

FCN Working Paper No. 5/2018

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**Institute for Future Energy Consumer
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Strategic Demand Response to Dynamic Pricing: A Lab Experiment for the Electricity Market*

Ayşe Tugba Atasoy[†] Marjolein Harmsen-van Hout[‡] Reinhard Madlener[§]

April 2018

Abstract

Despite the efforts of restructuring power markets over the last decades, the lack of demand response in the retail electricity markets remains a significant concern. Possible demand response would help to reduce prices and volatility by better matching supply and demand through improved price signals. In this paper we develop a laboratory tool to experimentally investigate the demand response in the electricity market. The baseline treatment constitutes a two-period ‘wait-or-buy’ game with an exogenous first period, an automated supplier, and twenty subject buyers. While the seller offers a fixed number of a product in the market, consumers decide on purchasing the product immediately or waiting until the next period, taking (i) price uncertainty and (ii) inventory risk into account. This treatment captures demand response in the retail market with scarce products. We design an additional treatment by removing the inventory constraint and introducing a devaluation rule, where consumers only bear the price risk – thus mimicking the demand response in the electricity market. We find that in both retail and electricity market treatments consumers play on average the equilibrium predictions and buy strategically. However, there are systematic deviations from rationality in both settings, i.e., consumers buy too soon or wait too long.

JEL-Classification: C92, D01, D81, M11, Q31

Keywords: Demand Response, Electricity, Dynamic Pricing, Strategic Behavior

*Financial support from the Strategy Fund of the Excellence Initiative at RWTH Aachen University is gratefully acknowledged. We also thank Robert Böhm, Peter Katuščák, Georg Kirchsteiger, Joachim Schleich, and Vincent Mak for valuable comments and discussions. We thank the participants at the AIXperimental Economics in Progress Brownbag Seminar at RWTH Aachen University, the TIBER 2017 Symposium at Tilburg University, the MAGKS Doctoral Workshop held in September 2017 in Rauischholzhausen, the 41st IAEE International Conference at the University of Groningen, and the 2018 ESA World Meeting at the Humboldt University of Berlin. Matthäus Czopek provided excellent research assistance.

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1 Introduction

Many countries and federal states have restructured their power markets in the past decades; however, the lack of demand response in the retail electricity markets remains one of the major weaknesses. Demand side response would help to reduce high prices and volatility.

Despite the fact that consumer valuation and marginal production costs vary significantly throughout the day, consumers (here: private households) have traditionally paid mostly a fixed rate for each kWh of electricity. Such a flat tariff does not provide end-users with the right economic incentives to shift load away from higher-priced supply periods. Figure 1 compares a typical flat rate with a real-time pricing rate. Unlike fixed pricing, dynamic pricing allows for passing part of the marginal costs of electricity production onto consumers and therefore facilitates demand response and management. In addition, during times of high peak demand, congestion in the power system does not only jeopardize security of supply but may at worst also lead to power outages. Introducing a dynamic pricing scheme would provide consumers with financial incentives to shift their usual electricity consumption as well as to avoid extreme peak events, thus mitigating network congestion. If consumers are responsive to the financial incentives in this context, implementation of dynamic pricing would decrease the deadweight loss, everything else held constant, resulting in an increase of both consumer and producer surplus.

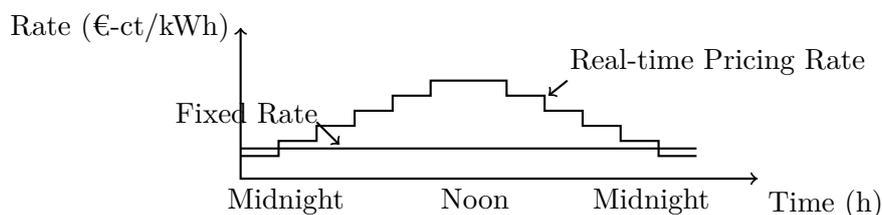


Figure 1: Fixed and Dynamic Electricity Price Schemes

Source: Own Illustration.

Several studies looked into whether dynamic pricing proves effective in shifting the electricity consumption in various contexts and under diverse pricing schemes (e.g., hourly pricing (HR), time-of-use pricing, critical peak pricing (CPP), critical peak pricing with a rebate (CPR)). Most of these studies constitute a field experimental setting and are often carried out as utility-run demonstrations/pilot projects with a restricted geographical coverage.

One of the first studies in this domain was conducted by Heberlein and Warriner (1983). In a field experiment, they collected data within a time-of-use demonstration project with three different time-of-day price ratios, where they also measured subject knowledge and attitude, and research what role attitudes have on shifting electricity consumption. They found psychological commitment to have a bigger impact than the price. Those who commit to shifting consumption do so even at the low price ratios. Wolak (2011) investigated the effectiveness (demand reduction)

of the household demand response under three different types of dynamic pricing: HR, CPP¹, and CPR, using a randomized controlled field trial. Wolak (2011) finds that both CPP and CPR lead to similar reductions in electricity consumption. However, when compared with HR customers, the reductions are significantly higher than those of either CPP or CPR customers. Borenstein et al. (2002) analyze the effect of economic incentives in the context of dynamic electricity pricing on the competitiveness and efficiency of the electricity market. Alongside these studies² that show that dynamic pricing works in reducing peak demand, Allcott (2011) argues that dynamic pricing also significantly lowers the total electricity consumption compared to flat pricing. Allcott (2011) finds no significant change in the off-peak hour, which refers to the overall reduction achieved in electricity consumption after real time pricing has been introduced.

It becomes clear after reviewing this literature that economic incentives – despite constituting very small stakes – seem to work effectively in this particular context, i.e., that consumers respond to the dynamic pricing schemes. However, the effect size varies tremendously across the studies.³ There are several design and context-related reasons contributing to this heterogeneity observed in the results, one of which might have to do with the random assignment of the subjects to different treatment groups. As the field experiments require the installation of smart meters at home, both the control and treatment groups are often aware of the pilot project. Other reasons for the existing heterogeneity of the cross-experimental evidence might be due to (i) sample design,⁴ (ii) small number of observations, (iii) ownership/availability of the enabling technology, and (iv) the exact days they examine the price rates (e.g., weekend vs. weekday).⁵ Moreover, installation of the smart meters is often a very costly way of testing such interventions, which, however, does not necessarily grant a strict randomization. Although testing these hypotheses in the field has a high external validity, it might still, besides being very costly, suffer from a lack of internal validity.

A few studies attempt to complement the evidence from the field experiments by conducting laboratory experiments, investigating the demand side under dynamic pricing in the electricity market (e.g., Adilov et al., 2004; Barreda-Tarrazona et al., 2012). Barreda-Tarrazona et al. (2012) test how subjects respond to two different dynamic pricing schemes compared to a time-invariant scheme: (i) dynamic pricing with bonus, where consumers receive a bonus payment if they reduce peak consumption and (ii) dynamic pricing with malus, where consumers are sanctioned consuming in peak-period hours. They find the dynamic pricing scheme with a malus to prove more effective in shifting peak consumption, which confirms the widely-agreed observation in the literature that losses are psychologically more powerful than gains, i.e., loss aversion.

¹Under critical peak pricing, consumers face significantly raised electricity prices only on the pre-determined days in the year on which utilities expect to observe high network congestion caused by excessive consumption during the peak events.

²For an extensive review of the main field experiments conducted in this domain, see the review paper written by Faruqui and Sergici (2010).

³Our review suggests potential peak demand reductions between 7% and nearly 40% under dynamic pricing compared to a flat pricing scheme.

⁴Different pilot programs test differences in the rate designs. Ownership of the underlying technologies might differ substantially in distinct settings.

⁵For a review of selected field experiments and possible reasons for the discrepancies in the results, we refer to the study by Faruqui and Sergici (2010).

However, the aforementioned studies (i) employ within-subject treatment, which may cause common method bias, (ii) have a substantially complicated set-up for a laboratory experiment,⁶ and (iii) have a design that involves framing, which might not be desirable in the laboratory setting for the electricity market, since part of the treatment effect then is potentially attributed only to the context rather than to the underlying mechanism. Besides a few lab experiments on the demand side, there are a number of studies that employ laboratory methods to scrutinize the supply-side responses to dynamic pricing in the wholesale electricity market (e.g., Cason and Sharma, 2001; Le Coq et al., 2017). Le Coq et al. (2017) studied how firms choose their generation capacity and compete in the uniform auction markets.⁷

Beyond these field and lab studies, there seems to be no research documented that investigates the behavioral mechanism underlying the observed demand response to dynamic electricity prices. Thus, little is known about the relative importance of behavioral factors that are expected to play a role in the decision framework of demand response under dynamic pricing. There is, however, research in the operations research and management science literature that investigates how consumers purchase under dynamic pricing (e.g., among others, Mak et al., 2014; Osadchiy and Bendoly, 2015), which examines how strategic consumers behave in such a setting and in how far they deviate from strategic behavior. The main objective of our research is to capture the core decision problem in a simple experimental design, which introduces a similar game as the ‘wait or buy’ game (Ovchinnikow, 2015). Thus, we develop a laboratory tool, which grants us a high degree of control and cost-effectiveness together with enabling us to research how strategic the demand response in the electricity market is. This question is particularly interesting for the electricity market to understand in how far the demand side should be automated and whether utilities can rely on consumers to make decisions on their consumption behavior, letting customers bear the price risk (Schneider and Sunstein, 2017). Like Mak et al. (2014), we investigate how consumers – showing their sophistication for the underlying mechanism – demonstrate deliberate strategic behavior under a dynamic scheme and systematically deviate from the strategic equilibrium, i.e., buying too soon (myopic foresight) or waiting too long (irrational waiting).

