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*Patent and false advertising damage awards are in disarray. Courts are imposing astronomically inflated awards that overcompensate companies for infringement or deceptive practices. The culprit is the Choice-Based Conjoint (CBC) method—a survey-based statistical method that seeks to estimate how much consumers value individual features of a product. Originally coming from marketing scholarship, this methodology has become the prevailing method federal courts use to calculate damages in these cases. And it is being consistently misused.*

*This Article is the first to highlight that misapplication and to use empirical methodology to explain why the method leads to exaggerated damage awards. The problem is that courts—when deploying this methodology—mistakenly only include patented (falsely advertised) features in the survey design and neglect to add other key nonpatented features. This creates the impression that products are only made up of their patented elements, which naturally overestimates the value of these elements. Doctrinally, patent damages seek to compensate parties only for the value of the patented feature as opposed to the full product. This Article realigns that statistical method so that all relevant features are included within the survey model and courts are better equipped to impose more precise awards that actually compensate for the infringement and false advertisement.*

## INTRODUCTION

Damage awards in patent and false advertising cases are in disarray. In many cases, these awards have been astronomically inflated. In both patent infringement and false advertising lawsuits, setting the damage award is a critical step in litigation. For patent infringement cases, if plaintiffs cannot prove more than nominal damages, there is really no point to bring a lawsuit.[1] Similarly, with

* Assistant Professor of Business Law, Indiana University. Affiliated Faculty, The Center for Intellectual Property Research, Indiana University Maurer School of Law.

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1. Section 289 of the Patent Act provides that damages need be proved in the infringement context: a person who manufactures or sells "any article of manufacture to which [a patented] design or colorable imitation has been applied shall be liable to the owner to the extent of his total profit . . . ." 35 U.S.C. § 289. The Patent Act reinforces the importance of damages to any successful patent infringement suit. *See id.*; *see also* Dobson v. Dornan., 118 U.S. 10, 17 (1886) (holding that a "plaintiff must show what profits or damages are attributable to the use of the infringing design"), *superseded by statute*, Act of July 19, 1952, ch. 950, 66 Stat. 792, 813–14 (1952) (codified as amended at 35 U.S.C. § 289), *as recognized in* Samsung Elecs. Co. v. Apple Inc., 137 S. Ct. 429 (2016). The Patent Act of 1952 reinforces the importance of damages to any successful patent infringement suit. *See* 35 U.S.C. § 289; *see also id.* § 284 (defining the scope of patent damages). Although one

false advertising, the only way for a class to be certified is for the plaintiffs to show that damages can be accurately measured on a class-wide basis.[2] Without this determination, the cause of action is effectively dead on arrival.

Most simply, damage awards seek to compensate plaintiffs for only the specific value of a patented (falsely advertised) feature of a product that is otherwise made up of many other features. This is a longstanding precedent in patent infringement lawsuits called "apportionment."[3] In effect, "[t]he patentee is entitled to capture value added by the infringing feature, but cannot recover [any] value attributable to everything else."[4] The plaintiff must apportion the value of an individual patented feature from the full value of the product.[5] For example, if a litigant infringes on the patented spell-check of Microsoft Word, damages are awarded only for the value of spell-check, not the full value of Microsoft Word.

Measuring this specific value, however, is a difficult task.[6] As such, experts—economists, marketers, accountants, and social scientists—are often called into court to assist a jury or a judge in the process of valuing these features.[7] These experts employ sophisticated empirical methodologies to come up with their valuations.[8]

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can get a ruling of infringement without a showing of damages flowing directly from the infringement, there is no monetary remedy. For a case that found infringement but no damages, hence canceling a jury trial, see Apple, Inc. v. Motorola, Inc., 869 F. Supp. 2d 901, 905–12 (N.D. Ill. 2012), *aff'd in part and rev'd in part*, 757 F.3d 1286 (Fed. Cir. 2014), *overruled by* Williamson v. Citrix Online, LLC, 792 F.3d 1339 (Fed. Cir. 2015). Judge Posner held that although there was an infringement under 35 U.S.C. § 284, no damages could be proved and hence the case was moot. *Id.* at 924; *see also infra* Part I.

2. *See* Comcast Corp. v. Behrend, 569 U.S. 27 (2013) (holding that plaintiffs must offer evidence of common damages at the certification stage). Rule 23(b)(3) of the *Federal Rules of Civil Procedure* creates a requirement that damages must be proved on a class-wide basis. FED. R. CIV. P. 23(b)(3). For cases denying certiorari based upon a lack of proof of cognizable harm, see Rahman v. Mott's LLP, No. 13-cv-03482, 2014 BL 339845 (N.D. Cal. Dec. 3, 2014); Dailey v Groupon, Inc., No. 11 C 05685, 2014 WL 4379232 (N.D. Ill. Aug. 27. 2014); Daniel F. v. Blue Shield of Cal., 305 F.R.D. 115 (N.D. Cal. 2014). *See also infra* Part I.

3. *See generally* Bernard Chao, *Implementing Apportionment*, 2019 PATENTLY-O PAT. L.J. 20.

4. *Id.* at 20.

5. J. Gregory Sidak & Jeremy O. Skog, *Using Conjoint Analysis to Apportion Patent Damages*, 25 FED. CIR. BAR. J. 581, 583 (2016).

6. *See, e.g.*, W. Kip Viscusi, *The Challenge of Punitive Damages Mathematics*, 30 J. LEGAL STUD. 313 (2001) (discussing the difficulty in setting an appropriate punitive damage amount in order to correctly deter action); R.F. Lanzillotti & A.K. Esquibel, *Measuring Damages in Commercial Litigation: Present Value of Lost Opportunities*, 5 J. ACCT., AUDITING & FIN. 125 (1990) (laying out the complicated task of estimating lost opportunity damages); Kenneth R. Cone & James E. Laurence, *How Accurate Are Estimates of Aggregate Damages in Securities Fraud Cases?*, 49 BUS. LAW. 505 (1994) (articulating the use of computer-simulated techniques to estimate damages).

7. *See* Shankar Iyer, *Patent Damages in the Wake of* Uniloc v. Microsoft, INTELL. PROP. LITIG., Spring 2012, at 9.

8. *See id.* at 12–13 (discussing the use of survey methods to apportion patent damages). There have been many patent and false advertising cases in which experts have used complicated methodology to estimate damages; we list just a few here: TV Interactive Data Corp. v. Sony Corp., 929 F. Supp. 2d 1006, 1020 (N.D. Cal. 2013) (using choice-based conjoint analysis to determine patent damages); Apple, Inc. v. Samsung Elecs. Co., 920 F. Supp. 2d 1079, 1111–12 (N.D. Cal. 2013) (using choice-based conjoint analysis to determine patent damages), *aff'd in part and rev'd in part*, 786 F.3d 983 (Fed. Cir. 2015), *rev'd*, 137 S. Ct. 429 (2016); *In re* Dial Complete Mktg. & Sales Pracs. Litig., 320 F.R.D. 326 (D.N.H. 2017) (using choice-based

The prevailing methodology to estimate damages in federal patent[9] and false advertising[10] cases is *Choice-Based Conjoint* (CBC),[11] a survey-based statistical method. The problem is the method is consistently being misapplied. In addition, more often than not, judges, juries, and lawyers are not equipped to critically police how experts use and misuse the method.

This Article seeks to open the proverbial black box of CBC[12] and argues that its *misuse* in patent and false advertising litigation is drastically inflating damage awards. Ultimately, we argue that billions of dollars of damages have been inappropriately awarded because the application of the CBC method supporting them has been wrong. This misapplication stems from the apportionment requirement in patent lawsuits. By focusing *only* on the value of the patented features, experts employing the CBC methodology ignore nonpatented features, and hence inflate estimates of the patented feature. Although this may seem intuitively aligned with the longstanding apportionment requirement, the statistical method, as we show in this Article, only works, ironically, when all features that make up the value of a product are included in the survey design (not just the patented ones).

CBC, originally derived from marketing research in business schools,[13] seeks to estimate the value that consumers place on various features of a

conjoint analysis to certify a class by showing that all consumers were hurt by Dial's false label claim); *In re* ConAgra Foods, Inc., 90 F. Supp. 3d 919 (C.D. Cal. 2015) (using choice-based conjoint analysis to certify a class by showing that all consumers were hurt by ConAgra's false claim).

9. The following is a nonexhaustive list of patent cases that have used the CBC method to estimate damages: *Apple, Inc.*, 920 F. Supp. 2d at 1079; *TV Interactive*, 929 F. Supp. 2d 1006; Visteon Glob. Techs., Inc. v. Garmin Int'l, Inc., No. 10-cv-10578, 2016 WL 5956325 (E.D. Mich. Oct. 14, 2016); Oracle Am., Inc. v. Google, Inc., 872 F. Supp. 2d 974 (N.D. Cal. 2012), *rev'd*, 750 F.3d 1339 (Fed. Cir. 2014); Glenn v. Hyundai Motor Am., No. 8:15-cv-02052-DOC-KES, 2019 WL 11790429 (C.D. Cal. Aug. 26, 2019); Seven Networks, LLC v. Google LLC, 315 F. Supp. 3d 933 (E.D. Tex. 2018); SimpleAir, Inc. v. Google LLC, 884 F.3d 1160 (Fed. Cir. 2018).

10. The following is a nonexhaustive list of false advertising cases that have used the CBC method to estimate damages: Kurtz v. Kimberly–Clark Corp., 321 F.R.D. 482 (E.D.N.Y. 2017); *In re* Scotts EZ Seed Litig., 304 F.R.D. 397 (S.D.N.Y. 2015); *In re ConAgra*, 90 F. Supp. 3d 919; Hadley v. Kellogg Sales Co., 324 F. Supp. 3d 1084 (N.D. Cal. 2018); *In re* NJOY, Inc. Consumer Class Action Litig., 120 F. Supp. 3d 1050 (C.D. Cal. 2015); *In re Dial Complete,* 320 F.R.D. 326.

11. *See* Greg M. Allenby et al., *Valuation of Patented Product Features*, 57 J.L. & ECON. 629, 639–41 (2014) (arguing that conjoint analysis has been applied in patent damage calculations widely but has not taken into consideration market competition); Sidak & Skog, *supra* note 5, at 591–619 (detailing the rise in use of CBC analysis to estimate patent damages); *see, e.g.*, *In re ConAgra*, 90 F. Supp. 3d at 1016–29 (holding that conjoint analysis is a reliable way to calculate class-wide damages and stating that "marketing researchers have used conjoint analysis since the early 1970s to determine the values consumers ascribe to specific attributes of multi-attribute products and to understand the features driving product preferences"); *TV Interactive*, 929 F. Supp. 2d at 1022 & n.6 (N.D. Cal. 2013) (holding that CBC analysis is "accepted [in] the relevant community" and citing "a handful of cases to demonstrate that conjoint analysis is increasingly used in litigation"); *see also* Dzielak v. Whirlpool Corp., 26 F. Supp. 3d 304 (D.N.J. 2014).

12. CBC is a specific form of conjoint analysis using a choice survey. For the seminal paper creating conjoint analysis, see Paul E. Green & V. Srinivasan, *Conjoint Analysis in Consumer Research: Issues and Outlook*, 5 J. CONSUMER RSCH. 103 (1978). *See also* Paul E. Green, J. Douglas Carroll & Stephen M. Goldberg, *A General Approach to Product Design Optimization via Conjoint Analysis*, 45 J. MKTG. 17 (1981).

13. For a full discussion of how conjoint analysis has developed and been applied in the business school context, see *infra* Part II.

product. In patent infringement cases, the method estimates how much a consumer is willing to pay for the patented feature at issue.[14] In false advertising cases, the method estimates how much a consumer is willing to pay for a product given its false claim.[15] These estimates of willingness to pay for a feature then directly translate to the damage award an infringer or false advertiser must pay.[16]

To estimate these values, the method asks consumers to make choices between hypothetical products that vary on several features.[17] For example, a consumer might see three products in a CBC survey (such as cell phones) that vary on several features (such as price, brand, color, service provider, and other criteria).

- Product 1: Black Verizon Samsung phone at $400.
- Product 2: White AT&T iPhone at $500.
- Product 3: Black T-Mobile Android phone at $550.

The consumer will then choose which of the three products she prefers the most. She will do this several times with a different set of three products that systematically vary on their color, carrier, brand, and price. Then, using the choices of the consumer, statistical analysis can be used to determine how much a consumer is willing to pay for a cell phone given that it is made by Apple instead of Samsung, or how much a black cell phone is worth in comparison to a white one.

The problem is that the method, although validated and used widely in several nonlegal contexts,[18] is consistently misapplied by federal courts. Courts are incorrectly choosing which features to use in CBC studies.[19] Products are made up of many features—some minor (not primary drivers of purchase decisions) and others major (primary drivers of purchase decisions). Choosing which features to include in a CBC study is a critical decision as omitting certain

14. *See* Allenby et al., *supra* note 11, at 630–31.

15. *See* E. Allen Jacobs et al., Berkeley Rsch. Grp., *The Use of Statistical Evidence in Class Action Litigation*, *in* INTERNATIONAL COMPARATIVE LEGAL GUIDES: CLASS & GROUP ACTIONS 2021 140, 141 (Nicholas Caitlin et al. eds., 13th ed. 2021), https://iclg.com/practice-areas/class-and-group-actions-laws-and-regulations/6-the-use-of-statistical-evidence-in-class-action-litigation.

16. Generally, the estimate of the willingness to pay for a patented feature is then multiplied by the number of products sold to get a total damage award. The same calculation applies in the false advertising context.

17. We use the terms *"feature"* and *"attribute"* interchangeably throughout.

18. CBC has been used to value features of various product categories including, but not limited to, airplanes, furniture, cars, cell phones, computers, and houses. The list of articles using choice-based conjoint analysis is vast and beyond the scope of this Article; the following list is just meant to be representative: Pinya Silayoi & Mark Speece, *The Importance of Packaging Attributes: A Conjoint Analysis Approach*, 41 EURO. J. MKTG. 1495 (2007); Dick R. Wittink & Philippe Cattin, *Commercial Use of Conjoint Analysis: An Update*, 53 J. MKTG. 91 (1989); Erik L. Olson, *It's Not Easy Being Green: The Effects of Attribute Tradeoffs on Green Product Preference and Choice*, 41 J. ACAD. MKTG. SCI. 171 (2013).

19. *See generally* Allenby et al., *supra* note 11.

features can affect the values the method produces. All features of a product cannot simultaneously be included in a CBC study, however, because the number of combinations of choices for the respondents grows and becomes cumbersome.[20]

As such, courts commonly reduce the set of features to be included in the survey. They routinely include only the minor patented (falsely advertised) features and mistakenly omit many of the major (nonpatented) features.[21] For example, to estimate the value of the patented rounded edges and app orientation of a smartphone, courts may omit major important features such as brand, color, or size of a smartphone.[22] Many federal courts design CBC surveys in the following way:

- Product 1: A smartphone with rectangle application orientation with rounded edges at $400.
- Product 2: A smartphone with square application orientation with sharp edges at $500.
- Product 3: A smartphone with no application orientation with rounded edges at $550.

This process of omitting major features produces an unrealistic survey. It creates the impression that products are only made up of relatively minor patented or falsely advertised features. When courts use this abridged design, the CBC methodology does not accurately value the patented features of a product. The omission of major features inflates the value of the included minor features, thereby inflating damage awards by compensating plaintiffs for more than just what the apportionment requirement seeks to value.[23]

For example, a misapplied CBC study in the now-famous *Apple v. Samsung* case found that consumers were willing to pay $102 for a specific patented autocorrect feature when the full price of the smartphone was only $149, leading to a damage award greater than $1 billion.[24]

This Article intends to realign the CBC method with the spirit of damages and the apportionment requirement: *compensating parties for only the value of the patented (falsely advertised) features*. But it does so by recommending and showing

20. For a discussion of how too many attributes can negatively affect how consumers interact with a choice experiment, see James R. Bettman, Mary Frances Luce & John W. Payne, *Construction Consumer Choice Processes*, 25 J. CONSUMER RSCH. 187 (1998); Barbara Fasolo, Gary H. McClelland & Peter M. Todd, *Escaping the Tyranny of Choice: When Fewer Attributes Make Choice Easier*, 7 MKTG. THEORY 13 (2007); Pablo Marshall & Eric T. Bradlow, *A Unified Approach to Conjoint Analysis Models*, 97 J. AM. STAT. ASS'N. 674 (2002).

