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A field experiment to estimate the effects of anchoring and framing on residents' willingness to purchase water runoff management technologies

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A B S T R A C T

Watersheds throughout the world have been severely polluted by nutrient-laden runoff that comes from industrial, agricultural, and residential sources. Efforts to reduce this runoff have focused on industrial and agricultural sources, while little attention has been paid to encouraging residents to reduce runoff from their properties. To study residents' willingness to adopt landscaping practices that reduce runoff, we conducted a field experiment in the Delaware River watershed. In the experiment, over three hundred adults participated in a series of random-price auctions that revealed their willingness to pay (WTP) for five products that reduce nutrient runoff. To study how WTP can be influenced by attributes of the choice architecture, we randomized the starting bid values (anchors) and the way in which the external benefits of the five practices were framed. Compared to a neutral framing, a positive framing (using the product can improve water quality) increased average WTP by about one-third, while the estimated effect of a negative framing (failing to use the product can worsen water quality) was also positive, but smaller and not statistically different from zero. The estimated effect on average WTP from the anchor depends on how bids of $0 are modeled, but the results imply that higher anchors lead to higher WTP. Although we believe the magnitudes of our results should be considered suggestive and we recommend replications with higher statistical power, the results add to the evidence base that environmental programs can achieve policy-relevant gains in program performance through a series of small changes to the decision environment.

The U.S. Environmental Protection Agency (EPA) has identified nutrient pollution as one of America's most widespread, costly, and challenging environmental problems (EPA, 2016). Nutrient pollution occurs when nutrients, mainly nitrogen and phosphorus, are transported from terrestrial human activities to aquatic ecosystems, where the pollution causes excessive growth of algae (National Oceanic and Atmospheric Administration (NOAA), 2016). In addition to hindering human uses of the water, the excessive algal growth depletes the oxygen in the water (eutrophication), which kills or displaces aquatic

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species of plants and animals. Moreover, the algal blooms can promote the growth of pathogens that harm humans through direct contact or through the consumption of fish and shellfish (EPA, 2016). Conservative estimates of the short-term impacts of eutrophication of U.S. freshwater systems put the cost at approximately $2.2 billion annually (Dodds et al., 2009).

The primary sources of nutrient pollution are industrial and municipal wastewater discharges, septic leaks, and runoff from agriculture, residential properties, and impervious surfaces. Point sources of industrial and wastewater discharges have received considerable attention (McClelland and Horowitz, 1999), and many of these sources in the US are well regulated by the EPA under the Clean Water Act. Among nonpoint sources, agricultural runoff is a major contributor (Stuart et al., 2014) and has been the primary focus of government efforts to reduce nonpoint-source pollution. For example, the U.S. Department of Agriculture (USDA) and its partners offer a variety of programs that subsidize best management practices (BMPs) that reduce nutrient runoff (e.g., Environmental Quality Incentives Program, Conservation Stewardship Program). These programs, and the pollution they aim to reduce, have also been the focus of academic economists, particularly in their efforts to elucidate what program attributes motivate producers to adopt BMPs (e.g., Segerson, 1988; Suter et al., 2008; Savage and Ribaudo, 2016; Miao et al., 2016; Paolisso and Maloney, 2000; Palm-Forster et al., 2019).

In contrast, economists have paid little attention to runoff from residential properties, which also contributes to nutrient runoff (NOAA, 2016). Although this source of pollution is small relative to agricultural sources, it is far from negligible. The EPA has a regulatory framework that targets residential-sourced pollution and requires municipalities to demonstrate the implementation of six control measures. One of these measures (Post-Construction Runoff Control) directs the municipalities to create and implement programs to control residential runoff. These programs typically involve encouraging residents to adopt BMPs, particularly with regard to landscaping practices.

Landscaping practices are impure public goods, which generate both private and public benefits. To encourage residents to adopt practices that generate greater public benefits, municipalities often subsidize the adoption and maintenance of these practices. Although there have been case studies measuring willingness to pay (WTP) and knowledge of residential BMPs in Chicago (Ando and Freitas, 2011) and Syracuse (Baptiste et al., 2015), little attention has been paid to program attributes that might increase residents' willingness to adopt BMPs.

