Perceptions of fundamental science: Evidence from a classroom experiment

Francesco Giffoni [a,b,*], Massimo Florio [b]

[a] CSIL – Centre for Industrial Studies, Corso Monforte 15, 20122, Milan, Italy
[b] Department of Economics, Management, and Quantitative Methods, University of Milan, Via Conservatorio 7, 20122, Milan, Italy

ARTICLE INFO

ABSTRACT

Large-scale research infrastructures such as particle colliders, radio telescopes, the International Space Station, are often funded through general taxation and taxpayers are called to contribute to scientific discovery. How much are people actually willing to pay for investments in science? What does drive such a giving behaviour? This paper explores the attitudes of young science-outsiders (the taxpayers of tomorrow) by a pilot experiment involving 230 undergraduate students in economics at University of Milan. The experiment takes the form of a Contingent Valuation Referendum-like interview aimed at eliciting the willingness-to-pay (WTP) for the discovery potential of the CERN Large Hadron Collider (LHC), the most powerful particle accelerator worldwide. Our results point to the attitudes of students about fundamental science measured through their WTP. Building on this pilot experiment, we put forward recommendations for future research.

1. Introduction

Discovery is not a free lunch. Since 2000, total global R&D expenditures have tripled in current euros, from EUR 624 billion to EUR 1.8 trillion (Congressional Research Service, 2019).[1] The total capital and operations costs of some very large-scale research infrastructures (RIs, hereafter) such as the International Space Station, the Square Kilometers Array Radiotelescope (SKA), the Human Genome Project, are in the region of billions of euro. For instance, the present value to 2025 of the Large Hadron Collider (LHC) total costs has been estimated around EUR 13.5 billion[2] (Florio et al., 2016), while the cost of the Human Genome Project is estimated at around EUR 2.5 billion.[3] Even minor RIs, only supported by national governments, such as the CNAO research centre for hadron therapy in Pavia (Italy), the ALBA synchrotron supported by the Spanish government[4] or other public research institutes in

developing countries require investments in the region of hundreds million euro (Battistoni et al., 2016; Biscari, 2012; Caliari et al., 2019; Sanz-Menéndez et al., 2013).

All these scientific projects are funded either by international and national agencies through government funding, hence ultimately by taxpayers. So, the questions to be addressed are: does society perceive (big-) science as a valuable investment? Are citizens outside the scientific community willing to pay for basic research with their own money? And what factors drive this willingness-to-pay (WTP, hereafter)? These questions are interesting for both academic research and science policy (Baneke, 2019; Florio, 2019). From the academic research perspective, the questions are particularly intriguing when basic research is considered, since its definition acknowledges 'any particular immediate application or use in view' (OECD, 2002). In his timeless essay, 'The Usefulness of Useless Knowledge' Abraham Flexner (Flexner, 1939)

---

[1] The figures correspond to USD 676 billion and USD 2 trillion, respectively.
[2] Estimated in 2013 prices; total costs include construction and operation costs net of scientific personnel salaries.
[3] It corresponds to USD 3 billion. See https://www.genome.gov. Other example of costs of RIs are: the the High-Luminosity Large Hadron Collider (HL-LHC) project aiming at cranking up the performance of the LHC after 2025 to increase the potential for discoveries is budgeted by CERN EUR 854 million (CHF 950 million) for construction expenditure only (Rossi, 2017); ITER, the experimental international fusion reactor, is taking about EUR 18 billion to be built (https://www.iter.org/FAQ); the capital expenditure for the construction (phase 1) of the SKA, the world's biggest radio telescope, now under development in South Africa and Australia, is estimated to be EUR 650 million; while the operating costs of the project (phase 2) are not yet established (http://skatelescope.org/project/Last access in January 2019.).
[4] http://www.gencat.cat/web/multimedia/eng/sincrotro/index_htm.htm.

argues that the search for answers to deep scientific questions driven solely by curiosity and deflected by considerations of immediacy of applications often leads not only to technological breakthroughs but also contributes to human welfare. In short, the cultivation of scientific curiosity would generate equally important satisfaction as the intellectual and the spiritual life do. Similarly, Flexner and Dijkgraaf (2017) says that society can tackle societal challenges, achieve deeper understanding, and pursue progress only by really valuing and funding the curiosity-driven "pursuit of useless knowledge" in both the sciences and the humanities. So, scientific curiosity would be the source of an increase in the people's utility, which feeds the willingness to contribute for investment in knowledge production. This paper wants to shed light on this public's preference for science. Interest in our questions goes even beyond utilitarian considerations. Since 2008, budget austerity has been forcing governments around the world to weigh carefully the economic and social benefits of all their investments, so from the science-policy perspective, there is great concern related to the allocation of resources for the conduct of science towards the goal of best serving the public interest and how the general public perceives this effort (Bauer, 2009; European Commission, 2016; Florio et al., 2020; Muñoz et al., 2012). Indeed, the main benefits generated by research infrastructures such as the creation of knowledge outputs, technological externalities, human capital accumulation, the cultural impact of the outreach, and service provision may only capture the use-value of these assets. To estimate their total economic value, the benefits related to the non-use value should also be considered (Johansson, 2016; Rousseau et al., 2021). As stated by Johansson and Kriström (2015, p. 24): "If the project being evaluated affects non-use values, this should be reflected in the cost-benefit analysis". For these reasons, it is a timely need to examine the WTP for scientific discovery, even when, as in the case of the Higgs boson or the gravitational waves, there are no particular applications or use in view.

This paper investigates on the WTP for particle physics research at LHC by a pilot experimental setting, drawing from the empirical literature on the valuation of non-use benefits of environmental or cultural goods (Carson, 2011; Snowball, 2008). A sample of 230 undergraduates at University of Milan was involved in a Contingent Valuation referendum-like (CV-SBDC)[5] survey, where some questions were designed to elicit the respondents' WTP and other to control for individual variability of some socioeconomic and psychological characteristics. Given the relatively small sample size and low heterogeneity of participants, our study should be intended as a "laboratory" experiment; namely, an attempt to learn how to estimate the WTP for basic research by examining the preferences of young students (Andrews, 2001; Ricciardelli et al., 2020; Vossler & McKee, 2006) not involved in science.

Lab experiments are widely applied in economic research to respond economic questions, including how various personal traits and context influence the behaviour of economic actors on certain issues (see, for instance, Kessler & Vesterlund, 2015). However, a recently handful of papers by Levitt and List (2007a, 2007b, 2009) has heavily critised the (external) validity of laboratory studies because, according to the authors, there are many reasons to suspect that lab findings fail when generalized to naturally-occurring settings (Levitt and List, 2008). A response to this critique has been moved, among others, by Camerer (2011), who argue that generalizability of lab results is an exaggerated concern among non-experimenters and "a typical experiment has no specific target for external validity; the target is the general theory linking economic factors to behaviour" (Camerer (2011, p. 46). Accordingly, what does really matter is whether the *qualitative* results are externally valid, and to a lesser extent to which the *quantitative* results are. There is no disagreement on the debate on the contribution of lab experiments to economics on this point (Kessler & Vesterlund, 2015). In

line with this argument, the contribution of this paper to the literature of welfare economics of big-science is two-fold: firstly, to explore variable of interest (awareness, attitude, personal characteristics) that influence the WTP for global research projects; secondly, put forward recommendations for follow-up research wishing to investigate on this field more deeply. The impact of big-science on society is an important issue to be investigated and deserves much more attention than is current the case.

To achieve this stated purpose, we use both parametric and non-parametric estimators to explore the drivers the respondents' WTP. Our results suggest that a non-zero positive WTP for the LHC discoveries exists and it is influenced by income, the offered bid, previous awareness of CERN and its experiments, and interest in science.

The paper is structured as follows. Section 2 briefly describes the analytical framework. Section 3 presents our results. Lessons learned for future research are discussed in Section 4. Section 5 concludes.

2. Material and methods

2.1. Analytical framework

Conceptually, the WTP for discovery can be interpreted as the individual preference for acquiring new (scientific) knowledge, which, as suggested by Stiglitz (1999) is a "*global public good*". Once produced, its consumption is typically not bounded in one specific locality, but its benefits widespread worldwide. Therefore, when taxpayers fund science in one country, they actually generate an externality to other citizens elsewhere. Similarly to the value people attach to safeguarding global ecosystems and heritage public goods (Strand et al., 2018), we argue that the production of new knowledge *per se* (i.e. even without predictable use of it) gives people a sense of pleasure and fulfilment, meaning and identity, which are source of increasing utility, and wellbeing.