21. *See* Sidak & Skog, *supra* note 5, at 604–09.

22. Both of these features are part of Apple's patent portfolio on its iPhone.

23. *See id.* at 604–09.

24. *See* Expert Report of John R. Hauser, Apple, Inc. v. Samsung Elecs. Co., 920 F. Supp. 2d 1079 (N.D. Cal. 2013), *aff'd in part and rev'd in part*, 786 F.3d 983 (Fed. Cir. 2015), *rev'd*, 137 S. Ct. 429 (2016). This is obviously a grossly exaggerated estimate of how much consumers are willing to pay for an autocorrect feature in part because of the omission of major features of a smartphone.

that damage calculation must still use nonpatented features in their survey design. This Article is in four Parts. Part I lays out how damages are calculated in the patent infringement context and why they are important to the false advertising context. Part II explains the CBC method, including its history, traditional uses, and empirical design. Part III explains how the method is being used in both patent and false advertising lawsuits. In particular, Part III discusses in detail how the method was applied in several representative cases and what the conclusions were. In Part IV, we criticize the way the method has been applied and show the consequences of its misapplication. We do this by empirically showing through a novel experimental CBC design how omitting major features of a product inflates the value of the included minor features—thereby inflating damage awards. We conclude with how the method can be better applied to the question of patent and false advertising damages.

## I. PATENT AND FALSE ADVERTISING DAMAGES: A PRIMER ON APPORTIONMENT

Estimating damages is critical for both patent infringement cases and class certification in false advertising cases.[25] This Part will first discuss how patent damages are apportioned, including the various forms of patent damages. We focus specifically on design and utility patents that are part of multi-component products (e.g., the patent covers only some feature or features of a product that is made up of many other noninfringed features)—for example, a design or utility patent may cover some aspect of a cell phone (e.g., texting software) but not cover other aspects of the phone (e.g., brand, color, price, size, or other criteria).

We will then discuss the importance of estimating damages in false advertising cases, particularly in the context of certifying a class. In this area, we again focus on a product that is described by many features—for example, an orange juice box that makes many product-oriented claims (e.g., 100% juice, all-organic, non-GMO, etc.). We do not intend for this Article to be an exhaustive discussion of damages in both of these forms of lawsuits, but we instead hope to give a brief background so that we can show and criticize how CBC methods have been applied in estimating such damages.

25. *See* City of New York v. Ransom, 64 U.S. 487, 487 (1859) ("In an action for damages for the infringement of a patent right, the plaintiff must furnish some data by which the jury may estimate the actual damage. If he rests his case after merely proving an infringement of his patent, he may be entitled to nominal damages, but no more."); *In re* NJOY, Inc. Consumer Class Action Litig., 120 F. Supp. 3d 1050, 1117 (C.D. Cal. 2015).

### *A. Patent Damages*

Calculating patent damages for multi-component products is a critical part of any patent infringement lawsuit. In order to prove infringement, a plaintiff must show (1) that their patent was validly granted, and (2) that the patent was copied (infringed upon) by the defendant.[26] However, this alone does not guarantee a monetary payout and often does not get the plaintiff's case to a jury in the first place.[27] A plaintiff needs a theory and, ultimately, an estimate of the damages they faced due to the infringement.[28]

In general, patent infringement damages can take two forms: the lost profits that the holder of the patent would have received had the infringer not used the patent or a reasonable royalty that the infringer would have paid the patent holder in a hypothetical negotiation.[29] For multi-component products, the damage award is further complicated. In this context, the courts require litigants to apportion damages with respect to the value of the patented component (i.e., a plaintiff only receives damages with respect to the value of the product that was patented and was infringed on, not with respect to the value of the full product).[30]

The apportionment requirement for multi-component products creates a need for experts to estimate the value of the patented feature independent from the other features of the multi-component product.[31] If patent law simply sought to compensate plaintiffs for the value of the full product, this would not require any sort of empirical expertise. The price of the product would be the foundation on which damages were calculated. However, the apportionment requirement on damages throws a wrench into the damage calculation. In order

26. 35 U.S.C. § 271(a) ("[W]hoever . . . sells any patented invention . . . during the term of the patent . . . infringes the patent.") Effectively, plaintiffs must prove that there was a patented invention and that the defendant used the patent in commerce.

27. *See Apple, Inc.*, 869 F. Supp. 2d 901. In that case, Judge Posner objected to the introduction of damages by experts (under a *Daubert* motion) and held that there was no cognizable damage even though there was an infringement. Other courts have held similarly. *See* Lindemann Maschinenfabrik GmbH v. Am. Hoist & Derrick Co., 895 F.2d 1403 (Fed. Cir. 1990).

28. *See* FED. R. CIV. P. 8(a).

29. *See* Sidak & Skog, *supra* note 5, at 583; s*ee also* Aro Mfg. Co. v. Convertible Top Replacement Co., 377 U.S. 476, 507 (1964); Panduit Corp. v. Stahlin Bros. Fibre Works, 575 F.2d 1152, 1157 (6th Cir. 1978). For a discussion of the characteristics courts take into consideration to evaluate a "hypothetical negotiation" for a reasonable royalty, see Ga.-Pac. Corp. v. U.S. Plywood Corp., 318 F. Supp. 1116, 1120 (S.D.N.Y. 1970). For a discussion of treatment of bargaining power in the estimation process, see J. Gregory Sidak, *Bargaining Power and Patent Damages*, 19 STAN. TECH. L. REV. 1, 5 (2015).

30. "[A] patentee . . . must . . . separate or apportion the defendant's profits and the patentee's damages between the patented feature and the unpatented features . . . ." Garretson v. Clark, 111 U.S. 120, 121 (1884); *see also* Sidak & Skog, *supra* note 5, at 585; Ericsson, Inc. v. D-Link Sys., Inc., 773 F.3d 1201, 1233 (Fed. Cir. 2014).

31. *See* FED. R. EVID. 702 advisory committee's note on 1972 proposed rules (acknowledging that an "intelligent evaluation of facts is often difficult or impossible without the application of some scientific, technical, or other specialized knowledge[,]" and that expert witnesses are the "most common source[s] of this knowledge . . . .").

to apportion the full value of a multi-component product into its individual patented feature or features, sophisticated statistical methodology is required. "In other words, the damages expert must employ a methodology that will enable him to disaggregate the profit that is 'properly and legally attributable to the patented feature' from the profit that is attributable to the non-infringing features of the multicomponent product."[32]

A simple example will make this multi-component requirement clear. Take, for example, a pair of headphones. Assume that Company X creates a new technology that molds the headphones into an oval design that more easily fits into an ear. Company X gets issued a design patent so that it is the only headphone manufacturer that can employ this kind of oval design. Company Y (a competitor to Company X) sees how great the design is and incorporates the design into its headphones. Company X then brings a suit for patent infringement. Assuming that it proves that it owns a patent and that Company Y infringed on it, Company X must still show that the infringer caused some damage to the patent owner. Here, given that a pair of headphones is a multi-component product (i.e., the headphones contain important features other than the oval design such as noise reduction, fidelity, etc.), Company X will have to apportion its lost profits or estimate a reasonable royalty of *just* the oval design—not the headphones as a whole.

In order to value the particular novel, patented feature of the multi-component headphone product, experts would opine on what portion of the price paid for the headphones was due only to its oval design.[33] Alternatively, what is the consumer willing to pay for a pair of headphones with the oval design in comparison to the same pair of headphones without the oval design? This is the so-called willingness to pay (WTP) of the patented feature.[34] Ultimately, to effectively calculate damages in this context, the plaintiff has to introduce evidence that estimates the WTP for an oval design of headphones.

It is here in which economists, marketers, and other business–academic scholars have been called into court. These experts have used various methodologies to estimate the WTP for a given patented feature of a multi-component product. The most common methodology is the subject of this paper—CBC analysis.[35] Below, we give more details on the method and how exactly the method can be used to estimate the WTP for a patented feature and thereby used to calculate total damages in infringement lawsuits.

32. Sidak & Skog, *supra* note 5, at 585 (quoting *Garretson*, 111 U.S. at 121).

33. *Id.*

34. Allenby et al., *supra* note 11, at 647.

35. *See supra* note 11 and accompanying text.

### B. *False Advertising Damages*

In addition to using CBC in patent damages, plaintiffs have been looking to the same method to certify classes in false advertising and misleading labeling lawsuits.[36] Having a theory and estimation of class-wide damages at the outset of a class action lawsuit is critical to getting over the hurdle of certification.[37] Rule 23 of the *Federal Rules of Civil Procedure* lays out the requirements for a class to be certified.[38] Most simply, they are proving an adequate class definition,[39] commonality,[40] ascertainability,[41] numerosity,[42] typicality,[43] adequacy,[44] and at least one of the requirements in Rule 23(b).[45]

Although the requirement for showing harm is not explicitly mentioned in Rule 23, it can be easily read into the requirements for class definition,[46] commonality,[47] and even Rule 23(b)(3).[48] Moreover, after *Comcast*, showing that class-wide damages can be estimated is effectively a requirement to getting certification.[49] Several class action lawsuits have failed at the certification stage because they have not shown a theory of how damages could be reliably

36. *See In re* Dial Complete Mktg. & Sales Pracs. Litig., 320 F.R.D. 326 (D.N.H. 2017) (using CBC analysis to certify a class by showing that all consumers were hurt by Dial's false label claim); Briseno v. ConAgra Foods, Inc., 844 F.3d 1121 (9th Cir. 2017) (using CBC analysis to certify a class by showing that all consumers were hurt by ConAgra's false claim).

37. *See* Comcast Corp. v. Behrend*,* 569 U.S. 27, 35 (2013).

38. FED. R. CIV. P. 23.

39. Marcus v. BMW of N. Am., LLC, 687 F.3d 583, 591–92 (3d Cir. 2012); Young v. Nationwide Mut. Ins. Co., 693 F.3d 532, 537–41 (6th Cir. 2012); Messner v. Northshore Univ. HealthSystem, 669 F.3d 802, 824–25 (7th Cir. 2012).

40. Wal-Mart Stores, Inc. v. Dukes, 564 U.S. 338, 349–50 (2011).

41. *See Marcus*, 687 F.3d at 592–93; Hayes v. Wal-Mart Stores, Inc., 725 F.3d 349, 354–56 (3d Cir. 2013).

42. *See Marcus*, 687 F.3d at 594–97; *Hayes*, 725 F.3d at 356–58.

43. *Hayes*, 725 F.3d at 360.

44. Amchem Prods., Inc. v. Windsor, 521 U.S. 591, 625–26 (1997).

45. FED. R. CIV. P. 23(b) provides that the class must be easily identifiable as one of three types of class actions.

46. Messner v. Northshore Univ. HealthSystem, 669 F.3d 802, 824 (7th Cir. 2012) (explaining that a class action must not be so broadly defined as "to include a great number of members who for some reason could not have been harmed by the defendant's allegedly unlawful conduct . . . ."); *see also* Edward F. Sherman, *Class Actions After the Class Action Fairness Act of 2005*, 80 TUL. L. REV. 1593, 1616 (2006).

47. Commonality effectively requires that the members of a class faced the same injury. For a detailed discussion of heightened commonality standards, see A. Benjamin Spencer, *Class Actions, Heightened Commonality, and Declining Access to Justice*, 93 B.U. L. REV. 441, 492 (2013).

48. *See* Lilly v. Jamba Juice Co., 308 F.R.D. 231 (N.D. Cal. 2014) (holding that a class was not certified because Rule 23(b)(3) was not satisfied when there was no evidence of damages in the record).

49. *See* Comcast Corp. v. Behrend*,* 569 U.S. 27, 35 (2013).

estimated: *Rice v. Sunbeam Products*,[50] *Dailey v. Groupon*,[51] *Rahman v. Mott's LLP*,[52] *Daniel F. v. Blue Shield of California*,[53] and *Cabbat v. Philip Morris USA, Inc.*,[54] among others. In some cases, estimating damages is difficult as the nature of injury is complicated. However, for many cases concerning false advertising including misleading packaging labels, the theoretical calculation of damages is quite simple.

In *Mott's*, the court held that the damages of mislabeling a product "No Sugar Added" would "likely involve demonstrating what portion of the sale price was attributable to the value consumers placed on the 'No Sugar Added' statement."[55] This is often the case with misleading labeling class actions. To estimate damages, plaintiffs must show that the class members were "duped" into buying a product and would have paid less for the product had the packaging been truthfully labeled; alternatively, plaintiffs must show what percentage of consumers would have bought the correctly labeled product at its current price.[56] This requirement is effectively analogous to the patent apportionment requirement discussed above.

Take, for example, a soap company that labels its soap as killing 99.9% of germs.[57] It turns out, however, that the claim is only true for 85% of germs. A reasonable measure of damages here would be how much more consumers were willing to pay for the soap with the 99.9% label as opposed to the true label of 85%. When phrased in this way, the calculation is effectively a consumer's WTP for a soap that is labeled as killing 99.9% of germs in comparison to the exact same soap that kills only 85% of germs. This form of damage calculation looks extremely similar to the calculation of a multi-product patented feature. In fact, they are the same. In the patent context, plaintiffs attempt to apportion how much the patented feature contributes to the total price of a product. Similarly, in the class action context, plaintiffs attempt to

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50. No. 12-CV-07923, 2014 U.S. Dist. LEXIS 26406, at *17–18 (C.D. Cal. Feb. 24, 2014) (denying certification of class action against Sunbeam for making various misrepresentations about safety because there was no introduction of expert evidence claiming a cognizable injury).

51. No. 11 C 05685, 2014 WL 4379232, at *9 (N.D. Ill. Aug. 27, 2014) (denying certification of class action against Groupon for incorrectly calculating employee overtime wages because there was no method of calculating class-wide damages).

52. No. 13-CV-03482, 2014 WL 6815779, at *9 (N.D. Cal. Dec. 3, 2014) (denying certification of class action against Mott's LLP for its misleading apple juice package labeled "No Sugar Added" because there was no readily available method introduced to calculate how much damage the label caused to consumers).

53. 305 F.R.D. 115, 130 (N.D. Cal. 2014) (denying certification of class action against Blue Shield of California for denial of health benefits because "plaintiffs ha[d] not offered any proof that damages can be calculated on a class-wide basis").

54. No. 10-00162, 2014 WL 32172, at *4 (D. Haw. Jan. 6, 2014) (denying certification of class action against Philip Morris for misleading consumers by using the term "light" in its description of cigarettes because plaintiffs did not introduce sufficient methodology for calculating damages).

55. *Mott's*, 2014 WL 6815779, at *8.

56. *See In re* ConAgra Foods, Inc., 90 F. Supp. 3d 919, 1021–25 (C.D. Cal. 2015).

57. This is adapted from the *In re Dial* litigation as described in detail *infra* Part III.

apportion how much the mislabeled feature contributes to the total price of a product.

Given the similarity in questions, it is not surprising that the same method (CBC analysis) has been used in false advertising lawsuits in addition to patent infringement suits. It is actually the success of the method in the patent context that has allowed it to be recently readily utilized in the false advertising context.[58]

Both patent infringement and false advertising lawsuits need estimates of how much consumers are willing to pay for a small part of a product (often technological products in the patent context and consumer packaged goods in the false advertising context). CBC analysis, developed by marketing scholars, has become the go-to method for this estimation task.[59] However, the method as we describe below has been inappropriately used. Therefore, experts using the method have often postulated drastically inflated WTP estimates, which have led to inflated damage awards in the billions of dollars.[60]

## II. A CRASH COURSE IN CHOICE-BASED CONJOINT (CBC) ANALYSIS

This Part provides a brief overview of the accepted and preferred method for estimating the WTP of patented features of multi-component products and the WTP of misleading labels for consumer packaged goods. At the outset we should note that conjoint analysis is a well-accepted survey methodology that has been used in various business applications.[61] Thousands of articles have been written on the method; those articles have innovated and provided new insights into the method and its uses.[62] We do not purport to summarize or do

58. Note that one could simply ask consumers how much they are willing to pay for a product that kills 85% of germs instead of 99%. Although this seems easy to do, most scholars recognize that simply asking respondents how much they are willing to pay for a good is often an invalid method, and scholars do not generally believe the results of these kinds of simple survey questions. *See* Baohong Sun & Vicki G. Morwitz, *Stated Intentions and Purchase Behavior: A Unified Model*, 27 INT'L J. RSCH. MKTG. 356, 356 (2010) (discussing how certain disparities exist between stated intentions and actual purchases).