In other impure public good contexts, numerous studies have found that providing information about the public benefits is effective in increasing consumers' willingness to contribute to providing those goods (e.g., Lusk et al., 2004; Bougherara and Combris, 2009; Rousseaua and Vrankenb, 2013; Li and McCluskey, 2017; Messer et al., 2008). The effectiveness of such information varies with how it is framed and whether it focuses on the positive aspects of the product of interest or highlights the negative effects of the alternatives (Gifford and Bernard, 2005; Okada and Mais, 2010; Liaukonyte et al., 2013). Tversky and Kahneman (1981), for example, found that people tended to avoid risk when presented with positive framing and sought risk when presented with negative framing. Other experiments showed that framing affected participants' contributions to public goods (Andreoni, 1995), justice judgements (Gamliel and Peer, 2006), and efforts to address climate change (Spence and Pidgeon, 2010).

In the context of pure private goods, psychologists and behavioural economists have reported that anchoring can influence consumer valuations (Ariely et al., 2003; Maniadis et al., 2014). For example, consider a consumer who is about to formulate and express a reservation value for a good. An anchoring effect exists if, prior to expressing the reservation value, the consumer considers or observes a specific number (e.g., a three-digit number) and that number subsequently affects the reservation value expressed by the consumer. Kahneman (2011) reports that anchoring is one of the most well-studied and, among psychologists, well-documented behavioral biases. Results from these studies, and their interpretations, have generated substantial debate among economists and psychologists about the coherence and stability of consumer preferences (Maniadis et al., 2014).

To contribute to the evidence base about how program attributes of residential runoff-management BMP programs may affect consumer preferences for the BMPs, we conducted a randomized field experiment in the Delaware River watershed. At a large annual event held at the University of Delaware, the experiment recruited over three hundred adults to participate in a series of random-price auctions that revealed their WTP for five runoff-management products. To study how WTP can be influenced by the auction attributes, we randomized the starting bid values (anchors) and the way in which the benefits of the five products were framed. We find evidence of a positive effects from framing (30–40% increase in WTP) as well as smaller anchoring effect. No effect on WTP from negative framing was detected: the estimated effect on WTP was smaller than the effect from positive framing, and not statistically different from zero.

1. Experimental design

We sought to design an experiment with the following features: (1) a subject pool of adults who lived in a watershed impaired by nutrient pollution; (2) opportunities to acquire, at cost, real pollution-reducing products or practices; (3) elicitation of home-grown[1] values for the products or practices using an incentive-compatible method; and (4) random assignment of anchoring and framing treatments (see below for treatment details). A design with these characteristics would have strong internal validity, construct validity, and external validity.

[1] "Home-grown values" come from the subject's own preferences, as opposed to "induced values"that come from the experimenter (Murphy et al., 2010).

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Table 1
Description of Explanatory Variables.

Variable	Definition
Female	Gender (Dummy, 1 if Female)
Age	Age (in years)
Children	Have children under 18 in household (Dummy, 1 if Yes)
Concern Drinking Water	Have concerns about the pollution of drinking water (Categorical, 1- not at all 4- a great deal)
Concern Watershed	Have concerns about the pollution of rivers, lakes, or reservoirs (Categorical, 1- not at all 4- a great deal)
Rural	Reside in rural areas (Dummy, 1 if Yes)
In State	Reside in Delaware (Dummy, 1 if Yes)
Own Residence	Own residence (Dummy, 1 if Yes)
Environmental	Belong to environmental organizations (Dummy, 1 if Yes)
Risk Preference	Risk preferences (Categorical, 1- completely unwilling to take risks 10- completely willing to take risks)
Native Plant	Auction product (Dummy, 1 if product is native plant)
Biochar	Auction product (Dummy, 1 if product is biochar)
Soil Test Kits	Auction product (Dummy, 1 if product is soil test kits)
Peat Moss	Auction product (Dummy, 1 if product is peat moss)
Soaker Hose	Auction product (Dummy, 1 if product is soaker hose)
Default Priming	Starting value on slider (Continuous, uniformly distributed between 0 and 25)
Positive Framing	If conserve, water quality will be better (Dummy, 1 if information displayed)
Negative Framing	If don't conserve, water quality will keep getting worse (Dummy, 1 if information displayed)

