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Designed Uncertainty in Mystery Products

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Abstract

Mystery products deliberately hide key attributes until after purchase and have become a common strategy in retail and services, yet systematic evidence on how to design them effectively remains limited. This research studies two managerial levers—outcome-set composition and uncertainty framing (risk vs. ambiguity)—in two incentive-aligned choice experiments: an induced-value lab study with vertically differentiated outcomes and a large-scale choice-based conjoint on apparel with horizontally differentiated brands. Willingness-to-pay is shaped primarily by the structure of the outcome set: when a dominant outcome is included, consumers discount the mystery product; when outcomes are similar in value, a premium can emerge. Ambiguity reduces valuation primarily when outcome differentiation is high, and it shifts attention away from brand and "mystery" cues toward tangible attributes such as fit and color. In market simulations, mystery products are more price-elastic than fully specified alternatives and shift profits toward participating brands, especially weaker ones, while non-participants lose. Overall, the results inform when and how designed uncertainty can be used as a marketing instrument.

Keywords: Mystery products; choice-based conjoint; hierarchical Bayes; market simulation; price competition

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Mystery products (also referred to as opaque or probabilistic products) are now common in retail and services. From blind vacation packages (e.g., Magical Mystery Tours) and surprise hotel bookings (e.g., Hotwire) to mystery clothing bundles (e.g., Stitch Fix) and lucky bags (e.g., Manga Mafia), these offers deliberately conceal some attributes until after purchase (Kovacheva and Nikolova 2024). While consumers routinely face uncertainty in everyday purchase decisions (e.g., not knowing how a new dish will taste, whether a product will meet expectations, or how long a delivery will take), mystery products are unique in that this uncertainty is explicit, intentional, and central to the product's design. Some formats disclose realization probabilities of possible outcomes (e.g., Pop Mart), while others leave them undefined (e.g., Lufthansa Surprise), which should affect how consumers interpret and evaluate these offers.

The scale of market adoption suggests economic value beyond ancillary promotions or clearance tactics. Initially framed as tools for inventory risk management and price discrimination (Fay and Xie 2008), mystery products now operate as a core channel for routine distribution. For instance, Pop Mart more than doubled its revenue to RMB 13.04 billion in 2024 and operates 521 stores (401 in mainland China and 120 overseas), as well as approximately 2,500 robot vending machines (Pop Mart 2024). Japan's capsule toy brand Gashapon reached a market of ¥80 billion in 2024, up 23% from the previous year (Bandai Namco 2024). In apparel, Stitch Fix has surpassed 100 million shipments and serves about 2.5 million active clients (Stitch Fix 2024). In food retail, Too Good To Go serves over 100 million registered users and roughly 175,000 business partners (Too Good To Go; Yang and Yu 2025).

With designed uncertainty increasingly used in practice,[1] the success of mystery products hinges on their design and on consumer response. Yet, despite growing adoption, empirical evidence on how consumers evaluate mystery products remains scarce. In particular, we know little about two managerially controllable levers: (i) the composition of the *outcome set* (i.e., which specific outcomes the mystery offer can include and how similar or different they are in value) and (ii) the *framing of uncertainty* (i.e., whether realization probabilities are disclosed or left ambigu-

[1] Depending on the context, mystery products can serve either as a dedicated marketing channel (for example, opaque selling and blind-booking formats) or as an alternative product offered alongside fully specified options.

ous). We also lack evidence on how these levers translate into substitution patterns, pricing, and profitability. We address this gap with incentive-aligned experiments that recover individual-level preferences and link them to market-level outcomes.

We define a mystery product as an offer in which one or more attributes remain undisclosed at purchase, with the realization drawn from a finite set of possible outcomes specified ex ante. For example, a retailer may sell a mystery T-shirt where buyers know they will receive either a red or blue version but learn the actual color only after making the purchase. The set of possible outcomes is specified ex ante, even though the realization is learned only after purchase. In contrast, a fully specified product discloses all attributes ex ante.

Two core design levers shape how mystery products are evaluated. *Outcome set* refers to the differences among possible realizations and the dispersion of consumer utilities across them: *outcome differentiation* is high when utilities are widely dispersed and low when they are similar. This applies regardless of whether the outcomes are *horizontally differentiated*, that is, they differ along dimensions of subjective preference such as color, flavor, or brand, or *vertically differentiated*, where they vary in objective quality (Spiller and Belogolova 2017). *Uncertainty framing* refers to whether realization probabilities are disclosed (risk) or left unspecified (ambiguity).

Existing research offers limited empirical evidence on how consumers evaluate mystery products. Many prior studies adopt a supply-side perspective, employing analytical models with stylized behavioral assumptions (e.g., Fay and Xie 2008; Shapiro and Shi 2008; Huang and Yu 2014; Zhang, Joseph, and Subramaniam 2015). Observational studies infer preferences from realized purchases rather than from the initial choice between mystery and fully specified options (e.g., Lee et al. 2012; Mang, Post, and Spann 2012; Courty and Liu 2013), which makes selection bias and endogeneity difficult to rule out.

Experimental studies have examined consumer responses to mystery offers (e.g., Hill, Fombelle, and Sirianni 2016; Lee and Jang 2013; Chen, Jai, and Yuan 2017; Chen and Yuan 2016; Huang, Chen, and Lai 2018), but most do not include direct comparisons with fully specified alternatives, limiting inferences about relative preference and, consequently, ecological validity. While some experimental research (e.g., Xie, Anderson, and Verma 2017; Urumutta Hewage and He 2022; Buechel and Li 2023) offers controlled comparisons between mystery and fully specified products, they generally do not link preferences to market outcomes or systematically explore the role of key design levers.

Yet, these design levers can critically shape consumer responses to mystery products. When possible outcomes are similarly desirable, mystery products can evoke curiosity, surprise, and hedonic value (Hill, Fombelle, and Sirianni 2016; Shen, Fishbach, and Hsee 2015). By contrast, high outcome differentiation can elevate perceived stakes and may trigger perceptions of unfairness or manipulation, leading consumers to avoid mystery products (Dutta et al. 2019; Lee and Jang 2013). Ambiguity further amplifies these effects, as consumers tend to be more averse to unknown probabilities than to known ones (Ellsberg 1961; Camerer and Weber 1992). Although horizontal differentiation may mitigate concerns about objective inferiority (Buechel and Li 2023), the evaluation of mystery products becomes more complex when consumer preferences across possible outcomes are heterogeneous. Given that firms can, in principle, control both design levers, a systematic investigation of their joint influence is critical for advancing theory and guiding design.

Our objective is to develop an understanding of how the design of mystery products shapes consumer preferences and firm outcomes, and to generate insights that enable a quantifiable assessment of when mystery products create or diminish value for both consumers and firms. We make three contributions. First, we show that consumers evaluate mystery products primarily by anchoring on the composition of the *outcome set*—its mean, dispersion, and whether it contains a dominant alternative—rather than responding to uncertainty per se. This reconciles mixed findings in prior work on whether uncertainty creates or destroys value, and identifies outcome-set composition as the primary design lever. Second, we find that ambiguity aversion is context-dependent: withholding realization probabilities substantially reduces valuation when outcome differentiation is high, but carries little penalty when outcomes are similar. Moreover, ambiguity shifts how consumers process product attributes, redirecting attention from brand and mystery cues toward tangible features. Third, we link these preference effects to market outcomes, showing that mystery products function as competitive instruments that systematically reallocate profits toward participating brands—especially weaker ones—while non-participants lose. Together, these findings offer behaviorally grounded guidance on when to disclose probabilities and how to price and position mystery products.

To that end, we conduct two incentive-aligned experiments (Ding, Grewal, and Liechty 2005). The first is an induced-value lab experiment (Smith 1976) with vertically differentiated monetary bundles; the second is a large-scale choice-based conjoint experiment in the apparel category with horizontally differentiated brands. In both experiments, we manipulate *uncertainty framing* (risk vs. ambiguity) and the composition of the mystery *outcome set*. Individual-level preferences are estimated using hierarchical Bayesian models (Rossi, Allenby, and McCulloch 2005), from which we derive willingness-to-pay (WTP) (Miller et al. 2011) to quantify the distribution of consumers' valuations for the unknown product feature. In the conjoint experiment, we leverage these estimates to conduct market simulations that quantify how consumers substitute between mystery and fully specified products and identify profit-maximizing prices under different designs of the mystery product.

Our findings show that the two design levers and heterogeneity shape consumer preference for mystery products. WTP for mystery products depends primarily on the *outcome set*. It is discounted when a dominant outcome is possible and higher when outcomes are similar. Ambiguity reduces WTP and profits when differentiation and stakes are high, but this effect is muted when differentiation is low, shifting attention from brand/mystery cues to tangible attributes. The mystery product is often the most price-elastic option and reallocates profit toward participating brands, especially the weaker partner, while non-participating brands lose.

The remainder of the paper is structured as follows. We begin with a review of the relevant literature and position our contribution. We then detail the experimental designs and present findings from both studies. We conclude with theoretical and managerial implications, limitations, and directions for future research.

Literature Review

This review spans supply-side motivations and consumer responses to mystery products. We synthesize research on two managerially controllable design levers – *outcome set* and *uncertainty framing* – and evaluate their effects on valuation, evidence by method, and connections to market outcomes. Table 1 organizes the literature most closely related to our work. Building on this review, we identify the gap addressed by our experiments.

Supply-side Rationales for Mystery Product Selling

Analytical work primarily treats designed uncertainty as a supply-side instrument. In horizontally and vertically differentiated markets under competition or monopoly, probabilistic or opaque selling can segment by preference strength, protect margins on fully specified offers, soften price competition, and manage inventory or capacity risk (e.g., Fay and Xie 2008; Shapiro and Shi 2008; Zhang, Joseph, and Subramaniam 2015). The behaviorally nuanced framework proposed by Huang and Yu (2014) allows for modest belief distortions but remains theoretical and assumes demand primitives rather than measuring how consumers evaluate mystery offers. Whether mystery products generate profits for firms hinges on how consumers perceive them at the moment of initial choice, which is an empirical question.

Observational studies in hospitality and air travel generally align with supply-side predictions. Mystery hotel rooms attract price-sensitive, brand-indifferent buyers and clear capacity without clear evidence of cannibalization of full-price sales (Tappata and Cossa 2014; Courty and Liu 2013). Airline evidence is similar, with blind-booking and flexible products yielding substantial incremental revenues and limited cannibalization by attracting flexible customers (Lee et al. 2012; Post and Spann 2012; Mang, Post, and Spann 2012). However, these studies infer preferences from realized bookings and seldom benchmark the mystery product against fully specified substitutes at initial choice, leaving conclusions vulnerable to selection bias and endogeneity as buyers self-select into mystery offers.

Table 1: Overview of prior work on mystery products.

Author(s) (Year)	Focus	Method	Domain	Hidden attribute (differentiation)	Mystery vs. specified?	Outcome set varied?	Framing varied?	Market outcomes?	Key findings
Fay and Xie (2008)	Supply-side	Analytical (monopoly)	—	Identity (horizontal)	✓	✓	✓	✓	Weak-preference buyers; equal probabilities 50/50; build outcome sets from adjacent variants with moderate differentiation.
Huang and Yu (2014)	Supply-side	Analytical (competitive)	—	Quality (vertical)	✓	✗	✗	✓	Exploit boundedly rational consumers with belief distortions.
Zhang, Joseph, and Subramaniam (2015)	Supply-side	Analytical (monopoly)	—	Quality (vertical)	✓	✗	✓	✓	Mystery used to dispose excess capacity and monetize low-valuation demand; set probabilities optimally not 50/50 default.
Lee et al. (2012)	Demand-side	Observational	Airline tickets	Destination (horizontal)	✗	✓	✗	✓	Design packages to encourage exclusions with a fee (e.g., nearby/same-language).
Tappata and Cossa (2014)	Demand-side	Observational	Hotel rooms	Identity, location (horizontal)	✗	✗	✗	✓	Segmentation rather than distressed clearance; Discounts larger at higher quality and smaller on weekends.
Post and Spann (2012)	Demand-side	Observational	Airline ticket	Destination (horizontal)	✗	✓	✗	✓	Segmentation on flexibility via exclusion fee; Theme-based sets filled with slack-capacity.
Urumutta Hewage and He (2022)	Demand-side	Experimental (scenario; field)	Experiential purchases	Identity (horizontal)	✓	✗	✗	✗	Mystery performs in experiential (vs. material) settings; excitement seeking increase purchase.
Hill, Fombelle, and Sirianni (2016)	Demand-side	Experimental (lab; online)	Mystery box	Content (horizontal)	✗	✓	✗	✗	Moderate (vs. minimal) information and delaying disclosure heightens curiosity and raises purchase motivation.
Xie, Anderson, and Verma (2017)	Demand-side	Experimental (CBC)	Hotel rooms	Identity/star rating (vertical)	✓	✗	✗	✗	Price-sensitive segments; show reviews to mitigate uncertainty; set channel-specific prices to raise revenue.
Buechel and Li (2023)	Demand-side	Experimental (scenarios)	Food, stress balls, hotels, songs, masks, rental cars	Identity, flavor, color (horizontal); Quantity (vertical)	✓	✓	✗	✗	Mystery preferred under horizontal (vs. vertical) differentiation; Discounts are not required as uncertainty alone can create value and even raise WTP.
This paper	Demand-side	Experimental (induced-value; CBC)	Induced-value, jeans	Value (vertical); brand (horizontal)	✓	✓	✓	✓	Outcome set anchors WTP; ambiguity lowers WTP more under high differentiation; profit reallocation to participating brands.

Notes. "Mystery vs. specified?" indicates whether study directly compares mystery products to fully specified alternatives. "Outcome set varied?" indicates variation in which realizations can occur. "Framing varied?" indicates any variation in how uncertainty is communicated (e.g., changes in known probabilities within risk or risk vs. ambiguity). "Market outcomes?" indicates whether study examines market-level outcomes (e.g., pricing, profits) vs. only individual-level outcomes (e.g., preferences, willingness to pay).

Consumer Responses Under Designed Uncertainty

Consumers facing intentionally concealed information encounter two opposing forces. First, uncertainty can carry intrinsic disutility. Prospect theory captures strong aversion to uncertain outcomes (Kahneman and Tversky 1979), and experiments on the uncertainty effect show that some individuals even value an uncertain prospect below its worst possible outcome (Gneezy, List, and Wu 2006). Second, uncertainty can offer hedonic value via curiosity and anticipated surprise (Loewenstein 1994; Shen, Fishbach, and Hsee 2015). "Mystery" retail tactics can lift exploration and purchase motivation (Hill, Fombelle, and Sirianni 2016; Huotari and Hamari 2017). Uncertain promotions can also perform well under specific designs (Goldsmith and Amir 2010; Ailawadi et al. 2014). Whether consumers treat designed uncertainty as a cost or a source of value is therefore an empirical question and depends on two managerially controllable levers: the *outcome set* and the *uncertainty framing*.