59. *See* Paul E. Green, Abba M. Krieger & Yoram (Jerry) Wind, *Thirty Years of Conjoint Analysis: Reflections and Prospects*, INTERFACES, May–June 2001, at S56, S56.

60. *See* Apple Inc. v. Samsung Elecs. Co., No. 11-CV-01846, 2014 WL 976898, at *10–16 (N.D. Cal. Mar. 6, 2014).

61. The following is a nonexhaustive list of some articles that have used conjoint analysis to answer questions regarding preferences of various features of products in a business context: Gastón Ares & Rosires Deliza, *Studying the Influence of Package Shape and Colour on Consumer Expectations of Milk Desserts Using Word Association and Conjoint Analysis*, 21 FOOD QUALITY & PREFERENCE 930 (2010); Green, Carroll & Goldberg, *supra* note 12; Georgios Koutsimanis et al., *Influences of Packaging Attributes on Consumer Purchase Decisions for Fresh Produce*, 59 APPETITE 270 (2012).

62. Again, the following is a nonexhaustive list of articles that have innovated based on the conjoint analysis method: Anocha Aribarg, Katherine A. Burson & Richard P. Larrick, *Tipping the Scale: The Role of Discriminability in Conjoint Analysis*, 54 J. MKTG. RSCH. 279 (2016); Joel Huber & John McCann, *The Impact of Inferential Beliefs on Product Evaluations*, 19 J. MKTG. RSCH. 324 (1982); Joel Huber, *What We Have Learned from 20 Years of Conjoint Research: When to Use Self-Explicated, Graded Pairs, Full Profiles, or Choice Experiments*, SAWTOOTH SOFTWARE RSCH. PAPER SERIES (1997), https://sawtoothsoftware.com/resources/technical-

justice to the large academic repository of information on conjoint analysis. Instead, we simply seek to introduce legal scholars, judges, and practitioners to the very basics of the method here.

### *A. The Various Forms of Conjoint Analysis*

Conjoint analysis can be best described as a form of survey methodology that seeks to determine which aspects (features) of a product consumers value and how much each aspect is valued.[63] To field a conjoint survey, researchers choose various features of a product and create "profiles" for respondents to interact with.[64] These profiles can be hypothetical configurations of products or real products that vary on a set of given features.[65]

For example, if a researcher wanted to understand how consumers value various aspects of a computer, she may choose several features of computers to create hypothetical products: screen size, memory, price, brand, speed, etc. Once these features are chosen, the researcher then chooses the various levels of each feature to include in the study. For example, the researcher may be interested in studying three different screen sizes (15 inches, 19 inches, and 20 inches), two different memory capacities (100GB and 250GB), three different prices ($400, $600, and $700), and four brands (Apple, Dell, Gateway, and Compaq). Using these features, and their respective levels, the researcher will create hypothetical products.

The ideal way to measure the values and tradeoffs of features is to run an experiment where several real products are introduced into a marketplace. Each product then is systematically manipulated in terms of the prices of the product and the features at issue in a patent or false advertising case. A researcher would then simply be able to observe which products sell and at what prices they sell for. This would give the researcher a precise estimate of the value of the features at issue. However, this is obviously costly and time consuming. Conjoint analysis is a survey methodology that attempts to simulate this ideal experiment with hypothetical products (and messages) shown to a sample of consumers.

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papers/what-we-have-learned-from-20-years-of-conjoint-research-when-to-use-self-explicated-graded-pairs-full-profiles-or-choice-experiments; Richard D. Johnson & Irwin P. Levin, *More Than Meets the Eye: The Effect of Missing Information on Purchase Evaluations*, 12 J. CONSUMER RSCH. 169 (1985).

63. Specifically, the method calculates trade-offs between various features. The modern application, relevant for this Article, seeks to answer how much a consumer values a given feature. The original method and its application were developed in the 1970s at The Wharton School, University of Pennsylvania, by Paul Green. *See* Green, Carroll & Goldberg, *supra* note 12, at 20–21.

64. *See* Keith Chrzan & Bryan Orme, *An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis*, SAWTOOTH SOFTWARE RSCH. PAPER SERIES, at 1 (2000), https://sawtoothsoftware.com/resources/technical-papers/an-overview-and-comparison-of-design-strategies-for-choice-based-conjoint-analysis.

65. *See supra* note 59, at S56–58.

Once these products are created, a researcher has three general options of how to structure the survey: ranking-based conjoint, rating-based conjoint, and choice-based conjoint.[66]

In a ranking-based conjoint, a consumer will simply rank all the products that a researcher puts in front of them from 1 to n (n = the number of products in the survey). The task may look something like the following:

*Please rank the following computers from 1–5 (1 being the most preferred and 5 being the least preferred).*

| Product | Price | Screen Size | Memory | Brand | Rank |
|---|---|---|---|---|---|
| A | $400 | 15 inches | 100 GB | Apple | ? |
| B | $700 | 19 inches | 100 GB | Dell | ? |
| C | $700 | 15 inches | 200 GB | Dell | ? |
| D | $600 | 20 inches | 100 GB | Gateway | ? |
| E | $400 | 20 inches | 200 GB | Compaq | ? |

This information is then analyzed in a linear regression form with the rank as a dependent variable and the features (and their levels) as the independent variables.[67] The regression would take the following form:

$$Y\ (Rank) = \alpha + \beta_1(Price) + \beta_2(Screen) + \beta_3(Memory) + \beta_4(Brand)$$

This allows the researcher to get estimates of the slopes of each of the features. These slopes represent the value (or utility) that the feature contributes to the overall value (or utility) of the product.[68] However, ranking many products can be difficult for a consumer.[69] Ranking, say, 20 products from 1–20 is not an easy task as it is time consuming and burdensome for the respondent. In addition, ranking only gives ordinal information to a researcher and hence misses any ability to compare the relative magnitude levels. Moreover, it does not allow for ties (e.g., if a respondent is indifferent between two products).[70]

As such, a ratings-based conjoint method can be used. In this method a consumer is given the same set of products but must rate them on a scale. The

66. *See* Green & Srinivasan, *supra* note 12, at 111–12; *see also* David Reibstein, John E. G. Bateston & William Boulding, *Conjoint Analysis Reliability: Empirical Findings*, 7 MKTG. SCI. 271, 272 (1988) (comparing the reliabilities of the various forms of preference elicitation in conjoint analysis).

67. *See* Green & Srinivasan, *supra* note 12, at 111–14.

68. *See id.*

69. *See* Kevin Boyle et al., *A Comparison of Conjoint Analysis Response Formats*, 83 AM. J. AGRIC. ECON. 441, 446–47 (2001) (finding that the various forms of conjoint do not always agree and that ranking problematically does not allow for ties); *see also* Green & Srinivasan, *supra* note 12, at 108.

70. Without ties, it is difficult for a researcher to fully understand the tradeoffs that a consumer would make in a real-life setting.

choice of what scale is often an important and consequential task. Rating, say, 20 products on a 1–100 scale will provide a lot of variability but may also be difficult for a respondent—the difference between a 50 and 51 is often a difficult task for a respondent to interpret.[71] A smaller scale is often employed (say 1–10), which is easier for a respondent to use, but then it is more difficult to analyze due to limited variability.[72] In addition, respondents often do not use a scale uniformly. They have a tendency to give all attributes a 9 or a 10 (on a 10-point scale).[73] This makes it more difficult to analyze the tradeoffs that respondents make between various features of products.

Again, once this data is collected, a linear regression is used with the rating as the dependent variable and the features as the independent variables.[74] Similar to the rankings-based conjoint, the estimates of the slopes represent the value that the consumer places on the given feature.[75]

Both rankings- and ratings-based conjoint studies are useful for certain applications. However, CBC has become the most generally accepted method of employing conjoint analysis.[76] This is because choices represent a real purchasing task more realistically than both rankings and ratings.[77]

In a CBC, a researcher gives consumers choices between some subset of the hypothetical products. Instead of seeing, say, twenty products at one time, a researcher will show three or four products at a time and simply ask the consumer which product they prefer the most. The researcher analyzes these choices to estimate the value that consumers place on each of the features at issue. Rather than using linear regression for the choices, a multinomial logit regression is the preferred method of analyzing the data.[78]

Someone new to this task might ask why only a certain subset of features are included in the design of a conjoint study. This is because research has shown that respondents are overwhelmed with more than six or seven

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71. *See* Carolyn C. Preston & Andrew M. Coleman, *Optimal Number of Response Categories in Rating Scales: Reliability, Validity, Discriminating Power, and Respondent Preferences*, 104 ACTA PSYCHOLOGICA 1, 5–13 (2000).

72. *See* Green & Srinivasan, *supra* note 12, at 111–12 (finding that the scaling of ratings in a conjoint design can affect the results).

73. *See* Caterina Masino & Tony Lam, *Choice of Rating Scale Labels: Implication for Minimizing Patient Satisfaction Response Ceiling Effect in Telemedicine Surveys*, 20 TELEMEDICINE & E-HEALTH 1150, 1150 (2014) (discussing the "ceiling effect" and its implications).

74. *See* Green & Srinivasan, *supra* note 12, at 111–14.

75. *See id.*

76. *See* Merja Halme & Makku Kallio, *Estimation Methods for Choice-Based Conjoint Analysis of Consumer Preferences*, 214 EUR. J. OPERATIONAL RSCH. 160, 160 (2011); Sidak & Skog, *supra* note 5, at 591–92.

77. Terry Elrod, Jordan J. Louviere & Krishnakumar S. Davey, *An Empirical Comparison of Ratings-Based and Choice-Based Conjoint Models,* 29 J. MKTG. RSCH. 368, 368 (1992) (arguing although ratings-based methods are valid, choice-based methods often predict choices better than others).

78. For a general discussion of the multinomial logit regression and how it is used, see Peter Guadagni & John Little, *A Logit Model of Brand Choice Calibrated on Scanner Data*, 2 MKTG. SCI. 203, 206–11 (1983). For a specific analysis of how a multinomial logit is used in choice-based conjoint, see Rick L. Andrews, Andrew Ainslie & Imran S. Currim, *An Empirical Comparison of Logit Choice Models with Discrete Versus Continuous Representations of Heterogeneity*, 39 J. MKTG. RSCH. 479, 479–82 (2002).

features.[79] If a conjoint design uses, say, twenty features, respondents will often ignore all the features except a few critical ones.[80] This will frustrate the purpose of the task.

In response to this, researchers simply choose a subset of features to present to a respondent and then ask the respondent to hold all features not present constant across all of the presented products.[81] This so-called *ceteris paribus* language effectively tells the respondent that each of the products are exactly the same except for the differences in features that are presented.[82] This is a very common practice in conjoint design analysis, and when used correctly, it does not create problematic results.

However, as we argue and empirically demonstrate below, using only a subset of minor features (features that do not drive the majority of the decision process) inflates the value of the included features. This is particularly problematic in patent and false advertising lawsuits as we delineate in Part III below.

### B. *A Simple Example of Using Choice-Based Conjoint Analysis*

Almost all the conjoint analysis that is used in litigation (both for patent infringement and misleading labeling cases) uses CBC as the preferred method.[83] Again, this method creates the most realistic experience for a respondent and hence is thought to have the most external validity.[84] We show here a simple CBC example using the computer products from above.

Again assume that a researcher wants to understand how consumers value various features of computers. In particular, a researcher wants to understand how much consumers are willing to pay for (1) a larger screen size, (2) more memory, and (3) an Apple computer versus a Dell. The design of each product will include price, screen size, memory, and brand. Note that there are many other features that are likely important in deciding on what computer one will buy (sound output, graphics card, speed of processing, etc.). These are not the

79. *See* Green & Srinivasan, *supra* note 12, at 108.

80. *See id.*

81. *See id.* at 107.

82. *See* Felix Eggers, John Hauser & Matthew Selove, *Scale Matters: How Craft in Conjoint Analysis Affects Price and Positioning Strategies* (Working Paper, 2017), http://www.mit.edu/~hauser/Pages/Eggers_Hauser_Selove%20Scale%20Matters%20June%202017.pdf (showing the various ways that *ceteris paribus* language can be used in a CBC and how that choice will affect the estimated WTP of features).

83. *See generally* Sidak & Skog, *supra* note 5, at 591–98.

84. External validity is a concept in experimental settings that basically means how realistic the study is in comparison to the reality it is attempted to approximate. *See* David H. Kaye & David A. Freedman, *Reference Guide on Statistics*, *in* REFERENCE MANUAL ON SCIENTIFIC EVIDENCE 211, 222 (Fed. Jud. Ctr. & Nat'l Rsch. Council eds., 3d ed. 2011). Studies can be very well-designed and replicable over and over again; however, they may have little external validity, in which case they are likely not useful for the legal context.

focal point of the study; a researcher will omit these features and instead hold them constant amongst all products through the choice task.

Once the product features are decided upon, a researcher will create product profiles to compete with each other. The process ends up being incredibly important. A researcher will not randomly choose which products appear next to each other and what features each has. Instead, a researcher will use a balanced fractional factorial design.[85] In most basic terms, this design allows a researcher to gain the most information about each feature, utilizing the fewest choices while reducing respondent fatigue.[86] A balanced design makes sure that the same level of feature (say $400) does not show up over and over again with another level of feature (say 200 GB). If these two levels show up with each other too often, it becomes difficult for the researcher to disaggregate the value of each of these features.

Once a design is decided upon, the choices are presented to the consumer. Often, consumers are asked to choose one product they prefer most amongst a set of three to five products and a "none of the above" option.[87] This is what one choice in a CBC analysis might look like:

*Please choose the computer that you prefer the most. If you prefer none, please choose "none." Note that all the computers are the same on features that are not presented here.*

| **Product 1** | |
|---|---|
| Price | $400 |
| Screen | 19 inches |
| Memory | 200 GB |
| Brand | Apple |

| **Product 2** | |
|---|---|
| Price | $500 |
| Screen | 15 inches |
| Memory | 150 GB |
| Brand | Compaq |

| **Product 3** | |
|---|---|
| Price | $500 |
| Screen | 20 inches |
| Memory | 200 GB |
| Brand | Dell |

| NONE OF THE ABOVE |
|---|

The respondent would do this several times with several sets of three products.[88] Once a respondent goes through the choice tasks, their answers are

85. For an extended discussion of this kind of design, see Chrzan & Orme, *supra* note 64; CONJOINT MEASUREMENT: METHODS AND APPLICATIONS (Anders Gustafsson, Andreas Herrmann & Frank Huber eds., 4th ed. 2007); Joel H. Steckel, Wayne S. DeSarbo & Vijay Mahajan, *On the Creation of Acceptable Conjoint Analysis Experimental Designs*, 22 DECISION SCI. 435 (1991).

86. Steckel, DeSarbo & Mahajan, *supra* note 85, at 435 (explaining that fractional factorial designs may "reduce the data collection burden on respondents").

87. "None" options are important because, in a realistic setting, sometimes consumers will prefer not to buy anything. Forcing them to make a decision when they otherwise would not will create problems in estimation. For a detailed discussion of the "none" option in CBC analysis, see Rinus Haaijer, Wagner Kamakura & Michel Wedel, *The 'No-Choice' Alternative in Conjoint Choice Experiments*, 43 INT'L J. MKT. RSCH. 93 (2001) (finding that not including a none option can result in much lower model and predictive fit and even biased estimates).

