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Postmodern Consumer And Functional Products: Use Of Innovative Techniques For The Analysis Of Behavior In Experimental Economics

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Abstract

In this study the experimental auction method is used in a between sample analysis to asses hypothetical bias and Willingness To Pay (WTP) for canned crushed tomatoes enriched with lycopene. The empirical analysis shows the presence of statistically significant bias between hypothetical and real bids at different level of bids. The difference in bids for the functional and control products defines the implicit WTP variable. Both WTP and implicit WTP show a statistically significant total difference between real and hypothetical bids only at the upper and lower levels of bids. These differences are of opposite signs and balance on average. Focusing on the factors driving the bias, the empirical analysis points out two main groups of variables: socio-demographic variables and attitude toward food technologies.

Keywords
Hypothetical bias, quantile regression, decomposition, experimental auctions

Introduction

The study of the discrepancy between intentions and actual behavior has a long tradition in the social sciences (Ajzen, Brown and Carvajal, 2004; Lusk, McLaughlin and Jaeger, 2007). The gap between people's intentions and behaviors (Ajzen and Fishbein, 2000) yields so-called *hypothetical bias*, a systematic overestimation of Willingness To Pay (WTP) in hypothetical compared to real scenarios (Harrison and Ruström, 2008; Loomis, 2011; Mitani and Flores, 2010; Murphy, Alle, Stevens and Weatherhead, 2005): "hypothetical bias is the difference between what people say they are willing to pay in a hypothetical survey question and what they will actually pay in a non-hypothetical experiment when money is really on the line" (Grebitus, Lusk, and Nayga, 2013, p. 12).
Various explanations for the observed difference between intentions and behaviors have been proposed. According to Campbell (1963), they are both affected by the individual's underlying latent disposition toward a certain target: people with highly positive or negative attitudes are expected to respond consistently in hypothetical and real contexts, whereas individuals who hold moderate attitudes would respond differently in the hypothetical context and in the more demanding real context.
A different interpretation relates the discrepancy between intention and behavior to the difference between symbolic representations and real-life representations (Blumer, 1956): salient features of a real situation could activate beliefs about a certain behavior differing

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from the beliefs that could be activated in a hypothetical situation (Ajzen and Sexton, 1999). In particular, a hypothetical scenario could activate more favorable (or less unfavorable) beliefs than an actual one (Ajzen et al., 2004).

Additional arguments have been proposed in the literature to explain the hypothetical bias: the uncertainty about the good values (Johannesson et al. 1999; Champ and Bishop, 2001; RIF), the individuals' strategic responses to influence the price or availability of goods (Carson and Groves, 2007), and the existence of social desirability bias (e.g., List et al. 2004; Lusk and Norwood, 2009; Lusk and Norwood, 2011). Finally, Aadland, Caplan, and Phillips (2007) recognized the absence of a universal explanation of hypothetical bias.

Understanding why people misstate their actual preferences for a good when asked a hypothetical question remains a major issue in non-market valuation. While biases have been observed in both directions, much of the specialist literature suggests that people tend to overstate their actual willingness to pay in hypothetical situations.

In the 1980s, much of the experimental hypothetical bias literature tested the overall validity of contingent valuation (Harrison and Rutström, 2008). However, in the 1990s there was a plethora of works that used the experimental auction technique (List and Shogren ,1998; Diamond and Hausman, 1994; Fox et al. ,1998; Neill et al. 1994), these studies show the presence of hypothetical bias, thus calling for the use of various calibration factors. There are exceptions to the conclusion about the existence of hypothetical bias (e.g., Champ et al., 1997; Johannesson, 1998; Sinden, 1988; Smith and Mansfield, 1998).

According to the above-cited works, hypothetical bias does not seem to exist either in the case of public or private goods. However, such studies appear to be in the minority: the average person would appear to exaggerate his or her actual WTP across a broad spectrum of goods with vastly different experimental protocols.

Nonetheless, it has been widely observed that the issue of hypothetical bias still represents a challenge for scholars, and further research is required to identify factors and clarify processes related to the hypothetical/real incongruence toward a general theory of hypothetical bias (Harrison and Rutström, 2008; Loomis, 2011; Mitani and Flores, 2010; Murphy, Allen, Stevens, and Weatherhead, 2005).

The paper starts with a description of the experimental design and the methodology. A short description of the estimators implemented and the discussion of the results lead to the conclusions.

Method

Experimental Design

Between the end of June and the first week of July 2014, several sessions of experimental auctions were conducted in the computer lab of the Department of Agricultural Science in Portici (Naples) in order to assess WTP for a specific functional product (crushed tomatoes enriched with lycopene). In all, 190 participants in the auctions were recruited among college students of the Department of Agricultural Science and other departments of the University of Naples. Upon their arrival participants, who were not informed about the

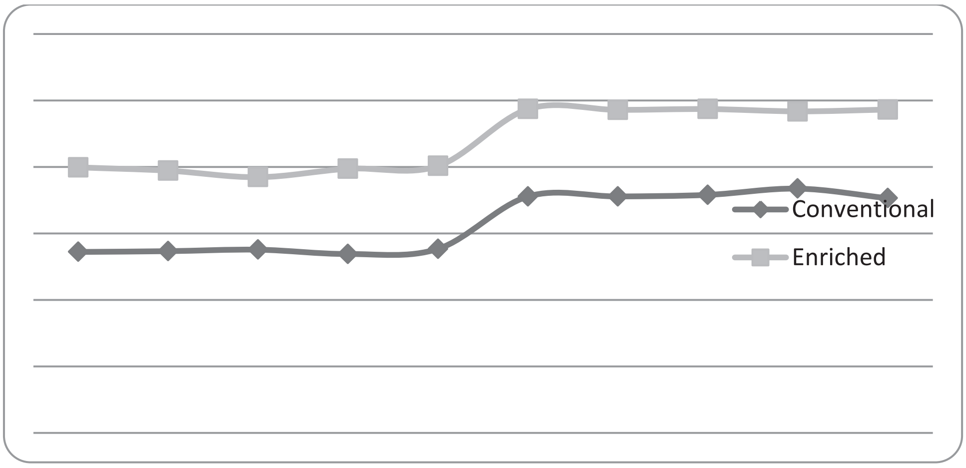
purpose of the experiment, received their endowment (15 euro). Each auction required the participation of ten people. The recruitment of undergraduate students, rather than those responsible for food purchasing, should not cause significant distortions in the results because there is a consistent convergence between student opinion and the responsible act of purchasing (Depositario et al., 2009). It should also be noted that students possess greater ability to perform the tasks required by the experiment which was completely computerized. Finally, the students belonged to the Y generation (Millennials), a social group more inclined to evaluate emerging new food styles (Howe and Strauss, 2009).
The entire experimental design was computerized both to accelerate data acquisition and to minimize the possibility of error in the data set collection phase. The software programs used were:

- *Z-tree* (Fischbacher, 2007), for the collection of bids in auctions. Through this program it was possible to speed up the evolution of the experiment and store real-time data obtained;
- *Google Drive*, to administer the questionnaires;
- *Millisecond Inquisit*, for the collection of data on implicit measures through a SC_IAT test (Single Category Implicit Association Test).

For this experiment, the fifth-price mechanism with a full bidding process was employed. Following Drichoutis, Lazaridis, and Nayga (2008), Bernard and He (2010), and Hellyer, Fraser, and Haddock-Fraser (2012), we did not use the reference price, since we were aware of the possibility of the occurrence of bid affiliation. No price feedback among multiple rounds was reported (Corrigan et al., 2012).
The experiment was divided into several stages. During the experiment each participant was asked to use an ID (identifier) in order to trace the source computer of the data, thereby preserving complete anonymity. The experimenter provided participants with all the information on the auction mechanism. The subjects were informed about the dominant strategy to reveal their true value for the products offered. To understand the bidding behavior and the mechanism, five training rounds were conducted using three different candy bars.
After the auctions, the participants were asked to complete a questionnaire about their demographic characteristics and consumption habits. They also answered questions on explicit measures validated to explain the behavior of consumer choice for food products, the Food Choice Questionnaire (FCQ), the Food Technology Neophobia Scale (FTNS), together with questions related to a psychometric scale, Trust in Science Scale (TISS), which measures public attitudes toward scientific research and technologies. Finally, to measure social desirability, the short form of the Marlowe-Crowne Social Desirability Scale was used. The data collected generate the variables summarized in the Appendix under the headings of Demographic Variables, Control Variables, Implicit Associations and Explicit Attitudes.
The 190 participants were divided into two sub-samples, joining two different types of auctions: 90 individuals were assigned to the first group, denoted by *hypothetical auction*. Subjects were fully briefed about the auction mechanism, and after the training session the products studied were presented. The second group, termed *non-hypothetical* or *real auction*, involved 100 subjects. In this type of auction participants are informed that the

winners will actually buy the product randomly selected by paying the fifth price figure 1 shows the trend of bids in the two groups.
The products in the auction were two packs of three 400-gram cans of crushed tomatoes: conventional crushed tomatoes, and crushed tomatoes enriched in lycopene (50% more). During the auction, each participant was asked to submit simultaneously a bid for each of the two crushed tomato products. The bids were collected and the step repeated for four additional rounds.
When all five rounds were completed, a random draw determined which of the five rounds was chosen. A random draw then defined which of the three crushed tomato products was selected. The top four bidders on the bidding product in each round purchased the crushed tomato package, paying a price equivalent to the fifth-highest bid for the product.

Figura 1. Mean bids by groups



Source: own elaboration

Methodology

Quantile regressions were computed in order to investigate the price bid model, for both real and hypothetical bids, not only on average but also at different quantiles. This indicates changes in the coefficients across quantiles: an explanatory variable may have a different impact on bids depending upon the chosen quantile, if the focus is on low or high bids.
Hypothetical and real bids were compared and the difference between the two was decomposed into coefficient and covariate effects, which meant splitting the discrepancy between real and hypothetical prices into respectively unexplained and explained effects. The former is due to differing estimated coefficients and in this context it represents the actual bias. The latter relates the difference in bids to the difference in the covariates of the two groups.
So far hypothetical bias has been measured in experiments considering within or between samples. The main problem in the former is the anchoring effect (Beggs and Graddy, 2009; Lusk and Shogren, 2007) while in the latter it is difficult to asses the comparability of the samples, at least with respect to the attitudinal variables.

Oaxaca (1973) and Blinder (1973) discuss average decomposition, while decomposition is here considered not only on average but also in the tails, at lower and higher bids/quantiles. The quantile regression estimates at various quantiles (Koenker, 2005) provide the tools to compute the decomposition. Machado and Mata (2005) introduce quantile regression-based decomposition, while Chernozhukov et al. (2013) provide tools to implement inference.
Consider the linear regression model $y_i=x_i\beta+e_i$, where x_i is the row vector including the i^{th} observation for all the explanatory variables of the model. The quantile regression objective function is an asymmetrically weighted regression, and the asymmetric weights allow the estimated line to move away from the mean of the conditional distribution. For the selected quantile θ, it assigns weights θ and $1-\theta$ to the observations depending on their position above or below the estimated equation. The coefficients are computed by minimizing the following objective function where the absolute value of the regression errors, is asymmetrically weighted by θ or $(1-\theta)$ and the weights set the position of the estimated line.
To analyze a data set split in two different subsets, each identified by an index assuming values 0 – for instance in hypothetical bid experiments, and 1 otherwise, in the real bid case, a decomposition approach can be implemented. Oaxaca (1973) and Blinder (1973) decomposition allows the difference between subsets to be written as

$$E(y_1 - y_0) = E(y_{1/1} - y_{0/1} + y_{0/1} - y_{0/0})$$

In the bids example $y_{1/1}$ coincides with Y_r and $y_{0/0}$ coincides with Y_h. The first term of the decomposition, $y_{1/1} - y_{0/1}$, measures the difference in bids due to changes in the regression coefficients, $(\beta_1-\beta_0)$. The second term instead looks at the difference in bids due to changes in the covariates, such as changes in the characteristics when moving from the real to the hypothetical subset, and provides a measure of the composition effect. These terms are generally computed at their average values. The result is an average measure of bid difference between the two subsets.
However, the terms in a decomposition can take different values according to the selected quantile of the Y distribution, the center, the lower and the upper tail. Therefore the decomposition can be estimated not only on average, but also in the tails by means of the quantile regression estimated coefficients. In a quantile regression decomposition it is possible to verify whether any discrepancy is statistically significant at each quantile and whether such a discrepancy is stable or changes across quantiles.

