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ORIGINAL ARTICLE

A meta-regression analysis on the willingness-to-pay for country-of-origin labelling

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Email: s.hirsch@uni-hohenheim.de**Abstract**

Food quality and food safety issues arouse increasing interest and concern among consumers and policy-makers. Consequently, the importance of country-of-origin labelling (COOL) is increasing in business, policy and research. Numerous studies have reported a wide range of estimates for consumers' willingness-to-pay (WTP) for COOL using stated preference methods and, in particular, discrete choice experiments. We apply meta-regression analyses to synthesise the heterogeneous results of 204 WTP for COOL estimates extracted from 59 studies which used discrete choice experiments and were published between 2009 and 2020. Meta-regression analysis allows an adjusted summary proxy to be derived for the WTP for COOL and the determinants of heterogeneity in reported WTP estimates are also investigated. Our results suggest that there is a significant positive WTP for COOL, and also reveal that the reported WTP estimates are unaffected by publication bias. In addition, they show systematic variation in WTP estimates across the context and methodological characteristics of the studies. More precisely, we find that the region and the product (animal- vs. plant-based) analysed, as well as certain characteristics of the choice design (e.g., the number of attributes used, or the inclusion of an opt-out option) can have a significant impact on the estimated WTP for COOL. Finally, our results reveal significant differences in price premiums between various types of COOL (e.g., domestic vs. foreign). This highlights that results from individual primary studies should not be generalised without further consideration of the underlying study design.

KEYWORDS

country-of-origin labelling, meta-regression analysis, publication bias, willingness-to-pay

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1 | INTRODUCTION

Consumers and policy-makers are becoming increasingly interested and concerned about food quality and safety. Consumers may well view the production origin of food as an extrinsic quality cue when making food purchase decisions (Bernab   et al., 2008; Fernqvist & Ekelund, 2014; Lobb & Mazzocchi, 2007; Newman et al., 2014; Th  gersen et al., 2017). Country-of-origin labelling (COOL) is mandatory for many food products, for example in the European Union (EU) or the United States, to address issues of food traceability and safety. Mandatory COOL was introduced in the USA by the Farm Security and Rural Investment Act of 2002 and was amended to include additional food commodities such as fresh fruit, vegetables and nuts by the Food, Conservation and Energy Act of 2008. In addition, the EU has also implemented mandatory country-of-origin labelling for an increasing number of products and primary ingredients (Commission Regulation (EU) No 1337/2013; Commission Implementing Regulation (EU) 2018/775). The purpose is not only to improve the warranty of food safety and quality along the supply chain, but also to promote trust by providing consumers with origin information. Furthermore, firms can use COOL on a voluntary basis to market their products (Byrne et al., 2021). Consumers may base their quality expectations on COOL, which can lead to discrimination against products from certain origins (Byrne et al., 2021). The production origin of foods and respective product labelling is therefore of great importance for agribusinesses, policy-makers and researchers.

The relevance of COOL has been investigated in a large number of articles and conclusions suggest that it is an important factor in consumers' food purchase decisions (Ehmke, 2006; Loureiro & Umberger, 2007; Schnettler et al., 2008). Moreover, several studies have reviewed consumers' willingness-to-pay (WTP) for COOL and found that there is generally a greater willingness-to-pay a premium for products with a COOL than for products lacking such information (Agnoli et al., 2016; Banovic et al., 2019; Gao & Schroeder, 2009; Yong et al., 2010; Zheng et al., 2013). Consumers' WTP a premium for COOL has been detected for a variety of countries and products (Gao & Schroeder, 2009; Xie et al., 2013) and it has been shown that consumers' WTP is generally higher for domestic food than for imported products (Mauracher et al., 2013; M  rkbak et al., 2009; Rihn & Yue, 2016; Yeh et al., 2018). Nevertheless, the WTP for COOL estimates reported in the literature vary considerably. Moreover, as individual studies generally focus on one product in one country at a specific point in time, it is impossible to derive generalisable results from a single primary study. A meta-analysis can identify any systematic differences in the WTP for COOL and thus aid a better understanding of consumers' preferences and valuation of respective labelling schemes.

We conduct a meta-regression analysis following the guidelines of Havr  nek et al. (2020) to identify systematic patterns in consumers' WTP for COOL across previous empirical literature. We focus on 204 WTP for COOL estimates obtained from 59 empirical stated preference studies. These studies employ discrete choice experiments to investigate consumers' food purchases with a special focus on COOL and were published over the period from 2009 to 2020. Meta-regression analysis enables us to evaluate the distribution of reported WTP for COOL estimates and derive a summarised WTP measure. This is important because deriving recommendations for practical decision-makers and researchers based on individual studies with a narrow geographic and product focus can be very limited. Moreover, we examine whether the results on WTP for COOL are affected by the presence of publication bias caused by the fact that authors and journal editors might prefer to publish statistically significant effects rather than null results (Stanley, 2005). This may help to achieve a higher level of transparency in the research thread by exposing potential misuse of statistical practices such as *p*-hacking. This

seems relevant in light of the recent discussion about the misuse of p -values in the economics literature (Goodman, 2019). In addition, potential drivers for the heterogeneity in reported WTP for COOL estimates include: factors such as the country where the empirical data for the study was collected (Xie et al., 2013); when the study was conducted (Ehmke, 2006); the product type analysed (Thøgersen et al., 2017); the definition of COOL; the number of (credence) attributes and pricing points considered in the study design (Ehmke, 2006; Gao et al., 2010); methodological differences including sample size (Gao & Schroeder, 2009); and the elicitation method used (Wendler et al., 2012). The meta-regression analysis allows us to evaluate the extent to which these research design characteristics affect the variance in reported WTP for COOL estimates. The meta-regression results can provide researchers and policy-makers with a concise synthesis of the research that uses stated preference methods to derive WTP for COOL estimates. Since the results highlight the importance of the DCE design and the studies' product and regional focus for the derived WTP they can not only assist researchers by providing recommendations for best practice in future WTP studies, but can also help market actors and policy-makers to arrive at informed decisions in highly competitive food markets.

Discrete choice experiments are the major preference elicitation method, allowing researchers to estimate respondents' WTP by observing the choices they make. In addition, discrete choice experiments can open the way to gaining a deeper understanding of the trade-offs between different attributes and levels (Adamowicz et al., 1998). Moreover, since WTP estimates for COOL from discrete choice experiments measure the same economic phenomenon across literature, they are an ideal proxy for investigation in a meta-regression analysis (Havránek et al., 2020; Hirsch, 2018; Oczkowski & Doucouliagos, 2015). On this basis, we focus specifically on the WTP estimates elicited using empirical studies applying discrete choice experiments.

Two previous studies have applied meta-regression analysis to investigate consumers' WTP for COOL on food products (Ehmke, 2006; Yu et al., 2016). Our article differs from these studies as follows. Firstly, the meta-regression analysis by Ehmke (2006) covers the timeframe 2001–2005, while Yu et al. (2016) include primary studies published between 1995–2013. In contrast, we provide a holistic review of the more recent literature on consumer's WTP for COOL published in the past decade (2009–2020). Secondly, in contrast to the two previous meta-regression analyses, we also examine whether the results on WTP for COOL are affected by the presence of publication bias caused by the fact that authors and journal editors might favour statistically significant effects over null results (Stanley, 2005). Thirdly, although the study by Yu et al. (2016) is closely related to our analysis from a methodological point of view, it is restricted to US beef products versus foreign beef, whereas our study is not restricted to any product group or region. Therefore, our study assesses whether results on the WTP for COOL hold independent of the product or region analyses or whether such differences in the study focus affect the results. Fourthly, our study differs from the two mentioned above, in that we concentrate on the relative percentage surcharge in the WTP caused by the presence of a COOL. The relative percentage surcharge reflects the monetary WTP for COOL in relation to the average pricing point for the product used in the underlying choice experiment. This provides a more relevant measure of WTP, which is comparable across heterogeneous product groups. Note that the comparability of the measure is a major precondition for its evaluation in a meta-regression analysis (Havránek et al., 2020; Hirsch, 2018; Oczkowski & Doucouliagos, 2015). Finally, our analysis not only investigates consumers' WTP for domestic COOL, but also includes estimates of the WTP for foreign COOL and, in particular, distinguishes between COOLs from developing and developed countries.