88. The more choice tasks the respondent goes through, the better the results. Often fourteen to twenty choices is standard. *See, e.g.*, *id.* at 99 (using twenty choice sets).

analyzed using a multinomial regression. This regression estimates the value (utility) that the respondent places on each of the features and their levels.[89] The estimates from this regression are called "part worths."[90] Part worths represent the utility that each feature adds to the total product. A small part worth means that the feature and its level only add a little utility to the total product, while a large part worth means that the utility of the feature and its level account for a large percentage of the total utility of the product.[91] Below is a sample of a choice-based conjoint output[92]:

| Attribute | Level | Part Worth (Utility) |
|---|---|---|
| Price | $400 | 1.10 |
| | $500 | 0.13 |
| | $600 | –1.50 |
| Screen Size | 15 inches | –1.00 |
| | 19 inches | 0.52 |
| | 20 inches | 1.36 |
| Memory | 250 GB | –0.56 |
| | 500 GB | 0.62 |
| Brand | Apple | 1.69 |
| | Compaq | –1.23 |
| | Dell | 1.01 |
| | Gateway | 0.06 |

This output allows the researcher to make at least three important insights. First, positive utility is better than negative utility. This means that a computer that is $400 is more preferred to one that is $600, which is intuitive. Second, the difference in the range of utilities for a given feature provides insight into how important that feature is relative to another feature. For example, the range of utility for "memory" is 1.18 (0.62–[–0.56]), while the range of utility for "brand" is 2.92 (1.69–[–1.23]). This means that the brand feature is more important to the respondent than memory as a feature. Third, the relative utility for a given level in comparison to price allows the researcher to compute a WTP for a given feature. This is the most important insight for the legal context.

To calculate a WTP, one first calculates a utility per dollar.[93] To do this one takes the difference between the highest and lowest dollar amount ($600–

89. *See* Green & Srinivasan, *supra* note 12, at 116.

90. A part worth is basically a means of scaling and presenting the value of each level of a given feature in a conjoint study. *See id.* at 104.

91. *See id.*

92. These part worths are just for purposes of explaining how CBC results are interpreted. These are just fabricated part worths. Below, in Part IV, we run an actual CBC and report estimated part worths based upon collected respondent data.

93. *See* Allenby et al., *supra* note 11, at 648.

$400=$200). This dollar difference is associated with a difference of 2.6 utils (1.10–[–1.50]). Taking the ratio of the two ($200/2.6=$76/util) gives us an estimate of how much one utility point is worth in terms of dollars. We can then use this to calculate a WTP. For example, the utility difference between a 19-inch computer screen and a 20-inch screen is 0.84 utils (1.36–0.52). We know that the consumer values one util at $76 so the WTP for a twenty-inch screen over a nineteen-inch screen is $76/util*0.84 utils = $63.84. This calculation can be done for whichever feature the researcher is interested in. In the patent context, as we show below, it is calculated between the infringed feature and the next best noninfringing alternative.

## III. CBC Applications in Patent and False Advertising Cases

As described above, the CBC is an incredibly powerful and useful tool to answer questions about how much consumers value a feature of a multi-component product. As such, it has garnered much attention and use in litigation where valuing a feature of a product (or valuing the claim that a company makes on a product) is an important part of estimating damages. We describe in detail below several of the applications of CBC analysis in legal cases. But first, we describe why the application in these contexts is problematic. In Part IV, we empirically show that the application of the method often creates biases in damage awards.

### *A. The Problem with CBC Analysis in Legal Cases*

There is a whole list of pitfalls that a designer of a CBC can fall into. Research in marketing scholarship has focused on various aspects of design that could bias results, including potential inferences that consumers make with omitted variables,[94] the presentation of nonsymmetrical leveled features,[95] missing levels of attributes,[96] and realistic portrayal of features.[97] In addition, there are many other generic issues associated with any kind of empirical survey that a court must be on the lookout for.[98]

94. *See, e.g.*, Johnson & Levin, *supra* note 62; Fredrik Carlsson, Mitesh Kataria & Elina Lampi, *Dealing with Ignored Attributes in Choice Experiments on Valuation of Sweden's Environmental Quality Objectives*, 47 ENV'T & RES. ECON. 65 (2010); Towhidul Islam, Jordan J. Louviere & Paul F. Burke, *Modeling the Effects of Including/Excluding Attributes in Choice Experiments on Systematic and Random Components*, 24 INT'L J. RSCH. MKTG. 289 (2007).

95. *See, e.g.*, Dick R. Wittink, Lakshman Krishnamurthi & David J. Reibstein, *The Effect of Differences in the Number of Attribute Levels on Conjoint Results*, 1 MKTG. LETTERS 113 (1990); Rüdiger von Nitzsch & Martin Weber, *The Effect of Attribute Ranges on Weights in Multiattribute Utility Measurements*, 39 MGMT. SCI. 915 (1993).

96. *See, e.g.*, Eric T. Bradlow, Ye Hu & Teck-Hua Ho, *A Learning-Based Model for Imputing Missing Levels in Partial Conjoint Profiles*, 41 J. MKTG. RSCH. 369 (2004).

97. *See, e.g.*, Eggers, Hauser & Selove, *supra* note 82.

98. These include issues such as choosing a representative sample, making sure respondents understand the items in a survey, eliciting a reliable measurement of output, and creating external validity.

Although application of CBC to legal cases implicates many of these problems, there is a specific, unexplored problem that has plagued the use of CBC in litigation. As described above, presenting too many attributes to respondents is problematic because it creates too high of a burden for respondents.[99] In effect, they will only look at a small subset of features to make their decisions. As such, researchers often limit the number of features and ask respondents to hold all other features constant across the choices throughout the survey task.[100]

In the legal context, the features that are relevant for a given case (both patents and misleading labeling) are often very minor features. Major features that drive purchasing decisions are often not patented or lied about by companies. Features like price, brand, size, and color are all incredibly important for consumers in choosing products and are never really the subject of lawsuits.[101] Instead, it is often relatively minor or unimportant features (e.g., design of edges, font type, orientation of icons, 99% safe versus 90% safe, etc.) that are the subject of lawsuits.[102]

By "minor attributes" we mean those that are not the primary purchase drivers and may not even be considered in a normal purchase process. This is not to say that major features are the only features that consumers care about. Instead, we just note that major features are relatively more important than minor features. These minor features are still important for the companies at issue. They can implicate billions of dollars of damages, as we describe further below. But, for the consumer, these features often play a very small (if any) role in the ultimate decision process. For example, the patented rounded edges of an iPhone are valuable to a consumer, but certainly not as valuable as the Apple brand, the price, the size, the color, and the camera.

To estimate the value of these minor features, litigation experts will simply omit more important major features in a CBC design and tell respondents to hold those omitted features constant across the choices throughout the choice task.[103]

We argue, and empirically show below, that this routine strategic design choice has plagued expert damage reports and caused an inflation of damage awards in the billions of dollars. Omitting major features in order to estimate the willingness to pay for minor features biases the valuation of those included minor features upwards. Moreover, once this application of CBC is accepted

For a detailed list of these issues and insights into good survey design practice, see Shari Seidman Diamond, *Reference Guide on Survey Research*, *in* REFERENCE MANUAL ON SCIENTIFIC EVIDENCE 359 (Fed. Jud. Ctr. & Nat'l Rsch. Council eds., 3d ed. 2011).

99. *See* sources cited *supra* note 20.

100. *See generally supra* Part II.

101. *See supra* text accompanying note 22.

102. *See infra* text accompanying note 112.

103. *See* Green & Srinivasan, *supra* note 12, at 107.

by a few courts, it spreads through both the patent infringement and misleading labeling arena. The method, as it is currently being applied, is readily accepted in litigation.[104]

Until courts, lawyers, and ultimately experts recognize the problem associated with omitting major features so as to value the relevant minor features, damages will continue to be inflated, unjust, and inefficiently awarded.

Below we describe several patent infringement and misleading labeling cases where CBC was used to value the relevant features. As we show, in all of these applications, the accepted approach was one that omitted major features from the design and included only minor features. In Part IV, we empirically show that this strategy leads to drastically inflated WTP estimates and, in turn, recommended damage awards. In turn, many of the applications of CBC in the legal context have been biased and led to inflated damage awards.

### *B. Sample CBCs Used in Patent Cases*

Given that the crux of patent damages seeks to value what a patent is worth, a CBC that assists litigants in determining what a consumer is willing to pay for a patented feature is critical to any successful lawsuit. As such, the use of CBC in patent infringement cases has increased substantially.[105] We summarize a few of these cases below spending most time on the recent *Apple v. Samsung* saga.

#### *1. Apple v. Samsung (2011, 2012)*

In 2011 and 2012, Apple sued Samsung alleging that Samsung had infringed on several Apple patents, which protected aspects of iPhones and iPads.[106] Specifically, Apple contested that Samsung had violated four design patents and three utility patents.[107] The cases implicated several novel issues concerning patent law, including how a multi-component product should be treated for patent damages purposes.[108] The procedural posture of each of the cases, their ultimate appeal to the Supreme Court of the United States, their remand, and their substantive issues[109] are all beyond the scope of this Article.

104. *See* sources cited *supra* note 11.

105. *See* sources cited *supra* note 11.

106. Complaint for Patent Infringement at 33–36, Apple, Inc. v. Samsung Elecs. Co., 920 F. Supp. 2d 1079 (N.D. Cal. 2013) (No. CV 11 1846), 2011 WL 1461508, at *18–20; Complaint for Patent Infringement at 6–12, Apple, Inc. v. Samsung Elecs. Co., 920 F. Supp. 2d 1079 (N.D. Cal. 2013) (No. CV 12-00630), 2012 WL 467632, at *4–8.

107. *See* sources cited *supra* note 106.

108. For an extensive discussion of the cases and how they were resolved, see Elizabeth M. Gil, Note, Samsung v. Apple*: Taking a Bite Out of the Design Patent "Article of Manufacture" Controversy*, 25 U. MIA. BUS. L. REV. 67 (2017).

109. For the Supreme Court's overturning of the lower court's jury award and subsequent remand, see Samsung Elecs. Co., Ltd. v. Apple Inc., 137 S. Ct. 429, 432–36 (2016).

Instead, here we just focus on the use of expert witness testimony in both cases and detail how experts used CBC to estimate the WTP for the patented features. Estimating how much consumers were willing to pay for the various patented features provided Apple a guideline with which to claim that the WTP per customer multiplied by the number of customers was an appropriate damage amount. This ended up being $1.05 billion, even though Apple had asked for close to $2.5 billion.[110]

In both cases, Apple contracted a marketing expert to perform a CBC survey to estimate the WTP for each of the patented features.[111] Several of the features at issue in both trials were intuitively very minor in the overall decision to buy an iPhone or an iPad. For example, in the 2011 trial, infringed patents included the rounded edges of the iPhone, the bezel on the iPad and iPhone, the orientation of the apps on the home screen, the rotation feature on the touch screen, and scrolling features.[112] In the 2011 case, Dr. Hauser, a marketing expert from MIT, was asked to design a CBC to estimate the WTP for the relevant patented features.[113] It was the data from that CBC that ultimately helped a jury find for the billion-dollar judgment.[114]

Dr. Hauser was also engaged to perform a CBC for the 2012 litigation.[115] This litigation implicated patents like the Slide to Unlock feature for an iPad, Automatic Word Correction, Quick Links, and Missed Call Screen Management.[116] Intuitively, these features play a relatively minor role in the overall choice of which smartphone or tablet to buy. Most consumers do not think about these features when deciding between an Apple smartphone and a Samsung smartphone. However, they do have some value to the consumer, and Dr. Hauser's job was to determine what that value was.

In designing his CBC, Dr. Hauser had to make several decisions on which features to include and which ones to exclude. Ultimately, he included all the minor patented features and only the following other major ones: screen size and price in the tablet design, and screen size, price, and camera in the smartphone design.[117]

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110. Craig Timberg & Haley Tsukayama, *Apple Patents Were Violated by Samsung, Jury Rules*, WASH. POST (Aug. 24, 2012), https://www.washingtonpost.com/business/economy/apple-patents-were-violated-by-samsung-jury-rules/2012/08/24/d4e44b2a-ee3b-11e1-afd8-097e90f99d05_story.html.

111. *See* Apple, Inc. v. Samsung Elecs. Co., 909 F. Supp. 2d 1147, 1156 (N.D. Cal. 2012), *aff'd in part and rev'd in part*, 735 F.3d 1352 (Fed. Cir. 2013).

112. *See Apple, Inc.*, 909 F. Supp. 2d at 1149. The specific patent numbers were: United States Patent Nos. 7,469,381; 7,844,915; 7,864,163; D504,889; D593,087; D618,677; and D604,305.

113. *See Apple, Inc.*, 909 F. Supp. 2d at 1156.

114. *See* Gil, *supra* note 108, at 76–80.

115. *See* Expert Report of John R. Hauser, *supra* note 24.

116. The exact patents were the '647 Patent, the '959 Patent, the '172 Patent, the '760 Patent, and the '414 Patent for smartphones; and the '721 Patent, the '647 Patent, the '959 Patent, the '172 Patent, and the '414 Patent for a tablet. *Id.* at 5.

117. *Id.* at 9.

Since there were so many minor patented features that Dr. Hauser had to include, in order to keep the CBC design reasonable, he decided to omit several important features and instead hold them constant throughout the choice tasks.[118] Nowhere in Dr. Hauser's design did brand, color, cell service provider, battery life, Bluetooth, and storage space show up.[119] Instead, he focused mainly on using minor features. In fact, the features page on Samsung's website "touted various entertainment related capabilities, such as Media Hub, the integrated IR blaster, the Smart Remote app, and the ability to use hands-free headsets, most of which were omitted by Professor Hauser in his analysis."[120]

We argue and show below that including only six features—of which the relevant patented four were extremely minor—at the expense of omitting various major features caused Dr. Hauser's results to be unreliable.[121] Specifically, we show below that when one omits major features in a CBC choice task in order to include only minor features, the valuations of those minor features are biased upwards.

### 2. *TV Interactive Data Corp. v. Sony Corp. (2013)*

A similar problem arose when Interactive Corporation alleged that Sony infringed on its autoplay feature patent when manufacturing the Sony PlayStation.[122] Interactive hired Stanford professor Dr. V. Srinivasan, a marketing expert, to perform a CBC analysis to determine the WTP for the autoplay feature on various Sony products (DVD player, Blu-ray player, and the PlayStation 3).[123] The autoplay feature allows consumers to continue to another disc in the console or player without having to manually select the next disc to play.

In designing his survey, Dr. Srinivasan took a two-step process. First, he had respondents "prioritize 18 attributes of each accused product to come up with a list of six attributes that have similar values as the autoplay feature."[124] In effect, the design specifically chose attributes that were of equal value to consumers as the ostensibly unimportant (minor) autoplay feature. The

118. "[I]nstructions were provided to focus respondents on making relative choices holding all other potential levels of feature categories of smartphones [tablets] constant . . . ." *Id.* at 38–39. *See generally* Rebuttal Expert Report (Redacted) of David Reibstein, Apple, Inc. v. Samsung Elec. Co., No. 12–CV–00630–LHK, 2014 WL 7496140, at *124 (N.D. Cal. Aug. 27, 2014) [hereinafter Rebuttal Expert Report of David Reibstein].

119. *See* Expert Report of John R. Hauser, *supra* note 24, at 21–41.

120. Rebuttal Expert Report of David Reibstein, *supra* note 118, at *120 ("Professor Hauser's surveys did not, however, include numerous other features that Samsung prominently highlighted to consumers.").

121. *Id.* at 119–20.

122. TV Interactive Data Corp. v. Sony Corp., 929 F. Supp. 2d 1006, 1011 (N.D. Cal. 2013).

123. *Id.* at 1020.

