Cost misperceptions and energy consumption: Experimental evidence for present bias and biased price beliefs*

Madeline Werthschulte[†1] and Andreas Löschel[‡1, 2, 3, 4, 5]

[1]University of Münster, Germany

[2]Leibniz Centre for European Economic Research (ZEW), Mannheim, Germany

[3]Crawford School of Economics & Government, Australian National University, Australia

[4]Research Institute for Global Value Chains, University of International Business and Economics, China

[5]Fraunhofer Center for the Economics of Materials (CEM), Halle, Germany

Abstract

The aim of this study is to link variation in energy cost misperceptions to variation in households' energy consumption. The focus is on two sorts of misperceptions: First, present biased discounting of future energy costs and second, biased energy price beliefs. By running an artefactual field experiment with a representative

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†Email: werthschulte@uni-muenster.de

‡Email: loeschel@uni-muenster.de

sample of 711 participants, we gather incentivized measures of these two misperceptions and observe participant's revealed electricity consumption. Our main finding is that participants with present bias are predicted to consume on average 9% more electricity than participants with time-consistent discounting. Our results further suggest that neither the true marginal electricity price nor the expected marginal electricity price can predict electricity consumption. Taken together our results raise doubt in the effectiveness of classical price based policies in reducing households' energy consumption.

JEL Classification

C93, D15, D81, D91, Q49

Keywords

Energy consumption, present bias, price beliefs, field experiment

1 Introduction

Governmental policy aims at reducing energy consumption due to greenhouse gas emissions associated with energy production. With households making up a quarter of total energy consumption (AGEB, 2018), such reductions are possible through behavioral changes in households' energy consumption. A necessary condition for achieving such reductions is to understand the drivers of households' energy consumption (Allcott & Mullainathan, 2010). This study investigates misperceived energy costs as potential driver, in particular present biased discounting of energy costs and biased energy price beliefs. We seek to explain to what extent these energy cost misperceptions can predict households' energy consumption.

Energy costs may be misperceived due to the intermittent billing structure of energy consumption. Intermittent billing is a decisive feature of energy markets. In contrast to other goods, which are consumed and paid at the same point in time, energy consumption and payment are separated in time. Due to intermittent billing, the costs of energy consumption are only paid in recurring billing cycles while the benefits of consuming energy are experienced immediately. This reasoning holds independently of the billing frequency[1] and independently of fixed monthly charges. As long as households are not charged in real-time, they face an intertemporal trade-off between the immediate benefits of consuming energy and delayed payment of costs. Further, households receive information about their energy costs just infrequently. Therefore, intermittent billing can induce two sorts of misperceptions of energy costs: [1] present biased discounting of the future costs and [2] biased beliefs of energy prices.

If the household is present biased, future energy costs are quasi-hyperbolically discounted. Thus, the immediate benefits from consuming energy are overly weighted compared to household's own ex ante perspective. This induces time-inconsistent energy consumption decisions. Particularly, the consequence is an overconsumption of energy compared to a time-consistent discounting household. In case of uncertainty in energy prices, the energy consumption decision will depend on household's energy price expectations. If the expected energy price deviates from the true energy price, households consume too much or too little compared to a decision with unbiased beliefs, depending on the direction of the deviation. In the end, at the moment when comparing the marginal benefits from energy consumption to its marginal future costs, marginal costs may be misperceived and energy consumption may deviate from its true optimum.

[1] In our representative sample of German households, 17% are on monthly billing, leaving 83% on conducting meter readings and receiving energy bills just once a year.

However, to our knowledge, there is no experimental evidence on the extent to which present bias and biased energy price beliefs predict revealed energy consumption. To fill this gap, we run an artefactual field experiment (Harrison & List, 2004), with a representative sample of 711 participants. In multiple, incentivized decisions we elicit each participant's present bias and energy price beliefs. Further, because the experiment was operated through face-to-face interviews, we are able to observe participants' revealed electricity consumption: Each participant was asked to show her last electricity bill to the interviewer. Thus, we are able to derive robust, trustworthy estimates of each participant's kWh consumption, present bias and price beliefs. While controlling for a vast set of control variables, we link variation in present bias and price beliefs to variation in electricity consumed.

Our results show that present bias predicts a 9% increase in electricity consumption compared to time-consistent, exponential discounting participants. This relationship is significant at the 5%-level and robust to other specifications and including control variables. Importantly, the results remain robust upon controlling for the energy efficiency level of appliances. This suggests a link between present bias and energy consumption apart from the link between present bias and energy efficiency investments already discussed in a different literature strand (Bradford *et al.* (2017), Schleich *et al.* (2019)). Hence, we provide evidence in favor of present biased energy consumption due to the intertemporal trade-off between consumption and billing of energy. In contrast, our results show that neither the true marginal price of electricity nor the expected marginal price can predict electricity consumption. This points to either a nearly zero (expected) price elasticity or to households maximizing their utility from energy consumption with respect to another price misperception than the one covered in this study. Taken together, our results raise doubt in the effectiveness of classical price based interventions in reducing electricity consumption. Households seem not to maximize their utility from energy consumption with respect to their true energy price, and devalue energy costs quasi-hyperbolically. As we suggest present bias resulting from intermittent billing as a major explanation for households' energy consumption, changes in the billing structure, such as prepayment schemes[2] should be considered. Such changes in the billing structure, which dissolve the lag between consumption and payment, can be promising tools to combat both the associated internality and externality, and therefore increase overall welfare.