Our subject pool was drawn from adult residents in the Delaware River watershed. The Delaware River begins in upstate New York and flows into the Delaware Bay, which separates New Jersey and Delaware. The watershed includes portions of New York, New Jersey, Pennsylvania, Delaware, and Maryland, and the river basin traverses extensive urban and suburban tracts in southeastern Pennsylvania and western New Jersey. In 2001, 14% of the land in the watershed was residential (Philadelphia Water Department, 2007). The watershed provides drinking water to approximately 6% of the U.S. population and ranks fifth among the country's most polluted watershed (Environment America, 2012).

The field experiment was conducted at AgDay in spring 2016 in northern Delaware. Held on the University of Delaware campus, AgDay is an annual public event that attracts about 8000 local residents per day, and traditionally takes place on the last Saturday in April. AgDay's most renowned component is its plant sale, and thus the event attracts a convenience sample of adults who are interested in lawn care and gardening. These people comprise a relevant population for estimating treatment effects: a group of adults from the watershed who are likely to be consumers of landscaping products. Because AgDay happens on a college campus, it also attracts college students, resulting in our sample being younger, on average, in comparison to the regional population (Appendix 1). In experimental and survey studies, the representativeness of respondents is always a concern. While we have no way of knowing how our sample's WTP for runoff-management products may differ from the WTP of the broader population in the watershed, our design has high internal validity for estimating the framing and anchoring effects given that we randomized treatments within the sample of recruited participants.

By posting and hand-distributing flyers to attendees, we recruited 336 participants. Subjects were paid $25 for participation in the experiment, which took 20–30 minutes to complete using a computer. Participants were seated inside at desks with privacy shields to ensure the confidentiality of decisions. After giving informed consent and then completing the experiment, each participant filled out a questionnaire that collected information about their environmental attitudes and demographics, including their gender, age, and household characteristics (rural vs. urban/suburban, owned or rented, and number of children in the household). The questionnaire also solicited participants' self-reported risk preferences. Previous studies have shown that attitudes about risk can influence consumers' preferences for environmentally friendly products (Li and McCluskey, 2017). See Table 1 for a list of the variables and their definitions, and Table 2 for summary statistics of the characteristics of the participants.

For the experiment, we chose a design in which participants would learn about and then be able to purchase landscaping products that reduce water runoff from their properties. These products were native plants, biochar (a soil amendment), soil test kits, peat moss, and soaker hoses, all of which had similar market prices at the time (~$12). The products were chosen based on advice from the University of Delaware's extension service (see Appendix 2 for descriptions of these products).[2]

Residents' WTPs for these products, and the effects of framing and anchoring on these WTPs, could be estimated using contingent valuation, a choice-based conjoint analysis, or an experimental auction design (Lusk and Hudson, 2004). To elicit residents' WTPs, we use a random-price auction (i.e., the Becker–DeGroot–Marschak (BDM) mechanism; Becker et al., 1964). The random-price auction is theoretically incentive-compatible (demand-revealing) and there is some experimental support for its demand-revealing properties (Irwin et al., 1998; Messer et al., 2010). In the auction, subjects do not bid against each other. Instead, they state their WTP and, afterwards, a price is randomly assigned to them. If the randomly generated price

[2] To identify the private products used in the experiment and to assess the construct validity of our treatments and outcome variables, we held focus group meetings with staff of the Delaware Center for the Inland Bays. We approached the Center for the Inland Bays because they have active outreach and educational programs, which encourage homeowners to adopt more environmentally-friendly practices at their homes. Furthermore, a group of student helpers pre-tested the experiment to make sure the instructions were well-structured, the computer program ran smoothly, and the questionnaire questions were transparent. Then the experimental design was pre-tested with a broader sample of staff and students at the University of Delaware."

Table 2
Summary Statistics of Participant Attributes.