The paper proceeds as follows. In Section 2 we describe the selection process for studies included in the meta-regression analysis and describe the study design characteristics to be evaluated in the model. Section 3 provides methodological information on the meta-regression framework and the results of the analyses are presented in Section 4. Finally, we conclude and summarise our findings in Section 5.

2 | STUDY SELECTION AND DESCRIPTIVE STATISTICS

In this section, we describe the selection process and decisions regarding the studies and WTP for COOL estimates included in the meta-regression analysis. This is followed by a descriptive overview of the studies selected and information on both the dependent variable and the explanatory variables used in the meta-regression.

2.1 | Selection of primary studies

An extensive literature search was conducted to identify all relevant published and unpublished empirical studies (i.e., peer-reviewed articles, working papers, conference contributions or theses) written in English with a focus on identifying the WTP for COOL using discrete choice experiments over the period from January 2009 to December 2020. To achieve this, we used the online search engines Emerald Insight, SpringerLink, Web of Science, ScienceDirect, Wiley Online Library, AgEcon search and Google Scholar. The literature search was based on the Boolean search phrases shown in Table 1 to ensure that all the relevant literature is identified. The systematic literature search process, including the number of studies excluded at each stage, is described in the ‘Preferred Reporting Items for Systematic Reviews and Meta-Analyses’ (PRISMA) flow diagram in Figure 1 (Liberati et al., 2009; Moher et al., 2009). The initial search resulted in 2635 studies linked to consumers’ WTP for COOL.

In the first phase, the articles were screened to establish their relevance based on the title, abstract and keywords. All those articles not directly related to the topic of interest were eliminated. In addition, studies that were not written in English or duplicates identified by more than one search engine were likewise excluded. The remaining 546 studies were then screened in-depth to assess their suitability for the meta-regression analysis. For example, the predetermined inclusion criteria involved the exclusion of those studies that do not focus on food and end consumers, that are not conducted based on a discrete choice experiment, or define the pricing level in the choice experiment by using percentage increments¹ in relation to the base price instead of fixed pricing points (e.g., Fitzsimmons et al., 2014). This led to the exclusion of a further 487 studies.

We exclude studies focusing on other origin indications apart from COOL, such as protected geographical indications (PGI) and protected designations of origins (PDO), and studies based on other stated preference elicitation methods, such as contingent valuation or experimental auction. More precisely, we intend to examine the relevance of the defined product-specific characteristics, particularly the pricing attribute applied in the choice design with varying pricing ranges, price increments, and numbers of pricing points. Johnston et al. (2017) and Adamowicz et al. (2018) suggest that the valuation mechanism of the contingent valuation method differs inherently from choice experiments in that it is defined as a valuation question examining an ‘indivisible whole’. This implies that in contingent valuation, respondents have to consider the evaluated food as a whole, while in choice experiments the evaluation task is based on individual attributes (to be seen as individual and separate characteristics) of the product being studied (Adamowicz et al., 2018; Johnston et al., 2017). In addition, contingent valuation and choice

TABLE 1 Search terms for the identification of relevant literature on the WTP for COOL.

Boolean search terms
(willingness-to-pay OR WTP) AND (food* OR beverage*) AND label* AND consumer* AND (country-of-origin OR COOL) AND (“choice experiment” OR “choice-based conjoint”)

¹Note that this only holds for a single study in which the authors applied a randomised DCE, with each participant receiving an individual base price in combination with randomised percentage price increments. As the authors did not report the average base price and the average percentage increment for each pricing level it was infeasible to calculate the relative WTP.

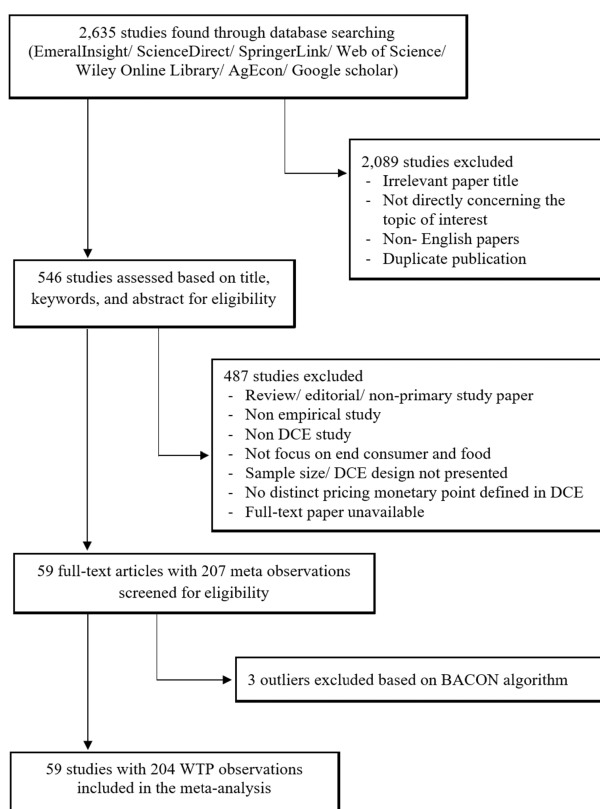


FIGURE 1 PRISMA flow diagram for the systematic literature search and selection process of empirical studies reporting WTP for COOL estimates.

experiments vary in the number of alternatives per valuation task. Although contingent valuation almost always compares a status quo scenario to a single alternative, choice experiments typically involve a status quo scenario plus two or more alternatives in a single choice set. Moreover, the number of valuation questions also differs between contingent valuation and choice experiments, with contingent valuation usually including only one valuation question whereas choice experiments involve a series of choice tasks, that is, at least four or sometimes as many as sixteen (Adamowicz et al., 2018; Johnston et al., 2017). In addition, there are various framing tactics, such as a double-bounded dichotomous choice, a payment card, a single referendum vote, or an open-ended question that can be used in contingent valuation questionnaires, whereas in choice experiment surveys the valuation task is generally phrased as a choice of the most preferred option from a range of alternatives, where each alternative is associated with a defined price.

Note that in addition to reporting results for their full sample, some studies also report additional WTP for COOL estimates for different consumer subsamples (e.g., Printezis & Grebitus, 2018). Since it is impossible to control for the heterogeneous characteristics of these consumer sub-clusters in the meta-regression analysis, we only include WTP estimates reported for the full sample of each study. Thus, WTP estimates derived from latent class analyses (Pouta et al., 2010) or consumer sub-samples² (Wang et al., 2018) were excluded. Moreover, since it is not feasible to control for study-specific treatment effects in the meta-regression analysis, we excluded WTP estimates for the treated group and only included results for the control group

²For example, the discrete choice experiment of Printezis and Grebitus (2018) focuses on two consumer subsamples from different cities within the country (i.e., Phoenix and Detroit).

from information treatment studies (Xie et al., 2013). Furthermore, studies investigating concepts that deviate from WTP—such as ‘willingness-to-accept’ or ‘willingness-to-donate’—were not considered, given their differing economic interpretation (Havránek et al., 2020). Finally, we excluded studies that failed to report information required to evaluate the accuracy of WTP estimation, such as the underlying sample size. The availability of information on the estimation accuracy of the parameter of interest is essential when investigating the presence of publication bias in a meta-regression analysis (e.g., Stanley, 2005; Stanley et al., 2008).

This screening process resulted in a set of 59 empirical studies reporting 207 WTPs for COOL estimates (cf. Figure 1). We apply the Blocked Adaptive Computationally-Efficient Outlier Nominators (BACON) algorithm to ensure that the sample is not affected by outliers or unreasonable observations due to, for instance, reporting errors in the original studies (Hirsch et al., 2020; Weber, 2010).³ This led to the exclusion of three observations and a final sample of 204 WTP for COOL estimates from 59 studies.

