How Long Does It Last -and Why? A Field Experiment on Information Provision and Energy Efficiency in China

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We study the short and long-term effects of information provision on efficient lighting through an online field experiment in China. Providing information on monetary and environmental benefits of LED light bulbs causes an immediate increase in willingness-to-pay (WTP). This effect decays hyperbolically over time: WTP decreases by half after three months, and only 20 percent of the initial impact is left after ten months. However, when information provision leads to knowledge acquisition, WTP for efficient light bulbs doesn't drop over time. Monetary and environmental information have similar impacts, though environmental information is less effective if outdoor air pollution is high.

JEL: D12, D83, Q54, C93

Keywords: energy efficiency; information provision; randomized field experiment

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Information policies aimed at helping people make better decisions have been tested in many different economic environments, such as healthy eating, resource use, retirement plans and so on. Results generally show positive effects of information provision (Duflo and Saez, 2003; Gerend, 2009; Roberto et al., 2010; Wichman, 2017; Tiefenbeck et al., 2016). However, in order to design policies, evaluate their cost-effectiveness and pin down the underlying mechanisms, a measurement of the long-term impacts is essential.

Long-term effects of information provision may occur when information influences a one-off decision, whose consequences persist until the decision is re-considered, particularly when deviating from the status quo requires effort: examples are enrolling in a saving plan, taking up insurance, purchasing an energy-efficient appliance, etc. For these cases, studies found some long-term effectiveness of behavioral interventions, for instance achieving persistent increases in employee savings (Thaler and Benartzi, 2004). More challenging are cases in which decision makers need to make active actions repeatedly, such as purchasing a healthy snack, going to the gym, and taking medications. In these cases, persistence requires following the best course of action every time. Some interventions, such as repeated social comparisons, goal setting, or real-time information feedback have been found to achieve some long-term effects, although the evidence is often mixed and the effect depends on the duration of interventions (Allcott and Rogers, 2014; Brandon et al., 2017; Dolan and Metcalfe, 2015; Truelove et al., 2014). To our best knowledge, evidence on the long term effect of one-time information provision on repeated behaviors is absent. Furthermore, the existing lit-

the European Research Council under the European Union's Seventh Framework Program (FP7/2007-2013) / ERC grant agreement n 336155 - project COBHAM "The role of consumer behavior and heterogeneity in the integrated assessment of energy and climate policies".

erature evaluating informational interventions mainly focuses on advanced economies. The aim of this paper is to fill these gaps, by evaluating the short and long-term impacts of information provision on purchasing behavior over time, namely on the adoption of energy efficient light bulbs in a major developing economy.

Studying the impact of information on energy use decisions is particularly important, given their economic and environmental repercussions and the various behavioral mechanisms underlying such decisions. A large number of articles has examined to what extent individuals undervalue energy costs. Evidence suggests there is an energy efficiency gap, indicating the difference between the cost-minimizing level of energy efficiency and the level of energy efficiency realized (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014; Jaffe and Stavins, 1994). Information programs aimed at raising awareness on the private and social costs of energy, such as workshops, mass media campaigns and home audits, have been implemented in several countries (Abrahamse et al., 2005). The first real-stakes randomized experiment studying how energy cost information affects choices of energy-using durables finds limited effect of information on a US representative sample (Allcott and Kessler, 2015). [1] In another field experiment, Allcott and Sweeney (2016) found that, although a combination of large rebates plus sales incentives substantially increases market share of energy-efficient durables, information alone has no statistical effect. Apart from monetary saving information, non-price incentives have also been studied. Asensio and

[1] Other related studies examine the effect of information on hypothetical choices (Houde, 2014; Newell and Siikamäki, 2014). Studies in consumer research providing energy information for appliances like fridges or dryers (Aravena, Riquelme and Denny, 2016; Heinzle, 2012), although conducted in the field with real stakes, generally do not include randomized treatments. Also see the review by Abrahamse et al. (2005).

Delmas (2015) found that environment and health-based information outperform monetary savings information to drive behavioral change in energy consumption. In a randomized controlled trial in Brazil, persuasive environmental information is found to increase efficient light bulbs take-up significantly, especially among women and higher income individuals (Toledo, 2016).

This study focuses on the adoption of energy efficient light bulbs, for a number of reasons. First, light bulbs are a useful case study of the energy-efficiency gap given its prevalence in households. Second, focusing on light bulbs allows observing multiple purchase decisions. Third, providing light bulbs as part of a real-incentivized experiment is easy to implement, given their low price compared to other appliances. There are mainly three types of light bulbs on the market: incandescent light bulbs, compact fluorescent light bulbs (CFLs), and light-emitting diodes light bulbs (LEDs). Traditional incandescent light bulbs have been phased out in many countries, including China. CFLs were designed as replacement for incandescent light bulbs. With development in technology and reductions in LED prices, LEDs are now replacing both incandescent lights and CFLs. Compared to CFLs, LEDs last about twice as long and consume half the electricity, so a 60-watt equivalent LED saves CNY 5.4 (USD 0.85) on energy bill per year on average. [2] Also because of lower electricity consumption, the use of LEDs is associated with fewer greenhouse gas and air pollutants.

Are consumers aware of the benefits of using LEDs? Will providing information on these benefits change their adoption behavior, and if so, for how long? What are the underlying mechanisms? In order to address these

[2]The estimated electricity saving is calculated based on average usage of 4 hours per day and electricity price of CNY 0.53 per kilowatt-hour.

questions, we conducted a field experiment on Chinese households through China‘s largest online survey platform (Sojump). China is a relevant setting for the study. It is the largest energy consumer of the world, the largest CO2 emitter and is plagued by major environmental problems, most notably local air pollution. To address these challenges, China's recent energy and environmental policies have put special emphasis on energy efficiency, especially on curtailing the fast-growing energy demand by residential users.

We contribute to the literature in three ways. First, we test the short and long-term impact of information provision by conducting two follow-up waves - after three and ten months of the information treatment respectively. We elicit subjects' WTP for a LED light bulb at each follow-up wave, without providing additional information, to test the persistence of the information given before.

Second, we provide information on both the environmental impact of LED light bulbs as well as monetary benefits. Rational and selfish individuals should only care about the cost-saving information, since they can free ride on the environmental public goods, such as reduced air pollution and climate change. Comparing the relative effectiveness of the cost-savings and environmental information is important, given the different mechanisms they activate. Furthermore, although from a normative perspective providing information on environmental should not decrease the effect of information on the monetary benefits, motivation crowding-out theory suggests that exogenously incentivizing an intrinsically motivated task may backfire (Bowles and Polana-Reyes, 2012; Gneezy et al., 2011; Kamenica, 2012; List et al., 2017; Schwartz et al., 2015). For instance, Schwartz et al. (2015) find that advertisements of energy saving programs emphasizing the program's monetary benefits reduced participants' willingness to enroll.

Third, we present the information on the environmental impact of purchasing LED light bulbs in two different ways: as worsening global warming or local air pollution. Since air pollution is a more tangible problem than climate change, by varying the perceived proximity of the consequences of one's energy use (Brgger et al., 2015), we contribute to the literature on the co-benefits of fighting global warming (Bain et al., 2016).

We have the following main results. First, we provide evidence of hyperbolic decaying: after three months, the increase in WTP resulting from information provision is reduced by more than half, then diminishes slowly, and eventually only 20 percent of the original impact is observed after ten months. Second, the individuals who learned the knowledge on the benefits of LEDs display higher WTP after ten months than those who did not, and show no effect of decay. Third, framing the environmental impacts as more proximate doesn't affect the short term impact of information: at the aggregate level, subjects respond almost equally to air pollution and climate change information. However, we find evidence that the relative air pollution levels experienced at the day of the information provision matters. If air pollution of that day is higher than the annual average at that location, the treatment effect of air pollution information is smaller.