124. *Id.* at 1021.

conjoint intentionally left out basically all major features, including brand, controllers, processing speed, and quality of picture.[125]

Second, Dr. Srinivasan fielded two CBCs where he used price, the autoplay feature, and six other similar minor attributes (three in each conjoint) to create his product profiles.[126] The court, however, did not see any issue with this design and did not exclude the survey or the testimony.[127]

### *3. Oracle America, Inc. v. Google Inc. (2010)*

In another case, Oracle sued Google's Android operating system because they alleged that Google used seven patents related to Oracle's Java technology.[128] Once again, the plaintiff, Oracle, hired an expert witness to opine on the value of the patents for damages.[129] Dr. Steven Shugan chose to run a CBC survey to value the patented smartphone features that Google allegedly infringed upon.[130]

In designing the survey, Dr. Shugan used only the following features: application multitasking, application startup time, availability of third-party applications, mobile operating system brand, price, screen size, and voice command capabilities.[131] Again, this CBC design omitted various important features that consumers might take into consideration when buying a smartphone, including battery time, camera, touch screen capability, and service provider.[132] In fact, for the court, this was egregious enough that Judge Alsup observed that "Dr. Shugan excluded from his analysis several important features unrelated to the patents in suit but included voice dialing, 'an arguably unimportant feature.'"[133] Judge Alsup held that the CBC "force[d] participants

125. *See id.*

126. *See id.*

127. *Id.* at 1021–22. Specifically, the court ruled that questions concerning Dr. Srinivasan's conjoint survey were questions for the jury. *Id.* at 1021. Although, there is a query as to how a jury would be able to adequately determine the reliability of such a complicated quantitative method. But see Expert Report of Dr. R. Sukumar, Microsoft Corp. v. Motorola, Inc., No. 210-cv-01823, 2012 WL 8010641 (W.D. Wash. July 24, 2012), where expert Dr. R. Sukumar fielded a CBC survey on a similar product (the Xbox 360). In that CBC, Dr. Sukumar made a list of the most important features of the product and used those important features along with the patented features at issue to design his conjoint. *Id.* This design, where many major attributes are included, is a much better practice that all experts should seek to emulate.

128. *See* Oracle Am., Inc. v. Google Inc., No. C 10–03561, 2011 WL 12449636, at *1 (N.D. Cal. May 9, 2011).

129. *See* Order Granting in Part and Denying in Part Google's *Daubert* Motion to Exclude Dr. Cockburn's Third Report, No. C 10–03561, 2012 WL 850705, at *2 (N.D. Cal. Mar. 13, 2012) [hereinafter Order Granting in Part and Denying in Part Google's *Daubert* Motion].

130. *See id.* at *9.

131. *See id.*

132. *See id.* at *9–10.

133. Sidak & Skog, *supra* note 5, at 605 (quoting Order Granting in Part and Denying in Part Google's *Daubert* Motion, *supra* note 129, at *10).

to focus on the patented functionalities, warping what would have been their real-world considerations."[134]

This represents but another case where major features were omitted in order to estimate the value of relatively minor features. There have been other similar patent cases where a CBC was used to value patented features.[135]

### *C. Sample CBCs Used in False Advertising Cases*

CBC surveys have also begun to be used in false advertising lawsuits to certify a class. Specifically, they have been used in the context of consumer packaged goods.[136] Consumers, when shopping in grocery stores, markets, or pharmacies, often rely upon packaging and labels to make their ultimate decision. When labels are misleading or make false claims, it is likely that this will affect how consumers make decisions. This is at the heart of false advertising lawsuits.

The CBC method has been applied to estimate the damage to a consumer in the face of a misleading or false claim on the packaging of a good. The theory is that the consumer paid a premium for the product because they believed the false claim.[137] To certify a class, plaintiffs must show that the class suffered a similar harm, amongst other things.[138] Showing that the consumer was willing to pay a premium due to the misleading or false claim at issue is a way to estimate damages in these kinds of lawsuits. As such, a CBC has been the accepted method of estimating the WTP for a given package claim.[139]

As we will show below, the problem is that, to do this, CBCs are omitting major features that drive a decision in the context of packaged goods and only including those minor features. The minor features are often, if not always, the exact ones at issue. This strategy is likely causing the WTP estimates of these minor features to be inflated upwards. It should also be disconcerting that several courts are accepting the results of these kinds of studies.

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134. *Id.* (alteration in original).

135. *See, e.g.*, Fractus, S.A. v. Samsung Elecs. Co., Ltd., Nos. 6:09–CV–203, 6:12–CV–421, 2013 WL 1136964 (E.D. Tex. Mar. 15, 2013).

136. Bryan Orme, *Special Features of CBC Software for Packaged Goods and Beverage Research*, SAWTOOTH SOFTWARE RSCH. PAPER SERIES, at 1 (2003), https://sawtoothsoftware.com/resources/technical-papers/special-features-of-cbc-software-for-packaged-goods-and-beverage-research ("CBC particularly has found widespread use in packaged goods and beverage research."). Some scholars have argued for false advertising causes of action in connection to social media product endorsements. *See* Alexandra J. Roberts, *False Influencing*, 109 GEO. L.J. 81 (2020). And we can predict that conjoint analysis would likely be used for assessing damages in that context as well.

137. *See* Jonathan Tomlin & Robert Zeithammer, *Product Labeling Class Actions—Identifying the 'Con' in Conjoint Surveys*, ANKURA (Nov. 9, 2018), https://ankura.com/insights/product-labeling-class-actions-identifying-the-con-in-conjoint-surveys/.

138. For a list of requirements that must be proven to certify a class, see *supra* Part I.B.

139. Sidak & Skog, *supra* note 5, at 581–82.

### 1. *In re: Dial Complete Marketing (2017)*

A CBC was used in a recent false advertising case against Dial Corporation.[140] Dial was accused of labeling their soap products with several misleading claims, including that Dial Complete soap "[k]ills 99.9% of Germs," it is "#1 Doctor Recommended," and it "[k]ills more germs than any other liquid hand soap."[141] In reality, plaintiffs alleged that the soap did not kill 99.9% of germs, but some smaller percentage, and that it did not necessarily kill more germs than other liquid soaps.[142]

Plaintiffs alleged damages equal to the premium consumers paid in reliance on the truth of Dial Complete soap's claims.[143] In estimating this premium for class certification purposes, plaintiffs relied upon an expert CBC study that attempted to calculate how much consumers were willing to pay for the soap, conditional on them thinking that it killed 99.9% of germs.[144]

The expert, Mr. Boedeker, designed a CBC that purported to measure how much more consumers were willing to pay for a soap that "Kills 99.9% of germs." Much like in the patent infringement context, this represents a need to value an ostensibly minor feature of a multi-component consumer product.

In designing the CBC, Mr. Boedeker chose the following features of soap to include in his product profiles: "Kills 99.9% of Germs," "antibacterial," "foaming," and "moisturizing."[145] Finally, he included price at nine different levels so he could measure the willingness to pay for liquid soap that had the label at issue.[146]

Again, much like the CBC designs above, Mr. Boedeker's design did not include any major features that consumers use when purchasing soap (e.g., brand, size, dispenser type, and scent).[147] Instead, the design only included the relatively minor features at issue in the case.[148] Yet, even though this CBC was clearly problematic, the court found that the method and its application were reliable—so much so that the court certified the class based upon the CBC analysis of Mr. Boedeker.[149]

140. *In re* Dial Complete Mktg. and Sales Pracs. Litig., 320 F.R.D. 326, 329 (D.N.H. 2017) (order granting certification).

141. *Id.* at 328.

142. *See id.*

143. *Id.* at 333.

144. *Id.* at 328–33. In order to prove that the plaintiffs could satisfy the class-wide damage calculation burden of Rule 23, they attempted to estimate damages using conjoint analysis. *Id.* at 337.

145. *Id.* at 329.

146. *See id.*

147. *See id.* at 329–30.

148. The minor aspect of the feature is the actual percentage of germs that are killed by the soap. The difference among 99%, 90%, and 85% is minor when considering why someone would purchase hand soap in the first place.

149. *Id.* at 337.

### 2. *Briseno v. ConAgra Foods Inc. (2015)*

Unfortunately, the *Dial Corp.* CBC is only one of many problematic studies that have been used to certify classes in false advertising lawsuits. In a similar case, ConAgra Foods, Inc. was alleged to have used the phrase "100% Natural" on its cooking oil packaging, when in reality the product was made from genetically modified organisms.[150]

The expert there, Elizabeth Howlett, performed a CBC to analyze the premium consumers placed on the "100% Natural" label. To do this, she first determined various interpretations that consumers may have had when reading the proposed language.[151] She came up with six interpretations: "(i) the absence of artificial colors; (ii) the absence of artificial flavors; (iii) the absence of artificial preservatives; (iv) the absence of pesticides; (v) the absence of GMOs; and (vi) the absence of artificial materials or chemicals . . . used during processing."[152]

Second, Dr. Howlett simply used these six interpretations as "features" in her conjoint study.[153] Nowhere in the study did brand, packaging, dispenser type, or even price show up.[154] At a bare minimum, price should be included so that damages in the amount of dollars can be estimated. "However, a conjoint survey can typically accommodate only six or seven product attributes. Hence, it is unclear how the proposed analysis could include other key product attributes, which must be included for the survey technique to work well."[155]

As such, the CBC was used to certify damages against ConAgra. Dr. Howlett's conjoint, like several others, employed a strategy of omitting major features and instead focused only on minor ones. Of course, the court, relying upon several other previous courts who have certified classes based upon conjoint data, blessed Dr. Howlett's study and certified the class.[156]

### 3. *Morales v. Kraft Foods Group, Inc. (2017)*

In a case very similar to *Briseno*, Kraft Foods Group was sued for their use of the label "natural cheese" on their "Natural Cheese Fat Free Shredded Fat

150. *In re* ConAgra Foods, Inc. 90 F. Supp. 3d 919, 919 (C.D. Cal. 2015) (granting in part and denying in part plaintiff's amended motion for class action).

151. *Id.* at 952–54, 1029; *see also* Greg Allenby et al., *Computing Damages in Product Mislabeling Cases: Plaintiffs' Mistaken Approach in* Briseno v. ConAgra, 45 PROD. SAFETY & LIAB. REP. (BL) 208 (2017) (arguing that the CBC used in *Briseno* was problematic for other reasons not contemplated in this Article).

152. Allenby et al., *supra* note 151, at 210.

153. *See In re ConAgra*, 90 F. Supp. 3d at 954.

154. Allenby et al., *supra* note 151, at 211.

155. *Id.* at 210–11 (explaining that the conjoint in *Briseno* "will not provide a reliable estimate of consumer demand because it is focused entirely on attributes related to the 100% natural label and therefore leaves no room for consideration of primary factors in the consumer's purchasing decision, such as brand, price, packaging etc.").

156. *See In re ConAgra*, 90 F. Supp. 3d at 1035.

Free Cheddar Cheese" packaging.[157] Again, like in *Briseno*, a CBC analysis was used to determine how much more consumers were willing to pay for the product with the "natural cheese" label.

Dr. Anand Bodapti was engaged to design and field a CBC that sought to estimate the WTP for the "natural cheese" label. In designing his conjoint, Dr. Bodapti varied only one feature in his choices. He presented consumers with three types of products: competitors to Kraft Fat Free Shredded Cheese, Kraft shredded cheese, and the same Kraft cheese but without the "natural cheese" label.[158] In addition, he included price so that he could calculate the WTP for the relatively minor feature of "natural cheese."[159]

Again, Dr. Bodapti explicitly argued that he did not want to complicate the task for consumers by varying basically any important features in the cheese purchasing decision, including the type of cheese, the cut of cheese, the packaging type, the brand, and the close and keep-fresh mechanism.[160] Instead, Dr. Bopdati only included the relatively minor feature of a "natural cheese" label in his conjoint analysis. In effect, this conjoint only used one minor feature rather than several major ones—it seems particularly problematic in comparison to the other already problematic conjoint studies identified above.[161]

## IV. THE MISAPPLICATION OF CBC IN LEGAL CASES AND ITS REALIGNMENT

### *A. The Problem with Omitting Major Features*

As we have shown above, CBC analysis has been a large influence in estimating damages in both patent infringement and false advertising causes of action. Its application, however, has been problematic. As the number of problematic applications of CBC increases, establishing precedent, the more likely courts will be to accept the method in its current form.

We shed light on how the current use of CBC to estimate the WTP for features is biasing their estimated values upwards. The problem stems from the design of the conjoint. Because having more than six or seven features creates an undue burden on respondents, experts have limited the number of features they present in any conjoint. In doing this, they have to make a choice on what features to include and which to omit.

157. Morales v. Kraft Foods Grp., Inc., No. CV14-04387, 2017 WL 2598556, at *1 (C.D. Cal. June 9, 2017).

158. *Id.* at *3.

159. *See id.* at *3–4.

160. *Id.* at *5.

161. In fact, when questioned on why he only varied one real feature in his conjoint, Bodapti testified that having one attribute only is good for the conjoint analysis "in the sense that it reduces cognitive overloading and thereby increases the fidelity of the decision making." *Id.*

Currently, the trend is to include the features at issue (almost always very minor features) at the expense of omitting major features. When this happens, the estimated value (and, in turn, estimated damage awards) of the relevant included minor features are biased upwards.

We first give some insight into how we define minor versus major. A major feature (e.g., brand, price, color, size, battery life, etc.) is a feature that drives the purchasing decision to some degree. This is not to say that major features are the only features consumers care about. Instead, we just note that major features are relatively more important than minor features. Minor features (e.g., rounded edges, "100% natural" label, slide to unlock, and icon orientation), in contrast, are not principal drivers in the decision process. This is not to say that consumers do not have a preference for the given features (many do like and prefer the rounded edges of the iPhone)—only that the feature is not something that a consumer would normally use in the process of buying a smart phone.[162]

Of course, what features are major and minor is not always clear. Often the importance of features lies on a spectrum, with some very important and others very unimportant. We hope, and strongly believe, that most of the features described above in the applications of conjoint analysis are intuitively minor features relative to price, brand, size, etc. In addition, we strongly believe that the minor features we use in our study below are also intuitively much less important than the major features we explicitly omit.

There are three reasons that omitting major features biases the estimates of minor features upwards. First, the choice method itself forces respondents to make a choice amongst profiles. Often, the method creates a situation where the products presented to a consumer all match on major features.[163] By this, we mean that the products have all the same major features. In those cases, the only difference among the products is the ostensibly minor feature or features. Therefore, the consumer is forced to make a choice wholly and solely based upon the minor feature, when in reality she would usually not base her decision solely on that feature.

Take a watch as an example. Most people when deciding among watches look at major features (price, brand, size, color, battery operated or automatic). It is reasonable to think that the engraving on the backside of a watch likely does not drive a decision in real life. However, take the following three choice-based conjoint profiles:

162. We note that there is heterogeneity in preferences. Some prefer minor features more than others. We can measure this heterogeneity, and do measure this, in our empirical study below. We also note, that even with heterogeneity, estimates of the value of minor features are biased upwards when major features are omitted.

163. David Reibstein & Robert Vigil, *Conjoint Surveys Can Lead to Inflated Values of Minor Product Features*, ANALYSIS GRP. (May 2020), https://www.analysisgroup.com/Insights/ag-feature/q-and-a/conjoint-surveys-can-lead-to-inflated-values-of-minor-product-features/.

| Product 1 | |
|---|---|
| Price | $100 |
| Size | 34mm |
| Brand | Omega |
| Engraving | Yes |

| Product 2 | |
|---|---|
| Price | $150 |
| Size | 29mm |
| Brand | Swatch |
| Engraving | Yes |

| Product 3 | |
|---|---|
| Price | $100 |
| Size | 34mm |
| Brand | Omega |
| Engraving | No |

Assume, further, that a consumer prefers a 34mm Omega watch and, holding all else constant, wants a cheaper watch. The consumer then would not choose Product 2, as it is expensive, smaller, and the nonpreferred brand. Between Product 1 and Product 3, the only difference is the presence of engraving. For this consumer, then, if he prefers engraving, he will choose Product 1 and, if not, he will choose Product 2. In effect, the engraving (for this product choice) is driving the full decision-making process when, in reality, no consumer really makes a decision based upon engraving. Instead, there are many other major features that are omitted here (color, battery operated or automatic, watch band type, watch band color, etc.) that could and should differentiate Product 1 and Product 3.

The statistical model, however, will put all the weight of the decision a consumer makes in this choice on the "engraving" feature. When this occurs a sufficient number of times, the value of the engraving feature will be inflated. The more major features that are omitted at the expense of including minor features, the higher the percentage of choices that will be completely driven by one of the minor included features.[164]

In this context, it is the choice aspect of the conjoint design that is problematic. If consumers could indicate not just that they preferred one product over another but also how much they preferred that product, we would not see the same problem. As described above, using a scale of preference rather than just a choice would give researchers more nuance in valuing preferences. However, having consumers rate products is more difficult than a choice-based procedure and is less representative of a real purchasing decision.