Variables	
Number of respondents	336
Average age	32
	Percentage of participants
Female	63%
Children under 18 present in household	28%
Own Residence	63%
In State	73%
Environmental	35%
Rural	13%
Concerned about drinking water	
Not at all	1%
Only a little	14%
A fair amount	41%
A great deal	44%
Concerned about watershed	
Not at all	1%
Only a little	7%
A fair amount	37%
A great deal	55%
Risk preference	
1 (completely unwilling to take risks)	2%
2	6%
3	7%
4	9%
5	18%
6	18%
7	20%
8	13%
9	3%
10 (completely willing to take risks)	3%

is at or below their bid, they pay the random price and receive the product. If it is above their bid, they do not receive the product. A utility-maximizing subject should submit a bid equal to their true WTP (i.e., truth telling is a weakly dominant strategy).

Our aim was to study how framing and anchoring may affect WTP, not to test the BDM mechanism. Thus, to enhance the transparency of the mechanism, the instructions directly informed subjects that they could do no better than to submit a bid equal to their maximum willingness to pay for an item. Subjects also went through two practice rounds in which they bid on a pen and a pencil using the random-price procedure. After each practice round, the computer program asked "Do you understand how the bidding mechanism works?" If the participant answered "yes," the experiment proceeded. If the subject answered "no," the program brought the subject back to the practice rounds to give them another opportunity to practice.

After the practice rounds, subjects were given an opportunity to submit a bid on each of the five landscaping products. Subjects were made aware that, after submitting a bid for each product, one of the items would be randomly selected and its sales price would be randomly selected. The sales price for each product was randomly determined from a normal distribution with mean set at the average price for the product and standard deviation set at one-fourth of the mean. Subjects were not given details about the distribution from which the sales price would be drawn except that the possible prices were distributed around the average true market price. If subjects purchased one of the products, their payment would be deducted from their participation fee, thus setting a limit on the maximum bid at $25. Subjects selected their bids using a slider that allowed them to choose any value between $0 and $25, in one-cent increments (see Appendix 3).

To test the effects of anchoring and framing, we use a between-subject design. To test the effects of anchoring, the starting value of the slider for each subject was randomly chosen from a uniform distribution between $0 and $25 (2501 possible starting values; see Appendix 3 for example images). We were interested in testing whether the starting bid position on the slider affected the final bid value (i.e., whether the initial position of the slider had an effect on the final position selected before submitting the bid). For each subject, the randomized starting bid value was constant across the five products.

To test the effects of framing, subjects were randomly assigned to one of three groups: a positive framing treatment, a negative framing treatment, or a no-framing baseline. Subjects experienced their framing after receiving a brief written introduction to the experiment that explained: (1) potential earnings; (2) the BDM auction format, and (3) the nutrient runoff problems affecting local Delaware River tributaries. For the positive and negative framing treatments, subjects saw a green-to-red "gauge" that was intended to provide a visualization of going from "good" to "bad" landscaping practices, from

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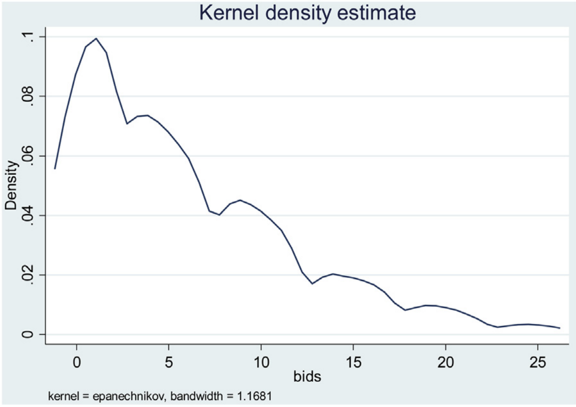

Fig. 1. Bid Density for Five Water Runoff Management Products (N = 1680).

a nutrient runoff perspective (see Appendix 4). For the positive frame, the gauge was underscored by a green arrow pointing down. For the negative frame, the gauge was underscored by a red arrow pointing up.