2 Experimental Setting

2.1 Baseline Setting

For the baseline treatment we replicate the design from a study by Mak et al. (2014), which introduces a simple abstract game setting that captures the strategic purchasing decision under dynamic pricing motivated by the retail market.

As in Mak et al. (2014), we consider a monopolist who sells a fixed amount of goods (a fixed inventory known to all market participants) to a fixed number of consumers in a market over

⁶The laboratory setting of Barreda-Tarrazona et al. (2012) does indeed rely heavily on calibrations using market data.

⁷Their setting for deciding the optimal generation capacity influences us in a couple of aspects for designing the behavior of the automated supplier for our electricity setting; see Section 2.2.

two different periods t_1 and t_2 , which are comparable to the situation in the electricity market.⁸ The automated seller offers a product over two different periods t_1 and t_2 and each consumer buys at most one unit of the goods offered. Likewise, the demand in t_2 is also automated. Upon deciding to postpone their purchase, only consumers with a payoff greater than zero will be assigned the product. The remaining inventory will be allocated randomly to the consumers in the market, if the number of consumers who (i) have a payoff greater than zero and (ii) postponed their purchase to t_2 is greater than that of the items in the remaining inventory. The setting introduces scarcity, indicating that fewer items are available for purchase in the market than the number of buyers.⁹ This procedure is repeated over several rounds. Consumers know their own valuation of the offered product in the beginning of each round. The seller knows the distribution of the randomly drawn consumer valuations.¹⁰ At the beginning of each first period (t_1), the seller announces a price P_1 , which is exogenous. If consumers decide to purchase the good, they leave the market with a net payoff of $V - P_1$. The price in the second period, P_2 , is not determined exogenously but optimized by the seller, whose objective is to maximize profit. Therefore, P_2 is dependent on consumer behavior in the first period t_1 . The valuation in the second period, however, is discounted with a factor δ ($0 < \delta \leq 1$) that exogenously takes the value of 0.5. Hence, in the second period the consumer receives a net payoff of $\delta(V - P_2)$. The outcomes for the subject decision in each round can be expressed as follows:

$$u_i^{baseline} = \begin{cases} V_i - P_1, & \text{if } D_i = 1 \text{ and } \sum D_{i=1} < I \\ \delta(V_i - P_2), & \text{if } D_i = 0 \text{ and } \sum D_{i=0} < I_2. \end{cases} \quad (1)$$

Equation (1) indicates the different payoff calculations in each period of a given round. If the consumer decides to purchase immediately in the first period, which is shown by $D_i = 1$, the payoff will be calculated by subtracting the exogenously set P_1 from the individual valuation for purchasing the product V_i . This is true if the number of consumers who would like to purchase is smaller than the number of items available in the inventory. If the individual decides to wait, indicated by $D_i = 0$, and the number of subjects postponing their purchase $\sum D_{i=0}$ is smaller than the remaining inventory in t_2 , indicated with I_2 , the payoff is calculated as $\delta(V_i - P_2)$, where the difference between the individual valuation V_i and the period 2 price, P_2 , is discounted by a fixed discount factor of δ . The experimental design aims at capturing the equilibrium behavior for strategic buying.¹¹ Let us demonstrate by the following example how P_2 is determined in the baseline setting:

Example (Baseline): Using backward induction and the remaining inventory I after the

⁸The pattern of electricity consumption differs significantly throughout the day. Hence, t_1 and t_2 are comparable to *peak* and *base* periods in which the valuation for consuming electricity differs substantially (e.g., day-/night-time).

⁹For our baseline treatment, we select the condition $I = 16$ from the two treatments Mak et al. (2014) introduce with different sizes of scarcity. The following two conditions are being tested in their setting; the condition with (i) less scarcity for which the inventory consists of 19 items and there are 20 buyers in the market, and (ii) more scarcity for which the inventory includes 16 items and there are 20 buyers in the market.

¹⁰Consumers are assumed to be risk-neutral in this setting.

¹¹Equilibrium behavior is indicated by a sub-game perfect solution over the two pricing periods. See Appendix B for the details on the equilibrium predictions.

first period, the seller concludes on the valuations of the remaining consumers in the market. Discretizing the experimental setting by the multiples of 10, there exists the following price set $\{40,50,\dots,220\}$ together with the following valuation set $\{45,55,\dots,235\}$ ¹². Let us consider an example with 14 remaining items ($I = 14$) left in the market after the first pricing period. This means that – for the condition with 16 available items – two consumers have purchased in t_1 using the following assumption:

Assumption: If there are items left after t_1 , the valuations of the buyers who have not purchased in t_1 must all be smaller than the valuations of the buyers who purchased in t_1 .

By the above assumption, the two buyers have the highest two valuations from the set of $\{45,55,\dots,235\}$: 225 and 235, respectively. Hence, valuations of the remaining buyers in the market consist of $\{45,55,\dots,215\}$. Consequently, the seller in this case determines the maximum valuation as $v_{max} - 215$. Given that the seller knows the distribution of the valuations, the seller picks the price that maximizes his or her profits from a possible set. For example, in the case of $P_2 = 200$, only two buyers with the highest valuations would purchase: 205 and 215. Hence, $\pi = 200 * 2 = 400$ in t_2 . Consequently, the seller considers π at other possible P_2 prices simultaneously before determining the optimal P_2 .

2.2 Setting Motivated by the Electricity Market

The setting suggested by Mak et al. (2014) serves as an established way of executing and/or testing strategic buying under dynamic pricing. The main finding by Mak et al. (2014) indicates that the consumers on average act as rational buyers under a dynamic pricing scheme. There are two types of uncertainties incorporated into consumer decision-making in the baseline setting: (i) price uncertainty, as the product might get cheaper in the second period in each round, (ii) inventory risk, as there is a risk of running out of inventory and not being able to purchase the product in the second period.¹³ It is worth noting that the study on demand response with scarce products by Osadchiy and Bendoly (2015) is based on a similar design, but includes only the inventory uncertainty in the game, as they introduce pre-commitment to price reductions.

Despite similar economic incentives, the Mak et al. (2014) design does not correctly reflect the constraints in the electricity market. Consequently, we make changes to the baseline experimental design in order to better capture the dynamics of the decision-making process in the electricity market. In the setting motivated by the electricity market, the decision problem is also in the simple form of ‘buying the product now or waiting until the second pricing period’. While we think that the price uncertainty is a relevant constraint in the electricity market, the inventory risk is not an issue in this particular context, as no risk is posed by running out of

¹²Each value for V_i is randomly drawn without replacement, such that each value in the set is allocated to a subject. Allowing a substantial variation in consumer valuation captures effectively different consumer types. This also takes distinct opportunity costs each consumer might have for being fully attentive to the pricing scheme into account.

¹³There is an inventory constraint imposed in the baseline setting – i.e., there are less items available in the market than the number of buyers in the market. Hence, consumers bear, by waiting, the risk that the game ends after the first period and that there are no goods left in the market.

electricity.¹⁴ Therefore, we have a treatment design without an inventory constraint, where only a price uncertainty is introduced. This price uncertainty is based on a price decrease between t_1 and t_2 .¹⁵ While the parameters v and P_1 remain exogenous in period t_1 , the valuation is lower in t_2 , not because of a seasonal good, but because of peak and base periods. In the electricity setting, we replace the discount factor by a devaluation rule. While in the retail market with scarce products, the net payoff of consumers changes over time, thereby making the discount factor over the seasons a relevant parameter, electricity consumption does not concern discounting over time periods. Instead, consumers' valuation of the product changes significantly between periods. Hence, we replace the discount factor rule of the retail setting, in which the parameter v is multiplied by $\delta = 0.5$ if the consumer waits until t_2 . Instead, we implement the following devaluation rule: if the consumer decides to purchase in period t_2 , the payoff is then calculated as $(\delta * V) - P_2$, where the consumer valuation is multiplied by the devaluation factor of 0.5. This can be summarized as follows:

$$u_i^{electricity} = \begin{cases} V_i - P_1, & \text{if } D_i = 1 \\ \delta V_i - P_2, & \text{if } D_i = 0. \end{cases} \quad (2)$$

Equation (2) indicates the payoff functions in both periods at a given round for the electricity treatment. If the consumer decides to purchase the product immediately, then the round payoff is calculated by subtracting the exogenously set price the subject observes in t_1 , P_1 , from that subject's valuation V_i . In contrast, if the consumer postpones to purchase, the consumer's valuation decreases, as the fixed factor δ halves the valuation V_i .¹⁶ If the consumer buys in t_2 , then his or her payoff is calculated by subtracting P_2 from the devalued sum δV_i . In contrast to the baseline setting, there is no inventory-related constraint in this treatment when calculating the round payoffs. With this additional treatment, we are able to examine whether individuals react differently to dynamic pricing when (i) there is only price uncertainty, while no inventory risk is posed and (ii) no discounting rule is used for calculating the payoff in the second period. While excluding the inventory risk from our experimental setting allows demand and supply to match at each t_1 outcome, eliminating the discounting rule captures the fact that electricity consumers would not discount their payoff over the seasons, but rather value consumption significantly less during the base hours. Also in this treatment, after individuals submit their purchasing decisions in t_1 , the automated seller calculates the optimal P_2 based on the left over capacity – where he or she assumes that consumers with the highest valuations must have purchased in t_1 . Using backward induction, we are able to determine not only how the seller sets the price,

¹⁴Practically, electricity can be consumed any time during the day and the decision to consume electricity is not affected/motivated by the risk of scarcity. Note that in specific situations the inventory constraint might be relevant also in the electricity setting, when a service requires electricity use, e.g., watching a specific show on TV. However, the storage technology today makes such rare instances negligible.