Outcome set

Consumers incorporate information about the set of possible realizations directly into valuation. Evidence from empirical work on opaque hotel websites shows that website and marketplace cues (e.g., star ratings, prices, and location hints) shift perceived risk, perceived benefits, and expected quality (Chen, Jai, and Yuan 2017; Huang, Chen, and Lai 2018; Chen and Yuan 2016). Mystery airline tickets define theme-based destination pools that customers can prune for a fee (Post and Spann 2012; Lee et al. 2012). Experimental studies show that providing moderate (vs. minimal) information elicits greater curiosity and increases purchase intent (Hill, Fombelle, and Sirianni 2016), and greater clarity about the mystery offer tends to raise purchase intent (Chen, Jai, and Yuan 2017). Dispersion in utilities across the *outcome set* amplifies these mechanisms. Low dispersion limits downside and allows curiosity to surface. High dispersion heightens the salience of a bad realization and tilts choices toward caution. Vertically differentiated outcomes make the disadvantageous outcome more aversive and can trigger fairness concerns, leading some consumers to forgo monetary gains to punish the seller (Lee and Jang 2013). By contrast, when outcomes are horizontally differentiated and similar in value, some consumers prefer the unknown because it can deliver a pleasant surprise without risk of ending up with an objectively inferior option (Buechel and Li 2023). Theory further recommends that *outcome sets* be built from adjacent variants and that they are most profitable when those variants exhibit moderate differentiation (Fay and Xie 2008), highlighting the composition of the *outcome sets* as a design lever. Hence, prior research indicates that the composition of the *outcome set* and the dispersion of utilities across its realizations are central to consumer responses to mystery products. Yet, evidence from studies that systematically vary the *outcome set* remains limited.

Uncertainty framing

Prior research shows that, holding payoffs constant, individuals often prefer known to unknown probabilities and often display ambiguity aversion beyond risk aversion (Ellsberg 1961; Camerer and Weber 1992; Epstein 1999). Moreover, evidence from experimental studies shows that how probabilities and uncertainty are communicated shifts attention across cues. Buechel et al. (2014) show that explicit probability specifications draw disproportionate attention in ex ante evaluation, and argue that when probabilities are less focal, attention should shift back to other aspects of the prospect. Yang, Vosgerau, and Loewenstein (2013) show that risk-laden frames (e.g., lottery ticket) make buyers focus more on the downside of the prospect and lower their WTP, relative to more neutral frames (e.g., gift certificate), even when payoffs are identical. In most observational and experimental settings, however, this distinction is rarely accounted for, and ambiguity is implicitly presented. Theory recommends sometimes equal weights (Fay and Xie 2008) or capacity-based probabilities (Zhang, Joseph, and Subramaniam 2015), implying that how probabilities are set is itself a design lever. Moreover, risk attitudes are highly sensitive to stake levels (Holt and Laury 2002), and survey evidence suggests that ambiguity attitudes can also vary with payoff magnitude (Camerer and Weber 1992). Collectively, these considerations motivate testing *uncertainty framing* and *outcome set* jointly in a unified design.

Predictions and research questions

Prior literature suggests that ambiguity should penalize mystery products relative to risk, but that the magnitude of this penalty should depend on the *outcome set*. When outcomes are closely valued and stakes are low, the downside of ambiguity is limited, and the hedonic upside can surface. When outcomes are highly differentiated and stakes are high, ambiguity should lower valuations more strongly. Yet the literature offers little causal, incentive-aligned evidence that jointly varies these levers and maps resulting preferences to market outcomes. We address this gap by asking: How do the *outcome set* and *uncertainty framing* shape consumer valuation of mystery products? How do these valuations translate into substitution patterns, price elasticities, and profits? We next present experiments that address these questions and report their results.

Experimental Studies

We present results from two incentive-aligned experiments built on a typical choice architecture. In each experiment, consumers choose among two fully specified alternatives, a mystery alternative that resolves to one of them, and a no-buy option. We vary the *outcome set* within participants and the *uncertainty framing* (risk vs. ambiguity) between participants. Study 1 is an induced-value laboratory experiment in which the concealed feature is value, yielding a vertically differentiated setting. Study 2 is a large-scale choice-based conjoint experiment in the apparel (jeans) category, with the concealed feature *brand*, which creates horizontal differentiation and allows us to link individual preferences to substitution and pricing outcomes. [2]

Study 1: Induced-value Laboratory Experiment

Experimental design and procedure

The goal of Study 1 is to examine how consumers evaluate mystery products in a clean and vertically differentiated decision environment. The study employed an induced-value experimental

[2] The data and code for both studies are available on OSF: https://osf.io/z45bw.

design programmed in z-Tree (Smith 1976; Fischbacher 2007). Participants completed 32 randomized choice tasks, each involving two fully specified alternatives, one mystery alternative, and a no-buy option. Fully specified alternatives differed systematically in value (20, 40, 60, 80) and corresponding price (15, 35, 55, 75), ensuring that each offered a constant net payoff of 5 experimental currency units. The mystery alternative conceals its value, determined by a random draw from the values of the two fully specified alternatives in the same choice task. The price of the mystery alternative was randomly sampled from a uniform distribution bounded by the prices of the fully specified alternatives in that task. This introduced uncertainty in the mystery alternative's net payoff while keeping the price structure realistic.

We manipulate *outcome set* within participants by varying the induced-value pair across choice tasks. From (20, 40, 60, 80) we formed the six pairs 20–40, 20–60, 20–80, 40–60, 40–80, and 60–80, where wider spreads indicate higher differentiation. In some tasks, both values were equal (e.g., 40–40), which sets differentiation to zero and makes the mystery outcome fully determined.

To manipulate *uncertainty framing*, participants were randomly assigned to one of two conditions. In the risk condition, the value of the mystery alternative was a 50/50 draw from the two fully specified alternatives in the same task. We chose equal probabilities as a natural benchmark: in the absence of information favoring either outcome, symmetric beliefs imply a 50/50 expectation under ambiguity. In the ambiguity condition, the value was drawn from the same set, but no probabilities were disclosed. Example choice tasks for each condition are presented in Web Appendix A, Figures W1 and W2.

To ensure incentive compatibility, participants received a fixed payment of 80 experimental currency units, plus additional earnings based on their choices. If the mystery alternative was chosen, its realized value was drawn and revealed after the choice and used to compute payoffs. This incentive-compatible procedure encouraged participants to choose in line with their preferences and beliefs about the mystery alternative's outcome.

After completing the choice tasks, participants answered a brief questionnaire that included socio-demographic variables, an affective state measure (current mood), an experience measure (experiment participation frequency), and validated scales capturing individual risk attitudes. An overview of the scales is presented in Web Appendix A, Table W1.

Participants

Participants were recruited from a large European public university. A total of 48 students (45.83% female, 54.17% male; gender was measured using a binary item, consistent with the institutional data collection procedure at the time) participated in the experiment, with equal assignment to the risk and ambiguity conditions. Details on sample characteristics and risk-attitude measures are presented in Web Appendix B, Tables W2 and W3. Differences between the risk and ambiguity conditions on socio-demographics and risk-attitude measures are small and consistent with successful randomization. In predicting mystery choice, self-reported risk propensity (Dohmen et al. 2011) is the only measure that shows a clear association. Participants who are more willing to take risks tend to choose the mystery alternative more often.

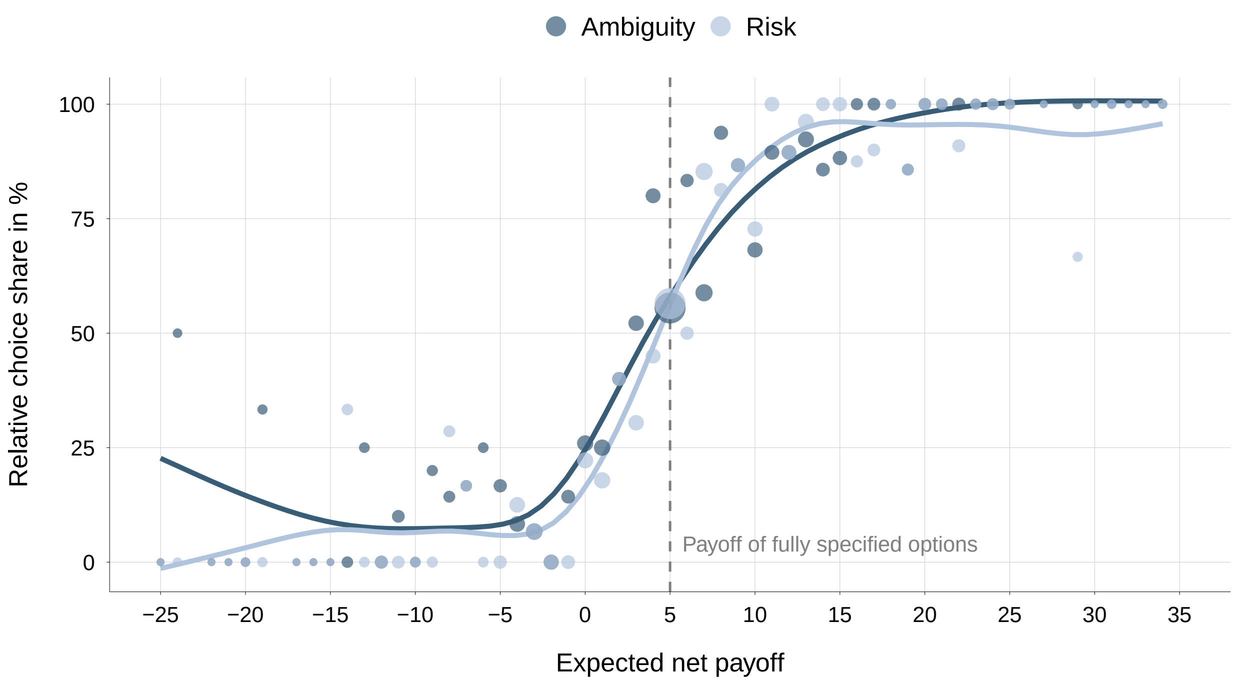
Descriptive choice behavior

We observe a strong baseline preference for the mystery alternative. Across all choice tasks, it was chosen in more than half of the cases (ambiguity: 54.43%; risk: 52.86%), indicating that participants view it as at least as attractive as the fully specified alternatives. Mystery choice shares are slightly higher under ambiguity, but the differences are small. The no-buy option was selected only three times in total (ambiguity: 2; risk: 1). The remaining choices were approximately evenly split between the two fully specified alternatives. Even under parity or when the mystery outcomes are fully determined (e.g., 20–20), the mystery alternative is still chosen nearly half of the time. Furthermore, in the quarter of tasks where all three alternatives had equal price and value, the mystery alternative was also chosen just over half the time.

Participants exhibited rational payoff-maximizing choice behavior. For instance, in all 36 choice tasks with clear economic dominance, where one fully specified alternative and the mystery alternative had the same price, while the second alternative was more expensive, nearly all choices favored the mystery alternative as the economically superior option.

Moreover, mystery choice shares generally rise with a higher expected value (i.e., mean of the values of the fully specified alternatives). Figure 1 plots the relative choice share of the mystery alternative as a function of its expected net payoff, calculated as the mean value of the two fully specified alternatives minus the price of the mystery alternative. As expected, when net payoff increases, the mystery alternative is chosen more frequently. This pattern suggests that participants are not choosing mystery alternatives at random but are responsive to the composition of the *outcome set*. Importantly, even when the expected net payoff is 5, indicating that the mystery alternative is economically equivalent to the fully specified alternatives, it is still selected in more than 50% of cases. This suggests that consumers attribute additional intrinsic value to the mystery alternative beyond what is explained by expected value alone.

Figure 1: Relative choice shares for the mystery alternative across expected net payoffs.



Notes. Circle sizes reflect the number of observations. The smooth curve is estimated using a weighted generalized additive model (GAM) with a penalized spline.

Model specification and estimation procedure

Following random utility theory (Train 2009), participants are modeled as utility maximizers who evaluate observable attributes and may form expectations about the unobserved value of the mystery alternative at the moment of choice. Let u_{ijt} denote the indirect utility that participant i derives from alternative j in choice task t:

$$u_{ijt} = m_{ijt}\delta_i + \gamma_i \,\text{value}_{ijt} - \alpha_i \,\text{price}_{ijt} + \varepsilon_{ijt}, \qquad \varepsilon_{ijt} \sim EV(0,1). \tag{1}$$

Here value_{ijt} represents the value of the fully specified alternatives scaled in units of 100, with associated individual-level preference parameters in the column vector γ_i. The price parameter α_i is sign-constrained to ensure economically plausible negative price sensitivity by modeling $\log(\alpha_i)$, which implies a log-normal distribution for α_i (Allenby et al. 2014). We linearly code the price and scale it by 100. The utility of the no-buy option is normalized to zero.

The mystery alternative conceals its value but is known to equal one of the two values shown for the fully specified alternatives in the same task. With four possible values, this yields six distinct value pairs. We represent these pairs with dummy-coded intercepts m_{ijt} and individual-level preferences δ_i that reflect participants' expectations about the unresolved outcome. We also consider four cases in which the two fully specified alternatives share the same value (e.g., 20–20), thereby revealing the mystery outcome. In these tasks, we treat the value of the mystery alternative as observed and include an indicator for "Mystery obvious" in m_{ijt} to capture any residual utility from the mystery label itself. This structure separates the utility contribution of the mystery feature from value and price, allowing us to quantify how participants evaluate the unknown under different design levers.

The error term ε_{ijt} is assumed to follow an i.i.d. extreme-value Type I distribution, yielding a multinomial logit model at the individual level (Sonnier, Ainslie, and Otter 2007). We stack the individual-level preference parameters into the vector $\theta_i = \{\delta_i, \gamma_i, \log(\alpha_i)\}$. To model heterogeneity, we specify a hierarchical structure (Rossi and Allenby 2003):

$$\theta_i = \Delta z_i + \zeta_i, \qquad \zeta_i \sim MVN(0, \Sigma), \tag{2}$$

where z_i denotes a vector of observed individual-level covariates, including the experimental condition, all collected socio-demographics, and the risk-taking scale from Dohmen et al. (2011). All covariates are binary-coded and mean-centered before entering z_i. Δ is a matrix of regression coefficients in which the intercept can be interpreted as the average part-worth. The residual term ζ_i captures unobserved heterogeneity and is assumed to follow a multivariate normal distribution with covariance matrix Σ.