This research contributes to three strands of literature. First, it contributes the literature on intermittent billing. That literature examines inatttention and information effects of intermittent billing (Gilbert & Zivin (2014), Grubb & Osborne (2015), Sexton (2015), Wichman (2017)) and studies the effects of changes in billing schemes, such as automatic withdrawal of costs (Sexton, 2015), bill shock alerts (Grubb & Osborne, 2015), more frequent billing (Wichman, 2017) and prepaid meters (Jack & Smith, Forthcoming). However, none of these studies has focussed on present bias due to intermittent billing. Most related to our results is the literature providing evidence of present bias in credit card consumption (Shui & Ausubel (2005), Meier & Sprenger (2010), Kuchler & Pagel (2018)). Credit card consumption faces a trade-off similar to energy consumption, and can be considered as a special case of intermittent billing.

Second, our research contributes to the literature on experiments eliciting house-

[2]Energy prepayment schemes are already implemented in Great Britain. See for example `https://www.ukpower.co.uk/home_energy/prepayment-meters`. In related market structures, prepaid credit cards and prepaid cell phone tariffs are promoted to households as measures to avoid undesired costs.

holds' preference parameters and correlating them to energy outcomes. Among this literature Qiu *et al.* (2014), Fischbacher *et al.* (2015), Newell & Siikamäki (2015), Bradford *et al.* (2017), Heutel (2017) and Schleich *et al.* (2019) need to be mentioned. These studies focus on households' energy efficiency investments and correlate them with individual risk preferences, time preferences and social preferences elicited through incentivized experiments. Fischbacher *et al.* (2015) and Bradford *et al.* (2017) further consider stated energy consumption measures, such as summer temperature in home. These studies based on stated electricity consumption rely on participants recalling their energy consumption correctly and might thus suffer from hypothetical bias. There is no experimental literature correlating of revealed energy consumption with preference parameters.

Third, literature suggests a causal relationship between energy price uncertainty and revealed energy consumption (Brounen *et al.* (2013), Blasch *et al.* (2017)). In line with this research, Ito (2014) has shown that households do not react to marginal energy prices but to average energy prices. Further, Jessoe & Rapson (2014) find that the price elasticity triples once price changes are combined with information provision. However, none of these studies elicited revealed own energy price beliefs. Therefore, we contribute evidence on the (missing) relationship between expected energy prices and energy consumption, as well as variance in price beliefs and energy consumption, which both have not been studied before.

The following section 2 describes the elicitation of energy consumption and the explanatory variables, present bias and price beliefs. Section 3 gives the summary statistics before section 4 outlines the empirical strategy. Section 5 gives the results. Finally, section 6 concludes and discusses policy recommendations.

2 Measurement and elicitation of data

To elicit experimental data, 711 representative face-to-face interviews (CAPI) were conducted between December 2017 and January 2018[3]. Participants were recruited to be representative for the German population given federal state, population size, age and gender.

Dependent variable

To measure revealed energy consumption participants are asked to show their electricity bill of the last contracting year to the interviewer. To avoid a large dropout rate when asking for the electricity bill, participants were informed on this requirement upon recruitment[4]. Of the 711 conducted interviews, 554 participants were able to show their last electricity bill to the interviewer. To avoid hypothetical bias, we restrict the sample to the 554 participants as the true electricity consumption and true electricity price was only observed for them[5].

Present bias

Our estimation of present bias builds on the assumption that participants directly consume the experimental payment on receipt (Cohen *et al.*, Forthcoming). That is, there is no consumption smoothing of experimental payments. In particular, we employ the Double Multiple Price List (DMPL)-method by Andersen *et al.* (2008) and confront participants with three decision situations: [1] Trade-off between a

[3]Preference parameters were elicited in an incentivized manner in a first part of the survey, the control variables in a second part. The participants answered the questions of the first part themselves on the computer. No interviewer conducted more than 25 interviews to avoid interviewer-effects.

[4]This might have biased the price belief estimations towards its true value but the participants were not aware of the incentivized price belief questions upon recruitment. Hence, there was no visible necessity to the respondents to check and remember their marginal electricity price.

[5]Hereafter, energy consumption is coded as monthly consumption to be consistent with the time preference estimations, which are also on a monthly basis.

smaller payment paid today and a larger payment paid in one month, [2] trade-off between a smaller payment paid in one month and a larger payment paid in two months, [3] trade-off between a lottery and a safe payment. Decisions are assumed to be made from maximizing intertemporal utility:

$$U_t = u_t + \beta \sum_{i=t+1}^{T} \delta^{i-t} u_i,$$

with flow utility $u_t = y_t^\alpha$ from the experimental payments y_t at time t. Thus, we assume quasi-hyperbolic discounting involving a time-consistent exponential discounting parameter $\delta \leq 1$ and a time-inconsistent present bias parameter $\beta \leq 1$ (Laibson, 1997). Due to the change in valuation of future utility once the present is involved, present bias can induce a reversal of choices. However, with $\beta = 1$ the standard exponential discounting model is recovered and choices are time-consistent. The α-parameter measures risk preferences, a value of $\alpha < 1$ implies risk aversion, $\alpha = 1$ means risk neutrality and $\alpha > 1$ indicates risk seeking behavior. We estimate the three parameters β, δ and α jointly for each individual using the decisions situations [1], [2] and [3].

The three decision situations are presented in three Multiple Price Lists (MPLs) (Andersen *et al.*, 2008), each to identify one parameter. The first MPL models 31 decisions of either receiving EUR 100 today or of receiving a larger amount in one month. Across the 31 decisions the later payments increases from EUR 100 to EUR 175, in increments of EUR 2.50, while the earlier payment stays constant at EUR 100. The second MPL uses the same 31 monetary amounts with only the payment dates being shifted to the future. Hence, the decision was between receiving EUR 100 in one month or a larger payment in two months. For the third MPL participants are asked to decide between a lottery with equal chances of winning EUR 300 or EUR 0, and a safe payment (Falk *et al.* (2016), Koch & Nafziger (2019)). The safe payment increases in 31 decisions from EUR 0 to EUR 300, in increments of EUR 10. The lottery was the same in all decisions. In each MPL, for each of the 31 decisions, participants indicate which payment option they prefer. Thus, for the first MPL, participants will prefer the EUR 100 today to EUR 100 in one month, but with the later payments increasing participants will at some point switch and prefer the payment in one month. For the third MPL, participants will prefer the lottery over a safe payment of EUR 0, but due to the increasing safe payments, at some point participants will switch to prefer the safe payment[6].

