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Measuring exaggeration bias in a contingent valuation study conducted in a retail environment

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Introduction

Contingent valuation (CV) methods provide a flexible approach to estimate willingness to pay (WTP). A concern for researchers, however, is potential bias that comes from collecting data using different modes (e.g. in-person, via mail, online). To estimate WTP for consumable items, such as food and floral, researchers often rely on convenience sampling. In particular, researchers may approach consumers in typical retail locations. There are several reasons why conducting surveys in a retail setting might lead to bias estimates of WTP.

Place and context can impact consumer perception of the product. This can be due to the event experience, i.e. the ambience or interaction; or a new product experience. There can also be interaction with salespeople that can influence the perception of the product. This may lead to exaggeration bias (Park and MacLachlan 2008), which occurs when survey respondents provide higher than normal WTP estimates.

Given the potential effect of the retail environment on consumers' WTP bids, we might expect that CV surveys offered in retail environments might result in higher WTP bids. That is, consumers participating in an on-site stated preference survey may exaggerate their WTP compared to a baseline group taken from an online survey. The purpose of this research project is to examine if data collection conducted in a retail environment results in significantly higher WTP estimates than WTP based on online data collection.

We create a CV survey which we administer to both an online sample and a sample of people attending farmers markets (FM). With this survey, we elicit consumer willingness to pay (WTP) for 3 products: lavender bundles, lavender oil and culinary lavender. We then compare WTP values across these different modes using a convolutions-based method. Finally, we also attempt to isolate potential hypothetical bias in both settings.

Overall, our results suggest that exaggeration bias does result in higher WTP estimates with the FM sample. Even when controlling for hypothetical bias, these effects still persist and appear to be exacerbated to some degree. These findings indicate that future research using on-site samples may need to consider the potential for exaggerated responses.

Survey design

To examine whether a retail-based survey might result in exaggeration bias, we created a double-bounded dichotomous choice contingent valuation survey (Hanemann et al 1991). The survey was administered in the summer and fall of 2018 at 5 farmers markets in Georgia. The online survey was administered in the fall of 2018 to respondents in all southeastern states. The farmers market respondents came from a convenience sample.

Survey respondents evaluate three products (lavender bundles, lavender oil and culinary lavender) made from Georgia grown lavender, which is a relatively new product with limited distribution. These products were chosen to represent varying levels of value add to the base product. The lavender bouquets contained 30 dried stems. The farmers market respondents received a free bundle of Georgia lavender for completing the survey. We provided a picture of the bundle with the online survey. The lavender oil was 0.5 ounces, which is a common size for such oils. We showed the farmers market respondents a non-branded bottle of lavender oil and showed a picture of the bottle online. The culinary lavender was also a 0.5 ounce jar. Again we showed a non-branded container to farmers market respondents and provided a picture online

We obtained a range of initial retail prices for each product from interviews with Georgia lavender growers. Based on those prices, we created 3 treatments for each product representing a low, average, and high price. The follow up bids for each of the treatment levels overlap as well.

We randomly assigned survey participants to one of the three treatment levels for each product (Table 1).

For each product (bundles, oil, culinary), survey respondents were asked if they would be willing to pay some initial bid for the lavender product. If the respondent rejected the initial bid, they were asked if they would be willing to pay for a lesser bid. If they accepted the initial bid, they were asked if they would be willing to pay for a higher bid. Using the survey responses, we can calculate the willingness to pay (WTP) for each survey respondent.

It is well known that CV methods can suffer from hypothetical bias. As such, we attempt to attempt to control for hypothetical bias using a cheap talk script (Appendix). Essentially, the script encourages the respondent to consider how much they would *really* be willing to pay and reminds them of the opportunity cost of such a decision if it were real.

A priori, our expectation is that survey respondents at the farmers market will be more prone to exaggerated bids due to the experience of FM environment and interaction with the survey presentation. To separate potential hypothetical bias from potential exaggeration bias, we implement a 2 x 2 design that varies by mode (online survey vs. FM survey) and hypothetical correction (cheap talk script and scaling vs. nothing). We obtained over 3 thousand responses online and over 200 at farmers markets (Table 2). Almost 48 percent of the online sample received the hypothetical script and almost 50 percent of the farmers market sample received the hypothetical script.