We estimate this model using Hierarchical Bayes (HB) (Rossi, Allenby, and McCulloch 2005) with Markov Chain Monte Carlo (MCMC) methods, drawing 200,000 posterior samples and discarding the first 100,000 iterations as burn-in. To reduce autocorrelation, we apply a thinning factor of 100, yielding 1,000 retained posterior draws per participant. These draws are used to summarize the posterior distribution of model parameters. Individual-level preference estimates are obtained by averaging over posterior draws.

Results

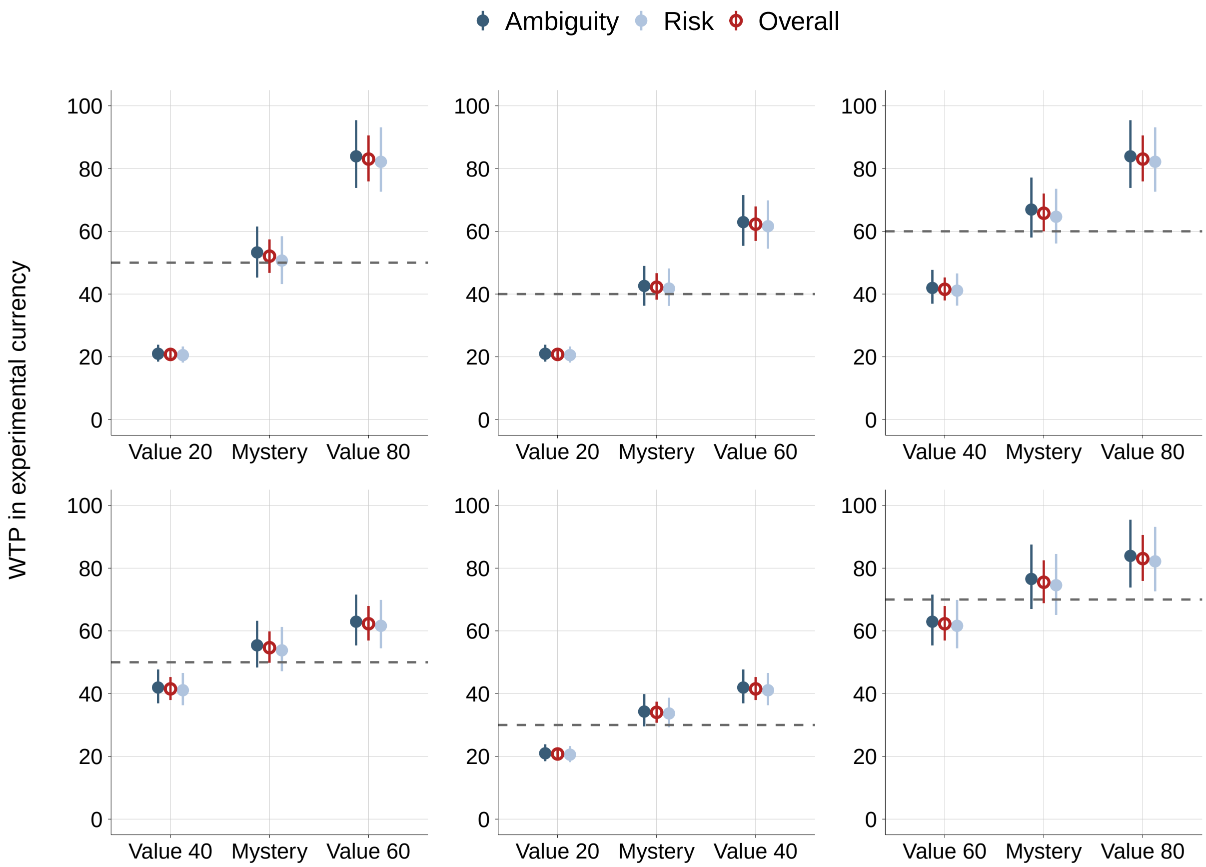
We estimate three model specifications. Model 1 includes a single intercept for the mystery alternative, assuming that consumers evaluate it independently of the *outcome set*. Model 2 replaces this with six separate intercepts plus the "Mystery obvious" indicator, allowing preferences to vary by the specific composition of the *outcome set*. Model 3 further extends the specification by incorporating mean-centered individual-level covariates.

Model comparisons based on the log marginal density (LMD), which penalizes additional parameters, show that accounting for *outcome set* meaningfully improves explanatory performance even after taking model complexity into account. LMD increases from −1,674.74 in Model 1 to −937.93 in Model 2. Incorporating individual-level covariates yields further gains, with Model 3 providing the highest LMD of -911.91. Accordingly, Model 3 is selected as the preferred specification and serves as the basis for subsequent analyses. Further details on parameter estimates are provided in Web Appendix D, Table W7.

In Model 3, the 95% credible intervals for all utility parameters exclude zero, indicating strong posterior evidence of nonzero effects. The mystery intercepts are all positive and increase with the *outcome set* mean, indicating that participants anchor the mystery alternative to its expected value. Moreover, at equal means, narrower ranges receive higher utility than wider ranges (i.e., Mystery 40–60 exceeds Mystery 20–80), consistent with aversion to greater outcome differentiation. The "Mystery obvious" indicator is also positive, which implies an incremental utility for the mystery label itself and indicates that participants prefer the mystery-labeled option over an otherwise identical fully specified alternative even when the outcome is known.

For the subsequent analysis, we use posterior predictive simulation to propagate both posterior uncertainty and individual heterogeneity. Details of the simulation procedure are provided in Web Appendix E. We compute WTP; full summaries appear in Web Appendix E, Table W9. For exposition, Figure 2 reports the overall median WTP with 95% credible intervals by *outcome set* and *uncertainty framing*. We highlight three main results. First, median WTP increases monotonically with the expected value of the *outcome set*, rising from 34.06 experimental currency units for Mystery 20–40 to 75.66 for Mystery 60–80. This pattern indicates that participants anchor their evaluations on the *outcome set* rather than choosing at random. Second, median WTP exceeds the expected value benchmark in every *outcome set*, with premiums ranging from 2 to 6. For example, median WTP for Mystery 20–40 equals 34.06 compared with an expected value of 30, and median WTP for Mystery 60–80 equals 75.66 compared with an expected value of 70. Moreover, the premium is larger under lower differentiation (Mystery 40–60) than under higher differentiation (Mystery 20–80), even when the expected value is held constant. This pattern suggests that participants place incremental value on the mystery label and hold optimistic beliefs about its resolution. Third, although not shown in the figure, even when the mystery product outcome is effectively "obvious" (i.e., prices of the fully specified alternatives are identical), we observe a small but positive

Figure 2: Heterogeneity in WTP estimates.



Notes. Each panel depicts a market scenario with a corresponding outcome set. Dashed lines indicate the expected value in each outcome set. Estimates are median WTP values with corresponding 95% CIs. Filled blue circles indicate the experimental conditions (dark blue: ambiguity; light blue: risk), and "pooled" results are shown in red open circles.

median WTP of 1.99 experimental currency units. This finding indicates a baseline appeal of mystery even when resolution is transparent. Overall, these results are consistent with the descriptive patterns reported earlier.

Observed heterogeneity is present but remains modest in magnitude. We find no effects for age, study, or frequency. Mood and gender effects are mixed, with a decrease in WTP of 3.40 (PD[3] = .97) for "Mystery obvious" among women. Greater risk willingness is associated with an increase in WTP of 3.52 (PD = .98) for "Mystery obvious". Posterior results lean toward a difference between conditions, while still implying substantial uncertainty ($.5 \leq \text{PD} \leq .8$). Hence,

[3]PD (probability of direction) is the posterior probability that the effect is strictly above or below zero in the estimated direction (Makowski et al. 2019).

uncertainty framing appears to have a modest influence on preferences for the mystery alternative, which may be attributable to the relatively low monetary stakes in this experiment.

Discussion

In Study 1 with vertical differentiation, participants exhibit rational patterns of responses under designed uncertainty. They are influenced by the *outcome set* and follow expected-value logic. The median WTP for the mystery alternative rises with the expected value of its *outcome set* and exceeds the expected-value benchmark in every set, indicating a premium beyond payoffs. This premium persists even when benchmarking against the simple average valuation of the two possible realizations and when the realization is fully determined, consistent with curiosity or surprise value from the mystery label itself (e.g., Ely, Frankel, and Kamenica 2015; Ruan, Hsee, and Lu 2018). Holding expected value constant, lower dispersion earns a larger premium than higher dispersion, indicating aversion to greater outcome differentiation. We do not find strong evidence for systematic differences between risk and ambiguity, which is consistent with the limited monetary stakes in this design.

Study 1 provides a clean test of expected-value anchoring because alternatives are vertically differentiated and objectively ranked, inducing common preference orderings across participants. However, three features limit its scope. First, the relatively low monetary stakes may attenuate *uncertainty framing* effects that could emerge when decisions carry higher consequences. Second, vertical differentiation imposes a common ranking; in real purchase contexts, horizontal differentiation, salient brand equity, and richer trade-offs across multiple attributes are more common. Third, the relatively small sample size ($N = 48$) and induced-value setting preclude market-level analyses such as substitution patterns or profit simulations.

Study 2 addresses these limitations. We move to a realistic category (jeans) with established brands and a multi-attribute choice environment in which consumers trade off brand, fit, color, and price. With a larger sample ($N = 1{,}097$) and a higher-stakes context, we test whether the outcome-set anchoring documented in Study 1 generalizes to horizontal differentiation and whether the framing effects suppressed by low stakes emerge under more consequential decisions. This setting also allows us to link design levers to market outcomes by mapping preferences to price elasticities and profit.

Study 2: Choice-based Conjoint Experiment

Experimental design and procedure

Study 2 seeks to assess consumer responses to mystery products in a more realistic setting by conducting an incentive-aligned choice-based conjoint (CBC) experiment in the apparel category with horizontally differentiated brands.

The questionnaire comprised four parts. First, participants reported their jeans-related purchasing habits (Allenby and Brazell 2016) and brand relevance (Fischer, Völckner, and Sattler 2010). Second, they completed 16 randomized-choice tasks and two fixed-holdout tasks (Tasks 6 and 12), in which the mystery products varied only in price. In each task, participants chose among two fully specified jeans, one mystery jeans, and a no-buy option. The mystery product revealed its fit, color, and price, but concealed the brand, which was randomly selected from the two visible brands shown in the task. Hence, we treat the mystery feature as an attribute alongside the other product attributes. This design isolates the incremental contribution of the mystery feature, allowing us to estimate how known and unknown attributes trade off in driving choice. Third, we measured personality traits and risk attitudes. Finally, we collected socio-demographic information.

Product profiles were generated using Sawtooth's balanced-overlap design based on the attributes and levels listed in Table 2. All participants saw instructions that explained and visualized the attributes and levels. Jeans brands were selected based on UK market data and represent four of the most widely purchased brands. Price levels reflected typical retail prices in the category.

To manipulate *uncertainty framing*, participants were randomly assigned to one of two experimental conditions. In the risk condition, the mystery brand was selected with known and equal probability (50/50) between the two visible brands. In the ambiguity condition, the brand was drawn from the same pair, but selection probabilities were unspecified. Examples of random

Table 2: Conjoint attributes and attribute levels.

Attributes	**Levels**			
Brand	Levi's	Tommy Hilfiger	Calvin Klein	Wrangler
Fit	Skinny	Slim	Regular	Wide
Color	Light blue	Blue	Black	
Price	£70	£85	£100	£115

choice tasks and the two hold-out tasks for each condition are presented in Web Appendix A, Figures W3–W5.

We incentivized choices using a mechanism adapted from Ding, Grewal, and Liechty (2005). All participants received a base payment of £1.80 for completing the survey. Additionally, two participants were randomly selected to receive a reward based on one of their stated choices across the 18 tasks. Each winner received a combination of cash and their selected choice, with a total reward value of £150.

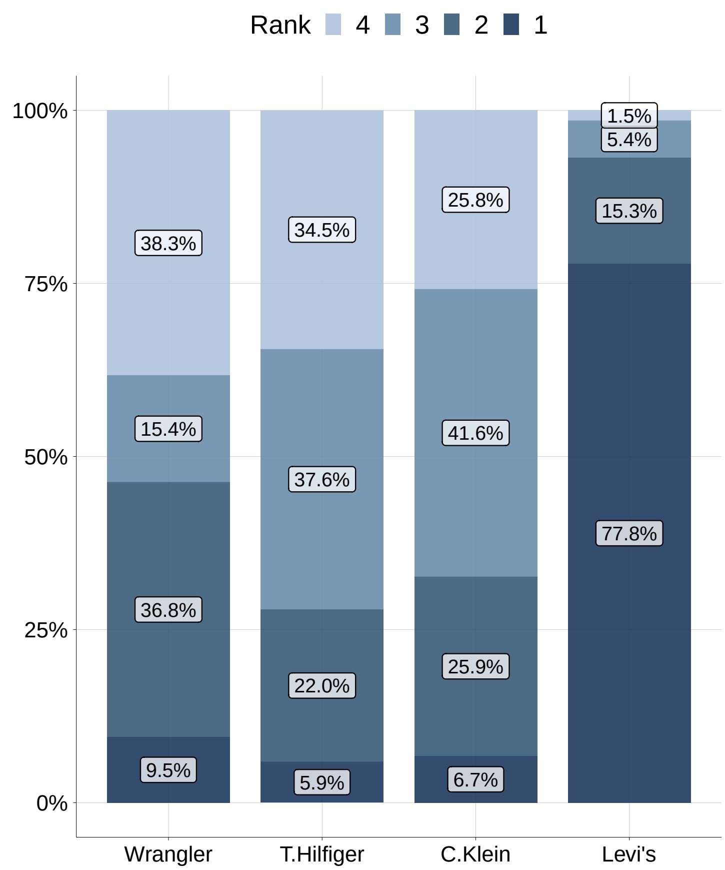
Participants

We fielded a single-wave online survey on Prolific, targeting UK-based participants and applying gender quotas to ensure balance. In total, 1,200 participants were randomly assigned to one of the two experimental conditions (ambiguity: 578; risk: 622).

To ensure data quality, we used two comprehension checks about the mystery product and excluded 17 (ambiguity: 11; risk: 6) participants who failed both. We also removed 14 (ambiguity: 4; risk: 10) participants who always chose the no-buy option and 72 (ambiguity: 35; risk: 37) participants with extreme CBC response times (below the 5th or above the 99th percentile within each condition). After applying these criteria (see Web Appendix B.1), the final analytic sample comprised 1,097 participants (50.68% female, 48.40% male, 0.55% nonbinary/transgender/third gender, 0.18% prefer to self-describe, 0.18% prefer not to answer; ambiguity: 528; risk: 569).