Results of the regression model

Results of the regression model

The selected model focuses on the enriched tomatoes as a function of three main groups of variables: socio-demographics, attitudinal and control variables. The definition of the variables can be found in the table 1, while the estimates of the regression coefficients are reported in tables 2, 3 and 4.

Next the analysis at the various quantiles can be implemented. At this stage we analyze two different dependent variables. In a first model the real and hypothetical bids for the enriched product are considered, WTPL50 in the tables, while in the second model the focus is on the willingness to pay for the specific functional attribute. The latter is computed as the difference between bids declared for the functional product and bids declared for the control product. The difference between the two measures the implicit willingness to pay for the functional attribute, IMPL_WTPL50 in the tables.

Table 1. Summary statistics of the variables

	REAL AUCTION				HYPOTHETICAL AUCTION			
DEPENDENT VAR.	STD. DEV.	.25	.50	.75	STD. DEV.	.25	.50	.75
BIDL50	1.392	1.02	1.80	2.70	2.429	1.50	2.00	3.00
IMPL_WTPL50	0.824	0.20	0.45	0.90	0.639	0.20	0.50	1.00
	REAL AUCTION				**HYPOTHETICAL AUCTION**			
SOCIO-DEMOGRAPHIC	STD. DEV.	.25	.50	.75	STD. DEV.	.25	.50	.75
age	4.007	21	23.8	25.7	2.820	20	22.1	24
gender	0.497	0	0.56	1	0.500	0	.47	1
children under 12	0.357	0	0.15	1	0.328	0	0.12	1
income	0.878	2.00	2.30	3	1.026	2	2.35	3
political orientation	0.444	0	.730	1	0.408	0	0.78	1
	REAL AUCTION				**HYPOTHETICAL AUCTION**			
CONTROL VARIABLES	STD. DEV.	.25	.50	.75	STD. DEV.	.25	.50	.75
consumption frequency	0.588	2	2.88	3	0.624	2	2.78	3
	REAL AUCTION				**HYPOTHETICAL AUCTION**			
MEASURES	STD. DEV.	.25	.50	.75	STD. DEV.	.25	.50	.75
SC_IAT	0.415	-0.41	-0.07	0.25	0.406	-0.24	-0.06	0.26
social desirability	0.650	3.58	3.97	4.33	0.749	3.33	3.88	4.33
FCQ health	0.806	5.50	5.81	6.50	0.808	5.16	5.73	6.33
FCQ natural	0.961	5.00	5.67	6.33	1.007	5.33	5.69	6.33
FCQ price	1.193	4.33	5.09	6.25	1.276	4.33	5.25	6.33
FCQ familiarity	1.355	3.33	4.32	5.33	1.284	3.00	4.13	5.00
FTNS unnecessary	1.128	2.50	3.45	4.33	1.130	3.16	3.83	4.50
FTNS risks	1.190	3.31	4.04	4.75	1.234	3.50	4.18	5.00
FTNS benefits	1.287	2.50	3.19	4.00	1.324	2.50	3.34	4.00
trust in science	0.491	1.80	2.13	2.40	0.490	2.00	2.20	2.40

Table 2. Single equation estimates for hypothetical, Yh, and real bids, Yr for the enriched product

	OLS Y_h	OLS Y_r	Huber Y_h	Huber Y_r
Age	0.139	0. 067	0.048	-0.026
	(0.067)	(0.035)	(0.018)	(0.013)
Gender	1.229	0. 632	0.760	0. 383
	(0.374)	(0.296)	(0.102)	(0.107)

Table 3 (continues). Single equation estimates for hypothetical, Yh, and real bids, Yr for the enriched product

	OLS Y_h	OLS Y_r	Huber Y_h	Huber Y_r
children under 12	*-0.194*	-0. 690	*-0.058*	-0.567
	(0.586)	(0.381)	*(0.160)*	(0.138)
family income	0.324	*0. 124*	0.174	*0.095*
	(0.181)	*(0.178)*	(0.049)	*(0.064)*
political orientation	-0.420	*-0. 445*	*-0.173*	-0.486
	(0.463)	*(0.315)*	*(0.126)*	(0.114)
consumption freq.	*-0.026*	0. 457	-0.134	0.222
	(0.297)	(0.246)	(0.081)	(0.089)
FCQ health	*0.202*	*0. 278*	*0.081*	0.239
	(0.228)	*(0.214)*	*(0.062)*	(0.077)
FCQ natural	*-0.043*	*-0. 157*	0.165	*-0.085*
	(0.192)	*(0.177)*	(0.052)	*(0.064)*
FCQ price	*-0.122*	*-0. 133*	-0.173	-0.194
	(0.155)	*(0.143)*	(0.042)	(0.052)
FCQ familiarity	*-0.048*	*0. 068*	*-0.006*	0.134
	(0.160)	*(0.119)*	*(0.043)*	(0.043)
FTNS unnecessary	*-0.151*	*-0. 111*	*0.021*	-0.137
	(0.212)	*(0.157)*	*(0.057)*	(0.057)
FTNS risks	*0.074*	*-0. 179*	-0.137	-0.208
	(0.196)	*(0.147)*	(0.053)	(0.053)
FTNS benefits	*-0.000*	0. 239	*-0.005*	0.120
	(0.153)	(0.127)	*(0.042)*	(0.046)
social desirability	*0.102*	*0.195*	*0.042*	*0.004*
	(0.258)	*(0.219)*	*(0.070)*	*(0.079)*
trust in science	*0.456*	*0. 425*	*0.121*	0.282
	(0.369)	*(0.296)*	*(0.100)*	(0.107)
SC-IAT test	*-0.458*	0. 655	-0.455	0.600
	(0.475)	(0.346)	(0.124)	(0.125)
constant	*-2.780*	*-2.781*	*0.329*	1.697
	(2.825)	*(1.779)*	*(0.770)*	(0.425)
N	450	500	450	500
R^2	0.20	0.32		

