Are Economics and Psychology Complements in Household Technology Diffusion? Evidence from a Natural Field Experiment

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Abstract

This paper uses a field experiment to estimate the effects of prices and social norms on the decision to adopt an efficient technology. We find that prices and social norms influence the adoption decision along different margins: while prices operate on both the extensive and intensive margins, social norms operate mostly through the extensive margin. This has both positive and normative implications, and suggests that economics and psychology may be strong complements in the diffusion process. To complement the reduced form results, we estimate a structural model that points to important household heterogeneity: whereas some consumers welcome the opportunity to purchase and learn about the new technology, for others the inconvenience and social pressure of the ask results in negative welfare. As a whole, our findings highlight that the design of optimal technological diffusion policies will require multiple instruments and a recognition of household heterogeneity.

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"Innovation is the market introduction of a technical or organisational novelty, not just its invention"
Joseph Schumpeter

1 Introduction

Economists have long argued that an essential driver of economic growth is innovation (see, e.g. Romer, 1990; Aghion and Howitt, 1992). Indeed, in his seminal work, Young (2005) argues that differences in production technologies represent an important source of disparities in patterns of long-run economic growth across countries. For instance, some estimates suggest that roughly 50 percent of U.S. annual GDP growth can be attributed to innovation (U.S. Chamber of Commerce Foundation, 2012).[1] Not surprisingly, policymakers have thus focused a great deal of attention on policies designed to stimulate innovation and the supply of new technologies.

Unfortunately, policymakers often overlook a critical component of innovation - the demand for and diffusion of new technologies. As Schumpeter's quote in the epigraph suggests, innovation includes not only creation, but also the diffusion of new technologies and products in the marketplace. For their part, economists, social scientists, and marketers have explored different factors that influence the diffusion of new technologies. Griliches (1957), for example, provides an early demonstration of the economic approach when he explored the adoption of hybrid corn technologies and focused on two fundamental drivers of behavior: the pecuniary cost and benefits of the technology.[2] Although economists highlight profit as the main motivation for technology adoption, other disciplines focus on non-pecuniary influences such as social networks and agents of change as underlying drivers of the adoption decision (e.g. Rogers, 1962).

The differing viewpoints across disciplines has fostered a lively academic debate between sociologists and economists that remains a common reference today (Skinner and Staiger, 2007). Influenced by this early debate, economists have expanded their focus to explore non-pecuniary aspects of technology adoption (see, e.g. the excellent survey by Hall, 2004). An example of this broadened approach is a number of recent studies exploring how information is passed through societies or social networks as a means to identify the role of social pathways on the adoption of new technologies (e.g. Bandiera and Rasul, 2006; Oster and Thornton, 2012; Chen *et al.*, 2010; Conley and Udry, 2010).

In this paper, we take an alternative approach to the problem and design a field experiment to explore the underlying economic and psychological factors that motivate technological adoption at the household

[1] Similar figures on the importance of research intensity on annual GDP growth are reported in Fernald and Jones (2014) and Jones (2002).

[2] Foster and Rosenzweig (2010) and Jaffe *et al.* (2002) contain broader overviews of research on technology adoption.

level. As a case study, we use the purchase of an energy efficient technology: compact fluorescent light bulbs (CFLs).[3] For the experiment, we approached nearly 9,000 households in the suburbs of Chicago, IL and offered them the opportunity to purchase either one or two packages of efficient bulbs.

Following DellaVigna *et al.* (2012) (**DLM** hereafter), a crucial aspect of our experimental design is the ability of households to sort in or out of the face-to-face interaction with the salesperson. Importantly, this affords a way to identify the extent to which purchase decisions reflect a consumers valuation for the efficient technology as opposed to social pressures or similar psychological constructs. To facilitate sorting, we use warning flyers placed on door knobs of households. The flyers also allow us to identify heterogeneity and simulate how sorting impacts the effectiveness of our policy instruments. We further randomize both the price at which households could purchase the efficient technology and the framing of a descriptive norm detailing the proportion of households in an area that report having at least one efficient light bulb in their home. Variation in both of these dimensions allow us to calculate an associated social norm "elasticity of demand".[4]

Data from our field experiment provide three main insights. First, we find that both prices and descriptive social norms impact the adoption decision. Conditional on answering the door, households are approximately 8.7 percentage points (or 40%) less likely to purchase a package of efficient light bulbs at our high ($5) price level. Social norms have also a significant (although less pronounced) impact on purchase decisions. Conditioned on answering the door, households in our social norm treatments are approximately 3.5 percentage points (or 43%) more likely than counterparts in our Neutral frame treatment to purchase at least one packet of efficient light bulbs - an effect that is independent of the proximity between the consumer and reference group.

Interestingly, we find that prices and descriptive norms influence behavior along different margins. Social norm statements affect behavior solely along the extensive margin. Prices, in contrast, affect behavior along both the intensive and the extensive margin. This is consistent with the notion that social pressure can be avoided by making a purchase (which will be the minimal purchase available for those whose willingness to pay for a second pack is lower than the price).[5]

[3] We designed our experiment to speak to the adoption of new (or efficient) technologies rather than the adoption of any specific technology. At the time this experiment was designed and run (2010), CFLs were the most efficient technology broadly available for lighting which accounts for approximately 9 percent of total electricity consumption in the residential sector in the United States and an even larger share of total electricity consumption in the residential sector worldwide. Since the time of our experiment, other efficient technologies such as LEDs have been introduced in the marketplace.

[4] As noted in prior work, the descriptive social norm statements could influence the decision to purchase through at least two different channels. As in a Becker household production model, the information could be used to update prior beliefs concerning the benefits of the technology. Alternately, descriptive social norms could operate through conformity motivations or increased social pressures (e.g Lapinski and Rimal, 2005; Cialdini, 2007; Schultz *et al.*, 2007; Ferraro and Price, 2013).

[5] This is also consistent with the notion that it is enough to purchase one unit in order to answer in the positive to the question "have you purchased efficient technology?". DellaVigna *et al.* (2016b) have documented that people experience a

To the best of our knowledge, we are the first to show that norms and prices are complements in the adoption decision.[6] If this is a general insight, as we believe it to be, it has implications for the design of policy. Depending on the underlying target, policymakers may wish to utilize a single instrument or a combination of economic and non-economic instruments to stimulate the diffusion of new technologies.

A second set of results involves sorting. Our Warning treatments highlight the dual role of sorting in the adoption dynamics. On the one hand, flyers lower the frequency with which households answer the door. This evidence is consistent with the idea that warned households lower the frequency of door opening in an attempt to avoid interacting with our salespeople and the resulting pressure to purchase efficient technology. Alternatively, conditional on answering the door, households in our Warning treatments are significantly more likely to purchase at least one pack of efficient light bulbs. This evidence confirms the idea that the Warning treatments alter the distribution of types who answer the door towards those with a greater preference for or curiosity about the more efficient technology.

The third set of results derives from a structural model in the spirit of DLM, that we extend to include three distinct motivations underlying the adoption of efficient technologies: 1) utility directly derived from the efficient technology (which is a combination of private returns and altruism), 2) social pressure or a desire to conform with the actions of others, and 3) curiosity, or the desire to seek information about energy efficient technologies.[7] Our structural estimations refine the descriptive analysis by providing quantitative assessments of the motivating forces behind consumption decisions, and allow us to conduct policy counterfactuals exploring various ways to promote the adoption of efficient technology.

We find that both estimated "curiosity" and "social pressure" play a role in the purchase decision, although only the former is significant at conventional levels. In addition, estimates from our structural model allow us to recover the distribution of efficient light bulbs valuations. Our estimates for the distribution of willingness to pay suggest a substantial amount of household heterogeneity and that a considerable number of households value efficient light bulbs less than the prevailing market price at the time of the experiment. Finally, through the policy counterfactual exercises, we estimate the degree of complementarity between social norms and prices. In this respect, importantly, our structural results confirm our reduced form estimations:

disutility from lying to the question "did you vote?", and both are examples of social norms.

[6]The closest analog to this finding is Holladay *et al.* (2019) who show that while social comparisons and rebates impact the likelihood a households completes and in-home energy audit, neither policy has a significant impact on the likelihood of installing energy efficient technologies following the audit.

[7]To recover the key parameters of our model, we employ an alternative structural estimation technique, namely, a Random Preference Probit (RPP) model (Hausman and Wise, 1976; Train, 1998). In doing so, our approach allows for correlation among the "random" components of utility (i.e., social pressure and curiosity) and, as a by-product, the explicit allowance for variation in tastes across individuals for the attributes of alternatives. Allowing for correlation across the structural components of our subjects' utilities is an important step in the direction of realism as reduced form results suggest correlations across actions taken by the same individuals at different stages of the decision-making process.

social norms and prices are complements, rather than substitutes. This holds because prices affect both the extensive and the intensive margins, while social norms operate along the extensive margin only.

Our paper is connected to several distinct strands of research. First, our paper is connected to the literature on technology adoption. A rich literature has developed in both the social sciences and the business and policy communities to help explain observed diffusion patterns. For example, the "Diffusion of Innovation Theory" is a social scientific construct developed by Rogers (1962), and still serves to explain how an idea or product diffuses. The theory has been used to explain the tremendous amount of variation that exists in technology adoption across products, as well as provide marketers a strategy to enhance product adoption. Our paper extends this literature by exploring the relationship between pecuniary and non-pecuniary motives for technology adoption by households within the context of a large-scale field experiment. In doing so, we provide an apples-to-apples comparison of strategies suggested in the fields of economics and social psychology and identify a potential complementarity between prices and norms on the diffusion of new technologies.

Second, our paper is methodologically connected to recent work in behavioral welfare economics exploring the welfare effects of *nudges* (Thaler and Sunstein, 2008) and other interventions.[8] To date, the behavioral welfare literature has predominantly focused on *internalities* (consequences for an individual of their own actions, that they do not take into account, Herrnstein *et al.*, 1993). In the context of environmental economics, Allcott and Taubinsky (2015) study the welfare effects of two interventions that provided different types of information and/or prices about CFLs, using the "sufficient statistic" approach developed by (Chetty, 2008) to identify the marginal individual after taking internalities into account.[9]

Our approach is different from most of the literature in behavioral welfare economics in three aspects. First, we use a different approach to measure welfare. Rather than adapting the sufficient statistics approach, we follow DLM and identify welfare effects through the ability of individuals in the experiment to sort into or out of treatments.[10] Second, rather than focusing on internalities, our approach centers on identifying psychological factors (moral costs) triggered by social pressures to take actions that are environmentally conscious (Yoeli *et al.*, 2013). Third, we focus on welfare effects in the context of technological adoption as opposed to behavioral change. In doing so, we explore behavior in a context where the effects of our intervention are likely to have persistent effects, provided that the adoption decision is difficult or costly to

[8]Contexts in which nudge-type interventions have been implemented include, but are not limited to, exercise (Charness and Gneezy, 2009; Acland and Levy, 2016), smoking cessation (Volpp *et al.*, 2006, 2009; Giné *et al.*, 2010) and energy/water conservation (Allcott, 2011; Schultz *et al.*, 2007; Ferraro *et al.*, 2011; Ferraro and Price, 2013).

[9]See also Chetty (2015) for a discussion of the sufficient statistic approach and its place in behavioral welfare economics.

[10]Other papers that apply the behavioral economics framework in the context of environmental/energy decisions are Allcott and Rogers (2014) and Allcott *et al.* (2014).

reverse (Brandon *et al.*, 2016).[11]

More broadly our paper contributes to a growing literature that develops empirical methods to measure the impact of behaviorally motivated policies. By using structural methods to uncover the underlying distribution of households' willingness to pay, and conducting policy counterfactuals to estimate the degree of complementarity between social norms and prices, we link closely to the literature that imposes structure on a model and corresponding field experiment (see, e.g., DellaVigna *et al.*, 2012, 2016b; Jin *et al.*, 2010). In doing so, we highlight how this approach complements the literature on structural behavioral economics (Chetty *et al.*, 2009; Laibson *et al.*, 2007; Conlin *et al.*, 2007; DellaVigna *et al.*, 2016a; Gerritsen, 2016). As such, we show how the combination of theory and field experiments can be used to evaluate a wide range of policy options - including those that combine insights from psychology and economics.