For MPL $j \in 1, 2, 3$ we assume indifference between options at the mean value $\bar{y}^j$ between the two payment options at which the participant switches. As an example for the first MPL, if the participant prefers EUR 100 paid today over EUR 105 paid in one month and prefers EUR 107.50 paid in one month over EUR 100 paid today, we assume indifference at $\bar{y}^1 = 106.25$. The participant is indifferent between receiving EUR 100 today and receiving EUR 106.25 in one month.

[6]We present the MPLs with the staircase method (Abdellaoui *et al.* (2008), Falk *et al.* (2016), Haushofer *et al.* (2017), Riis-Vestergaard *et al.* (2018)), such that participants only had to make five consecutive decisions instead of 31. Due to this method, we do not allow for multiple switching points. There are 11 participants who never switched in the first MPL and 2 additional participants who never switched in the second MPL. Because these 13 participants were not willing to forgo EUR 100 a month earlier to get EUR 175 a month later, we exclude these participants. Further, we exclude 29 participants, who preferred the lottery when offered a safe payment of EUR 290. These excluded participants either did not understand the MPLs or did not trust in payments, as the resulting annual discounting rates and risk aversion parameters are not corresponding to other estimates reported in the literature.

Formally, indifference is given by:

$$
\begin{aligned}
&(1) \quad 100^{\alpha} = \beta\delta \cdot (\bar{y}^{1})^{\alpha} \\
&(2) \quad \beta\delta \cdot 100^{\alpha} = \beta\delta^{2} \cdot (\bar{y}^{2})^{\alpha} \\
&(3) \quad 0.5 \cdot 300^{\alpha} + 0.5 \cdot 0^{\alpha} = (\bar{y}^{3})^{\alpha}.
\end{aligned}
$$

Equation (1) gives the indifference equation of the first MPL. As this MPL involves a trade-off between a payment of EUR 100 today ($t = 0$) and a payment in one month ($t = 1$), the future payment is discounted by β and δ. Equation (2) gives the indifference equation of the second MPL. The trade-off is now between two future payments at $t = 1$ and $t = 2$. Equation (3) presents indifference for the third MPL. Both the lottery and the safe payment are paid immediately ($t = 0$), thus no discounting is involved and participants trade-off the expected utility from the lottery to the utility from the safe payment. These three equations are jointly solved for the three parameters β, δ and α for each participant[7].

Intuitively, if the participant switches in the first and second MPL at the same monetary amount, that is $\bar{y}^{1} = \bar{y}^{2}$, we measure $\beta = 1$. The participant is not present biased, but a time-consistent exponential discounter. If the participant switches in the first MPL at a higher amount than at the second MPL, i.e. $\bar{y}^{1} > \bar{y}^{2}$, a higher payment is needed to compensate for forgone present utility. The participant is present biased: $\beta < 1$. We speak of future bias if $\beta > 1$, i.e. less money is needed to compensate for forgone present utility compared to forgone future utility. The present bias parameter β serves as measure of energy cost misperceptions.

[7] See also Schleich *et al.* (2019).

Price beliefs

We elicit participants' electricity price beliefs by using the incentivized quadratic scoring rule (Trautmann & Kuilen, 2015). First, we explained the energy pricing system to the participants, containing a marginal energy price, paid per kilowatt-hour, and a base price. Then, for five price intervals, participants are asked to estimate the probability that their marginal electricity price of the last contracting year was inside that interval. The five price intervals, in Eurocent, are $[8-14]$, $[15-21]$, $[22-28]$, $[29-35]$, $[36-42]$[8]. The estimates in these five intervals are required to add to 100%. Alternatively, participants could state a 100%-probability that their electricity price is either lower than 8 Eurocent or higher than 42 Eurocent. Participants were informed that their payment depends on the precision of their estimations. With q_i being the stated probability for interval i, the participant received EUR $20 - 20 \cdot q_i^2$, if her true price was not inside the interval and EUR $20 - 20 \cdot (1 - q_i)^2$, if her true price was within the interval. The true electricity price paid was observed through the electricity bill which was shown to the interviewer after this question[9].

We gather the expected energy price $\mathbb{E}(p_b)$ and the variance in price beliefs $\sigma^2(p_b)$ by assuming a uniform distribution of price beliefs p_b within intervals and discrete jumps between intervals[10]. Intuitively, if the expected electricity price deviates

[8]Price intervals are chosen such that price estimations measured by Blasch *et al.* (2017) in a survey of 2000 households in Switzerland are largely covered.

[9]As a second measure of price uncertainty, we include a question asking participants for a point estimate of their electricity price paid in the last contracting year. The estimation is again incentivized with the quadratic scoring rule.

[10]If the participant states a 100%-probability that her price is lower than 8 Eurocent or higher than 42 Eurocent in the price intervals, we use the point estimate as expected energy price, if it fits to that statement. In two observations it was stated that there is a 100%-probability that the price is lower than 8 Eurocent but the point estimate was higher than 8 Eurocent. We exclude these observations. Further, if there is no answer to the point estimate but a 100%-probability is given to having a price lower than 8 Eurocent, we use 4 Eurocent as expected energy price. There are no equivalent observations in the 'higher than 42 Eurocent'-statement.

from the true energy price, the participant misperceives her energy costs. A larger variance in price beliefs indicates that the participant is less confident in her estimation. If numeraire utility is non-linear, the participant may counter risks from a larger variance in price beliefs with less energy consumption.