Source: own elaboration, estimated coefficients not statistically different from zero in italics

The results for the first, second and third quartile regression are reported in table 3 for hypothetical and real bid regressions and in table 4 for the implicit willingness to pay. It can be seen that across quartiles the estimated coefficients do change and, depending on the selected quantile, the explanatory variables have a different impact on the dependent variable, a different explanatory power. The comparison of hypothetical and real bids shows that quite a number of variables are not statistically significant in the hypothetical bids while they are significant in the real bids. This is the case of *children under 12, political*

orientation, frequency consumption, FCQ health, FCQ natural, FCQ familiarity, all the *FTNS* variables: *FTNS unnecessary, FTNS risk, FTNS benefit, trust in science* and *SC-IAT test.*
Social Desirability, instead, is the only variable which is not statistically different from zero in both the hypothetical/real bids and the hypothetical/real implicit WTP equations. Since the products of the experiments are very common and frequently used, and don't present any attribute (Fisher, 1993; Böhm, 2012) this results is not surprising even if it partially contradicts Norwood and Lusk (2011).

Table 3. Quantile regression estimates, hypothetical and real WTPL50 samples

WTPL50	Yh			Yr		
	.25	*.50*	*.75*	*.25*	*.50*	*.75*
age	**.092***** (.028)	.043 (.056)	**.091*** (.043)	-.007 (.024)	.003 (.034)	.003 (.043)
gender	**.841***** (.153)	**.702***** (.252)	**1.419***** (.220)	**.583***** (.167)	.229 (.147)	**.557**** (.255)
children under 12	-.273 (.264)	-.104 (.217)	.130 (.362)	-.215 (.174)	**-.599***** (.165)	**-.782***** (.236)
family income	**.177***** (.060)	**.355**** (.104)	**.242***** (.065)	.136 (.082)	.037 (.123)	.171 (.139)
political orientation	-.148 (.207)	-.275 (.180)	-.391 (.258)	**-.587**** (.225)	**-.379***** (.124)	**-.569**** (.231)
consumption frequency	.059 (.090	.000 (.140)	**-.735***** (.248)	**.230*** (.155)	**.438**** (.186)	.348 (.214)
FCQ health	.115 (.157)	.137 (.086)	**.428***** (.206)	**.513***** (.110)	.221 (.159)	.161 (.158)
FCQ natural	.039 (.078)	.144 (.099)	.113 (.199)	**-.214***** (.061)	.004 (.105)	.131 (.153)
FCQ price	**-.148**** (.061)	**-.259***** (.070)	**-.306***** (.053)	**-.174**** (.073)	**-.244**** (.094)	**-.256***** (.097)
FCQ familiarity	-.027 (.089)	.045 (.065)	-.007 (.094)	**.151**** (.066)	.114 (.081)	.142 (.100)
FTNS unnecessary	-.072 (.090)	-.091 (.114)	-.252 (.189)	**-.187**** (.077)	**-.165**** (.061)	-.125 (.123)
FTNS risk	-.020 (.095)	-.043 (.076)	.197 (.135)	-.099 (.076)	**-.201***** (.059)	**-.281*** (.162)
FTNS benefit	-.009 (.074)	.048 (.075)	-.053 (.088)	.074 (.068)	.050 (.067)	**.389**** (.157)
trust in science	**.332**** (.156)	.047 (.166)	.184 (.150)	.091 (.093)	**.432**** (.221)	**.708**** (.326)
social desirability	-.011 (.030)	.084 (.148)	.290 (.185)	.044 (.118)	.060 (.129)	.089 (.142)
SC-IAT test	-.316 (.225)	**-.575**** (.265)	-.140 (.413)	**.465***** (.128)	**.724***** (.234)	**.851**** (.350)
constant	-1.638 (1.701)	-.118 (2.293)	-.075 (2.595)	-.449 (.986)	1.103 (1.429)	-1.148 (3.200)
n	450	450	450	500	500	500

Source: own elaboration, standard errors in parentheses

Table 4. Quantile regression estimates, hypothetical and real implicit WTP samples

IMPL_WTPL50		Y_h			Yr	
	.25	*.50*	*.75*	*.25*	*.50*	*.75*
age	.018	.035	**.090****	-.000	.002	.023
	(.018)	(.026)	(.043)	(.011)	(.009)	(.018)
gender	-.015	**.347*****	**.730*****	**.165*****	**.253*****	.069
	(.115)	(.106)	(.231)	(.034)	(.076)	(.103)
children under 12	-.293	-.306	.048	.066	.026	**-.283*****
	(.206)	(.228)	(.390)	(.072)	(.073)	(.106)
family income	**.100****	.049	.025	.051	**.120****	.100
	(.049)	(.053)	(.058)	(.042)	(.052)	(.080)
political orientation	**-228****	-.207	-.157	**-.155****	**-.207****	**-.389****
	(.111)	(.184)	(.248)	(.083)	(.094)	(.093)
consumption frequency	**.161***	.085	.096	**.094****	**.165****	**.337*****
	(.096)	(.063)	(.111)	(.044)	(.074)	(.097)
FCQ health	.095	-.020	.061	**.109****	**.139****	**.222*****
	(.070)	(.072)	(.057)	(.053)	(.057)	(.056)
FCQ natural	.009	.052	**.161****	**-.074****	-.060	.017
	(.046)	(.049)	(.074)	(.033)	(.050)	(.068)
FCQ price	**.089****	.021	-.045	**-050***	-.046	**-.191*****
	(.035)	(.051)	(.090)	(.030)	(.040)	(.036)
FCQ familiarity	-.011	-.074	**-.193*****	**.059*****	**.043***	.031
	(.077)	(.045)	(.066)	(.022)	(.023)	(.045)
FTNS unnecessary	-.035	-.052	.061	**-.103*****	-.062	**-**.012
	(.053)	(.054)	(.080)	(.031)	(.043)	(.067)
FTNS risk	**.055****	.034	-.017	-.013	**-110*****	**-.192*****
	(.024)	(.046)	(.095)	(.032)	(.040)	(.048)
FTNS benefit	-.030	-.023	-.003	.018	**.072****	.063
	(.030)	(.029)	(.057)	(.025)	(.030)	(.050)
trust in science	.170	.156	**.210***	**-127****	**.289*****	**. 325*****
	(.108)	(.129)	(.109)	(.051)	(.098)	(.123)
social desirability	.073	.002	.051	.127	.004	.117
	(.109)	(.066)	(.078)	(.089)	(.044)	(.075)
SC-IAT test	.103	-.062	.032	-.065	**.198*****	**.309*****
	(.113)	(.146)	(.209)	(.048)	(.084)	(.148)
constant	**-2.388****	-.355	-2.846	.206	-.438	-1.408
	(.093)	(1.167)	(1.908)	(.494)	(.731)	(1.385)
n	450	450	450	500	500	500