¹⁵Thus, t_1 is comparable to the *peak* and t_2 to the *base* in this setting. One must note that the pricing scheme in our experimental setting captures a tariff, in which the price uncertainty is borne by the consumer, compared to a case where the price might be capped for the consumers.

¹⁶This captures a 'base' period in the tariff, where the valuation to consume electricity is essentially much lower for everyone, e.g., during the night hours.

but also the equilibrium predictions for the buyers given different P_1 prices.¹⁷ Furthermore, by having an abstract design, we are not only able to have a high degree of control but also to capture a number of markets similar to the electricity market, e.g., transport market (dynamic road pricing).

Let us demonstrate how P_2 is determined in the electricity market-motivated setting by the following example:

Example (Electricity Market-Motivated Setting): Using backward induction and the information on the remaining generation capacity after the first pricing period, the seller concludes on the valuations of the remaining consumers in the market. Similar to the baseline setting, valuations of the buyers are $v = \{45, 55, \dots, 235\}$ ¹⁸. If there are 14 units of generation capacity left, six consumers must have decided to consume electricity in the peak period t_1 . By the same aforementioned assumption and the algorithm described for the baseline setting, the seller determines the v_{max} , - i.e., $v_{max} = 185$, in this case. The seller decides on the exact same steps as above; however, now the supply of electricity matches the demand at any period of the game. That is, there is no constraint on the availability of the product. Hence, in the case of $P_2 = 200$, the seller calculates his or her profit π as $\pi = 200 * 6 = 1200$. The seller then compares π at different P_2 levels and decides for the optimal P_2 .¹⁹

2.3 Equilibrium Predictions in the Baseline and Electricity Treatments

The equilibrium predictions of consumer demand in both periods are constructed contingent on the P_1 levels observed by adopting the rational expectations framework. These and other important parameters, such as the number of buyers who hold off to purchase rationally, the remaining inventory at the equilibrium demand, and the equilibrium prices for both periods, are reported in Table 1.

Given the specific P_1 level, players form expectations of what the other players will do in a round, based on the information they hold on the history of the game. The equilibrium values are constructed based on the cutoff valuation v , which indicates the minimum valuation for consuming in t_1 to be the best response.

¹⁷There are other experimental studies (e.g., Cason and Sharma, 2001; Güth et al., 2004; Reynolds, 2000), which focus on response to dynamic pricing and do not pose an inventory constraint; in all these studies there is also a price decrease in the later periods rather than an increase.

¹⁸Just like in the baseline treatment, valuations are discretized in decimal steps and each value is randomly (without replacement) allocated to a subject at the beginning of each round.

¹⁹See Appendix B for a detailed documentation on the calculation of the different best-response P_2 prices in both experimental settings.

Table 1: Equilibrium Predictions by Treatment and Different Period 1 Price Levels

Baseline Treatment (Mak et al., 2014)						
Period 1 (t_1)				Period 2 (t_2)		
Price (p_1)	Equilibrium demand	Cutoff valuation for purchasing	No. of buyers with valuation $> p_1$, but holding off purchase	Remaining inventory at beginning	Equilibrium price	Equilibrium demand
90	14	105	1	2	80	2
100	12	125	2	4	80	4
110	10	145	3	6	80	6
120	8	165	4	8	80	8
130	7	175	4	9	80	9
140	6	185	4	10	90	9

Electricity Market Treatment						
Period 1 (t_1)				Period 2 (t_2)		
Price (p_1)	Equilibrium demand	Cutoff valuation for purchasing	No. of buyers with valuation $> p_1$, but holding off purchase	Remaining capacity at beginning	Equilibrium price	Equilibrium demand
90	12	125	5	8	30	6
100	10	145	6	10	30	8
110	10	145	7	10	30	8
120	8	165	7	12	40	8
130	6	185	8	14	40	10
140	6	185	8	14	40	10

Notes: The table indicates the equilibrium predictions by treatment and selected t_1 price levels. Depending on the distinct exogenous price observed in t_1 , corresponding cutoff valuations, equilibrium demand, and number of buyers who rationally postpone their purchase are listed. Cutoff valuations are calculated using the conditions (5) and (6) in the Appendix, indicating the maximum valuation for which purchasing would be the best response.

3 Experimental Design Overview, Procedures, and Data

3.1 Experimental Design and Procedures

Our experimental design constitutes a between-subjects design to investigate the demand response in the retail (baseline) and electricity markets. Table 2 indicates the dimensions of our experimental design.

Table 2: Experimental Design Overview

	Lab Setting	
	Baseline Mak et al. (2014)	Electricity Market Setting
Simple Dynamic Pricing	✓	✓

Notes: The experimental design constitutes a baseline treatment that captures consumer purchase decisions under dynamic pricing in the retail market, where consumers bear both price and inventory risk (i.e., there are only scarce products available in the market), while deciding whether or not to postpone their purchase. Our design includes an additional treatment mimicking demand response in the electricity market, where consumers observe only price uncertainty and use a devaluation rule while deciding on their purchasing decision.

The experiment was computerized using the software *z-Tree* for the economic laboratory experiments (Fischbacher, 2007). The experimental sessions have been conducted in the Laboratory for Economic Research *AIXperiment* at RWTH Aachen University in Aachen, Germany. Subjects were recruited using the online recruitment tool ORSEE (Grenier, 2015). Participants who are registered in the subjects pool and enrolled in various degree programs²⁰ at one of the universities in Aachen, were randomly invited. The original language of the experiment was German. Each subject participated in the experiment only once.²¹ After coming to the laboratory session, all subjects were randomly assigned to separate computer terminals and were instructed not to communicate. After each participant was seated, the experimenters have distributed the instructions. Subjects had enough time to finish reading the instructions and were asked to raise their hands in the case of questions or unclarities. An average session in both treatments lasted one and a half hours. When the experiment was over, subjects were asked to participate in an incentivized survey on risk preferences as well as a general socio-demographics, strategy-related additional survey. Each subject was paid out individually and the data were treated completely anonymously.

²⁰A considerable share of subjects are enrolled at engineering or other technically-oriented degree programs.

²¹There was an exceptional case of a subject appearing twice in the participation list for the two experimental sessions in the electricity treatment. We are aware that this incidence might potentially contaminate our session data. The knowledge acquired the first time might have an effect on subject's purchasing strategy the second time, hence leading to different outcomes for the aggregate demand and the P_2 levels observed as a result. To control for this, we look at the individual and aggregate behavior over the two sessions where the same subject has participated twice and confirm that there are no statistically significant differences between the two sessions. Additionally, we compare the aggregate buying behavior from the session the subject participated the second time with the data from the other sessions. By running a simple non-parametric Wilcoxon rank-sum test between sessions, we cannot reject the null hypothesis (which indicates that the distribution of the data points from the different sessions are identical), that is, there are no significant differences between this session and the others. Moreover, we observe that the overall payoff earned by the subject does not differ substantially between the sessions.

3.2 Data

Using a computerized and incentivized laboratory experiment – which constitutes a between-subjects design – we have executed five sessions during the Summer Term 2017²² for the baseline treatment and seven sessions during the Winter Term 2017/2018²³ for the electricity treatment. In each session we had twenty subjects participating in the experiment – mimicking a market with twenty participants. Each session consisted of sixty rounds and each round of two pricing periods. Hence, we gathered data from 100 subjects for the baseline and 140 for the electricity treatment over 60 rounds.

4 Results

4.1 Aggregate Strategic Buying Behavior

First, we analyze in how far consumers act strategically and play by the equilibrium predictions. Our findings so far confirm that consumers on average act as fully strategic buyers, confirming the results by Mak et al. (2014).²⁴ We capture the average behavior by looking into average demand in t_1 over the different sessions for each round and randomly (exogenously) chosen P_1 . The average t_1 demand is contingent on the randomly set P_1 at the beginning of each round, as the cutoff valuation changes based on P_1 .

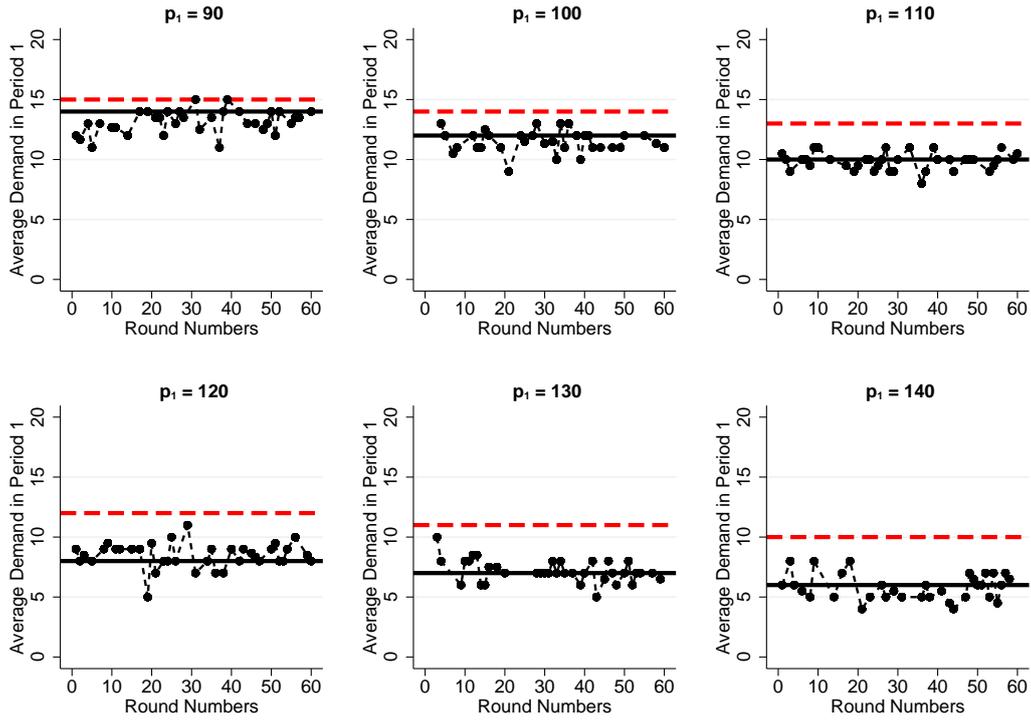
Figure 2 plots the average demand over all sessions in t_1 for different price levels observed in both treatments. The plotted dots represent the average demand in t_1 for each round and price level. While the black line indicates the equilibrium demand for the corresponding level of p_1 as listed in Table 1, the red dashed line marks the myopic demand for a given condition.