Empirical Methods

We specify WTP for each person i for each of the j products as a linear function:

$$(1) WTP_{ij} = z_i' \beta + \varepsilon_{ij},$$

where z identifies demographic characteristics and responses to survey questions, and $\varepsilon_{ij} \sim N(0, \sigma^2)$. We then use a person's response to the first bid (t^1) and second bid (t^2) to define WTP intervals. Defining a person's response (*Yes*, *No*) to each bid as $\{response\ 1, response\ 2\}$, we can infer the WTP for each person lies one of the four intervals:

$$\{Yes, No\}: t^1 < WTP < t^2,$$

$$\{Yes, Yes\}: t^2 < WTP < \infty,$$

$$\{No, Yes\}: t^2 < WTP < t^1,$$

$$\{No, No\}: 0 < WTP < t^2.$$

If we assume each bid follows the same valuation function, we can define these intervals as a likelihood function (Lopez-Feldman 2012), such that for each product we have:

$$(2) \sum_{i=1}^N \left[d_i^{yn} \ln \left(\Phi \left(z_i' \frac{\beta}{\sigma} - \frac{t^1}{\sigma} \right) - \Phi \left(z_i' \frac{\beta}{\sigma} - \frac{t^2}{\sigma} \right) \right) + d_i^{yy} \ln \left(\Phi \left(z_i' \frac{\beta}{\sigma} - \frac{t^2}{\sigma} \right) \right) + d_i^{ny} \ln \left(\Phi \left(z_i' \frac{\beta}{\sigma} - \frac{t^2}{\sigma} \right) - \Phi \left(z_i' \frac{\beta}{\sigma} - \frac{t^1}{\sigma} \right) \right) + d_i^{nn} \ln \left(1 - \Phi \left(z_i' \frac{\beta}{\sigma} - \frac{t^2}{\sigma} \right) \right) \right],$$

where d are indicator variables that take a value of one or zero depending on each person's responses and the superscript values (y, n) identify $\{response\ 1, response\ 2\}$. We estimate equation (2) using maximum likelihood to obtain $\hat{\beta}$ and $\hat{\sigma}$ ¹.

Using our parameter estimates, we create WTP values for each survey respondent, creating a distribution of WTP values. Relevant to our study, we create four WTP distributions based on the survey mode and whether their survey controls for hypothetical bias or not.

Convolutions methods

¹ We use the comman *doubleb* in Stata 13 written by Lopez-Feldman (2012) to estimate our models.

To test whether WTP values are significantly different between groups, we use the convolutions method developed by Poe, Giraud and Loomis (2005). To do this, we generate WTP estimates for each group we are comparing using bootstrap simulations. For example, the simulated vector of WTP estimates for i farmers market respondents is X_i and the WTP estimates for j online market respondents is Y_j . We then use the complete combinatorial approach suggested by Poe, Giraud and Loomis (2001) to compare the vectors. Essentially, this approach compares every WTP estimate from one group with every WTP estimate from the other group. Specifically, we calculate:

$$(3) \hat{X}_i - \hat{Y}_j \forall i, j.$$

We then sort the resulting $i*j$ vector. The proportion of negative values provides the α level for testing if the two distributions are statistically different. The benefit of this approach, rather than just comparing mean WTP values, is that we do not have to make assumptions about the normality of our WTP distributions, which are unlikely. We use this methods to compare WTP in our two sample groups in several ways.

First, we test for the presence of hypothetical bias in either sample as:

$$(4) \widehat{FM}_i - \widehat{FM}_b \forall i, j,$$

$$(5) \widehat{OL}_i - \widehat{OL}_b \forall i, j$$

where FM and OL are the WTP for respondents who did not receive the hypothetical script and FM_b and OL_b are the WTP for respondents who did receive the hypothetical script. Both (4) and (5) assume that without the hypothetical script, respondents are likely to respond with higher WTP values.

We also test for the presence of exaggeration bias across samples as either:

$$(6) \widehat{FM}_i - \widehat{OL}_i \forall i, j \text{ or}$$

$$(7) \widehat{FM}_b_i - \widehat{OL}_b_i \forall i, j$$

Equation (6) allows us to see whether the WTP estimates from the FM group are different than the online group. Equation (7) allows us to determine whether hypothetical bias exacerbates any exaggeration bias.