I. Experiment

A. Survey Platform

We implemented an artefactual field experiment (Harrison and List, 2004) through Sojump, an online platform providing a nationwide sample of 2.6 million individuals for computer-based surveys. In Online Appendix B we provide a list of papers published using Sojump platform. Subjects were recruited randomly through emails and telephone calls, and the sample was restricted to subjects who were invited to take part in the study. Sojump collects socioeconomic and demographic information on its panel of users, allowing researchers to specify the characteristics of their desired sample. In our case, given the focus of the experiment on household goods purchasing decisions, we recruited only non-students panel members. Our sample covers 30 out of 34 provincial-level divisions in China.[3] The six richest provincial-level areas are over-represented in our sample, with 60 percent of our subjects residing there. [4] This is due to the fact that the surveys were conducted online, and that Internet accessibility, associated with economic development, is not distributed equally across provinces. In the analysis we include demographic characteristics in the regressions to control for heterogeneity. About 84 percent of the subjects who began the survey completed it. We forced subjects to answer all the questions, except for their postal address.

B. Experimental Design: Overview

The experiment was articulated in three waves of data collection: the first wave, when information was provided (henceforth, the information wave), and two follow-up waves conducted three and ten months later, respectively. At each follow-up wave, we invited the subjects who have participated the information wave, and also recruited new subjects who have never participated in our experiment before. Figure 1 presents a demonstration.

[3] Excluding Tibet, Hong Kong, Macau and Taiwan.

[4] They are Beijing, Shanghai, Shandong, Guangdong, Jiangsu, Zhejiang. The total population of these six provincial-level divisions is about 30 percent of the total Chinese population.

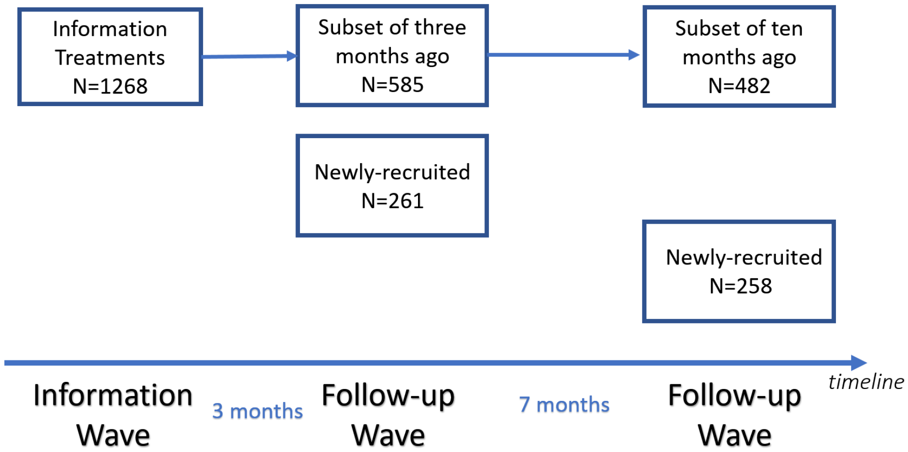

Figure 1. Three waves of the experiment

Each wave involves the elicitation(s) of WTP for a LED light bulb. The WTP elicitation is incentive compatible. At the beginning of each wave, each subject was endowed CNY 30 (about USD 4.5) as shopping budget, and was asked to make a series of choices between a CFL and a LED light bulb of the same luminosity and brand. Across choices, the price of the CFL light bulb was fixed to CNY 8, which was its median sales price on the market. While the price of the LED light bulb varied between CNY 6 and 30, depending on the subject's previous choice, with CNY 30 being higher than the highest sales price on the market.[5] Each subject made at most three pairwise choices per elicitation round, following a standard bi-section procedure (for the elicitation procedure and the determination of WTP, see Appendix B).

All choice screens displayed the pictures and the sale prices of the two light bulbs. The positions of the two light bulb options were randomized

[5]We obtained LED prices by searching on www.taobao.com, the largest consumer-to-consumer, business-to-consumer and business-to-business online platform in China.

to eliminate possible ordering effects. At the end of each wave of data collection, for each subject, we randomly drew one of the pairwise choices across all decisions: we sent the light bulb chosen by the subject in that specific question, charged the price corresponding to the selected choice, and paid the remaining endowment (that is CNY 30 minus the price of the light bulb) to the subject's account on the survey platform. The money earned on the survey platform can be deposited to a bank account owned by the subject.

C. The Information Wave

The information wave was composed of three rounds of WTP elicitation (hence force, WTP in round 1 as baseline, and WTP in round 3 as endline). In between each round, subjects were given information, as shown in Figure 2. The information wave concluded with a post-experiment survey including questions on beliefs, demographics, awareness of knowledge on LEDs, etc. Experimental instructions and questionnaires (originally in Chinese, translated to English) can be found in Online Appendix A.

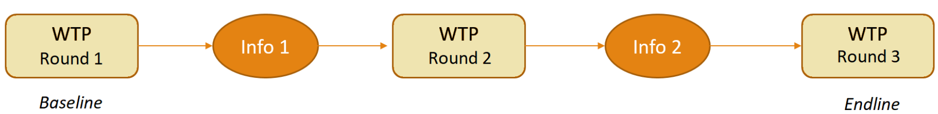

FIGURE 2. FLOW OF THE INFORMATION WAVE

In the information wave, each subject was randomly assigned to a treatment or a control condition. The conditions differ in the content and order of the pieces of information provided. Treatment conditions provide two broad categories of information, on the monetary cost and on the environmental impact of the two types of light bulbs.

Monetary information explained that LED light bulbs consume about 50 percent less energy and last twice as long compared to CFLs, thus generating significant savings even factoring in the higher purchase price. As for environmental impact information, a common text on the relation between electricity consumption and emission was followed by a description of the impact of emissions either in terms of air pollution or climate change. Each treated subject was presented with the monetary cost information and one version of the environmental impact information. Since we repeatedly measured the WTP for three consecutive rounds, any increase in WTP could be due to demand effects rather than to the effect of information. To capture the potential effect of repeated measuring, the design includes control conditions. Subjects in control conditions received information on light bulb manufacturing and online sales trends, which is not expected to have influence on WTP for LEDs.

More specifically, the different pieces of information provided are in the following (Appendix A shows all information materials used in the experiment):

- **Monetary cost (M):** reported one-year energy cost comparison of LED and CFL light bulbs (CNY 5.41 and CNY 10.82 per year respectively), ten-year total energy cost saving, plus difference in sales price, and the average lifespan of the two light bulbs (10 years vs. 5 years), see Appendix Figure A2.

- **Air pollution (AP):** reported the benefits of LEDs over CFLs on reduction of air pollutant emissions. The text explained that, in China, electricity is mainly generated from coal, that burning coal is directly related to greenhouse gas emission and air pollutant emissions, and that inhaling air pollutants leads to health problems. It also made the link between each individual's choice of light bulbs and air pollution explicit, as LEDs produce 50 percent fewer air pollutants than CFLs. The text was accompanied by a map of Beijing displaying particulate matter levels (PM 2.5) on a summer day, with all PM 2.5 concentrations shown on the map exceeding the WHO guideline threshold of 25mg/m3.