Table A1 in the Appendix S1 presents an overview of the 59 studies and provides information on the main study characteristics. Of these, 36 studies (61.0%) reported several WTP estimates as they either considered more than one food category (Balcombe et al., 2016; Forbes-Brown et al., 2016; Wendler et al., 2012), focused on more than one country (Agnoli et al., 2016; Banovic et al., 2019), or applied more than one modelling approach to derive WTP for COOL estimates (Carlucci et al., 2017; Lim et al., 2012; Wendler et al., 2012). Among the 59 studies included, 49 (83%) are peer-reviewed journal articles, 8 (13.6%) are working papers and 2 (1.7%) are dissertations.

2.2 | Dependent variable: Relative WTP estimates

Our dependent variable is the estimated value of consumers' WTP for COOL. Havránek et al. (2020) emphasise that measured effects must be comparable if they are to be evaluated in a meta-regression. We follow the procedure applied by Lusk et al. (2005), Dannenberg (2009), Dolgoplova and Teuber (2018) and Printezis et al. (2019) and use the percentage price premium consumers are willing to pay for COOL to ensure the comparability between WTP for COOL estimates that are expressed in different currencies and obtained in different years as well as for products whose per kilogram or per litre values differ significantly (e.g., milk versus oysters). This relative WTP value is calculated by taking the reported WTP estimate and dividing it by the average value of all pricing points defined in the price attribute used in the choice design of the respective study. Table A1, online, shows that the relative WTP varies between −153% and 233% and that the majority of the estimates are positive, with an overall average of 26% (Table 2).

2.3 | Independent variables

In accordance with the meta-regression analysis guidelines formulated by Havránek et al. (2020), the independent variables of a meta-regression analysis should capture the underlying drivers for heterogeneity in the parameter of interest (the WTP for COOL estimates) as perfectly as possible. Therefore, we coded all relevant contextual and research design characteristics of the studies included as binary variables allowing us to identify their impact on the estimates of WTP for COOL. Table 2 summarises those independent variables. The explanatory variables are classified

³The BACON algorithm identifies multivariate outliers based on an iterative procedure. Initially, it is assumed that a subset of $m > p$ observations from the sample of n observations and p variables is free of outliers. Subsequently, this subset is extended by adding those observations with the smallest Mahalanobis distances. This procedure is continued until the distance falls below the threshold defined by the 0.85 percentile of the χ^2 distribution (e.g., Weber, 2010). Observations not included in the final subset are treated as outliers and removed from the sample (Billor et al., 2000; Weber, 2010).

TABLE 2 Descriptive analysis of the WTP for COOL meta-regression data.

Variables	Description	Number of studies	Number of obs.	Share ^a	Average relative WTP (S.D.)
Dependent variable					
Relative WTP estimate	Continuous variable calculated as the reported WTP for COOL divided by the average of all price points defined in the respective discrete choice experiment	59	204		0.26 (0.57)
Publication type and study context variables					
Non-peer-reviewed papers (working paper/ project report/ thesis)	1 = Yes; 0 = No	10	50	0.25	0.20 (0.40)
Peer-reviewed journal article	1 = Yes; 0 = No	49	154	0.75	0.29 (0.62)
Geographical location: North America	1 = Yes; 0 = No	19	48	0.24	0.33 (0.46)
Geographical location: Asia	1 = Yes; 0 = No	13	35	0.17	0.36 (0.57)
Geographical location: Europe	1 = Yes; 0 = No	25	115	0.56	0.23 (0.61)
Geographical location: Other (including Oceania and Africa)	1 = Yes; 0 = No	2	6	0.03	−0.24 (0.49)
Sample recruited via market research agency	1 = Yes; 0 = No	31	131	0.64	0.21 (0.56)
Web survey	1 = Yes; 0 = No	42	165	0.81	0.25 (0.57)
Personal interview (using computer-assisted interviews, face-to-face interview, or pen-and-pencil survey)	1 = Yes; 0 = No	17	39	0.19	0.32 (0.60)
Experimental setting					
Estimate relates to COOL in general	1 = Yes; 0 = No	4	4	0.02	0.33 (0.11)
Estimate relates to 'domestic country-of-origin'	1 = Yes; 0 = No	35	88	0.43	0.55 (0.48)
Estimate relates to 'foreign country-of-origin'	1 = Yes; 0 = No	29	112	0.55	0.04 (0.55)
Estimate relates to 'foreign (developing country) COOL'	1 = Yes; 0 = No	12	22	0.11	−0.26 (0.50)
Estimate relates to 'foreign (developed country) COOL'	1 = Yes; 0 = No	25	88	0.43	0.13 (0.53)
Estimate relates to 'foreign COOL (without a country specified)'	1 = Yes; 0 = No	1	2	0.01	−0.78 (0.22)

(Continues)

TABLE 2 (Continued)

Variables	Description	Number of studies	Number of obs.	Share ^a	Average relative WTP (S.D.)
Number of attributes defined in the choice design >3	1 = more than three attributes defined in the choice design 0 = up to three attributes defined in the choice design	43	139	0.68	0.27 (0.64)
Number of pricing levels defined in the price attribute >3	1 = more than three pricing levels defined in the price attribute 0 = up to three pricing levels defined in the price attribute	19	82	0.40	0.30 (0.66)
Number of levels defined in the COOL attribute ≥3	1 = three or more levels defined in the COOL attribute 0 = binary levels defined in the COOL attribute	14	63	0.31	0.04 (0.60)
Opt-out alternative included in the choice tasks	1 = Yes; 0 = No	52	176	0.86	0.26 (0.61)
Number of alternatives in the choice set (excluding the opt-out option) ≥3	1 = Yes; 0 = No	24	110	0.54	0.38 (0.56)
Number of choice sets each participant received in the survey ≥10	1 = Yes; 0 = No	24	118	0.58	0.18 (0.51)
Number of blocking versions applied in the choice survey ≥2	1 = Yes; 0 = No	33	114	0.56	0.22 (0.64)
Plant-based product as study object ^b	1 = Yes; 0 = No	23	82	0.40	0.23 (0.52)
Animal-based product as study object ^b	1 = Yes; 0 = No	37	121	0.59	0.28 (0.61)
Estimation model					
Aggregate statistical model ^c	1 = Yes; 0 = No	20	76	0.37	0.21 (0.56)
Heterogeneity specific model ^c	1 = Yes; 0 = No	43	128	0.63	0.30 (0.58)

^aShare is calculated by dividing the number of WTP estimates relating to the respective category by the total number of WTP estimates.

^bLasagna is coded as meat-based product; non-alcoholic (e.g., coffee) and alcoholic beverages (e.g., wine), as well as pastry products (e.g., bread) are coded as plant-based products.

^c*Aggregate model* includes multinomial logit and conditional logit models; *Heterogeneity specific model* refers to the mixed logit model.

into three categories: publication type and study context, settings of the discrete choice experiment, and elicitation models used.

We distinguish between results from articles published in peer-reviewed journals and non-peer-reviewed publications, such as working papers, project reports or theses. We assume that the peer review process, as an established mechanism of editorial decision-making, serves to control quality so that working papers of lower scientific quality in the research design are less likely to be published (Newton, 2010; Scott, 2007).⁴ This allows us to assess the relevance

⁴Since it can be assumed that researchers intend ultimately to have their research published in a peer-reviewed journal, we cannot evaluate the presence of publication bias by comparing published and working papers (Rusnák et al., 2013; Valickova et al., 2015). It must also be noted that the peer-review process can also have shortcomings—for example, caused by power imbalances between authors and reviewers (Newton, 2010).

of quality control and publication type on the reported results. Table 2 shows that 10 of the 59 studies included are non-peer-reviewed publications which provide 50 WTP for COOL estimates with an average value of 0.20. The remaining 49 articles are published in peer-reviewed journals and provide 154 WTP estimates with an average value of 0.29.