Randomization checks do not reveal systematic socio-demographic differences across conditions, as the differences are small and subject to statistical uncertainty. Category engagement is high, with over 80% reporting purchasing jeans at least annually and about two-thirds wearing jeans at least three times per week. Brand awareness is high, and brand relevance ratings are moderate. Brand rankings identify Levi's as the dominant favorite (first-place votes: 77.8%), followed by C. Klein and T. Hilfiger (Figure 3). Wrangler is polarizing, receiving some first-place votes but the largest share of last-place votes. These patterns highlight substantial heterogeneity in brand preferences across participants. Differences between conditions on these measures are small and statistically uncertain. Further details are presented in Web Appendix B, Tables W4 and W5.

Figure 3: Ranking of jeans brands.



Notes. Respondents ranked the jeans brands and blue shading indicates rank, ranging from light blue (lowest) to dark blue (highest). Shares sum to 1 within each brand (across ranks) and within each rank (across brands).

Consistent with Study 1, participants display classic ambiguity aversion and preference-reversal patterns (Trautmann, Vieider, and Wakker 2011), and higher self-reported willingness to take risks (Dohmen et al. 2011). Mean gambling propensity is below the scale midpoint (Ailawadi et al.

2014), whereas optimism exceeds it. We also measured perceived risk specific to mystery jeans, using a custom scale adapted from prior work (Thelen, Yoo, and Magnini 2011; Bruner 2013). The proportion of mystery choices has a statistically detectable negative association with perceived risk (Thelen, Yoo, and Magnini 2011), and a positive association with gambling proneness (Ailawadi et al. 2014) and willingness to take risks (Dohmen et al. 2011), replicating Study 1. Differences between conditions on these measures are small and statistically uncertain. We include the perceived risk of mystery jeans measure in the HB model as it captures product-specific risk and is closest to the mechanism of interest. Further details are presented in Web Appendix B, Table W6.

Descriptive choice behavior

We find no evidence of straight-lining, and choice shares are balanced across the three product alternatives in both conditions, while the no-buy option was selected less often. Relative choice shares of brands closely mirror participants' stated familiarity and brand attitudes, and no participant showed uniform brand loyalty. Participants demonstrated clear price sensitivity in decision-making, with statistically detectable lower relative choice shares at higher price points, particularly £115, which many participants consistently avoided. These patterns indicate that including a mystery product did not induce atypical choice behavior or excessive market exits; instead, participants engaged meaningfully with the choice tasks.

The mystery product functioned as a viable alternative whose choice share varied systematically with price and the composition of the *outcome set*. It was chosen more often than most brands, and its share of choice ranked second only to Levi's. At the individual level, most participants chose the mystery product three to five times. A few selected it in more than half of their choices, and a few never selected it. The probability of choosing the mystery product increased when it appeared alongside lower-ranked brands and decreased as its price rose. These effects held in both experimental conditions. Notably, mystery product choices were highest under ambiguity when visible brands were least preferred, suggesting that perceived downside risk is attenuated when visible alternatives are weak. The two fixed holdout tasks provided additional support, showing that a price reduction increased mystery product choices in both conditions (ambiguity: McNemar's test, $\chi^2(1) = 31.01$, $p < .001$; risk: McNemar's test, $\chi^2(1) = 22.12$, $p < .001$). These findings indicate that the mystery product was systematically evaluated within a structured decision process. Further descriptive details are presented in Web Appendix C.

Model specification and estimation procedure

We adopt the same HB framework and estimation procedure as in Study 1 (see the model specification of Study 1). Let u_{ijt} denote the indirect utility that participant i derives from alternative j in choice task t:

$$u_{ijt} = m_{ijt}\delta_i + b_{ijt}\gamma_i + x_{ijt}\beta_i - \alpha_i \,\text{price}_{ijt} + \varepsilon_{ijt}. \quad (3)$$

The row vector x_{ijt} captures dummy-coded non-brand non-price attributes (i.e., color, fit), with corresponding individual-level partworths in the column vector β_i. The row vector b_{ijt} represents brand dummies for the fully specified products, with associated individual-level preference parameters in the column vector γ_i. Price is linearly coded and scaled in units of £100. We enforce negative price sensitivity by modeling $\log(\alpha_i)$.

The mystery product reveals all attributes except the brand. With four brands in total, six distinct brand pairs can underlie the mystery product. A balanced-overlap design prevents the same brand from appearing twice within a task. We index these six brand-pair combinations with dummy-coded intercepts in m_{ijt}, and we model individual-level preferences δ_i reflecting consumers' expectations over the uncertain brand outcomes.

The utility of the no-buy option is normalized to zero. This facilitates interpretation as the brand and mystery intercepts represent utilities for a baseline product (a blue pair of regular-fitted jeans). The complete parameter vector is $\theta_i = \{\delta_i, \gamma_i, \beta_i, \log(\alpha_i)\}$. Observed individual-level covariates include the experimental condition, a perceived risk measure (Thelen, Yoo, and Magnini 2011), and socio-demographics (gender, age, income, occupation, and education), which enter the estimation as binary and mean-centered variables. Age, income, and perceived risk are dichotomized via sample-median splits. Table E2 in Web Appendix E provides further details on coding.

Results

We estimate three model specifications. Model 1 includes a single intercept for the mystery product, assuming that consumers evaluate it independently of the *outcome set*. Model 2 replaces this with six separate intercepts, allowing preferences to vary by the specific composition of the *outcome set*. Model 3 further extends the specification by incorporating individual-level covariates.

Model comparisons based on the log marginal density (LMD) show that accounting for *outcome set* meaningfully improves explanatory performance. LMD increases from −7,835.61 in Model 1 to −7,494.47 in Model 2. Incorporating individual-level covariates yields further gains, with Model 3 providing the highest LMD of −7,439.04. Accordingly, Model 3 is selected as the preferred specification and serves as the basis for subsequent analyses. Further details on parameter estimates are provided in Web Appendix D, Table W8.

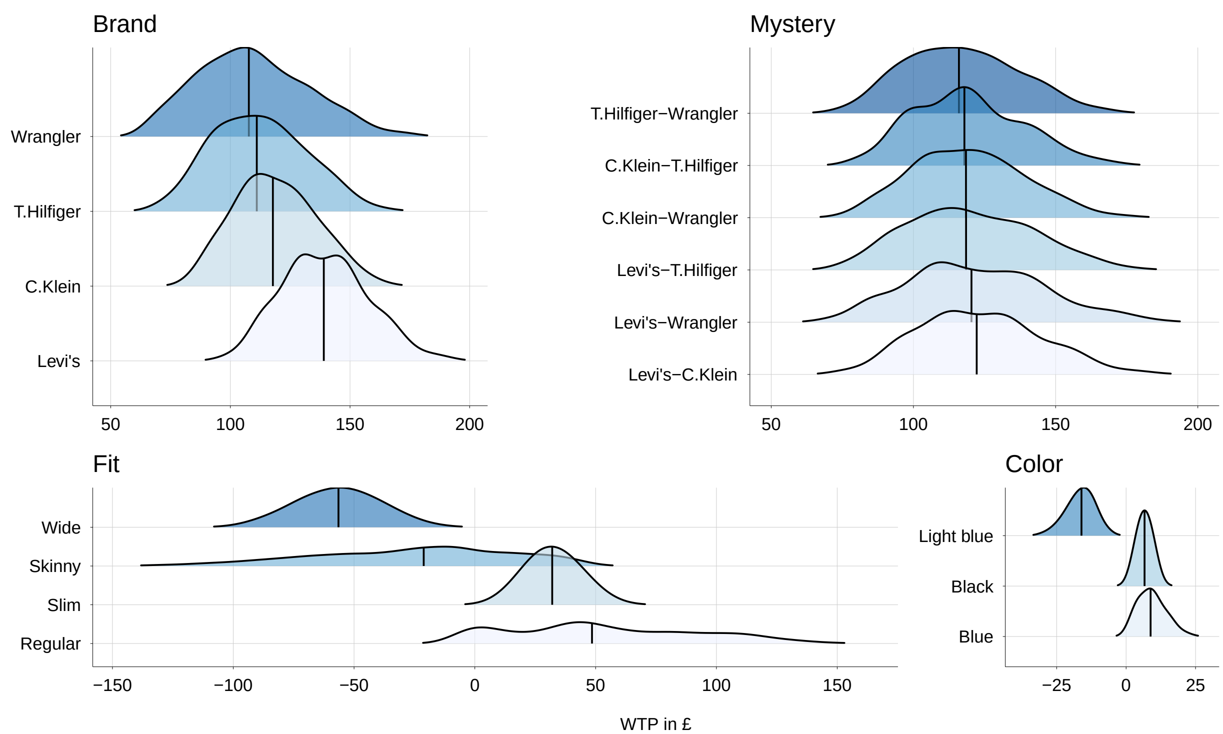
The estimates are precise, as indicated by relatively narrow 95% credible intervals. All brand and mystery utility parameters are positive, and their 95% credible intervals exclude zero, indicating strong posterior evidence for positive effects.

For the subsequent analysis, we apply the same posterior predictive simulation approach as in Study 1, propagating posterior uncertainty and preference heterogeneity to derive WTP, elasticities, and optimal prices (see Web Appendix E).

WTP. Full summaries appear in Web Appendix E, Table W10. Levi's has the highest median WTP (£138.47; 95% highest density interval (HDI) [129.78, 148.29]), exceeding C. Klein (£117.66), T. Hilfiger (£110.95), and Wrangler (£107.85). This ordering matches the model-free rank pattern in the descriptive analysis, supporting the face validity of the estimates. Moreover, Levi's HDI does not overlap with those of the other brands, indicating a sizable premium consistent with the descriptive analysis of perceived quality differences (see Web Appendix C).

Figure 4 shows substantial heterogeneity in WTP across attributes. Although the median implies a clear brand ranking, the corresponding WTP distributions are wide and overlap, indicating meaningful preference heterogeneity and respondent-level variation in brand ranking. Median WTP for the mystery option also varies by outcome set (i.e., the brands of fully specified jeans noted next to each mystery WTP density in Figure 4), but these differences are smaller than the cross-brand differences; mystery WTP is likewise heterogeneous. Fit and color exhibit more stable patterns: regular fit and blue are most preferred at the median. Median differences are larger for fit than for color, suggesting greater attribute importance for fit. Compared with regular fit, wide, skinny, and slim fits have lower median WTP (with substantial overlap in the distributions). Light blue jeans have lower WTP than black or blue ones.

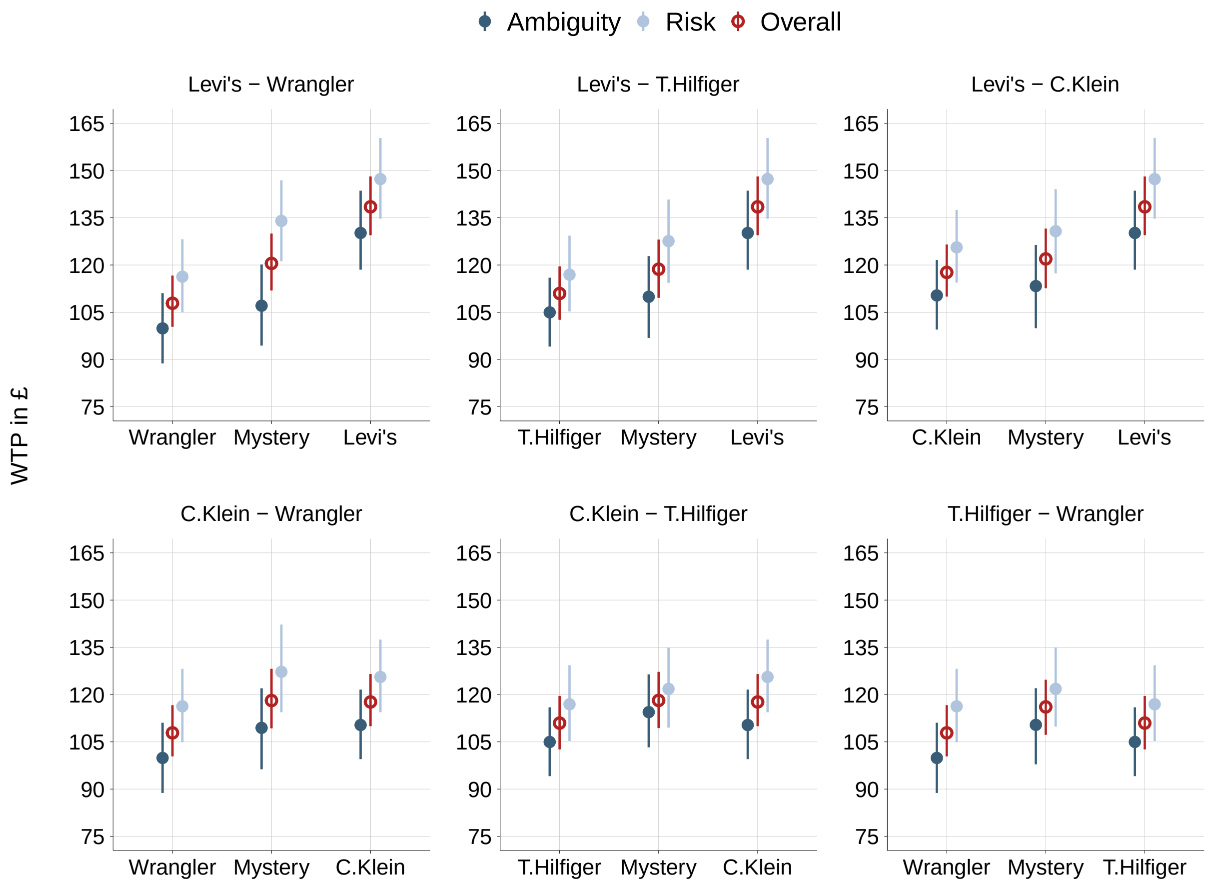
Figure 4: Heterogeneity in WTP estimates.



Notes. The panels show the distributions of WTP estimates across respondents. Vertical lines indicate the medians of the distributions. Brand and mystery WTPs are provided for regular blue jeans. For each mystery jeans, the brands refer to the fully specified jeans in the outcome set. For fit and color, we report the implied WTP distributions for the part-worths of all attribute levels.