Control variables

Further preference measures serve as a first set of variables we control for in the regressions. In addition to risk preferences, α, and exponential discounting, δ, we also control for environmental preferences, which were elicited from the average of seven statements based on the OECD Greening Household Behaviour classification (OECD, 2014). In a second step, we control for characteristics of the house and the household by including the number of persons living in the household, the number of persons younger than eighteen living in the household and a categorical variable on the size of the dwelling. A third set of variables controls for socio-demographic characteristics of the participant. We observe age, gender, a categorical education variable, a dummy on whether the participant is employed and a categorical variable describing the participant's income status. In a fourth step, we include a categorical measure on the share of energy efficient light bulbs in the dwelling, including LED, compact fluorescent bulbs or halogen bulbs. The higher the categorical value, the higher is the share of energy efficient light bulbs.

Incentives

The explanatory variables, present bias and price beliefs, plus the risk aversion and exponential discounting elicitation are incentivized. In particular, each participant had a 3.5% chance that one of her decisions in the MPLs plus one price interval question plus the price point estimate question is chosen to be paid. The MPLs include high stake incentives. For the price beliefs we work with rather low stakes (maximum EUR 20) to ensure the necessary assumption of risk neutrality for incentive compatibility of the quadratic scoring rule (Trautmann & Kuilen, 2015).

After each interview, a computerized random mechanism decided whether the participant was selected for payment and which decision was selected. Payment logistics included a check. The check was directly given to the participant after the interview if the first MPL was chosen and if the participant chose the 'today' option. If the participant chose a delayed payment in the first MPL, or the second MPL was selected for payment, she received a check via mail on the chosen date. This payment method ensures constant transaction costs across time as the check needed to be refunded at all dates. If the third MPL was selected for payment, the interviewer gave a check on the monetary amount to the participant directly after the interview. If the participant chose the lottery in the selected decision, a computer determined the lottery outcome. Since the interviewers and the interviewing company are certified in terms of quality research[11] and the checks were registered, we believe our sample experienced low payment uncertainty. In total, 25 participants were paid an average amount of EUR 188.76, the minimum payment was EUR 0, the maximum payment was EUR 339.60.

3 Summary statistics

Table 1 gives the summary statistics of our main variables[12]. The average monthly energy consumption is 276.81 kWh, the standard deviation is 104.30. The smallest consumption is 83.5 kWh, the largest 676.25 kWh. These estimates compare quite

[11]They are certified as ESOMAR member (`https://www.esomar.org/what-we-do/code-guidelines`).

[12]Table A1 gives the summary statistics of the control variables.

Table 1: Summary statistics of energy consumption and explanatory variables

Variable	Average [Std. dev.]	Percentile 10th	25th	50th	75th	90th	N
kWh	276.81 [104.30]	158.00	198.00	268.00	328.83	413.00	535
β	1.13 [0.90]	0.96	1.00	1.00	1.04	1.15	514
$\mathbb{E}(p_b) - p$	-0.19 [9.29]	-9.22	-3.00	0.10	3.96	10.26	510
$\sigma^2(p_b)$	20.00 [24.58]	4.00	4.00	15.76	21.64	53	474

Note: Standard deviations in parentheses.

well to the statistics provided by Frondel *et al.* (2015). Accordingly, the average energy consumption we observe corresponds to the average energy consumption of a two-person household. Concerning the explanatory variables, Table 1 shows that the average present bias estimate is 1.13, suggesting a rather future biased sample. The median participant is a time-consistent discounter. 15% of our sample can be classified as present biased and 50% are future biased. However, our data includes some extreme future bias values (such as a $\beta = 12.31$), which also bring the average estimate upwards. Because we do not want to restrict our sample by some self-imposed rule about what could be outliers and the empirical magnitudes are not the point of this study, the further analysis pools the continuous present bias measure into three groups: individuals with present bias ($\beta < 1$), with future bias ($\beta > 1$) and with time-consistent discounting ($\beta = 1$) (see also Ashraf *et al.* (2006) and Meier & Sprenger (2010)).

Comparing estimates across studies is difficult because of different methodologies, samples, framing or stakes. One major difference to other studies is that the staircase method only allows for one switching point, such that our participants were forced to make consistent choices. Other studies report fewer outlier values because they exclude participants with multiple switching points (Bradford *et al.* (2017), Schleich *et al.* (2019)). Our median β-value is however in line with other estimates. Andreoni *et al.* (2015) estimate an average $\beta = 0.99$ when employing the DMPL method. Bradford *et al.* (2017) estimate an average $\beta = 1.02$. Schleich *et al.* (2019) estimate an average value of $\beta = 1$, with also a large share of participants being future biased. Burks *et al.* (2012) find 15% being present biased.

Considering price beliefs, the deviation between the expected and the true energy price exhibits conservative estimates with only slight underestimation on average. The reason might be the design of the price intervals with the middle interval containing most true energy prices. The distribution is, however, quite symmetric around zero, showing both over- and underestimation of energy prices[13]. The average variance in price beliefs is 20.00, where a variance of 4 means that the participant chooses one interval with certainty and a variance of 102 means that the participant puts equal probabilities on all five intervals. So participants have believed to have some idea about possible magnitudes of their energy price. We are not aware of other studies who have elicited incentivized own energy price beliefs.