Results

We estimate equation (1) for each of our 3 products, excluding demographic variables, to obtain a baseline WTP estimate. We do this by mode (farmers market and online) and by whether the respondent received the hypothetical script or not.

All of the calculated WTP values are statistically significant at the $p = 0.001$ level and within the range of values that we were quoted by farmers who are currently selling lavender (Table 3). The WTP estimates for those who received the hypothetical script are lower than those that did not. Although it is not clear if they are statistically different as the confidence intervals generally overlap. For example, the people at the FM have a WTP of \$10.28 for lavender bundles when seeing the hypothetical script and \$10.32 without.

Across modes, we find that the FM WTP values are higher than online WTP values for all products except the lavender bundles with no bias script. Again, the confidence intervals overlap significantly across modes as well.

Hypothetical Bias

Using 500 bootstrap simulations for each group, we next compare the WTP for respondents that received the hypothetical script to those that didn't for each survey mode. There appears to be

hypothetical bias with the online WTP estimates for lavender bundles, but not the FM estimates (Table 4). Specifically, the willingness to pay is \$0.82 higher for the online respondents that didn't receive the script, with an alpha of 0.001. Comparing the distribution of the two groups by mode provides a good picture of the different WTP values as well (Figure 1). In particular, the online samples overlap only at the tails, whereas the FM sample is almost entirely overlapping.

With the lavender oil, the WTP estimates are \$0.60 larger online ($p = 0.01$) and \$1.06 larger at FMs ($p = 0.075$), suggesting hypothetical bias with this product as well. The difference in distributions is easy to see with the online group but is harder to differentiate with the FM group (Figure 2).

Finally, the distribution of WTP estimates for the culinary lavender have much more overlap with both the online and FM samples. (Figure 3). Although the WTP distributions have separate peaks for those that received the script and did not, the difference between the distributions have an alpha that is not within conventional ranges of significance (Table 4).

Exaggeration Bias

We next compare the FM sample WTP with the online sample WTP to see if we in fact find evidence of exaggeration bias with the FM sample. With the lavender bundles, the group that receives the hypothetical script has a WTP that is \$0.58 larger, which is significant at an alpha of 0.092 (Table 5). The group that does not receive the script has a lower WTP at the FM, although the value has a much higher alpha of 0.749. Figure 4 provides more evidence that the group that did not receive the script has more substantial overlap with their WTP estimates. In this scenario, it does not appear that hypothetical bias exacerbates the exaggeration bias associated with the FM location.

The WTP estimates for the lavender oil suggest a significant amount of exaggeration bias due to FM location. The distributions have no overlap with either group (Figure 5). And the FM group is \$2.57 larger for the group receiving the script and \$3.03 for the group not receiving the script. This result provides some evidence as well that hypothetical bias might exacerbate the higher WTP associated with FMs.

The WTP estimates for culinary lavender further suggest there is exaggeration bias with the FM sample. Specifically, the group receiving the script have a \$0.62 higher WTP at an alpha of 0.073 and the group not receiving the script have a \$0.92 higher WTP at an alpha of 0.01. Again, hypothetical bias results in slightly larger values as well. The histogram of WTP estimates also reveals a far more dispersed distribution for FM WTP estimates (Figure 6). Whereas the distribution of online WTP estimates are more tightly centered around the mean. So while there is evidence of exaggeration bias, the result is driven more by the extreme higher values.

Discussion

Overall, the results of this analysis suggest that hypothetical bias has some effect on the estimated WTP for lavender products. However, there appears to be more extreme and consistent evidence of exaggeration bias with the WTP estimates for survey respondents at farmers markets.

The use of CV methods continues to be prevalent with products being sold in retail environments (e.g. food and floral). Further, data collection for such analyses often occurs in actual retail environments. The results of this research suggest that accounting for potential

exaggeration biases is important for obtaining more accurate results with stated preference methods. This is likely to be important for other stated preference WTP methods as well.