Under the gauge was a description of the pollution associated with residential runoff and the potential benefits from using the items offered in the auction. The differences in the framings are highlighted in bold below (subjects did not see the text bolded).

Positive Frame: "As shown by the arrow, residents that choose to install water conservation items on their lawn **will reduce the amount of pollution they contribute to** local watersheds. The nutrients in your lawn like Nitrogen and Phosphorus can cause algal blooms and kill fish once they enter local water bodies. **Upon installing water conservation items in your lawn, your contribution of nutrients and sediments will decrease. These items encourage healthy habitats and superior water quality in your local waterways.**"

Negative Frame: "As shown by the arrow, residents that choose **not** to install water conservation items on their lawn **are continuing to pollute** local watersheds. The nutrients in your lawn like Nitrogen and Phosphorus can cause algal blooms and kill fish once they enter local water bodies. **If you choose not to install water conservation items in your lawn, your contribution of nutrients and sediments will continue. Without installing these items, your local habitats and the water quality in your local waterways will continue to be damaged.**"

The experimental instructions, bidding interface, and questionnaire were presented in a Qualtrics platform augmented with JavaScript for the purposes of randomization. In addition to the anchoring and framing treatment arms, three attributes of the decision environment were randomized: (1) the order in which the five products were presented to participants (to eliminate order effects); (2) the one product among five that would be chosen, after the subjects' expressed their WTP for each product, for potential purchase through the random-price mechanism; and (3) the random price for the selected product. Subjects were aware of the latter two randomization procedures.

Once all of the bids were submitted and the questionnaire completed, the auction losers received their $25 participation fee in cash (a loser's bid was lower than the random price for their selected item). The winners received the product they had purchased plus the remainder, if anything, of their $25 participation fee (Remainder = $25 – Random Price).

2. Results

Each of the 336 adult participants placed five bids (one for each product), resulting in 1680 observations. The overall average bid was $5.87 (SD = $5.73). The distribution of bids is illustrated in Fig. 1. Recall that, if we assume subjects played the weakly dominant strategy in the BDM auction, these bids are equal to the subjects' WTP. On average, the residents were willing to pay the least for native plants ($4.55) and were willing to pay the most for soaker hoses ($7.34). Thus the average WTPs range from approximately 40% to 60% of the average market prices of the products.

The average bid for those who received the positively framed message ($6.90; SD = 6.10) was higher than the average bid of members of the baseline group who received no message ($5.22; SD = 5.14). The average bid for those who received the negative framing treatment was similar to the baseline group ($5.47; SD = 5.79). A nonparametric test of equality of the median values of the three framing treatment arms rejects the null hypothesis of equality (Pearson chi-squared test; $p < 0.001$). The same pattern can be observed for each product individually (Fig. 2).

To facilitate hypothesis testing and to estimate the impacts of the multi-valued anchoring treatment, we report results from three regression estimators: a random effects generalized least squares (GLS) estimator (Table 3), a random effects two-limit Tobit estimator (Table 3), and a linear hurdle model estimator (Table 4).

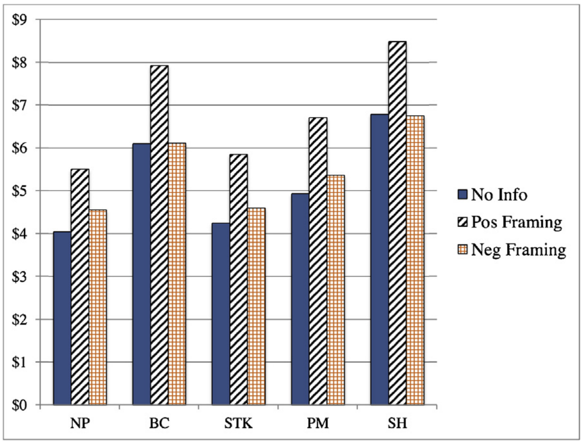

Fig. 2. Average WTP Bids for each Water Runoff Management Practice by Framing. NP is the abbreviation for native plant; BC for Biochar; STK for soil test kit; PM for peat moss; SH for soaker hose. The vertical axis measures average bids in USD.

Table 3
Regression Model Estimates of Treatment Effects.