Source: own elaboration, standard errors in parentheses

Results of the decomposition analysis

The comparison between real and hypothetical WTPL50, computed on average by the Oaxaca-Blinder approach, yields a total difference Ey1 - Ey0 = 0.452. The latter is split into endowment effect (Ex1 -·Ex0) = -.267, and coefficient effect (·1 -··0)=0.719. All these terms are statistically relevant, as can be seen in the top section of table 7. Therefore, there is a difference between real and hypothetical bids, which is only partially explained by a difference in the covariates. The unexplained/coefficient component can be interpreted as the actual bias. Indeed, the covariate effect is opposite in sign with respect to the coefficient effect, thus resulting in a smaller total difference.

For the IMPL_WTPL50 variable, Oaxaca-Blinder decomposition yields the following results: total difference Ey_1 - Ey_0 = 0.030, endowment effect (Ex_1 - Ex_0) = -0.154 and coefficient effect ($\cdot_1$ - $\cdot\cdot_0$) = 0.184. The total difference is not statistically relevant, and this is the case since in the decomposition the coefficient and covariate effects are statistically significant but have the opposite sign. The components of the decomposition balance each other on average.

Next the decomposition is computed at various quantiles, table 5 presents the results of the decomposition of WTPL50. The first two columns compute the total difference at each selected quantile between distributions of hypothetical and real bids together with the standard errors. The difference is positive and statistically different from zero, showing that the two distributions differ from one another. The next four columns report the decomposition of such differences between covariate and coefficient effects. It can be noted that they are all statistically significant, but if the covariate effect is negative and becomes more severe across quantiles, the coefficient effect is positive and grows across quantiles. Thus the global comparison of real and hypothetical bids proves less evident than the actual bias. The terms of the decomposition partially balance each other and the total difference presents a u-shaped pattern across quantiles reaching the lowest value around the median. This shows how the analysis at the various quantiles detects effects that cannot otherwise be revealed.

Table 6 reports the results of the Machado and Mata (2005) decomposition approach for the IMPL_WTPL50 variable. In this case the total difference between distributions is significant only in the lower tail, the two deciles at the bottom and the 40th decile of the total difference of the distributions, and furthermore they are opposite in sign. On the one hand, this result confirms the Oaxaca-Blinder decomposition result of a non-significant difference between distributions on average, but while before the components of the decomposition seem to balance each other on average, now is the opposite sign of the total difference that cancels out on average. Indeed, looking at the quantile decomposition, the covariate effect is not statistically relevant, while the coefficient effect, unexplained by the model, is significant at the bottom decile and from the 40th upward. The actual bias has the opposite sign, the opposite behavior in the tails, with hypothetical larger than real at the upper IMPL_WTPL50 values, from the 40th decile up. Conversely, real is greater than hypothetical IMPL_WTPL50 at the lowest decile.

Finally, the Oaxaca-Blinder decomposition (table 7), albeit implemented only on average, yields additional information about the relevance of each explanatory variable within the average decomposition. The table shows that on average the impact of most of the covariates is hardly ever significant for both WTPL50 and IMPL_WTPL50. The coefficient effect shows a statistically relevant difference between real and hypothetical WTPL50 in the case of *gender, family income, frequency consumption, FTNS risk, FTNS benefit, SCIAT.*

Table 5. Differences between the hypothetical and real bid distributions of WTPL50

	total effect		covariate effect		coefficient effect	
quantile		std. err.		std. err.		std. err.
.10	**.5182**	.076	-.1080	.076	**.6262**	.060
.20	**.4000**	.057	**-.2216**	.072	**.6216**	.061
.30	**.3065**	.062	**-.3033**	.077	**.6098**	.063
.40	**.2893**	.063	**-.2932**	.094	**.5826**	.075
.50	**.2890**	.060	**-.2903**	.117	**.5793**	.073
.60	**.2773**	.071	**-.2983**	.147	**.5756**	.079
.70	**.2199**	.085	**-.4812**	.186	**.7011**	.114
.80	**.3684**	.100	**-.5511**	.228	**.9195**	.168
.90	**.7806**	.148	**-.7968**	.363	**1.577**	.281

Table 6. Differences between the hypothetical and real bid distributions of IMPL_WTPL50

	total effect		covariate effect		coefficient effect	
quantile		std. err.		std. err.		std. err.
.10	**-.2737**	.027	.0042	.076	**-.2779**	.084
.20	**-.0536**	.024	.0092	.047	-.0628	.038
.30	-.0006	.019	.0576	.040	-.0583	.033
.40	**.0585**	.026	-.0048	.040	**.1066**	.028
.50	.0506	.029	-.0752	.046	**.1259**	.025
.60	.0591	.034	-.0719	.056	**.1310**	.039
.70	.0592	.040	-.0846	.073	**.1438**	.054
.80	.0847	.055	-.1918	.110	**.2766**	.075
.90	.1847	.096	-.3652	.189	**.5500**	.135