To assess geographic differences in WTP for COOL, we coded the regional focus of the underlying survey. The geographical focus of the included studies covered 19 countries on five continents (Europe, North Americas, Asia, Africa and Oceania). Given that only a few WTP for COOL estimates are available for several countries, we coded the geographical location at the continent level. Table 2 reveals that the vast majority of WTP estimates are obtained from surveys conducted in Europe (56%; average relative WTP = 0.23), followed by North America (24%; average relative WTP = 0.33) and Asia (17%; average relative WTP = 0.36), although very few WTP estimates are available from studies carried out in other locations, such as Oceania and Africa (3%; average relative WTP = -0.24).

We also include a dummy variable capturing the source of the panels recruited in the WTP for COOL studies included since there is evidence for differences in the quality of self-collected panels and panels provided by market research agencies. Although purchased panels have the advantage of increased response rates and shorter field times, they can be negatively affected by the presence of professional survey takers who participate only for rewards, which can lead to unreliable response behaviour (Gritz, 2004; Smith et al., 2016). Table 2 shows that 64% of the WTP estimates are derived from samples recruited by market research agencies (average relative WTP = 0.21), while the rest is based on individual data collection, for example via field research, or the use of student samples at the university. Moreover, there is evidence that web surveys are more likely affected by self-selection biases and that there are specific motives for participation (Brüggen et al., 2011; Matthijsse et al., 2015). In turn, social desirability might be lower in web surveys compared to personal paper surveys (Dodou & de Winter, 2014). We therefore capture whether the data was collected via an online web survey rather than personal surveys conducted by an interviewer. Web-based surveys are predominant in our sample (81%; average relative WTP = 0.25), while 19% of WTP for COOL estimates are based on data from offline surveys, or through personal interviews (average relative WTP = 0.32).

Regarding the experimental setting of the discrete choice experiment, it must be noted that not all studies focus on domestic COOL. Several articles also investigated the WTP for a foreign COOL, a generic country-of-origin information (for example, whether or not a product has a COOL in general), or several different COOL levels in a single choice experiment. To disentangle the relevance of these different types of COOL to WTP, we created dummies for the three types of COOL characteristics. This allows us to investigate if different definitions of the COOL attribute are associated with significantly different WTP for COOL. Table 2 shows that 2% of the relative WTP for COOL estimates relate to the evaluation of 'generic COOL information' (average relative WTP = 0.33), 43% to the domestic COOL category (average relative WTP = 0.55), while 55% of reported WTP estimates refer to foreign COOL (average relative WTP = 0.04). The 'foreign COOL' category can be further subdivided into those focusing on a developing country (11%; average relative WTP = -0.26), those focusing on a developed country (43%; average relative WTP = 0.13), and those investigating a foreign COOL in general without a country specified (1%; average relative WTP = -0.78).

The design of a choice experiment impacts the results (Caussade et al., 2005; Islam et al., 2007; Street et al., 2005). For example, there is a trade-off between task complexity and omitted variable bias when selecting the number of attributes (Hensher, 2006; Witt et al., 2009). Complexity can increase cognitive burdens, leading to lower reliability, and may cause a status quo bias where participants increasingly choose the opt-out option (Boxall et al., 2009; Hensher, 2006). In addition, Caputo et al. (2017) and Gao and Schroeder (2009) show that particular 'cue' attributes such as COOL, which do not stand for themselves but likely include information or trigger perceptions about other unobserved product characteristics (e.g., reputation) might lose some of

their relevance if more information in the form of additional attributes is included. We therefore control for the total number of attributes used in the choice design. Moreover, it has been shown that the definition of attribute levels can affect the results (e.g., Caussade et al., 2005; Ryan & Wordsworth, 2000). We therefore control for the number of price levels defined in the price attribute, and the number of levels defined in the COOL attribute. As most studies evaluating the relevance of the number of attributes in DCEs use three attributes, including a price attribute with three levels, as the base scenario (e.g., Caputo et al., 2017; Gao & Schroeder, 2009) we use three as the threshold when coding the number of attributes and the number of pricing levels defined in the choice design. Table 2 reveals that 68% of the WTP estimates were derived using a choice design with more than three attributes (average relative WTP = 0.27), and 40% of the WTPs were elicited from a choice design involving more than three price levels (average relative WTP = 0.30). We code a dummy variable to capture whether the number of levels defined in the COOL attribute is larger than or equal to three, to evaluate the effect of the use of non-binary COOL attributes (i.e., those with more than two levels) in the choice design. This provides information on whether analysing multiple labels simultaneously changes the effect on WTP. An example of a study where the number of levels defined in the COOL attribute is larger than or equal to three is Agnoli et al. (2016), who implement a choice design where the COOL attribute is defined by the three levels 'unknown', 'imported' and 'national', leading to WTP estimates for generic, foreign and domestic COOL. In contrast, Forbes-Brown et al. (2016) use a binary COOL attribute to elicit consumers' WTP for dairy products carrying the 100% Canadian Milk label leading to a single domestic WTP for COOL estimate. We find that 31% of the WTPs for COOL estimates were obtained using a choice design with three or more levels for the COOL attribute (average relative WTP = 0.04).

In addition, other design dimensions could have a significant impact on the heterogeneity of WTP for COOL estimates, that is, the number of alternatives in each choice situation, whether an opt-out alternative was included in the choice task, the number of choice sets each participant received, and the number of blocking versions used in the survey (e.g., Caussade et al., 2005). Caussade et al. (2005) estimate the effect of design parameters on error rates in DCEs and find that the optimal design has 4 alternatives (including an opt-out) and 9–10 choice sets. We therefore use these values as thresholds. It can be observed that 54% of the WTP estimates (average relative WTP = 0.38) are derived from a design with three or more alternatives in each choice set (excluding the opt-out option) whereas 58% of the WTP estimates (average relative WTP = 0.18) are elicited from a choice design where each participant received ten or more choice sets. The inclusion of an opt-out option can be important as otherwise consumers might be forced to purchase a specific option (Adamowicz & Boxall, 2001). Moreover, 86% of the WTP estimates are retrieved from an experimental design that includes an opt-out alternative (average relative WTP = 0.26) whereas 14% of estimates are retrieved from a design without an opt-out alternative (average relative WTP = 0.29). Finally, 56% of WTP values (average relative WTP = 0.22) are obtained from an experimental setting that consisted of two or more blocking versions for the discrete choice experiment survey.

We also include dummies for the product categories analysed in the discrete choice experiment to allow us to assess the degree to which the type of food product studied drives heterogeneity in reported WTP estimates and whether COOL has a different effect on different products. It is unfeasible to control for each product individually due to the wide range of products investigated in the WTP for COOL literature and the fact that many products are only analysed in a few studies. Therefore, we decided to adopt the same strategy as Printezis et al. (2019), and only differentiate between the two main product categories, animal-based (i.e., meat, and meat products, seafood, eggs and dairy products) and plant-based (i.e., vegetables, fruit, bread, wine, beer and coffee). We observe that the shares of WTP estimates for animal- and plant-based products across the studies included are 59% and 40%, respectively. According to Table 2 there is some indication that the relative premium consumers are willing to pay for COOL is higher for

animal products (average relative WTP = 0.28) than for plant-based products (average relative WTP = 0.23).

Finally, we include dummies capturing the type of econometric model used to estimate the value of WTP for COOL from the choice data. More specifically, we capture whether WTP was derived using aggregate models, such as multinomial logit and conditional logit models (e.g., Gonçalves et al., 2020), or approaches such as random parameter logit models that consider individual-specific preference heterogeneity (e.g., Balcombe et al., 2016). The latter have the advantage of accounting for heterogeneity in consumer preferences, so that variation in attributes is captured across consumers (Train, 2009). From Table 2 it can be observed that over half of the values (63%) are estimated employing models that consider preference heterogeneity among consumers such as random parameters logit (average relative WTP = 0.30). The remaining 37% of the WTP measures are estimated based on aggregated statistical models, such as conditional logit or multinomial logit which, on average, lead to lower WTP for COOL estimates (average relative WTP = 0.21).⁵

2.4 | Meta-regression methodology

Our meta-regression analysis involves: (i) the generation of a summary measure of WTP for COOL based on the set of estimates reported in the primary literature; (ii) analysing the extent to which WTP for COOL estimates are affected by publication bias; and (iii) investigating the extent to which reported WTP estimates vary across products, regions, COOL definitions and in how far WTP is influenced by researchers' decisions on the study design.