Table A2 gives the distribution of the bias in price beliefs conditional on present bias. The distribution is broadly similar across individuals with present bias, with

[13]For the point estimates these intervals where not given. This contributes to an increase in the misperception towards an underestimation of around 9 Eurocent on average. Overall the distribution shows a strong tendency to underestimate the price of energy. The number of observations also decreases to 445, probably because it was much more difficult for participants to give an answer without the guidance of the intervals.

time-consistent discounting and future bias. If anything, then we find a more pronounced underestimation of the true energy price conditional on time-consistent discounting. Hence, participants have no systematic misperception over both domains, ruling out general confusion in answers.

4 Empirical strategy

Going back to our research question, we are interested in the extent to which cost misperceptions relate to energy consumption. Cost misperceptions encompass present bias and price beliefs. For a closer examination of present bias, we define as in Ashraf *et al.* (2006) and Meier & Sprenger (2010) two indicator variables based on the parametric estimations described above, indicating either *PresentBias* (i.e. $\beta < 1$) or *FutureBias* (i.e. $\beta > 1$). Time-consistent discounting (i.e. $\beta = 1$) will be the omitted category.[14]

If participants have biased energy price beliefs, their expected energy price instead of their true energy price will influence energy consumption. Further, the variance in price beliefs may impact energy consumption. Similar to Ito (2014), we run a regression including the true energy price p, the expected energy price $\mathbb{E}(p_b)$ and the variance $\sigma^2(p_b)$ in price beliefs. This allows us to test a model of biased energy price beliefs against a model of full information. If the coefficient of the true energy price is insignificant, whereas the coefficient of the expected energy price is significant, this would be evidence against a model of full information[15].

[14] As robustness check, we will use two alternative non-parametric indicator variables for present and future bias. The non-parametric estimations rely on either a switching point higher ($SP_{higher} = 1$) or lower ($SP_{lower} = 1$) in the first MPL than in the second MPL. The same switching point in both MPLs will be again the omitted category.

[15] An alternative measure of price beliefs will be the expected energy price given from the point estimation question. To distinguish between both expected price estimations, we will use the

All measures of $\mathbb{E}(p_b)$ and p will be in logarithms, to interpret them as (expected) price elasticity. The variance $\sigma^2(p_b)$ is standardized for interpretive reasons.

To analyze the relationship between energy consumption and cost misperceptions, we estimate the following equation:

$$\begin{aligned} log(kWh_i) = \gamma_0 + \gamma_1 PresentBias_i + \gamma_2 FutureBias_i + \gamma_3 log(p_i) + \gamma_4 log(\mathbb{E}(p_b)_i) \\ + \gamma_5 \sigma_i(p_b)^2 + \boldsymbol{\gamma_6 X_i} + \epsilon_i. \end{aligned}$$

The outcome is the logarithm of each participant's monthly kilowatt-hour consumption[16]. The coefficients are given by the γ-values, i is the index for each participant, $\boldsymbol{X}$ is a vector of all control variables and ϵ is the error term.

5 Results

The regressions on households' energy consumption are displayed in Table 2, using the parametric estimations of *PresentBias* and *FutureBias* as well as the expected price and variance from the price intervals. Control variables are subsequently added. The first set of control variables encompasses risk, environmental and time-consistent preferences. The second set covers household and dwelling characteristics. Socio-demographic characteristics of the participant are included in the third set of controls. Equipment with energy efficient appliances, measured through the share of energy efficient light bulbs, is included by the fourth set of

index 2 whenever we refer to the expected price from the point estimation question.

[16] As a robustness check we will use the logarithm of equalized kilowatt-hour consumption as outcome. Equalized kilowatt-hour consumption corrects the absolute kWh by the number of persons in the household.

controls. Robustness checks are provided in tables A3-A7[17].

Table 2 shows that present bias significantly positively correlates with electricity consumption. According to regression (1), participants with present bias are predicted to consume on average around 12% more electricity than individuals with time-consistent discounting. Accordingly, a t-test on equal kWh means of present biased and not present biased participants can be rejected at the 5%-level[18]. Once including the price misperceptions in specification (3), the estimate increases to 17% and stays significant at the 1%-level. As Table 2 (5) shows, the estimate decreases when including household and dwelling characteristics. Still, present biased participants are predicted to consume on average about 8% more electricity than time-consistent discounters. The estimate is significant at the 5%-level. In absolute amounts this is 22 kWh per month or 264 kWh per year. The drop in the estimate is caused by the present bias coefficient catching up some of the relation between household characteristics and electricity consumption in specification (1) to (4)[19]. In specification (6) of Table 2, the present bias estimate increases slightly to 9%. The difference to exponentially discounting participants remains significant at the 5%-level. Further, when testing the coefficient of present bias against the coefficient of future bias, equality of coefficients is rejected at the 5%-level.

Our finding is particularly remarkable given that specification (7) of Table 2 controls for energy efficiency investments. The estimate slightly drops, which is due to the relation between present bias and energy efficiency investmens on the one hand

[17]For more details on the robustness checks see footnote 14 for present bias, footnote 15 for price beliefs and footnote 16 for energy consumption.

[18]A Mann-Whitney test rejects the hypothesis of equal medians at the 5%-level.

[19]Table A6 investigates the attrition when including controls by keeping the number of observations constant throughout specifications. The results of A6 show that the drop in the present biased coefficient in Table 2 (4) is indeed caused by the inclusion of household characteristics, not by the reduced sample size.