- **Climate change (CC):** reported the benefits of LEDs over CFLs on reduction of greenhouse gas emission. The text was similar to that in the AP condition, except that it framed the consequences of burning coal in terms of global climate change, which leads to extreme weather, affecting agriculture, ecosystems and health outcomes both in China and the rest of the world. The text was accompanied by a map of the world displaying changes in global temperatures from 1884 to 2015.

- **Manufacturing:** reported the key features of the Chinese light bulb manufacturing sector, such as its export capacity, the major brands producing in the country, the number and location of most manufacturing plants.

- **Online sales:** reported the growing importance of online sales in the light bulb market, reporting shares of online sales and values.

We did not test subjects' understanding of the information provided before eliciting WTP, as we wanted to reproduce the situation in real world purchases during which consumers are offered information that they are free to read or not. Instead, in the post-experiment survey of the information wave, we asked subjects if the information provided was known to them or not before the experiment.

Information awareness.— After each piece of information provision, subjects were asked if they knew the information provided before participating in the experiment. Take monetary information as an example. The question was: “Before the experiment, did you know that for the same lighting effect, a LED light bulb only cost half on energy bill compared to a CFL?” Subjects chose among four options: (i) No, I did not know that a LED cost less than a CFL; (ii) I knew that a LED cost less than a CFL, but I did not know that the difference was so much; (iii) I knew that a LED cost less than a CFL, but I thought the difference was larger; (iv) I knew exactly and precisely how much a LED saved me compared to a CFL. The question on environmental benefits was similar. These questions were meant to collect subjects’ prior awareness of the information, and facilitate the measurement of knowledge acquisition in the follow-up waves.

To summarize, the design of the information wave has a within-subjects dimension, comparing WTPs of the same individual as she acquires different pieces of information (monetary and environmental), and a between-subjects dimension, comparing the effect of different types of information, both between monetary and environmental information, and between information on air pollution and climate change. See Table 1 for an overview of treatments.

D. The Follow-up Waves

As presented in Figure 1, we recruited 261 and 258 subjects after three and ten months of the information wave, respectively. During the follow-up

Table 1—Experimental conditions in the information wave

Information		Acronym	N
Info 1	Info 2		
Treatment conditions			
Monetary	Air Pollution	M-AP	274
Air Pollution	Monetary	AP-M	261
Monetary	Climate Change	M-CC	262
Climate Change	Monetary	CC-M	261
Control conditions			
Manufacturing	Online Sales		105
Online Sales	Manufacturing		105
Total			1268

Note: N is the number of subjects.

waves, we first elicited WTP without any information provision, and then conducted a post-experiment survey, featuring questions aimed at testing knowledge on the information provided in the information wave.

In order to identify possible mechanisms underlying changes in WTP, at the end of each follow-up wave, we included questions aimed at understanding subjects' changes in knowledge over time.

Knowledge Acquisition.— At the end of each follow-up wave, we asked two quiz questions concerning the information we provided at the information wave, one on the monetary and the other on the environmental benefits of LED light bulbs. For each question, subjects were asked to choose the statement closest to their knowledge among four options. The correct answers were "For the same lighting effect, compared to a CFL, a LED saves about CNY 60 on energy cost over 10 years" and "For the same lighting effect, compared to a CFL, a LED emits more than 50 percent less greenhouse gas/air pollutants." Appendix C shows all the options of the two questions.

II. Data

One thousand, two hundred and sixty eight (N=1268) subjects participated in the information wave. After three and ten months, we invited them by email to participate in the follow-up waves. Of those, 585 and 482 subjects came back and successfully completed at least one of the follow-up surveys, respectively. Three-hundred and seventy subjects participated in all three waves. At each follow-up wave, we also recruited additional groups of subjects who had not taken part in the information wave (N=261 and 258, respectively), to test for time trends in WTP and knowledge on LED light bulbs.

A. Descriptive Statistics

Our subjects are similar to the national average in terms of age and gender distribution, but display higher income and education levels. About 47 percent of subjects are female. Median age is between 30 to 35 years old. About 76 percent have at least one child, and a similar share have university degree. Mean household income is CNY 169,500 (about USD 24,610). About 38 percent of subjects report using mostly LEDs in their residence, while 56 percent mostly CLFs. This reassures of the ample scope to increase LED light bulbs take-up within our sample.

Online Appendix C shows correlates of baseline WTP before any information provision: having children, earning more income, being male and being more risk seeking significantly increase baseline WTP. Climate change non-believers have marginally lower baseline WTP. These correlations are expected and consistent with previous studies (Allcott and Taubinsky, 2015).

B. Randomization and Attrition

Within the information wave, observable characteristics are generally balanced across treatment conditions and control conditions, with a few exceptions, namely age and gender. Subjects in the control conditions are slightly older (although both groups have median age of between 30 to 35), and less likely to be female (38.1% vs. 49.6%). Subjects' characteristics and their balance across the information treatments are shown in Online Appendix E.

We compare the characteristics of subjects participating in more than one wave, of those dropping out between waves, and of the new group of subjects recruited at each follow-up wave. Table 2 presents summary statistics of observable characteristics and their balance across four groups of subjects: the restricted sample of subjects that were surveyed across all three experimental waves (1); the group of subjects that did not complete at least one of the follow-up surveys (2); and the newly recruited subjects at the first (3) and second (4) follow-up wave. We test for selective attrition by comparing (1) and (2), and we check that the newly-recruited subjects represent a valid control group for the original sample by comparing (1), (3) and (4). Columns (5) and (6) of Table 2 show the p-value of the two comparisons, respectively, using Kruskal-Wallis tests. Compared to subject who missed at least one wave, those who participated all three waves are slightly older, and more likely to have children. These subjects differ significantly along these same two dimensions from newly recruited subjects at three and ten months. Since having children is associated with higher baseline WTP, it is possible that the stronger interest in energy efficiency of subjects with children is what drives their higher likelihood to participate in all waves of the study. The long-term treatment effects we observe could potentially be influenced by selective attrition. In the regression analysis we control for subjects' demographic characteristics to capture this effect.

Table 2—Attrition in sessions

	Participated all three waves	Missing at least one wave	Newly recruited after three months	Newly recruited after ten months	KW p-values	
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline WTP	19.73	19.40	18.35	20.03	0.7501	0.1226
Income (in CNY)	167,597	170,291	173,602	193,367	0.9951	0.4527
University	77.03%	75.95%	73.56%	82.17%	0.6811	0.0612
Female	46.22%	48.33%	42.53%	48.84%	0.4936	0.3493
Age	3.91	3.63	3.76	3.72	0.0000	0.0178
Has Children	82.70%	72.94%	73.18%	81.01%	0.0002	0.0109
N	370	898	261	258		

Note: Age is a categorical variable, with 3 means 26 to 30 years old, and 4 means 31 to 35 years old. Reported are mean values. Column (5) provides p-values of comparisons between (1) and (2). Column (6) provides p-values of comparisons between (1), (3) and (4).

C. Air Pollution

We use air pollution measurements from China National Environmental Monitoring Center (CNEMC). It provides real time data on the level of the major air pollutants in 334 prefecture-level administrative divisions. In two of our treatment conditions (M-AP and AP-M), we used PM 2.5 index as an indication of air pollution, and provided PM 2.5 figures in the information message. We analyze the effect of PM 2.5 index on information impact. We obtain the PM 2.5 levels from CNEMC on the day and hour of the survey, and over the previous 365 days at the location of each subject.

III. Results

This section begins by showing the immediate effects of information provision on WTP, followed by results on the long-term effects. Then we provide evidence on possible channels underlying the increase in WTP.