Figure 5 illustrates WTP medians with 95% credible intervals by *outcome set* and *uncertainty framing*. In both studies, we benchmark mystery WTP against the simple average valuation of the two possible realizations. In Study 2, we benchmark each mystery product against the simple average of the two brands it may resolve into. When Levi's is included in the *outcome set*, mystery WTP falls below this benchmark (Levi's–T.Hilfiger: £-6.04; Levi's–C.Klein: £-6.13; Levi's–Wrangler: £-2.66). A dominant outcome induces *quasi-vertical* differentiation (i.e., one option becomes stochastically dominated in expectation), and consumers' implied beliefs appear pessimistic. They behave as if the lower-valued brand were more likely than an even split with the dominant brand, consistent with uncertainty aversion.

Figure 5: Overall brand and mystery WTP medians.



Notes. Each panel depicts a market scenario with a corresponding outcome set. Estimates are median WTP values with corresponding 95% CIs. Filled blue circles indicate the experimental conditions (dark blue: ambiguity; light blue: risk), and "pooled" results are shown in red open circles.

When Levi's is excluded from the *outcome set*, and brands are closer in value, the discount disappears. Mystery WTP meets or exceeds the benchmark (C.Klein–T.Hilfiger: £+3.83; C.Klein–Wrangler: £+5.34; T.Hilfiger–Wrangler: £+6.69) and the "better" brand (C.Klein–T.Hilfiger: £+.48; C.Klein–Wrangler: £+.44; T.Hilfiger–Wrangler: £+5.14). These patterns indicate that, absent a dominant brand, perceived downside risk recedes and upside potential becomes salient, consistent with evidence that horizontally differentiated yet similarly valued options can render uncertainty attractive (Buechel and Li 2023).

Uncertainty framing shifts WTP. Ambiguity lowers WTP across all brands and mystery products, with the strongest effects in *outcome sets* that include Levi's. The median change equals £-26.35 for the Levi's–Wrangler mystery (PD = 1.00) and about £-17 for Levi's–C.Klein and Levi's–T.Hilfiger (PD $>$ .95). When brands are closer in value, the ambiguity penalty is weaker, for example £-7.24 for C.Klein–T.Hilfiger (PD = .81). Moreover, ambiguity increases WTP for tangible features. Slim rises by £28.03 (PD = 1.00) and Skinny by £27.71 (PD = .97), while Wide remains indistinguishable from zero (PD = .54). These shifts indicate that, under ambiguity, consumers redirect their attention from brand or mystery signals to tangible, observable features, demonstrating design-driven attribute weighting.

Higher perceived risk yields a parallel pattern. WTP for brands and for mystery products declines by £16 to £31 (PDs $>$ .95), while Slim, Skinny, and Light blue increase by about £20.17, £28.06, and £11.22 (PDs $>$ .95) respectively. When the downside of the unknown is salient, because probabilities are undisclosed or risk is perceived to be higher, consumers discount brand and mystery signals and rely more on fit and color.

Socio-demographics also contribute. Women show lower WTP for all brands (£-19 to £-26, PDs $>$ .95) and markedly higher WTP for Slim and Skinny. Older participants report higher WTP for Wrangler (£16.25, PD = .98) and lower WTP for non-regular fits. Participants with a university degree place more value on brands (e.g., Levi's increases by £17.10, PD = .96) and less on Skinny and Light blue. Income effects are weak.

Price elasticities. Next, we analyze own- and cross-price elasticities for regular-fit blue jeans using realistic price levels ordered by median WTP: £115 (Levi's), £100 (Calvin Klein), £85 (Tommy Hilfiger), and £70 (Wrangler). We price each mystery product at the average of the two brands in its *outcome set*. Results are reported as posterior means across 1,000 MCMC draws in Web Appendix E.2, Table W11.

Across the six markets, own-price elasticities are negative and mostly lie between -1.4 and -2.6, indicating price-elastic demand for all products.

The mystery product is consistently among the most price-sensitive. For illustration, in the

Levi's–Wrangler market under risk, a 1% price reduction raises Levi's share by 2.04%, T. Hilfiger's share by 2.03%, and the same cut for the mystery product raises its share by 2.37%.

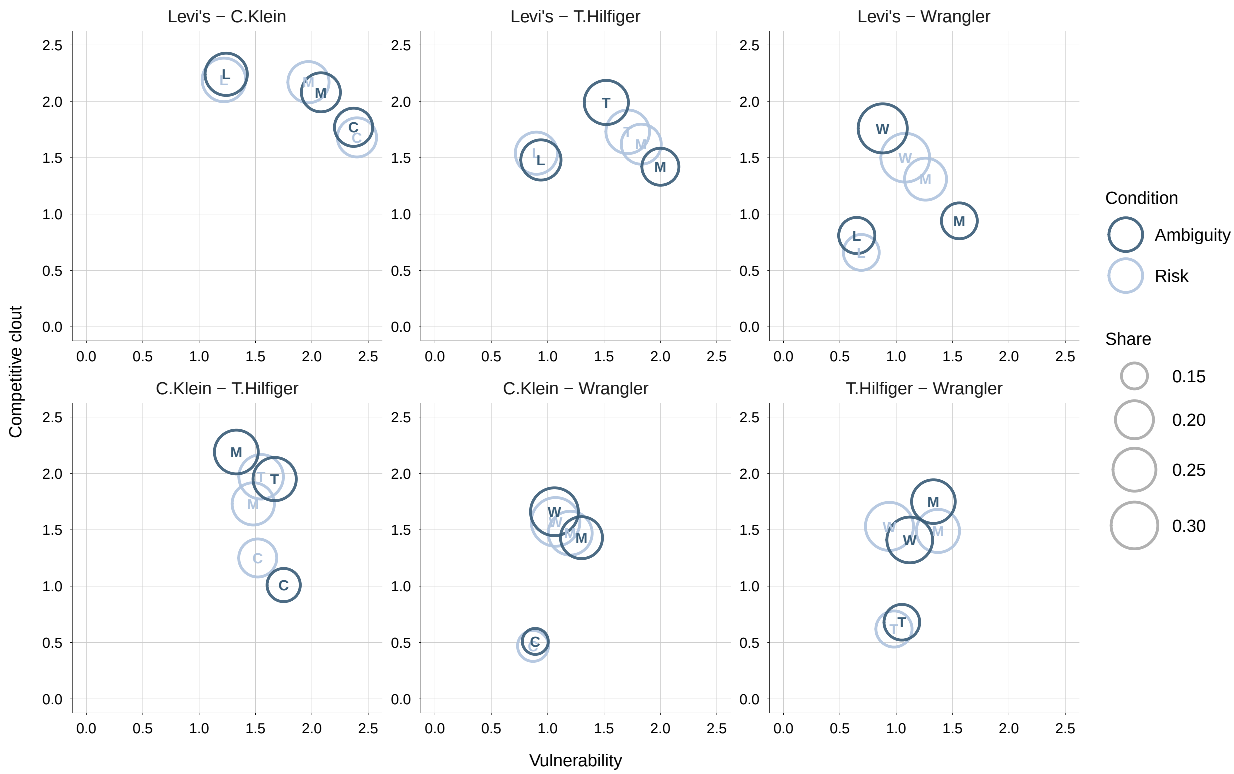
Ambiguity modestly increases own-price sensitivity, suggesting stronger demand responses to price changes when probabilities are not communicated. For instance, in Levi's–C.Klein the mystery elasticity shifts from -2.49 to -2.63 and in Levi's–T.Hilfiger from -2.37 to -2.53 under ambiguity.

Substitution patterns are asymmetric and mirror the brand hierarchy observed in WTP. When the higher-valued brand raises its price, shares shift to both the lower-valued brand and the mystery product, with the mystery gaining at least as much as the lower-valued brand. In the Levi's–T.Hilfiger market under risk, a 1% price increase for Levi's raises shares of T. Hilfiger by .82% and the mystery product by .88%. When the mystery product raises price, share flows back disproportionately to the lower-valued brand. In the same market, a 1% increase in price for the mystery product raises shares of T. Hilfiger by 1.02% and Levi's by .69%. These rankings persist under ambiguity, although magnitudes are slightly damped, indicating that consumers become more cautious about switching.

Price changes at the lower end trigger more market exits. In the Levi's–T.Hilfiger market under risk, a 1% increase in T. Hilfiger's price raises the no-buy option share by .51%, compared with .32% when Levi's increases price and .30% when the mystery product increases price. A similar pattern appears in T.Hilfiger–Wrangler under risk, where a 1% price increase of Wrangler lifts the no-buy share by .41% compared with .21% for T. Hilfiger and .37% for the mystery product. Hence, lower-valued brands serve as the primary price anchor for price-sensitive consumers, because increases in their prices trigger greater category exit than comparable increases in premium brands' prices.

Figure 6 plots competitive *clout* and *vulnerability* derived from the cross-price elasticities (Kamakura and Russell 1989). Clout captures how strongly other options' shares respond to a focal option's price changes, whereas vulnerability captures how strongly a focal option's share responds to competitors' price changes. Bubble sizes reflect market shares, indicating that the positions in

Figure 6: Vulnerability and competitive clout.



Notes. Each panel depicts a market scenario with a corresponding outcome set. Brands in the outcome set are abbreviated by their first letter: L = Levi's, C = C.Klein, T = T.Hilfiger, and W = Wrangler. M denotes the mystery jeans option. Blue color shades indicate the experimental conditions, and circle sizes represent market shares.

the clout-vulnerability space correspond to economically meaningful demand levels (including the mystery option).

Across outcome sets and framings, Levi's is consistently among the least vulnerable alternatives, with moderate clout, consistent with a comparatively insulated position. The mystery option typically exhibits high vulnerability (often the highest or second-highest within an outcome set), indicating that its demand is particularly sensitive to competitors' pricing. At the same time, its clout is frequently substantial, implying that changing the mystery price can induce sizable share shifts among competing brands. Relative to C. Klein, the mystery option generally shows higher clout and comparable vulnerability; relative to Levi's (and typically Wrangler), it is more vulnerable, suggesting a weaker defensive position. Finally, in several outcome sets, the ambiguity framing accentuates dispersion across alternatives, with more pronounced differences in clout and vulnerability than under risk.

Profit implications

Since WTP is an individual-level monetary measure that ignores substitution and competitor pricing responses, we next examine profits as a firm-relevant outcome by solving for equilibrium prices that reflect competitive dynamics (Allenby et al. 2014). We quantify how introducing a mystery product reshapes firms' pricing and the distribution of profits across participation and framing choices.

Setup. We consider a market with five stock-keeping units, four branded pairs of regular-fit blue jeans, and one mystery pair sold exclusively by an independent retailer. Consumers can also choose not to purchase, and the no-buy option absorbs the residual demand so that choice probabilities sum to one. The market size is normalized to one, and all products share the same unit variable cost $c = £60$. Participating brands receive a fixed share, ϕ, of the mystery profit. 80% of mystery profit is split evenly between the two brands ($\phi = .4$), and the retailer retains 20%. We treat this sharing rule as an exogenous contractual feature and explore robustness to alternative splits in Web Appendix E.3.

Given this market setup, we compute profit-maximizing prices under Bertrand competition for the six *outcome sets* under both risk and ambiguity. We solve by iterating prices to the profit-maximizing fixed point and record the corresponding profits (Morrow and Skerlos 2011). The first-order conditions are defined by the following system:

$$\mathbf{s}(\mathbf{p}) + (\Omega \circ \Delta(\mathbf{p}))\,(\mathbf{p} - \mathbf{c}) = \mathbf{0}, \tag{4}$$

which implies best-response prices

$$\mathbf{p} = \mathbf{c} - (\Omega \circ \Delta(\mathbf{p}))^{-1}\mathbf{s}(\mathbf{p}). \tag{5}$$

where $\mathbf{s}(\mathbf{p})$ denotes the vector of market shares implied by the estimated demand system. The no-buy option is not priced. The ownership structure reflects the profit-sharing mechanism. For a participating pair, each brand internalizes part of the mystery demand effect, as shown in Web Appendix E.3, Equations W1 and W2. The analysis uses the same posterior predictive simulation approach as for WTP, thereby carrying both individual heterogeneity and posterior uncertainty into the pricing results. We summarize by reporting the median of optimal prices and profits across 1,000 posterior draws in Web Appendix E.3, Table W12.

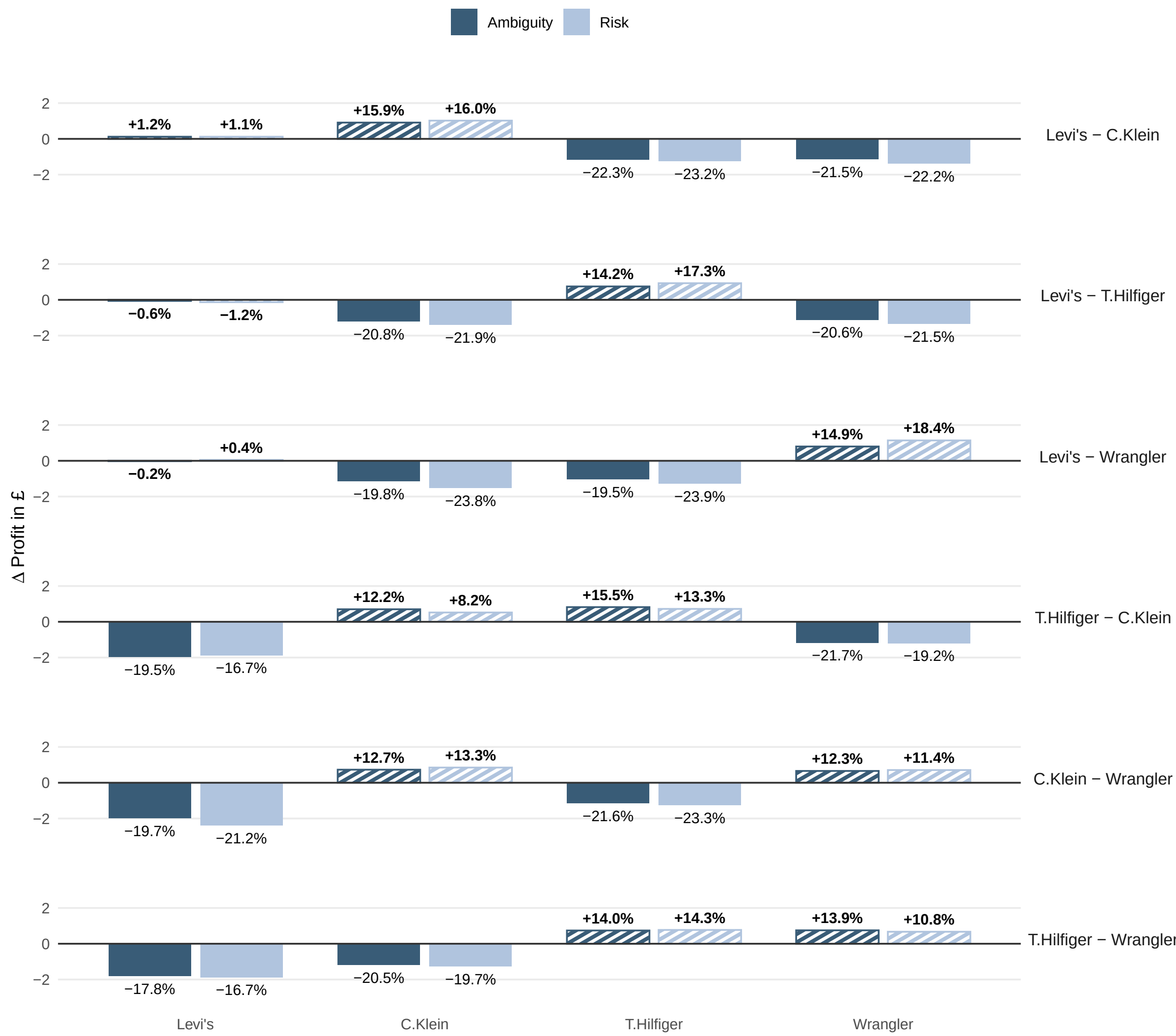
Results. Participating brands raise optimal prices by about £1-2 while non-participants reduce prices by about £2-3. For example, in the Levi's–Wrangler *outcome set* with risk framing, prices increase by £1.64 for Levi's and £1.89 for Wrangler, while T. Hilfiger and C. Klein cut prices by £2.47 and £2.90. The mystery price is £95.91, and the retailer earns about £1.40 per pair of jeans.