	Generalized Least Squares		Tobit	
Variable	Coefficient (Standard Error)	95% CI	Coefficient (Standard Error)2	95% CI3
Default Starting Bid	0.068 (0.038)	[-0.006, 0.142]	0.073 (0.049)	[-0.023, 0.169]
Positive Framing	1.563 (0.633)	[0.323, 2.803]	1.942 (0.823)	[0.318, 3.567]
Negative Framing	0.328 (0.639)	[-0.925, 1.581]	0.498 (859)	[-1.193, 2.188]
Constant	4.39 (0.596)	[3.222, 5.557]	3.26 (0.807)	[1.673, 4.847]
	Chi^2 Test Statistics	p-value	Chi^2 Test Statistics	p-value
H0: PF=NF	3.13	0.07	2.66	0.104

Note: **GLS** with N = 1680 bid values and standard errors clustered by 336 individual participants.
Tobit with N = 1680 bid values (306 left-censored, 10 right-censored) and standard errors clustered by 336 individual participants. *PF* = positive framing treatment effect, *NF* = negative framing treatment effect.

Table 4
Linear Hurdle Model Estimates of Treatment Effects.

Variable	Coefficient (Standard Error)	95% CI
Participation — Lower Limit (Submitting a Positive Bid)		
Default Starting Bid	0.000 (0.010)	[-0.192, 0.197]
Positive Framing	0.180 (0.172)	[-0.158, 0.517]
Negative Framing	0.081 (0.174)	[-0.262, 0.423]
Constant	0.820 (0.168)	[-0.490, 1.150]
Conditional on Submitting a Positive Bid		
Default Start bid	0.229 (0.110)	[0.013, 0.445]
Positive Framing	3.989 (1.769)	[0.510, 7.468]
Negative Framing	0.565 (2.086)	[-3.538, 4.667]
Constant	−5.199 (3.050)	[-11.199, 0.800]
	F Test Statistic	p-value
H*$_0$*: PF = NF	2.98	0.085

Note: Hurdle Model with N = 1680 bid values and standard errors clustered by 336 individual participants.
PF = positive framing treatment effect, *NF* = negative framing treatment effect.

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2.1. Random-effects GLS and tobit regression estimators

The random-effects GLS estimator uses the model:

$$Y_{ij} = \beta_0 + \beta_1 X_{ij} + u_i + \varepsilon_{ij} \quad (1)$$

Where Y_{ij} is the WTP (bid) by participant *i* for product *j* and X_{ij} is a vector of treatment variables: two dummy variables represent the positive and negative framing treatments and a continuous variable (anchor) measures the default starting bid value. Furthermore, u_i is a random between-participant error term and ε_{ij} is a within-participant random error term. Random assignment of treatments allows one to interpret the estimated treatment variable coefficients as the estimated causal effects of treatment on WTP. Standard error estimates are clustered on participant. In the appendix, we present results from covariate-adjusted models in which $\mathbf{X}_{ij}$ also includes demographic and attitudinal predictor variables from the questionnaire, and a series of dummy variables for each product. Given the treatments are randomized, the estimated effects are nearly identical with the covariate-adjusted model.

The estimated coefficients in Table 3 imply that the positive framing increases the average WTP by 25%, although the confidence interval is wide, ranging from 5% increase to a 45% increase. The estimated effect of the starting bid anchor is also positive. A one-dollar increase in the default starting position of the slider increased the average bid by about seven cents (again, with a wide confidence interval). Thus going from a slider position of $0 (min) to $25 (max) increases the average WTP by about 30% (about a third of a standard deviation).

By design, participants' bids were restricted to a range of $0 to $25, and there is some clustering of bids at those extremes, especially at the $0 value (Table 3). Thus one potential alternative model for estimating the treatment effects is a random-effects two-limit Tobit model. We assume that a latent variable, B^*, exists and represents the participant's true WTP for the product. The latent variables are related to the observed B_{ij} (bid) by

$$B_{ij} = \begin{cases} 0 \; if \; B^*_{ij} \le 0 \\ B^*_{ij} = \mathbf{X}'_{ij}\beta + u_i + \varepsilon_{ij} \; if \; 0 < B^*_{ij} < 25 \\ 25 \; if \; B^*_{ij} \ge 25, \end{cases} \quad (2)$$

where *i* represents the participant and *j* represents the product. $\mathbf{X}_{ij}$ represents the treatment variables, u_i is the between-participant error term, and ε_{ij} is the within-participant error term.