Finally, our paper contributes to a literature exploring whether and why policies or interventions have differential impacts along the intensive and extensive margins. For example, in the charity literature, there is ample evidence that matching gifts impact the number of donors (extensive margin) but have little impact on out of pocket contributions (intensive margin) (Karlan and List, 2007; Huck and Rasul, 2011). In the context of labor economics, (Fehr and Goette, 2007) show how temporary wage changes have differential impacts on the number of shifts worked (extensive margin) and the effort exerted during a shift (intensive margin). Given the recent emphasis in replication and generalization of results (Czibor *et al.*, 2019), one of our paper's contributions is showing complementarities between prices and social norms. In this regard, our paper reinforces findings in (List *et al.*, 2017) showing a complementarity between social comparisons and financial incentives to conserve energy.

The remainder of our study proceeds as follows. Section 2 details our experimental methods and strategy for estimating the structural model. Section 3 presents descriptive statistics from the experiment and our reduced form results. Section 4 summarizes results from the structural model and policy simulations. Finally, Section 5 concludes, followed by the Appendices containing additional statistical evidence and a detailed account of our structural identification strategy.

[11] The literature in behavioral welfare economics has recently emphasized the importance of focusing on general equilibrium effects (Handel, 2013; Spiegler, 2014; Jimenez-Gomez, 2019). We believe that general equilibrium are indeed of great importance, but we only focus on the partial equilibrium effect of our intervention, due to logistical constraints. The general equilibrium effects of our interventions are *a priori* ambiguous, partly because social norms (and therefore social pressure) depend on aggregate behavior, and it is difficult to make ex-ante predictions, although it is likely that as the efficient technology becomes adopted by a larger share of the population, the social pressure to adopt it (for those who have not) would increase.

Table 1: Treatment Sample Size

Price per Pack	Social Norm	No Warning	Warning	Opt-Out
	No	480	474	473
$1	Low	447	508	535
	High	454	469	481
	No	435	546	501
$5	Low	493	544	491
	High	431	511	542
Total		2740	3052	3023

Each cell gives the number of households approached for each treatment group.

2 Methods

2.1 Field Experimental Design and Implementation

Our field experiment was implemented by offering households the opportunity to purchase up to 2 packages of efficient light bulbs within the context of a door-to-door design (each package contained 4 CFLs). A priori, approaching consumers at their doors may not appear to be the most applicable method for technology adoption. However, energy conservation programs often employ door-to-door approaches to encourage the adoption of efficient technologies. Examples of recent programs are the Clean Development Mechanism projects in the South Urban Lahore district of Pakistan and Visakhaptanam India, and a door-to-door energy conservation campaign distributing environmental technologies in Boulder, Colorado in the summer of 2010. Further, approaching households directly allows for greater ease of allowing sorting, which is necessary to identify pieces of our structural model.

In total, there are 18 treatment cells in the experimental design. Table 1 provides the sample size by treatment cell. In the experiment, student solicitors that were hired through the Becker Center at the University of Chicago approached households in the Chicago area on weekends.[12] Students were hired upon responding to job advertisements placed around campus and on the University's main electronic help wanted web site (marketplace.uchicago.edu). After responding to the advertisement, students were briefly interviewed. Every student who completed the interview was hired and given a time to come back for a training session. Each training session lasted approximately 30 minutes and was conducted with multiple students.

Students were driven to designated neighborhoods on Saturdays and Sundays to approach households

[12]The suburbs in the study include; Arlington Heights, Elmwood Park, Evanston, Lemont, Libertyville, Oak Park, River Forest, Roselle, Skokie, and Wheaton. Median household income for these suburbs range from $7,315 to 89$,284 as reported in the 2000 U.S. Census - figures that are substantially higher than the median income for both Illinois and the United States.

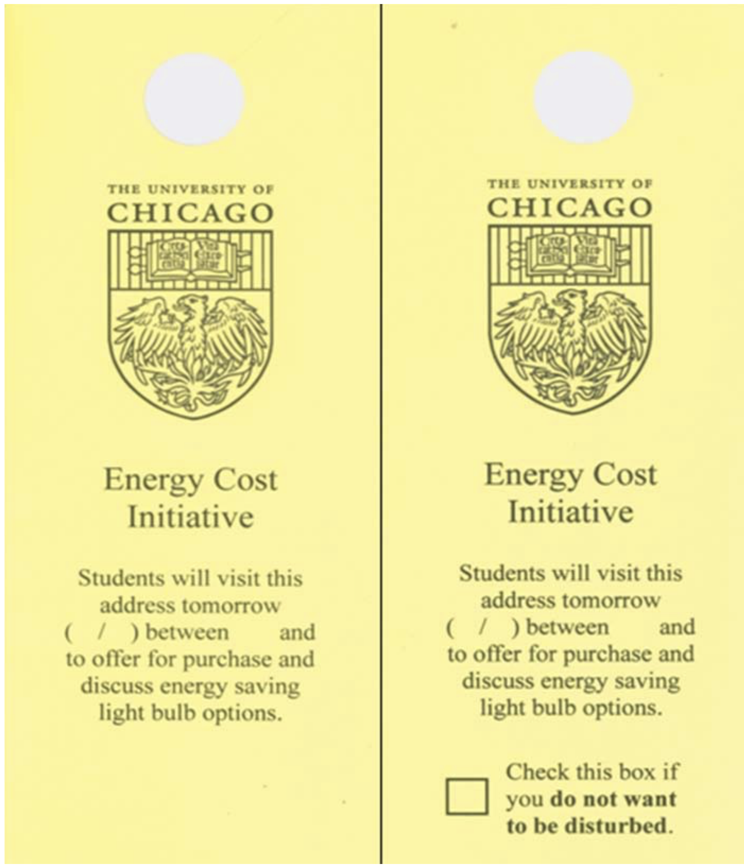
over 4 one-hour blocks of time: 10 a.m. to 11 a.m., 11 a.m. to noon, 1 p.m. to 2 p.m. and 2 p.m. to 3 p.m. Households were grouped into blocks containing roughly 25 houses. As each block of houses was randomly assigned to a treatment, a typical worker approached households using a different treatment script each hour. The experiment was conducted on weekends starting in June 2009 and lasted for a year with breaks in the winter months and on weekend days when it was either too cold or raining.

The theoretical model underlying our structural estimation suggests a way to parse the impacts of the valuation for efficient light bulbs (private and altruistic) vs. social pressure on the adoption decision, allowing consumers to select into or out of interacting with a salesperson. In order to provide households this opportunity, a team of researchers and interns placed flyers on households in the Warning and Opt-Out treatments the day prior to the students visiting households. These flyers, shown in figure 1, informed the household that it would be visited the following day by someone with an "offer for purchase and discuss energy saving light bulb options".[13] This ensures that some fraction of the households that we warn that see the warning have an ability to adjust the likelihood of being home and answering the door, compared with the No Warning treatment, in which no flyer is delivered.[14]

[13]While placing the flyers on doors, the researchers and interns only interacted with members of the households if they were approached directly (i.e. household members were outside in the yard and witnessed the placement of the flyer). Although the student salespersons were aware of the different scripts and prices for each treatment, they were not aware that only some houses had been warned of the visit the day prior via the flyers.

[14]Social norm and price treatments provide variation to identify the impact of social pressure and price on the decision to purchase. However, the decision to purchase could be due to underlying social pressure present in all treatments vs. the private and public attributes of the purchase. Moreover, we are unable to separately identify the public vs. private sources of valuation for efficient light bulbs and thus consider a measure of value that combines the two potential sources.

Figure 1: Door-hanger examples



Note: Warning on left (W), Opt-Out on right (OO).

The main treatments were delivered through scripts given to student salespersons for each one-hour treatment block of households. The scripts varied along two dimensions: whether it included a statement of social norms and the price of the CFL package. The efficient light bulbs sold door-to-door were priced between \$3.85 and \$7.15 for a package of 4 CFLs in stores throughout the Chicago area. The price tended to be around \$5.00 when tax was included so we set our baseline price for a package of 4 CFLs at \$5.00. We included one other price point, a low price of \$1.00 which was a good approximation of the price of a package of incandescent bulbs at the time of the experiment.

We incorporate social norms by using three different variants of the sales script; one devoid any normative content, referred to as the "Neutral Frame" treatment, and two treatments that include information on the ownership of CFLs buy like others - "Social Norm Low" and "Social Norm High" (hereafter N, L, H, respectively). The Social Norm Low treatment augments the neutral frame script by including the phrase:

"*For instance, did you know that* ***70% of U.S. households*** *own at least one CFL?"*. The Social Norm High treatment alters the proximity of the reference group by including the phrase: "*For instance, did you know that* ***70% of the households that we surveyed in this area*** *own at least one CFL?*" The change in the proximity with which the social norm is stated follows in line with Goldstein *et al.* (2008).

Before proceeding, variation in both social norms and price allows a way to "price" normative statements. Further, analyzing not only the decision to purchase but also how many packages of efficient light bulbs were purchased allows us to evaluate if the normative appeals work because consumers want to be "buy out" of social pressure or "buy in" to a new technology.

3 Descriptive statistics and reduced-form results

For the purpose of identification of both the reduced-form regressions and our structural model, we consider a household's decision problem as a sequence of four binary choices defining the interaction between a potential customer (call her *Anna*) and a solicitor (call him *Beppe*).

1. In Stage 1, Anna may receive a flyer of Beppe's upcoming visit. If the flyer has an Opt-Out box (Opt-Out treatment, see Section 2.1 above), she has to decide whether to opt in by checking the box ($y^1 = 0$) or not ($y^1 = 1$). If $y^1 = 0$, the interaction between Anna and Beppe ends here.

2. In Stage 2, Beppe visits the home. Anna has decide whether to answer the door ($y^2 = 1$) or not ($y^2 = 0$). If $y^2 = 0$, the interaction between Anna and Beppe ends here.

3. In Stage 3, conditional on answering the door, Anna has to decide whether to buy at least one pack of efficient light bulbs ($y^3 = 1$) or not ($y^3 = 0$). This binary choice defines, in our behavioral timeline, the *extensive margin* of the adoption decision. If $y^3 = 0$, the interaction between Anna and Beppe ends here.

4. Finally, in Stage 4, conditional on having purchased one pack of efficient light bulbs already, she may also decide to buy an additional one ($y^4 = 1$) or not ($y^4 = 0$). This is our *intensive margin*, the final stage of the interaction.

3.1 Descriptive statistics

Table 2 reports summary statistics of the distributions of the various outcomes of interest broken out by the different warning conditions. The first column in table 2 shows the descriptive statistics for the Opt-Out treatment, which is the first stage of the decision problem described above. This result measures sorting by households that checked the appropriate box in the flyer (conditional on seeing the flyer). Columns 2-4 contain summary statistics on the remaining three stages of the decision problem; the probability of answering the door and probability of purchasing one or two packages.

