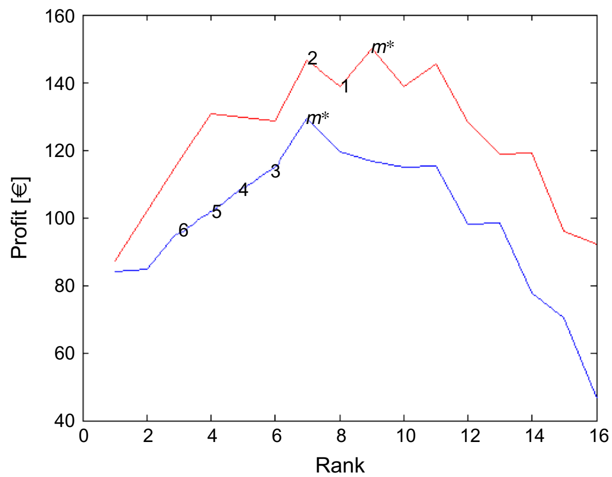
As bonus step sizes can vary, profit differences are normalized[8] by the absolute differences in neighboring one-time bonuses, $|b_{zi} - b_{z(i-1)}|$. In the final implementation of ECO, profits of each region were additionally normalized by the maximum profit in each region. Then, the N regions with the lowest decrease in normalized profit are selected, and the bonuses of the N selected regions, i.e., those with the weakest negative effect on profitability, are set to b_{zi}, whereas the other regions remain at the more profitable bonuses, $b_{z(i-1)}$. The number of bonus changes in an iteration (N) is determined such that it is larger at the beginning and decreases once the deviation from the target values decrease. $Q(\Psi)$ is then calculated based on the new solution.

Figure 6 shows the logic of the constrained search heuristic for the profit curves of two regions. The sales target in this case was set higher than the sales projected at the profit maximum (rank 9 for the top curve; rank 7 for the bottom curve). The numbers at the two curves indicate the order of the six required steps

[7] Alternatively, we tested the decrease in normalized per-unit margin $(m_z(b_{zi}) - m_z(b_{z(i-1)}))/|b_{zi} - b_{z(i-1)}|$.

[8] In the first phase, only identical bonus step widths were used. Hence, no normalization was necessary.

Figure 6 (Color online) Search Order of the Constrained Search Heuristic Used in ECO



Notes. The red and blue curves show ranks vs. profits for two sample regions. Starting points for the constrained search heuristic for each region are denoted by m^* (profit optimum of unconstrained search).

in which the two regions iteratively deviate from their profit maximum based on the slope of the respective (normalized) profit curves. The search heuristic path in Figure 6 actually leads to the optimal constrained solution in this setting.

3.3.2. Test of the Search Heuristic. We investigated the performance of the described search heuristic using a simulation in which we created 500×2 different profit curves similar to those observed in our data. To calculate the optimal solution and compare the heuristic performance with the optimal solution, we limited the number of regions to two. We calculated the mean deviance of our search heuristic from the optimum over 500 replications. On average, the profit outcome deviated from the optimal solution by 9.76% with a standard deviation of 7.55%. As indicated by the shape of the curves in Figure 6, the loss in profit often increases more steeply the farther away one has to move from the profit maximum. Consequently, an increasing number of regions (in our case approximately 8,200) should lead to a lower average decrease in profit relative to the situation of only two regions.

3.4. Test of Model Assumption for Competitive Reactions

As ECO's optimization procedure accounts for profit margins and sales, it usually does not yield top ranks as solutions. We do not expect immediate competitive reactions on medium and lower ranks. The optimization procedure therefore does not anticipate short-term competitive reactions. We conducted a number of tests (see the Web Appendix) to determine whether this assumption is appropriate.

Our analysis of pricing strategies aimed at price comparison sites indicates that competitive reactions mainly occur at the top ranks. Furthermore, very few top competitors vary the amount of their bonuses regionally. This limits the possibility of effective reactions to ENTEGA's regionally differentiated pricing approach. Overall, the assumption that price-ranking relationships for constant prices are not systematically biased from one period to the next seems valid. According to ENTEGA's management, the main reason for the rather low speed at which price-rank relationships change is attributable to the substantial menu costs associated with publishing new prices. New prices must be uploaded to various systems in different formats, requiring substantial time and personal effort. Therefore, many providers adapt bonuses only when costs and prices also change.