Table 2: Regression results of electricity consumption on present bias and price beliefs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log(kWh)	log(kWh)	log(kWh)	log(kWh)	log(kWh)	log(kWh)	log(kWh)
PresentBias	0.123***		0.165***	0.160***	0.0848**	0.0917**	0.0868**
	(0.0465)		(0.0490)	(0.0572)	(0.0335)	(0.0390)	(0.0384)
FutureBias	0.0220		0.0453	0.0638	0.00373	0.00386	-0.00453
	(0.0372)		(0.0400)	(0.0443)	(0.0257)	(0.0300)	(0.0303)
log(p)		-0.172	-0.196	-0.0501	-0.111	0.0268	0.0493
		(0.284)	(0.278)	(0.299)	(0.250)	(0.274)	(0.276)
$\log(\mathbb{E}(p_b))$		0.0943	0.104	0.0245	-0.0647	-0.0640	-0.0425
		(0.1000)	(0.101)	(0.110)	(0.0664)	(0.0733)	(0.0739)
$\sigma^2(p_b)$		-0.00369	-0.00630	-0.0112	-0.00533	-0.00224	0.000261
		(0.0190)	(0.0194)	(0.0204)	(0.0126)	(0.0123)	(0.0122)
Control 1				X	X	X	X
Control 2					X	X	X
Control 3						X	X
Control 4							X
N	516	454	436	378	367	316	313
Adj. R^2	0.007	-0.004	0.013	0.006	0.651	0.625	0.630

Note: Present bias and future bias are estimated parametrically, price beliefs are estimated from price intervals. Robust standard errors are in parentheses. Significance levels: * : $p < 0.10$, ** : $p < 0.05$, *** : $p < 0.01$.

and energy efficiency investments and energy consumption on the other hand[20]. The robustness of the present bias estimate in specification (7) implies a relationship between present bias and energy consumption, holding energy efficiency investments constant. Therefore, we identify a channel between present bias and energy consumption beyond the investment channel already discussed in the literature (e.g. Gillingham & Palmer (2014), Bradford *et al.* (2017), Schleich *et al.* (2019)). Our initial motivation of intermittent billing causing a lag between consumption and payment of energy, and thus, causing present biased overconsumption of energy, seems to be a natural explanation for this additional channel.

None of the other explanatory variables has a significant relationship with electricity consumption. Noteworthy is that neither the true electricity price nor the expected electricity price can predict electricity consumption in any specification. This result is robust towards including all control variables. Further, the coefficient of the expected energy price is not significantly different from the coefficient of the true energy price. This supports both a nearly zero price elasticity and a different misperception in energy prices than the one studied here[21].

The results of Table 2 are remarkably robust across our various robustness checks. Both the parametric and non-parametric estimates of present bias are significant at the 5%-level for all tables. Also the size of the estimate remains constant, varying between 7% and 10% in specifications (3), (4) and (5) of all tables. The same

[20]In Table A3 and A5, a lower energy consumption is correlated at the 5%-level with having 'most' energy efficient lighting at home. In Table A7 the correlation between the share of energy efficient lightning and energy consumption is significant at the 1%-level.

[21]Existing literature provides support for low price elasticities. Just to mention a few, Reiss & White (2005) estimate a price elasticity of -0.39, Allcott (2011) estimates -0.1, Deryugina *et al.* (Forthcoming) estimate -0.09 in the short-run and -0.27 in the long-run. The results by Ito (2014) on the other hand provide evidence of households making their energy consumption choice with respect to their average energy price.

holds for the other explanatory variables. They remain insignificant through regressions. These results support the hypotheses that present bias positively relates to electricity consumption. Present biased participants discount the future electricity bill to a greater extent than non-present biased participants, which leads to an unintended overconsumption of electricity. However, we cannot support the hypothesis of price beliefs relating to electricity consumption. Interestingly, the true electricity price also cannot explain consumption behavior.

6 Conclusion

The aim of this study is to analyze the extent to which energy cost misperceptions can predict households' energy consumption. By understanding this relation, policy can implement corresponding strategies to decrease final energy consumption and accordingly contribute to lower carbon emissions. Attention is given to two sorts of energy cost misperceptions stemming from the intermittent billing structure of energy consumption: first, present biased discounting of future energy costs and second, biased energy price beliefs. By running an artefactual field experiment, we are able to gather incentivized measures of these two misperceptions.

By each participant making a series of decisions between earlier and later payments, some of them involving the present, we elicit individual present bias parameters. By asking participants to estimate the probability that their electricity price lies in certain price intervals, we elicit individual price beliefs. Further, because the experiment was operated through face-to-face interviews, we are able to observe participants' revealed electricity consumption and true electricity price. The measures of present bias and price beliefs are correlated with electricity consumption. To our knowledge, this is the first study correlating preference parameters to revealed electricity consumption. Further, this is the first study eliciting participants' energy price beliefs in an incentivized manner.

Our main result is the significant correlation between present bias and electricity consumption, which stays robust upon including control variables and across specifications. Participants with present bias are predicted to consume on average 9% more electricity than participants with time-consistent discounting. In absolute amounts this is 22 kWh per month. Importantly, the results remain robust upon controlling for the energy efficiency level of appliances. This suggests a link between present bias and energy consumption resulting from intermittent billing, beyond the link between present bias and energy efficiency investments already discussed in a different strand of literature. Our results further show that neither the true electricity price nor the expected electricity price can predict electricity consumption.

Taken our two main results together, households seem to quasi-hyperbolically discount energy costs and seem to be not sensitive to energy prices, doubt is raised in the effectiveness of traditional price-based polices to reduce energy consumption. In contrast, alleviating cost misperceptions seems to play an important role when designing energy polices. As we identify present bias resulting from intermittent billing as a major predictor for energy overconsumption, changes in the billing structure could be promising tools to improve households' decision-making and overall welfare. Relatedly, other markets involving intermittent billing have already adopted prepayment schemes, such as prepaid credit cards or prepaid cell phone tariffs. Prepayment schemes reverse the intertemporal structure of consuming and paying for electricity, thereby dissolving the cause of present biased overconsumption. Alternatively, commitment technologies could be promoted, which motivate households to stick to their ex ante consumption plans. Finally, a recent research strand investigates the consequences of intermittent billing and potential policy measures which help households to perceive their energy costs correctly (e.g. Jack & Smith (Forthcoming) or Wichman (2017)). This research is an important avenue to better understand a decisive feature of energy markets, intermittent billing, and needs more attention in the future.