Table 2: Summary Statistics

	Opted Out	Answer Door	Buy	Buy|Answer	Q=2|Buy
No Warning		0.367	0.0321	0.087	0.443
		(0.482)	(0.176)	(0.283)	(0.500)
Obs.		2740	2740	1006	88
Warning		0.332	0.038	0.115	0.564
		(0.471)	(0.192)	(0.320)	(0.498)
Obs.		3052	3052	1014	117
Opt-Out	0.116	0.274	0.028	0.103	0.529
	(0.321)	(0.446)	(0.165)	(0.307)	(0.502)
Obs.	3023	3023	3023	828	85
Total	0.116	0.323	0.033	0.102	0.517
	(0.321)	(0.468)	(0.178)	(0.302)	(0.500)
Obs.	3023	8815	8815	2848	290

Note: Figures in table are means and standard deviations (in parentheses). For example, "Opted Out" is calculated as 0.116=352 households checking the box divided by 3023 total households. In the remaining figures for this treatment the 352 households of the 3023 are included as doors knocked on but not answered.

A quick inspection of Table 2 reveals two important characteristics of our data set. In the presence of a prior warning *i*) Anna is less likely to answer the door and *ii*) more willing to buy (along both margins). This, in turn, implies that, by analogy with DLM, *social pressure has a negative impact on the adoption decision*: given the chance, some households avoid the interaction with the salesperson. On the other hand, *sorting has a positive impact on adoption*, conditioned on answering the door, warned households exhibit a higher willingness to buy, along both margins.

Table 3 reports a data summary of the adoption decisions across the three psychological frames: i) Neutral frame, ii) Low social norm, and iii) High social norm and for the two price levels. Within each frame, we report purchases for both the pooled data and for each respective price level. Data is Table 3 provide evidence that social norms impact the third stage decision to purchase a package of efficient bulbs. Whereas 2.7 percent of all households approached in our Neutral treatment ultimately purchase at least one package of efficient light bulbs, purchase rates in our Low norm treatment are approximately 18.5 percent higher. Increasing the proximity between the household and comparison group, as in the High norm treatment, leads to even further increases in purchase rates: people in this treatment are 44.4 percent more likely than counterparts in the Neutral group to purchase efficient light bulbs. We observe similar differences if we focus on purchase rates conditioned on answering the door. For example, the results in table 3 show that households that answer the door in our High (Low) social norm treatment are approximately 58 percent (41.7 percent) more likely to purchase efficient light bulbs than their counterparts in the neutral treatment. These differences suggest the importance of proximity when using social norms, and are consonant with previous research (Goldstein *et al.*, 2008). Interestingly, however, the data in Table 3 suggest that normative statements have no impact on the fourth stage (intensive margin) decision. As noted in the final column of the table, there is no discernible difference in the likelihood of purchasing a second pack of efficient bulbs across the three normative treatments.

Table 3: Treatment Effects on the Purchase Decision

Social norm \ Price	Buy			Buy | Answer			Q = 2 | Buy		
	$p = 1$	$p = 5$	Total	$p = 1$	$p = 5$	Total	$p = 1$	$p = 5$	Total
Neutral Frame	0.040	0.015	0.027	0.110	0.046	0.079	0.631	0.182	0.506
	(0.196)	(0.121)	(0.163)	(0.313)	(0.210)	0.270	(0.487)	(0.395)	(0.503)
Obs.	1427	1482	2909	520	475	995	57	22	79
Social Norm Low	0.048	0.016	0.032	0.174	0.055	0.112	0.667	0.320	0.577
	(0.215)	(0.127)	(0.176)	(0.379)	(0.230)	(0.316)	(0.475)	(0.476)	(0.496)
Obs.	1490	1528	3018	414	451	865	72	25	97
Social Norm High	0.055	0.024	0.039	0.158	0.073	0.115	0.538	0.333	0.474
	(0.230)	(0.154)	(0.195)	(0.366)	(0.260)	(0.320)	(0.502)	(0.478)	(0.501)
Obs.	1404	1484	2888	492	496	988	78	36	114
Total	0.0480	0.018	0.033	0.145	0.058	0.102	0.609	0.289	0.517
	(0.214)	(0.135)	(0.178)	(0.352)	(0.234)	(0.302)	(0.489)	(0.456)	(0.501)
Obs.	4321	4494	8815	1426	1422	2848	207	83	290

Note: Figures in table are means and standard deviations (in parentheses). For example, column 1 "Buy" is calculated as 0.04=57 households buying at least a pack of efficient light bulbs divided by 1427 total households approached in Neutral treatment with price=1\$. Column 2 "Buy | Answer" is calculated as 0.11 = 57 households buying at least a pack of efficient light bulbs divided by 520 total households who answer the door when approached in Neutral treatment with price=1\$. Column 3 "Q=2 | Buy" represents households that choose to buy two packs of efficient light bulbs.

3.2 Reduced form regressions

Given the multi-stage structure of our field experiment, our reduced form analysis is built around a multivariate linear probability model, where we estimate the joint probability of our three binary actions (answering the door and choosing along the extensive/intensive margin) using different covariates depending on the information sets of each stage (stage 2, 3 and 4 described above).[15]

We therefore also examine the correlation structure of the error terms from a system of three equations. The general specification of our equations is

$$y_{ijk}^s = \beta^s \cdot X_{ijk}^s + \gamma_j^s + \lambda_k^s + \epsilon_{ijk}^s, \quad s = 2, ..., 4; \tag{1}$$

[15]Stage 1 is not included in our system of equations because of a collinearity problem, since only households in the warning condition OO participate to Stage 1.

where

- $y^s_{ijk} \in 0, 1$ is household i's decision at Stage s located in suburb k and solicited by salesperson j;
- β^s is the vector of estimated treatment parameters of our reduced form;
- X^s_{ikt} is the vector of stage specific covariates, which includes a constant and treatment dummies (conditional on i's information set at stage s). Respectively, in stage 2 the choice to answer the door is assumed to depend on the warning and opt-out condition only (to the extent that price and social norm message are revealed only after answering the door).[16]
- γ^s_j and λ^s_k are salesperson (j) and suburbs of residence (k) specific controls that are designed to control for possible randomization fixed effects that are uncontrolled in the raw data analysis;
- ϵ^s_{ijk} is the error term, a random draw from a multivariate normal distribution (one distribution for each decision stage, s). We assume ϵ^s_{ijt} to be independent across individuals, i, and controls j and k, but not across stages, s. In this respect, table 5 reports the correlation matrix of ϵ_s derived from the estimation of table 4.

Finally, we cluster robust standard errors at date-solicitor time blocks level. As discussed in section 2, treatments were randomized within a date-solicitor time block, but not all treatments were run in all time periods. We estimate model 1 by maximum likelihood.[17] Parameters are consistently estimated in two steps, where we treat each equation as a linear probability specification taking into account the ordinal nature of the choices: *i)* a set of equation-by-equation linear estimations and *ii)* a set of simultaneous estimations that treats them as related to each other. In other words, the simultaneous estimation maximizes a likelihood function that includes all three equations in order to take into account the full covariance structure of three decisions and the interdependence across choices (the three equations are not independent since they are computed on a gradually reducing subject pool).

The number of observations varies by task given the sequential structure of the experiment (see Figure 2). As such, each equation is conditioned on a reduced data sample: 8815 (2848) [290] observations in stages 1 (2) [3], respectively. that is built on a maximum - likelihood estimator.

Table 4 shows results for the simultaneous estimations of our system of equations. We report the first set of conditional results related to the equation-by-equation estimations in Appendix A (see table A1). Table

[16]We use the "warning" treatment dummy to collect information for warning as well as opt-out treatments.
[17]The estimation is performed using the CMP user-provided package in STATA (Roodman, 2011).

4 complements table 2 and 3 summarizing the raw data by reporting econometric estimates that take into account the correlation in choices made by any given individual.

Table 4: Simultaneous estimations

	Answer Door	Buy | Answer	Q=2 | Buy
Warning	-0.026*		
	(0.015)		
Opt-Out	-0.077***		
	(0.015)		
Warning treatments		0.062**	0.055
		(0.026)	(0.092)
Social Norm Low		0.005	-0.058
		(0.018)	(0.085)
Social Norm High		0.038***	-0.061
		(0.014)	(0.107)
Price $5		-0.085***	-0.374*
		(0.012)	(0.207)
Constant	0.351***	0.463*	-1.109
	(0.031)	(0.243)	(2.066)
Solicitors FE	YES	YES	YES
Suburbs FE	YES	YES	YES
Obs.	8815	2248	290

$*p < .1$; $**p < .05$; $***p < .01$

Note: All regressions include solicitors and suburbs fixed effects. Standard errors (in parentheses) are clustered at date-solicitor blocks level.

Together, Tables 2-4 yield three stylized facts which are central to our narrative.

Result I: Warning leads to sorting.

Column 1 of Table 4 confirms the evidence of Table 2, in that the estimated probabilities of answering the door are significantly lower in the W and OO treatments, compared with the baseline: Households in the Warning and Opt-out treatments are 2.6 and 7.7 percentage points less likely to answer the door than their counterparts approached without warning.[18] This result suggests that warning households leads to sorting and, therefore, that social pressure is a significant driver of the behavior observed in our experiment.

Result II: Social norms affect consumers on the extensive margin, while prices affect both the intensive and extensive margins.

Tables 3 and 4 provide empirical support for Result II. First, summary results in table 3 indicate that an increase in price from $1 to $5 generates a significant decrease along both margins. For example, households facing a $5 are 62.5 percent less likely to purchase the first package of efficient bulbs and 52.5 percent less likely to purchase a second package than counterparts facing a $1 price. The estimated parameters of column

[18] Identical result is found in table A1 in appendix A.

2 of table 4 show that both prices and social norms affect the extensive margin. Conditioned on answering the door, individuals in the Social Norm High treatment are 3.8 percentage points more likely to purchase a package of CFLs than counterparts in the neutral frame treatment. Similarly, households facing a price of $5 per package are 8.5 percentage points less likely to make a purchase than counterparts facing the $1 price. Column 3 summarizes effects along the intensive margin and highlight a fundamental difference in the effect of prices and norms: only prices matter for the purchase of a second package. Viewed in their totality, these reduced form results suggest an important complementarity between pecuniary and non-pecuniary factors on the diffusion of new technologies - the policies work along different margins.

Result III: correlation across choices.

Table 5 reports the estimated correlation between the residuals from the system of three linear probability specifications.

Table 5: Correlation structure of the error terms

	Buy | Answer	Q=2 | Buy
Answer Door	-0.681***	0.866***
	(0.238)	(0.116)
Buy | Answer		-0.458
		(0.694)

$*p < .1$; $**p < .05$; $***p < .01$

Addressing simultaneously empirical estimations we find evidence of a correlation between answering the door and choosing along both the extensive and intensive margins. Indeed, the two equations related to the decisions to answer the door and the decisions to purchase at least 1 or 2 packages of efficient light bulbs are strongly correlated (-0.681 and 0.916, respectively). Looking to the correlation between the error terms of the second and third equation (-0.712), it appears that households with a higher likelihood of purchasing at least 1 pack of efficient light bulbs are less likely to purchase a second package. This suggests that the choices are largely independent - perhaps reflecting that our treatments attract different types for whom the underlying motivation for purchasing the first package of efficient light bulbs differ from those who would purchase in the absence of a normative appeal.

4 Structural estimation

We view the reduced form results as providing interesting insights on their own, yet we can complement those by imposing further structure on the estimation. Identification of theoretical parameters through structural estimation permits a quantitative evaluation of the relative welfare impact of social-psychology statements in comparison with financial incentives. In this respect, our experimental design provides the ideal setting for such a comparison as randomization of both instruments has been carefully controlled for.

We model adoption choice as a sequential individual decision process under uncertainty in the sense of Erdem and Keane (1996): agents - drawn from a heterogeneous population with respect to a finite set of latent behavioral characteristics - maximize expected utility conditional on the realization of these random characteristics, which are known at the time in which they are relevant for choice, but random at any prior decision in the sequence. Our approach thus shares similarity with Laibson (1997) in that we assume Anna is playing a dynamic game with her future selves. Further, following DLM, we assume *rational expectations* in that agents - although they do not know their own realization of the latent characteristics that affect future choices - are informed about the relevant parameters (in terms of their means and co/variances) of the joint distributions.