While plotted aggregate round demand in Figure 2a, indicates that consumers on average act as fully strategic buyers in the baseline setting, confirming the results by Mak et al. (2014), Figure 2b plots the aggregate t_1 round demand over all seven electricity sessions by different price levels. Similar to the baseline setting, we observe that the consumers buy strategically on average. This is observed as the plotted dots are either situated directly on the solid strategic equilibrium line or indicate only modest aggregate deviations of undergoing a more profitable purchase option. Individuals are worse off both by buying immediately, when waiting would have been the optimal decision and postponing their purchase when buying immediately would have been more profitable.

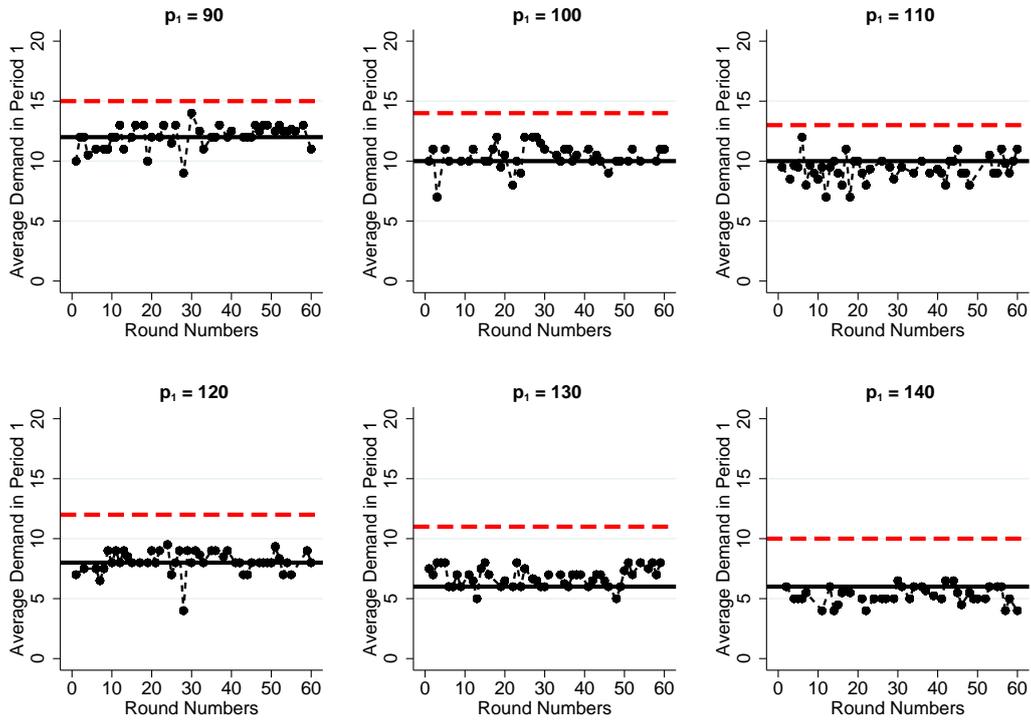
²²We conducted the baseline sessions in June and August 2017.

²³The sessions for the electricity setting have been conducted in January, February, and March 2018.

²⁴Note that while our experiment took place in Germany at RWTH Aachen University, the experiment by Mak et al. (2014) was conducted at another university outside Germany. We conclude that possible other unobserved differences between the subject pools do not play a significant role in this specific context, as we observe no significant differences in buying behavior across the samples.



(a) Baseline Treatment



(b) Electricity Treatment

Figure 2: Aggregate (Average) Round Demand in Period 1 by Different Price Levels

Notes: While the solid line indicates the strategic demand for different prices observed in t_1 , the dashed line shows the average demand over all baseline sessions for each round and price level. The red dashed line shows the myopic demand. While (a) shows the average demand in the baseline retail market, (b) includes the observations from the electricity market treatment.

4.2 Individual Buying Behavior and Deviations from Strategic Equilibrium

We further categorize the deviations from the equilibrium behavior into two main consumer segments: individuals who buy too soon (myopic behavior) and individuals who wait too long (irrational waiting). We do this by quantifying the individual deviations from the sub-game perfect equilibrium solutions in t_1 ²⁵, as indicated in Table 1. The deviation rates show how often an individual has bought immediately in t_1 or postponed buying irrationally to t_2 , undergoing a more profitable option in both cases over the sixty rounds. Hence the deviations refer to a percentage rate for each consumer. The calculation of the individual deviation rate for the myopic buying can be expressed as follows:

$$Dev_i^{myopia} = \frac{\sum_{r=1}^{60} D_{i=1}}{\sum_{r=1}^{60} V_i < c_i^*}. \quad (3)$$

The deviation rate for myopic buying is expressed as a fraction between the number of cases the individual buys immediately over the 60 rounds and the number of cases in which the individual has a valuation V_i lower than the cutoff valuation c_i^* , indicating how often the individual has undergone a more profitable option by not waiting.

The deviation rate for irrational waiting is expressed as a fraction between the number of cases the individual postpones his purchase over the 60 rounds and the number of cases in which the individual has a valuation V_i equal to or greater than the cutoff valuation c_i^* , indicating how often the individual has undergone a more profitable option by not buying immediately.

$$Dev_i^{waiting} = \frac{\sum_{r=1}^{60} D_{i=0}}{\sum_{r=1}^{60} V_i \leq c_i^*}. \quad (4)$$

We find the two groups to be statistically significantly different from each other. For the baseline treatment, our findings – confirming the results by Mak et al. (2014) – show that consumers are purchasing strategically on average with deviations from the equilibrium behavior. Furthermore, by using the original data from the experiment conducted by Mak et al. (2014), we perform nonparametric tests to assess whether the two independent samples are statistically significantly different from each other. Results indicate that the sample distributions differ between the two experiments.²⁶ Additionally, we find that the deviation becomes systematically smaller over the repeated rounds of the game, which suggests a potential learning effect.

Although the baseline and the electricity market settings are defined by similar monetary incentives and comprise comparable economic situations for the decision maker, we find signifi-

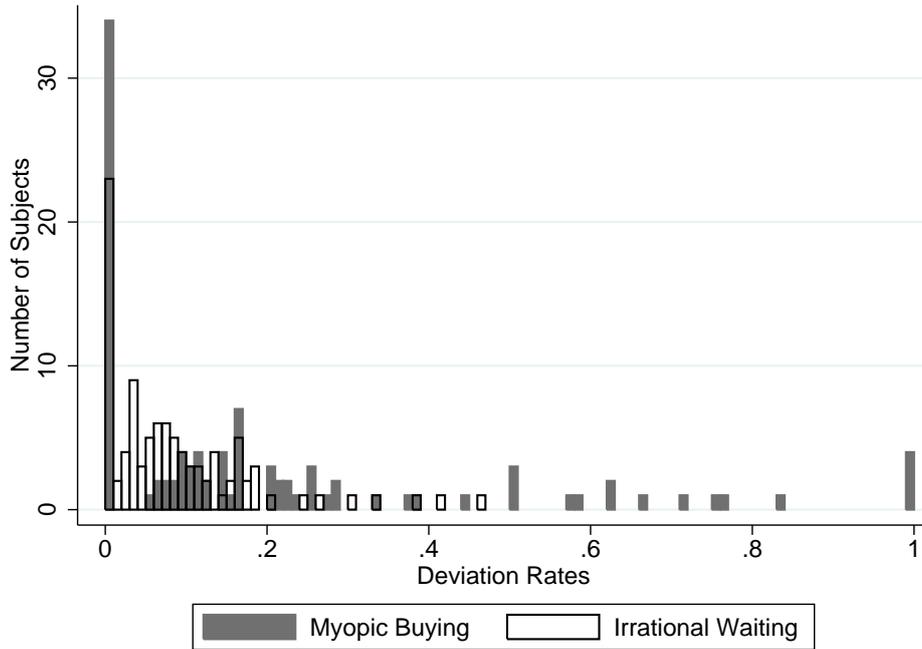
²⁵Note that deviation rates are calculated based on the purchasing behavior in t_1 , given that the decision to buy or postpone is based on the parameters observed in the first period. Upon receiving the information of market participants and the offered product capacity left in the market, the second period is played out automatically.

²⁶Results from the Wilcoxon rank-sum (Mann-Whitney) two-sample statistics test reveal a p -value of 0.000 for both myopia and irrational waiting deviation rates. Rejecting the null hypothesis that the sample distributions do not differ significantly from each other, implies that the two independent samples are drawn from populations with statistically significantly different distributions.