Moreover, as for many years, there will be no market for (most) knowledge generated by a discovery in basic science, and no prices to convey signals to investors; therefore governments must rely on taxes. The theory of taxation for public goods suggests that citizens' preferences, elicited by some detection mechanisms, should be considered as pseudo-prices (Hindriks & Myles, 2013) and that the optimal provision of a pure public good requires that the sum of the individual WTP equals the production cost. While some large scale RIs involve a unique design, i.e. "take it or leave it" investments, more often there is a range of variants that engineers and scientists need to negotiate with funders.[6] Whatever the case is, costs are observable variables or can be predicted when designing an RI; in contrast, the individual WTP is private information, and different elicitation methods have been suggested and implemented in applied welfare economic literature (Johansson & Kriström, 2015).

To estimate the WTP for scientific discoveries, we discuss both the use of parametric and distribution-free nonparametric estimators. Over the last decades, researchers have started to argue that parametric estimation relies on quite strict *a priori* assumptions about the underlying distribution of WTP in the target population that are effectively not testable at operational samples sizes (Borzykowski et al., 2018). In response to this argument, nonparametric and semiparametric methods started to receive more attention (Cooper, 2002; Huang et al., 2008; Kristrom, 1990;

---

[5] The referendum-like approach is also known as single-bounded dichotomous choice (SBDC) approach.

[6] For example, in the case of particle colliders, synchrotron light sources or hadrontherapy with proton accelerators, the energy of the accelerated beams is function of the radius of the circular trajectory of particles, the power of certain devices, and the generators of magnetic fields. All these elements (and others) may imply different project designs that are conditioned by available funds. Other examples are radiotelescopes where the number of antennas is a function of available funds, genomic platforms where the number of sequencing machines depends upon funds as well. More in general, the operating cycle of certain RIs is not always determined by the scientific needs, but it can be longer or shorter according to available funds. If time and operating costs enter in the overall project cost, the majority of RIs have a potential element of budget flexibility.

Watanabe & Asano, 2009). The non-parametric approach can be applied either using Ayer et al.'s (1955) pooling adjacent violators algorithm or Turnbull's (1976) distribution-free estimator; the latter originally applied in contingent valuation by Carson et al. (2003) and Haab and McConnell (1997). For contingent valuation (hereafter, CV) with discrete responses, the Turnbull is similar to applications by Kristrom (1990) and McFadden (1994) of the pool adjacent violator algorithm.

The nonparametric estimators provide welfare measure estimates unconditional on psycho, socio-economic and demographic characteristics of the respondents or characteristics of the good to be valued, however, they provide a benchmark which is robust to potential parametric specifications errors (Borzykowski et al., 2018).

As a consequence, both parametric and non-parametric estimators are worth considering in our context since little is known about the "size" of individual preferences on basic research and what drives them. As regards drivers, we consider financial variables (e.g. the availability of personal or family income), personal interest in scientific research and awareness of the research carried out at CERN LHC (see Florio at al., 2020 for a theoretical discussion on such drivers).

The reference model we employ to parametrically estimate the willingness to pay for the research activity at CERN is the utility difference model developed by Hanneman (1984), while the non-parametric elicitation procedure is mainly based on Kristrom (1990). Details and formulas are provided in Appendix A in the online supplementary material. The experiment design, implementation, and WTP estimation follow, as far as possible, the CV guidelines by the NOAA blue ribbon panel (Arrow et al., 1993)[7] and also take on board some insights from their more recent version by Johnston et al. (2017), largely used worldwide to elicit the intrinsic value of environmental and cultural goods. We apply this framework to ask uinversity students to directly report their perceptions, opinions and WTP about the research at the CERN LHC.

2.2. Implementation and design

Our experiment was conducted at University of Milan in two rounds and it involved 230 undergraduate students in economics. In June 2016, 120 students were surveyed; the remaining 110 were interviewed after one year in June 2017. Data were treated confidentially and anonymity was guaranteed to all the participants in the experiment, who agreed to volunteer for the purpose of research. Students were not financially compensating for participating in the research (see below for details).[8]

The experiment proceeded as follows. Several days prior to the experiment session, students were informed about the opportunity to take part in an upcoming research project and they were made aware that the participation in the experiment was on a voluntary basis. On the day of the experiment, upon arrival in the classroom, two expert interviewers gave participants a randomly-drawn, anonymized CV-like questionnaire containing an ID number. Different pre-printed bid (see below) were randomly assigned by groups, each containing around 40 students. Afterwards, students were partitioned to ensure that they could not communicate during the session, nor observe others in the room. To ensure anonymity and reduce the risk of social desirability bias, interviewers announced that information would be linked only to participants' ID-numbers and not to individual names; yet data would be elaborated in aggregate format only. Only participants and the interviewers were present in the experimental session.

Once all participants were seated and ready to fill in the questionnaire, interviewers began the session by reading a short introductory script. Participants were informed that they would be asked to complete a number of tasks (which interviewers would gradually describe to them) and make a number of choices. Importantly, prior to beginning the experimental tasks, and mainly in the first part of the experiment, participants were given no information about the aims of the research project, nor about what the experiment sought to elicit. This experimental design was implemented to correctly measure and analyse opinions and interests in scientific issues and the respondent prior awareness of the RIs before revealing the exact purpose of the study (Carson et al., 2003, p. 264).

The questionnaire was designed to be consistent, as far as possible, with the NOAA panel guidelines by Arrow et al. (1993), while some modifications were applied to take into account the peculiarities of the public good under evaluation.

The questionnaire (online Supplementary Material) consisted of three parts. The first part described information and perception of a respondent about issues related to research infrastructures in general as well as the respondent's interest in scientific discoveries. As showed by Heberlein et al. (2005), attitudes, interests, knowledge of the (public) good under evaluation can lead to different evaluations (and thus WTPs) by respondents; therefore attitudinal and behavioural scope sensitivity tests can be performed to validate and support results (see also Muñoz et al., 2012).

The second part contained questions aiming at eliciting the WTP for scientific discoveries.

First of all, a description of the LHC was provided to interviewees in the form of a shortened version of the Wikipedia entry "Large Hadron Collider", including five photos showing the particle accelerator in its 27-km tunnel and the particle detectors ATLAS, CMS, ALICE and LHCb placed at four locations around the accelerator. In this way, respondents were given common information set about the functioning of the LHC, its research activity, and the answers that scientists expect from this research facility. Students were explained that collisions are examined to find answers to issues left unsolved by the Standard Model of particles and forces[9] such as the origin of particles' mass, a comprehensive explanation of the interactions between the fundamental forces of the universe and the phenomena responsible for dark matter (Giudice, 2010). The description was previously and repeatedly revised to refine the information it presented and to improve its clarity by means of focus groups and pilot tests carried out at University of Milan in 2015, before the experiment took place.

Just before asking the WTP questions, the questionnaire disclosed that the projects carried out by CERN, including the realisation of the LHC, are funded by the CERN Member States[10] through taxation, according to a share calculated on the respective national GDP, meaning that citizens indirectly support such projects and public contributions enable the CERN to continue its research activity. No information was however given about the actual amount of the Italian government contribution to the CERN budget.

The NOAA guidelines suggest to use a referendum-like approach

---

[7] The (CV) method is the most commonly applied of all the methods available for valuing preferences for nonmarket goods with thousands of applications conducted worldwide. The concern on how to correctly eilicit the WTP quantifying a-prior poorly formed or even non-existent preferences for public goods was deeply debated in the occasion of the CV estimation of damages arising from the Exxon Valdes oil spill (Carson et al, 1994a, 2003; Diamond & Hausman, 1993). Much of the dabate was mainly addressed through the influential U.S National Oceanic and Atmospheric Administration (NOAA) panel report on CV (Arrow et al., 1993) which, since then, has provided guidelines for future applications. A key recommendation of this report concerned the elicitation method through which the WTP responses should be elicited. The NOAA panel recommended the use of a 'one-shot' or referendum style question.