There is concern that the results are affected by the use of two different sampling frames: and online sample and the FM convenience sample. Ideally, we would have used one sample frame for both studies, but that is infeasible to accomplish. To this point, we find only one study (Boyle et al 2016) has simultaneously controlled for sample mode and sample frame in their WTP analysis. They find no impact of sampling frame on their analysis. Still, future studies would benefit from controlling for sampling frames.

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Citations

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Poe, G.L., K.L. Giraud, and J.B. Loomis. 2005. “Computational Methods for Measuring the Difference of Empirical Distributions.” *American Journal of Agricultural Economics* 87(2): 353–365.

Tables

Table 1. Contingent Valuation Survey Structure

Product	Treatment	Initial Bid	<u>Follow-up Bid</u>	
			<i>Reject</i>	<i>Accept</i>
Bundles	Low	\$ 8	\$ 6	\$ 10
	Average	\$ 12	\$ 10	\$ 14
	High	\$ 16	\$ 14	\$ 18
Culinary	Low	\$ 4	\$ 3	\$ 5
	Average	\$ 6	\$ 5	\$ 7
	High	\$ 8	\$ 7	\$ 9
Oil	Low	\$ 8	\$ 6	\$ 10
	Average	\$ 12	\$ 10	\$ 14
	High	\$ 16	\$ 14	\$ 18

Table 2. Survey Participants by Mode and Treatment

	Hypothetical Script		Total
	<i>Yes</i>	<i>No</i>	
Online	1,432	1,578	3,010
Farmers Market	101	102	203
Total	1,533	1,680	3,213

Table 3.

		<u>Farmers Market Sample</u>					
		<u>Hypothetical Bias Script</u>			<u>No Bias Script</u>		
		<i>Bundles</i>	<i>Oil</i>	<i>Culinary</i>	<i>Bundles</i>	<i>Oil</i>	<i>Culinary</i>
WTP		10.28***	11.93***	6.398***	10.32***	13.03***	6.881***
		0.000	0.000	0.000	0.000	0.000	0.000
		[9.394 - 11.16]	[10.89 - 12.96]	[5.614 - 7.182]	[9.429 - 11.20]	[11.98 - 14.08]	[6.103 - 7.659]
Obs		97	97	96	99	97	95

		<u>Online Sample</u>					
		<u>Hypothetical Bias Script</u>			<u>No Bias Script</u>		
		<i>Bundles</i>	<i>Oil</i>	<i>Culinary</i>	<i>Bundles</i>	<i>Oil</i>	<i>Culinary</i>
WTP		9.750***	9.357***	5.807***	10.57***	9.964***	5.961***
		0.000	0.000	0.000	0.000	0.000	0.000
		[9.399 - 10.10]	[8.970 - 9.744]	[5.621 - 5.992]	[10.22 - 10.92]	[9.600 - 10.33]	[5.770 - 6.152]
Obs		1,414	1,423	1,415	1,431	1,427	1,424

Confidence Intervals in brackets

*** p<0.001, ** p<0.01, * p<0.05

Figures

Figure 1. Online and Farmers Market Willingness to Pay estimates for Lavender Bundles