As in GLS model, the Tobit model implies that the positive framing is estimated to increase WTP. This framing increases the average WTP by 33%, although the confidence interval is rather wide, ranging from a 5% increase to a 60% increase. As in GLS model, the estimated effect of the starting bid anchor is positive, with a one-dollar increase in the default starting position of the slider increasing the average WTP by about seven cents.

2.2. Linear hurdle regression estimator

The Tobit model was based on an assumption that participants form a WTP for the item, and censoring is based entirely on that WTP. However, individuals first choose whether they are interested in the product, and that decision could be based on a choice function different from the bidding function. We therefore estimated an additional regression model in which the bids were a function of $\mathbf{X}_{ij}$ and $\boldsymbol{\beta}$ (as in the Tobit model) and to which was added a set of variables and parameters, $\mathbf{Z}_{ij}$ and $\boldsymbol{\alpha}$, to describe the decision function ($\mathbf{Z}_{ij}$ are the treatment variables):

$$B_{ij} = \begin{cases} 0 \; if \; \mathbf{Z}'_{ij}\alpha + \varepsilon_{ij} \le 0 \; and \; B^*_{ij} \le 0 \\ or \; \mathbf{Z}'_{ij}\alpha + \varepsilon_{ij} > 0 \; and \; B^*_{ij} \le 0 \\ \\ B^*_{ij} = \mathbf{X}'_{ij}\beta + \varepsilon_{ij} \; if \; \mathbf{Z}'_{ij}\alpha + \varepsilon_{ij} > 0 \; and \; 0 < B^*_{ij} < 25 \\ \\ 25 \; if \; \mathbf{Z}'_{ij}\alpha + \varepsilon_{ij} > 0 \; and \; B^*_{ij} \ge 25 \end{cases} \quad (3)$$

Note that the "hurdle" specification appears only on the lower end of the censoring. We assumed that a $0 bid could represent both participants who explicitly chose not to bid and participants who wanted to bid less than or equal to $0 but could not because of the experiment design. At the upper limit, we include only the Tobit censoring and assumed that those participant had well-formed valuations that were greater than $25. This latter assumption has little effect on the estimates given that only 10 of the 1680 observations were at the $25 value.

In contrast to Table 3, Table 4 reports two estimated effects for each treatment variable: the effect on whether the subject submits a positive bid or not, and the effect on the bid value, conditional on submitting a positive bid. None of the treatments had a detectable effect on the probability of submitting a positive bid. Among the non-zero bids, the positive framing increased, relative to the neutral framing, the average positive bid, which was $7.18 (SD = 5.5), by about 55%. As in

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the other models, no effect could be detected from the negative framing compared to the baseline, and the hypothesis of equality of the negative and positive framing treatment effects can be rejected only at the 10% level.

Among the non-zero bids, a one-dollar increase in the default starting position of the slider increased the average bid by twenty-three cents. Given the average positive bid was $7.18 going from a slider position of $0 (min) to $25 (max) increases the average bid by about 80% (over one standard deviation). As with all of our models, the effect is imprecisely estimated, with the confidence interval ranging from an increase of about 5% to an increase of about 150%. The estimated treatment effect of an 80% increase in the average WTP is consistent with estimates found in the psychology literature, which range from 50% to more than 200% (see Maniadis et al., 2014).

2.3. Results summary

Across all three models, the estimated framing treatment effects across all models are consistent with the estimates from the unadjusted means. The estimated effect of positive framing on WTP is much larger than the effect of negative framing, but because the estimated effect of negative framing is imprecise, the difference between positive and negative framing effects is only weakly statistically significant (see last two rows in Table 3 and Table 4).