[8] The experimental protocol was in compliance with the regulations ratified by the ethics committee of the University of Milan Dean decree 19 July 2011.

[9] To further details on the main goals of the LHC and on a non-physicists understandable version of Standard Model of particles and forces see the LHC guide available at http://cds.cern.ch/record/1165534/files/CERN-Brochure -2009-003-Eng.pdf.

[10] Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Israel, Italy, Netherlands, Norway, Poland, Portugal, Romania, Slovak Republic, Spain, Sweden, Switzerland, and United Kingdom.

according to which, people should be asked to state only 'yes' or 'no' to the proposed bid; in contrast, Hanemann et al. (1991) have stressed the importance of follow−up questions addressed to estimate the maximum WTP value. The bid level offered in the follow−up question should be greater than that offered in the initial payment offer if the answer to the initial payment question is 'yes', otherwise the follow-up procedure is stopped. Although this approach is statistically more efficient than referendum approach, Alberini et al. (1997) found that the average WTP estimated after the follow−up approach can be lower than that implied by the responses to the initial payment question. A possible explanation is that some respondents may treat the suggested bid as a signal for the quality of the good and/or might erroneously believe that the program to be valued in the follow−up is different from the initial one. Furthermore, in favour of the referendum approach there is the argument that it mimics behaviour in regular markets, where people usually purchase, or decline to purchase, a good at the posted price. It also closely resembles people's experience with political markets and propositions on a ballot (Mitchell & Carson, 1989). On the other side, single referendum elicitation format is highly vulnerable to anchoring effects (Green et al., 1998).

Although the debate is still open, in this exploratory attempt to elicit the WTP for basic science, we adopted a referendum-like approach, which seems the most accepted one in the current literature. Respondents were asked to vote 'yes' or 'no' to fund for the research activity at the LHC given the amount of income reduction (e.g. the offer price). The exact wording of the WTP question was: "*Would you willing to pay EUR _ every year to fund the research activity at LHC turning down other personal expenses*? With one of the following pre-printed bids: EUR 1, EUR 2, EUR 5, EUR 10, EUR 15, EUR 30. The minimum and the maximum price offered to respondents was based on previous focus groups and surveys aimed at calibrating the experiment. For those who voted 'yes', to get additional information, an open-ended question was asked to explain why they chose to vote for the program. For those who vote 'no', the follow-up question was asked to identify protest bid respondents. Moreover, in order to collect further evidence about respondents' WTP, an open-ended question of the maximum WTP was added as well: "*What is the maximum amount you would pay each year to fund the research activity of the LHC (Please insert the amount in EUR)?*" (Johansson & Kriström, 2020).[11] In line with the CV procedures (Johnston et al., 2017, p.357) students were not financially compensated for participating in the experiment; however, the hypothetical giving to the LHC project was explicit set against decreasing consumption on other items to take into account the budget constraint underlying the utility-theoretic foundation of preferences (Carson et al., 2003; Appendix A in the online supplementary materials).

---

[11] A debate exists on the use of open-ended questions in stated preferences studies. The open-ended format is known to not be incentive compatible (see for instance Carson & Groves, 2007; 2011 and Carson et al., 2014). Carson and Groves (2007) argue that an open-ended format may induce the respondent to act strategically to influence the outcome of the experiment. The optimal strategy would be to report either a small or a very large WTP response (Carson & Groves, 2007, p. 202). Johansson & Kriström, 2020 recognise the lack of incentive compatibility of an open-ended format, but they show that such a format can cope with pure altruism, including any non-use values. In contrast, closed-ended formats could be incentive compatible but cannot cope with pure altruism as that one we are looking for with this research (see below). Their suggestion is therefore to use a procedure involving both the types of elicitation format.

[12] Students were asked to fill-in the questionnaire on their own and no face-to-face interviews were carried out. Interview bias arises when the interviewer accidentally leads respondent in a particular direction when answering the questionnaire, while strategic behaviour occurs when a systematic error is introduced into the sampling, when respondents select one answer over others in order to not to reveal their true opinion/position. A well-known case is that of perceived government-supported surveys leading people to skip highly-sensible information like income.

Finally, this questionnaire-based experiment were conducted by experienced researchers in order to minimize interview bias and strategic behaviour.[12]

The third part of the questionnaire included questions on the individuals' demographic and socio-economic characteristics such as age, sex, gross income (both personal income and family one) and household size.

3. Results

Data were analysed using both descriptive and econometric procedures (Appendix A, online supplementary material). Table 1 (Panel A) shows

Table 1
Descriptive statistics (N = 230).

Panel A: socio-economic characteristics				
Variable	Mean	Std. Dev	Min	Max
Continuous Variables				
C1 Age (years)	21.8	3.8	19	54
Categorical variables	Code	Number	Percent	Total (number)
C2 Sex	0 = Female	99	43.0	230
	1 = Male	131	57.0	
C6 Family income (EUR)	1= <1,000	8	3.7	215[a]
	2 = 1,000–3,000	91	42.3	
	3 = 3,000–5,000	81	37.7	
	4= > 5,000	35	16.3	
C7 Personal income	0 = No	180	78.3	230
	1 = Yes	50	21.7	
C8 Household Composition	1 = 1-2	30	13.3	
	2 = 3-5	189	83.6	226[b]
	3 = > 5	7	3.1	

Panel B: Perceptions of research infrastructures and interest in scientific discoveries				
A1 Knowing what an RI is	0 = No	43	18.9	228[c]
	1 = Yes	185	81.1	
A4 Interest in research	0 = No	29	12.7	229[d]
	1 = Yes	200	83.3	
A6 Importance of funding an RI	1 = Useless	0	0	230
	2 = Insignificant	6	2.6	
	3 = Important Enough	38	16.5	
	4 = Important	100	43.5	
	5 = Very Important	86	37.4	
B1 Having heard about LHC	0 = No	118	51.3	230
	1 = Yes	112	48.7	
B3 Having heard about Higgs boson	0 = No	58	25.2	230
	1 = Yes	172	74.8	
B5 Having visited the CERN	0 = No	217	94.3	230
	1 = Yes	13	5.7	

Question C1: Age; Question C2: Sex; Question C6: Family income; Question C7: Availability of a personal income; Question C8: Household Composition (all members).
Question A1: Do you know what a research infrastructure is?
Question A4: Are you interested in scientific discoveries and in research activities in general?
Question A6: how do you rate the importance of funding research infrastructures?
Question B1: Did you hear about the LHC before this questionnaire?
Question B3: Did you ever hear of "Higgs boson"?
Question B5: Have you ever been to the CERN?
[a] 15 observations are missing.
[b] 4 observations are missing.
[c] 2 observations are missing.
[d] 1 observation is missing.

descriptive statistics related to demographic and socio-economic characteristics of the respondents. Our sample of students is aged, on average, 22; while, 57% of the sample, i.e. 131 respondents is male. The distribution of respondents based on their monthly family income is: 91 (42.3%) belong to a family with a monthly income between EUR 1,000 and 3,000; 81 (37.7%) between EUR 3,000 and 5,000; 35 (16.3%) more than EUR 5,000 and 8 (3.7%) respondents belong to a family earning less than EUR 1,000. Only 50 (21.7%) students earn an own income.[13] Almost all respondents (84%) belong to a family consisting of 3-5 components.

The gross income distribution of the respondents' families is comparable with the available data on income distribution in the North-West of Italy, where the University of Milan is located. The average family income in our data is about EUR 38,200 per annum (EUR 3,187 per month) with respect to a mean in Northwestern Italy of about EUR 33,000 (the national mean is about EUR 29,500).[14] While we did not design the experiment seeking for statistical representativeness of the (Northwestern) Italian population which was not our objective, the family background of the respondents does not suggest a sample biased towards relatively high income levels (but certainly the educational background is higher than for the Italian average).

Results of the investigation about awareness and perception of RIs and interest in science of respondents are shown in Table 1 (Panel B), and Table 2.

The majority of respondents (81.1%) (Table 1, Panel B) declare that they were aware of what an RI is. Multiple options were possible in

Table 2
Awareness of research infrastructures and source of information (N = 230).