In the past decades, 'publication selection bias' has been widely recognised as a potential threat to the validity of empirical research (Alinaghi & Reed, 2018; Dickersin, 2006; Rothstein et al., 2006; Stanley, 2007; Stanley & Doucouliagos, 2012, 2013; Thornton, 2000). Publication bias occurs when researchers, referees or editors tend to opt for selective reporting, such as highlighting certain statistically significant results or findings that confirm a specific theory merely by having the 'right' sign. This means that researchers are more likely to shelve studies that present null results or do not conform to these expectations, and is therefore also known as the 'file drawer' problem (Stanley, 2005, 2017). Thus, the investigation of publication bias aims to identify possible exaggeration of the magnitude and statistical significance of the reported empirical effects.

The presence of publication bias can be assessed by the relationship of WTP estimates and estimation precision, where the latter can be measured by the WTP estimates' standard errors or the square root of the size of the sample used to generate the effect (Stanley, 2005).⁶ This is based on the rationale that confidence intervals and *p*-values used to measure statistical significance are derived from the relationship of estimates and their estimation precision. Therefore, a strong relationship between estimates and their precision is an indication for a systematic search of a specific level of statistical significance in the underlying literature.⁷

We start our analysis by investigating whether the literature on WTP for COOL is affected by publication selection bias and by determining whether a significant WTP for COOL effect exists after controlling for publication bias (Stanley & Doucouliagos, 2012). The most common approach for testing publication bias is the funnel asymmetry test (FAT), which involves a graphical assessment of reported estimates in the form of a funnel diagram combined with a statistical analysis of the graphs' asymmetry (Stanley & Doucouliagos, 2010). The funnel diagram is a

⁵The dataset is available from the authors upon request.

⁶Note that the square root of sample size is proportional to the inverse of the standard error (Stanley, 2005).

⁷A typical example are *t*-statistics averaging around an absolute value of 2, which is the approximate value for statistical significance at the 5% level, across the investigated literature.

scatterplot of the effect estimates (relative WTP for COOL) against a measure of their estimation precision. The form of this plot, that is, its degree of asymmetry, can provide a first visual indication of the presence of publication bias (Sterne & Egger, 2001). The FAT is a statistical assessment of the funnel's asymmetry based on a regression model capturing the relationship between effect size and estimation precision. In the present case, since standard errors are not usually reported for WTP estimates and cannot be derived from the information provided in the primary studies,⁸ the square root of the sample size is used as the precision measure (Stanley, 2005).⁹ Thus, the FAT is based on the following model:

$$relative\ WTP_i = \beta_0 + \beta_1 \left(\sqrt{N_{WTP_i}} \right) + \varepsilon_i, \text{ with } i = 1, 2, \dots, m \quad (1)$$

where *relative WTP_i* refers to the *i*th relative WTP for COOL estimate while $\sqrt{N_{WTP_i}}$ is the square root of the sample size used to estimate the related WTP measure. ε_i is a stochastic i.i.d. error term. The FAT is based on the estimate of β_1 and $H_0 : \hat{\beta}_1 = 0$, can be used to evaluate the presence and degree of publication bias (Egger et al., 1997; Gallet & Doucouliagos, 2017; Stanley, 2007; Stanley & Doucouliagos, 2013). In the case of publication bias, relative WTP estimates will be correlated with their precision (the square root of sample size), resulting in a certain level of statistical significance (Oczkowski & Doucouliagos, 2015). Thus, in these cases, the estimate of β_1 will differ significantly from zero, that is, $H_0 : \hat{\beta}_1 = 0$ will be rejected if publication bias is present.

In turn, the constant of Equation (1) (β_0) is a proxy for the empirical WTP for COOL after controlling for publication bias (Stanley, 2005). Accordingly, the test of $H_0 : \hat{\beta}_0 = 0$ is called the precision effect test (PET) and Equation (1) can be referred to as the FAT-PET model.

However, it has been shown that $\hat{\beta}_0$ tends to underestimate the true empirical effect in cases where the effect is non-zero (Doucouliagos et al., 2014; Stanley, 2010; Stanley et al., 2017). Stanley and Doucouliagos (2013) and Stanley (2017) recommend the use of squared precision, that is, $\left(\sqrt{N_{WTP_i}} \right)^2$, instead of $\sqrt{N_{WTP_i}}$ in Equation (1) to generate more precise estimates of the summarised effect ($\hat{\beta}_0$). In this way, potential non-linear relationships between WTP estimates and their precision can also be captured and leads to the following specification (Stanley & Doucouliagos, 2012, 2013):

$$relative\ WTP_i = \beta_0 + \beta_1 \left(\left(\sqrt{N_{WTP_i}} \right)^2 \right) + u_i, \text{ with } i = 1, 2, \dots, m \quad (2)$$

where $H_0 : \hat{\beta}_1 = 0$ again serves as the test for publication bias. Doucouliagos and Stanley (2011) indicate that the degree of publication bias should be considered as 'little to modest' if $|\hat{\beta}_1| < 1$ or insignificant, 'substantial' if $|\hat{\beta}_1| \geq 1$ and significant and 'severe' if $|\hat{\beta}_1| \geq 2$ and significant. Testing $H_0 : \hat{\beta}_0 = 0$ based on Equation (2) is known as the *precision-effect estimate with the standard error* (PEESE) test and Equation (2) is referred to as the PET-PEESE model (Stanley, 2017; Stanley & Doucouliagos, 2012, 2013).¹⁰

⁸WTP is calculated as the quotient of two regression coefficients for which the standard error cannot be calculated without further information on the estimation output, such as standard errors of individual coefficients (e.g., Printezis et al., 2019).

⁹Stanley (2005) shows that the correlation between the inverse of the standard error and the square root of sample size is 0.9. See also Sterne et al. (2000) and Macaskill et al. (2001) who show that the square root of sample size is even more precise as a measure for estimation precision than standard errors.

¹⁰Stanley (2007) examined the properties of the PEESE test and concluded that it is an effective tool for testing the presence of a genuine effect, even in small samples and regardless of the extent of publication selection bias.

The explanatory variables related to the underlying study design derived in Section 2.3 are added to Equation (2) to explain variation in the relative WTP for COOL estimates. This leads to the following full meta-regression model:

$$relative\ WTP_i = \alpha_0 + \alpha_1 \left(\sqrt{N_{WTP_i}} \right)^2 + \sum \beta_w x_{wi} + \sum \beta_m x_{mi} + \sum \beta_n x_{ni} + v_i \quad (3)$$

where the intercept $\hat{\alpha}_0$ denotes the summarised empirical effect beyond publication bias, given that all the explanatory variables related to the underlying study design are set equal to zero (Stanley et al., 2013). $\hat{\alpha}_1$ captures the degree of publication bias when accounting for variations in reported relative WTP estimates driven by underlying study-design characteristics. x_{wi} , x_{mi} and x_{ni} are vectors of explanatory variables related to the three groups of underlying study design characteristics, including the study context, the experimental design and econometric approach used, as described in Table 2 above. The vectors $\hat{\beta}_w$, $\hat{\beta}_m$ and $\hat{\beta}_n$ represent the respective regression coefficients. Finally, v_i is the stochastic error term.

Several econometric difficulties must be overcome when estimating the meta-regression models defined by Equations (1)–(3) (e.g., Hirsch, 2018; Printezis et al., 2019). Firstly, when synthesising WTP values from multiple primary studies, it is important to account for differences in the estimation precision of the WTP estimates across studies. This is necessary as heterogeneous variances of the WTP effects included might cause heteroscedasticity in the error terms of models (1) to (3). Therefore, we estimate all models using weighted least squares (WLS) regression. We use $\frac{1}{(\sqrt{N_{WTP_i}})^2}$ as weights because those estimates with a smaller standard error

should receive relatively more weight in the statistical analysis as they contribute more precise information.