Overall, our analysis indicates that the model provides valid forecasts if the planning horizons do not exceed 1–4 weeks. Furthermore, if a provider has a cost structure that allows it to profitably target the top ranks, competitive reactions should be incorporated in the model.

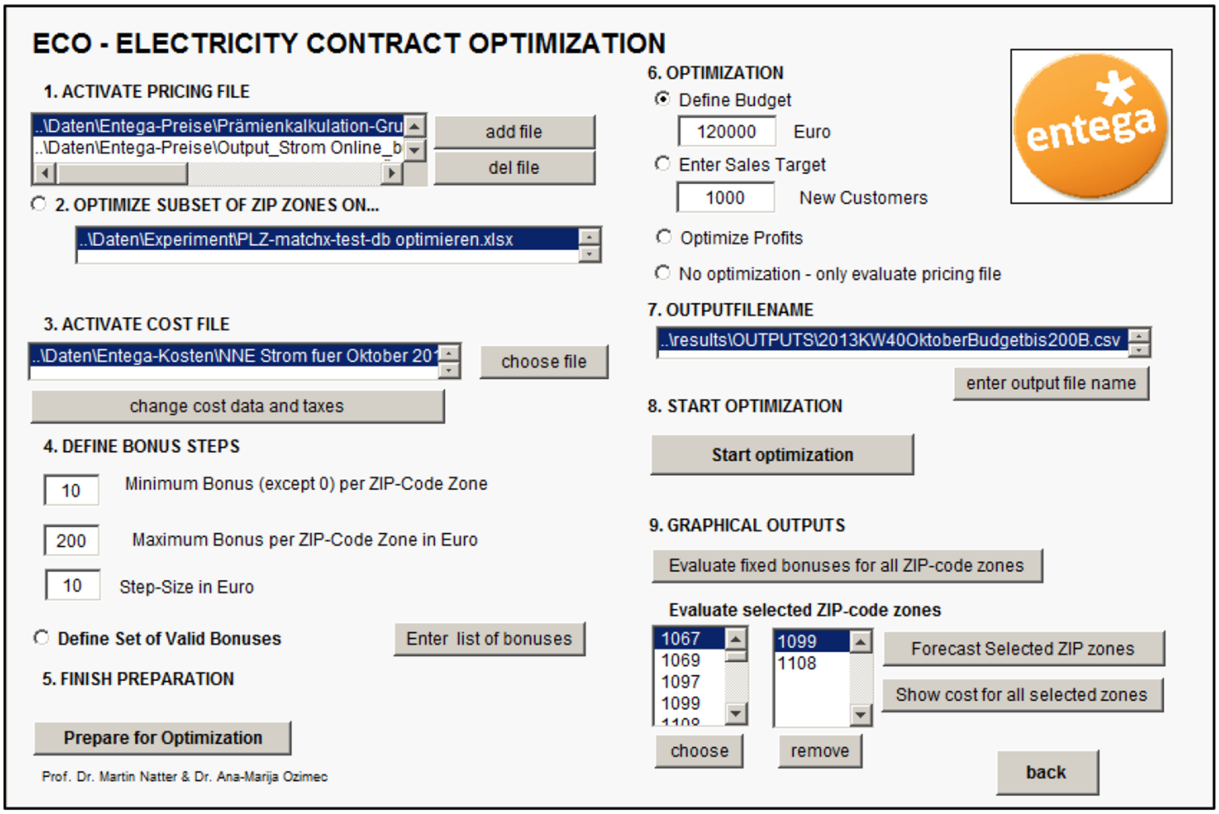
3.5. User Interface of ECO

ECO, a MATLAB-based tool with a graphical user interface, is easy to use. The user must upload the most recent files that describe the actual market (online sales data for the past month, data on the current ranking, and price information for the market). Then (see Figure 7), the user is asked to upload the zip code regions for which bonuses are to be determined by ECO as well as their current actual price (step 1) and cost information (step 3). The uploaded files should be in Excel and CSV and are delivered in a standardized layout.