The most significant departure from DLM's identification strategy involves the introduction of a novel structural parameter, which we call *curiosity*. This parameter measures the individual's expectation about her utility gain from the interaction with the solicitor, independent of any price, social norm and purchasing decision. In other words, it measures the expectation of the gain from the interaction itself, which is precisely what we understand by curiosity. Note that this parameter is not present in DLM since, in that case, the flyers contained sufficient information relevant to the treatments (prices and social pressure). In our design the flyers contain minimal information. While this approach is customary in real-world interventions that target energy efficiency, it is by design impossible to have a measure of households sorting behavior based on the information that is absent from the flyer (prices and social norms), although they are still able to sort due to their curiosity.

Scientifically, the motivation to include a curiosity parameter in estimation arises from a growing series of psychological studies where "curiosity" has been defined as *"the desire to know"*. (i.e. Litman *et al.*, 2005).[19] In particular, Loewenstein (1994) highlights that curiosity can be characterized as a loss-aversion phenomenon, that is a situation in which the opportunity to loss information is considered to be worse than a situation in which one merely does not acquire the same information (i.e. Alós-Ferrer *et al.*, 2018). This phenomenon is related to the interest in learning something new (Charness *et al.*, 2003). Hence, the curiosity effect may similarly be generalized to all goods that have an element of uncertainty associated with them, since curiosity arises from a perception gap in knowledge. Indeed, curiosity might motive consumers to purchase a desirable new product (see among others, Bernard *et al.*, 2005; Loewenstein, 2000); alternatively,

[19]These studies analyze two categories of epistemic curiosity: the *interest-type* curiosity and the *deprivation-type* curiosity. The first involves the anticipated pleasure of new discoveries and the second reduces uncertainty of knowledge gaps.

curiosity may play a role in setting expectations in prices, causing the endowment effect (Van De Ven *et al.*, 2005).

4.1 Identification

We here streamline the stylized theoretical model that guided our structural estimation strategy, given the design and implementation of our field experiment (details in Appendix B).

The sequence of events of our structural model is the same as the one of our reduced form regressions (see Section 3). That is, we assume that Anna's timeline is broken down into four binary decisions, or stages, as shown in Figure 2. Let $\beta^s \in [0,1]$ denote the probability of $y^s_{ijk} = 1$, estimated, by maximum likelihood, assuming that the three parameters of interest distribute normally within the household population. By the same token, let $\beta^s_{s'}$ Anna's expectation over $\beta^s \in [0,1]$ formulated at stage $s' < s$, conditional on the information set at s'.

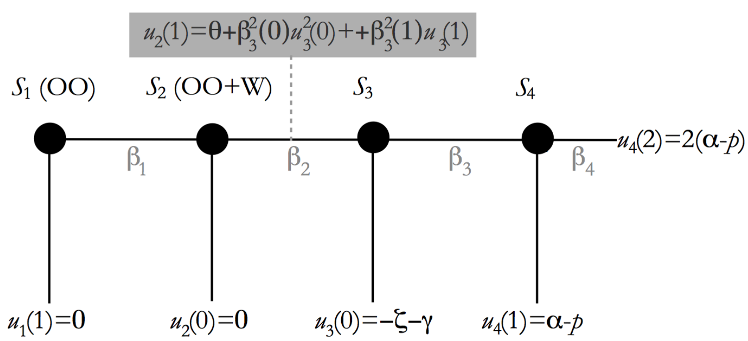


Figure 2: Timeline of the structural model

Figure 2 displays the sequential decision problem Anna is facing and identifies the three behavioral parameters governing her (binary) decisions. Specifically:

- Anna's *value* for a CFL pack, α, accounts for financial considerations (i.e., a reduction in energy costs) as well as for pure and impure altruism (warm glow) that reflect reduced energy use and associated carbon emissions when switching to efficient bulbs. Since the experiment is not designed to identify these components, we use a specification that is general enough to encompass all these potential sources of value.

- Anna's *sensitivity to social pressure*, ς, is positive when Anna feels bad about not buying anything facing Beppe in a face-to-face interaction (i.e., after answering the door). In this respect, this parameter is very similar to that introduced by DLM.

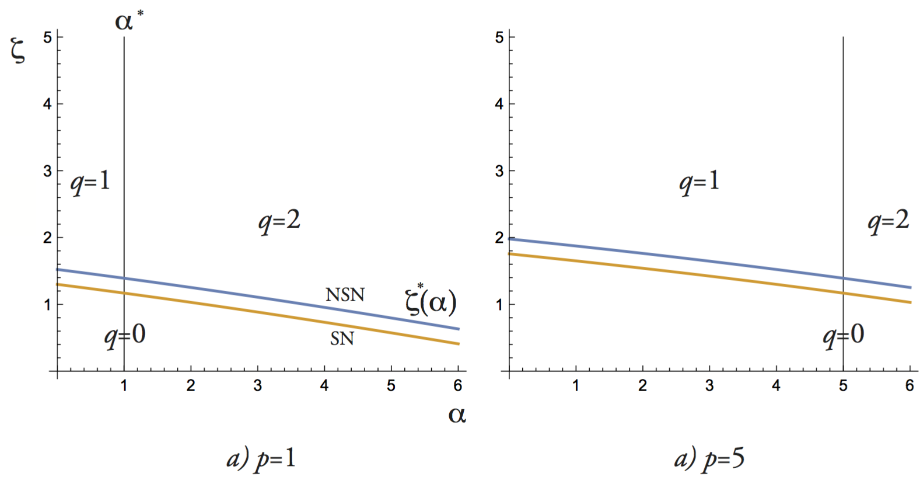


Figure 3: Testable hypotheses. Figure 3 indicates the different regions for buying, no buying [$q = 0$], extensive margin [$0 < q < 2$] and intensive margin [$q = 2$]. The regions are a function of the value parameter, α, and the social pressure parameter, ς.

- Anna's *curiosity*, θ, is positive when Anna is interested in learning more about energy saving solutions independent her willingness to purchase efficient technology.

In Appendix B we solve the model "backwards", starting from Stage 4, under the assumption Anna is aware of her own parameter preferences at the time the latter are relevant for choice (i.e., α in Stage 4, ς in Stage 3 and θ in Stage 2) and rationally anticipates her response conditional on her information state at each stage. Figure 3 summarizes the main features of the solution of our model as far as the extensive (Stage 3) and intensive (Stage 4) margins are concerned.

Denote by $\alpha^* = p$ the threshold for α which identifies the marginal buyer in Stage 4 - the intensive margin choice. Given our linearity assumption, Anna will buy a second pack whenever $\alpha > \alpha^* = p$. Therefore, the belief associated with the intensive margin choice, at all prior stages $s < 4$ is thus given by $\beta_s^4 = 1 - \Psi(\alpha^*)$, where $\Psi(\cdot)$ denotes the cumulative (normal, in the structural estimations of Section 5) density that defines our heterogenous population.

By the same logic, in Stage 3, Anna decides whether to buy at least one pack or nothing (the extensive margin) and will do so if ς is sufficiently high. In Appendix B we identify the marginal buyer for the stage 3 decision as a function of the parameters α, ς. Figure 3 illustrates the case of the normal distributions of α and ς as in Model 1 in our structural estimations (see Section 5). As Figure 3 shows, α^* corresponds to the prevailing price, p, while $\varsigma^*(\alpha)$ is decreasing in α. This is because a higher value of α (i.e., higher evaluation for the CFL) lowers the impact of social pressure on the marginal adopter. Also notice that a positive social norm facilitates adoption by shifting down the extensive margin threshold.

While Figure 3 is calibrated according with the structural estimation of Model (1) (see Table 6 below). In Appendix B we prove that the qualitative features of our model are preserved under very mild distributional restrictions.

4.2 Estimated Parameters

The estimated parameters of the structural estimations under three alternative specifications are reported in Table 6. Informed by the reduced form results of Section 3, Model (1) does not condition the estimate of μ_α on social norms. In other words, Model (1) restricts social norms to have an impact on the extensive margin only while allowing prices to impact decisions along both the extensive and intensive margins. Model (2) relaxes this restriction by allowing social norms to influence both margins, positing direct effects on μ_α. Specifically, in Model 2 we restrict our normative statements -which are captured by β_L and β_H- to have impacts via shifts in the parameter mean. Finally, Model (3) maintains the same structure as Model (1), but allows for the existence -for both μ_α and μ_ς- of *selection effects* due to the warning conditions, that is, shifts in the corresponding parameter means caused by sorting by households who were warned about the upcoming solicitation (both W and OO conditions together). These parameters are labelled as β_W and γ_W, respectively.

The parameter estimate for μ_α in Model (1) suggests that the marginal utility (willingness to pay) for a pack of efficient light bulbs is approximately \$2.33 for the representative household in our sample. Importantly, this estimate provides a potential rationale for why many consumers do not purchase efficient light bulbs -*ceteris paribus* they value them less than the prevailing market price. The negative and highly significant estimate of μ_ς - that is, *negative social pressure* - accounts for the large proportion of subjects not buying anything despite answering the door and having a valuation for a pack of efficient light bulbs that exceeds the \$1 of our low price condition.[20] As the estimated parameter for social pressure in Model (1) is even higher than μ_α, the average household in our experiment would only purchase a pack of efficient light bulbs if the price was negative (i.e, we paid them to do so). By contrast, both social norms - L and H - have a positive (and significant) impact on the extensive margin suggesting that the normative statements mitigate spite towards our solicitors and/or increases the valuation households place on the first pack of efficient light bulbs purchased. Interestingly, our structural model does not detect any significant difference

[20]Unfortunately, we are unable to determine what drives this estimate. One possibility is that households dislike being solicited and asked to purchase a pack of light bulbs. A second possibility is that the estimate captures a fixed cost of either having to store the bulbs for future use or replacing existing lighting in the home. Future work should explore the possibilities to better understand what drives the low rates of purchase in our experiment.

Table 6: Structural estimations

	(1)	(2)	(3)
μ_α	2.327***	2.067***	1.381**
	(.416)	(0.588)	(0.690)
β_L		0.779	
		(0.477)	
β_H		0.008	
		(0.791)	
β_W			1.362
			(0.882)
μ_ζ	-2.542***	-2.23**	-1.058
	(0.867)	(0.957)	(1.063)
γ_L	0.222**	-0.901	0.218**
	(0.103)	(0.694)	(0.103)
γ_H	0.222**	0.218	0.212*
	(0.113)	(1.111)	(0.121)
γ_W			-2.04
			(1.262)
μ_θ	-3.01***	-3.063***	-3.549*
	(0.857)	(0.854)	(1.075)
h_0	0.351***	0.349***	0.351***
	(0.011)	(0.012)	(0.011)
r	0.207***	0.207***	0.207***
	(0.019)	(0.019)	(0.019)
σ_α	4.810***	4.827***	4.774***
	(1.101)	(1.109)	(1.107)
σ_ζ	0.925***	0.963***	0.863***
	(0.228)	(0.223)	(0.264)
ρ	-0.9	-0.9	-0.9
	(-)	(-)	(-)
Obs.	8815	8815	8815
Log lik.	7585.7101	-7583.935	-7583.372

$^{*} = p < .1$; $^{**} = p < .05$; $^{***} = p < .01$

between the two normative statements. This result challenges the claim of the relevance of "*proximity*", that has been documented in prior work in social psychology.