Secondly, the independence of error assumption is potentially violated since 36 of the 59 primary studies included in our sample reported more than one WTP for COOL estimate. This is due to the fact that multiple estimates from the same study are unlikely to be independent of each other, causing heteroscedasticity in the error terms and potential biases in the standard errors of Equations (1) to (3) (Hedges et al., 2010). We deal with multiple WTP estimates from a single study by allowing each study to represent a cluster of estimates, irrespective of the number of estimates it reports (Genc et al., 2012). We then adjust for this within-study dependence through cluster robust standard errors in the WLS estimation. In addition, some estimates proposed by the same author are published in different articles¹¹ (Mørkbak et al., 2009, 2010; Tait et al., 2018, 2019), and it can be assumed that this author might well repeat the same analytical procedures, and potentially the same errors, during the research process, leading to correlated estimates within author clusters. Therefore, we also grouped the WTP estimates by authors and estimate (1) to (3) using author cluster robust standard errors.

3 | RESULTS

In the following, we present an initial analysis of the reported WTP values to give a first overview of the degree of publication bias and the magnitude of the empirical WTP for COOL effect. Subsequently, we present results for the full meta-regression models that not only quantify the degree of publication bias and summarise the WTP for COOL effect, but also consider the impact of study design characteristics.

¹¹We only focus on the first authorship of each primary study to identify author clusters. In addition, we also checked to confirm that the same author did not publish exactly the same result in more than one study.

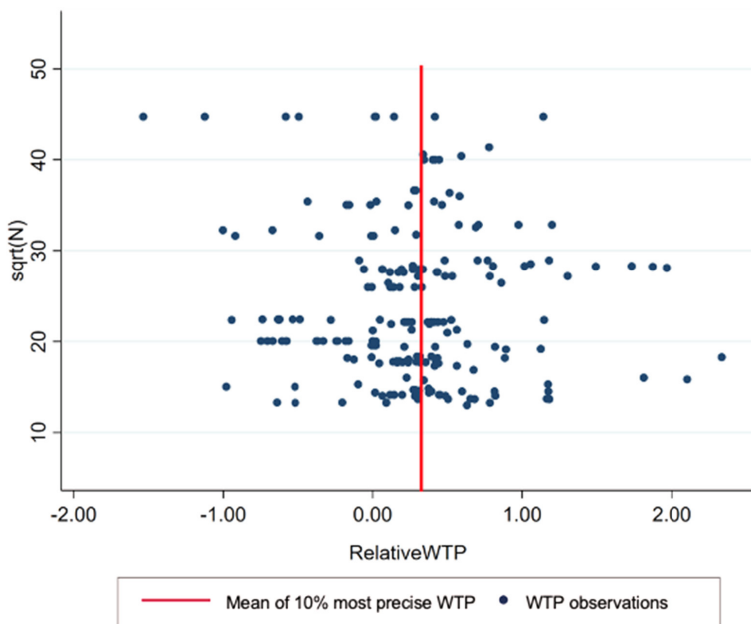


FIGURE 2 Funnel graph for the WTP for COOL estimates. Proxy for summarised empirical WTP indicated by the red vertical line at 0.31 is generated by averaging the top 10% most precise WTP estimates. [Colour figure can be viewed at wileyonlinelibrary.com]

3.1 | Primary analysis of publication bias and the WTP effect

Firstly, we conduct a visual inspection to detect the presence of publication selection bias in reported WTP for COOL estimates using a funnel diagram that plots WTP estimates against their estimation precision. In the present case, this is measured by the square root of sample size $\sqrt{N_{WTPi}}$. If there is no publication selection bias, there should be no systematic relationship between estimates and their estimation precision. This implies that the graph should be symmetric and shaped approximately like an inverted funnel around the summarised empirical WTP estimate. At the top of the plot, WTP estimates from studies with larger samples and high precision should show a small variation and hence form the funnel's neck. If there is no publication bias, less precise estimates from studies with smaller samples should be widely scattered at the bottom of the plot causing the graph to look like an inverted funnel. In turn, an asymmetric or skewed funnel indicates the presence of publication selection bias as this signifies a systematic relationship between estimates and their precision. In accordance with Stanley (2005) and Hirsch (2018), we average the top 10% of the most precisely estimated relative values of WTP for COOL to derive a summarised proxy for the empirical value. Figure 2 illustrates the funnel graph where the vertical line at 0.31 indicates this proxy. Thus, this procedure leads to a slightly higher WTP compared to the sample mean of 0.26. Although a clear funnel shape cannot be observed, there does not seem to be any distinct evidence of publication bias as the estimates are not strongly asymmetrically distributed around the summarised empirical effect. However, note that the informal visual inspection of publication bias based on the funnel graph is purely a matter of subjective interpretation. In the next step, we provide a more objective evaluation based on the meta-regression models defined by Equations (1) to (3).

Columns (1) and (2) of Table 3 present the results of the 'FAT-PET' models specified by Equation (1). The results of the FAT test performed to evaluate the presence of publi-

TABLE 3 Results of FAT-PET and PET-PEESE meta-regression models.

	FAT-PET				PET-PEESE			
	(1) WLS with author cluster robust standard errors	(2) WLS with study cluster robust standard errors	(3) WLS with author cluster robust standard errors	(4) WLS with study cluster robust standard errors				
No. of obs.	204	204	204	204				
No. of studies	59	59	59	59				
<i>F</i> stat.	0.61	0.66	0.59	0.63				
Prob > <i>F</i>	0.44	0.42	0.45	0.43				
<i>R</i> ²	0.005	0.005	0.004	0.004				
Relative WTP	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Constant (β_0)	0.42**	0.18	0.42**	0.17	0.34***	0.10	0.34***	0.10
$\sqrt{n}(\beta_1)$	-0.01	0.01	-0.01	0.01				
$(\sqrt{n})^2(\beta_1)$					-0.00	0.00	-0.00	0.00

Abbreviations: FAT, funnel-asymmetry test; PEESE, precision-effect estimate with the standard error; PET, precision-effect test; WLS, weighted least squares where $(1/\sqrt{n})^2$ is used as weight.

** $p < 0.05$, *** $p < 0.01$.

cation bias in the reported WTP for COOL estimates are based on $H_0 : \hat{\beta}_1 = 0$ and reveal that H_0 cannot be rejected ($\hat{\beta}_1 = -0.01$, $p > 0.1$) either for the WLS model with author-cluster or study-cluster robust standard errors. This implies that there is no evidence for the presence of publication bias in the WTP for COOL literature. The significant $\hat{\beta}_0$ coefficients in columns (1) and (2) ($\hat{\beta}_0 = 0.42$, $p < 0.05$) confirm the presence of a significant relative WTP for COOL effect after controlling for publication bias. Therefore, after controlling for publication bias, consumers are on average willing to pay a 42% price premium for COOL. In the full meta-regression model below, we additionally accounted for underlying study design characteristics, which allows us to investigate whether this price premium varies across product groups or regions.

As described above, the $\hat{\beta}_0$ from the FAT-PET model specified by Equation (1) tends to underestimate the true empirical effect when the effect is non-zero. In these cases, the PET-PEESE model based on Equation (2) provides a more precise estimation of $\hat{\beta}_0$ and a more accurate reflection of publication bias (Stanley & Doucouliagos, 2012). The respective results are reported in the right panel of Table 3 (columns 3 and 4) and reveal that $H_0 : \hat{\beta}_1 = 0$ can again not be rejected ($\hat{\beta}_1 = -0.00$, $p > 0.1$). This confirms that there is no evidence for the presence of publication bias. Finally, the positive significant coefficient $\hat{\beta}_0$ ($\hat{\beta}_0 = 0.34$, $p < 0.01$) in columns 3 and 4 again provides evidence for the existence of a significant positive relative WTP effect for COOL of 34%. Since publication bias does not seem to be an issue the value is close to the sample average of 0.26 calculated above.