Table 7. Oaxaca-Blinder decomposition: difference between hypothetical and real distributions

	WTPL50		**IMPL_WTPL50**	
		std. err.		std. err.
Total difference	**.4524**	.098	.0299	.060
Explained	**-.2670**	.067	**-.1546**	.042
Unexplained	**.7196**	.102	**.1845**	.058

Table 7 (continues). Oaxaca-Blinder decomposition: difference between hypothetical and real distributions

	covariates			
		std. err.		std. err.
age	**-.1378**	.047	**-.0953**	.032
gender	**-.0734**	.030	**-.0251**	.011
children under 12	.0168	.013	.0074	.006
family income	.0109	.012	.0034	.004
political orientation	-.0225	.012	-.0109	.006
consumption frequency	-.0243	.013	**-.0188**	.009
FCQ health	-.0185	.014	-.0159	.011
FCQ natural	-.0016	.006	-.0007	.003
FCQ price	-.0165	.010	-.0051	.004
FCQ familiarity	.0032	.007	-.0041	.005
trust in science	**.0285**	.014	.0226	.011
FTNS unnecessary	**-.0382**	.019	-.0255	.011
FTNS risks	-.0076	.007	-.0010	.003
FTNS benefits	.0215	.013	.0134	.008
social desirability	-.0152	.009	-.0135	.007
SC_IAT	.0079	.006	.0046	.004
	coefficients			
		std. err.		std. err.
age	1.6169	1.034	-.6260	.637
gender	**.3067**	.113	.1043	.068
children under 12	.0629	.035	-.0124	.024
family income	**.4667**	.224	.0659	.128
political orientation	.0158	.171	-.1935	.117
consumption frequency	**-1.3668**	.456	-.4706	.263
FCQ health	-.4344	.766	-.6020	.475
FCQ natural	.6462	.579	.5001	.344
FCQ price	.0550	.390	**.6386**	.236
FCQ familiarity	-.4987	.345	**-.4468**	.207
trust in science	.0684	.444	¤ .1231	.256
FTNS unnecessary	-.1572	.350	.1125	.196
FTNS risks	**1.0448**	.372	**.7767**	.19 8
FTNS benefits	**-.7851**	.272	**-.3075**	.156
social desirability	-.3657	.567	-.2726	.372
SC_IAT	¤ **.0435**	.017	**.0194**	.007

Discussion

The previous analysis has explained the hypothetical bias, and socio-demographic and attitudinal variables turn out to be the main triggering factors. The results highlight the crucial role of technophobic traits for functional food. The quantile regression and quantile decomposition have been crucial to attain these results.

In the regression model the differences between hypothetical and real auctions of Table 3 are particularly important in the case of implicit associations (SC_IAT): in line with what was expected, these variables are not significant at all quantiles in the hypothetical auction while they are highly significant in the real auction. It has been observed that implicit association affects impulsive rather than reflexive systems (Strack and Deutsch, 2004). Therefore a non-significant effect of implicit associations can be expected in hypothetical scenarios while a significant effect can be anticipated in real auctions. Our results confirm this hypothesis. Result suggests the importance of the implicit measures of attitudes in the interpretation of hypothetical bias. Also other variables linked to technophobia show different effects in non-hypothetical and hypothetical auctions and different impacts at different quantiles. All the three variables used to capture the three dimensions of the FTNS are significant only in the real auction. In particular, the impact of the perception of risk linked to food technology (FTNS risk) increases along quantiles, highlighting the importance of risk perception in addressing both real WTP and hypothetical bias.

Consistent with the literature (Frewer et al., 1996; Siegrist, 2000; Poortinga and Pidgeon, 2005), our results confirm the importance of trust mainly in the real auction, with an increasing impact on WTP from the first to third quantile.

Socio-demographic variables seem to have more effect in the hypothetical scenario. Gender and income are significant in the hypothetical auction and present an increasing impact on WTP. However, when actual payments are involved their impact is lower, as in the case of gender, or is no longer significant, as in the case of income. Table 4 confirms that these same general results hold also in the case of the implicit willingness to pay for the attribute, yet aspects related to health are significant in all three quantiles of the real auction.

In the decomposition, *gender, family income* and *frequency consumption* affect hypothetical bias: women tend to bid higher in the hypothetical scenario; as income increases so does the discrepancy between hypothetical and real WTP; vice versa, higher consumption frequency tends to reduce the bias. In this case, more experienced consumers show a greater ability to keep hypothetical and actual bids aligned.

The variables *FTNS risks, FTNS benefits, SC_IAT,* refer directly and indirectly to food technophobia. Risk perception and benefit perception toward food technology play an active role to determine the bias but with opposite effects: the higher the perception of risk, the higher the hypothetical bias. By contrast, perception of benefit stemming from food technologies contributes to mitigate the gap between bids declared in the different scenarios (hypothetical versus non-hypothetical). In addition to the self-report measures also the implicit measure shows, on average, a statistically relevant coefficient effect.

Turning to the Oaxaca-Blinder decomposition for the IMPL_WTP50 variable, on average the total effect is not significant. However, the decomposition highlights once again a significant effect both in covariates and coefficients, which are opposite in sign, such that the overall

effect is close to zero and not significant. The coefficient effect is significant for *FCQ price, FCQ familiarity, FTNS risks, FTNS benefits and SC_IAT.* In the case of implicit WTP the relevance of the variables linked to food technophobia is also confirmed.
The results show that distributions of real and hypothetical bids differ and decomposition provides significant estimates. However, while the covariate/explained effect has a negative sign, the coefficient/unexplained effect is positive, therefore the total difference is not as wide as the actual bias. For the implicit WTP variable, the total difference is not statistically different from zero at and above the mean, but in the lower tail the difference is significant and of opposite signs. It thus confirms the Oaxaca-Blinder result that shows that the difference between the two distributions at the mean is not statistically different from zero. The difference in the lower tail could not be detected by the Oaxaca-Blinder decomposition on average. It could only be revealed through a quantile-based decomposition analysis.