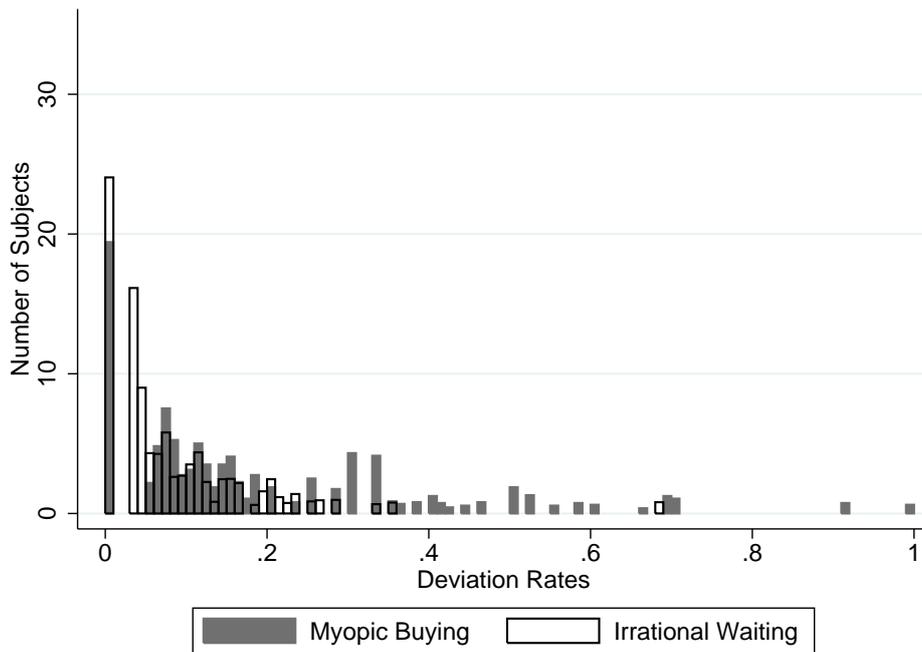
cant differences in the deviation from the equilibrium strategy, as the psychological setting differs substantially between the two treatments. We find that also in the electricity setting consumers buy on average strategically; however, we observe significantly more irrational waiting and less myopic buying. This is due to two main differences between the settings: (i) the product offered in the market is different with respect to scarcity, as there is no effective inventory constraint allowing the consumers purchase at any point, and (ii) consumer profits – if they postpone their consumption to the off-peak periods – are not discounted, but profits fall merely due to devaluation in the electricity setting. Two main psychological effects are worth mentioning in the electricity market: the difference in P_2 becomes more salient and consumption in t_2 eliminates the risk factor of scarcity, making the decision of postponing (relatively) more attractive. While the absence of ‘scarcity’ in the market might explain the drop in the number of myopic buyers, the increase in the number of irrational waiters may be attributable to increased incentives in the electricity setting.

Figure 3 indicates the distribution of the deviation rates for myopic buying and irrational waiting in both online retail market with scarce seasonal products as well as the electricity market. The figure shows a marked difference in the distribution of the deviation rates between the two experimental settings. While the consumers demonstrate significantly more myopic buying behavior in the baseline treatment, we observe more irrational waiting in the electricity market treatment.

The deviation from the strategic behavior differs significantly from the baseline treatment. In the electricity market setting, we observe a notably higher share of irrational waiters and a lower share of myopic buyers. Two psychological mechanisms might explain the observed difference between the settings: While the decrease in the myopic consumer segment can be attributed to the absence of product scarcity, the increase in irrational waiting can be explained by the increased incentives to ‘rationally’ wait in the electricity setting.



(a) Baseline Treatment



(b) Electricity Treatment

Figure 3: Distribution of Deviation Rates for Myopic Buying and Irrational Waiting

Notes: The figure indicates the deviation rates, defined as a ratio between the total number of cases the subject actually executed myopic buying or irrational waiting behavior and the number of cases he or she can potentially execute it. Myopic buying rate is determined as a ratio between the total number of cases the buyer has purchased immediately in t_1 , even though that subject's randomly drawn valuation was lower than the cutoff valuation, divided by the total number of rounds the subject had a randomly assigned valuation lower than the cutoff valuation in t_1 of that round. Similarly, we define the irrational waiting rate as a ratio between the total number of rounds the buyer postponed his or her purchase to t_2 , even though that subject's randomly drawn valuation was higher than the cutoff valuation, divided by the number of total number of rounds the subject has a randomly assigned valuation higher than the cutoff valuation in t_1 of that round.

4.3 Explaining the Deviation Rates

Several possible margins explain the individual deviation rates from the equilibrium behavior. The risk neutrality assumptions both in the baseline and in the electricity treatment are strong, since risk aversion, known from various contexts, is a significant predictor for decision making under uncertainty (Chavas and Holt, 1996; Dow and Costa Werlang, 1992). To control for this assumption, we include a standard incentivized risk questionnaire at the end of each treatment, which aims to scale the risk aversion at the individual level. In the risk questionnaire participants choose between a pair of options, where the first option is to receive a payoff for sure and the second option is to receive a higher payoff with a probability that ranges from 10% to 100% in a consistently increasing scale.²⁷

While we find no statistically significant relationship between myopic consumption and risk aversion²⁸, risk aversion correlates significantly with irrational waiting in the baseline setting, as indicated in Figure 4. The former finding can be explained in the light of the role ‘discounting’ plays in the model. Buying immediately, effectively, refers to a discount factor of zero, which means there is theoretically no economic risk associated with myopic buying in the set-up. This means that myopic buying itself is not associated with any uncertainty in this setting. The latter finding is in line with the expectation that those who more risk averse are more likely to buy in t_1 and those who are less risk averse are more likely to postpone their purchase and take the price risk in this context.

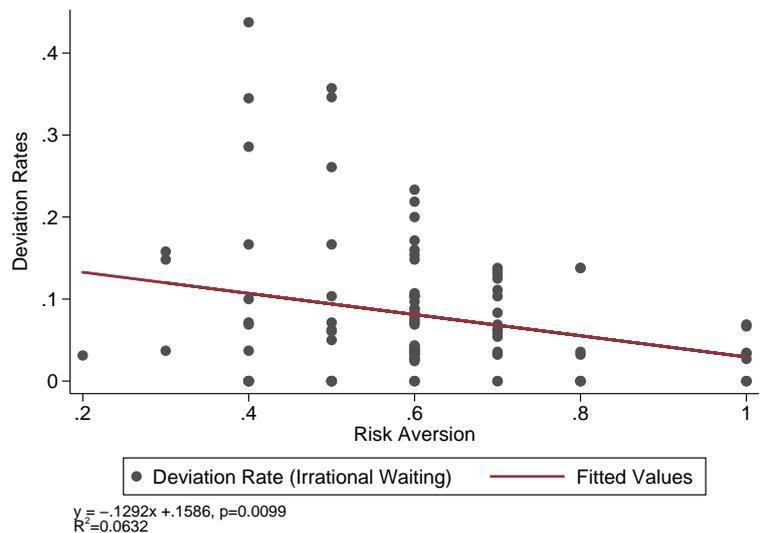


Figure 4: Irrational Waiting and Risk Aversion

Notes: The scatter plot indicates the correlation between irrational waiting and individual risk aversion in the baseline treatment. Each dot represents a data point and scales it between the deviation rates for the irrational waiting on the y-axis and the risk aversion on the x-axis. The solid red line shows the basic level-level OLS fit between the two indicators. At the bottom of the figure, the results from the OLS regression are reported, the p-value indicating that the correlation between the variables is significant at the 1% level.

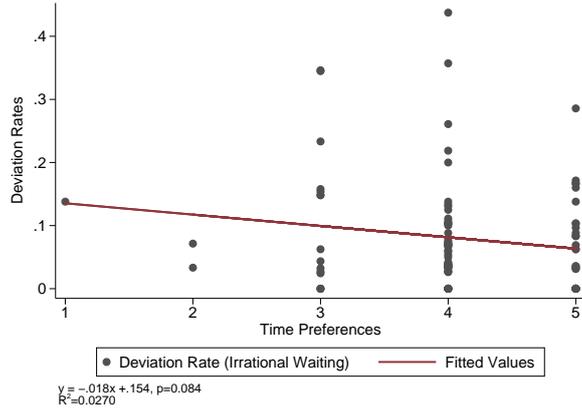
Although we find that the sign of the coefficient indicates a similar economic relationship as

²⁷For the screenshot of the risk questionnaire, see Appendix C.

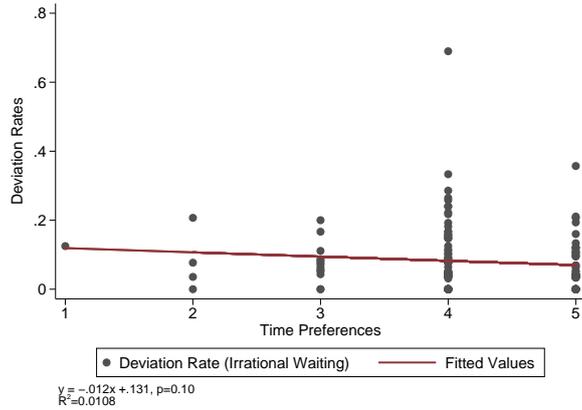
²⁸The results from simple OLS regressions indicate a p-value of 0.442 for the baseline and of 0.668 for the electricity setting.

in the baseline setting, risk aversion and irrational waiting are not statistically significantly correlated at the conventional levels in the electricity market treatment²⁹. This might be due to the elimination of the inventory uncertainty in the electricity treatment.

Additionally, in the post-experiment survey questionnaire we include a qualitative measure for the time preferences, using the survey question of Falk et al. (2016) with a 5-point Likert scale. While myopic buying is not statistically significantly correlated³⁰ with the time preferences, irrational waiting is in both settings (at the 10% level). Figure 5 illustrates this relationship.