Regarding model diagnostics, it must be noted that with 0.005 and 0.004, the R^2 statistics for both the FAT-PET and PET-PEESE models are rather small, indicating that the simple meta-regression models defined by Equations (1) and (2) can only explain up to 0.5% of the variability in relative WTP for COOL. This is due to the lack of publication bias. In the following section, we present the full meta-regression model (Equation 3) including all relevant study design covariates.

TABLE 4 Full meta-regression model.

	(1) WLS with author cluster robust standard errors		(2) WLS with study cluster robust standard errors	
No. of obs.	204		204	
No. of studies	59		59	
<i>F</i> stat.	28.49***		21.99***	
Prob > <i>F</i>	0.00		0.00	
<i>R</i> ²	0.52		0.52	
Relative WTP	Coef.	S.E.	Coef.	S.E.
Constant ($\hat{\alpha}_0$)	−0.85*	0.49	−0.85*	0.48
$(\sqrt{n})^2 (\hat{\alpha}_1)$	0.00	0.00	0.00	0.00
Peer-reviewed journal article	−0.25*	0.10	−0.25*	0.10
North American countries	0.87*	0.42	0.87*	0.41
Asian countries	1.07*	0.42	1.07*	0.42
European countries	0.68	0.42	0.68	0.42
Web survey	0.01	0.16	0.01	0.16
Sample recruited by marketing institute	−0.24*	0.13	−0.24*	0.13
Animal-based product	0.28*	0.14	0.28*	0.13
Number of attributes >3	0.25*	0.10	0.25*	0.10
Number of pricing levels >3	0.07	0.14	0.07	0.14
Number of COOL levels ≥3	−0.18	0.15	−0.18	0.15
Opt-out option included in the choice tasks	0.38*	0.19	0.38*	0.18
Focus on domestic COOL level	0.31*	0.13	0.31*	0.13
Focus on foreign (developing) country COOL level	−0.65***	0.11	−0.65***	0.11
Focus on foreign (developed) country COOL level	−0.24	0.13	−0.24	0.13
Number of alternatives (excluding opt-out option) in a choice set ≥3	0.55**	0.16	0.55**	0.16
Number of choice sets used ≥10	−0.17	0.09	−0.17	0.10
Number of blocking version ≥2	−0.05	0.10	−0.05	0.10
Heterogeneity specific elicitation models	−0.11	0.11	−0.11	0.11

Abbreviation: WLS, weighted least squares where $(1/\sqrt{n})^2$ is used as weight.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

3.2 | Full meta-regression with study design covariates

We now turn our attention to the meta-regression model specified by Equation (3) in order to evaluate the relevance of study design characteristics in driving heterogeneity in reported WTP for COOL estimates. Results from the estimation of Equation (3) are provided in Table 4. Again, we report results for WLS models taking the potential heteroscedasticity in the standard errors caused by study or author cluster dependency into account. Since study design characteristics are coded as dummy variables (cf. Table 2), the regression constant captures the WTP for COOL for the base group of estimates. The base group is defined by the following categories: estimates derived from non-peer-reviewed articles, for ‘other’ geographical locations such as Oceania or Africa, using plant-based products as study object and using personal interviews without involving a marketing agency. Moreover, the base group includes effects of discrete choice experiments which have three or less attributes and price levels, use only two levels for the COOL attribute,

have no opt-out option, focus on generic COOL, have less than three alternatives in a choice set, include less than ten choice sets and have only one version of the choice survey. Finally, the base group refers to estimates generated using aggregate logit models.

Regardless of the type of standard error correction and after controlling for publication bias and checking methodological and study design characteristics, the results reveal a significant constant of -0.85 ($p < 0.1$) for the base group (Table 4) which indicates the presence of an overall negative WTP for COOL effect. However, since the constant only reflects the summarised WTP beyond publication bias if all study design characteristics are set equal to zero (i.e., for the base group), it should be interpreted in the context of the significant covariates related to the study design. We discuss these results based on some examples below.

The coefficient of $(\sqrt{N_{WTPi}})^2$ in the full meta-regression model is insignificant ($\hat{\alpha}_1 = 0.00, p > 0.1$), once again confirming the absence of publication bias in the WTP for COOL estimates, after controlling for heterogeneity in study design characteristics.

However, several independent variables related to study design and methodological differences across studies turn out to be significant drivers of the heterogeneity in reported WTP for COOL estimates. Note that the results have to be interpreted with respect to the base group defined above. We found that the coefficient of *Peer-reviewed journal publication* is significant and negative, implying that the estimates of consumers' WTP for COOL reported in peer-reviewed articles are on average lower (by 25 percentage points) than in non-peer-reviewed articles, such as working papers or theses. This implies that articles of potentially lower quality that have not undergone a peer-review process might yield estimates with an upward bias.

We further discover that estimates from *North American* and *Asian countries* are significantly higher (by 0.87 and 1.07, respectively) than results for countries located in *Oceania* and *Africa*. This might be due to the fact that consumers in the former geographical locations are more concerned about production origin labelling due to food safety issues associated with increasing globalisation (Bonti-Ankomah & Yiridoe, 2006; Rana & Paul, 2017), and are rich enough to be willing to pay for 'better' products. In contrast, in developing countries consumer attention is more on food safety issues and information on the foods' origin is not yet considered important (Su & Canavari, 2018). In addition, we find that using samples recruited by a market research organisation leads to significantly lower estimates of consumers' WTP for COOL (by 24 percentage points) compared to using data not recruited by a professional panel provider. This finding may reflect potential differences in data quality by sample source such as lower response quality of professional paid panels compared to self-collected panels, caused, for instance, by respondents rushing through the questionnaire without sufficiently considering the information provided (Gritz, 2004; Smith et al., 2016). However, we do not find systematic differences in results generated with online and face-to-face interviews, which implies that the variation in reported results is not caused by social desirability bias in personal interviews (e.g., Dodou & de Winter, 2014). Besides, when looking at the products analysed in the discrete choice experiment, our meta-regression results reveal that WTP is higher (by 28 percentage points) when a COOL is used on *animal-based* compared to *plant-based products*. This is in line with previous research, (e.g., Printezis et al., 2019; Sackett et al., 2016) who detect a higher WTP for 'locally produced' animal-based food compared to local plant-based products, and Scarpa et al. (2005) who report that the COOL effect may vary across products.

In addition, we find that several characteristics of the choice design drive the heterogeneity in WTP for COOL estimates. Choice designs involving more than three attributes yield WTP estimates that are on average significantly higher by 25 percentage points. Gao and Schroeder (2009) show that for cue attributes like COOL the inclusion of additional quality attributes either leads to a weakening of the COOL effect or to a stronger focus on the cue attribute due to information overload. Our results show that the latter seems to be the case for COOL. In addition, including an *Opt-out option* in the choice design leads to estimates that are significantly higher by 0.38 and

we find a significant and positive coefficient for the variable that captures whether the choice design consists of three or more alternatives in each choice set (+0.55). This confirms that the design of a choice experiment impacts the results and highlights the fact that researchers must assess the robustness of their findings towards variations in the research design that deviate from best-practice recommendations (e.g., Caussade et al., 2005).

Moreover, the significant and positive coefficient of the *Focus on domestic COOL* level indicates that consumers' WTP for COOL is on average higher (by 31 percentage points) when an alternative in the discrete choice experiment is labelled with domestic COOL information rather than generic COOL information. However, a significant and negative coefficient is detected for the *Focus on foreign developing country COOL* level which shows that consumers' WTP for COOL is 65 percentage points lower when the COOL refers to a foreign developing country compared to generic country-of-origin information. This confirms previous findings that consumers are willing to pay more for domestic products compared to foreign alternatives (Xie et al., 2013). Hence, consumers discriminate between the different types of labels that convey the products' COOL and therefore food processors and retailers should be aware that the origin indicated on the label may well influence the effect of COOL.