164. To quantitatively explore this, we ran a CBC simulation where we used four features, each at one of two levels: two major features and two minor ones. When we analyzed the choice tasks, we found that in about 10% of the choice tasks, the minor features were completely driving the decision choice. The part worth estimates of this simulation showed inflated values for these minor features, although the major features were not inflated. As we added more major features to the simulation, we found that the number of choice tasks that were driven by the minor features went down substantially. In turn, the values of those features were depressed as well and approached previously defined known values. Because we simulated data, we avoided consumer behavior biases (like focalism) yet still found an inflation of estimates of minor features. This only furthers our conviction. CBC studies that omit major features cause many decisions in the survey to be driven solely by minor features, thereby inflating those features.

Second, when presented with features that are minor (i.e., not really used in a real-life decision context), a consumer will overweigh those attributes because her attention will be drawn to them.[165] This phenomenon is called "focalism."[166] In effect, when a consumer is told about features that he otherwise would not consider in buying a product, he tends to overweigh the importance of those features in a choice task.[167]

As one conjoint expert puts it:

> Evaluation tasks intentionally force respondents to attend to attributes that they might otherwise not notice. In doing so, attention can elevate the importance of particular attributes to a level that is greater than would occur in the marketplace. For example, featuring the attribute "surge protector" may make this attribute salient even though it may not be salient in actual choices. . . . Simply mentioning an attribute increases its importance, raising the specter of attributes appearing important that otherwise would be ignored in the market choices.[168]

For example, in the task above, many consumers will have never thought about whether they prefer a watch that has an engraving on the back. However, when they are presented with an option to have an engraving, they are more likely to pay attention to the feature in a way that they otherwise would not in a real choice task.

This is a natural consequence of limiting features and having to value ostensibly minor features for patent infringement and misleading advertising cases. However, the phenomenon is made much worse when these minor features are included at the expense of major ones being omitted. In the misleading labeling examples above, most of the studies focused on showing respondents the "100% Natural" language or some variant thereof. When it is the only feature presented (or just one of a few), consumers will focus their

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165. *See* David A. Schkade & Daniel Kahneman, *Does Living in California Make People Happy? A Focusing Illusion in Judgments of Life Satisfaction*, 9 PSYCH. SCI. 340, 345 (1998) (showing that citizens rate their cities higher on metrics that are easily observable and their attention is focused on those features that are presented to them on a daily basis); *see also* Paul Dolan & Robert Metcalfe, *'Oops. . .I Did It Again': Repeated Focusing Effects in Reports of Happiness*, 31 J. ECON. PSYCH. 732, 735 (2010) (finding that having respondents focus on certain features of a soccer game changed their forecasts of happiness of future soccer games); David M. Sanbonmatsu et al., *Overestimating the Importance of the Given Information in Multiattribute Consumer Judgment*, 13 J. CONSUMER PSYCH. 289, 297 (2003) (showing that consumers overvalue presented attributes leading to evaluations that are overly extreme).

166. *See* Timothy D. Wilson et al., *Focalism: A Source of Durability Bias in Affective Forecasting*, 78 J. PERS. SOC. PSYCH. 821, 821 (2000) (explaining focalism as a phenomenon whereby people focus too much on present events as opposed to future events).

167. *See* Elizabeth W. Dunn, Timothy D. Wilson & Daniel T. Gilbert, *Location, Location, Location: The Misprediction of Satisfaction in Housing Lotteries*, 29 PERS. SOC. PSYCH. BULL. 1421, 1424–25 (2003) (finding that students rated their preferences of housing based upon highly variable physical features that were presented to them rather than nonpresented more-social features); *see also* Rebuttal Expert Report of David Reibstein, *supra* note 118, at *111.

168. Huber, *supra* note 62, at 2, 10.

attention on that feature and therefore will express a stronger preference for it than they otherwise would in a real-life setting.

Third, many times, features at issue in patent infringement cases are not readily known to consumers. They are simply not aware of the dynamics of the particular feature at issue or maybe that the feature even exists. For example, in *Apple v. Samsung*, one feature at issue was the form of the spell check that the iPhone employs.[169] Very few, if any, customers are aware of the particular spell check software on their phone.[170] They know they have one, and that is about all.[171] Of course, when trying to value spell check in a CBC, that feature and its nuances must be included. In turn, consumers will seem to make decisions on features that they were not aware of before the survey started. This phenomenon is exacerbated when the majority of features presented in a conjoint are minor and less known. So not only is attention drawn to these features, but also consumers start utilizing these minor features in a way that they never would in a realistic setting because there was no awareness of them in the first place.[172]

These three effects (the forcing of a binary choice, focalism, and lack of awareness) lead the valuations of included minor features to be biased upwards when major features are omitted from a CBC. Little work has sought to show this phenomenon in both the legal and the marketing context. Below, we introduce a novel CBC experiment, field the experiment, and analyze it to empirically show that omitting major features causes the estimated WTP for minor features to be biased upwards.

169. *See* Apple Inc. v. Samsung Elecs. Co., 816 F.3d 788, 806 (Fed. Cir. 2016), *vacated in part on en banc reh'g*, 839 F.3d 1034 (Fed. Cir. 2016).

170. *See* Farhad Manjoo, *Yes, Ill Matty You: How Your Cell Phone's Autorcorrect Software Works, and Why It's Getting Better*, SLATE (July 13, 2010), https://slate.com/technology/2010/07/how-your-cell-phone-s-autocorrect-software-works-and-why-it-s-getting-better.html.

171. *See id.*

172. *See* Rebuttal Expert Report of David Reibstein, *supra* note 118, at *112–13 ("Including features that customers are not currently aware of may not be a problem in every conjoint analysis. Such an approach is necessary with new products or products with new attributes in which survey respondents have not yet had real world experience in the marketplace. This deviation from reality is justified where respondents will be exposed to marketing or other communication such that at some point in the future the consumers are expected to be as informed about the product features as the survey respondents were when completing the exercises. . . . In this case, however, the patented features are not unknown because they are new, but rather because they are minor features that the companies marketing the products and others evaluating the products consider relatively unimportant. As such, there is no expectation that the awareness of these features would change if the patented features were unavailable and design-around alternatives were offered instead. Simply put, consumers in the actual market can only react to information that they are aware of, and my review suggests that very few would be aware of the patented features.")

### B. *A Novel Empirical Example of Problematic CBC Analysis*

#### 1. *Overview of Study*

In the following study, we attempt to show that when a CBC omits major features and includes mostly minor ones, the WTP estimates of those minor features are biased upwards. We attempt to mirror as much as possible how CBCs are fielded in legal settings, with the hope to show that many of the damage awards that have relied upon CBC analysis by experts have been inflated for the included minor features.

In order to show this inflation, we have to experimentally field two randomized CBC studies and compare the results of each.[173] In one CBC, we chose four major features and two ostensibly minor features (we discuss how we chose them below). In effect, we treat these two minor features like the features at issue in a patent infringement or misleading labeling context.

In our second CBC, we include these same two minor features and omit three of the major ones, replacing them with other minor features. This second CBC study represents exactly what many experts are testifying is appropriate science.[174]

If omitting major features does not inflate the estimated willingness to pay for the included minor features, then both CBC studies should show similar estimates of the minor features that are the same across the studies.[175]

However, what we find is that the estimated willingness to pay for the two minor features, consistent across both of the studies, is statistically significantly higher for the study in which the major attributes are omitted. We describe below in detail our stimuli, sample, procedure, model, analysis, and results.

#### 2. *Product Stimuli*

For our experiment, we chose cars as our product of study. We did this for a variety of reasons. First, most consumers above the age of eighteen have at least some experience with cars: buying a car, selling a car, driving a car, or at least riding in a car. In this way, many consumers are aware of cars and

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173. As we describe further below, we use a between-subjects design and randomly assign respondents to one of two CBC studies.

174. Reibstein & Vigil, *supra* note 163.

175. Although these are two separate CBC studies with different respondents, we note that we randomize the assignment of each respondent to each CBC. Therefore, even though the people differ between the conjoint studies, and hence individual preferences might be different, the overall preferences when averaged out should be the same across both studies, provided there is no bias. This is a standard assumption of experimental designs that seeks to find differences between two samples. *See* Paul E. Green & V. "Seenu" Srinivasan, *Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice*, 54 J. MKTG. 3, 12 (1990). If the differences are so large (relative to the standard deviation), then we can conclude the differences are not by chance. *Id.* at 13. This is exactly what we find below.

understand the various features associated with cars. This is an important factor in our study because, if we focused on products or features consumers did not have experience with, our results may not be valid.

Second, determining what consumers value in a car is a relatively easy task. There are several manufacturer websites, blogs, used car searches, and rental car websites that describe cars with a wide range of features.[176] When one searches for a car or attempts to "build a car" on a website, the features that a consumer can choose from provide us some guidance in choosing major versus minor features.

Third, we use cars because judges in patent infringement cases have alluded to car decision-making as an easy way to understand how a CBC study is designed and how it is used to estimate WTP.[177]

Lastly, cars have been used extensively in other conjoint studies and, as such, have been validated as a useful product category to study the effects of conjoint design.[178]

Using publicly available information from autotrader.com, consumerreports.org, and J.D. Power and Associates' rankings on cars, we chose four car features that seemed to be important (major features) in the marketplace.[179] These major features were the price of a car, the manufacturer or brand, the miles per gallon of a car, and the vehicle type. Each of these features had three levels.[180]

We also chose five attributes that seemed to be relatively unimportant (minor features) for consumers when making decisions. These minor features

176. *See, e.g.*, TOYOTA, https://www.toyota.com (last visited Sept. 12, 2021); *2021 Best Cars for the Money*, U.S. NEWS, https://cars.usnews.com/cars-trucks/best-cars-for-the-money (last visited Sept. 12, 2021); *My Car's Value*, KELLEY BLUE BOOK, https://www.kbb.com/whats-my-car-worth/ (last visited Sept. 12, 2021); Matt DeLorenzo, *5 Tips on Buying a Used Rental Car*, KELLEY BLUE BOOK, (June 23, 2020), https://www.kbb.com/car-news/5-tips-on-buying-a-used-rental-car/.

177. *See, e.g.*, Apple Inc. v. Samsung Elecs. Co., 735 F.3d 1352, 1368 (Fed. Cir. 2013) ("This is not to suggest that consumers' willingness to pay a nominal amount for an infringing feature will establish a causal nexus. For example, consumers' willingness to pay an additional $10 for an infringing cup holder in a $20,000 car does not demonstrate that the cup holder drives demand for the car. The question becomes one of degree, to be evaluated by the district court.").

178. *See, e.g.*, Olson, *supra* note 18, at 174–78; Wann Yih Wu, Ying Kai Liao & Anon Chatwuthikrai, *Applying Conjoint Analysis to Evaluate Consumer Preferences Toward Subcompact Cars*, 41 EXPERT SYS. WITH APPLICATIONS 2782 (2014); Green & Srinivasan, *supra* note 175.

179. When visiting the J.D. Power and Associates ranking website, the first thing consumers see are categories of cars including various brands, types of cars, performance ratings, depreciation ratings, and customer service ratings. J.D. POWER, https://www.jdpower.com (last visited Sept. 12, 2021). In addition, when visiting autotrader.com, the first set of search options include: price, vehicle type, year, brand, mileage, and fuel economy. AUTOTRADER, https://www.autotrader.com (last visited Sept. 12, 2021).

180. For brands, we chose Ford, Toyota, and Volkswagen. For MPG, we chose thirty, forty, and fifty miles per gallon. For price, we chose $20K, $30K, and $40K. For vehicle type, we chose a coupe (two door sports car), a sedan, and an SUV.

were the number of cup holders, the location of the gas cap, the clock style, the door-handle type, and whether the car had coin slots.[181]

In choosing these minor features, we attempted to choose features that we think do not play a large role in the decision to buy a car for most consumers.[182] Since many patented features and misleading labels at issue in litigation implicate minor features,[183] we wanted our minor features to closely parallel legal cases. We contend that, for the most part, these minor features are objectively minor relative to the major features we chose. In addition, we attempted to choose features that would stand independent of each other.[184] Again, we suspect that most consumers have some preference on the minor features, yet *in reality* it is the major features that drive their decisions.

*3. The Two CBC Studies*

Once we decided on our stimuli, we had to design two separate conjoint studies. To do this we created what we define as an important conjoint (IMP) and subsequently an unimportant conjoint (UMP). The IMP conjoint represents a design that includes major features and a few minor ones of interest. The UMP conjoint represents a problematic design that omits several major features, and mostly includes minor features.

There are two minor features that are consistent across both the IMP conjoint and the UMP conjoint studies: the number of cup holders and the gas cap location. If we are correct in our criticism of the application of CBC to legal cases, then we should see the WTP estimates for cup holders and gas cap location inflated in the UMP conjoint in comparison to their estimates in the

181. For cup holders we chose three orientations: one, two, or four cup holders. Gas cap represented which side of the car gas was pumped into; we chose either the passenger side of the car or the driver side. Clock style represented how the time was presented on the dashboard of the car; we chose three orientations: a digital clock, an analog clock, or a combined digital and analog clock. Handle type represented how the door handle to each door was designed. There, we chose a flat handle (similar to the Tesla door handle), a bottom handle which is a handle one must reach under to open, and a top handle which is one that can be grabbed from above. Lastly, we chose how many coin slots the car dashboard had: one or two. A coin slot is a device that allows a driver to hold a few quarters for easy access.

182. There is, of course, heterogeneity to some degree in the sample we use. However, given that we are using a random experimental design, we think this heterogeneity does not affect our results.

183. *See* Reibstein & Vigil, *supra* note 163.

184. In effect, we did not want any of the features presented to interact with each other. This is an important point, and we did perform a post hoc test for interaction effects and did not find any statistically significant ones. Interaction effects are important because they can cause estimates to be biased upwards or downwards depending on the relationship among various features. For example, if consumers assume that a higher priced car has better cup holders than a cheaper car, this might influence the WTP for cup holders in our study. In our studies, we have specifically chosen features that we have no prior reason to believe will suffer from interaction effects. If, instead, we had chosen a feature like leather seats, we might reasonably hypothesize that people would think a higher priced car or a more luxuriously branded car would have better leather seats. This would make interpreting our results more difficult. For extended discussions on how conjoint analysis estimates are affected by interaction effects, see Green, *supra* note 12; Bradlow & Marshall *supra* note 20; Bradlow, Hu & Ho, *supra* note 96; Joseph W. Alba & Alan D.J. Cooke, *When Absence Begets Inference in Conjoint Analysis*, 41 J. MKTG. RES. 382 (2004); Huber & McCann, *supra* note 62.

IMP conjoint. This would mean that when major features are omitted from a conjoint design (as they are in many legal cases) in order to estimate a relatively minor feature, those minor feature estimates are inflated.

Table 1 below shows the car features we use and their respective levels. It also shows which features we used for each of our conjoint studies. Appendix 1 reproduces the photos of each of the features we showed respondents so that respondents were informed about the various features presented.

**Table 1: Attributes and Levels for CBC Experiment**

| Attribute | Levels | Important/ Unimportant | Conjoint |
|---|---|---|---|
| Price | $20K<br>$30K<br>$40K | Important | IMP & UMP |
| Brand | Ford<br>Toyota<br>Volkswagen | Important | IMP |
| Miles Per Gallon (MPG) | 30<br>40<br>50 | Important | IMP |
| Vehicle Type | Coupe<br>Sedan<br>SUV | Important | IMP |
| Cup Holders | One<br>Two<br>Four | Unimportant | IMP & UMP |
| Gas Cap Location | Passenger side<br>Driver side | Unimportant | IMP & UMP |
| Clock Style | Analog<br>Digital<br>Analog & Digital | Unimportant | UMP |
| Handle Type | Flat<br>Bottom<br>Top | Unimportant | UMP |
| Coin Slot | None<br>One<br>Two | Unimportant | UMP |

### 4. *Sample*

We used Amazon Mechanical Turk to recruit respondents to field our CBC studies. Amazon Mechanical Turk is an online marketplace that allows businesses and individuals to quickly coordinate with human subjects to perform tasks.[185] This includes fielding surveys and other empirical studies for many social scientists.[186] Thousands of articles from disciplines including psychology, sociology, marketing, management, political science, and the law have utilized Mechanical Turk samples.[187] Mechanical Turk Respondents have been shown to be just as reliable as laboratory experiments in most cases.[188] Using this online marketplace produces reliable and valid results and has become a norm in social science.[189]

We recruited a sample of 752 (n=396 for IMP Conjoint and n=356 for UMP Conjoint) respondents and paid each at a rate of $1 per ten minutes of their time, which is the going rate for Mechanical Turk surveys.[190] Our sample was 58% male, had an average age of 35, and had an average income of between $45,000 and $65,000. Eighty-six percent of the sample indicated that they used their personal car "often" or "somewhat often."