Panel A: Question A2. Among those listed below, what is, according to you, a research infrastucture ?	
Item	Number of ticks
Astronomical observatory	192
Particle accelerator	159
Software and data elaborations	62
Database and Archives	62
Library	59
Planetarium	57
Telescope	42
Computer	32

Panel B: Question A5. If you are interested in scientific discoveries, or in research more in general, what are your sources of information?	
Item	Number of ticks
On-line news	170
TV	109
Specialised magazines	62
Other	14
Radio	6

Note: multiple-answer questions.

identifying a RI. The option related to a particle accelerator was chosen by

159 (70%) students (Table 2, Panel A); 200 (83.3%) respondents said that they were interested in scientific discoveries; online news was selected by 170 students (74%) as source of information (Table 2, Panel B).

Respondents were initially asked about their view about the importance of funding RIs on a qualitative scale. Table 1 (Panel B) shows that 186 (81%) interviewed think that funding RIs is important or very important, 38 (16.5%) think that is fairly important, and 6 (2.6%) chose the options "Useless or Insignificant".

About 49% of the sample (112 respondents) had heard about LHC, 74.8% (172 respondents) about the Higgs boson; in contrast only 13 respondents (5.7%) visited CERN. The latter information is important, being the CERN at a travel distance of around 4 h from Milan by train and often targeted for visits by high schools. Thus, we have indirect evidence that this sample is not particularly exposed to previous direct information on the LHC, hence all the information students have was based on exposure to the media or on the summary information distributed during the experiment.

Table 3 (Panel A) reports statistics related to WTP when asked according to the referendum-like approach. The percentage of 'yes' and 'no' is presented for each offered bid to respondents. We expect that the higher the bid, the lower the percentage of 'yes' is. Table 3 shows that no respondents rejected the first bid (EUR 1), 5% rejected the second bid (EUR 2), 18% rejected the third bid (EUR 5) and 21% rejected the forth bid (EUR 10). At the bid EUR 15 the percentage of 'no' reduced rather than increasing; in contrast and as expected, at bid EUR 30 it increased again. Although this distribution is not perfectly smooth (that is the reason why we adopt the pooling adjacent violators algorithm) overall, in our experiment the percentage of WTP 'yes' is a fairly well behaved distribution.

On the question that includes WTP motivation, respondents stated different reasons, which are shown in Table 3 (Panel B) based on their importance. Inspection of the answers suggest quite generic altruistic motivations for giving, without a preference for one statement against

Table 3
Response rates to offered bids (N = 230).

Panel A: Would you willing to pay EUR _ every year to fund the research activity at LHC turning down other personal expenses?		
Bid (EUR)	Yes	No
1	100%	0%
2	95%	5%
5	82%	18%
10	79%	21%
15	81%	19%
30	73%	27%

Panel B: Reasons of respondents' WTP 'Yes' for the research activity at LHC	
Motivation	Number of ticks
The LHC is a useful machine to better understand the universe and the origin of mankind	134
I think it is a good thing to contribute to basic research according to my availability of money	128
Investing in research is necessary so that next generation may benefit from new discoveries	120
The LHC is a useful machine for experiment with protons' acceleration which can be used for different purposes	72
The research at LHC is worth to me at least as the offered bid	64
Other	9

Panel C: Reasons of respondents' WTP 'No' for the research activity at LHC	
Motivation	
I can't afford to pay anything at this time	4
The activities at LHC are not worth anything to me	4
The LHC is a machine that affects only physicists' and scientists' world, so it unfair to expect me (or my family) to pay for the LHC	3
I do not think the LHC would achieve its objectives;	1
The LHC is an useless machine whose construction could have been avoided	0
The LHC is a dangerous machine for the risk of nuclear accidents	0
I am opposed to any new governments' programs;	0
Other	3

Note: multiple-answer question.

---

[13] The family income (i.e. the income related of student's parents) is a relevant variable for students' choices and wellbeing because the great majority of students in Milan (and in Italy in general) live with their parents or financially depend on them (e.g. students who migrate to university cities from their town of origin, and especially from the South to the North of the country) (D'Agostino et al., 2019; Abramo et al., 2016).

[14] The average sample income in our data was calculated as a weighted average: we use the mid-point in each category (e.g. EUR 2,000 in the category EUR 1,000–3,000) weighted with the share of respondents in that category. The amount of EUR 5,001 was used for the highest income category in our sample. National data were retrieved on April 18, 2017 from the Italian National Institute for Statistics (ISTAT). The distribution of the average family income in Italy is as follows: North-West EUR 32, 888; North-East EUR 32,700; Centre EUR 30,400; South EUR 24,400 and Islands EUR 22, 600. These data refer to disposable income in 2014 net of taxes, but gross of house rents. See for details http://dati.istat.it/Index.aspx?DataSetCode=DCCV_REDNETFAMFONTERED.

another one. Differently, among respondents who rejected the offered bid, the most quoted options were "I can't afford to pay anything at this time", "The activities at LHC are not worth anything to me", "The LHC is a machine that affects only physicists' and scientists' world, so it unfair to expect me (or my family) to pay for the LHC", and finally "I do not think the LHC would achieve its objectives"; (Table 3, Panel C). They are all valid reasons to reject the bid offered, so no protest bids were identified.

Table 4 presents the results of the logit model as defined by Equation A.1. Model 1 includes the bid, the family income and demographic characteristics. Model 2 is extended by including variables expressing interest in scientific research. Model 3 leaves out the variables expressing interest in research and plugs in variables related to the awareness and knowledge about research activity at LHC. The full model is presented in Column 4. The estimated coefficient of the bid was found statistically significant in each specification at 1% level with the expected negative sign. This is in line with the basic axioms of utility choice indicating that the probability of WTP 'yes' decreases (increases) as the price of offer increases (decreases) (Johnston et al., 2017, p. 357). The estimated co-efficient of income variable was found statistically significant at both 5% and 1% level at the highest categories with respect to the lowest category (<EUR 1,000) and the sign was positive as expected. The finding suggests that the probability of WTP 'yes' increases as the income increases. Age is not statistically significant. Conditional to our sample, this is not a

surprising results since 91% our respondents are aged between 20 and 25. The variable "Male" shows no statistical significance as well, with negative sign in contrast with the existing literature on WTP for science and technology (European Commission, 2014). The coefficients on "A4 Interest in Research" and "A6 Importance of funding an RI" are significant at the 10% and 1% level respectively, with the expected positive sign (Model 2 and 4) meaning that judging funding RIs important increases the probability of WTP 'yes'. The coefficient on "A2 Particle accelerator" is statistically significant at 1% level (Model 3) and 5% level (Model 4) and the sign is positive. Therefore, recognising a particle accelerator as an RI, increases the probability of being willing to pay for its research activity. In line with the scope tests suggested by Heberlein et al. (2005), these results support the idea that behavioural intentions, as the willingness to pay for science, are influenced by attitudinal and cognitive dimensions towards this pubic good (Sanz-Menéndez et al., 2013).

The alternation of negative and positive signs (e.g. in the case of the variable "A1 Knowing what an RI is" between Model 3 and 4) and/or absence of statistically significance on the remaining variables related to having heard about LHC or visited CERN are caused by the strong collinearity among them. For instance, the odds ratio between the variable "B5 Having visited CERN" and the variables "B1 Having heard about LHC"and "B3 Having heard about Higgs boson" is higher than 1 in both cases and statistically significant at 5% level. Similarly, the odds ratio between the variable "A1 Knowing what an RI is" and the variables "A4 Interest in Research" and "A6 Importance of funding an RI" is still above 1 and statistically significant at 1% level in both cases as well.

The Count R^2 at the bottom of Table 4 reveals that about 87% of respondents were correctly allocated to predicted WTP either 'yes' or 'not' in the models, indicating a relatively good fit to the data.[15]

We test the same specifications (unreported regressions) by using the personal income rather than the family income. The availability of personal income shows positive sign but never results statistically significant in explaining the probability of a WTP 'yes'. This was likely due to the lack of sufficient variability in this variables since only a low share of students in our sample (20%) earned an own income. We also test a further specification including a dummy variable discriminating the year in which the experiment was carried out. We found this dummy never statistically significant suggesting that no differences in WTP responses exist between students surveyed in 2016 and those surveyed in 2017. This points to robustness of the results across different cohorts of students.