For the estimated anchoring effects, the estimated magnitudes and the precision of the estimates differ by estimator, but all three estimators imply that higher anchors increase a subject's WTP, on average. The estimated effect from the hurdle model is, in percentage terms, about double the estimated effect from the GLS and Tobit estimators, with the difference partly due to the hurdle model isolating the effect of anchors on positive bids (as opposed to anchors moving zero bids to something positive).

Nevertheless, like most studies in this literature, our design is underpowered to detect small or moderate treatment effect sizes and thus is prone to exaggeration bias (Type M error; see Gelman and Carlin, 2014). The magnitudes of the estimated anchoring effects and the estimated framing effects should be evaluated within this light. We encourage other researchers to replicate our design with an eye towards increasing its statistical power, or combining results in a meta-analysis. Statistical power could be increased with a larger sample size or, for the anchor treatment, by only using anchors at the extremes of the support ($0 and $25). Using our experimental data in a simulation of statistical power using our covariate-adjusted, GLS estimator, we estimate that future experiments seeking 80% power and 5% Type 1 error rates should plan on recruiting 1300 subjects to be able to detect a true treatment effect of 0.10 standard deviation or larger, which we think would be an appropriate estimate of the true effect. A smaller sample (900) would be adequate if one were to assume the treatments would have no effect on zero bids and thus the hurdle model would be appropriate.

2.4. Other correlates of bids

Adding other product and questionnaire covariates to the model (Appendix 5) does not increase the precision of our estimates and the estimated coefficients of the questionnaire covariates have no clear causal interpretations. Nevertheless, we note that answers to the risk attitude question are strongly correlated with WTP for the product. Recall that answers ranged from 1 to 10, with risk aversion declining as the response number increased (Table 1). Every one unit decline in risk aversion increases the bid by an expected $0.41, or about 7%. The estimated coefficients for the other variables are imprecisely estimated, although the evidence is in favor of a positive contribution from age and owning a residence, and a negative contribution from living in a rural area (variables that are likely correlated with income).

3. Conclusion

Nutrient pollution originating from industrial, agricultural, and residential sources is a widespread, costly, and challenging environmental problem. There is a large body of research on efforts to control such pollution from agricultural and industrial sources, but little attention has been paid to encouraging individuals to restrict the amount of nutrients transported from lawns and landscaping to waterways, a relatively small but consequential contributor. We sought to elucidate the willingness of residential households to adopt products that can decrease the amount of runoff from their properties, and to explore how attributes of the choice environment influence that willingness.

Our study implies that many consumers are willing to adopt runoff-reducing products, if they were subsidized. The average WTP for the products in this study ranged from 40%–60% of the market prices, which is in line with the cost-share percentages in many agri-environmental programs and in more recent local programs to address residential runoff. For example, the city of Raleigh, NC pays 75% of applicable costs for individual homeowners or businesses to install storm water-reduction practices like permeable pavement, green roofs, and rain barrels (City of Raleigh, 2015). The city of Lincoln, NE pays up to 50% for the installation of rain gardens and associated runoff management infrastructure on residential properties (Lincoln Public Works, 2017). The relative effectiveness of the runoff-reducing products offered in this study is uncertain, but the results imply that subsidies are a potential way to reduce non-point source pollution because they can increase the market share of nutrient management practices. Nevertheless, cost-benefit analysis would be needed to determine the efficiency of this policy instrument.

With regard to moderators of residential willingness to adopt the products, positive framing about the public good attributes of the products increased the average WTP for the products, whereas the effect of negative framing was much smaller and not statistically different from zero at $p < 0.05$ (the difference between negative and positive framing effects, however, could only be rejected at $p < 0.10$). We also found evidence that varying seemingly irrelevant anchor values can play a role in affecting how much consumers would pay for environmentally-friendly products. Thus our experimental results are consistent with claims by psychologists and behavioral economists that consumer preferences are malleable, and affected by seemingly irrelevant attributes of the decision environment, like the way in which benefits or costs are framed, or the initial suggested prices. Were these effects to be generalizable to other environmental program contexts, they would have important implications for how we design programs to more cost-effectively achieve environmental benefits.

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