The estimate of μ_θ is negative and highly significant in Model (1) suggesting that individuals do not desire and in fact dislike information on energy efficiency and energy saving strategies. Such dislike accounts for the large proportion of subjects who do not answer the door in our warning treatments. To the best of our knowledge, we are the first to document that individuals may actually dislike information on energy efficiency and are willing to take a costly action to avoid receiving such. This result might provide insights into why informational treatments have had little impact on energy savings in the previous literature (see, e.g., Holladay *et al.* (2019)) and highlights that even though information is supplied, for it to be valuable there must be sufficient demand for it. In this regard, our result has a distant antecedent in considering demand for information in the area of health. For example, people frequently avoid information about their own health (Thornton, 2008; Zanella and Banerjee, 2016), which has been attributed to the fact that people who are ignorant of their health can be more optimistic about it - i.e., it provides a sort of anticipatory utility (or, alternatively, avoiding information may allow them to avoiding anxiety associated with knowledge of bad outcomes, Oster *et al.*, 2013). Viewed in its totality, Model (1) provides two potential explanations for why households eschew the purchase of efficient light bulbs despite the documented energy savings: (i) individuals do not seem to care about energy efficiency and actually dislike receiving energy savings information, and (ii) most individuals value efficient light bulbs substantially less than the market price- a result we will return to when conducting our policy simulations. In this regard, our structural model provides a plausible underpinning for the "*energy paradox*."

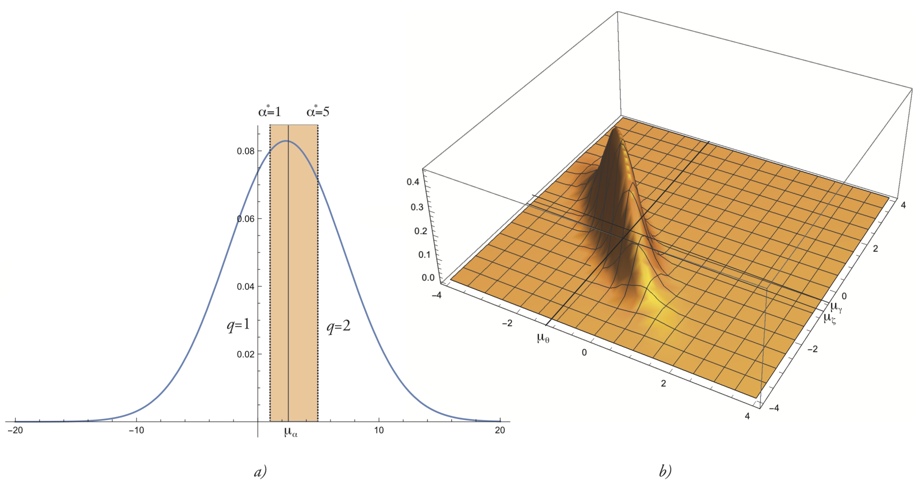
Concerning Model (2), while most of the estimated parameters remain practically unchanged -with specific reference to μ_α and μ_θ- the dependency of μ_ς on social norm disappears. Moreover, we are unable to establish an effect of the social norms on the intensive margin in that we fail to reject both null hypotheses $H_0 : \beta_H = 0$ and $H_0 : \beta_L = 0$. Combined with results from Model (1), our structural estimates provide evidence that normative statements operate exclusively along the extensive margin. From a positive perspective, this suggests that normative appeals should be modeled as something akin to fixed costs, or "warm glow" that impacts choice along the extensive margin but has no impact on the valuation for inframarginal units. Whether and to what extent this insight extends to other domains is an important research agenda.

As for Model (3), we confirm our Result 1 on sorting: it influences both margins, raising the utility of consumption and lowering social pressure (although neither effect turns out to be significant at conventional levels). Directionally, these insights open up an interesting possibility since this is exactly how sorting should impact treatment effects. For example, in the warning treatment those individuals who are most susceptible to social pressures should sort out so we should find a reduction in the effect of social pressure. Likewise, those with greater curiosity should sort in, causing a higher estimated valuation for those who answer the door in the warning conditions. In this manner, the structural estimates from Model (3) reveal a potential benefit of a policy approach that is voluntary in nature, allowing people to sort according to their preferences because such an allowance permits a shifting of the distribution effects.[21]

4.3 Heterogeneity

Figure 4 sketches *a*) the estimated normal distribution of α and *b*) the joint (normal) distribution of ς and θ according to Model (1). As for Panel *a*), the estimated relative frequency of households willing to buy 2 packs at the price $p = 1$ ($p = 5$) against 1 are set equal to 61 % (29 %), respectively. These figures match perfectly the observed frequencies of Table 3.

Figure 4: Estimated distributions of α, ς and θ (Model II)



Note: Panel *a*) shows the estimated normal distribution of α. Panel *b*) the joint (normal) distribution of ς and θ according to Model (1).

As we know from Table 6, ς and θ display a very high *negative* correlation, which reflects the shape of the joint distribution.[22] The estimated probability of answering the door in the No Warning condition, h_0,

[21] In terms of model fit, the three functionals are not nested, so one cannot use nested test statistics to test between them. However, one can use the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) to provide a ranking of the various functionals (Amemiya, 1980). Both criteria In deal with the trade-off between the goodness of fit of the model and the simplicity of the model (i.e., the number of parameters to be estimated). In this respect under both criteria, Model (1) (Model (3)) [Model (2)] ranks first (second) [third], respectively. This is some confirmation that the most parsimonious model tailored upon the reduced-form regressions is also the one which fits best our experimental evidence.

[22] We estimated the models by fixing the value of the correlation coefficient, ρ, from a finite grid. This is why the associated standard errors have not been reported.

is estimated around 35 % and follows closely the observed frequency (37%, see Table 2). By the same token, the probability of noticing the flyer, r, is lower than the corresponding estimate in DLM (20% *vs.* 32%). Then, the ex-ante probability of not answering the door conditional on warning derived from Model (1) is then $(1-r)(1-h_0)+r(1-\beta_2(\mu_\alpha,\mu_\varsigma,\mu_\theta)) = 32\%$ (compare with Table 2).

4.4 Willingness to Pay and Policy Simulations

We next take advantage of our structural model to estimate expected changes in demand at prices outside the narrow range of parameters implemented in our field experiment. Table 7 reports the "simulated demand" derived by Models (1-3) for a wider range of prices, from -1 to 5, than those tested in the field experiment. In doing so, we are able to simulate the effect of policies whereby efficient light bulbs are given to households at no cost, or are actually *subsidized.* Furthermore, we are able to examine the complete interaction between subsidies and social norms. For example, whether normative statements on the usage of others affects observed price elasticities, and the role of sorting as induced by our warning treatments. We can derive such effects across our three model specifications. As such, we are able to examine the existence of a "social norm effect" and simulate it at different price levels. We are also able to examine how the effectiveness of any policy option is impacted by sorting and subsequent changes in the distribution of types that are exposed to the policy.

As we allow the effect of prices and social norms to vary along the extensive and intensive margins, we simulate and report the effects along the two margins separately - i.e., we allow different elasticities along the extensive and intensive margins. Moreover, all figures in Table 7 represent *relative frequency of purchases conditional on answering the door,* and should thus be interpreted as the effect of a treatment on the treated. In this regard, we are unable to directly simulate the effect of a policy that allows sorting. Rather, we are able to examine whether the effect of price changes and normative appeals is impacted by changes in the set of people exposed to the policy across the warning and no-warning conditions.[23]

Figures in Table 7 can be read as follows. The table is divided into four distinct blocks that capture whether households were warned about the solicitation and whether the household was provided a normative statement on the adoption decisions of others. For example, the first block corresponds to our baseline treatment whereby households are not warned in advance of the solicitation request and are not provided any information about the adoption decisions of others whereas the final block corresponds to the predicted

[23] Of course, one could use estimates on the likelihood of answering the door to recover the effect of sorting and the total effect of policy options in the presence of sorting. By the same token, we condition intensive margin effects on the set of individuals that purchased at least one pack of efficient light bulbs but can easily recover the total effect of any policy change from the information reported in Table 7.

frequencies for households that were warned in advance of the solicitation and were provided information on the adoption decisions of others upon answering the door.

Within each block, we calculate predicted frequencies for five different price levels - the prevailing market price for a pack of efficient light bulbs at the time of our experiment (\$5), two prices that reflect partial subsidies on the purchase (\$3 and \$1), a full subsidy on purchase that would correspond to giving away the pack (\$0), and a negative price that would correspond to a policy of fully subsidizing the purchase of efficient light bulbs and providing households a tax credit or similar rebate (of \$1) should they accept the pack. The first column of the table presents results that simulate demand using parameter estimates from Model (1) in Table 6 whereas the second and third columns present simulations that rely upon parameter estimates from Models (2) and (3) of Table 6, respectively. Within each column, we present two distinct frequencies - the likelihood that a household who answers the door elects to purchase at least one pack of efficient light bulbs (the extensive margin) and the conditional likelihood of purchasing a second pack (the intensive margin).

Table 7: Counterfactuals (1)

			Model (1)		Model (2)		Model (3)	
W	Social Norms	Price	Ext. Marg.	Int. marg.	Ext. Marg.	Int. marg.	Ext. Marg.	Int. marg.
		5	0.042	0.289	0 .042	0.274	0.036	0.224
		3	0.069	0.444	0.069	0.425	0.059	0.367
No	No	1	0.114	0.608	0.113	0.588	0.096	0.531
		0	0.145	0.685	0.145	0.666	0.123	0.613
		-1	0.183	0.755	0.182	0.737	0.156	0.691
		5	0.066	0.289	0 .066	0.301	0.063	0.224
		3	0.104	0.444	0.104	0.457	0.098	0.367
No	Yes	1	0.162	0.608	0.163	0.619	0.152	0.531
		0	0.201	0.685	0.203	0.695	0.188	0.613
		-1	0.248	0.755	0.249	0.763	0.232	0.691
		5	0.042	0.289	0 .042	0.274	0.046	0.318
		3	0.069	0.444	0.069	0.425	0.075	0.479
Yes	No	1	0.114	0.608	0.113	0.588	0.124	0.643
		0	0.145	0.685	0.145	0.666	0.158	0.717
		-1	0.183	0.755	0.182	0.737	0.199	0.784
		5	0.066	0.289	0.066	0.301	0.071	0.318
		3	0.104	0.444	0.104	0.457	0.112	0.479
Yes	Yes	1	0.162	0.608	0.163	0.619	0.175	0.643
		0	0.201	0.685	0.203	0.695	0.217	0.717
		-1	0.248	0.755	0.249	0.763	0.266	0.784

We begin by exploring the effect of policy changes as simulated using estimates from Model (1). Recall that, under this specification, prices are allowed to influence choice along both the extensive and intensive margins whereas social norms are restricted to impact behavior along only along the extensive margin. Hence, estimates for the proportion of households that purchase at least one pack of efficient light bulbs at any given price differ across the first and second blocks of the table but there are no differences in intensive margin effects across these two blocks. Similarly, as Model (1) does not condition behavior on our warning treatments, there are no differences in predicted probabilities across blocks one and three (two and four) which differ only in whether or not the estimates are conditioned on warning the household in advance of the solicitation request.