A. Short-term Impact of Information

Figure 3 provides an overview of mean WTP for LEDs over the three rounds of elicitation influenced by different information by treatments. Each set of bars shows WTP before information was provided (baseline WTP), and after the first and second information provision, respectively. Across the four treatment conditions, WTP increases as each piece of information is given (Wilcoxon paired test, $p<0.001$ for all). In contrast, WTP in the two control conditions remains constant (Wilcoxon paired test, $p=0.5969$ and $p=0.4413$ for each piece of information, respectively).

Which type of information is more effective? By comparing the increase in WTP after the first provision of information in the AP-M and CC-M conditions, we see that air pollution and climate change have similar effects (Wilcoxon unpaired test, $p=0.9563$). Therefore, in what follows we pool the conditions AP-M and CC-M into a unique condition, labeled E-M (E as environmental), and similarly the M-AP and M-CC conditions into a condition labeled M-E. The E-M and M-E conditions also lead to similar increases in WTP from round 1 (baseline) to round 2 (Wilcoxon unpaired test, $p=0.1024$). Each piece of information increases WTP by CNY 3.07 on average, which is about 16 % of the baseline WTP. In combination, the two pieces of information increase WTP of CNY 4.95 on average (about 25 % of the baseline WTP).

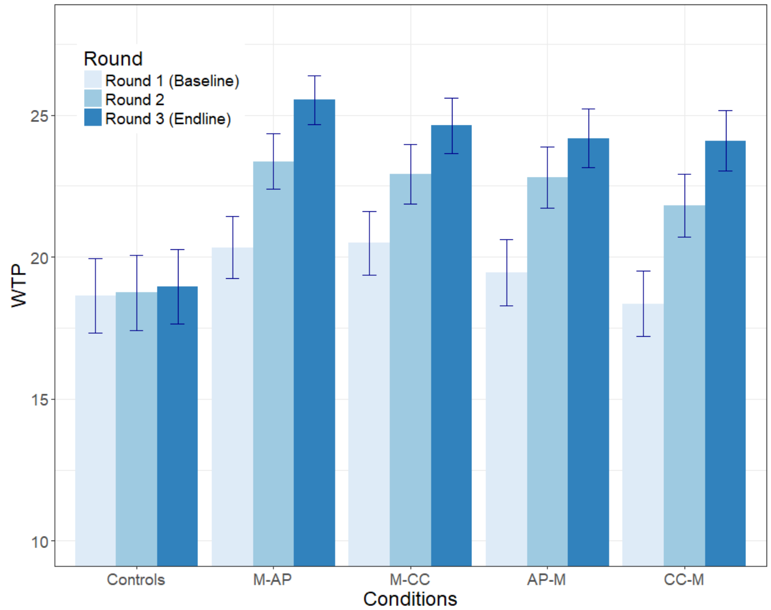

Figure 3. Mean WTP by conditions in the information wave

Note: Error bars show 95 % confidence interval.

The increase in mean WTP is not driven by only a few people: Figure 4 shows the demand curves for LED light bulbs in the treatment conditions. We distinguish between M-E conditions, where the monetary cost information was given first (Panel A), and E-M conditions, where the environmental impact information was given first (Panel B). Each piece of information shifts the demand curves upward: at endline the proportion of people whose WTP reaches CNY 30 is larger than 60 percent in all treatment conditions, which is an increase of 30 percent compared to baseline WTP. It is worth noticing that there are about 10 percent of subjects who have lower WTP for a LED light bulb than for a CFL, even after two rounds of information provision.

The experimental design allows the test of possible crowding out between

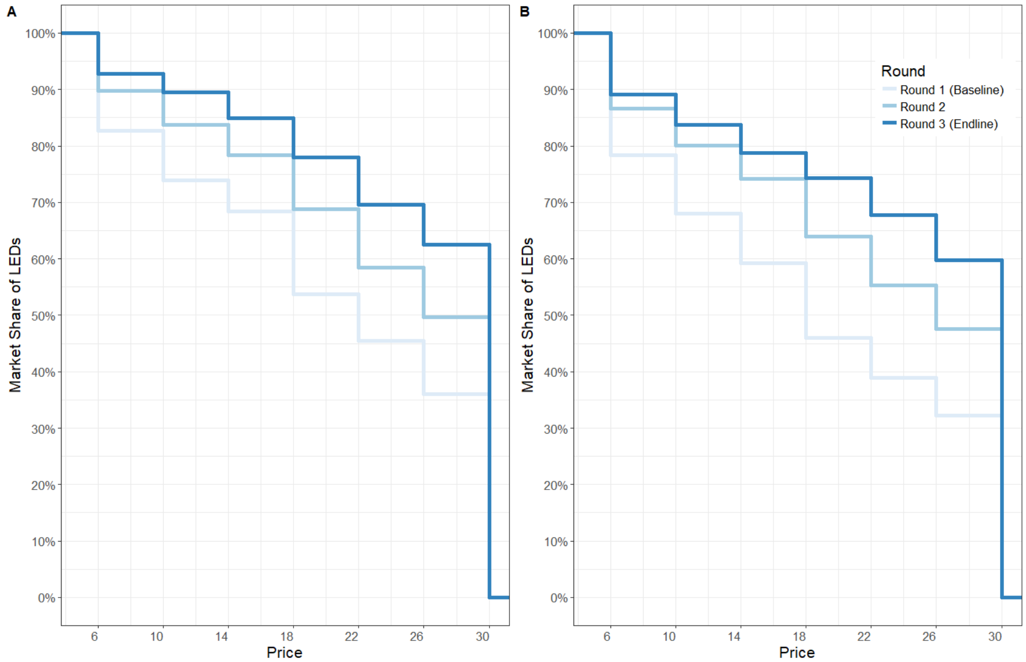

Figure 4. Demand curves over information provision

Note: This figure plots the demand curves in the price range of 6 to 30.

monetary and environmental information. Comparing changes in WTP when environmental information is given in isolation and when it is combined with monetary information gives an indication of whether crowding-out occurs. Namely, if crowding-out happens, then we should find the endline WTP of E-M groups to be lower than their WTP after the environmental information. On the contrary, we find that the combined effect of the monetary and environmental information is always larger than that of the environmental information alone (p=0.0000 for both, Wilcoxon paired tests). This suggests that mentioning money does not crowd out the environmental motive to contribute to energy-efficiency. Instead, it points to a complementarity between the two pieces of information, as also confirmed by recent experimental evidence (List et al., 2017).

We show different results in regression form and explore sources of heterogeneity in treatment effects by running the following specification:

$$\begin{aligned} WTP_{ij} = \beta_0 + \beta_1 info.M_{ij} + \beta_2 info.E_{ij} + \beta_3 round_j + \beta_4 X_i \\ + \beta_5 info.M_{ij} \times X_i + \beta_6 info.E_{ij} \times X_i + \beta_7 Z_i + \varepsilon_{ij} \end{aligned}$$

where WTP_{ij} is subject i's WTP in period j $\in \{0, 1, 2\}$ in the information treatments; $info.M_{ij}$ and $info.E_{ij}$ are equal to 1 if subject i received information on energy cost or on environment, respectively, in period j; X_i are individual characteristics, which we consider as potential sources of heterogeneity in the effect of information: baseline WTP and opinions on climate change; and Z_i are demographic controls, including age and gender. Table 3 shows regression results: Columns 1 and 2 show treatment effects without controls nor interactions using a linear and a Tobit model, respectively; Column 3 adds the demographic controls; and Columns 4 and 5 examine heterogeneity on the basis of Baseline WTP and opinions on climate change, respectively.