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Appendix

Table A1 gives the summary statistics of the control variables. The average participants exhibits an exponential discount factor of 0.80, which is comparable to the estimate by Bradford *et al.* (2017). The α-parameter confirms the common result of risk aversion. Its magnitude is in line with the estimates by Schleich *et al.* (2019). Environmental preferences are on average weakly pro-environmentalist. The average answer is 'Agree' to seven pro-environmental statements). The average participant lives in a dwelling with two persons and no children. The size of the dwelling is classified in: 'Up to $42m^2$', '$43-65m^2$', '$66-90m^2$', '$91-120m^2$', '$121-200m^2$', 'More than $200m^2$'. The average size of dwelling category is '$91-120^2$'. Regarding sociodemographic characteristics, the average participant is 49 years old, the sample has an equal split of male and female participants and the average participant has a 'General Certificate of Secondary Education (Mittlere Reife)' as highest educational degree. The categories for education are: 'No formal education or below primary', 'Primary education', 'Certificate of Secondary Education (Hauptschulabschluss)', 'General Certificate of Secondary Education (Mittlere Reife)', 'General qualification for university entrance (Abitur)', 'Tertiary education first stage, i.e. bachelor or master', 'Tertiary education second stage (PhD)'. About 50% of the sample is either full- or part-time employed, the other 50% are 'Long time not employed (more than 3 months)', 'Retired/pensioner', 'Student' or 'Other economically inactive person'. Participant's income status is measured in the categories: 'Living comfortably on present income', 'Coping on present income', 'Finding it difficult on present income', 'Finding it very difficult on present income'. The average income category is 'Coping on present income'. The average dwelling has 'Most' light bulbs being energy efficient. The alternative categories are: 'None', 'Some', 'About half', 'All'.

Table A1: Summary statistics of control variables

Variable	Average [Std. dev.]
δ	0.79 [0.20]
α	0.91 [1.06]
Environmental preferences	2.78 [0.52]
Number of persons in household	2.39 [1.23]
Number of children	0.40 [0.75]
Size of dwelling	3.67 [1.27]
Age	48.80 [18.81]
Female	0.50 [0.50]
Education	3.14 [1.27]
Employed	0.54 [0.50]
Income status	2.77 [0.79]
Efficient lightning	3.66 [0.90]

Note: Standard deviations in parentheses.

Table A2: Distribution of bias in price beliefs conditional on present bias

	Average	Percentile				
Price intervals:	[Std. dev.]	10th	25th	50th	75th	90th
$\mathbb{E}(p_b) - p \mid \beta < 1$	-0.64 [8.46]	-9.84	-2.86	0.21	4.44	9.34
$\mathbb{E}(p_b) - p \mid \beta = 1$	-1.27 [9.06]	-20.8	-3.80	0.00	3.45	10.01
$\mathbb{E}(p_b) - p \mid \beta > 1$	-0.31 [8.14]	-8.80	-2.26	0.09	3.51	9.10
Point estimate:						
$\mathbb{E}(p_b) - p \mid \beta < 1$	-8.89 [7.33]	-17.60	-13.27	-9.03	-4.00	0.98
$\mathbb{E}(p_b) - p \mid \beta = 1$	-8.59 [7.58]	-17.14	-14.20	-9.69	-3.90	2.15
$\mathbb{E}(p_b) - p \mid \beta > 1$	-8.48 [6.63]	-16.73	-12.78	-9.71	-4.59	0.75

Note: Standard deviations in parentheses.

Table A3: Regression results of electricity consumption on present bias and price beliefs using point estimate question

	(1)	(2)	(3)	(4)	(5)
	log(kWh)	log(kWh)	log(kWh)	log(kWh)	log(kWh)
PresentBias	0.166^{***}	0.166^{***}	0.0809^{**}	0.0951^{**}	0.0907^{**}
	(0.0513)	(0.0587)	(0.0336)	(0.0390)	(0.0388)
FutureBias	0.0413	0.0722	0.00450	0.0130	0.00704
	(0.0408)	(0.0445)	(0.0266)	(0.0305)	(0.0310)
log(p)	-0.241	-0.0502	-0.121	0.0309	0.0578
	(0.282)	(0.299)	(0.249)	(0.284)	(0.288)
$\log(\mathbb{E}(p_b)_2)$	0.0698^{*}	0.0245	-0.0265	-0.0407	-0.0351
	(0.0404)	(0.0420)	(0.0274)	(0.0323)	(0.0339)
Control 1		X	X	X	X
Control 2			X	X	X
Control 3				X	X
Control 4					X
N	427	372	361	309	305
Adj. R^2	0.018	0.008	0.649	0.629	0.634

Note: Present bias and future bias are estimated parametrically, price beliefs are estimated from point estimate question. Robust standard errors are in parentheses. Significance levels: * : $p < 0.10$, ** : $p < 0.05$, *** : $p < 0.01$.