(a) Baseline Treatment



(b) Electricity Treatment

Figure 5: Irrational Waiting and Time Preferences

Notes: The scatter plots indicate the correlation between irrational waiting and individual time preferences. Each dot represents a data point and scales it between time preferences on the x-axis and the deviation rates for the irrational waiting on the y-axis. The solid red line shows the basic level-level OLS fit between the two indicators. At the bottom of the figure, the results from the OLS regression are reported, the p -value indicating that the correlation between the variables is significant at the 10% level.

5 Discussion and Conclusions

Our results show that consumers, on average, buy strategically under dynamic pricing in the retail and electricity markets – confirming the findings of the study by Mak et al. (2014) on

²⁹This is observed with a p -value of 0.4603.

³⁰Running simple OLS regressions indicate p -values of 0.606 for the electricity and of 0.930 for the baseline treatment.

the retail market with scarce products. We further observe that individual deviations from the equilibrium strategy occur systematically over the rounds (e.g., we observe a number of subjects that play only myopically during the entire game, whenever they can execute myopic buying) in both treatments. Yet, the share of consumer segments for the deviation rates differ significantly between the treatments. That is, we observe less ‘myopic buying’ in the electricity treatment and instead a significantly higher share of consumers who wait irrationally. Part of this observation might be attributable to the increased salience of the price decrease between P_1 and P_2 . Moreover, in the electricity market consumers typically do not face scarcity of the available products, which puts a psychological constraint on the buyer, as each buyer bears the risk that he or she cannot purchase the good if the buyer decides to postpone the purchasing decision until t_2 . This explains the higher share of myopic buyers in the baseline setting and the higher share of irrational waiting in the electricity market.

We look into risk attitude as a possible source of explanation for the deviation rates. Since consumers who decide to buy in t_1 do not discount their payoff ($\delta = 0$), we do not expect to find a statistically significant relationship between myopia and risk aversion. Yet, we observe a statistically significant relationship between risk aversion and irrational waiting for the baseline treatment. That is, subjects who are risk-averse are less likely to postpone their purchase to t_2 and wait irrationally. This observation is in line with the theoretical expectation, since those buyers who purchase in t_2 use a discount factor ($\delta = 0.5$) while calculating their net payoff.

Our results have important policy implications in favor of automation of the demand response, as there are consumer segments that systematically deviate from the equilibrium behavior. While on average demand response would be effective, there is a significant heterogeneity across different consumer segments. This suggests that implementing dynamic pricing would burden especially those consumer segments that are most prone to systematic deviations and behavioral anomalies. The aggregate behavior suggests, however, that these would on average cancel each other out. Hence, automating demand response would be consumer-friendly and benefit most of those consumers who demonstrate to be most ‘behavioral’. Understanding whether the costs of automation outweigh the costs incurred by consumers under dynamic pricing should be investigated in future research.

Future research might address some of the limitations of this study. For instance, including a seller who (i) is not a monopolist and (ii) sets prices in both periods optimally would make the setting more realistic, while the latter causing both pricing periods to be endogenous. In this case, the sub-game perfect equilibria can be calculated probabilistically, based on how the seller updates his prior beliefs.

Finally, we are able to implement a cost-effective lab tool for the electricity market using a very simple decision setting, which can then be extended and applied for testing further behavioral interventions in the demand response domain. Deviations from strategy can further be tested and the external validity of the setting be corroborated in a randomized field trial.

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Appendix A: Instructions for both Treatments

A.1: Baseline Treatment (Translated from German)

Instruction

Welcome to a decision-making experiment. You are about to participate in a computer-controlled experiment on buying perishable goods in a small market. Please read the instructions carefully. If you follow them, you may earn a considerable amount of money. Your earnings depend on your decision and the other participants' decisions. This will be explained below.

The unit of transaction in this experiment is called point. At the end of the session, your earnings will be converted to Euros at the rate of 200 points = 1 EUR. These will be paid to you in cash.

After entering the laboratory, we ask you not to communicate with the other participants. If one or more participants do communicate with one another, then the session will be terminated. If you have any questions before or during the experiment, please raise your hand and the experimenter will come to assist you.

Description of the Task

The experiment is concerned with a monopolist (hereafter called **seller**), who wishes to sell **16** units of a perishable good in a market with **20** consumers (hereafter called **buyers**). The selling season (hereafter called **round**) consists of two periods, referred to as period 1, t_1 , and period 2, t_2 . In each period every buyer may purchase **at most a single unit** of the good. The experiment consists of 60 identical rounds that are structured in exactly the same way.

Period 1

The 20 participants are all assigned the role of **buyers**. The seller is played by a central computer. In every round, the seller is provided with an inventory of 16 units of the good. Inventory cannot be replenished during the round.

The task proceeds as follows. At the beginning of t_1 , the (computerized) seller will decide on an asking price per unit good for t_1 , namely, the price it charges for each unit of its inventory. Its price will be a multiple of 10 (i.e., 0, 10, 20, 30, ...).

The buyers will be presented with a Period 1 Buyer Screen (illustrated below). The screen displays the period number (1 in this example), the value of a unit of good for this particular buyer (150 in this example), the seller's asking price (100 in this example), and the profit for

the buyer if she purchases a unit of the good in period 1 ($150-100=50$ in this example).

*Please notice: As a buyer your value is the **maximum price** you should be willing to pay for a unit good. Buyers' values differ from one buyer to another. In this experiment, buyer values are randomly sampled from a set of values between 45 and 235 in intervals of 10 (i.e., 45, 55, 65, ..., 215, 225, 235). In other words, each buyer has an equal chance of being assigned any one of the twenty possible values.*

After you have observed the value and the asking price, each buyer will be asked to respond YES or NO, depending on whether the purchaser wishes to purchase a unit of the goods in period 1 for the price of the seller or not.

Period 1 Buyer Screen

Round: 1
Total Score: 0.0

This is period 1

Your valuation is:	185
Seller's asking price is:	90
Available units of inventory for purchase:	16
If you decide to purchase, you will earn:	95

Would you like to try to buy an inventory?

No
Yes

Please make your decision

- If the buyer responds YES, then he or she will purchase a unit of the good if the total number of buyers responding YES is equal to, or smaller than, the seller's inventory (16 units). If more than 16 buyers respond YES, then 16 buyers will be randomly chosen among them to purchase the good in period 1.
- If the buyer responds NO, then he or she will have the opportunity to purchase the good in the next period (if there are units left from the previous period).

Summary of Period 1

- The (computerized) seller is assigned an initial inventory of 16 units of the good.

- The (computerized) seller chooses an asking price per unit of the good 0, 10, 20, 30, ...
- Each buyer is assigned a value (maximum buying price) of the good randomly distributed between 45 and 235, i.e., 45, 55, ..., 225, 235.
- The buyer responds YES or NO to the question whether or not he or she wants to purchase the good in period 1.
 - If fewer than 16 buyers ask to buy, then they all purchase the good, and the round moves to period 2 with the remaining inventory.
 - If exactly 16 buyers ask to buy, then the entire seller's inventory is sold and the round is over.
 - If more than 16 buyers ask to buy, then 16 of them are randomly chosen to purchase the good, the entire inventory is sold, and the round is over.

Please notice: Buyers have an option to delay their purchase to period 2. Even if he or she can make a profit in period 1, buyers may prefer to wait with their request for purchase to period 2.

Period 2

Please notice: The difference between periods 1 and 2 is that the profits in period 2 are discounted. Each buyer who purchases a unit during period 2 is only paid 50% of her potential profit in this round.

Similar to period 1, the seller first sets a price. Then, the seller chooses an asking price, which may be higher, equal, or lower than the asking price chosen earlier in period 1.

Please notice: The computerized seller will choose his price with the aim of maximizing its profit in period 2.

In contrast to period 1, in period 2 buyers will not have to decide whether or not to purchase the item at the new asking price. Under the assumption that buyers would rather earn a profit than not, all the players who have a value that is higher than the period 2 asking price will automatically purchase the item and receive the discounted profit.

Example: Once the computer figures out who among the buyers purchase(s) the item in period 2, all players are presented with the results of the round. Below is an example of the Round Results Screen. In this example, the buyers' value was 150 and the seller's in period 1 was 100. Eleven players decided to purchase at that price in period 1, so that 5 units were left in the seller's inventory after that period. Trying to maximize its profit, the seller sets the period 2 price at 80. Since this price is lower than the player's value, the buyer automatically purchases in period 2 and the resulting profit is $0.5 \times (150 - 80) = 35$. Please note that due to the period 2 discounting, the profit for this period is only 50% of the difference between value and asking price.

Round Results Screen

Round: 1
Total Score: 0.0

Result

Your valuation was: 185

Seller's asking price in period 1 was: 90

You have decided to purchase in period 1.

Remaining inventory after period 1 was: 14

Seller's asking price in period 2 was: 110

You have purchased an inventory in period 1.

Therefore, your profit is: 95

Please press "Next" to continue.

History

Round: 2
Total Score: 95.0

Round	Your Valuation	Start Inventory (P1)	Price (P1)	No. of Buyers (P1)	End Inventory (P1)	Price (P2)	No. of Buyers (P2)	End Inventory (P2)
1	185	19	90	2	14	110	0	14

At any stage during the game you may press the History Button in order to review information about your previous decisions and the outcomes of all previous rounds. An example of the History Screen is displayed below. It shows that in period 1 of round 1, the particular participant had a value of 150, the seller priced the item at 100 and, consequently, sold 11 units at that price. In period 2 of the same round, the seller's asking price was 80, and 5 more players purchased at that price.

Press the button **Back** to return to the game after inspecting the past history on previous rounds.

Questionnaire

After you have completed playing 60 rounds, you will be asked to respond to a questionnaire in which you have to choose between pairs of gambles. At the end of the session, you will also be paid for one of your choices chosen by chance.