Both types of information increases WTP with similar magnitude, consistent with the results from the nonparametric tests. WTP is positively and significantly correlated with income, being male and having children, and negatively correlated with university education. Both monetary and environmental information have significant lower impacts on subjects with high baseline WTP, consistent with ceiling effects in WTP. Non-believers of climate change, who have low WTP to begin with, react negatively to information provision: information on monetary savings has no impact on climate change skeptics' WTP, and environmental information even appears to backfire. Ideology has been shown to be an important determinant of the

Table 3—WTP in the information round

	(1)	(2)	(3)	(4)	(5)
Info.M	2.11	5.06	5.38	13.60	5.36
	0.36****	0.90****	0.90****	0.56****	0.89****
info.E	2.50	5.58	5.87	17.17	6.00
	0.36****	0.88****	0.89****	0.91****	0.87****
Round 1	0.66	1.57	1.24	1.71	1.54
	0.32**	0.92*	0.92	0.80**	0.90*
Round 2	0.34	1.55	0.97	1.11	1.57
	0.53	1.48	1.49	1.09	1.45
Log(Income)			2.79		
			0.65****		
Age			0.35		
			0.48		
Male			1.81		
			0.81**		
University			−2.60		
			1.01***		
Has children			2.72		
			1.03***		
Baseline WTP				1.97	
				0.06****	
Info.M × Baseline WTP				−0.52	
				0.05****	
Info.E × Baseline WTP				−0.69	
				0.04****	
Non-believer					−9.50
					2.06****
Info.M × Non-believer					−5.26
					2.65**
Info.E × Non-believer					−8.83
					2.22****
Constant		23.99	13.76	−16.03	23.92
		0.52****	2.45****	1.40****	0.53****
Demographics	No	No	Yes	No	No
Model	Linear	Tobit	Tobit	Tobit	Tobit
N. of obs.	3804	3804	3804	3804	3804
N. of sub.	1268	1268	1268	1268	1268

Note: Significance: < 0.1: *; <0.05: **; <0.01: ***; <0.001: ****. Robust standard errors below regression coefficients.

effectiveness of non-monetary, social norm nudges for energy conservation in the US (Costa and Kahn, 2013). Our results confirm this effect on Chinese households.

B. Long-term Impact of Information

We now turn to the evaluation of the long-term effects of information provision. Before doing so, it is important to rule out the presence of time trends in WTP over the three data collection waves, by comparing baseline WTP of our original sample with WTP of newly-recruited participants at the three and ten months follow-ups. Kruskai-Wallis test confirm that there is no difference in WTP of the three groups of subjects across the three waves (p=0.1383).

To explore the long-term impact of information, we run the following regressions including all the subjects who have participated in the information wave and the follow-up waves,

$$WTP_{ij} = \beta_0 + \beta_1 T_j \times information_{ij} + \beta_2 T_j + \beta_3 X_i + \varepsilon_{ij}$$

where WTP_{ij} is subject i's WTP at *time* $j \in \{T_0, T_1, T_2\}$ with T_0 indicating the endline of the information wave, and T_1 and T_2 the three and ten months follow-ups. For subjects recruited in the information wave and assigned to the information conditions, the *information* dummy is 1 at all time points. For the subjects recruited at the information wave but assigned to control conditions, and the subjects recruited at the follow-up rounds, the *information* dummy is 0 at all time points where we observe them. The regressions control for time fixed effects. The results are in Table 4: Column 1 uses a linear regression model, Column 2 to 5 use Tobit ones given the censored nature of the dependent variable. Column 3 excludes, among the subjects recruited for the information wave, those whom we don't observe at follow-ups, while Column 4 excludes subjects with WTP equal to 6 or 30 (upper and lower bounds). Finally, individual characteristics X_i, including age, income, gender, university education, having children, and believing in climate change, are added as controls in Column 5.

Table 4—Long-Term Effects of Information Provision

	(1)	(2)	(3)	(4)	(5)
Information	5.20	12.12	11.03	12.35	12.11
	0.36****	0.67****	1.45****	0.91****	0.67****
Information × T_1	−2.83	−7.42	−2.83	−7.39	−7.59
	0.72****	1.38****	2.78	1.89****	1.37****
Information × T_2	−4.11	−10.30	−7.91	−10.23	−10.17
	0.75****	1.43****	2.89***	2.11****	1.43****
T_1	−0.14	0.36	−1.58	0.82	0.47
	0.53	1.05	2.09	1.42	1.04
T_2	1.05	1.83	1.44	1.54	1.58
	0.54*	1.06*	2.04	1.61	1.07
Constant	19.42	21.51	21.52	21.19	7.63
	0.23****	0.51****	0.97****	0.64****	2.68***
Individual Characteristics	No	No	No	No	Yes
Exclude baseline WTP=30 or endline WTP=6	No	No	No	Yes	No
Exclude dropped subjects	No	No	Yes	No	No
Regression Model	Linear	Tobit	Tobit	Tobit	Tobit
N. of obs.	4122	4122	1203	2332	4122
N. of sub.	1787	1787	889	1226	1787

Note: Significance: < 0.1: *; <0.05: **; <0.01: ***; <0.001: ****. Standard errors below regression coefficients. The full regression of column 5 including coefficients for demographics is provided in Online Appendix D. "Dropped subjects" are those who have participated in the information wave, but did not attend the follow-up waves for at least once.

Consistent with the results on the short-term effect of information, the coefficients of the information treatment dummy are positive and statistically significant for all models, indicating an immediate positive impact of information on WTP. Such impact diminishes over time: the increase in WTP generated by information provision is still larger than zero after three months, but is almost gone after ten months (except for model (3) that after three months the effect does not decrease significantly). The average marginal effect of information provision at the three time points are 5.20, 2.76 and 1.09 (p-values = 0.0000, 0.0000 and 0.0962 respectively. Marginal effects are calculated from linear regression in column (1)).

Figure 5 graphically shows how the initial increase in WTP due to the information treatments decays over time. The vertical axis reports the difference between WTP at time points T_0, T_1, T_2 and the baseline WTP, and the horizontal axis shows the three time points: T_0 (endline of the information wave), T_1 (3 months follow-up wave) and T_2 (10 months follow-up wave). The decay follows an hyperbolic pattern characterized by a large drop in the short-term and a stabilization in the long-term to a level slightly above zero.

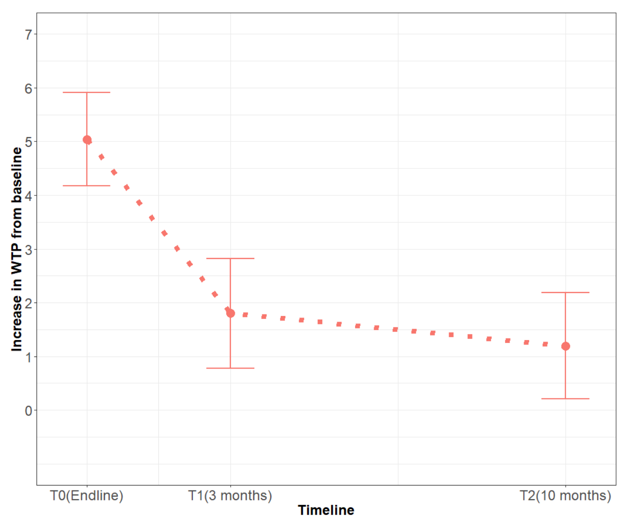

Figure 5. Decay of treatment effects on WTP over time

Note: Error bars show 95 % confidence interval.

C. *Possible Mechanisms*

As introduced in Section Experiment, we created measures on information awareness in the information wave and knowledge acquisition in the follow-up waves. In this section, we use these measures to provide evidence on a possible channel behind the changes in WTP, and its decay over time.