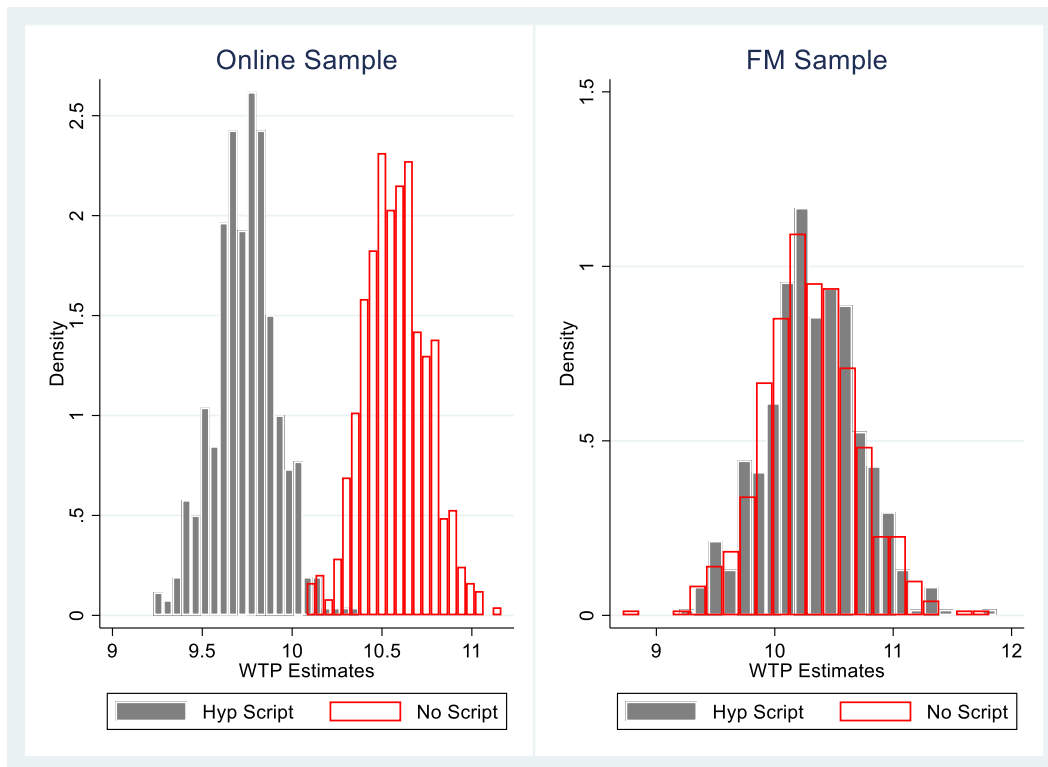


Figure 2. Online and Farmers Market Willingness to Pay estimates for Lavender Oil

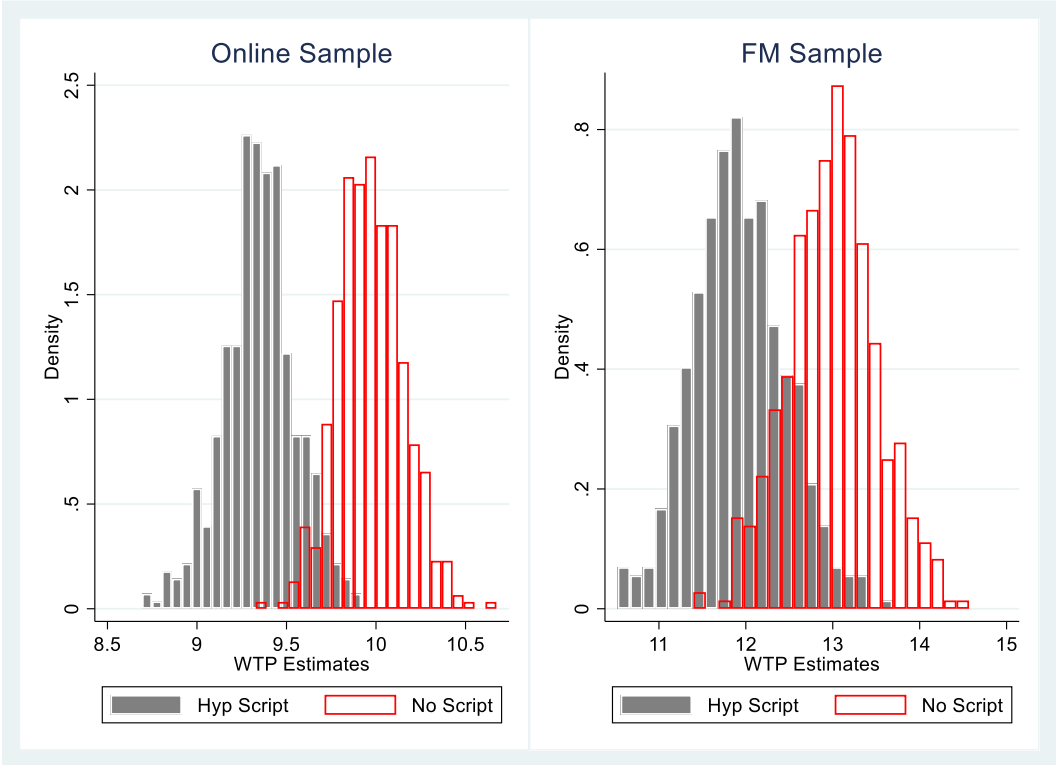


Figure 3. Online and Farmers Market Willingness to Pay estimates for Culinary Lavender