Profit reallocation mirrors these pricing shifts. On average, the two participating brands gain, while the two non-participants lose between 17% and 24% of their profit relative to the baseline without a mystery product. Gains are asymmetric within the pair. When Levi's participates, its partner captures most of the profits, while Levi's gains little or can even lose, which makes participation for the premium brand mainly defensive (see Figure 7).

Uncertainty framing changes magnitudes rather than directions. In the Levi's–Wrangler *outcome set*, ambiguity dampens the effect. Wrangler's gain declines from $+18.4\%$ under risk to $+14.9\%$, and C. Klein's loss improves from -23.8% to -19.8%. In the T–C *outcome set*, ambiguity amplifies differences. C. Klein increases from $+8.2\%$ to $+12.2\%$, and Levi's becomes more negative from -16.7% to -19.5%. These shifts align with the design logic that ambiguity is less penalized when the two brands are similar and more penalized when differentiation is high.

The mechanism is consistent with the estimated elasticities and substitution patterns. Own price elasticities lie mainly between -1.5 and -3, and the mystery product is the most price-sensitive. Raising the premium brand's price diverts demand to the mystery and to the lower-valued brand, while a higher mystery price sends demand back mainly to the lower-valued brand. Ambiguity increases price sensitivity and vulnerability to competitor prices while leaving the ordering of substitutes intact.

Figure 7: Net profit changes with mystery vs. without mystery (baseline).



Notes. The figure reports changes in profits under a counterfactual scenario in which a mystery option enters the market. Bars show absolute profit changes (y-axis), and the numbers above/below the bars show relative changes compared to the baseline market without the mystery option. Each row represents a market with a different outcome set (brands shown on the right-hand side). Hatched bars and bold numbers also highlight brands included in the outcome set. Blue shading indicates the experimental condition.

Additional scenarios. We examine robustness to alternative profit-sharing scenarios. Reducing or eliminating profit sharing intensifies competition among participating brands, lowering both brand and total channel profits below the no-mystery baseline. Allocating unequal shares of mystery profit to the two participating brands in favor of the more-preferred brand leaves total channel profit virtually unchanged, and its primary effect is distributional, shifting profit toward that brand.

Further details are reported in Web Appendix E.3.

Discussion

We show that the mechanics observed in Study 1 generalize, and reverse in predictable ways under horizontal differentiation. In Study 2, we move to a more realistic jeans purchase context, where a more utilitarian, higher-stakes mindset is made salient through priming with questions about purchasing habits. Brand WTPs show a clear hierarchy (Levi's dominates), and the mystery product's position varies with the pair it may resolve into. When the set includes a dominant brand, mystery valuations fall below the average of the two brands, and ambiguity further depresses WTP relative to this benchmark. Hence, high differentiation makes losses salient and reduces the mystery label premium. When brands are closer in value, mystery valuations meet or exceed that benchmark and sometimes surpass the better brand. Ambiguity lowers WTP most when differentiation is high (e.g., sets including Levi's), but carries a limited penalty when the pair is closer, thereby quantifying conditions under which ambiguity aversion materially affects valuation. Furthermore, the data reveal a reallocation of attribute weights under ambiguity and heightened perceived risk, as participants discount brand/mystery cues and place more weight on tangible, observable features (i.e., fit and color).

Ultimately, these preferences are reflected in distinct market mechanics. Own-price elasticities are more negative for the mystery product than for brands, and ambiguity modestly increases own-price sensitivity. In Bertrand-Nash equilibria, participation tends to increase the combined profit of the two participating brands, while non-participating brands lose. However, the stronger brand often captures a smaller share of the gain and therefore participates in defending its position. Ambiguity reduces profits when differentiation is high, but is comparatively not harmful when differentiation is low.

General Discussion

Mystery products, i.e., offerings in which key attributes remain concealed until after purchase, represent a deliberate deployment of uncertainty as a marketing instrument. Despite their growing prevalence across categories, systematic evidence remains limited on how different design choices shape consumer valuation and market outcomes—and, in turn, what this implies for how firms should design uncertainty. This research addresses that gap by isolating two managerially controllable design levers, the composition of the *outcome set* and the *framing of uncertainty*, and documenting their effects from individual valuation through to market equilibrium.

Our contribution is both conceptual and empirical. Conceptually, we characterize mystery products as instances of designed uncertainty, governed by two structural features: the possible outcomes (outcome-set composition) and whether the realization probabilities are disclosed (uncertainty framing). Empirically, we deploy two incentive-aligned experiments—an induced-value laboratory study with vertically differentiated monetary outcomes and a large-scale choice-based conjoint study with horizontally differentiated jeans brands, to provide causal evidence on how these design levers shape consumer valuation, attribute processing, and competitive dynamics.

Summary of Findings

Table 3 synthesizes the empirical results that emerge across both studies, organizing them by design dimension and market outcome.

Three core insights emerge from our findings. Across studies, our central finding is that consumers do not evaluate uncertainty per se; instead, they evaluate the structure of the possible outcomes. *Uncertainty framing* matters primarily insofar as it amplifies or attenuates perceived downside risk embedded in that structure. Importantly, *uncertainty framing* operates at two analytically distinct levels: it affects the overall level of valuation (i.e., willingness to pay) and it reshapes how consumers weigh and process product attributes when forming those valuations.

First, consumers anchor valuation on the structure of the *outcome set*. WTP rises systematically

Table 3: Summary of empirical findings.

Dimension	Integrated empirical finding
(1) Outcome-set mean	WTP increases with the expected value of the outcome set, indicating anchoring on possible realizations rather than random choice.
(2) Outcome-set dispersion	Greater differentiation across outcomes lowers WTP at equal expected values, reflecting heightened sensitivity to downside risk.
(3) Intrinsic value of mystery	Mystery products often earn a premium over expected value, including when the outcome is effectively known, indicating intrinsic appeal of the mystery label.
(4) Dominant outcomes	When a clearly dominant alternative is included in the outcome set, mystery products are discounted and may fall below the expected-value benchmark.
(5) Uncertainty framing	Ambiguity lowers WTP relative to disclosed probabilities when outcome differentiation and stakes are high; effects are attenuated when outcomes are similar.
(6) Attribute reweighting	Under ambiguity, consumers place less weight on brand and mystery cues and greater weight on tangible attributes (e.g., fit and color).
(7) Price sensitivity	Mystery products exhibit higher price elasticity than fully specified alternatives, implying strong demand responses to price changes.
(8) Competitive and profit effects	Introducing a mystery product shifts demand and profits toward participating alternatives, especially weaker ones, while non-participants lose share and profitability.

with expected value, consistent with expected-value-based anchoring rather than random choice or purely novelty-driven evaluation. At the same time, holding the mean constant, greater dispersion across possible outcomes reduces WTP, revealing sensitivity to downside risk. Crucially, the nature of differentiation matters: when the *outcome set* includes a clearly dominant alternative, the mystery product is discounted below the simple average, consistent with pessimistic beliefs about realization probabilities. When outcomes are horizontally differentiated and closer in value, mystery products can command premiums over expected value and, in some cases, over the better alternative.

Second, *uncertainty framing* operates as a context-dependent moderator. When outcomes differ sharply in value, ambiguity substantially reduces WTP relative to disclosed probabilities, particularly when stakes are high, and a dominant outcome is present. When outcomes are similar, the ambiguity penalty largely disappears. Beyond level effects, ambiguity reallocates cognitive resources: consumers reduce reliance on brand and mystery cues and increase weight on tangible attributes such as fit and color, reflecting compensatory rather than shallow processing.

Third, these preference effects translate into market outcomes. Mystery products are among the most price-elastic options, indicating that they function primarily as demand expanders rather than margin-generating products. Introducing a mystery product shifts demand toward participating alternatives—especially weaker ones—while reducing market shares and profits of non-participating options. As a result, whether mystery products create or destroy value depends on how uncertainty is designed.

Theoretical Implications

This research contributes to the literature on consumer choice uncertainty in three ways. First, we show that consumers evaluate mystery products by anchoring on both the mean and dispersion of the *outcome set*. This extends prior work by demonstrating that valuation depends not only on whether uncertainty exists, but on the design of the uncertainty. Importantly, these effects cannot be reduced to expected-value calculations or stable ambiguity preferences alone: identical expected values and probability structures generate systematically different valuations depending on how outcomes are differentiated and framed. The finding that dispersion reduces WTP even at a constant expected value indicates sensitivity to the shape of the distribution, not merely its central tendency. More importantly, we show that the type of differentiation fundamentally alters response: vertical differentiation triggers discounting, whereas horizontal differentiation can generate premiums. This distinction helps reconcile mixed findings in prior research and clarifies when uncertainty creates versus destroys value.

Second, we identify a boundary condition for ambiguity aversion: the effect of withholding probabilities depends critically on outcome dispersion. While classic work shows that consumers prefer known to unknown probabilities (Ellsberg 1961; Camerer and Weber 1992), our results demonstrate that this preference is contingent on the stakes. Ambiguity sharply reduces valuation when realizations differ markedly in value but carries a minimal penalty when outcomes are comparable. Ambiguity aversion in our context thus emerges as a context-dependent response rather than a stable trait.

Third, by linking individual valuation to market outcomes within a stylized competitive environment, we show that designed uncertainty functions as a competitive instrument. Behavioral responses to outcome-set composition and *uncertainty framing* propagate into substitution patterns, price elasticities, and profit allocation. Mystery products systematically reallocate demand toward participating brands—particularly weaker ones—while disadvantaging non-participants, bridging behavioral research on uncertainty with analytical models of opaque selling.

Implications for Practice

Table 4 translates the empirical results summarized in Table 3 into implications for the design and deployment of mystery products. Importantly, the table does not introduce new effects; rather, each row reinterprets a documented empirical pattern through a product-design and competitive lens. The discussion below highlights the logic underlying these implications and clarifies their scope and limits.

Table 4: Implications for the design and deployment of mystery products.

Design lever (Dimension)	**Design implication**
Outcome-set composition (1, 2, and 4)	Construct outcome sets from alternatives with similar perceived value. Avoid bundling clearly dominant and inferior options unless the objective is clearance rather than value creation.
Probability disclosure (5)	Evaluate disclosure jointly with outcome-set dispersion: disclose probabilities when differentiation is high; withholding probabilities is comparatively less costly when outcomes are close in value.
Attribute emphasis (6)	When using ambiguous framing, ensure that observable attributes (e.g., fit, color, functionality) are strong and salient to support valuation.
Pricing strategy (7)	Price mystery products as demand expanders rather than margin extractors. Modest discounts can generate large demand responses; novelty premiums are unlikely to be sustained.
Portfolio participation (8)	Evaluate mystery products at the portfolio and market level. Weaker brands have the strongest upside; stronger brands may participate defensively to avoid competitive erosion.
Strategic role of mystery products (3 and 8)	Use mystery products as a strategic instrument to strengthen weaker brands, manage competition, and influence category dynamics when consumer response aligns with design.

Notes. Dimension numbers (in parentheses) correspond to the empirical findings summarized in Table 3.

First, *outcome-set* composition is the primary managerial lever. Across both studies, valuation responds strongly to the mean and dispersion of the *outcome set*, as well as to the presence of dominant outcomes. These effects imply that firms should treat outcome-set construction as a core design decision rather than a secondary implementation detail. When *outcome sets* contain alternatives that are close in perceived value, downside risk is muted, and mystery products can sustain higher valuation. In contrast, mixing clearly dominant and inferior options induces discounting, as consumers behave as if the inferior outcome were more likely. This logic also clarifies what mystery products are *not* well suited for: they are ineffective at bundling large quality gaps without explicit compensation.

Second, probability disclosure should be evaluated jointly with outcome-set dispersion. The ambiguity penalties documented in Table 3 arise primarily when outcome differentiation and stakes are high. In such settings, disclosing probabilities meaningfully increases valuation by limiting pessimistic inference. When outcomes are similar, however, ambiguity incurs little cost, and disclosure yields only a limited incremental benefit. This implies that disclosure decisions cannot be assessed in isolation; the same framing choice can be value-enhancing or largely irrelevant depending on which outcomes are bundled.

Third, *uncertainty framing* reshapes the structure of attribute evaluation underlying consumer choice. Under ambiguity, consumers place less weight on the brand and the mystery cue and more weight on tangible attributes. This pattern suggests that firms relying on ambiguous framing should ensure that observable attributes are sufficiently differentiated and salient. Ambiguity does not reduce attention, but it changes what consumers attend to. Designs that withhold probabilities while also offering weak observable attributes are therefore particularly vulnerable to valuation losses.

Fourth, pricing and participation decisions must be evaluated at the market level. Mystery products are consistently more price elastic than fully specified alternatives, indicating that they function primarily as demand expanders rather than margin extractors. Introducing a mystery product redistributes demand toward participating brands—especially weaker ones—and away from non-participants. For stronger brands, participation is often defensive, trading off cannibalization against competitive erosion. These dynamics underscore that the profitability of mystery products depends less on standalone margins and more on how they reshape substitution patterns within the competitive set.