Short run: Awareness.— At the time of the information wave, prior awareness of both economic and environmental benefits of LEDs are positively correlated with baseline WTP ($\rho = 0.28$ and 0.15, p=0.00 for both, Pearson tests), suggesting a close relationship between the energy-efficiency gap and the information gap. Figure 6 shows the average increase in WTP, between baseline and endline of the information wave, for subjects with different levels of prior knowledge of the economic (Panel A) and environmental (Panel B) information. The horizontal axis reports the different answers to the knowledge awareness questions and the shares of subjects giving each answer. The two dimensions of information awareness, monetary and environmental, are highly correlated ($\rho = 0.40$, p=0.0001, Pearson test), although subjects generally report knowing less about the environmental advantages of LEDs (p=0.0000, Wilcoxon paired test).

Subjects who were completely unaware of or underestimated the benefits of LED light bulbs, either monetary or environmental, experienced a significant increase in WTP immediately after the corresponding information; while those who were fully aware, or even overestimated the benefits, did not display any increase in WTP (except for the rightmost bar of Panel A where the increase is significant at 5% level). We interpret these results as evidence that people's low WTP for LED light bulbs is mostly due to lack of awareness of the benefits of LEDs, which can be addressed by information

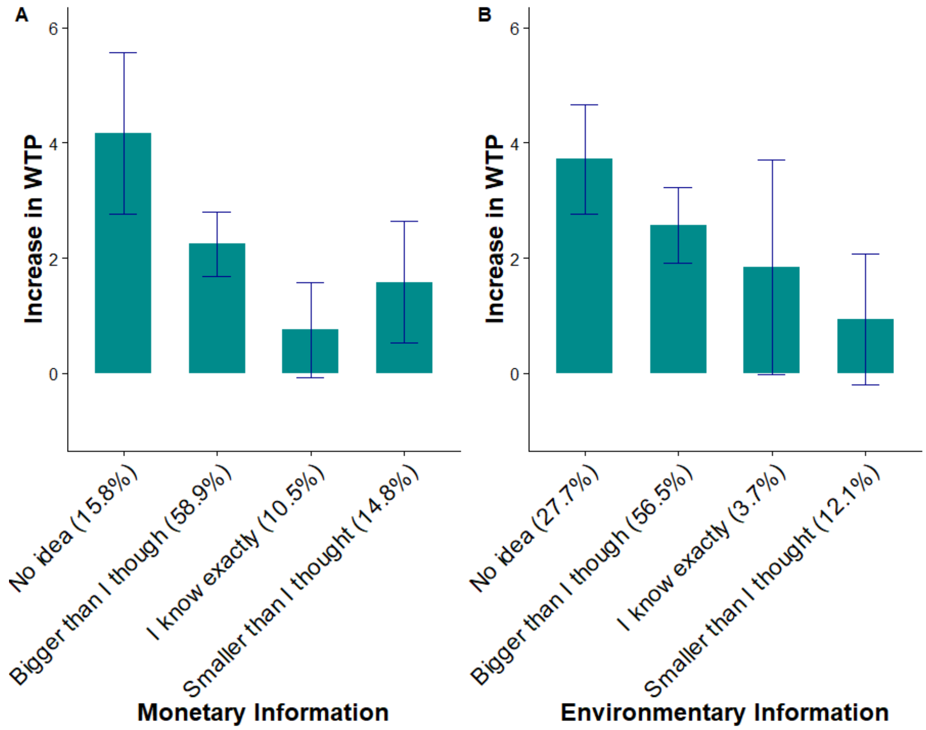

Figure 6. Information Awareness and Increase in WTP

Note: 95 percent confidence intervals reported in each bar.

provision at least in the short-run.[6]

Long run: Knowledge acquisition.— Table 5 shows the share of subjects who answered the knowledge questions correctly at the follow-up waves. We test if their knowledge level is the same as that of newly-recruited subjects using proportional tests. As expected, subjects treated with information (Column 3) are significantly more likely than newly-recruited subjects to know the correct answer to both monetary and environmental questions after three months. However, the knowledge difference cannot be detected any

[6]In the follow-up waves, the subjects who had no or little prior awareness in the past also maintained their increase in WTP afterwards. Online Appendix F shows these results.

longer after ten months. Subjects in the control groups also perform better than newly-recruited subjects at the three-months follow-up, suggesting that they acquired knowledge in other ways than through direct information provision within the experiment. A possible explanation of this result is that subjects who did not receive information, but were asked for their awareness of the information at the end of the information wave, realized what they did not know, and therefore paid attention to, or even actively searched for the information outside the experiment. In other words, being asked the knowledge question may have prompted subjects to learn what they did not know [7].

Table 5—Knowledge across different groups

		Newly-recruited		Treatment groups	Control groups
		(1)	(2)	(3)	(4)
Monetary	3 months	43.68%		65.38%****	59.57%***
	10 months		56.59%	58.97%	66.67%
Environmental	3 months	32.95%		53.77%****	48.94%***
	10 months		41.86%	45.45%	46.67%

Note: The table shows the proportion of subjects who answered the corresponding knowledge question correctly. Unpaired proportion tests compare subjects who participated in the information wave with the newly-recruited subjects taking surveys at the same point in time. Significance: < 0.1: *; <0.05: **; <0.01: ***; <0.001: ****.

In order to test the role of knowledge change in the long-term impact of information, we need to distinguish knowledge acquisition from the level of knowledge. Indeed, high levels of knowledge at follow-up waves may merely indicate high levels of knowledge prior to the information provision, while

[7] Sloman and Fernbach (2017) call this effect "illusion of explanatory depth". In an experiment using students from Yale, they found that students asked to rate their own knowledge level of devices used everyday, such as toilets and zippers, gave lower ratings if they had previously been asked questions about these devices, because the questions revealed to the students their own ignorance

knowledge acquisition can only be observed for subjects who at baseline were unaware or underestimated the benefits of LEDs. If knowledge fills the energy-efficiency gap, we expect to observe increases in WTP only among subjects who acquired knowledge over the course of the experiment, but not necessarily among those with high initial knowledge.

We build a knowledge improvement measure indicating knowledge acquisition as a dummy variable equal to 1 if a subject's knowledge on the advantages of LED light bulbs increases over the course of the experiment. We distinguish two cases: subjects, who at baseline said to be completely unaware of these advantages, are coded as having acquired knowledge as long as they knew at the follow-ups that LED was better than CFL (chose A or B in the questions in Appendix C); subjects who, instead, reported to underestimate the advantages, acquired knowledge only if they correctly identified the amount of savings generated by LEDs over CFLs at follow-ups (chose A in the questions in Appendix C).

Acquisition of knowledge on both monetary and environmental benefits is positively and significantly correlated with WTP after ten months (Spearman correlation tests, ρ=0.12, p=0.0096 and ρ=0.10, p=0.0253, respectively). The correlation is positive, but not significant at the three-month follow-up for both types of information (Spearman correlation tests, ρ=0.07, p=0.1043 and ρ=0.03, p=0.2782, respectively).

The trend in WTP over time is different, depending on whether subjects learnt from the information. WTP decreases over time for subjects who did not acquire new knowledge in the information wave, while it remains constant for those who did. Figure 7 visually shows the effect. Within each panel, we distinguish between subjects who acquired new knowledge between the information and the follow-up waves, and those who did not, regardless of whether was assigned to treatment conditions or control conditions. We distinguish between knowledge acquisition of the monetary (Panel A) and environmental (Panel B) benefits of LEDs. Subjects who did not learn within the experiment show a decay in WTP between follow-up waves, while those who did display constant or even slightly increasing WTP over time. The difference in WTP between these two groups with or without information acquisition is statistically significant after ten months.