The user can then adapt the optimization procedure to her specific needs. For example, she can choose a subset of zip code regions to be optimized (step 2), limit the interval bonuses and their stepwise increments (step 4), and determine a specific kWh-usage group (also included in step 3). Finally, the user must decide whether the goal is to optimize profits alone, profits subject to budget constraints or profits subject to acquisition of a given number of new customers (step 6). ECO produces both files in a format that is suitable for price comparison sites with prices and one-time bonuses for each zip code region, and files that contain predictions (sales, costs, average ranks, and profit margins) and statistics (e.g., the number of regions that receive a certain bonus).

After optimization, the user may graphically evaluate forecasts in terms of performance measures (step 9) such as projected profit margins, new customer acquisitions, market share, and costs for a scenario in which a fixed bonus is set for all zip code regions and kWh-usage groups (see Figure 8). Figure 8 depicts some screenshots that show the effects of a fixed bonus (i.e.,

Figure 7 (Color online) Screenshot of the User Interface of ECO



one identical bonus for all zip codes) for the selected set of zip code regions (see the top-left box).

As Figure 8 shows, a bonus of €50 would maximize the total profit margins, whereas a bonus greater than €70 would yield negative profit margins. Based on this type of graphical analysis, ENTEGA's management was fully aware of the negative consequences of excessively high bonuses on profitability. In addition to offering insights into the consequences of a fixed bonus across all regions, ECO provides graphical insights from various viewpoints for individual zip code regions or combinations of regions to better understand the reasons for implementing different bonuses in different regions. Because the differences in bonuses allocated to different regions are sometimes large, data visualization was important for ENTEGA managers to enhance their confidence in the implemented logic of ECO.

4. Field Experiments: Data and Measures

4.1. Data

For development of ECO, ENTEGA provided us with (1) data from the two largest price comparison sites that constitute approximately 95% of ENTEGA's online sales, (2) cost data, and (3) acquisition data.

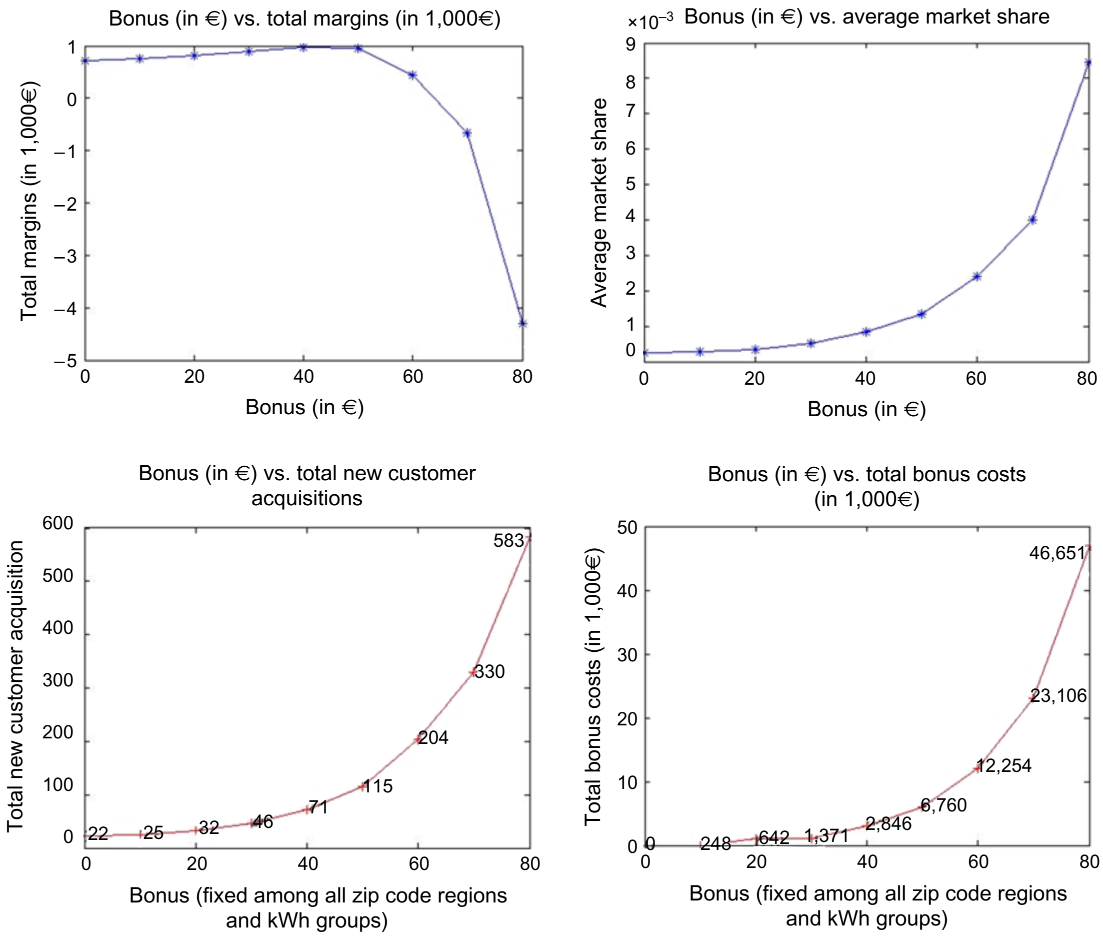
(1) Data from price comparison sites: We received monthly (January 2012–June 2013) sales data from a price comparison site that links sales to kWh usage, rank, and zip code region. In addition, we received weekly data (Week 1, 2012–Week 27, 2013) from another large price comparison site that provides information about the ranking and actual prices of ENTEGA and its competitors.