Taken together, these implications suggest that mystery products are most effective not when uncertainty is maximized, but when it is carefully constrained. The value of mystery arises when downside risk is limited, when framing choices align with outcome-set structure, and when pricing and participation decisions are evaluated at the market rather than the product level. In this sense, mystery products are best understood not as novelty devices, but as instruments for shaping substitution and competitive dynamics through the deliberate design of uncertainty.

Limitations and Future Research

Some limitations of our studies suggest avenues for future research. First, our uncertainty manipulation contrasts disclosed 50/50 probabilities with complete ambiguity. While this choice provides a clean and symmetric benchmark, real-world implementations often involve skewed probabilities (e.g., 40/60), bounded ranges, or qualitative likelihood cues. Consumers may exhibit biases, overweighting small probabilities and underweighting moderate to high probabilities (Tversky and Fox 1995). Future research should vary probability structures to study how different framings shape preferences for the mystery products.

Second, both studies capture static, single-shot choices. In practice, consumers learn from realized outcomes, update beliefs, and share experiences. This is especially salient in collectibles markets (e.g., Pop Mart blind-box toys, Xu et al. 2025), where repeat buying and community chatter about pulls and scarcity shape expectations. Longitudinal and field studies could examine belief updating, trust formation, and the sustainability of mystery-product demand under repeated purchase.

Third, both studies employ binary outcome sets. Real-world mystery products often draw from larger sets, e.g., a blind-box series may contain twelve or more distinct figures, which may dilute individual-outcome anchoring, introduce long-tail value distributions, and create “chase item” dynamics absent in our design. Future research should examine how outcome-set size moderates the effects documented here.

Fourth, our market analysis relies on a stylized static Bertrand-Nash framework. Extending this framework to incorporate cost heterogeneity, capacity constraints, bargaining over participation terms, multi-platform competition, and dynamic pricing could strengthen external validity.

Finally, we focus on demand and firm profits, not consumer surplus or perceived fairness. Given regulatory interest in probabilistic selling, future work should examine welfare and fairness, as well as the effects of disclosure or auditing interventions.

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Web Appendix:
Designed Uncertainty in Mystery Products

Contents

Web Appendix A: Experimental Materials and Measures

This Web Appendix reports the experimental materials (e.g., choice tasks) and all measures (e.g., risk scale items) used in both studies, presented by condition.

Figure W1: Example of a choice task in the ambiguity condition – Study 1.

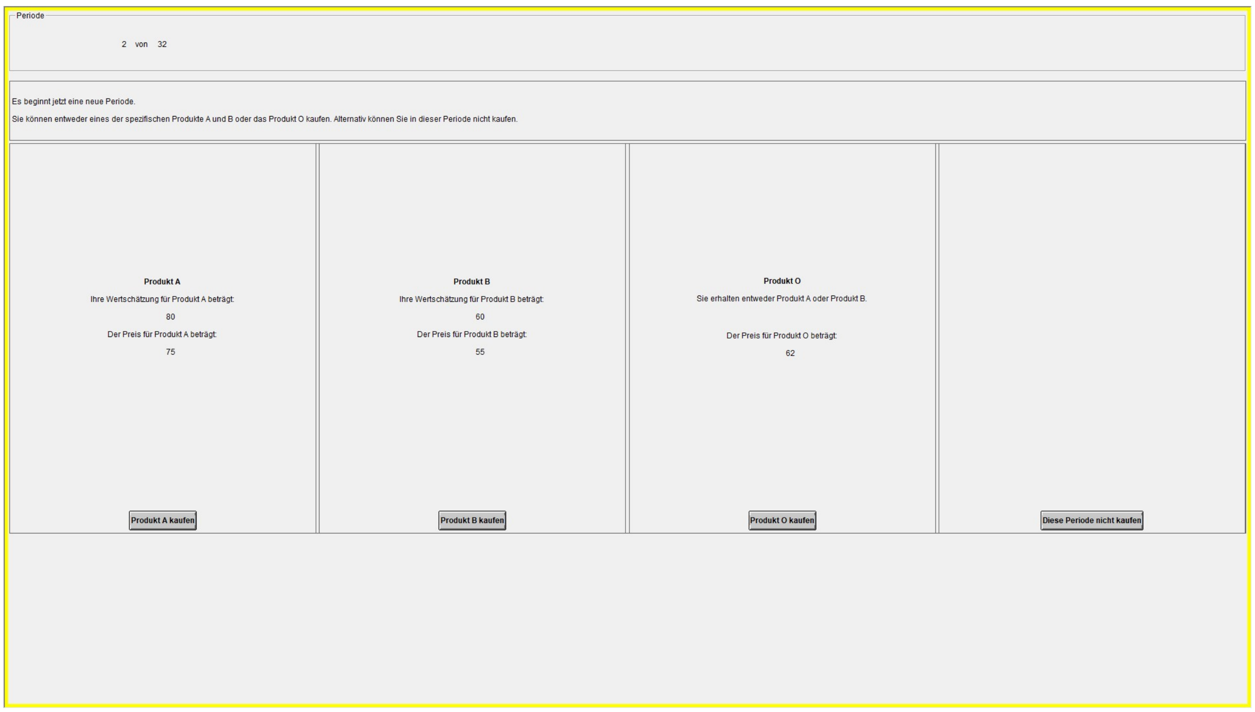

Figure W2: Example of a choice task in the risk condition – Study 1.

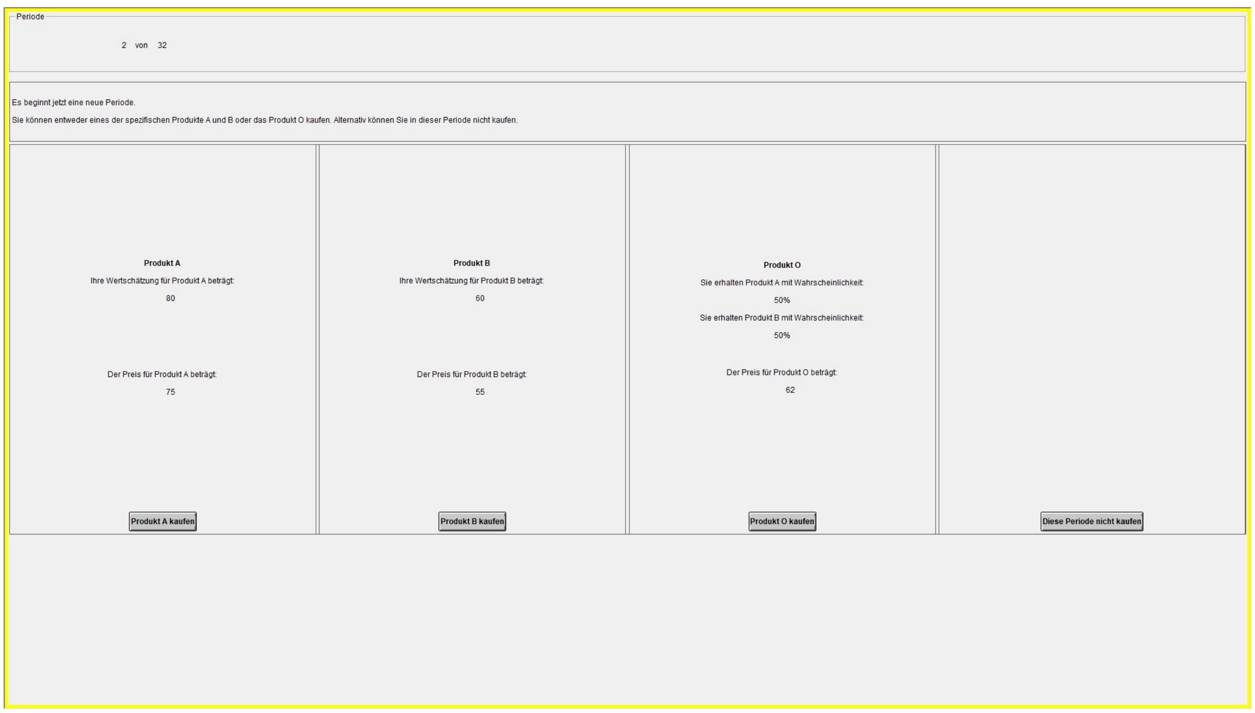

Figure W3: Example of a random choice task in the ambiguity condition – Study 2.

If you were considering buying a new pair of jeans and these were your only options, which would you choose?

Please review the options **carefully** and choose the one you **personally** would **prefer to buy.** (There is no right or wrong choice, just choose the option you personally prefer.)

Remember that the choice you make here **could actually be implemented** (you could get the alternative you selected).

Remember that the brand of the mystery jeans "? (Mystery Jeans)" is **randomly** selected with **unknown** probabilities **from the two specific brands** of the other options shown below.

(1 of 18)

Brand	Wrangler	? (Mystery Jeans)	Calvin Klein
Fit	Wide	Skinny	Slim
Colour	Light blue	Blue	Black
Price	£115	£70	£100
	Select	Select	Select

NONE: I wouldn't choose any of the jeans above.

Select

Figure W4: Example of a random choice task in the risk condition – Study 2.

If you were considering buying a new pair of jeans and these were your only options, which would you choose?

Please review the options **carefully** and choose the one you **personally** would **prefer to buy.** (There is no right or wrong choice, just choose the option you personally prefer.)

Remember that the choice you make here **could actually be implemented** (you could get the alternative you selected).

Remember that the brand of the mystery jeans "? (Mystery Jeans)" is **randomly** selected with **equal** probabilities **from the two specific brands** of the other options shown below.

(1 of 18)

Brand	Wrangler	? (Mystery Jeans)	Calvin Klein
Fit	Wide	Skinny	Slim
Colour	Light blue	Blue	Black
Price	£115	£70	£100
	Select	Select	Select

NONE: I wouldn't choose any of the jeans above.

Select

Figure W5: Hold-out choice tasks – Study 2.

(6 of 18)

Brand	Levi's	? (Mystery Jeans)	Tommy Hilfiger
Fit	Slim	Regular	Wide
Colour	Light blue	Blue	Black
Price	£115	£100	£85
	Select	Select	Select

NONE: I wouldn't choose any of the jeans above.

Select

(12 of 18)

Brand	Levi's	? (Mystery Jeans)	Tommy Hilfiger
Fit	Slim	Regular	Wide
Colour	Light blue	Blue	Black
Price	£115	£70	£85
	Select	Select	Select

NONE: I wouldn't choose any of the jeans above.

Select

Table W1: Personality and risk attitudes scales and items.

Construct	**Items and scale**
Ambiguity Aversion (Trautmann, Vieider, and Wakker 2011) Study 1 & 2	1) You have to choose between the two prospect options. Which do you choose? • Option A (bet on a color to win £100 from bag with 20 red and 20 green chips) • Option B (bet on a color to win £100 from bag with unknown proportion of colors) 2) How much would you maximally pay for the right to participate in the prospects? Please indicate your valuations: I would pay _____ (in £) to participate in Option A (bet on a color to win £100 from bag with 20 red and 20 green chips). I would pay _____ (in £) to participate in Option B (bet on a color to win £100 from bag with unknown proportion of colors).
Willingness to take risks (Dohmen et al. 2011) Study 1 & 2	How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? 7-point scale: 1 = completely unwilling to take risks 7 = completely willing to take risks
Gambling proneness (Ailawadi et al. 2014) Study 2	I like to gamble. I like to take risks. 7-point scale: 1 = strongly disagree – 7 = strongly agree
Optimism (Taute, McQuitty, and Sautter 2011) Study 2	I never give up when faced with a challenge. I keep going in the face of adversity. I keep trying in the face of obstacles. I don't let anxiety keep me from accomplishing my goals. I have the will to win. I continue to try even when it seems hopeless. 7-point scale: 1 = strongly disagree – 7 = strongly agree
Perceived risk of mystery jeans (Thelen, Yoo, and Magnini 2011) Study 2	I think buying a mystery jeans ... ... is risky. ... can lead to bad results. ... can have uncertain outcomes. ... makes me feel anxious. ... causes me to worry. 7-point scale: 1 = strongly disagree – 7 = strongly agree
Variety-seeking behavior (Steenkamp and Baumgartner 1995) Study 1	I like to continue doing the same old things rather than trying new and different things. I like to experience novelty and change in my daily routine. I like a job that offers change, variety, and travel, even if it involves some danger. I am continually seeking new ideas and experiences. I like continually changing activities. When things get boring, I like to find some new and unfamiliar experience. I prefer a routine way of life to an unpredictable one full of change. 7-point scale: 1 = strongly disagree – 7 = strongly agree
Risk aversion (Holt and Laury 2002) Study 1	Which of the following two options do you prefer? • Option A: A 1/10 (... 10/10) chance of €200 and a 9/10 (... 0/10) chance of €160 • Option B: A 1/10 (... 10/10) chance of €385 and a 9/10 (... 0/10) chance of €10

Web Appendix B: Participants

B.1 Study 2: Data Quality

This Web Appendix summarizes the exclusion criteria (comprehension checks, straight-lining, and extreme response times). The initial sample comprises $N = 1{,}200$ participants.

Comprehension Checks

We included two comprehension checks on the mystery-jeans concept (i.e., the definition and timing of brand revelation). We excluded participants who failed both checks ($n = 17$; ambiguity: 11; risk: 6), yielding $N = 1{,}183$. Failure rates did not differ across conditions for either check (check 1: $\chi^2(1) = 0.12$, $p = .728$; check 2: $\chi^2(1) = 2.90$, $p = .089$) or for failing both ($\chi^2(1) = 1.89$, $p = .169$).

Straight-lining

Following Allenby et al. (2014), we excluded participants who always chose the no-buy option ($n = 14$; ambiguity: 4; risk: 10), yielding $N = 1{,}169$.

Response Time

We trimmed CBC completion times at the 5th/99th percentiles (overall: 2.04–11.06 min; risk: 1.92–12.46 min), excluding $n = 72$ participants (ambiguity: 35; risk: 37). Exclusion rates and response times (survey total and CBC only) did not differ significantly across conditions.

The final sample is $N = 1{,}097$ (ambiguity: 528; risk: 569).

B.2 Balance Checks

This Web Appendix reports participant characteristics for both studies. The tables present descriptive statistics (e.g., counts, means, and standard deviations) for relevant pre-treatment variables (e.g., age, gender, and risk attitudes) by condition and for the pooled sample. Overall, participant characteristics are highly comparable across conditions, with no meaningful differences. This pattern suggests that randomization was successful in both studies and that pre-treatment covariates are well balanced. Results from covariate-by-covariate statistical tests (by study) are available upon request.

Table W2: Sample characteristics – Study 1.