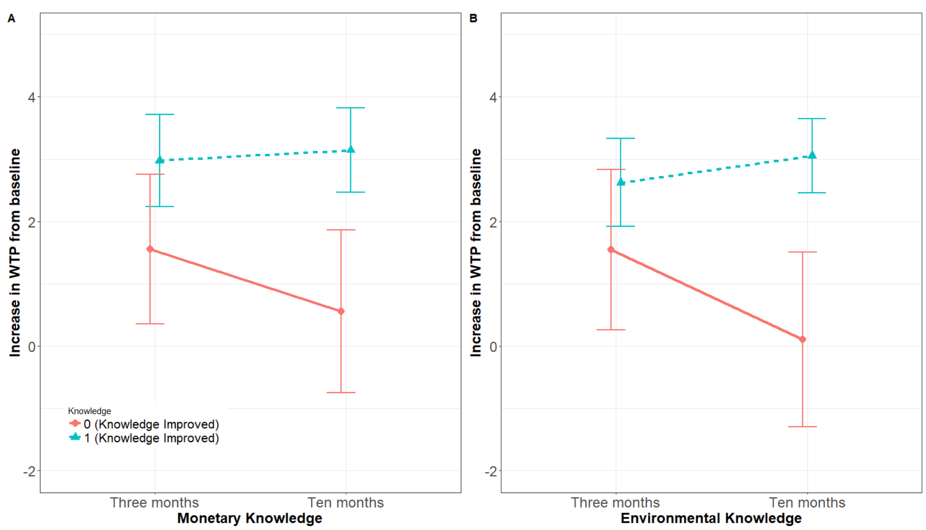

FIGURE 7. KNOWLEDGE IMPROVEMENT AND WTP DECAY

Note: Error bars show 95 % confidence interval.

Perceived Air pollution and treatment effect of information provision.— In the information wave, we provided two framings of the environmental benefits from using LED light bulbs, one in terms of alleviating air pollution and the other of mitigating climate change. While, as already mentioned, we do not observe different effects of the two framings at the aggregate level, we find that the relative air pollution level influences the immediate impact of information concerning air pollution, but not climate change. We investigate the impact of information and its heterogeneity across subjects through Tobit regressions (Table 6):

$$
\begin{aligned}
WTP_{ij} = \beta_0 + \beta_1 info.M_{ij} + \beta_2 info.AP_{ij} + \beta_3 info.CC_{ij} + \beta_4 DPM_i \\
+ \beta_5 info.AP_{ij} \times DPM_i + \beta_6 info.CC_{ij} \times DPM_i + \beta_7 X_i + \varepsilon_{ij}
\end{aligned}
$$

where WTP_{ij} is subject i's WTP at round $j \in \{0, 1, 2\}$ in the information wave; $info.M_{ij}$, $info.AP_{ij}$ and $info.CC_{ij}$ are dummy variables equaling 1 if subject i received the corresponding information on monetary and environmental benefits, framed in terms of air pollution or climate change, in round j, and 0 otherwise; DPM_i is a dummy variable that equals 1 if the PM 2.5 index on the survey day was higher than it had been on average over the previous 365 days, and 0 otherwise; X_i are individual characteristics. The regressions include the full sample in Column 1, and restricted samples of subjects living in and around Beijing[8] (Column 2), and in Beijing only (Column 3).

All the three columns show that the impact on WTP of providing air pollution information is lower when the PM 2.5 index on the survey day was higher than the mean over the previous 365 days. The magnitude of the interaction effect is larger the closer subjects live to Beijing. Column 2 and 3 show that the effect of air pollution information on WTP is almost nullified when outdoor air quality is worse than average. This result may be due to the fact that a map of PM 2.5 index in Beijing, showing high pollution levels in the city, accompanied the air pollution information. That making

[8]The areas around Beijing include Tianjin, Hebei and Shandong.

Table 6—Information Provision and Air Pollution

	Full sample (1)	Beijing and surroundings (2)	in Beijing (3)
1(info.M)	5.84	5.21	5.28
	0.89****	1.40****	2.02***
1(info.CC)	3.07	0.32	0.14
	1.12***	2.40	3.65
1(info.AP)	7.60	8.84	8.32
	0.87****	1.58****	2.72***
1(DPM)	0.96	2.50	−0.70
	1.00	1.59	2.50
1(info.CC) × 1(DPM)	−0.31	2.96	6.11
	1.32	2.61	3.83
1(info.AP) × 1(DPM)	−3.59	−7.41	−7.64
	1.32***	2.02****	3.40**
Constant	24.39	24.32	26.48
	0.55****	1.18****	2.18****
N. of obs.	3804	915	411
N. of sub.	1268	305	137

Note: Significance: < 0.1: *; <0.05: **; <0.01: ***; <0.001: ****.
Standard errors below regression coefficients. Including demographics do not change the results. Robustness checks on other PM 2.5 measures are shown in Online Appendix G.

more salient a tangible problem may lead subjects to ignore the information, especially when the problem is perceived as more serious, is consistent with theory and recent empirical results on information avoidance (d'Adda et al., 2018): when subjects know that they would feel compelled to act upon a piece of information, and action is costly, they tend to avoid the information.

The negative impact of high PM 2.5 levels on the effectiveness of air pollution information is just a short-term phenomenon. In fact, neither the PM 2.5 index on the day of the information wave, nor the PM 2.5 index on the day of the follow-up waves affect WTP in the long-run. Regression results are provided in Online Appendix I.

IV. Conclusion

We study the short and long-term effect of information provision intervention on energy efficiency through an online field experiment with Chinese households. In the short term, information provision significantly increases WTP for LED, mostly on people who were unaware of or underestimated the benefits of the energy-efficiency device, suggesting an information gap. Information serves as the cue that changes the perceived costs and benefits of LEDs, but its impact can be affected by subtle external factors, such as outdoor air pollution levels. In the long term, the effect of information decays. Three months after the intervention the effect on WTP drops by more than half. After ten months, the effect has almost disappeared. Crucially, no decay is observed for subjects who acquired knowledge on the benefits of LEDs during the experiment.

There are two main policy implications. First, we demonstrate that information provision can only affect WTP in the short term, unless it leads to real knowledge acquisition. Therefore, policies show focus on how to best ensure that information provision leads to knowledge acquisition. Second, the short-term effect of certain types of information can be affected by external factors, such as contemporaneous air pollution. People do not respond to negative information if it would compel them to take costly actions. Future research on information provision should identify when and why people attend to information as it is provided and translate the information into knowledge in the long-run.

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Appendix A: Information Materials

A1. Pre-information choices

An example of the pre-information choice situation is shown in Figure A1. The iteration process is provided in Appendix B.

	60-watt equivalent LED (7w)	60-watt equivalent CFL (14w)
		
Price	￥16	￥8

Figure A1. Pre-information choice situation

A2. Choice with information on monetary benefit

An example of the choice situation with monetary benefits is shown in Figure A2.