(2) Cost data: To optimize bonuses in terms of profit margin, ENTEGA provided us with all relevant fixed and variable cost data for each zip code region for the period January 2012 to June 2013. Fixed costs include the base fee and cable fee per year that must be paid to a local utility provider in a zip code region. The costs include sourcing and all relevant taxes, which are proportional to customers' consumption level (kWh-usage group).

(3) Customer acquisition data: We received all online acquisition/new customer data, which contained information about the detailed contract price, consumption level (kWh-usage group), regional zip code, corresponding sales channel, and bonus received.

To investigate the financial impact of ECO while protecting ENTEGA's sensitive cost structure, we conducted a series of experiments in which we reported sales or profit metrics but avoided simultaneously reporting both of them.

Figure 8 (Color online) Illustrative Example of the Consequences of Alternative Fixed Bonuses vs. Performance Measures for a Subset of Zip Code Regions



4.2. Experimental Design

To analyze the effect of ECO on profitability, ENTEGA's management allowed us to perform two field tests in which we compared the traditional approach with alternative ECO settings.

Field test 1: *"Basic profit optimization"*: The first test was conducted in May 2013. The goal was to compare the profit margins obtained through the application of ECO's optimization method with the average profit margins obtained through a common "traditional method" of ENTEGA. A typical traditional method that ENTEGA practiced before adopting ECO was targeting one specific rank across all regions and all kWh-usage groups.

From the overall set of zip code regions, a specific subset was excluded for specific periods because of other events and activities. The remaining 8,064 different zip code regions were divided into two groups. Because the management team already doubted the effectiveness of their traditional method, we divided the zip code regions unevenly (362 regions for the traditional method and 7,702 regions for ECO) to avoid overly negative effects. The control group represented the traditional method. The intuition of the management team was to set the bonus such that the target rank was $r = 15$ for an average kWh-usage group, as ranks 1–19 still appear on the first page of the price comparison site. In our treatment group, we allocated bonuses by maximizing the profits per zip code region.