Table A4: Regression results of electricity consumption on present bias and price beliefs using non-parametric estimations

	(1)	(2)	(3)	(4)	(5)
	log(kWh)	log(kWh)	log(kWh)	log(kWh)	log(kWh)
SP_{higher}	0.152***	0.149***	0.0861**	0.0886**	0.0842**
	(0.0508)	(0.0575)	(0.0340)	(0.0394)	(0.0389)
SP_{lower}	0.0396	0.0563	0.00151	0.000109	-0.00798
	(0.0395)	(0.0434)	(0.0253)	(0.0297)	(0.0301)
log(p)	-0.173	-0.0495	-0.111	0.0290	0.0511
	(0.280)	(0.299)	(0.250)	(0.275)	(0.277)
$\log(\mathbb{E}(p_b)_2)$	0.116	0.0302	-0.0622	-0.0613	-0.0398
	(0.101)	(0.110)	(0.0667)	(0.0738)	(0.0743)
$\sigma^2(p_b)$	-0.00564	-0.00968	-0.00426	-0.00209	0.000421
	(0.0194)	(0.0204)	(0.0126)	(0.0123)	(0.0122)
Control 1		X	X	X	X
Control 2			X	X	X
Control 3				X	X
Control 4					X
N	439	378	367	316	313
Adj. R^2	0.009	0.003	0.651	0.625	0.630

Note: Present bias (SP_{higher}) and future bias (SP_{lower}) are estimated non-parametrically, price beliefs are estimated from price intervals. Robust standard errors are in parentheses. Significance levels: $^{*}: p < 0.10$, $^{**}: p < 0.05$, $^{***}: p < 0.01$.

Table A5: Regression results of electricity consumption on present bias and price beliefs using non-parametric estimations and point estimate question

	(1)	(2)	(3)	(4)	(5)
	log(kWh)	log(kWh)	log(kWh)	log(kWh)	log(kWh)
SP_{higher}	0.160***	0.164***	0.0826**	0.0916**	0.0882**
	(0.0536)	(0.0597)	(0.0345)	(0.0399)	(0.0396)
SP_{lower}	0.0371	0.0663	0.00231	0.00842	0.00292
	(0.0403)	(0.0435)	(0.0260)	(0.0301)	(0.0307)
log(p)	-0.216	-0.0535	-0.123	0.0339	0.0597
	(0.283)	(0.299)	(0.249)	(0.285)	(0.289)
$\log(\mathbb{E}(p_b)_2)$	0.0672*	0.0262	-0.0260	-0.0389	-0.0332
	(0.0404)	(0.0420)	(0.0274)	(0.0323)	(0.0338)
Control 1		X	X	X	X
Control 2			X	X	X
Control 3				X	X
Control 4					X
N	430	372	361	309	305
Adj. R^2	0.014	0.007	0.649	0.629	0.634

Note: Present bias (SP_{higher}) and future bias (SP_{lower}) are estimated non-parametrically, price beliefs are estimated from point estimate question. Robust standard errors are in parentheses. Significance levels: * : $p < 0.10$, ** : $p < 0.05$, *** : $p < 0.01$.

Table A6: Regression results of electricity consumption on present bias and price beliefs with constant sample size

	(1)	(2)	(3)	(4)	(5)
	log(kWh)	log(kWh)	log(kWh)	log(kWh)	log(kWh)
PresentBias	0.151**	0.156**	0.0878**	0.0956**	0.0922**
	(0.0607)	(0.0639)	(0.0363)	(0.0390)	(0.0385)
FutureBias	0.0712	0.0758	0.0000878	0.00453	0.00243
	(0.0479)	(0.0488)	(0.0286)	(0.0300)	(0.0303)
log(p)	0.0602	0.0535	-0.0601	-0.00627	0.0245
	(0.320)	(0.321)	(0.274)	(0.276)	(0.276)
$\log(\mathbb{E}(p_b))$	0.0859	0.0617	-0.0418	-0.0631	-0.0538
	(0.121)	(0.119)	(0.0716)	(0.0722)	(0.0722)
$\sigma^2(p_b)$	0.0171	0.0169	-0.00218	-0.00109	-0.000849
	(0.0244)	(0.0243)	(0.0134)	(0.0124)	(0.0123)
Control 1		X	X	X	X
Control 2			X	X	X
Control 3				X	X
Control 4					X
N	313	313	313	313	313
Adj. R^2	0.007	0.004	0.633	0.628	0.632

Note: Present bias and future bias are estimated parametrically, price beliefs are estimated from price intervals. Robust standard errors are in parentheses. Significance levels: $^*: p < 0.10$, $^{**}: p < 0.05$, $^{***}: p < 0.01$.

Table A7: Regression results of equalized electricity consumption on present bias and price beliefs

	(1)	(2)	(3)	(4)	(5)
	$\log(\frac{kWh}{capita})$	$\log(\frac{kWh}{capita})$	$\log(\frac{kWh}{capita})$	$\log(\frac{kWh}{capita})$	$\log(\frac{kWh}{capita})$
PresentBias	0.0770*	0.0952**	0.0727**	0.0969**	0.0963**
	(0.0396)	(0.0413)	(0.0331)	(0.0381)	(0.0382)
FutureBias	0.00276	0.0124	0.0299	0.0402	0.0367
	(0.0339)	(0.0358)	(0.0278)	(0.0324)	(0.0328)
log(p)	-0.0520	0.0100	-0.127	-0.0234	-0.00158
	(0.274)	(0.303)	(0.265)	(0.297)	(0.303)
$\log(\mathbb{E}(p_b))$	-0.102	-0.156*	-0.0873	-0.109	-0.0911
	(0.0851)	(0.0899)	(0.0671)	(0.0741)	(0.0770)
$\sigma^2(p_b)$	0.000750	0.00579	0.00700	0.00840	0.0105
	(0.0143)	(0.0151)	(0.0123)	(0.0118)	(0.0120)
Control 1		X	X	X	X
Control 2			X	X	X
Control 3				X	X
Control 4					X
N	436	378	367	316	313
Adj. R^2	0.000	0.003	0.410	0.403	0.404

Note: The outocme $\log(\frac{kWh}{capita})$ is the logarithm of kWh divided by the number of persons in household. Present bias and future bias are estimated parametrically, price beliefs are estimated from price intervals. Robust standard errors are in parentheses. Significance levels: $^*: p < 0.10$, $^{**}: p < 0.05$, $^{***}: p < 0.01$.