How will you be paid?

The session will include 60 identical rounds with values randomly assigned in each round. Your total earnings will be converted to Euros at the rate of 200 points = 1 EUR. In addition, you will receive a 5 EUR participation bonus plus the payment for completing the questionnaire. The payment will be made at the end of the session in private and in cash. All the earnings are confidential.

Please place the instructions on the table in front of you to indicate that you have completed reading them. The experiment will begin shortly. Please remember that no communication is allowed during the experiment. If you encounter any difficulties, please raise your hand and an experimenter will come to assist you.

Thank you.

A.2: Electricity Treatment (Translated from German)

Instruction

Welcome to a decision-making experiment. You are about to participate in a computer-controlled experiment on buying perishable goods in a small market. Please read the instructions carefully. If you follow them, you may earn a considerable amount of money. Your earnings depend on your decision and the other participants' decisions. This will be explained below.

The unit of transaction in this experiment is called point. At the end of the session, your earnings will be converted to Euros at the rate of 200 points = 1 EUR. These will be paid to you in cash.

After entering the laboratory, we ask you not to communicate with the other participants. If one or more participants do communicate with one another, then the session will be terminated. If you have any questions before or during the experiment, please raise your hand and the experimenter will come to assist you.

Description of the Task

The experiment is concerned with a monopolist (hereafter called **seller**), who wishes to sell **20** units of a perishable product in a market with **20** consumers (hereafter called **buyers**). The selling round (hereafter called **round**) consists of two periods, referred to as period 1 and period 2. In each period every buyer may purchase **at most a single unit** of the good. The experiment consists of 60 identical rounds that are structured in exactly the same way.

Period 1

The 20 participants are all assigned the role of **buyers**. The seller is played by a central computer. In every round, the seller is provided with a total capacity of 20 units of the product. The capacity cannot be replenished during the round.

The task proceeds as follows. At the beginning of period 1, the (computerized) seller will decide on an asking price per unit for period 1, namely, the price it charges for each unit of its total capacity. Its price will be a multiple of 10 (i.e., 0, 10, 20, 30, ...).

The buyers will be presented with a Period 1 Buyer Screen (illustrated below). The screen displays the period number (1 in this example), the value of a unit of product for this particular buyer (150 in this example), the seller's asking price (100 in this example), and the profit for the buyer if she purchases a unit of the product in period 1 (150 - 100 = 50 in this example).

*Please notice: As a buyer your value is the **maximum price** you should be willing*

to pay for a unit good. Buyers' values differ from one buyer to another. In this experiment, buyer values are randomly sampled from a set of values between 45 and 235 in intervals of 10 (i.e., 45, 55, 65, ..., 215, 225, 235). In other words, each buyer has an equal chance of being assigned any one of the twenty possible values.

After you have observed the value and the asking price, each buyer will be asked to respond YES or NO, depending on whether the purchaser wishes to purchase a unit of the product in period 1 for the price of the seller or not.

Period 1 Buyer Screen

Round: 1
Total Score: 0.0

This is period 1

Your valuation is: 150
Seller's asking price is: 100
Available units of capacity for purchase: 20
If you decide to purchase, you will earn: 50

Would you like to try to purchase?

No
Yes

Overview of previous rounds

Please make your decision

- If the buyer responds YES, then he or she will purchase a unit of the product.
- If the buyer responds NO, then he or she will have the opportunity to purchase the product in the next period (if there are units left from the previous period).

Summary of Period 1

- The (computerized) seller is assigned a total capacity of 20 units of the product.
- The (computerized) seller chooses an asking price per unit of the product 0, 10, 20, 30, ...
- Each buyer is assigned a value (maximum buying price) randomly distributed between 45 and 235, i.e., 45, 55, ..., 225, 235.
- The buyer responds YES or NO to the question whether or not he or she wants to purchase the product in period 1.

- If fewer than 20 buyers ask to buy, then they all purchase the product, and the round moves to period 2 with the remaining capacity.
- If exactly 20 buyers ask to buy, then the entire seller’s capacity is sold and the round is over.

Please notice: Buyers have an option to delay their purchase to period 2. Even if buyers can make a profit in period 1, they may prefer to wait with their request for purchase to period 2.

Period 2

Please notice: The difference between periods 1 and 2 is the reduction of the value in period 2. The depreciation implies that any buyer who purchases a product during period 2 is only willing to pay 50% of the original value. This means that the value a buyer is provided with for purchasing the product decreases by 50% in period 2 compared to period 1.

Similar to period 1, the seller first sets a price. Then, the seller chooses an asking price, which may be higher, equal, or lower than the asking price chosen earlier in period 1.

Please notice: The computerized seller will choose its price with the aim of maximizing its profit in period 2.

In contrast to period 1, in period 2 buyers will not have to decide whether or not to purchase the item at the new asking price. Under the assumption that buyers would rather earn a profit than not, all the players who have a value that is higher (reduced) than the period 2 asking price will automatically purchase the product and receive the associated profit.

Example: Once the computer figures out who among the buyers purchase(s) the product in period 2, all players are presented with the results of the round. Below is an example of the Round Results Screen. In this example, the buyers’ value was 150 and the seller’s in period 1 was 100. Eleven players decided to purchase at that price in period 1, so that 9 units were left for the next period. Trying to maximize its profit, the seller sets the period 2 price at 30. Since this price is lower than 50% of the player’s value, the buyer automatically purchases the product and the resulting profit is $(0.5 \times 150) - 30 = 45$. Please note that due to the purchase in period 2, the value of the buyer for this period is only 50% of the original value due to the reduction.

Round Results Screen

Round: 1
Total Score: 0.0

Result

Your valuation was: 150

Seller's asking price was: 100

You have decided against a purchase in period 1.

Remaining units after period 1 was: 9

Seller's asking price in period 2 was: 30

You have purchased a unit in period 2.

Therefore, your profit is: 45.0

Please press "Next" to continue.

History

Round: 2
Total Score: 0.0

Round	Your Valuation	Start Capacity (P1)	Price (P1)	No. of Buyers (P1)	End Capacity (P1)	Price (P2)	No. of Buyers (P2)	End Capacity (P2)
1	150	20	100	11	9	30	7	2

At any stage during the game you may press the History Button in order to review information about your previous decisions and the outcomes of all previous rounds. An example of the History Screen is displayed below. It shows that in period 1 of round 1, the particular participant had a value of 150, the seller priced the item at 100, and consequently it sold 11 units at that price. In period 2 of the same round, the seller's asking price was 30, and 7 more players purchased at that price.

Press the button **Back** to return to the game after inspecting the past history on previous rounds.

Questionnaire

After you have completed playing 60 rounds, you will be asked to respond to a questionnaire in which you have to choose between pairs of gambles. At the end of the session, you will also be paid for one of your choices chosen by chance.

How will you be paid?

The session will include 60 identical rounds with values randomly assigned in each round. Your total earnings will be converted to Euros at the rate of 200 points = 1 EUR. In addition, you will receive a 5 EUR participation bonus plus the payment for completing the questionnaire. The payment will be made at the end of the session in private and in cash. All the earnings are confidential.

Please place the instructions on the table in front of you to indicate that you have completed reading them. The experiment will begin shortly. Please remember that no communication is allowed during the experiment. If you encounter any difficulties, please raise your hand and an experimenter will come to assist you.

Thank you.

Appendix B: Equilibrium Calculations and Determining the Optimal P_2

Equilibrium Calculations in the Experiment

The parameters from the continuous model are discretized in the experiment. There are 20 consumers in the market and each receives a valuation from a discretely distributed set of $V = \{45, 55, \dots, 235\}$. Different levels of $P_1 = \{90, 100, 110, 130, 130, 140\}$ are selected based on two major motivations: (i) to keep the electricity setting as comparable as possible to the baseline, (ii) as they lead to a two period selling and model consistent t_2 outcomes. Moreover, having a distinct set of period 1 prices increases the variation in the strategic equilibrium behavior, allowing for heterogeneity in possible deviations from the strategic behavior.

Determining the Optimal P_2

We use, as argued in Mak et al. (2014), the theoretical concept of rational expectations to determine the unique equilibrium conditions. This concept indicates that each player forms consistent beliefs about what all the other players will do for the rest of each round, contingent on the information on the history of the game available to them. Using this framework enables us to compare our findings to those of the baseline study and serves as a reasonable baseline to define equilibrium strategy in which outcomes depend not only on the player's decision, but also on the decisions of the other players.

The automated seller in each treatment determines the corresponding P_2 as a function of the remaining units of inventory (or capacity) left in the market. Following the simplifying assumption that the seller is a monopolist, whose objective is to maximize profits, we end up having a number of tie cases for the equilibrium calculations. In these cases, for a given remaining inventory level, there are two different P_2 prices that produce the same profit for the seller. However, using the rational expectations framework, we are able to report in Table B1 the only P_2 , which is consistent with the above mentioned assumption on player's expectations of how the others will do in the game.

In these tie cases, we have to consider an additional scenario for the remaining inventory (or capacity) level to check for model consistency. That is, one has to consider the off-the-equilibrium path for which the buyer with the cutoff valuation (which indicates the lowest valuation among the buyers, for whom buying in t_1 is still the best response) decides to wait instead of buying. Hence, this makes the prior inventory level relevant for the equilibrium calculations.