Field test 2: *"Optimization under budget constraints"*: In June 2013, we conducted our second field study. Together with ENTEGA's management, we planned to allocate bonuses in 5,602 zip codes in Germany. The remaining areas were excluded because of specific marketing activities, which may have affected the results. Again, for a reduced set of 548 zip code regions, ENTEGA decided to determine the bonuses by having their regional marketing and sales management apply their traditional method without the aid of ECO (control group). With this method, bonuses that lead to rank 15 for an average kWh-usage group were set as the target for each of the 548 zip code regions. For the remaining zip codes, we were allowed to divide the allocation of regions into two equally distributed and comparable treatment groups (i.e., treatments 1 and 2). We matched the zip codes to ensure that the treatment groups did not significantly differ in terms of their mean consumer purchase index, cost structure, and spatial distribution. For treatment group 1, we attempted to mimic the traditional approach of ENTEGA (i.e., to target a specific rank) but with the support of ECO, i.e., we analyzed alternative ranks for all zip code regions and their effects on ENTEGA profitability. After a scenario analysis with ECO (similar to the example in Figure 8), we targeted rank 19 in the zip code regions that belonged to treatment group 1. For treatment group 2, we optimized the bonuses by using ECO subject to a budget constraint. To facilitate comparability, the budget constraint was set to the budget that was predicted by ECO based on targeting rank 19 (treatment group 1).

5. Results and Impact

5.1. Predictive Accuracy

As a first test of the predictive accuracy of the ECO sales forecast, we compared weekly sales projections ($Q = 382$) and actual sales ($Q = 292$) for eight weeks in September and October 2012. Both months were unaffected by any additional marketing campaigns and therefore provided a suitable testing period. The squared correlation between the projected (by ECO) and actual new customer contracts was $r^2 = 0.90$, which was perceived to be sufficiently accurate by ENTEGA top management. After validating the predictive accuracy of the model, ENTEGA management decided to actually calculate new bonuses based on ECO and to upload them to the various price comparison sites. Every month thereafter, ENTEGA determined the bonuses by using varying scenarios in ECO or ran alternative scenarios by using ECO.

5.2. Financial Impact

Field test 1: *"Basic profit optimization"*: The results showed an average negative profit margin for the first year of €−15.48 per contract for the control group and a positive profit margin of €4.33 for the treatment group optimized with ECO. The difference between the groups of €19.81 is statistically significant. More important for ENTEGA, however, projections for a one-year effect indicate the financial impact of ECO as well: For 2012, assuming that each approach is used for all regions over an entire year, ECO leads to a projected reduction of 28.3% in total sales costs for new customers relative to the traditional approach (see Table 2). This represents a substantial improvement in ENTEGA's new customer business.

Field test 2: *"Optimization under budget constraints"*: Results from field test 2 (Table 2) show that the average profit margin per contract achieved by control group is €−25.41, which is lower than the profit margin for the control group in the field experiment conducted in May 2013. The average profit margin achieved by treatment group 1 (optimized rank 19) was €1.01 (which is also lower than the average profit margin achieved in the first field experiment). This results in a difference of €26.42 relative to the traditional method and a projected yearly reduction in sales costs of 37.7%. Treatment group 2 had the highest average profit margin (€1.10) and a projected yearly reduction in sales costs of 37.9%.

The average savings in sales costs across the different field tests was 34.6%. This reduction was considered a substantial improvement for ENTEGA.

In 2012, apart from a few test runs that started in October, ENTEGA did not yet use ECO to set one-time bonuses, whereas in 2013, ENTEGA used ECO monthly to set most bonuses for most regions. As sales targets and actual new customer acquisitions were approximately the same in both years (30,000 new contracts), ENTEGA's management compared the effects of ECO on sales costs over a longer period. ENTEGA reports that ECO helped reduce total sales costs by approximately 35%, which resulted in an 11% profit increase.

5.3. Organizational Impact

This project not only showed tangible financial benefits but also a substantial impact on the organization.

From rules of thumb to using a Decision Support System (DSS): Before using ECO, ENTEGA's management did not have a straightforward strategy for determining bonuses to acquire new customers. Instead, the management team intuitively determined bonuses or aimed to reach a specific rank within the highly competitive price comparison sites for an average kWh-usage group. This approach has not always resulted in positive profit margins.

More structure to the allocation of decision making and the use of new heuristics in budgeting decisions: With ECO, ENTEGA's managers can now evaluate strategies to maximize profit margins with or without budget constraints or even with the objective of acquiring a specific number of new customers. Hence, managers can better assess the consequences of different strategies and improve the efficiency of their marketing activities.