Conclusions

An experimental auction was implemented to analyze hypothetical bias and to assess WTP for canned crushed tomatoes enriched with lycopene. Hypothetical and non-hypothetical auctions on independent samples were used. The empirical analysis implements quantile regressions and quantile regression-based decomposition together with the standard Oaxaca-Blinder decomposition based on average values. Quantile regression decomposition shows statistically significant bias between hypothetical and real bids at all quantiles. Implicit WTP shows a statistically significant total difference between real and hypothetical bids only at the lower quantiles of opposite signs. However, looking at the coefficient component of the decomposition, i.e. what we consider the actual bias, it can be seen that while hypothetical bias is lower than the real at the 10th decile, the opposite is true and the sign is reversed from the 40th to the 90th quantile.
Comparing these results with the Oaxaca-Blinder decomposition the total difference between hypothetical and real bids is positive and statistically relevant which is somewhat smaller than the coefficient component, i.e. the actual average bias, due to the partial compensation of the covariate effects. In implicit WTP, the total difference on average does not significantly differ from 0. While in Oaxaca-Blinder the actual bias on average is balanced by covariate effects, in the quantile regression decomposition the balancing occurs across quantiles. The somewhat coinciding results show the irrelevance of the bias in implicit WTP around the mean.
Focusing on the factors driving the bias, Oaxaca-Blinder analysis points out two main groups of variables: socio-demographic and attitude toward food technology variables.
Quantile regression and quantile decomposition has been fundamental to analyze hypothetical bias in the tails and could be further implemented to compare different strategies to reduce the bias, such as cheap talks and solemn oaths. These topics are left to further research.

References

Ajzen I., Fishbein M. (2000) Attitudes and the attitude-behaviour relation: Reasoned and automatic processes. In W. Stroebe and M. Hewstone (Eds.), *European review of social psychology,* pp 1–33. New York: John Wiley and Sons. DOI: 10.1080/09540120412331269558.

Ajzen I., Sexton J. (1999) Depth of processing, belief congruence, and attitude–behavior correspondence. In S. Chaiken and Y. Trope (Eds.), *Dual process theories in social psychology*,.pp.117–138). New York: Guilford.

Ajzen I., Brown T. C., Carvajal F. (2004) Explaining the discrepancy between intentions and actions: The case of hypothetical bias in contingent valuation. *Personality and Social Psychology Bulletin* 30,.pp.1108–1121. DOI: 10.1177/0146167204264079

Bak H. (2001) Education and public attitudes toward science: implications for the "Deficit Model" of education and support for science and technology. *Soc Sci Q* 82(4),.pp.779–795.

Beggs, A., Graddy, K. (2009). Anchoring effects: Evidence from art auctions. *The American Economic Review*, 1027-1039.

Bernard J. C., Na H. (2010) Confounded by the Field: Bidding in Food Auctions When Field Prices Are Increasing*. Agricultural and Resource Economics Review* 39,.pp.275–287.

Blinder A. (1973) Wage discrimination: reduced form and structural estimates, *Journal of Human Resource*s 8,.pp.436–455.

Blumer H. (1956) Sociological analysis and the" variable". *American sociological review*, pp.683-690.

Bohm P. (1972) Estimating the Demand for Public Goods: An Experiment', *European Economic Review* 3, pp.111–130.

Böhm, V. (2012) Lycopene and heart health, *Molecular nutrition & food research*, 56(2), pp. 296-303.

Campbell D. T. (1963) Social attitudes and other acquired behavioural dispositions. In S. Koch (Ed.) *Psychology: A study of a science,* pp. 94–172. New York: McGraw-Hill.

Carson R. T., Groves T. (2007) Incentive and informational properties of preference questions. *Environmental and resource economics* 37(1), pp.181-210.

Champ, P. A., Bishop, R. C., Brown, T. C., and McCollum, D. W. (1997). Using donation mechanisms to value nonuse benefits from public goods. Journal of environmental economics and management, 33(2), 151-162.

Champ P. A., Bishop R. C. (2001) Donation payment mechanisms and contingent valuation: An empirical study of hypothetical bias. *Environmental Resource Economics* 19, 383–402. DOI 10.1023/A:1011604818385

Chernozhukov V., Fernandez-Val I., Melly B. (2013) Inference on counterfactual distributions, *Econometrica* 81,.pp.2205–2268.

Corrigan J. R., Drichoutis A., Lusk J., Nayga R., Rousu M. C. (2012) Repeated Rounds with Price Feedback in Experimental Auction Valuation: An Adversarial Collaboration. *American Journal of Agricultural Economics,* 94 (1),.pp.97–115

Cox D. N., Evans G. (2008) Construction and validation of a psychometric scale to measure consumers' fears of novel food technologies: The food technology neophobia scale. *Food quality and preference* 19(8),.pp.704-710.