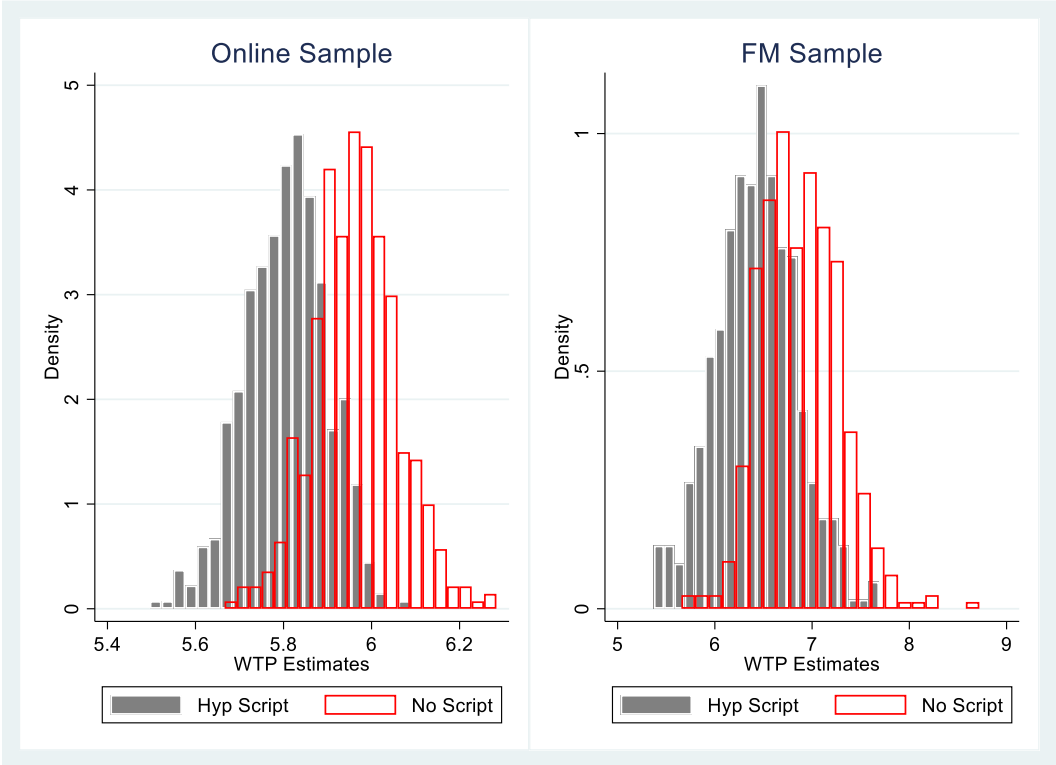


Figure 4. Willingness to Pay estimates for Lavender Bundles by Hypothetical Scenario