More strategically planned sales campaigns and the allocation of sales budgets: According to ENTEGA's CEO Rene Sturm, ECO also helps ENTEGA coordinate its targets: "The software clearly states the consequences of online pricing on profitability and new customer targets and therefore helps to coordinate activities of the sales department and the top management." Although ECO was initially developed to support the work of the ENTEGA sales department, it was soon clear to the top management team that the tool was particularly effective for implementing and coordinating goals.

Table 2 Field Experiments and Treatments with the Resulting Average Profit Margin per New Customer and Projected Difference from the Traditional Method for One Year Based on Sales Cost Reduction and Total Customers Acquired in 2012

Month/Year	Treatment group	Average profit margin [in €] for a new customer	Sales cost reduction per year (%)
May 2013	Control group: Traditional method (rank 15)	−15.48	—
May 2013	ECO: Max profit margin	4.33	28.3
June 2013	Control group: Traditional method (rank 15)	−25.41	—
June 2013	ECO: Rank 19	1.01	37.7
June 2013	ECO: Budget constraint	1.10	37.9
Average			**34.6**

Change management: Implementation of ECO changed ENTEGA's organizational thinking. The predictive accuracy of ECO, including the availability of new key decision metrics, resulted in higher departmental accountability and decision confidence. ECO has increased transparency within the company and raised interest in analytic tools. A recent customer (lifetime) management project also received increased support as implementation of ECO revealed the existence of high churn rates and their sensitivity towards incentives (e.g., bonuses).

5.4. Transferability

ENTEGA is also a provider in the German gas market; ENTEGA's sister company (HSE Medianet) is a broadband Internet provider. In both markets, contracts are also sold via price comparison sites. The department responsible for the gas market is already planning to implement a similar DSS to improve their decision-making process. Transfer of the developed methodology to other markets that sell contracts via price comparison sites is straightforward. Application of a model such as ECO, however, is not limited to these industries. Car insurance and mobile communication industries, for example, also face the challenge of allocating bonuses to acquire new contracts via price comparison sites. For less homogeneous product categories, however, where brands, delivery times or other product or service features play an important role, the proposed electricity sales model will be too simplistic and will need to be extended to a more encompassing sales response model.

6. Theoretical and Practical Findings and Future Challenges

In line with previous research on price comparison sites, we find high price dispersion in the market for household electricity contracts. However, by contrast to other markets, such as online bookstores, brand effects do not seem to play an important role in the electricity market (price-rank models without brand effects fit extremely well). The lack of brand effects may be due to market liberalization where many customers still switch from the previous monopolist that typically has the highest brand awareness. Hence, prospective savings are the main motivation for switching providers.

Iyer and Pazgal (2003) expect that retailers trade off between taking advantage of loyal consumers, and thus charging the reservation price, and charging lower prices to attract new consumers. Offering one-time bonuses to new customers in the first year is one way to implement such a mixed strategy. However, our research shows that the success of such a mixed strategy depends on the approach to setting such bonuses. More specifically, our results underscore the relevance of considering regional demand- and supply-side patterns in pricing strategies aimed at price comparison sites.

Practical findings: This project was initiated by ENTEGA's CEO. Our experience in this project confirms that having a high-level champion, holding several in-house presentations, and involving multiple departments are important for the organizational acceptance of an organizational change (Lilien et al. 2013). In addition, the assistant to the CEO, who holds a Ph.D. in marketing, played an important role in this project. Her ability to understand the logic implemented in ECO and to identify and discuss critical model assumptions (requiring appropriate tests to understand the sensitivity of different model parameters) fostered the company's willingness to adopt, trust, and continuously use ECO. Furthermore, understanding incentive schemes in academia and practice, it was possible to set up a contract wherein we could use this material for a publication in case of success. Mutual trust often seems to be a key success factor in academic-practitioner partnerships. Thus, an interface person such as the assistant to the CEO can play an important role. Supporting academic sabbaticals in practice during postdoctoral research could be a way to create such interfaces, which could increase the use of marketing science models in practice (Lilien et al. 2013).

Future challenges: Together with ENTEGA, we are further improving ECO. Currently, we are using a customer lifetime (CLT) estimation based only on the rank at which a contract was closed and the length of the existing relationship. We recently started developing a more elaborate CLT model that builds on the entire set of available customer data related to churn behavior.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0943.

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