We first examine the effects of a policy that subsidizes the purchase of efficient light bulbs and thus lowers the unit price. As noted in the first block of Table 7, it is hard to stimulate the purchase through price changes. For example, we estimate that approximately 4.2 percent of households would purchase at least one pack at the prevailing market price ($5). If, instead, we were to offer a 40 percent (or $2) subsidy on the purchase of a pack, the probability of a household purchasing at least one pack would only increase by 2.7 percentage points. Increasing the subsidy by an additional $2 would lead to an approximate 4.5 percentage point increase in the likelihood a household purchases at least one pack. In fact, even if we were to fully subsidize the purchase of efficient light bulbs and offer to give away packs for free, only 14.5 percent of households would take up the offer. That such a significant fraction of households would turn down a "free" pack of efficient light bulbs suggests that such households view them as inferior to (or imperfect subsititute for) the existing stock of lightbulbs in their home.[24]

Comparing the effect of price changes along the intensive margin reveals a more elastic pattern of behavior. For example, we estimate that approximately 28.9 percent of the households who purchase efficient light bulbs at the prevailing market price ($5) would buy multiple packs. If, instead, we were to offer a $2 subsidy on the price per pack, the conditional probability of a household purchasing a second pack of efficient light bulbs would increase by approximately 15.5 percentage points. Combined with the estimated extensive margin effects, we would thus expect a $2 per pack subsidy to generate a 35 unit increase in the overall number of packs purchased per one thousand people.[25] Yet, even in this case if we were to give away packs for free, only 68.5 percent of those who take up the offer would demand a second pack which, when combined with the effects along the extensive margin, would generate a 179 unit increase in the overall number of packs purchased per one thousand people.[26]

We next examine the effect of an alternate policy, grounded in behavioral economics, that would provide households information on the fraction of others in their area that report owning and using at least one CFL. As the effects of such policies in Model (1) are restricted to the extensive margin, we focus our discussion on the extensive margin effects and subsequent changes in the likelihood that a household will elect to purchase at least one pack of efficient light bulbs at different price levels. As noted in the second block of Table 7, the

[24]While we are unable to identify why the households in our study dislike CFLs, our findings are consistent with concerns that fluorescent lights do not work well in colder temperatures and take longer to achieve full brightness.

[25]At the prevailing price, our estimates suggest that we would sell approximately 65 packs per 1000 households. At $3 per pack, we would expect to sell approximately 100 packs per 1000 households.

[26]Our estimates thus suggest that we would have to spend somewhere in the range of $5.71 to $6.82 to stimulate the purchase of one additional pack of efficient light bulbs.

inclusion of normative information leads to an approximate 35.5 to 57.1 percent increase in the likelihood a household elects to purchase at least one pack of efficient light bulbs with the effect more pronounced at higher price levels. For example, at a price of $5 per pack, provision of our normative information is estimated to generate an approximate 57.1 percent (2.4 percentage point) increase in the likelihood a household purchase a pack of efficient light bulbs. At a price of $1 per pack, in contrast, providing households normative information is estimated to generate an approximate 42.1 percent (4.8 percentage point) increase in the likelihood of purchase.

Results using estimates from our other two specifications are qualitatively similar. However, it is worth noting that allowing households to sort -as in our warning treatments- does alter the effectiveness of our various policy instruments. For example, comparing estimates for Model (3) across the first and third blocks, the effect of a $2 subsidy on the per pack price of efficient light bulbs would nearly double if households were allowed to sort. Without the ability to sort, such a subsidy would generate an approximate 26 unit increase in the overall number of packs purchased per one thousand people. If, instead, households were allowed to sort, such a subsidy would generate an approximate 70 unit increase in the overall number of packs purchased per one thousand people.[27] From a policy perspective, allowing households to sort, reduces the necessary budget to stimulate the purchase of an additional pack of efficient light bulbs by almost a dollar - $4.40 per additional pack in the warning condition versus $5.38 per additional pack in the no warning condition.

In contrast, allowing households the ability to sort, reduces the effectiveness of social norms. For example, in our no warning condition, our normative statement increases the likelihood a household purchases a pack of efficient light bulbs by approximately 75 percent (2.7 percentage points) when the price is $5 per pack. In our warning condition, however, including a normative statement only increases the likelihood a household purchases a pack of efficient light bulbs by 54 percent (2.5 percentage points). Interestingly, such differences are even more pronounced at lower prices. These results hold import for the recent discussion regarding scaling and generalizability of experimental results. As Al-Ubaydli *et al.* (2017, 2019) show, the properties of the population and situation importantly influence whether and to what extent empirical results from original small-scale studies transfer to a larger setting. In this case, our results show that sorting in and of itself leads to dramatically different policy interpretations. For policymakers interested in understanding benefit cost ratios at scale, this result reveals the importance of a rarely discussed activity, sorting.

In this spirit, we can also use our structural model to determine the maximum prices that could be charged to ensure a target frequency of adoption (we provided a sneak preview of this approach in Figure

[27]In the no warning condition, the estimated number of packs purchased at $5 ($3) is 44 units (70 units) respectively. If, instead, we allow people to sort and condition the estimates on whether or not households were warned, the expected number of packs purchased at $5 ($3) is 60 units (110 units) respectively.

5). Results from these simulations are presented in Table 8, and can be read as follows. As with our prior discussion, the table is divided into four distinct blocks that capture whether households were warned about the solicitation and whether they were provided a normative statement about the adoption decisions of others. Within each block, we calculate the maximum price that could be charged given a target that $X = 1, 5, 10, 25, 50$ percent of households would purchase at least one pack of efficient light bulbs (extensive margin) or an additional one (intensive margin). The first column of Table 8 presents results that simulate demand using parameter estimates from Model (1) in Table 6 whereas the second and third columns present simulations that rely upon estimates from Models (2) and (3) of Table 6.

Table 8: Counterfactuals (2)

			Model (1)		Model (2)		Model (3)	
W	Social Norms	Target	Ext. Marg.	Int. marg.	Ext. Marg.	Int. marg.	Ext. Marg.	Int. marg.
		1 %	$ 10.90	$ 13.51	$ 10.97	$ 13.39	$ 10.30	$ 12.48
		5 %	$ 4.32	$ 10.24	$ 4.35	$ 10.08	$ 3.66	$ 9.23
No	No	10 %	$ 1.53	$ 8.49	$ 1.53	$ 8.31	$ 0.84	$ 7.49
		25 %	$ -2.41	$ 5.57	$ -2.44	$ 5.36	$ -3.13	$ 4.59
		50 %	$ -6.34	$ 2.32	$ -6.37	$ 2.08	$ -7.05	$ 1.37
		1 %	$ 13.33	$ 13.51	$ 13.19	$ 13.78	$ 12.71	$ 12.48
		5 %	$ 6.28	$ 10.24	$ 6.22	$ 10.47	$ 5.63	$ 9.23
No	Yes	10 %	$ 3.19	$ 8.49	$ 3.18	$ 8.70	$ 2.51	$ 7.49
		25 %	$ -1.04	$ 5.57	$ -1.01	$ 5.75	$ -1.75	$ 4.59
		50 %	$ -5.07	$ 2.32	$ -5.02	$ 2.47	$ -5.79	$ 1.37
		1 %	$ 10.90	$ 13.51	$ 10.97	$ 13.39	$ 11.17	$ 13.85
		5 %	$ 4.32	$ 10.24	$ 4.35	$ 10.08	$ 4.64	$ 10.59
Yes	No	10 %	$ 1.53	$ 8.49	$ 1.53	$ 8.31	$ 1.88	$ 8.86
		25 %	$ -2.41	$ 5.57	$ -2.44	$ 5.36	$ -2.04	$ 5.97
		50 %	$ -6.34	$ 2.32	$ -6.37	$ 2.08	$ -5.95	$ 2.75
		1 %	$ 13.33	$ 13.51	$ 13.19	$ 13.78	$ 13.57	$ 13.85
		5 %	$ 6.28	$ 10.24	$ 6.22	$ 10.47	$ 6.57	$ 10.59
Yes	Yes	10 %	$ 3.19	$ 8.49	$ 3.18	$ 8.70	$ 3.51	$ 8.86
		25 %	$ -1.04	$ 5.57	$ -1.01	$ 5.25	$ -0.68	$ 5.97
		50 %	$ -5.07	$ 2.23	$ -5.02	$ 2.47	$ -4.69	$ 2.75

Consistent with our previous analysis, we consider two distinct policy instruments - price changes (subsidies) and the use of a nudge that provides information on the fraction of households in one's area that report having installed at least one CFL in their home -and examine whether the effectiveness of such instruments are effected when we warn households and thus allow sorting.

Considering the extensive margin, we begin by exploring the effect of policy changes as simulated using estimates from Model (1). As noted in the first column of Table 8, any policy that targets adoption rates in excess of 25 percent would require that policy makers offer households compensation for accepting a pack of efficient light bulbs. For example, estimates from the first block suggest that we would have to offer compensation of approximately \$2.41 if we wanted adoption rates of 25 percent. If instead, our target was for the median household to purchase a pack of efficient light bulbs, compensation of approximately \$6.34

would be required. Provision of social information, however, reduces the amount of compensation required to meet adoption targets in excess of 25 percent. As noted in the second block of Table 8, the amount of compensation required to ensure a 25 (50) percent adoption threshold amongst households that are provided social information falls to \$1.04 (\$5.07) respectively.

Introducing the ability to sort, as in Model (3), also serves to reduce the level of compensation required to achieve target adoption rates in excess of 25 percent. For example, in the absence of social information, the compensation required to induce 25 percent of households to adopt falls from \$3.13 in our no warning condition to \$2.04 when households can sort.[28] We observe a similar effect of sorting on the level of compensation required in the presence of social information. For example, the level of compensation required to achieve a 25 percent adoption rate in the presence of social information falls from \$2.04 to \$0.68 when households are allowed to sort.

We now turn our attention to intensive margins where, by construction, the median household in the baseline condition evaluates the purchase of an additional pack exactly as what the estimates of μ_α in Table 7 indicate, for all models. Also notice that the impact of social norms (Model 2) and sorting (Model 3) are in line with those we discussed for the extensive margins, but lower in magnitude. As for social norms, the presence of a social norm statement can act as a substitute for a price reduction that ranges from 3 to 16 % (depending on the target of adoption). By comparison, sorting (Model 3) has an even greater impact: it substitutes for a price reduction that ranges from 10 to 50 % (again, depending on the target: the lower the target, the lower the reduction).

As a whole, our policy simulations question the cost effectiveness of policies to promote the adoption of efficient light bulbs. Demand for efficient light bulbs is low and a substantial fraction of households appear to dislike such technologies and would require compensation in order to accept a pack of efficient light bulbs.[29] Moreover, while social information and the ability to sort do serve to stimulate demand, such effects do little to reduce the costs required to achieve adoption rates in excess of 25 percent.

Figure 5 provides a graphic sketch of the interaction between monetary incentives and social norm based nudges in the adoption patterns. Extrapolating the numerical simulations of Table 8, we report on the x axis any specific adoption target along both the extensive (left panel) and the intensive (right panel) margins. The upper panels sketch the implicit inverse demand schedules along both margins, where the dashed (solid) lines track the corresponding selling price needed to reach any specific adoption target with(out) the nudge,

[28] We observe a similar reduction in the level of compensation required to induce the median household to accept a pack of efficient light bulbs. In the absence of social information, the median household in our no warning condition requires \$7.05 to accept a pack of CFL's whereas counterparts who are allowed to sort require only \$5.95 to accept a pack.

[29] Although outside the scope of our current analysis, this result has implications for work on the energy paradox. If households view CFLs as an inferior technology, it could be a rational decision to eschew their purchase even though doing so would save the household money on monthly energy bills.

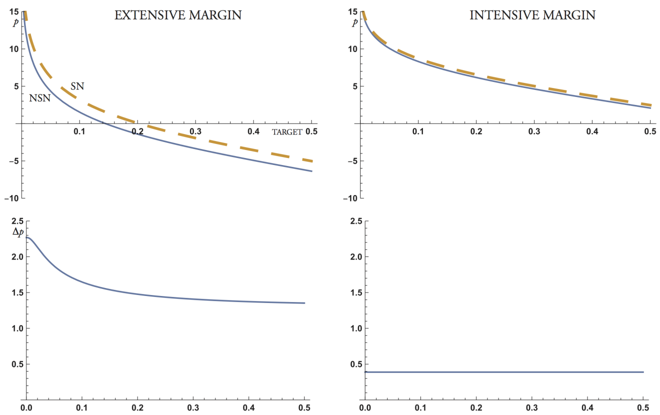


Figure 5: Structural model: cost effectiveness of social norms on both margins

respectively. The price differences between the two lines, reported in the lower panels of Figure 5 provide an account of the cost-effectiveness of the nudge, reporting, for each adoption target, how much money can be saved of the price subsidy in the social norms treatments, compared with the baseline, in which no nudge is administered. As Figure 5 clearly shows, the impact of social norms is much stronger for the extensive margin (where the reduction in the subsidy is never lower than \$1.5) compared with the intensive margin (where it is never higher than \$ 0.5).