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185. AMAZON MECHANICAL TURK, https://www.mturk.com (last visited Sept. 12, 2021).

186. AMAZON MECHANICAL TURK WORKER, https://www.mturk.com/worker (last visited Sept. 12, 2021).

187. Thousands of articles have used Amazon Mechanical Turk and currently do. The following is a nonexhaustive list of articles that used the online marketplace specifically for conjoint studies: Thomas H. Stevens, Aaron K. Hoshide & Francis A. Drummond, *Willingness to Pay for Native Pollination of Blueberries: A Conjoint Analysis*, 2 INT'L J. AGRIC. MKTG. 68 (2015); Karoline Mortensen & Taylor L. Hughes, *Comparing Amazon's Mechanical Turk Platform to Conventional Data Collection Methods in the Health and Medical Research Literature*, 33 J. GEN. INTERNAL MED. 533 (2018); Kirk Bansak et al., *The Number of Choice Tasks and Survey Satisficing in Conjoint Experiments*, 26 POL. ANALYSIS 112 (2018); Cindy Wu et al., *What Do Our Patients Truly Want? Conjoint Analysis of an Aesthetic Plastic Surgery Practice Using Internet Crowdsourcing*, 37 AESTHETIC SURGERY J. 105 (2017); Yu Pu & Jens Grossklags, *Using Conjoint Analysis to Investigate the Value of Interdependent Privacy in Social App Adoption Scenarios* (Thirty Sixth Int'l Conf. on Info. Sys., Completed Rsch. Paper, 2015).

188. *See* Leib Litman, *Strengths and Limitations of Mechanical Turk*, CLOUDRESEARCH, https://www.cloudresearch.com/resources/blog/strengths-and-limitations-of-mechanical-turk/ (last visited Sept. 12, 2021).

189. *See* Michael Buhrmester, Tracy Kwang & Samuel D. Gosling, *Amazon's Mechanical Turk: A New Source of Inexpensive, Yet High-Quality, Data?*, 6 PERSPS. ON PSYCH. SCI. 3, 5 (2011) (arguing that Amazon Mechanical Turk respondents are more diverse and the data obtained is just as reliable as more traditional methods); Frank Bentley, Nediyana Daskalova & Brooke White, *Comparing the Reliability of Amazon Mechanical Turk and Survey Monkey to Traditional Market Research Surveys* (CHI'17 Extended Abstracts, 2017) (discussing the reliability of traditional marketplace consumer research versus Amazon Mechanical Turk).

190. *See* Kotaro Hara et al., *A Data-Driven Analysis of Workers' Earnings on Amazon Mechanical Turk*, 2018 ACM DIGIT. LIBR. (Apr. 2018), https://doi.org/10.1145/3173574.3174023.

### 5. *Design and Procedure*

To design and field the conjoint studies, we used Sawtooth Lighthouse Software.[191] Sawtooth is a widely recognized company that provides software for companies and researchers to build and field surveys. In particular, the company has developed somewhat of an expertise in CBC studies.[192] Many of the experts in patent infringement and misleading labeling cases have used and continue to use Sawtooth software to design, field, and analyze their conjoint studies.[193]

In designing a conjoint, there are three major choices to make. First, what are the features and levels of those features for the product of study? We discussed those above. Second, how many product profiles will respondents see for each choice task? In both of our conjoint studies, we used three car profiles and a none option (i.e., the respondents could choose one of the three products we presented, or indicate that they would choose none). Third, how many choices will respondents make? Too many choices leads to unreliable results because respondents get fatigued and stop caring.[194] Too few give a researcher too little information to draw nuanced insights. We decided upon giving respondents fourteen choices to make, which was the recommended number in the software.

Once these decisions are made, Sawtooth Software creates a balanced fractional factorial design of choices. In doing this, the software calculates the best way to present products given the number of features and levels we designated so as to maximize the information gained from the least number of choices.[195]

191. For details on the software licensing and technical details, see SAWTOOTH SOFTWARE, https://www.sawtoothsoftware.com/ (last visited Sept. 18, 2021).

192. Sawtooth has become the main resource for experts in economic damages lawsuits. *See* PROCEEDINGS OF THE SAWTOOTH SOFTWARE CONFERENCE 3 (2016). In addition, Sawtooth publishes white papers on best practices in conjoint analysis with the assistance of marketing scholars, economists, statisticians, and business practitioners. For a sample of these white papers, see Eggers et al., *supra* note 82; Martin Meissner, Harmen Oppewal & Joel Huber, *How Many Options? Behavioral Responses to Two versus Five Alternatives Per Choice*, *in* PROCEEDINGS OF THE SAWTOOTH SOFTWARE CONFERENCE 19 (2016); Karen Buros & Jeremy Christman, *What a Difference Design Makes*, *in* PROCEEDINGS OF THE SAWTOOTH SOFTWARE CONFERENCE 315 (2016); Jeroen Hardon & Marco Hoogerbrugge, *Preferences Based Conjoint: Can it Be Used to Model Markets with Many Dozens of Products*, *in* PROCEEDINGS OF THE SAWTOOTH SOFTWARE CONFERENCE 87 (2018).

193. *See, e.g.*, Apple, Inc. v. Samsung Elecs. Co., No.: 12-CV-00630, 2014 WL 794328, at *16 (N.D. Cal. Feb. 25, 2014).

194. Richard M. Johnson & Bryan K. Orme, *How Many Questions Should You Ask in Choice-Based Conjoint Studies?*, SAWTOOTH SOFTWARE RSCH. PAPER SERIES, at 7 (1996), https://sawtoothsoftware.com/resources/technical-papers/how-many-questions-should-you-ask-in-choice-based-conjoint-studies (finding that researchers can ask respondents to make up to twenty choices without seeing a degradation of results).

195. For a detailed discussion of fractional factorial design, see sources cited *supra* note 85.

Once we recruited respondents via Amazon Mechanical Turk, they were randomly directed to one of two Sawtooth-designed CBCs: the IMP conjoint or the UMP conjoint.

Instructions on the home page informed respondents that they would be making choices between several cars and that they should pay attention to the features and attributes presented to them. After this page, respondents going through the IMP conjoint study received detailed information about each of the six attributes and their levels that we chose in the IMP conjoint (Appendix 1 reproduces these images and descriptions). Those in the UMP conjoint study received detailed information about each of the six attributes and their levels that we chose for the UMP conjoint.

At the end of these information pages, respondents were told that they would be presented with fourteen choices, each among three cars and one "none" option, and they should choose the car they preferred the most. If they did not prefer any, they should choose the "none" option. Most importantly, they were told that "aside from the features presented in the study, all other features of each of the cars were the same"—standard instructions for a CBC study.[196]

Once they started, the choices on each page consisted of three car profiles and one "none" option and asked respondents: "If these were your only options for a car, which would you choose? All other features of the cars are the same."[197] Appendix 2 shows a sample of a choice set that a consumer might see in the IMP conjoint and in the UMP conjoint. We programmed the survey so that at any point, consumers could hover their mouse over the particular feature and its level and see a photo of it. We did this because it helps respondents remember what each feature refers to and also increases the realistic aspect of the survey.[198]

The respondents then went through their assigned fourteen-choice sets. Finally, the respondents answered some demographic questions about their gender, age, ethnicity, and experience buying and driving cars.

### 6. *Model*

We analyzed our results from each of the conjoint studies separately with the intention of comparing the WTP estimates of each of the two minor attributes we held constant across the studies. To estimate a WTP, we first had

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196. *See* Eggers, Hauser & Selove, *supra* note 82, at 17.

197. This so-called *ceteris paribus* language (making sure that respondents know that all other nonpresented attributes are the same across profiles) is said to control for the omission of various major attributes. It is a staple of choice-based conjoint design. *See generally id.* However, we show that even with this language, omitting features does bias the valuations of included minor features upwards.

198. *See id.* at 5 (explaining that using images as opposed to just text creates more realistic choice tasks and hence increases external validity).

to estimate part worth utilities[199] for each of the feature levels for both conjoint studies.

To estimate part worth utilities for our various features, we assume that consumers make decisions with the following random utility model[200]:

$$U_{ik} = V_{ik} + \varepsilon_{ik}$$

Where $U_{ik}$ is the utility derived by individual *i* for a given product, $V_{ik}$ is the deterministic part of the utility from profile *k*, and $\varepsilon_{ik}$ is the random component of *i*'s utility for product *k*. The deterministic part of utility simply means the utility that the actual product gives to a consumer that is explainable. For example, in buying a smart phone, there is some level of utility that an iPhone gives to a consumer because of its features and functions. However, there is also a random component of utility that represents the unexplainable part of a product's utility. Researchers can never understand "all facets of behavior germane to particular behavioral outcomes of interest."[201] Therefore, we assume some randomness in the decision to buy a product.

We can further express $V_{ik}$ as:

$$V_{ik} = \sum B_{jk} x_{jk}$$

Where $V_{ik}$ is the value of the product k for individual *i*, $x_{jk}$ is the value of the feature j for product *k*, and $B_{jk}$ is the utility weight placed on feature j for product k for individual *i*. In simple terms, this means that we assume the observable utility that a consumer gets from a product is equal to the sum of the value of each of the features that describe the product. The values of each feature ($B_{jk}$) then become the exact parameters we hope to estimate. These feature values are part worth utilities.[202]

199. For a discussion of part worth utilities, see *supra* Part II.B.

200. This model has been popularized in both conjoint studies as well as other choice modelling studies. It was originally popularized by Daniel McFadden and has been used subsequently in several empirical choice modeling contexts. *See generally Structural Analysis of Discrete Data and Econometric Applications*, *in* STRUCTURAL ANALYSIS OF DISCRETE DATA AND ECONOMETRIC APPLICATIONS 198–272 (Charles F. Manski & Daniel L. McFadden eds., 1981); George Baltas & Peter Doyle, *Random Utility Models in Marketing Research: A Survey*, 51 J. BUS. RSCH. 115, 115–16 (2001); Greg M. Allenby & Peter E. Rossi, *Marketing Models of Consumer Heterogeneity*, 89 J. ECONOMETRICS 57, 59 (1998); P. B. Seetharaman, *Modeling Multiple Sources of State Dependence in Random Utility Models: A Distributed Lag Approach*, 23 MKTG. SCI. 263, 264 (2004); Naresh K. Malhotra, *The Use of Linear Logit Models in Marketing Research*, 21 J. MKTG. RSCH. 20, 21 (1984).

201. Jordan Louviere et al., *Dissecting the Random Component of Utility*, 13 MKTG. LETTERS 177, 181 (2002).

202. While this is a common model of choice, we note that there is a newer, less used model called the surplus model. In the surplus model, rather than estimating part worths and then using those part worths to calculate a willingness to pay with respect to the price feature part worth, we could incorporate a WTP within the model itself. This so-called surplus model takes the form: $S_{ij}\left(q_j, p(q_j)\right) = WTP_{ij}(q_j) - p(q_j) + \varepsilon_{ij}$ where $p(q_j)$ is the price associated with $q_j$ units of product *j* and $WTP_{ij}(q_j)$ represents the WTP that consumer *i* associated with $q_j$ units of product *j*. This models directly the price premium (WTP) of an attribute. For an application of the surplus method to conjoint data, see Raghuram Iyengar & Kamel

Most modern conjoint analysis uses Hierarchical Bayes estimation to estimate these part worths and we follow suit.[203] Hierarchical Bayes allows for the estimation of part worths accounting for heterogeneity in consumer preferences.[204] To do this, we assume that the individual consumer part worths follow a multivariate normal distribution of the following form:

$$B_i \sim N(\alpha, D)$$

Where $B_i$ is a vector of utility part worths for individual *i*, $\alpha$ is a vector of means of the distribution of individual part worths and $D$ is the matrix of variances and covariances of the distribution of part worths across individuals.

We also assume the following multinomial logit model[205] for predicting which profile in each task a consumer will choose:

$$P_{ik} = e^{V_{ik}} / \sum_{k=1}^{j} e^{V_{ik}}$$

Where $P_{ik}$ is the probability of individual *i* choosing product *k*, and *j* represents the number of alternative products in the choice context.

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Jedidi, *A Conjoint Model of Quantity Discounts*, 31 MKTG. SCI. 334, 336 (2012); ROBERT WILSON, NONLINEAR PRICING (1993).

203. For sample papers that have used Hierarchical Bayes in estimating part worths in a conjoint setting, see Peter E. Rossi & Greg M. Allenby, *Bayesian Statistics and Marketing*, 22 MKTG. SCI. 304 (2003); Peter J. Lenk et al., *Hierarchical Bayes Conjoint Analysis: Recovery of Partworth Heterogeneity from Reduced Experimental Designs*, 15 MKTG. SCI. 173 (1996); Kenneth Train, A Comparison of Hierarchical Bayes and Maximum Simulated Likelihood for Mixed Logit (June 18, 2001) (unpublished manuscript), https://eml.berkeley.edu/~train/compare.pdf; Bryan Orme & Gary Baker, *Comparing Hierarchical Bayes Draws and Randomized First Choice for Conjoint Simulations*, *in* PROCEEDINGS OF THE SAWTOOTH SOFTWARE CONFERENCE 239 (2000).

204. Most simply, the statistical method allows us to estimate a unique part worth for each individual in our sample. If we did not use a Hierarchical Bayes estimation procedure, we would simply have to estimate one part worth for our whole sample. This of course would ignore the fact that people are different and that they have different preferences. So, the Hierarchal Bayes method allows us to use both the individual observations we have from our respondents and aggregate observations we have from all our respondents to calculate a unique part worth for each feature for each individual. For a more detailed technical discussion of the method, its assumptions, and implementation, see Greg M. Allenby & Peter E. Rossi, *Hierarchical Bayes Models*, *in* HANDBOOK OF MARKETING RESEARCH: USES, MISUSES, AND FUTURE ADVANCES 418 (Rajiv Grover & Marco Vriens eds., 2006); see also Jeffrey N. Rouder & Jun Lu, *An Introduction to Bayesian Hierarchical Models with an Application in the Theory of Signal Detection*, 12 PSYCHONOMIC BULL. & REV. 573 (2005).

205. A multinomial logit model is a common model that is used to analyze choice data. Generally, if a researcher has collected data that has a continuous dependent variable a linear regression can be used. However, when we have choice data (a binary dependent variable), a more accurate way to analyze it is to use a logit. The multinomial logit equation above most simply means that when consumers see the three product choices in our conjoint studies, the probability of a consumer choosing any one of the products over the others is equal to the ratio of utilities of the product to the sum of the utilities of the other products. For a more detailed technical discussion of the multinomial logit model, see Guadagni & Little *supra* note 78; *see also* Raymond J. Adams, Mark Wilson & Wen-chung Wang, *The Multidimensional Random Coefficients Multinomial Logit Mode*l, 21 APPLIED PSYCH. MEASUREMENT 1, 2 (1997); Joffre Swait & Jordan Louviere, *The Role of Scale Parameter in the Estimation and Comparison of Multinomial Logit Models*, 30 J. MKTG. RSCH. 305, 305 (1993).

We are then left with three parameters to estimate $B_i$, $\alpha$, and $D$. To estimate these parameters, we use a Markov Chain Monte Carlo[206] iterative process with conservative starting points equal to zero for all three parameters. We estimate one parameter while holding the other two constant. We estimate another parameter using the values from previous estimates for the other two parameters. Finally, we estimate the third parameter using the values of the previously estimated parameters. We do this over several thousand iterations until our estimates converge. Our estimation converged after 20,000 iterations, and we averaged the utility part worths that were drawn from the iteration process.