Finally, WTP for COOL is not affected if three or more attribute levels for COOL are used. This suggests that the simultaneous analysis of different COOLs (generic, domestic, foreign) does not lead to overcomplexity of the experiment (e.g., Caussade et al., 2005). Moreover, the econometric estimator used has no impact on the resulting WTP for COOL measures. This is somewhat surprising as approaches such as mixed logit, which consider heterogeneity in consumer preferences, might generate more accurate results (Train, 2009).

So far, we have derived several summary values for WTP for COOL starting from the simple average (0.26, Table 1), the top 10% most precisely estimated WTP values (0.31, Figure 2) and the constant of the simple FAT-PET model (0.34–0.42, Table 3). We can now use the constant of Table 4, that is, the estimated value for the base group (−0.85) as our starting point for further interpretation of the regression constant as a proxy for the empirical WTP for COOL. This value serves as a basis from which we can derive proxies for WTP for COOL for any combination of study design characteristics. For example, focusing on the results from peer-reviewed articles that study plant-based products and use a choice design with more than three attributes, with an opt-out option, and at least three alternatives per choice set as a best practice example (Caussade et al., 2005) leads to a statistically significant WTP for domestic COOL of 0.39 for consumers from Oceania and Africa. If the study focus is on animal-based products, this value increases by 28 percentage points to a 67% price premium that consumers from Oceania and Africa are willing to pay for domestic COOL. When focusing on North American consumers, this value increases by 87 percentage points. If the focus is now on a foreign (developing) country COOL instead of domestic COOL, we obtain a value of 0.58, that is, a 58% price premium that North American consumers are willing to pay for animal-based products with a COOL that relates to a developing country.

Model diagnostics reveal that the full meta-regression model is overall statistically significant ($F = 28.49$, $p < 0.01$) and explains around 52% of the variation in reported relative WTP for COOL estimates.

4 | DISCUSSION AND CONCLUSION

There is an increasing volume of research focusing on consumers' WTP for country-of-origin labelling (COOL) on food products. This literature provides a range of estimates that vary considerably across regions, product groups and the type of COOL applied, making it impractical to draw general conclusions from individual studies. We provide a comprehensive overview of the empirical literature analysing consumers' WTP a price premium for COOL using stated

preference discrete choice experiments. In particular, our objective is to generate a holistic estimate of the WTP for COOL and evaluate the extent to which the estimates vary across characteristics of the used study design. To this end, we conducted a meta-regression analysis to identify systematic patterns in consumers' WTP for COOL. A total of 204 WTP for COOL estimates were extracted from 59 primary studies using discrete choice experiments. We find that, in general, there is a significant, positive mean estimate for the premium that consumers are willing to pay for COOL. The simple mean of the 204 WTP for COOL estimates shows that, on average, consumers are willing to pay a 26% premium for COOL. Estimating a meta-regression that controls for publication bias, which is not evident in these studies, yields a 34%–42% price premium that consumers are willing to pay for COOL. Estimating a full meta-regression model that also includes all relevant study design variables allows us to calculate the resulting WTP for COOL for each combination of study design characteristics. We find that WTP for COOL is positive under most combinations. For example, on average, peer-reviewed studies that focus on North American consumers and plant-based products and apply a choice design with at least four attributes, an opt-out option and at least three alternatives per choice set, report a statistically significant relative WTP for generic COOL of 0.71. This implies that consumers are willing to pay a price premium of 71% for COOL. These findings are consistent with current literature, which indicates that consumers are generally willing to pay a price premium for products with COOL (see, e.g., the reviews by Newman et al., 2014; Thøgersen et al., 2017). Our results also lie within the range for other product claims, such as 'local production', for which Printezis et al. (2019) report that consumers are willing to pay a 52% price premium.

Unlike several previous articles that use meta-regression analysis to systematically investigate consumers' WTP for product claims (e.g., Printezis et al., 2019), we find no evidence for the presence of publication bias in reported WTP for COOL estimates. This means that our meta-regression analysis was unable to detect any trend for authors and journal editors to preferably publish statistically significant price premiums.

However, the meta-regression results reveal that WTP estimates vary considerably depending on the characteristics of the studies' choice design. For example, we find that the results reported are noticeably affected by the region and the product (animal- vs. plant-based) analysed. This is in line with Scarpa et al. (2005) who find that the effect of COOL may vary significantly across products and Printezis et al. (2019) and Sackett et al. (2016) who detect a similar difference regarding the price premium consumers are willing to pay for labels indicating local production for animal- and plant-based products. This suggests that researchers and policy-makers should be cautious when generalising results from different regions. Moreover, food processors and retailers must consider the different impacts of COOL in relation to the respective product, particularly regarding the varying affects between animal- and plant-based food.

Agribusiness actors should also be aware of the varying effect regarding the type of COOL used since generic, domestic and foreign country-of-origin information can have a significantly different impact on the price premium that consumers are willing to pay for these labels. In particular, we found that labels with a domestic focus generate a much higher WTP than generic COOL, while foreign COOL referring to a developing country-of-origin results in a significantly lower WTP. These results resemble those of Alfnès and Rickertsen (2003), Schjøll (2016) and Tonsor et al. (2012) who find that consumers have a distinct preference and WTP for domestic products compared to imported products. This result can also be due to consumers' ethnocentrism (Sharma et al., 1995; Shimp & Sharma, 1987), which relates to consumers' principles about the appropriateness of purchasing products imported from foreign countries. For example, highly ethnocentric consumers may refuse to purchase imported products as their evaluation of domestically produced products is probably defined by this attitude (Orth & Firbasová, 2003).

Moreover, the results indicate that the magnitude of WTP effects is influenced by certain characteristics of the choice design and the experimental setting. For example, the inclusion of an opt-out alternative in the choice design has a positive and significant effect on WTP for

COOL estimates. This supports Veldwijk et al. (2014) who found that choice behaviour changes when respondents are given the opportunity to opt out. However, they also suggest that choice sets should be kept as simple as possible in order to reduce the share of participants choosing to opt out due to complexity of the choice tasks. In addition, the results reveal that the number of attributes defined in the choice design and the number of alternatives presented have a significant influence on consumers' WTP for COOL. In this context Caussade et al. (2005) found that the number of attributes used to define the choice alternative and the number of alternatives presented to each respondent have a significant influence on choice variance and consistency.

Finally, in contrast to the choice design, the reported results are not affected by the type of econometric estimator applied to the choice data or the type of survey method used (personal vs. web based). However, we find that data obtained from panels recruited by marketing research agencies has a significant negative impact on the WTP estimates. This finding can be explained by differences in data quality due to diverse sample sources (Smith et al., 2016). Although we do not draw any conclusions about the most efficient choice design types or sample recruiting methods, these results indicate that researchers should assess the robustness of their findings towards these types of variations in their research design.

It must be acknowledged that our meta-regression analyses do exhibit some limitations. Firstly, the number of articles included is limited by our search criteria and the time-frame imposed. Our aim was to provide a holistic overview of the most recent literature on the WTP for COOL. However, future studies might extend the analysis and also include earlier periods. Secondly, this meta-regression analysis did not consider other stated preference methodologies, such as contingent valuation and experimental auctions. This ensured comparability of the WTP estimates summarised and allowed us to examine the effect of choice design characteristics, such as pricing levels, the number of attributes and the number of alternatives used, as well as the inclusion of an opt-out option. However, contingent valuation and experimental auctions were excluded as they are based on different design mechanisms. This implies that WTP for COOL could be reflected more completely by further meta-regression analyses that focus specifically on the results generated with stated preference methods other than discrete choice experiments. Thirdly, it must be noted that the mean values of the relative WTP reported in Table 3 and Figure 2 may overstate the WTP for COOL, since several regions, such as South America, are not covered by our meta-dataset. Therefore, it is clear that additional empirical studies are needed applying discrete choice experiments to regions that have so far been neglected. Finally, we did not consider sociodemographic and socioeconomic information of the samples explored in the primary studies since several studies did not report such information (e.g., Abate et al., 2018; Balcombe et al., 2020; Banovic et al., 2019). Therefore, for further research, we recommend the use of model specifications that incorporate additional sociodemographic characteristics extracted from previous empirical work.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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