The expected value of mean WTP, which represents the "non-use value" of basic research at LHC was calculated by numerical integration, ranging from 0 to maximum bid (Equation A.2) after parameters from logit models were estimated. The coefficients estimated in Model 4 were used to determine the mean WTP, leading to a value of EUR 29 per person annually according to the following formula[16]

Table 4

Results of the logit model: determinants of the WTP for discovery potential at the LHC.

	Model 1	Model 2	Model 3	Model 4
BID	-0.0530***	-0.0670***	-0.0504***	-0.0661***
	(0.017)	(0.0197)	(0.0178)	(0.0207)
C6 Family income				
1,000–3,000	1.8546**	1.7355*	1.9985**	1.9494**
	(0.9923)	(0.9992)	(1.0059)	(1.0690)
3,000–5,000	2.1375**	1.8751**	2.4691**	2.2211**
	(1.0160)	(0.9994)	(1.0762)	(1.1000)
>5,000	2.2935**	2.4564**	2.5703**	2.7398***
	(1.1213)	(1.0616)	(1.0895)	(1.0786)
C1 Age	0.0299	-0.0314	0.0373	-0.0101
	(0.0726)	(0.0529)	(0.0651)	(0.0557)
C2 Male	-0.4095	-0.6108	-0.5376	-0.5720
	(0.4031)	(0.4431)	(0.4650)	(0.4794)
C8 Household size	-0.2337	-0.3444	-0.2375	-0.2160
	(0.5395)	(0.5488)	(0.5254)	(0.5675)
A1 Knowing what an RI is			0.0749	-0.4083
			(0.5347)	(0.5942)
A2 Particle accelerator			1.2949***	1.1513**
			(0.4778)	(0.4734)
A4 Interest in research		0.7691*		0.8195*
		(0.4730)		(0.5049)
A6 Importance of funding an RI		1.0757***		1.0873***
		(0.3236)		(0.3390)
B1 Having heard about LHC			-0.3477	-0.6283
			(0.4802)	(0.4753)
B5 Having visited CERN			-0.6306	-0.5491
			(0.8592)	(0.7595)
Constant	0.5739	-2.3253	-0.3717	-3.4089
	(2.0552)	(2.0941)	(1.8869)	(2.1259)*
Observations	212	212	212	212
McFadden's R2	0.10	0.22	0.15	0.26
Count R2 (% of correct predictions)	86%	87%	87%	88%
Log Likelihood	-78.3	-67.6	-73.7	-67.0
Likelihood ratio test	15.6	24.2	25.2	27.8

Robust standard errors in parenthesis. ***,**,* denote significance at the 1%, 5% 10% level respectively. The oods ratio between the variable "B Having heard about Higgs boson" and "B1 Having heard about LHC" is about 3 significant at 1% level suggesting high correlation between the variables; so the former variable was not used in Model 2 and Model 4.

---

[15] The Count R-Square is a pseudo R-Square and measures the goodness of fit of a model in a different way with respect to the R-squared as explained variability in the OLS approach. It transforms the predicted probabilities by the logit model into a binary variable on the same scale as the dependent variable (0–1). Then it considers the observations with a predicted probability of 0.5 or higher as having a predicted outcome of 1; in contrast, it assigns the value of 0 to any observation with a predicted probability lower than 0.5. At this point, the Count R-Square compares the actual 1s (0s) with the predicted 1s (0s). The resulting number is the ratio between the number of correct predictions (observations) out of their total number. For more details see https://stats.idre.ucla.edu/other/mult-pkg/faq/general/faq-what-are-pseudo-r-squareds/Last access on 15.09.2020.

[16] One can question the assumptions behind the chosen distribution from zero to the maximum bid. Therefore, for the sake of transparency, by integrating Eq, A.2 from zero to the maximum bid returns a mean WTP of EUR 71.24. Actually, as discussed in Appendix A (online supplementary materials) an infinite upper bound on willingness to pay is inconsistent with budget constraints and also requires a projection well beyond the range of the data. We thanks an anonymous referee for this comment.

$$E(WTP) = \int_0^{30} \left[1 + \exp(-(4.7 - 0.0661A))\right]^{-1} \delta A = €29$$

As shown in Appendix A, the non-parametric estimations require only minor theoretical restrictions such as weak monotonicity. Pool adjacent violator algorithm estimate for the mean (WTP), Equation A.5, is:

$$E(WTP) = \sum_{j=0}^{J} \widehat{S}(A_j)\left[A_j - A_{j-1}\right] = €23$$

This figure can be compared with the parametric estimate. Both figures should be interpreted as a life-time commitment and consistent with many studies in the CV literature (see among others Hutchinson et al., 2001; Haab & McConnell, 1997; Carson, Hanernann, et al., 1994), we found the non-parametric estimate more conservative than the parametric one.

4. Lessons learned for future research

Lessons learned from this pilot experiment, which is novel in the literature, are now reported.

An obvious issue is that one should be able to design the experiment for a representative sample of citizens (taxpayers). This, *per se,* is not impossible, as social attitudes (including the ones towards science) are regularly performed with statistically representative samples of the population (see for instance European Commission, 2014). The main difficulty however, is that while research on social attitudes often tends to ask generic questions, here it is of essence to elicit a WTP for a specific project, as it is needed in a cost-benefit analysis setting. This poses challenges as the previous knowledge of the discovery potential related to a specific research infrastructure, or its mere existence, is an information which is usually unavailable to the public, or unevenly available through exposure to the media. Moreover, the nature of information is unavoidably superficial for the average citizen, who certainly cannot grasp the scientific importance of, e.g., knowing that the Higgs boson actually exists. In principle, one should take on board the previous exposure of respondents to outreach of science news in the media to be sure that the sample of respondents is not affected by sample bias over a key dimension of individual preferences. This is clearly revealed by our experiment which shows that previous knowledge about what is a research infrastructures, is strongly correlated to the elicited WTP. The challenge is diluted in environmental cost-benefit analysis, as surveyed respondents can be assumed to fully understand, for example, the implications for biodiversity in a given area of a specific project. Given the importance of this issue, it would be advisable to add to the usual demographics of the sampling strategy, a set of variables capturing attitudinal and cognitive information related to the project under evaluation as well as add questions about the reasons, designed such that the non-use value of science as compared to the use-value can be identified.

The second important point raised by our approach is in terms of the way to elicit the WTP in terms of opportunity cost. In our experiment and in line with the majority of CV literature, it was clearly stated that virtual giving to the LHC project was to be set against decreasing consumption on other items to consider budget constraints. While this was important, however, we investigated on the WTP without requiring the participants to actually pay anything. Some studies shows that individuals tend to overstate their WTP if not properly incentivised (List & Gallet, 2001; Murply et al., 2005), while behavioural economics often relies on the involvement of actual money to close the gap between the hypothetical and actual choices (Chaudhuri, 2008). Therefore, the main point for future research is to understand the extent to which our results reflect mere cheap talk rather than real intentions considering that we targeted students who are more likely sympathetic towards the pursuit of scientific research. Our WTP response data show consistency with basic axioms of choice, i.e. the proportion of students who would pay the amount should not increases as the bid amount increases and the relevance of the budget constraints (as revealed by the positive impact on income on the

stated WTP) (Johnston et al., 2017). In addition, the survey results reveal a positive WTP, with the mean ranging from EUR 23 to 29 per person annually obtained by using both parametric and non-parametric estimators. This is of comparable size with the results of a recent study in the same field which involve a sample of 1,000 people representative of the French population (Florio & Giffoni, 2020). That study estimates a WTP for future particle accelerators at CERN (not the LHC) ranging from EUR 4 to EUR 17 per person per year and it is likely to be even higher for more educated people suggesting a positive association between lab experiments and field behaviour. By considering other global pubic goods, our findings can be also compared with Graham et al. (2019) investigating on the WTP for policies to reduce health damages from climate change. The authors shows that there is public support for policies to address future health impacts of climate change and the level of support varies with people's awareness of the seriousness of these impacts, their financial circumstances, and the level of education, being people with a degree or above more prepared to contribute to such policies (Graham et al., 2019, p. 114; Table 4). Our results are also in line with previous findings about the "non-use" values of some cultural and environmental goods. To mention a few, the average annual WTP for the performances at Royal Theatre in Copenhagen "as public good" was found to be EUR 27 per person by Hansen (1997); while Thompson et al. (2002) found an average annual WTP for Arts ranging from EUR 4 to 19 per households.[17] In the field of environmental economics the paper by Amirnejad et al. (2006) estimated an average annual WTP for the north forests of Iran of about EUR 30 per households and Carson et al. (2003) found that for preventing damages from another Exxon Valdez type oil spill people were willing to pay a median lump-sum WPT amounting to about EUR 20.[18]

Our suggestion is hence to primarily stick to the CV approach when estimating non-use values of big-science. Recurring to an experimental setting where giving of real and possibly earned income is involved is obviously attractive, but a trade-off arises. The experimental economics literature is typically based on small-scale laboratory experiments with students (as in our case) but it does not aim then to expand to a population of taxpayers the empirical analysis, as it usually would be too costly and would pose a number of additional design problems. This unfortunately means that laboratory experiments with actual money have very limited implications for (science) policy. However, future research may try to replicate our experiment in a laboratory setting involving actual, possibly earned money, in order to highlight some qualitative issues arising in this area.