Let us demonstrate this with the example of a remaining capacity level of 10 in the electricity setup: the P_2 can either be 30 or 40 in this case and both can be consistent with a period 1 price of 90 and a cutoff valuation of 145. By considering the consistency with the rational expectations framework, the remaining inventory level of 9 becomes relevant for the possibility that it produces the same decision outcomes. In the case of a remaining inventory of 9, the buyer with the cutoff valuation – 135 in this case – has to decide between buying and waiting in period 1. For the case in which the buyer with the cutoff valuation decides to wait (which is referred

as off-the-equilibrium path), the same aggregate decision outcome of a remaining inventory of 10 and the cutoff valuation of 145 can be observed. We apply a procedure to decide on the unique P_2 level that satisfies the following inequality conditions for both the ‘equilibrium’ and ‘off-the-equilibrium’ paths:

$$c^* - 10 - P_1 < 0.5c^* - P_2^{c^*+10} \quad (5)$$

which can be rearranged and expressed as:

$$c^* \geq 2P_1 - 2P_2^{c^*+10}$$

The inequality 5 expresses the above mentioned condition. Where c^* is the cutoff valuation and $c^* + 10$ in $0.5c^* - P_2^{c^*+10}$ refers to the case in which the buyer with the cutoff valuation c^* might deviate from the equilibrium – by deciding to wait instead of purchasing in t_1 – inducing a change in the seller’s optimal P_2 price.

$$c^* - 10 - P_1 < 0.5c^* - P_2^{c^*} \quad (6)$$

which can be expressed shortly as:

$$c^* < 2(P_1 + 10) - 2P_2^{c^*}$$

The second inequality, on the other hand, implies that the buyer with the valuation immediately lower than the cutoff valuation c^* , i.e., $c^* - 10$, would not purchase in t_1 .

Hence, we apply a procedure to consider both the equilibrium and off-the-equilibrium paths in the tie cases to determine the single P_2 that is consistent for the expectations of the players and hence with both paths. The model-consistent best response P_2 prices are listed in the Table B1 for both treatments.

In the first five experimental sessions of the electricity treatment, we have adopted a best response price, which is not model-consistent but is sub-game perfect and satisfies the buyer’s maximization problem for the revenue management. Precisely, we have only adopted the model-inconsistent prices for two remaining inventory levels – namely, the remaining inventory levels of 6 and 10. The price differences between the model-consistent and -inconsistent values are substantially very small. In the case of a remaining inventory of 6, we have adopted a P_2 of 30 instead of 20 and for the remaining inventory level of 10, we have adopted a P_2 of 40 instead of 20. While we are aware that players might update their beliefs throughout the game and learn with a specific P_1 and a remaining inventory level combination, a specific P_2 price is set, the selection of these prices do not change the equilibrium strategy and the cutoff value for buying in the first period. Moreover, assuming that upon observing the randomly chosen P_1 at the beginning of each round the buyer can compute the cutoff valuation and work out which P_2 to expect for each remaining inventory level and that the buyer knows that the seller decides using backward induction (with the crucial assumption that the consumers who buy have the highest valuation), this should not affect his expectations, given that the observed P_2 is in all

Table B1: Optimal P_2 in both Experimental Treatments

Baseline Treatment (Mak et al., 2014)			Electricity Market Treatment		
Remaining Inventory	v_{max}	P_2	Remaining Capacity	v_{max}	P_2
1	85	80	1	45	20
2	95	80	2	55	20
3	105	80	3	65	20
4	115	80	4	75	20
5	125	80	5	85	20
6	135	80	6	95	20
7	145	80	7	105	30
8	155	80	8	115	30
9	165	80	9	125	30
10	175	90	10	135	30
11	185	100	11	145	40
12	195	100	12	155	40
13	205	100	13	165	40
14	215	110	14	175	40
15	225	120	15	185	50
16	235	120	16	195	50
			17	205	50
			18	215	50
			19	225	60
			20	235	60

Notes: This table indicates the pre-programmed, model-consistent t_2 equilibrium prices for different levels of remaining inventory (or capacity) units as well as the maximum valuation after the first buying period.

cases absolutely in line with the assumption of a profit maximizing seller. Despite the fact that the instances for which the model-inconsistent P_2 levels appear throughout the sessions are seldom³¹, we also provide evidence for the above mentioned argument by testing the aggregate demand behavior in t_1 between the sessions with inconsistent P_2 levels and the ones with the consistent P_2 levels. Even though we believe the two cases should not change players' beliefs and as a result the expected t_1 demand and individual deviations, we conduct two additional sessions as a control for this. In these additional sessions, we only adapt the consistent values indicated as in Table B1. The Wilcoxon rank sum non-parametric test results indicate that we cannot reject the null hypothesis, which indicates that the average t_1 demand between the sessions is statistically not significantly different from zero.

³¹Throughout all five sessions inconsistent prices occur 13% of the time. The rates are heterogeneous among the sessions and for specific inventory levels. For example, the remaining inventory level of 6 appears only once in the second and third session and otherwise does not throughout the entire game for the other sessions. Yet, the appearance of inconsistent P_2 prices at the remaining inventory level of 10 is relevant in all five sessions. The model-inconsistent P_2 prices appear 6 times in the first session (10%), 8 times in the second session (13%), 5 times in the third session (8%), 10 times in the fourth session ($\sim 17\%$), and 9 times in the fifth session (15%).

Appendix C: Risk Questionnaire

The experiment is over.

Please choose between two options for each decision displayed. Please click on "Done" when you have made your decisions. The computer will randomly choose ONE of your choices and play the decision. Your payout is carried out from the resulting outcome. In contrast to the previous decisions, you are only asked for ONCE. Please be certain.

Decision 1	<input type="radio"/> 1€ profit for sure <input type="radio"/> 1/10 probability for 2€ profit - 9/10 probability for 0€ profit
Decision 2	<input type="radio"/> 1€ profit for sure <input type="radio"/> 2/10 probability for 2€ profit - 8/10 probability for 0€ profit
Decision 3	<input type="radio"/> 1€ profit for sure <input type="radio"/> 3/10 probability for 2€ profit - 7/10 probability for 0€ profit
Decision 4	<input type="radio"/> 1€ profit for sure <input type="radio"/> 4/10 probability for 2€ profit - 6/10 probability for 0€ profit
Decision 5	<input type="radio"/> 1€ profit for sure <input type="radio"/> 5/10 probability for 2€ profit - 5/10 probability for 0€ profit
Decision 6	<input type="radio"/> 1€ profit for sure <input type="radio"/> 6/10 probability for 2€ profit - 4/10 probability for 0€ profit
Decision 7	<input type="radio"/> 1€ profit for sure <input type="radio"/> 7/10 probability for 2€ profit - 3/10 probability for 0€ profit
Decision 8	<input type="radio"/> 1€ profit for sure <input type="radio"/> 8/10 probability for 2€ profit - 2/10 probability for 0€ profit
Decision 9	<input type="radio"/> 1€ profit for sure <input type="radio"/> 9/10 probability for 2€ profit - 1/10 probability for 0€ profit
Decision 10	<input type="radio"/> 1€ profit for sure <input type="radio"/> 10/10 probability for 2€ profit - 0/10 probability for 0€ profit

Done

Figure C0: Screenshot: Risk Questionnaire

List of the latest FCN Working Papers

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- Koenen J., Madlener R. (2018). Predictive Analysis of an Energy Trading Company's Outstanding Receivables Using Markov Chains, FCN Working Paper No. 1/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, January.
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- Pereira G.I., Specht J.M., Pereira da Silva P., Madlener R. (2018). Technology, Business Model, and Market Design Adaptation Toward Smart Electricity Distribution: Insights for Policy Making, FCN Working Paper No. 3/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, March.
- Heesen F., Madlener R. (2018). Revisiting Heat Energy Consumption: Household Production Theory Applied to Field Experimental Data, FCN Working Paper No. 4/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April.
- Atasoy A.T., Harmsen – van Hout M.J.W., Madlener R. (2018). Strategic Demand Response to Dynamic Pricing: A Lab Experiment for the Electricity Market, FCN Working Paper No. 5/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April.

2017

- Demikhovskiy M., Madlener R., Garbuzova-Schlifter M., Golov R. (2017). Energy Performance Contracting in Russia: A Real Options Approach on Project Valuation, FCN Working Paper No. 1/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, January.
- Frieling J., Madlener R. (2017). Fueling the US Economy: Energy as a Production Factor from the Great Depression Until Today, FCN Working Paper No. 2/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, February (revised May 2017).
- Risthaus K., Madlener R. (2017). Economic Analysis of Electricity Storage Based on Heat Pumps and Thermal Storage Units in Thermal Power Plants, FCN Working Paper No. 3/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, March.
- Schach M., Madlener R. (2017). Impacts of an Ice-Free Northeast Passage on LNG Markets and Geopolitics, FCN Working Paper No. 4/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April.
- Goebbels L., Madlener R. (2017). Resilience of a Modular Expansion Microgrid: Concepts, Indicators and Performance Evaluation, FCN Working Paper No. 5/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, May.
- Goebbels L., Madlener R. (2017). Investment Valuation of a Modular Expansion Microgrid: A Real Options Analysis, FCN Working Paper No. 6/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, May.
- Frieling J., Madlener R. (2017). The Turning Tide: How Energy Has Driven the Transformation of the British Economy Since the Industrial Revolution, FCN Working Paper No. 7/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, June.
- Walgern J., Peters L., Madlener R. (2017). Economic Evaluation of Maintenance Strategies for Offshore Wind Turbines Based on Condition Monitoring Systems, FCN Working Paper No. 8/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, July.
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- Schmitz H., Madlener R. (2017). Direct and Indirect Rebound Effects of German Households: A Linearized Almost Ideal Demand System Approach, FCN Working Paper No. 10/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.
- Hof E., Madlener R., Kukla P. (2017). Power-to-Gas for Rail Transport: Economic Evaluation and Concept for the Cost-Optimal Hydrogen Supply, FCN Working Paper No. 11/2017, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.
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