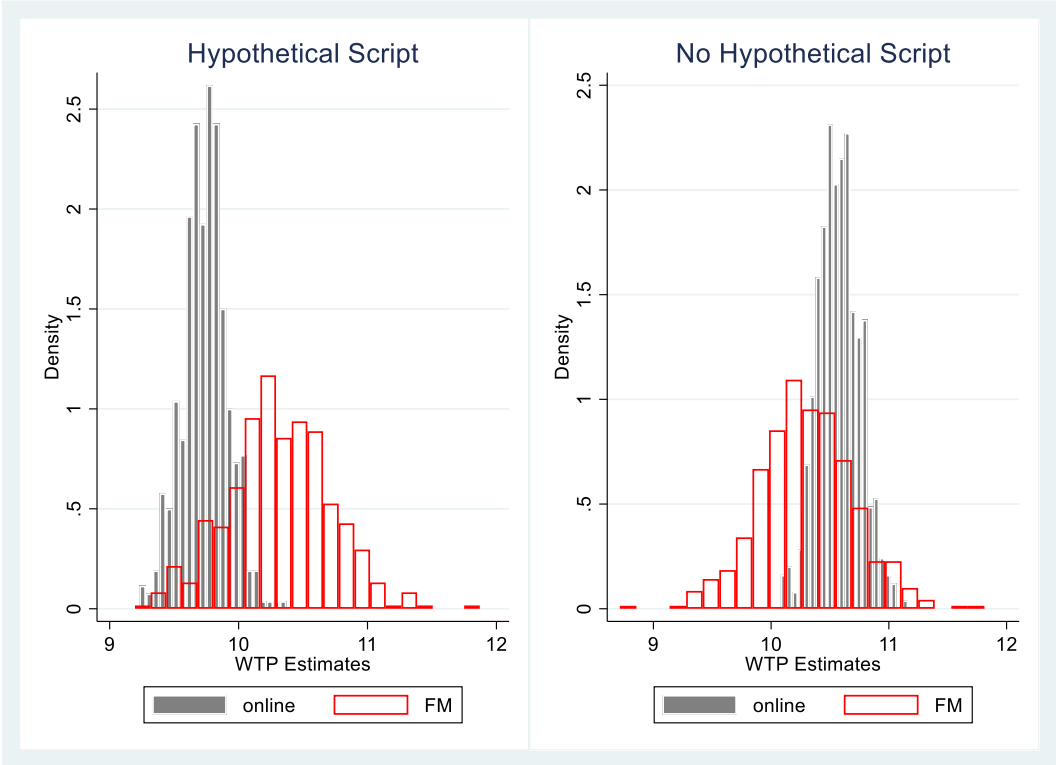


Figure 5. Willingness to Pay estimates for Lavender Oil by Hypothetical Scenario

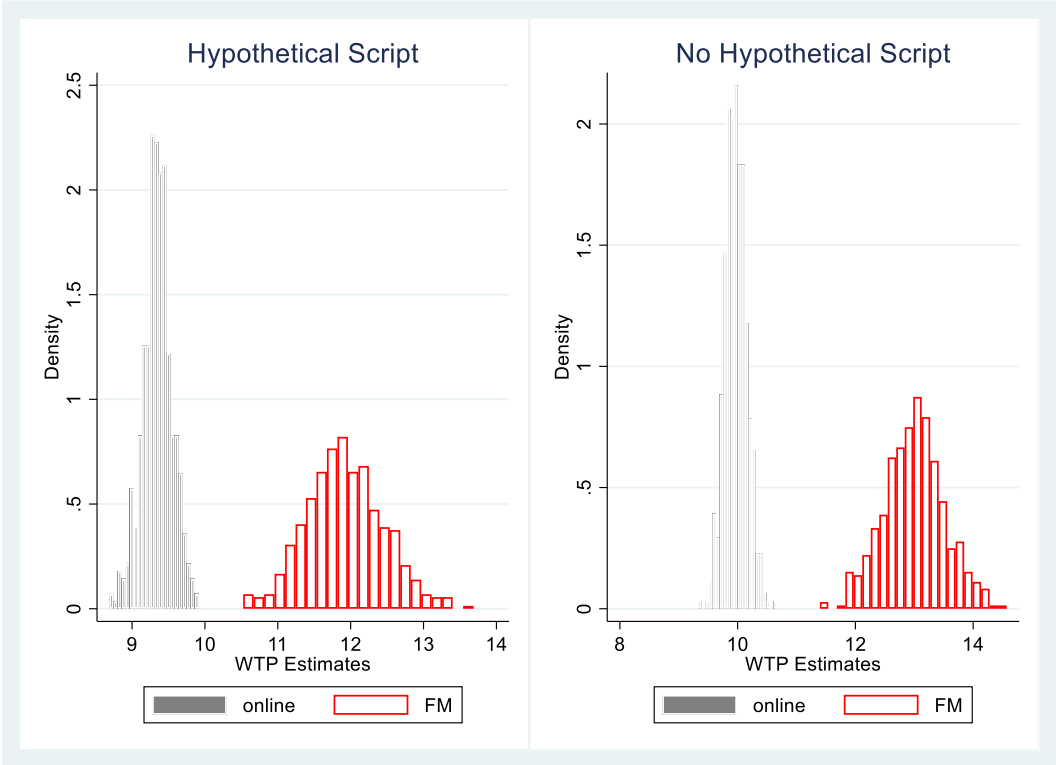


Figure 6. Willingness to Pay estimates for Culinary Lavender by Hypothetical Scenario