Finally, it would be interesting to check the robustness of results when alternatives are given. This would lead to the complication of adding bids for competing scientific or non-science projects, adding information in terms of consumer choice but also introducing some risks of distorting elicited preferences just because of the specific set of suggested alternatives (e.g. comparing fundamental physics to medical science projects).

5. Conclusions

This paper reports a "laboratory experiment" on the drivers of individual preferences expressed in monetary form for basic science. We involved a sample of 230 undergraduates in a non-science related curriculum in a classroom environment. Our findings reveal a positive WTP mainly driven by the offered bid, previous awareness of CERN and its experiments, and interest in science, and income. The interest of such an experimental approach lies in the fact that scientific knowledge is often a pure public good, funded by governments who need to guess how much they should spend to support its production. Ultimately, all citizens fund

---

[17] This corresponds to USD 6 to USD 27. The average 2002 EUR-USD exchange rate was 1.4670.

[18] This corresponds to USD 30. The average 2003 EUR-USD exchange rate was 1.5209.

the research through taxation. Indeed, big-science projects are mostly funded by governments or international organisations such as CERN, which in turn is entirely funded by transfers by its Member States.

With all these reservations and caveats underlying a classroom experiment, it seems worth exploring ways to empirically estimate the "useless" value of fundamental research. Our contribution is to suggest that this study may offer valuable information that can be useful from science policy and academic research. In order to be funded, curiosity-driven science has to continuously justify its existence. Eliciting the willingness to pay for large scale research infrastructures may suggest to governments to what extent people (at least the most educated segment of the population) have preferences for public funding of science even if there is no-use in view of the potential new knowledge. For policy makers, this evidence would represent a step forward in relation to the longstanding political disputes in research funding on how to get more economic and social value for investments in research and innovation (Giffoni & Vignetti, 2019; OECD, 2019; European Commission, 2018). In fact, the non-use value generated by research infrastructures adds to their use value (Rousseau et al., 2021) and may play in favour of economic benefits when costs and benefits of such infrastrutures are put at stake, and would avoid a bias in favour of the research promising more direct economic returns.

In terms of academic research, the paper contributes to the literature on public goods by putting forwards some recommendations on how to assess the non-use value of the discovery potential of a large research infrastructures, whose awareness by public is somewhat blurred as compared to experienced goods such as environmental ecosystems and cultural amenities. As far as we know, this is an entirely new field in cost-benefit analysis and would greatly enlarge the perspective of environmental and cultural economics (Del Bo et al., 2016; Florio, 2019; Johansson, 2016). Additional work may investigate other fields as well, beyond high-energy physics.

CRediT authorship contribution statement

Francesco Giffoni: Conceptualization, Writing - original draft, Writing - review & editing, Methodology, Formal analysis, Data curation. **Massimo Florio:** Conceptualization, Project administration, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssaho.2020.100091.

Appendix A. Parametric and non-parametric estimation of the willingness-to-pay for research at CERN LHC

5.2 Parametric Estimation

The reference model to estimate the existence of intrinsic value of environmental and cultural goods is the utility difference model in contingent valuation developed by Hanneman (1984). Let's assume that the dependent variable of interest, $S_i (i = 0, 1)$ is a binary variable. $S_i = 0$ identifies individuals, who would not be willing to pay for the public good being evaluated; in contrast, $S_i = 1$ identifies people willing to pay the bid proposed by the interviewer. Each individual has an indirect utility function of the form $V(M; Y_i; Z_i)$ where Y_i is income, Z_i is the vector of variables affecting individuals' preferences, and M is a binary variable describing the state of the world with or without the good under evaluation, which, in our case, is (potential) scientific discovery by LHC and any new knowledge created by it over time.

When interviewed, the respondent has two options: (a) to answer '*no*' and face the state of the world in the absence of the good ($M = 0$) and keep all of his/her income (Y_i); (b) to choose '*yes*' and thus having his/her income reduced by the bid (A) but the good available for the future ($M = 1$). An individual will respond '*yes*' if and only if his/her utility under option (b) is greater than or equal to that under option (a): $\delta V_i^* = V(1; Y_i - A; Z_i) - V(0; Y_i; Z_i) + v_i \geq 0$ where v_i is the error term with zero expected value.

Empirically, the probability that the individual accepts the offer (A) is approximated with a binomial logit model given by:

$$\Pr(S_i = 1) = \Lambda\left(\delta V_i^*\right) = \Lambda(\alpha + A\beta_1 + Y_i\beta_2 + Z_i\beta_3) \tag{A.1}$$

where the latent variable δV_i^* measures the difference in utility, $\Lambda(.)$ is the logistic c.d.f. of the error term v and α, β_1, β_2, β_3 are the parameters of the model to be estimated, where $\beta_1 \leq 0$ and $\beta_2 > 0$ are expected. Once equation (A.1) is estimated, the expected value of WTP is obtained by numerical integration. According to Duffield and Patterson (1991), there are three methods to compute the value of WTP. The first one is to compute the WTP by integrating equation (A.1) over the bid (A) from $-\infty$ to $+\infty$ obtaining the so-called overall mean WTP. Since the WTP is nonnegative in our context, as we assume that nobody would pay to avoid a discovery (i.e. not less than a zero pseudo price is attached to potentially harmful knowledge, if any), this method is not appropriate. The remaining two alternative approaches are to compute the expected value of the WTP by integrating equation (A.1) from 0 to $+\infty$ or the truncated mean WTP integrating it from 0 to maximum bid (A). Duffield and Patterson (1991) suggest that the truncated mean WTP is the most appropriate method because satisfies theoretical constraints (the upper limit of the WTP is not infinity but something less than income), is statistical efficient in the sense that reduces the influence of the upper tail of the empirical distribution of WTP and satisfies the aggregation criteria. By using this method the value of the maximum bid (A) has to be assigned to all recorded WTP above (A). Thus:

$$(WTP) = \int_0^{MAX\ A} \Lambda\left(\delta V_i^*(A)\right) \delta A = \int_0^{MAX\ A} \left[1 + \exp\left(\widehat{\alpha}^* + A\widehat{\beta}_1\right)\right]^{-1} \delta A \tag{A.2}$$

where $\widehat{\alpha}^*$ is the estimated adjusted intercept which was added by the socio-economic characteristics and other independent variables entering into the model to the original constant $\widehat{\alpha}$.

5.3 Non-parametric Estimation

The Turnbull's (1976) estimator is based on the estimation of a survivor function in presence of interval-censored data.[19] Following Bateman et al. (2002), the survivor function is defined as:

$$\widehat{S}(A_j) = \frac{n_j}{N_j} \quad 0 \le j \le J \tag{A.3}$$

where A_j is the offered bid and n_j/N_j is the percentage of 'yes' responses in the sub-sample of respondents that received the bid A_j. In cases wherein the survivor function is not a non-strictly decreasing function, it will not generate a valid survivor function. To correct such a problem, the Ayer et al.'s (1955) pooling adjacent violator algorithm can be employed (Bateman et al., 2002; Kristrom, 1990). The technique includes pooling data for two adjacent bid levels if the estimate of the survivor function for the higher bid level is greater than that for the lower bid; that is:

$$\widehat{S}(A_j) = \frac{n_j + n_{j+1}}{N_j + N_{j+1}} \quad 0 \le j \le J - 1 \tag{A.4}$$

Once the survivor function is estimated, the mean WTP is given by:

$$E(WTP) = \sum_{j=0}^{J} \widehat{S}(A_j)\left[A_j - A_{j-1}\right] \tag{A.5}$$

where the mean WTP is the sum of the probabilities of the respondent voting behaviour times the difference between two adjacent bid levels.