*7. Results*

In Table 2 and Table 3 below, we present the part worth utilities for each of the CBC studies we fielded. The part worth utilities we see here represent the value that the respective features and their levels add to the total value of the product. The higher the value of the part worth, the higher the utility of the feature, and therefore the more that feature figures into the decision-making process.

Part worths are meant to be interpreted as changes in utility from one level of a feature to another. For example, in the IMP conjoint, having a car that gets 40 MPG, as opposed to 30 MPG, increases the utility of the product by 1.04 (0.15–[–0.89]). Negative values should be interpreted as a less desired level of a feature. So, unsurprisingly, in both conjoint studies the utility is highest for the $20,000 feature level and lowest (most negative) for the $40,000 feature level. This simply means that consumers in both conjoint studies prefer a car that is cheaper to one that is more expensive.

We present two versions of estimated part worths. First, we present raw part worth utilities. These are simply the exact utilities that the estimation procedure produces. In addition, we present the median value of the distribution of part worths. The Hierarchical Bayes estimation calculates a unique part worth for each individual person. This is the benefit of using this estimation procedure, as opposed to others that just give one global part worth value.[207]

The difficulty is determining what to do with the distribution of part worths. In order to estimate a willingness to pay (as court cases necessitate), one value has to be agreed upon. Using the mean is potentially problematic because it can easily be skewed by individual part worths that are extreme on either end of the spectrum. As such, the norm in a CBC that calculates a

206. For an introduction to the Markov Chain Monte Carlo iterative process, see Don van Ravenzwaaij, Pete Cassey & Scott D. Brown, *A Simple Introduction to Markov Chain Monte-Carlo Sampling*, 25 PSYCHONOMIC BULL. & REV. 143 (2018).

207. *See* Rouder & Lu, *supra* note 204, at 577.

distribution of part worths is to use the median part worth to calculate a WTP, and we follow suit.[208]

In the tables below, the grey cells represent the part worth values of the two minor features that are held constant across both of the conjoint studies.

**Table 2: IMP Conjoint Estimated Part Worths**

| **Attribute** | **Level** | **Raw Part Worth (Median)** | **Zero Centered Part Worth (Median)** |
|---|---|---|---|
| Price | $20,000 | 0.91 | 55.53 |
| | $30,000 | 0.15 | 8.35 |
| | $40,000 | -1.14 | -66.29 |
| Miles Per Gallon | 30 MPG | -0.89 | -53.25 |
| | 40 MPG | 0.15 | 8.67 |
| | 50 MPG | 0.72 | 42.47 |
| Car Type | Coupe | -0.49 | -33.87 |
| | Sedan | 0.21 | 12.70 |
| | SUV | 0.36 | 22.50 |
| Brand | Ford | -0.04 | -2.67 |
| | Volkswagen | -0.27 | -16.21 |
| | Toyota | 0.28 | 16.67 |
| Cup Holders | 1 Cup Holder | -0.36 | -21.60 |
| | 2 Cup Holders | 0.08 | 4.28 |
| | 4 Cup Holders | 0.34 | 19.91 |
| Gas Cap Location | Passenger Side | -0.07 | -4.61 |
| | Driver Side | 0.07 | 4.61 |

**Table 3: UMP Conjoint Estimated Part Worths**

| **Attribute** | **Level** | **Raw Part Worth (Median)** | **Zero Centered Part Worth (Median)** |
|---|---|---|---|
| Price | $20,000 | 1.10 | 74.74 |
| | $30,000 | 0.20 | 12.33 |
| | $40,000 | -1.53 | -91.13 |
| Cup Holders | 1 Cup Holder | -0.74 | -45.41 |
| | 2 Cup Holders | 0.07 | 4.16 |
| | 4 Cup Holders | 0.68 | 38.86 |

208. *See* Allenby et al., *supra* note 11, at 651 (commenting on whether to use the mean or median part worth when a distribution of part worths is estimated: "However, there is no compelling reason to prefer the mean over any other scalar summary of the distribution of WTP. Some propose using a median value of WTP instead.").

| | | | |
|---|---|---|---|
| Gas Cap Location | Passenger Side<br>Driver Side | -0.26<br>0.26 | -15.49<br>15.49 |
| Door Handle Type | Flat Handle<br>Bottom Handle<br>Top Handle | -0.57<br>0.20<br>0.39 | -33.3<br>10.52<br>23.57 |
| Coin Slot | None<br>1 Coin Slot<br>2 Coin Slots | -0.089<br>-0.091<br>0.19 | -5.58<br>-5.47<br>10.92 |
| Clock Style | Digital<br>Analog<br>Digital & Analog | 0.25<br>-0.47<br>0.21 | 15.1<br>-27.91<br>12.16 |

If omitting major attributes (like we do in the UMP conjoint) does not bias the included minor features (cup holders and gas cap location), the estimated WTP for each of the two features should be relatively the same across both conjoint studies. To determine this, we calculate a WTP using the ratio of the price part worth and the feature part worths.

For the IMP conjoint, we calculate the dollar value for one utility point. To do this, we take the difference in part worths between $20,000 and $40,000 (55.53–[–66.29])=121.82 and then divide this difference by the price difference ($20,000/121.82)=$164.17/util. Once we have a dollar per util value, we can simply multiply this by the feature levels that we are interested in. So if we want to know the value (i.e., the consumer WTP) of 2 cup holders versus 1 cup holder, we simply multiply the $164.17/utils*(4.28–[–21.60])utils=$4,248, which represents how much consumers in our sample are willing to pay to have one more cup holder in their car.

We do the same procedure for the UMP conjoint in calculating the dollar per util ($20,000/(74.74–[–91.13])=$120.58/util. With this value, we can again calculate how much consumers in our sample are willing to pay for one more cup holder in our UMP conjoint.

Table 4 presents the WTP for the minor features that we held constant across both the IMP and UMP conjoint studies.

**Table 4: WTP Estimates from IMP/UMP Conjoint Studies**

| **Attribute** | **WTP IMP Conjoint** | **WTP UMP Conjoint** |
|---|---|---|
| 1 to 2 Cup Holders | $ 4,248.89 | $ 5,976.97 |
| 2 to 4 Cup Holders | $ 3,971.43 | $ 5,187.19 |
| 1 to 4 Cup Holders | $ 6,814.97 | $ 10,160.97 |

| | | |
|---|---|---|
| Passenger Side to Driver Side | $ 1,510.43 | $ 3,735.46 |

What we notice here is that the WTP for cup holders and gas cap location is drastically (statistically significantly)[209] higher in the UMP conjoint than in the IMP conjoint. The WTP for four versus one cup holder is 150% higher in the UMP conjoint than in the IMP conjoint. Even more shocking is that the WTP to move a gas cap from the passenger side to the driver side is more than 200% higher in the UMP conjoint. If only including minor features in a conjoint (as the UMP does) is not problematic, as many experts seem to contend and courts seem to agree with,[210] the differences in WTP for these minor features would not be so large.

Of course, this difference occurs precisely because the UMP conjoint omitted major features and only included a set of minor features. This is exactly what CBCs are doing in the legal context. By designing these conjoint studies to omit major features like brand, color, size, etc., court-approved conjoint studies are inflating the WTP of those included features.

Our UMP conjoint represents exactly the forms of the CBCs that we describe above. Omitting major features in order to value many ostensibly minor features at the same time is inflating the value of these minor features. When the WTP is inflated, the damage awards are in turn also inflated as they rely directly upon the WTP calculation.

We note that our IMP conjoint also likely inflates the WTP for cup holders and gas cap location. We find it hard to believe that consumers would be willing to pay $1,500 to move the gas cap from one side of the car to another. We believe this is the case because so many other important features are still missing from both conjoint studies. No CBC can ever exactly mimic reality and produce completely valid results. However, the more major attributes that are included in a CBC, the more valid the WTP estimates become. As such, our WTP estimates from IMP conjoint likely match reality more than the ones from the UMP conjoint.

In terms of litigation, we advise courts, litigants, and experts to heavily police the omission of major attributes in a CBC study. Although any CBC that is employed is likely going to have some problems, the notion of omitting attributes is shockingly problematic. Our results show that estimates are almost double for some features when major features are omitted. In the patent context, this means that when Apple received over $1 billion in damages that resulted from a CBC that omitted numerous major features, damages might have been less than half of that amount had an appropriate CBC been fielded.

209. We note that the WTP estimates in the UMP conjoint are all significantly higher (at 5% confidence) than the WTP estimates in the IMP conjoint. That is, the differences between the conjoint estimates are significantly different at the 95% confidence level.

210. *See supra* Part III.

In addition, if the expert in *Briseno* had appropriately designed a CBC using major features and including the "100% Natural" label at issue, the estimated WTP of the label might have been drastically smaller, leading a court to deny the certification of the class. If there is such a small, insignificant price premium for the "100% Natural" label, then a court is not likely to certify a full class.[211] Therefore, we think this particular problem of omitting major features has caused several lawsuits to pass the Rule 23 hurdle, when the reality of the matter is that the price premium estimates have been drastically inflated.

### *C. Realigning the Method*

So, what can experts and courts do in the face of this potential bias? We seek to briefly introduce three solutions here but acknowledge that more work needs to be done to better understand how CBCs can be effectively used to measure a WTP of minor features.

First, we observe that the relative preferences of features can be validly estimated even in our UMP conjoint. Notice that in both the UMP and IMP conjoint studies, cup holders had a higher WTP and were more important in the decision-making process than gas cap location.[212] The chosen features do not influence whether a given feature is more important than another feature. If a CBC is only being used to determine whether a feature is more important than another, its application in court cases is perfectly valid.[213] However, as soon as litigants seek to determine *how much more important* a feature is in terms of dollars, then biases of the sort we have identified here creep in.

Second, we recommend that when designing a CBC for patent infringement and misleading labeling applications, major features of the relevant products are always included. These cases generally implicate estimating damages for mostly minor features. In doing this, experts must focus on attempting to include as many major features as possible even if this means having to field several CBCs. For example, in *Apple v. Samsung*, there were several minor patented features that Apple claimed Samsung infringed.[214] The CBC attempted to value all of these features in one study.[215] Of course, given

211. *See In re* ConAgra Foods, Inc., 90 F. Supp. 3d 919, 969 (C.D. Cal. 2015).

212. To get a quick sense that cup holders are more important, we simply look at the range of part worths. The larger the range of part worths, the more important the feature. So, for the IMP and the UMP conjoint studies, price was the most important conjoint, which makes sense with how consumers choose cars in the marketplace.

213. For example, if a researcher knows how much a certain patented feature is worth (either due to the fact that it is currently being licensed or another market drive valuation), a CBC can be used to determine if another patented feature is valued less or more than the feature with the known value. This would not allow for an exact WTP estimate of the feature at issue, but knowing whether it is valued more or less than an existing feature can provide a ceiling or a floor depending on the context.

214. Apple, Inc. v. Samsung Elecs. Co., No. 12-CV-00630, 2014 WL 794328, at *1 (N.D. Cal. Feb. 25, 2014).

215. *See id.* at *13–17.

that there can only be so many features presented to consumers, the expert had to omit major features.

Instead, a better (albeit more expensive) method would be to have run a different CBC for each of the patented features, including only one minor feature at a time. In this way, each CBC could have used the major features of a smartphone and one minor patented feature. This would have likely depressed the estimated values of the patented features to more realistic levels and, in turn, the actual damage amounts.

Third, above we discussed two other forms of conjoint analysis: ranking- and ratings-based. We note that when analyzing choice versus ranking or ratings, there is less information. A CBC only tells a researcher that a consumer prefers one product over another. Ratings, however, inform the researcher exactly *how much* a consumer prefers one product over another. Often, when it comes to minor features, consumers do have a preference but a small one. For example, consumers do prefer a driver-side gas cap over a passenger-side one. With only a CBC analysis, this is all the information a researcher obtains. Therefore, it is more difficult to estimate how much more a consumer prefers a driver-side gas cap versus a passenger-side one. With a ratings-based conjoint study, a consumer tells the researcher exactly how much they prefer a car with a different gas cap location. This increase in information allows for a more accurate estimate of WTP.

As such, we recommend that conjoint studies seek to revert back to ratings-based or rankings-based preference elicitation. This is particularly important for estimating the value of relatively minor features because consumers often have such small preferences for these features relative to ones that are more likely to drive the purchasing decision.

## CONCLUSION

We have sought to do two main things in this Article. First, we hope to unpack the black box of CBC analysis for legal practitioners, as it is an increasingly common method to estimate patent infringement and misleading labeling damages. In doing this, we have highlighted a common problematic practice in the design of CBCs: experts, in the face of attempting to value minor (patented) features, are omitting major (nonpatented) ones when designing a CBC. Although this seems consistent with the spirit of apportionment, we argue how the method should include all features in the survey design, not just the patented ones.

Second, we empirically showed through two experimental CBC studies that this process of omitting major features is causing the estimates of the WTP of minor features to be inflated. When calculating the WTP of minor features, our UMP conjoint inflated values. This, of course, leads to higher, inefficient damage awards that do not represent the reality of the marketplace.

We hope that this Article sparks more research into how conjoint analysis is being used—and abused—in litigation. Ultimately, we hope that courts can act as policing mechanisms to make sure that CBCs are not being used to drastically inflate damage awards, leading to unfair, unrealistic, and inefficient judgments.

## APPENDIX 1: CAR FEATURES AND THEIR DESCRIPTIONS

The sixth feature you will consider the clock of a potential car. The following types of clocks will be used:

**Analog:**

**Digital:**

**Analog and Digital:**

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The third feature you will consider is the type of potential car. The following three types will be used:

**Coupe:** (2 Door Four Seater)

**Sedan:** (4 Door Four Seater)

**SUV:** (Sports Utility Vehicle)

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The first feature you will consider is the brand of the potential car. The following three brands will be used.

**Ford**-An American manufacturer:

**Toyota**-A Japanese manufacturer:

**Volkswagen**-A German manufacturer:

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The fourth feature you will consider is the number of coin slots in a potential car. The following three options will be used:

**No Coin Slot**

**One Coin Slot:**

**Two Coin Slots:**

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The third feature you will consider is the door handle style of a potential car. The following three types will be used:

**Flat Handle:**

**Bottom Handle:**

**Top Handle:**

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The fifth feature you will consider is the number of cup holders in a potential car. The following number of cup holders will be used:

**One Cup Holder:**

**Two Cup Holders:**

**Four Cup Holders** (two in front, two in back):

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The first feature you will consider is the location of the gas cap on the car. The following two orientations will be used:

**Passenger Side:**

**Driver Side:**

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## APPENDIX 2: SAMPLE IMP & UMP CONJOINT CHOICE TASKS

### IMP Conjoint:

If these were your only options for a car, which would you choose? All other features of the cars are the same.

(1 of 14)

| | | | |
|---|---|---|---|
| Miles Per Gallon (MPG) | 30 MPG | 40 MPG | 50 MPG |
| Gas Cap Location | Passenger Side | Driver Side | Driver Side |
| Car Type | Sedan | SUV | Coupe |
| Brand | Ford | Volkswagen | Toyota |
| Price | $30,000 | $20,000 | $40,000 |
| Cup Holders | 2 Cup Holders | 4 Cup Holders | 4 Cup Holders |
| | Select | Select | Select |

NONE: I wouldn't choose any of these.

Select

### UMP Conjoint:

If these were your only options, which would you choose? All other features of the cars are the same.

(1 of 14)

| | | | |
|---|---|---|---|
| Price | $30,000 | $40,000 | $40,000 |
| Cup Holders | 2 Cup Holders | 1 Cup Holder | 1 Cup Holder |
| Door Handle Type | Flat Handle | Top Handle | Bottom Handle |
| Coin Slot | No Coin Slot | No Coin Slot | No Coin Slot |
| Gas Cap Location | Passenger Side | Driver Side | Passenger Side |
| Clock Style | Digital and Analog | Digital and Analog | Digital |
| | Select | Select | Select |

NONE: I wouldn't choose any of these.

Select

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