5 Conclusions

Viewed broadly, our contribution is to highlight the importance of both economic and non-economic factors to the diffusion process. Importantly, our research provides the first direct comparison of prices and social norms, since our study affords an apples-to-apples comparison in the context of a single, large-scale field experiment. In doing so, our approach provides greater understanding of the motives surrounding consumer adoption and should help inform policy makers interested in promoting the adoption of technologies more broadly. In this light, our major result points to prices affecting behavior along both extensive and intensive margins while social norms impact the extensive margin only.

More narrowly, our results speak to adoption of technologies that have externalities. Although market-based environmental policies have been on the minds of economists since Pigou's seminal work on welfare in 1912, subsidizing new technologies to encourage adoption stands as a somewhat controversial approach under the standard economic assumption of informed rational agents. Non-pecuniary techniques to motivate residential energy conservation used in research by social psychologists and behavioral economists have generally focused on changing energy usage behavior rather than focusing on encouraging adoption of energy efficient products. This is evident in broad reviews of the existing literature such as Abrahamse *et al.* (2005), as well as more recent research such as Schultz *et al.* (2007), Allcott (2009), List and Price (2016), or Price (2014). Our main result of complementarity can be used as a policy starting point when considering how to motivate consumers to utilize new technologies.

Moreover, there is a growing literature on behavioral welfare economics that assumes individuals are subject to internalities (so that they do not consider all the consequences for themselves of their own decisions), which would also might be affected by prices and social norms. In this regard, the importance of heterogeneity found in our structural estimation results cannot be understated since interventions that ignore heterogeneity will often under-perform those that take it into account, for example by assigning treatments to individuals according to observed and/or elicited characteristics. This would allow individuals who would benefit from treatment to receive it, while those who would be hurt can be assigned to a control group, or receive other treatment that can help them. We view this approach as an exciting area of future research. Another avenue for future research is to disentangle the effects of the private valuation for the efficient light bulbs from those of altruism. By using treatments that prime private economic concerns versus public environmental concerns interesting insights can be obtained.

References

Abrahamse, W., Steg, L., Vlek, C. and Rothengatter, T. (2005) A review of intervention studies aimed at household energy conservation, *Journal of environmental psychology*, **25**, 273–291.

Acland, D. and Levy, M. (2016) Habit formation and Naivete in gym attendance: evidence from a field experiment, *Working paper*.

Aghion, P. and Howitt, P. (1992) The schumpeterian approach to technical change and growth, in *Economic Growth in the World Economy: Symposium*, vol. 1993.

Al-Ubaydli, O., List, J. A. and Suskind, D. (2019) The science of using science: Towards an understanding of the threats to scaling experiments, Tech. rep., National Bureau of Economic Research.

Al-Ubaydli, O., List, J. A. and Suskind, D. L. (2017) What can we learn from experiments? understanding the threats to the scalability of experimental results, *American Economic Review*, **107**, 282–86.

Allcott, H. (2009) Social norms and energy conservation working paper, *Massachusetts Institute of Technology (MIT), Cambridge, MA https://files. nyu. edu/ha32/public/research. html.*

Allcott, H. (2011) Social norms and energy conservation, *Journal of Public Economics*, **95**, 1082–1095.

Allcott, H., Mullainathan, S. and Taubinsky, D. (2014) Energy policy with externalities and internalities, *Journal of Public Economics*, **112**, 72–88.

Allcott, H. and Rogers, T. (2014) The Short-Run and Long-Run Effects of Behavioral Interventions : Experimental Evidence from Energy Conservation †, *American Economic Review*, **104**, 3003–3037.

Allcott, H. and Taubinsky, D. (2015) Evaluating behaviorally-motivated policy: Experimental evidence from the lightbulb market, *American Economic Review*, **105**, 2501–2538.

Alós-Ferrer, C., García-Segarra, J. and Ritschel, A. (2018) Performance curiosity, *Journal of Economic Psychology*, **64**, 1–17.

Amemiya, T. (1980) Selection of regressors, *International economic review*, pp. 331–354.

Bandiera, O. and Rasul, I. (2006) Social Networks and Technology Adoption in Northern Mozambique, *The Economic Journal*, **116**, 869–902.

Bernard, J. C., Schulze, W. *et al.* (2005) The next new thing: curiosity and the motivation to purchase novel products, *Economics Bulletin*, **3**, 1–8.

Brandon, A., Ferraro, P. J., List, J. A., Metcalfe, R. D., Price, M. K. and Rundhammer, F. (2016) Do The Effects of Social Nudges Persist? Theory and Evidence from 38 Natural Field Experiments, *Working Paper*.

Charness, G. and Gneezy, U. (2009) Incentives to exercise, *Econometrica*, **77**, 909–931.

Charness, G., Levin, D. *et al.* (2003) Bayesian updating vs. reinforcement and affect: A laboratory study, *Levine's Bibliography 666156000000000180, UCLA Department of Economics*.

Chen, J., Humphreys, M. and Modi, V. (2010) Technology diffusion and social networks: Evidence from a field experiment in Uganda, *Manuscript, Columbia University*.

Chetty, R. (2008) Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods, *Annual Review of Economics*, **1**, 451–488.

Chetty, R. (2015) Behavioral Economics and Public Policy: A Pragmatic Perspective, *American Economic Review*, **105**, 1–33.

Chetty, R., Looney, A. and Kroft, K. (2009) Salience and taxation: Theory and evidence, *American Economic Review*, **99**, 1145–1177.

Cialdini, R. B. (2007) Descriptive social norms as underappreciated sources of social control, *Psychometrika*, **72**, 263.

Conley, T. G. and Udry, C. R. (2010) Learning about a new technology: Pineapple in Ghana, *American economic review*, **100**, 35–69.

Conlin, M., O'Donoghue, T. and Vogelsang, T. J. (2007) Projection bias in catalog orders, *American economic Review*, **97**, 1217–1249.

Czibor, E., Jimenez-Gomez, D. and List, J. A. (2019) The Dozen Things Experimental Economists Should Do (More of), *Southern Economic Journal*, **86**, 371–432.

DellaVigna, S., List, J. A. and Malmendier, U. (2012) Testing for Altruism and Social Pressure in Charitable Giving, *The Quarterly Journal of Economics*, **127**, 1–56.

DellaVigna, S., List, J. A., Malmendier, U. and Rao, G. (2016a) Estimating social preferences and gift exchange at work, Tech. rep., National Bureau of Economic Research.

DellaVigna, S., List, J. A., Malmendier, U. and Rao, G. (2016b) Voting to tell others, *The Review of Economic Studies*, **84**, 143–181.

Erdem, T. and Keane, M. P. (1996) Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets, *Marketing science*, **15**, 1–20.

Fehr, E. and Goette, L. (2007) Do workers work more if wages are high? evidence from a randomized field experiment, *American Economic Review*, **97**, 298–317.

Fernald, J. G. and Jones, C. I. (2014) The future of us economic growth, *American economic review*, **104**, 44–49.

Ferraro, P. J., Miranda, J. J. and Price, M. K. (2011) The persistence of treatment effects with norm-based policy instruments: evidence from a randomized environmental policy experiment, *American economic review*, **101**, 318–322.

Ferraro, P. J. and Price, M. K. (2013) Using Nonpecuniary Strategies to Influence Behavior: Evidence from a Large-Scale Field Experiment, *Review of Economics and Statistics*, **95**, 64–73.

Foster, A. D. and Rosenzweig, M. R. (2010) Microeconomics of technology adoption, *Annu. Rev. Econ.*, **2**, 395–424.

Gerritsen, A. (2016) Optimal taxation when people do not maximize well-being, *Journal of Public Economics*, **144**, 122–139.

Giné, X., Karlan, D. and Zinman, J. (2010) Put your money where your butt is: a commitment contract for smoking cessation, *American Economic Journal: Applied Economics*, pp. 213–235.

Goldstein, N. J., Cialdini, R. B. and Griskevicius, V. (2008) A room with a viewpoint: Using social norms to motivate environmental conservation in hotels, *Journal of consumer Research*, **35**, 472–482.

Griliches, Z. (1957) Hybrid corn: An exploration in the economics of technological change, *Econometrica, Journal of the Econometric Society*, pp. 501–522.

Hall, B. H. (2004) Innovation and diffusion, Tech. rep., National Bureau of Economic Research.

Handel, B. R. (2013) Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts, *American Economic Review*, **103**, 2643–2682.

Hausman, J. A. and Wise, D. A. (1976) A conditional probit model for qualitative choice: discrete decisions recognizing interdependence and heterogenous preferences.

Herrnstein, R. J., Loewenstein, G. F., Prelec, D. and Vaughan, W. (1993) Utility maximization and melioration: Internalities in individual choice, *Journal of Behavioral Decision Making*, **6**, 149–185.

Holladay, S., LaRiviere, J., Novgorodsky, D. and Price, M. (2019) Prices versus nudges: What matters for search versus purchase of energy investments?, *Journal of Public Economics*, **172**, 151–173.

Huck, S. and Rasul, I. (2011) Matched fundraising: Evidence from a natural field experiment, *Journal of Public Economics*, **95**, 351–362.

Jaffe, A. B., Newell, R. G. and Stavins, R. N. (2002) Environmental policy and technological change, *Environmental and resource economics*, **22**, 41–70.

Jimenez-Gomez, D. (2019) Nudging and Phishing: A Theory of Behavioral Welfare Economics, *Working Paper*.

Jin, G., Kato, A. and List, J. A. (2010) That's news to me! information revelation in professional certification markets, *Economic Inquiry*, **48**, 104–122.

Jones, C. I. (2002) Sources of us economic growth in a world of ideas, *American Economic Review*, **92**, 220–239.

Karlan, D. and List, J. A. (2007) Does price matter in charitable giving? Evidence from a large-scale natural field experiment, *American economic review*, **97**, 1774–1793.

Laibson, D. (1997) Hyperbolic discounting and golden eggs, *Quarterly Journal of Economics*, **112**, 443–477.

Laibson, D., Repetto, A. and Tobacman, J. (2007) Estimating discount functions with consumption choices over the lifecycle, Tech. rep., National Bureau of Economic Research.

Lapinski, M. K. and Rimal, R. N. (2005) An explication of social norms, *Communication Theory*, **15**, 127–147.

List, J. A., Metcalfe, R. D., Price, M. K. and Rundhammer, F. (2017) Harnessing policy complementarities to conserve energy: Evidence from a natural field experiment, Tech. rep., National Bureau of Economic Research.

List, J. A. and Price, M. K. (2016) The use of field experiments in environmental and resource economics, *Review of Environmental Economics and Policy*, **10**, 206–225.

Litman, J., Hutchins, T. and Russon, R. (2005) Epistemic curiosity, feeling-of-knowing, and exploratory behaviour, *Cognition & Emotion*, **19**, 559–582.

Loewenstein, G. (1994) The psychology of curiosity: A review and reinterpretation., *Psychological bulletin*, **116**, 75.

Loewenstein, G. (2000) Emotions in economic theory and economic behavior, *American economic review*, **90**, 426–432.

Oster, E., Shoulson, I. and Dorsey, E. R. (2013) Optimal Expectations and Limited Medical Testing: Evidence from Huntington Disease, *American economic review*, **103**, 804–830.