References

Abramo, G., D'Angelo, C. A., & Rosati, F. (2016). The north–south divide in the Italian higher education system. *Scientometrics, 109*(3), 2093–2117.

Alberini, A., Kanninen, B., & Carson, R. T. (1997). Modelling response incentive effects in dichotomous choice contingent valuation data. *Land Economics, 73*(3), 309–324.

Amirnejad, H., Khalilian, S., Assareh, M. H., & Ahmadian, M. (2006). Estimating the existence value of north forests of Iran by using a contingent valuation method. *Ecological Economics, 58*(4), 665–675.

Andrews, T. P. (2001). A contingent valuation survey of improved water quality in the brandywine river: An example of applied economics in the classroom. *Pennsylvania Economic Review, 10*(1), 1–13.

Arrow, K., Solow, R. S., Learner, E., Portney, P., Rodner, R., & Schuman, H. (1993). Report of the NOAA-panel on contingent valuation. *Federal Register, 58*(10), 4601–4614.

Ayer, M., Brunk, H. D., Ewing, G. M., Reid, W. T., & Silverman, E. (1955). An empirical distribution function for sampling with incomplete information. *The Annals of Mathematical Statistics, 26*(4), 641–647.

Baneke, D. (2019). Let's not talk about science: The normalization of big science and the moral economy of modern astronomy. *Science, Technology & Human Values, 45*(1), 164–194. https://doi.org/10.1177/0162243919846600

Bateman, I. J., Carson, R. T., Day, B., Hanemann, M., Hanley, N., Hett, T., & Pearce, D. W. (2002). *Economic valuation with stated preference techniques: A manual.* Cheltenham, UK: Edward Elgar Publishing Ltd.

Battistoni, G., Genco, M., Marsilio, M., Pancotti, C., Rossi, S., & Vignetti, S. (2016). Cost-benefit analysis of applied research infrastructure. Evidence from health care. *Technological Forecasting and Social Change, 112,* 79–91.

Bauer, M. W. (2009). The evolution of public understanding of science-discourse and comparative evidence. *Science Technology & Society, 14*(2), 221–240.

Biscari, C. (2012). *CNAO Commission and operation: Report of the Italian national physics laboratories – national Institute of nuclear physics (LNF – INFN).* Frascati (Rome), Italy.

Borzykowski, N., Baranzini, A., & Maradan, D. (2018). Scope effects in contingent valuation: Does the assumed statistical distribution of WTP matter? *Ecological Economics, 144,* 319–329.

Caliari, T., Rapini, M. S., & Chiarini, T. (2019). Research infrastructures in developing countries: The Brazilian case. Retrieved from http://pdf.blucher.com.br.s3-sa-east-1.amazonaws.com/engineeringproceedings/enei2019/6.2-069.pdf. Last access on March, 16th 2020.

Camerer, C. (2011). The promise and success of lab-field generalizability in experimental economics: A critical reply to Levitt and List. Available at SSRN 1977749 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1977749.

Carson, R. T. (2011). *Contingent valuation: A comprehensive bibliography and history.* Northampton, MA, USA: Edward Elgar.

Carson, R. T., & Groves, T. (2007). Incentive and information properties of preference questions. *Environmental and Resource Economics, 37*(1), 181–210. https://doi.org/10.1007/s10640-007-9124-5

Carson, R. T., & Groves, T. (2011). Incentive and information properties of preference questions: Commentary and extension. In J. Bennett (Ed.), *The international handbook on non-market environmental valuation* (pp. 300–321). Cheltenham, United Kingdom: Edward Elgar.

Carson, R. T., Groves, T., & List, J. A. (2014). Consequentiality: A theoretical and experimental exploration of a single binary choice. *J. Assoc. Environ. Resource Eco., 1*(1/2), 171–207. https://doi.org/10.1086/676450

Carson, R. T., Hanernann, W. M., Kopp, R. J., Krosnick, J. A., Mitchell, R. C., Presser, S., Ruud, P. A., & Smith, V. K. (1994). *Prospective interim lost use value due to DDT and PCB contamination in the southern California bight.* NOAA Contract No. - DCNC-1-00007.

Carson, R. T., Mitchell, R. C., Hanemann, W. M., Kopp, R. J., Presser, S., & Ruud, P. A. (1994a). *Contingent valuation and lost passive use: Damages from the Exxon Valdez, discussion paper 94-18, resources for the future.* Washington, D.C.

Carson, R. T., Mitchell, R. C., Hanemann, M., Kopp, R. J., Presser, S., & Ruud, P. A. (2003). Contingent valuation and lost passive use: Damages from the Exxon Valdez oil spill. *Environmental and Resource Economics, 25*(3), 257–286.

Chaudhuri, A. (2008). *Experiments in economics: Playing fair with money.* London, UK: Routledge.

Congressional Research Service. (2019). global research and development expenditures: Fact sheet. Retrieved from: https://fas.org/sgp/crs/misc/R44283.pdf. Last access on March, 16th 2020.

Cooper, J. C. (2002). Flexible functional form estimation of willingness to pay using dichotomous choice data. *Journal of Environmental Economics and Management, 43*(2), 267–279.

Del Bo, C. F., Florio, M., & Forte, S. (2016). The social impact of research infrastructures at the frontier of science and technology: The case of particle accelerators. *Technological Forecasting and Social Change, 112,* 1–3.

Diamond, P. A., & Hausman, J. A. (1993). On contingent valuation measurement of nonuse values. In J. Hausman (Ed.), *Contingent valuation: A critical assessment* (pp. 3–38). Amsterdam: North Holland Press, 1993.

---

[19] By interval-censored data, we mean that a random variable of interest is known only to lie in an interval, instead of being observed exactly as in the case of dichotonmous choice contingent valuation. In such cases, the only information we have for each individual is that their WTP falls in an interval, but the exact amount is unknown.

Duffield, J. W., & Patterson, D. A. (1991). Inference and optimal design for a welfare measure in dichotomous choice contingent valuation. *Land Economics*, 225–239.

D'Agostino, A., Ghellini, G., & Longobardi, S. (2019). Out-migration of university enrolment: The mobility behaviour of Italian students. *International Journal of Manpower, 40*(1), 56–72.

European Commission. (2014). Special Eurobarometer 419. Public Perception of science, research and innovation. Retrieved from http://ec.europa.eu/public_opinion/arch ives/ebs/ebs_419_en.pdf. Last access on May, 27th 2019.

European Commission. (2016). Science and policy making: Towards a new dialogue. In *The 2nd international network for government science advice conference 29-30 september 2016, brussels*. Retrieved from: http://ec.europa.eu/research/conferences/2016/ ingsa2016/index.cfm. Last access on May, 27th 2019.

European Commission. (2018). State of play – literature review. In F. Giffoni, S. Vignetti, H. Kroll, A. Zenker, T. Schubert, E. Griniece, J. Angelis, O. Gulyas, & A. Reid (Eds.), *Technical report prepared for the RIPATHS project (charting impact pathways of investment in research infrastructures)*. Retrieved from: https://ri-paths.eu/wp-content/ uploads/2018/08/T3.2_Literature-review.pdf. Last access on March, 16th 2020.

Flexner, A. (1939). The usefulness of useless knowledge. *Harpers, 179*, 545–552.

Flexner, A., & Dijkgraaf, R. (2017). *The usefulness of useless knowledge*. Princeton, USA: Princeton University Press.

Florio, M. (2019). *Investing in science: Cost-benefits analysis of research infrastructures*. Cambridge, USA: MIT Press.