Depositario D. P., Nayga R., Wu X., Laude T. P. (2009) Should students be used as subjects in experimental auctions? *Economics Letters* 102(2),.pp.122–124.
Diamond P., Hausman J., (1994) Contingent valuation: Is some number better than no number? *Journal of Economic Perspectives* 8, pp.45-64.
Drichoutis A. C., Lazaridis P., Nayga R. M. (2008) The role of reference prices in experimental auctions. *Economics Letters* 99(3),.pp.446–448.
Fisher R. J. (1993). Social desirability bias and the validity of indirect questioning. *Journal of consumer research*, pp.303-315.
Fox J., Shogren J., Hayes D., Kliebenstein J., (1998) CVM-X: Calibrating contingent values with experimental auction markets, *American Journal of Agricultural Economics* (in press).
Frewer, L. J., Howard, C., Hedderley, D., and Shepherd, R. (1996). What determines trust in information about food-related risks? Underlying psychological constructs. Risk analysis, 16(4), pp. 473-486.
Frykblom P. (1997). Hypothetical question modes and real willingness to pay. *Journal of Environmental Economics and Management*, *34*(3), 275-287.
Fischbacher U. (2007) z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental economics* 10(2),.pp.171–178.
Grebitus C., Lusk J., Nayga, R. (2013) Explaining differences in real and hypothetical experimental auctions and choice experiments with personality. *Journal of Economic Psychology* 36,.pp.11–26. DOI: 10.1016/j.joep.2013.02.004
Greenwald A. G., Nosek B. A., Banaji M. R. (2003) Understanding and using the Implicit Association Test: I. An improved scoring algorithm. J*ournal of Personality and Social Psychology* 85, pp.197–216. DOI: 10.1037/0022-3514.85.2.197
Harrison G. W., Rutström E. E. (2008) Experimental evidence on the existence of hypothetical bias in value elicitation methods. In C. R. Plott, L. S. Vernon (Eds.), *Handbook of Experimental Economics Results*, Amsterdam (The Netherlands): North Holland
Hellyer N. E., Fraser I., Haddock-Fraser J. (2012) Food Choice, Health Information and Functional Ingredients: An Experimental Auction Employing Bread. *Food Policy* 37, pp.232–245.
Hofler, R. A., and List, J. A. (2004) Valuation on the frontier: Calibrating actual and hypothetical statements of value, *American Journal of Agricultural Economics*, 86(1), pp. 213-221.
Howe N., Strauss W. (2009) *Millennials rising: The next great generation*. Vintage.
Huber P. (1981) *Robust Statistics*, New York: Wiley.
Johannesson M. (1997) Some Further Experimental Results on Hypothetical versus Real Willingness to Pay. *Applied Economics Letters* 4,.pp.535–536.
Johannesson, M., Liljas, B., and Johansson, P. O. (1998). An experimental comparison of dichotomous choice contingent valuation questions and real purchase decisions. Applied Economics, 30(5), 643-647.
Karpinski A., Steinman R. B. (2006) The Single Category Implicit Association Test as a measure of implicit social cognition. *Journal of Personality and Social Psychology* 91,.pp.16–32. DOI:10.1037/0022-3514.91.1.16
Koenker R. Bassett G. (1978) Regression quantiles. *Econometrica* 46,.pp.33–50.
Koenker R. (2005) *Quantile regression*, Cambridge University Press.

List J. A., Gallet C. A. (2001) What experimental protocol influence disparities between actual and hypothetical stated values?. *Environmental and Resource Economics* 20(3),.pp.241-254.
List J. A., Shogren J. F. (1998) Calibration of the difference between actual and hypothetical valuations in a field experiment. *Journal of Economic Behavior and Organization* 37(2),.pp.193-205.
Loomis J. (2011) What's to know about hypothetical bias in stated preference valuation studies? *Journal of Economic Surveys* 25,.pp.363–370. DOI: 10.1111/j.1467-6419.2010.00675.x
Lusk, J. L., McLaughlin L., Jaeger S. (2007) Strategy and response to purchase intention questions. *Marketing Letters* 18,.pp.31–44.
Lusk J. L., Schroeder T. C. (2004) Are Choice Experiments Incentive Compatible? A Test with Quality Differentiated Steaks. *American Journal of Agricultural Economics* 86,.pp.467–482.
Lusk J. L., Shogren J. (2007) *Experimental Auctions: Methods and Applications in Economic and Marketing Research*. Cambridge: Cambridge University Press.
Lusk J. L., Norwood F. B. (2009) An inferred valuation method. *Land Economics* 85(3),.pp.500–514.
Machado J., Mata J. (2005) Counterfactual decomposition of changes in wage distributions using quantile regression, *Journal of Applied Econometrics* 20,.pp.445-465.
Melly B. (2006) Estimation of counterfactual distributions using quantile regression, *SIAW*, University of St. Gallen.
Mitani, Y., Flores N. (2010) Hypothetical bias reconsidered: Payment and provision uncertainties in a threshold provision mechanism. *Paper presented at the World Congress on Environmental and Resource Economics, Montreal Canada. July 1, 2010*
Murphy J. J., Allen P. G., Stevens T. H., Weatherhead D. (2005) A meta-analysis of hypothetical bias in stated preference valuation. *Environmental and Resource Economics* 30,.pp.313–325.
Neill H., Cummings R., Ganderton P., Harrison G., McGukin T., (1994) Hypothetical surveys and real economic commitments. *Land Economics* 70,.pp.145-154.
Oaxaca R. (1973) Male-female wage differentials in urban labor markets, *International Economic Review* 14,.pp.693–709.
Poortinga, W., and Pidgeon, N. F. (2005). Trust in risk regulation: Cause or consequence of the acceptability of GM food?. Risk Analysis, 25(1), 199-209.
Reynolds W. M., Gerbasi M. C. (1982) Development of reliable and valid short forms of the MCSDS. *Journal of Clinical Psychology* 38,.pp.119–25.
Siegrist, M. (2000). The influence of trust and perceptions of risks and benefits on the acceptance of gene technology. Risk analysis, 20(2), 195-204.
Sinden, J. A. (1988) Empirical Tests of Hypothetical Biases in Consumers’ Surplus Surveys, *Australian Journal of Agricultural Economics* 32,.pp.98–112.
Smith V. K., Mansfield C. (1998) Buying Time: Real and Hypothetical Offers, *Journal of Environmental Economics and Management* 36,.pp.209–224.
Steptoe A., Pollard T. M., Wardle J. (1995) Development of a measure of the motives underlying the selection of food: the food choice questionnaire. *Appetite* 25(3),.pp.267–284.

Strack F., Deutsch R. (2004). Reflective and impulsive determinants of social behavior.*Personality and Social Psychology Review*, 8, 220-247.DOI: 10.1207/s15327957pspr0803_1

Tonsor, G. T., and Shupp, R. S. (2011) Cheap talk scripts and online choice experiments: "looking beyond the mean", *American Journal of Agricultural Economics*, 93(4), pp. 1015-1031.

Verneau F., Caracciolo F., Coppola A., Lombardi P. (2014) Consumer fears and familiarity of processed food. The value of information provided by the FTNS *Appetite* 73, pp.140–146.