Oster, E. and Thornton, R. (2012) Determinants Of Technology Adoption: Peer Effects In Menstrual Cup Take-Up, *Journal of the European Economic Association*, **10**, 1263–1293.

Price, M. K. (2014) Using field experiments to address environmental externalities and resource scarcity: major lessons learned and new directions for future research, *Oxford Review of Economic Policy*, **30**, 621–638.

Rogers, E. M. (1962) *Diffusion of innovations.*, New York: Free Pr. of Glencoe.

Romer, P. M. (1990) Endogenous technological change, *Journal of political Economy*, **98**, S71–S102.

Roodman, D. (2011) Fitting fully observed recursive mixed-process models with cmp, *Stata Journal*, **11**, 159–206(48).

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J. and Griskevicius, V. (2007) The Constructive, Destructive, and Reconstructive Power of Social Norms, *Psychological Science*, **18**, 429–434.

Skinner, J. and Staiger, D. (2007) Technological diffusion from hybrid corn to beta blockers, *Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches. University of Chicago Press and NBER.*

Spiegler, R. (2014) On the Equilibrium Effects of Nudging, *Journal of Legal Studies*.

Thaler, R. H. and Sunstein, C. R. (2008) *Nudge: Improving decisions about health, wealth, and happiness*, Yale University Press.

Thornton, R. L. (2008) The demand for, and impact of, learning HIV status, *The American economic review*, **98**, 1829–1863.

Train, K. E. (1998) Recreation demand models with taste differences over people, *Land economics*, pp. 230–239.

U.S. Chamber of Commerce Foundation (2012) Enterprising states: Policies that produce., https://www.uschamber.com/sites/default/files/documents/files/Enterprising-States-2012-web.pdf.

Van De Ven, N., Zeelenberg, M. and Van Dijk, E. (2005) Buying and selling exchange goods: Outcome information, curiosity and the endowment effect, *Journal of Economic Psychology*, **26**, 459–468.

Volpp, K., Troxel, A. B., Pauly, M. V., Glick, H. A., Puig, A., Asch, D. A., Galvin, R., Zhu, J., Wan, F., DeGuzman, J., Corbett, E., Weiner, J. and Audrain-McGovern, J. (2009) A Randomized, Controlled Trial of Financial Incentives for Smoking Cessation, *The New England Journal of Medicine*, **360**, 699–709.

Volpp, K. G., Levy, A. G., Asch, D. A., Berlin, J. A., Murphy, J. J., Gomez, A., Sox, H., Zhu, J. and Lerman, C. (2006) A randomized controlled trial of financial incentives for smoking cessation, *Cancer Epidemiology and Prevention Biomarkers*, **15**, 12–18.

Yoeli, E., Hoffman, M., Rand, D. G. and Nowak, M. a. (2013) Powering up with indirect reciprocity in a large-scale field experiment., *Proceedings of the National Academy of Sciences of the United States of America*, **110 Suppl**, 10424–9.

Young, A. (2005) Increasing returns and economic progress, in *Readings In The Economics Of The Division Of Labor: The Classical Tradition*, World Scientific, pp. 234–248.

Zanella, G. and Banerjee, R. (2016) Experiencing breast cancer at the workplace, *Journal of Public Economics*, **134**, 53–66.

Appendices

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Appendix A Additional Statistical evidence

Table A1 shows the first set of conditional results related to the equation-by-equation estimations of our system of three three linear probability specifications introduced in section 3.

Table A1: Equation-by-equation linear estimations

	Answer Door	Buy | Answer	Q=2 | Buy
Warning	-0.026*		
	(0.016)		
Opt-Out	-0.077***		
	(0.015)		
Warning treatments		0.033**	0.115
		(0.014)	(0.0701)
Social Norm Low		0.003	-0.054
		0.018)	(0.095)
Social Norm High		0.0356**	-0.0761
		(0.014)	(0.079)
Price \$5		-0.084***	-0.317***
		(0.013)	(0.065)
Constant	0.351***	0.0904***	0.421**
	(0.032)	(0.028(	(0.190)
Solicitors FE	YES	YES	YES
Suburbs FE	YES	YES	YES
Constant	0.351***	0.090***	0.510***
	(0.024)	(0.030)	(0.168)
Obs.	8815	2248	290

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Note: All regressions include solicitors and suburbs fixed effects. Standard errors (in parentheses) are clustered at date-solicitor blocks level.

Appendix B Solution of the structural model

In our structural model, households' decisions are framed by way of a multi-stage game with incomplete information, where the individual -call her "Anna"- interacts at each stage with her "future selves" of which, at the time she has to make prior decisions along the sequence, she has limited knowledge. Information sets consist of what Anna knows about the 3 treatment interventions: *i*) the *warning level* $\omega \in \{NW, W, OO\}$; *ii*) the *social pressure* $s \in \{N, L, H\}$; and *iii*) the price $p \in \{1, 5\}$. Similarly, Anna has partial information about her own realization of the three behavioral parameters of our structural model: *i*) α (which measures the combination of private benefits from CFLs and altruism), *ii*) ς ("sensitivity to social norms") and *iii*) θ ("curiosity"). In this respect, we assume that Anna comes to know the realization of her own behavioral parameter only when the latter directly affects her choice, while prior decisions are made conditional on the expectation of the behavioral parameter(s) in object.

To summarize, these are the information sets characterizing our Bayesian game. Let $h_k \in H$ denote Anna's information set at stage $k = 1, ..., 4$, where

1. $h_1 = \{w, \mu_\alpha, \sigma_\alpha, \mu_\varsigma, \sigma_\varsigma, \theta, \rho\}$,
2. $h_2 = h_1$,
3. $h_3 = h_2 \bigcup \{p, s, \varsigma\}$,
4. $h_4 = h_3 \bigcup \{\alpha\}$.

We solve the model "backwards", starting from Stage 4, using the standard notation of dynamic Bayesian games by conditioning payoffs upon the information available at each stage. Let $u_h(a)$ and $u_h^{h'}(a)$, denote the "true" utility of action $a_h \in \{0, 1\}$, i.e. the one directly affecting the likelihood function, and its expectation conditional on the information available at stage $h' < h$, respectively. By the same token, β_h ($\beta_h^{h'}$) are Anna's "true" behavioral strategy (its expectation formulated at stage $h' < h$, modeling Anna's beliefs over her own future behavior), respectively.[30]

Stage 4: intensive margin: $a_4 \in \{0, 1\}$

In Stage 4 Anna's quantity decision $q = a_4 + 1$ is only affected by her *altruism* parameter, α:

$$u_4(q) = (\alpha - p)q. \tag{2}$$

Let $\alpha^\star = \{\alpha : u_4(1) = u_4(2)\}$ be the value of α that makes Anna indifferent with respect to her quantity decision, i.e., $\alpha^\star = p$. This, in turn, implies that, in Stage 4, Anna is indifferent over her quantity choice when $\alpha = \alpha^\star = p$ and that $\beta_4(\alpha) = 1$ ($\beta_4(\alpha) = 0$) when $\alpha > \alpha^\star$ ($\alpha < \alpha^\star$), respectively.

[30]Since, at each information set, Anna has only two available actions, we indicate with β the probability of choosing $a_h = 1$ in the corresponding Stage respectively.

Stage 3: extensive margin: $a_3 \in \{0, 1\}$

Let $u_3(a_3)$ be Anna's "direct" utility evaluated at Stage 3. If Anna decides not to buy anything (i.e., $a_3 = 0$), her utility will be $u_3(0) = -\varsigma - \gamma$, where $\gamma = 0$ ($\gamma = \gamma_L$) [$\gamma = \gamma_H$] for $s = N$ ($s = L$) [$s = H$], respectively. The parameter ς captures the impact of social pressure that Anna experiences by being approached in person by Beppe. The level of social pressure, γ, is a function of the "*proximity*", referenced in the social norm, either H or L. In this respect, we assume that the social pressure s yields shift in the value of ς, so that social pressure under treatment s is $-(\varsigma + \gamma_s)$, where $\gamma_s = 0$ ($\gamma_s = \gamma_L$) [$\gamma_s = \gamma_H$], depending on the assigned social norm $s = N$ ($s = L$) [$s = H$], respectively.

If Anna decides to buy something (i.e., $a_3 = 1$) her utility will be her expectation of her payoff at Stage 4, i.e.,

$$u_3(1) = (\alpha_L - p)(1 - \beta_4^3) + 2(\alpha_H - p)\beta_4^3, \tag{3}$$

where $\alpha_L = \int_{-\infty}^{p} x\psi_\alpha(x)dx$ and $\alpha_H = \int_{p}^{-\infty} x\psi_\alpha(x)dx$ are the conditional means of the values for the intensive marginal purchase in Stage 4 evaluated at Stage 3 and $\psi_\alpha(\cdot)$ is any smooth density function (not necessarily the normal distribution used in the structural estimations of Section 5).

Clearly, $u_3(1)$ is increasing in μ_α. By analogy with Stage 4, let $\varsigma^* = \{\varsigma \in \Re : u_3(1) = u_3(0)\} = -\gamma - u_3(1)$ be the value of ς for the (extensive) marginal buyer. Therefore, $\varsigma^\star$ is decreasing in μ_α and a positive social norm yields a downward shift of ς^*, for all smooth densities $\psi_\alpha(\cdot)$.

Stage 2: choosing whether answering the door $a_2 \in \{0, 1\}$ ($\omega \neq NW$)

Before answering the door, Anna does not know her treatment assignment in Stage 2 over the price $p \in \{1, 5\}$ and the social norm $s \in \{N, L, H\}$ randomization. In this respect, consistently with our assumption regarding the behavioral parameters, we shall assume that Anna knows that her treatment assignment is the result of two uniform i.i.d. draws from the corresponding supports. This, actually, corresponds to the implementation of the randomization over our treatment conditions. Then, her expected utility $u_3^2(a_2)$ can be derived as follows:

$$u_3^2(0) = \frac{1}{3} \times \sum_s u_{h_3^s}(0) = \frac{1}{3} \sum_s E[u_3(0)|s] \tag{4}$$

$$u_3^2(1) = \frac{1}{2} \times \sum_p u_{h_3^p}(1) = \frac{1}{2} \sum_p E[u_3(1)|p] \tag{5}$$

Note that, if θ and ς are correlated, Anna could use her information about θ to infer information about ς. However, we assume that Anna behaves as if she believes as if θ and ς were uncorrelated. Because of that, Anna's beliefs over her decisions in Stage 3 are evaluated using the same methodology we used to evaluate her beliefs over her decision in Stage 4. We define this assumption - which is needed to avoid the implicit fixed point problem for which beliefs over Stage 3 are needed to evaluate optimal behavior in Stage 2 - although behavior in Stage 2 and 3 is estimated simultaneously- as the *independence bias* assumption (IB). Once we allow for IB, the analysis of Stage 2 is straightforward, namely:

$$u_2(0) = 0; \tag{6}$$

$$u_2(1) = (1 - \beta_3^2)u_3^2(0) + \beta_3^2 u_3^2(1) + \theta. \tag{7}$$

Therefore, by analogy of Stages 3 and 4 we can identify a threshold $\theta^* = -(1 - \beta_3^2)u_3^2(0) - \beta_3^2 u_3^2(1)$, for each warning level $\omega \in \{W, OO\}$, such that Anna answers the door if and only if $\theta \geq \theta^*$.

Stage 1: choosing whether to check the flyer $a_1 \in \{0, 1\}$ ($\omega = OO$)

In our experimental design, we include a treatment (OO) which allows for Anna to "opt out" without any cost by simply marking a box on the flyer. This decision is only relevant for those in the OO treatment. In this case, Anna decides not to check the box if $\theta \geq \theta^*$.