Florio, M., Forte, S., & Sirtori, E. (2016). Forecasting the social impact of the large hadron collider: A cost-benefit analysis to 2025 and beyond. *Technological Forecasting and Social Change, 112*, 38–53.

Florio, M., & Giffoni, F. (2020). A contingent valuation experiment about future particle accelerators at CERN. *PloS One, 15*(3), Article e0229885. https://doi.org/10.1371/ journal.pone.0229885

Florio, M., Giffoni, F., & Catalano, G. (2020). Should governments fund basic science? Evidence from a willingness-to-pay experiment in five universities. *J. Eco. Pol. Reform, 23*(1), 16–33.

Giffoni, F., & Vignetti, S. (2019). Assessing the socioeconomic impact of research infrastructures: A systematic review of existing approaches and the role of cost-benefit analysis. *L'Industria, 1*, 75–102.

Giudice, G. F. (2010). *A zeptospace odissey. A journey into the physics of the LHC*. New York, USA: Oxford University Press.

Graham, H., de Bell, S., Hanley, N., Jarvis, S., & White, P. C. L. (2019). Willingness to pay for policies to reduce future deaths from climate change: Evidence from a British survey. *Public Health, 174*, 110–117.

Green, D., Jacowitz, K. E., Kahneman, D., & Mcfadden, D. (1998). Referendum contingent valuation, anchoring, and willingness to pay for public goods. *Resource and Energy Economics, 20*(2), 85–116.

Haab, T. C., & McConnell, K. E. (1997). Referendum models and negative willingness to pay: Alternative solutions. *Journal of Environmental Economics and Management, 32*(2), 251–270.

Hanemann, W. M. (1984). Welfare evaluations in contingent valuation experiments with discrete responses. *American Journal of Agricultural Economics, 66*(3), 332–341.

Hanemann, W. M., Loomis, J., & Kanninen, B. (1991). Statistical efficiency of double-bounded dichotomous choice contingent valuation. *American Journal of Agricultural Economics, 73*, 1255–1263.

Hansen, T. B. (1997). The willingness-to-pay for the royal Theatre in copenhagen as a public good. *Journal of Cultural Economics, 21*(1), 1–28.

Heberlein, T. A., Wilson, M. A., Bishop, R. C., & Schaeffer, N. C. (2005). Rethinking the scope test as a criterion for validity in contingent valuation. *Journal of Environmental Economics and Management, 50*(1), 1–22.

Hindriks, J., & Myles, G. D. (2013). *Intermediate public economics*. Cambridge, USA: MIT press.

Huang, J. C., Nychka, D. W., & Smith, V. K. (2008). Semi-parametric discrete choice measures of willingness to pay. *Economics Letters, 101*(1), 91–94.

Hutchinson, W. G., Scarpa, R., Chilton, S. M., & McCallion, T. (2001). Parametric and non-parametric estimates of willingness to pay for forest recreation in northern Ireland: A discrete choice contingent valuation study with follow-ups. *Journal of Agricultural Economics, 52*(1), 104–122.

Johansson, P. O. (2016). On lessons from energy and environmental cost–benefit analysis. *Technological Forecasting and Social Change, 112*, 20–25.

Johansson, P. O., & Kriström, B. (2015). *Cost-benefit analysis for project appraisal*. Cambridge, UK: Cambridge University Press.

Johansson, P. O., & Kriström, B. (2020). On misrepresentation of altruistic preferences in discrete-choice experiments. *Journal of Agricultural and Resource Economics*. https://

doi.org/10.22004/ag.econ.303599. Preprint available at https://ageconsearch .umn.edu/record/303599/files/Johansson_preprint.pdf.

Johnston, R. J., Boyle, K. J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T. A., Hanemann, W. M., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., & Vossler, C. A. (2017). Contemporary guidance for stated preference studies. *J. Assoc. Environ. Resource Eco., 4*(2), 319–405.

Kessler, J. B., & Vesterlund, L. (2015). The external validity of laboratory experiments: Qualitative rather than quantitative effects. *Handbook of experimental economic methodology*. https://doi.org/10.1093/acprof:oso/9780195328325.003.0020

Kristrom, B. (1990). A non-parametric approach to the estimation of welfare measures in discrete response valuation studies. *Land Economics, 66*(2), 135–139.

Levitt, S. D., & List, J. A. (2007). a. "What do laboratory experiments measuring social preferences reveal about the real world? *The Journal of Economic Perspectives, 21*, 153–174.

Levitt, S. D., & List, J. A. (2007b). Viewpoint: On the generalizability of lab behaviour to the field. *Canadian Journal of Economics, 40*, 347–370.

Levitt, S. D., & List, J. A. (2009). Field experiments in economics: The past, the present, and the future. *European Economic Review, 53*, 1–18.

List, J. A., & Gallet, C. A. (2001). What experimental protocol influence disparities between actual and hypothetical stated values? *Environmental and Resource Economics, 20*(3), 241–254.

McFadden, D. (1994). Contingent valuation and social choice. *American Journal of Agricultural Economics, 76*(4), 689–708.

Mitchell, R. C., & Carson, R. T. (1989). *Using surveys to value public goods: The contingent valuation method*. Washington D.C, USA: The Johns Hopkins University Press for Resources for the Nature.

Muñoz, A., Moreno, C., & Luján, J. L. (2012). Who is willing to pay for science? On the relationship between public perception of science and the attitude to public funding of science. *Public Understanding of Science, 21*(2), 242–253.

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*(3), 313–325.

OECD. (2002). *Frascati manual 2002: Proposed standard practice for surveys on research and experimental development*. Paris, FR: Organisation for Economic Co-operation and Development.

OECD. (2019). *Reference framework for assessing the scientific and socio-economic impact of research infrastructures*. Retrieved from https://www.oecd-ilibrary.org/docserver /3ffee43b-en.pdf?expires=1584117263&id=id&accname=guest&che cksum=1A6C56B559BA698180B8670AD41031BC. March, 16th 2020.

Ricciardelli, L. A., Nackerud, L., Quinn, A. E., Sewell, M., & Casiano, B. (2020). Social media use, attitudes, and knowledge among social work students: Ethical implications for the social work profession. *Social Sciences & Humanities Open, 2*(1), 100008.

Rossi, L. (2017). Introduction to the HL-LHC project. Presentation held at CERN on February 2, 2017. Retrieved from: https://indico.cern.ch/event/606369/contribut ions/2443838/attachments/1405928/2148075/HL-LHC_Introduction_Rossi_2fe b2017.pdf.

Rousseau, S., Catalano, G., & Daraio, C. (2021). Can we estimate a monetary value of scientific publications? *Research Policy, 50*(1), 104–116.

Sanz-Menéndez, L., Van Ryzin, G. G., & Del Pino, E. (2013). Citizens' support for government spending on science and technology. *Science and Public Policy, 41*(5), 611–624.

Snowball, J. D. (2008). The contingent valuation method. In J. D. Snowball (Ed.), *Measuring the value of culture*. Berlin, DE: Springer.

Stiglitz, J. E. (1999). Knowledge as a global public good. In K. Inge, I. Grunberg, & M. Stern (Eds.), *Global public goods: International cooperation in the 21st century* (pp. 308–326). Oxford University Press Scholarship Online.

Strand, J., Soares-Filho, B., Costa, M. H., Oliveira, U., Carvalho Ribeiro, S., Ferreira Pires, G., … Toman, M. (2018). Spatially explicit valuation of the Brazilian amazon forest's ecosystem services. *Nat Sustain, 1*, 657–664. https://doi.org/10.1038/ s41893-018-0175-0

Thompson, E., Berger, M., Blomquist, G., & Allen, S. (2002). Valuing the Arts: A contingent valuation approach. *Journal of Cultural Economics, 26*(2), 87–113.

Turnbull, B. W. (1976). The empirical distribution function with arbitrarily grouped, censored and truncated data. *Journal of the Royal Statistical Society: Series B*, 290–295.

Vossler, C. A., & McKee, M. (2006). Induced-value tests of contingent valuation elicitation mechanisms. *Environmental and Resource Economics, 35*(2), 137–168.

Watanabe, M., & Asano, K. (2009). Distribution free consistent estimation of mean WTP in dichotomous choice contingent valuation. *Environmental and Resource Economics, 44*(1), 1–10.