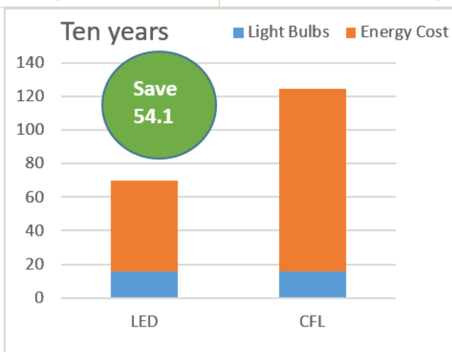
	60-watt equivalent LED (7w)	60-watt equivalent CFL (14w)
	 	
Life duration	10 years (4 hours/day)	5 years (4 hours/day)
Energy Cost	￥5.41/year	￥10.82/year
Total Cost	 	
Price	￥16	￥8

FIGURE A2. CHOICE SITUATION WITH MONETARY BENEFITS

A3. *Information on air pollution*

Subjects were given the following text:

"In China, electricity is mainly generated from coal. Burning coal is directly related to greenhouse gas emission and air pollutant emissions (e.g. pm2.5, pm10). Inhaling air pollutant leads to health problems such as heart or lung disease. Older adults and children are at greater risk from air pollutant.

Your choices of light bulbs affect air pollution. For the same amount of light (for instance, that of a 60w incandescent), LEDs produce more than 50% less air pollution compared to CFLs.

Figure A3 shows the pm2.5 level in Beijing in a day in June."

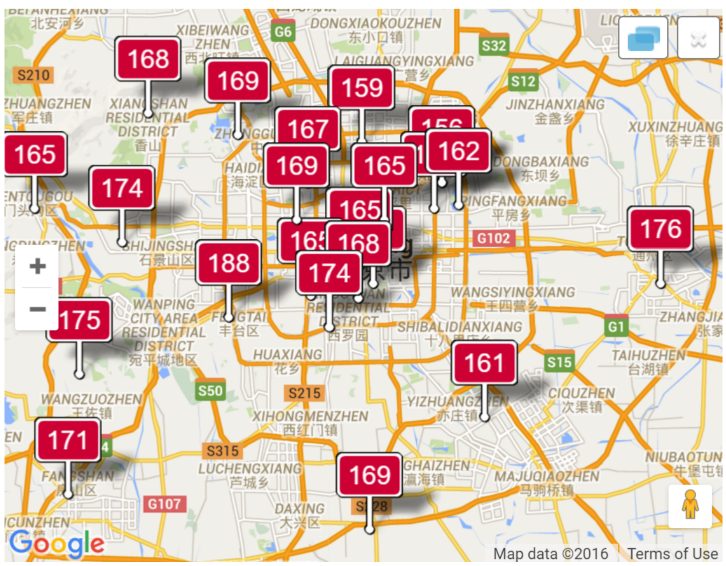


Figure A3. Air pollution map in Beijing

A4. *Information on climate change*

Subjects were given the following text:

"In China, electricity is mainly generated from coal. Burning coal is directly related to greenhouse gas emission and air pollutant emissions. Global warming generated by greenhouse gas emissions leads to extreme weather which affects agriculture, ecosystems and health both in China and the rest of the world. Older adults and children are at greater risk from climate change.

Your choices of light bulbs affect greenhouse gas emission. For the same amount of light (for instance, that of a 60w incandescent), LEDs produce more than 50% less greenhouse gas compared to CFLs.

Figure A4 shows the change in global temperature from 1884 to 2015."

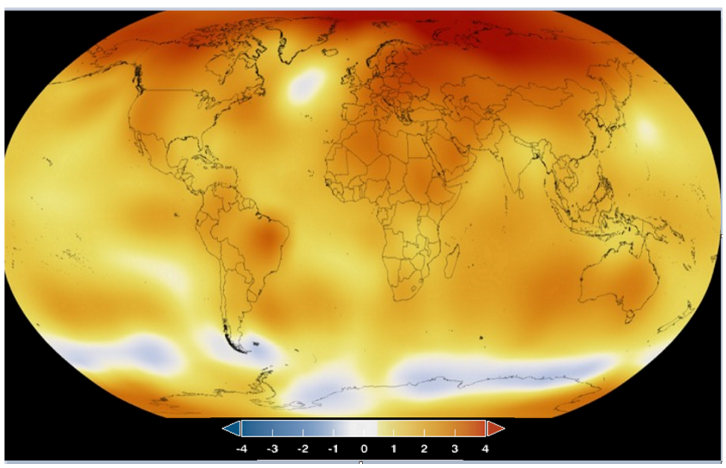


Figure A4. Map of Climate Change

A5. Information on manufacturing

Subjects were given the following text:

"China is the largest lighting production country in the world, the lighting products made in China has been exported to over 200 countries.

World famous lighting companies such as PHILIPS, OSRAM, GE etc. have stationed in the Chinese market since the 90s last century.

There are over 10,000 lighting manufacturers in China. These manufactures are mainly distributed in Chinas southeastern coastal areas, including Guangdong, Fujian, Jiangsu, Zhejiang and Shanghai."

A6. Information on online selling

Subjects were given the following text:

"Online sale is the new trend for lighting companies.

Some brands dont have very complete sales system, therefore more willing to seek for opportunities online.

Many emerging enterprises have already taken a favorable position in online sales. Market data shows that in 2014 the size of the market amounted to about 14.68 billion yuan, accounting for 14,4% of all sales channels."

Appendix B: The iteration process in eliciting WTP

The iteration process serves to measure WTP for LEDs in each choice session, with price of the CFL always equal to 8. Respondents always chose between a CFL and a LED. Each session contains 3 choices at most.

1. In the first choice, the starting price of the LED was 16.
2. In the second choice, the price of the LED was decreased to 8 if the CFL was chosen, and increased to 24 if the LED was chosen.
3. The process continues as illustrated in Figure B1.

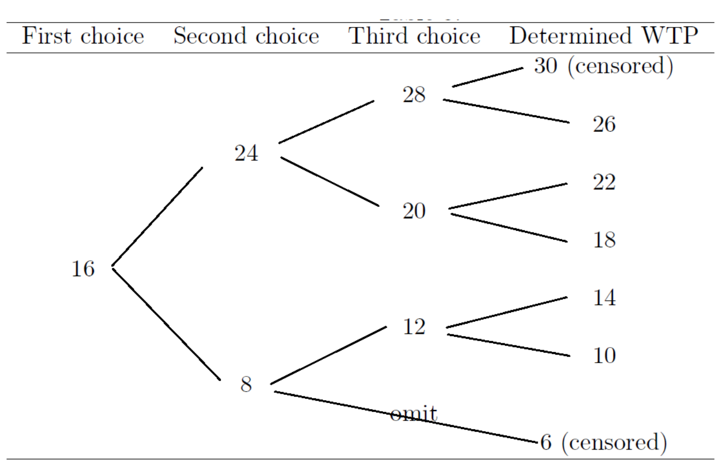


Figure B1. Iteration process and determination of WTP

Appendix C: Knowledge Questions in Follow-up Sessions

In the survey the order of the answers were randomized.

Cost Information

Please choose the statement that is closest to your knowledge:

A. For the same lighting effect, compared to a CFL, a LED saves about CNY 60 on energy cost over 10 years.

B. For the same lighting effect, compared to a CFL, a LED saves about CNY 20 on energy cost over 10 years.

C. For the same lighting effect, compared to a CFL, a LED costs about CNY 60 more on energy cost over 10 years.

D. For the same lighting effect, compared to a CFL, a LED costs about CNY 20 more on energy cost over 10 years.

Environmental Information

Please choose the statement that is closest to your knowledge:

A. For the same lighting effect, compared to a CFL, a LED emits more than 50% less greenhouse gas/air pollutants.

B. For the same lighting effect, compared to a CFL, a LED emits more about 20% less greenhouse gas/air pollutants.

C. For the same lighting effect, compared to a CFL, a LED emits more than 50% more greenhouse gas/air pollutants.

D. For the same lighting effect, compared to a CFL, a LED emits more about 20% more greenhouse gas/air pollutants.