	Condition		
	Ambiguity $N = 24$	**Risk** $N = 24$	**Pooled** $N = 48$
Female in %	54.17	37.50	45.83
Mean age in years	23.21 (5.44)	24.25 (6.54)	23.73 (5.97)
Current program of study in %			
Economics	16.67	8.33	12.50
Business Administration	25.00	29.17	27.08
Other Social or Economic Sciences	12.50	8.33	10.42
Psychology	0.00	4.17	2.08
Humanities	8.33	16.67	12.50
Law	0.00	4.17	2.08
Natural Sciences/Engineering	20.83	8.33	14.58
Other	16.67	20.83	18.75
Current mood in %			
Very good	8.33	8.33	8.33
Good	62.50	66.67	64.58
Neutral	25.00	16.67	20.83
Bad	4.17	8.33	6.25
Very bad	0.00	0.00	0.00
Frequency of experiment participation in %			
Never before	8.33	0.00	4.17
Once before	8.33	20.83	14.58
2–5 times	41.67	41.67	41.67
More often	41.67	37.50	39.58

Notes. Standard deviations are reported in parentheses where applicable. Gender was collected using a binary item (female/male).

B.3 Further Insights

The data also reveal descriptive, model-free patterns that align with prior findings in the literature and motivate the inclusion of selected covariates to account for observed heterogeneity in our HB models.

Table W3: Risk attitudes – Study 1.

	Condition		
	Ambiguity $N = 24$	**Risk** $N = 24$	**Pooled** $N = 48$
Ambiguity Aversion			
Choice for option A (risky urn) in %	87.50	100.00	93.75
Willingness-to-pay for option A in €	15.54 (9.69)	19.71 (11.24)	17.62 (10.59)
Willingness-to-pay for option B in €	8.96 (8.94)	12.04 (9.49)	10.50 (9.25)
Willingness to take risks	4.08 (1.18)	4.42 (1.14)	4.25 (1.16)
Variety-seeking behavior	4.80 (0.65)	4.52 (0.76)	4.66 (0.71)
Risk aversion	4.98 (1.15)	5.04 (1.19)	5.02 (1.17)

Notes. Standard deviations are reported in parentheses where applicable. Scale descriptions and response labels appear in Table W1.

Study 1

We measured individual risk-related traits using validated scales (Table W1). Consistent with classic ambiguity aversion, most participants preferred the risky prospect and reported higher willingness to pay (WTP) for it than for the ambiguous prospect (Wilcoxon signed-rank test: $V = 521$, $p < .001$). This pattern also appears among participants who ultimately selected the ambiguous option, consistent with preference reversal. At the same time, the ambiguity-elicitation measures did not predict the proportion of mystery choices (WTP risky urn: linear regression, $F(1,46) = 1.18$, $p = .282$; WTP ambiguous urn: $F(1,46) = .90$, $p = .347$). Risk aversion likewise showed no systematic association with mystery choice behavior (linear regression, $F(1,46) = .78$, $p = .382$). In contrast, self-reported willingness to take risks was positively associated with the proportion of mystery choices (linear regression, $F(1,46) = 18.03$, $p < .001$). Variety-seeking was above average but not associated with mystery choice behavior (linear regression, $F(1,46) = 1.66$, $p = .205$).

Study 2

The ambiguity-aversion measures again showed no reliable association with the proportion of mystery choices (choice: linear regression, $F(1,1095) = 3.34$, $p = .068$; WTP risky urn: $F(1,1095) = .15$, $p = .699$; WTP ambiguous urn: $F(1,1095) = .66$, $p = .415$). Willingness to take risks was

Table W4: Socio-demographic characteristics – Study 2.

	Condition		
	Ambiguity $N = 528$	**Risk** $N = 569$	**Pooled** $N = 1{,}097$
Gender in %			
Female	50.19	51.14	50.68
Male	48.86	47.98	48.40
Non binary/ transgender/ third gender	0.57	0.53	0.55
Prefer to self describe	0.19	0.18	0.18
I prefer not to answer	0.19	0.18	0.18
Mean age in years	42.35 (13.70)	41.91 (14.22)	42.12 (13.97)
Annual household income (before taxes) in %			
Up to £20,000	19.89	16.87	18.32
£20,000 - £34,999	28.98	26.19	27.53
£35,000 - £49,999	20.08	24.25	22.24
£50,000 - £74,999	17.80	20.21	19.05
£75,000 - £99,999	8.71	8.61	8.66
£100,000 or above	4.55	3.87	4.19
Current occupation in %			
A student	5.30	7.56	6.47
Employed for wages	58.90	58.35	58.61
Self-employed	11.74	10.90	11.30
Out of work and looking for work	5.11	5.80	5.47
Out of work, but not currently looking for work	5.30	4.92	5.10
A homemaker	6.25	6.15	6.20
Other	7.39	6.33	6.84
Highest level of education in %			
Less than high school	1.14	0.70	0.91
High school (or equivalent)	30.68	33.74	32.27
Undergraduate degree	40.91	37.08	38.92
Graduate degree	25.76	25.48	25.62
Prefer not to say	0.76	0.88	0.82
Other	0.76	2.11	1.46

Notes. Standard deviations are reported in parentheses where applicable.

positively associated with the proportion of mystery choices (linear regression, $F(1,1095) = 8.48$, $p = .003$), as was gambling proneness (linear regression, $F(1,1095) = 11.29$, $p < .001$). Optimism was not associated with mystery choices (linear regression, $F(1,1095) = .52$, $p = .471$). Finally, perceived risk of the mystery jeans was negatively associated with the proportion of mystery choices (linear regression, $F(1,1095) = 19.25$, $p < .001$).

Table W5: Familiarity and attitudes toward jeans – Study 2.

	Condition		
	Ambiguity $N = 528$	**Risk** $N = 569$	**Pooled** $N = 1{,}097$
Frequency of jeans purchase in %			
Once a month	1.14	1.05	1.09
Every two months	4.17	4.75	4.47
2-3 times per year	42.23	42.36	42.30
Once a year	31.06	33.22	32.18
Less than once a year	21.40	18.63	19.96
Frequency of jeans usage in %			
Everyday	19.13	20.74	19.96
3-5 times a week	48.30	46.92	47.58
Once a week	16.29	15.99	16.13
2-3 times a month	9.09	8.08	8.57
Once a month	2.65	2.28	2.46
Less than once a month	3.41	4.57	4.01
Never	1.14	1.41	1.28
Jeans brand awareness in %			
Levi's	95.27	99.12	97.27
Tommy Hilfiger	68.75	72.23	70.56
Diesel	70.27	75.22	72.84
Calvin Klein	68.18	74.17	71.29
Primark	72.73	74.34	73.56
Gap	67.42	71.18	69.37
Wrangler	67.23	69.07	68.19
H&M	69.70	72.93	71.38
Next	75.38	78.21	76.85
Zara	56.44	59.58	58.07
None of the above	0.95	0.00	0.46
Mean brand relevance score	2.95 (1.59)	3.21 (1.66)	3.09 (1.63)

Notes. Standard deviations are reported in parentheses where applicable. Brand relevance is measured on a 7-point scale.

Table W6: Personality and risk attitudes – Study 2.

	Condition		
	Ambiguity $N = 528$	**Risk** $N = 569$	**Pooled** $N = 1{,}097$
Ambiguity Aversion			
Choice for option A in %	86.17	89.28	87.78
Willingness-to-pay for option A in £	11.74 (15.69)	12.11 (16.77)	11.93 (16.25)
Willingness-to-pay for option B in £	6.84 (12.05)	6.84 (11.90)	6.84 (11.97)
Willingness to take risks	3.77 (1.48)	3.74 (1.49)	3.76 (1.49)
Gambling proneness	3.12 (1.33)	3.20 (1.42)	3.17 (1.38)
Optimism	4.99 (1.13)	5.03 (1.19)	5.01 (1.16)
Perceived risk of mystery jeans	3.69 (1.31)	3.83 (1.31)	3.76 (1.31)

Notes. Standard deviations are reported in parentheses where applicable. Scale descriptions and response labels appear in Table W1.

Web Appendix C: Study 2: Descriptive Choice Patterns

These supplemental CBC results support data quality and economic validity: choices show no straight-lining, clear price sensitivity, and systematic evaluation of the mystery option.

General. Across 16 tasks, the three in-market alternatives each received slightly more than 25% share in both conditions; no-buy was chosen slightly less often. Aggregate choice frequencies did not differ by condition ($\chi^2(3) = 3.07$, $p = .381$). No participant always chose the same jeans alternative; 323 participants (ambiguity: 154; risk: 169; 29.4%) never chose no-buy, and within each condition no-buy was selected less often than the jeans options (ambiguity: $\chi^2(3) = 45.11$, $p < .001$; risk: $\chi^2(3) = 87.97$, $p < .001$).

By Brand or Price. Relative shares (adjusted for display frequency) were highest for Levi's (ambiguity: 30.49%; risk: 30.27%), followed by the mystery option (26.05%; 26.42%), and lowest for Wrangler (23.08%; 23.53%), consistent with stated brand attitudes. No participant always chose the same brand; mystery choices were typically 10–30% of tasks (18 participants >50%; 28 never; 1 always). Shares declined with price: £70 (ambiguity: 31.86%; risk: 32.04%), £85 (29.53%; 29.79%), £100 (23.01%; 23.47%), £115 (18.33%; 18.78%). No participant always chose any price; 247 always avoided £115 (ambiguity: 136; risk: 111).

Brand Context × Price (Mystery Evaluation). Mystery shares were higher when visible brands were less preferred and when the mystery price was lower. A mixed-effects logit showed a positive effect for the weakest brand context (ranks 3–4; $\beta = .25$, $z = 2.88$, $p = .004$) and a negative price effect ($\beta = -.58$, $z = -11.30$, $p < .001$), with no condition or interaction effects ($\beta = -.17$, $z = -.68$, $p = .496$). In a fixed holdout task, lowering the mystery price increased its share from 34.92% to 47.09% (ambiguity) and from 41.40% to 50.32% (risk), with corresponding declines in the visible alternatives, providing model-free evidence that prices affect mystery choices.

Web Appendix D: Model-Based Results

This Web Appendix reports detailed estimation results for the HB-MNL models in Studies 1 and 2.

For all CBC estimations, we impose a negative sign restriction on the price coefficient, following Allenby et al. (2014), because even small posterior mass on positive price sensitivity can yield implausible counterfactuals (e.g., no finite optimal/equilibrium prices). In `bayesm`, the restriction is implemented via the re-parameterization $\alpha_i = -\exp(\alpha_i^*)$ with $\alpha_i^* \in \mathbb{R}$, implying a negative log-normal distribution for the price coefficient and placing priors on the unconstrained latent parameter. We estimate the HB-MNL model using `bayesm::rhierMnlRwMixture()` with a multivariate normal heterogeneity distribution, i.e., $\theta_i \sim N(\mu, \Sigma)$ for K utility coefficients (α^* is one coefficient in θ_i). Under the sign-constrained defaults, $\mu \sim N(\bar{\mu}, a_{\mu}^{-1}\mathbf{I}_K)$ with $a_{\mu} = .1$ and $\bar{\mu}_k = 2$ for constrained coefficients (0 otherwise), and $\Sigma \sim IW(\nu, V)$ with $\nu = K + 15$ and $V = \nu\,\mathrm{diag}(d)$ where $d_k = .1$ for constrained coefficients and $d_k = 4$ otherwise. We run 200,000 MCMC iterations, discard the first 100,000 as burn-in, and retain every 100$^{\text{th}}$ draw, yielding 1,000 posterior draws. Trace plots and standard diagnostics indicate satisfactory mixing and convergence (details available upon request).

Tables W7 and W8 report posterior means and 95% credible intervals for population-level means and standard deviations (square roots of the diagonal elements of Σ). For each study, we report three specifications: Model 1 includes a single (heterogeneous) mystery indicator; Model 2 adds outcome-set context; and Model 3 adds observed heterogeneity via covariates (best in- and out-of-sample fit).

As mentioned above, the price coefficient is modeled as a negative log-normal random variable. Its implied mean is $-\exp\left(\mathrm{M}_{\text{price}} + .5\,\mathrm{SD}^2_{\text{price}}\right)$ and the corresponding standard deviation $\sqrt{\left(\exp\left(\mathrm{M}_{\text{price}} + .5\,\mathrm{SD}^2_{\text{price}}\right)\right)^2\left(\exp\left(\mathrm{SD}^2_{\text{price}}\right) - 1\right)}$; table notes report transformed moments.

Table W7: Estimation results – Study 1.

Parameter	Model 1		Model 2		Model 3	
	M	SD	M	SD	M	SD
Value	2.59 [2.04, 3.19]	1.14 [.77, 1.61]	46.46 [42.54, 50.05]	5.64 [3.43, 8.57]	56.02 [51.93, 59.95]	7.00 [4.85, 10.09]
Mystery	2.13 [1.78, 2.51]	.95 [.75, 1.23]				
Mystery obvious	–	–	1.12 [.36, 1.87]	2.35 [1.79, 3.06]	1.11 [.33, 2.01]	2.28 [1.69, 3.12]
Mystery 20–40	–	–	15.36 [14.17, 16.53]	1.82 [1.29, 2.57]	18.28 [16.88, 19.79]	2.15 [1.48, 3.09]
Mystery 20–60	–	–	19.03 [17.46, 20.46]	2.11 [1.49, 3.01]	22.79 [21.15, 24.51]	2.36 [1.61, 3.31]
Mystery 20–80	–	–	23.66 [21.79, 25.75]	3.01 [1.91, 4.58]	27.99 [25.89, 30.12]	3.04 [2.05, 4.27]
Mystery 40–60	–	–	24.55 [22.58, 26.54]	2.69 [1.79, 4.00]	29.38 [27.31, 31.58]	3.35 [2.24, 4.89]
Mystery 40–80	–	–	29.59 [27.21, 31.93]	2.87 [2.01, 4.12]	35.32 [32.79, 37.66]	3.35 [2.38, 4.77]
Mystery 60–80	–	–	33.82 [31.13, 36.41]	3.46 [2.31, 5.09]	40.60 [37.71, 43.38]	4.21 [2.85, 6.23]
Price	-0.00 [-.58, .45]	.73 [.45, 1.10]	3.78 [3.65, 3.90]	.33 [.27, .41]	3.97 [3.85, 4.09]	.36 [.30, .44]
LMD	-1674.74		-937.93		-911.91	

Notes. M and SD denote the posterior mean and standard deviation of each parameter. Brackets report 95% credible intervals. The no-buy utility is normalized to zero. The price coefficient is modeled as negative log-normal; the implied population mean (SD) of the price sensitivity is -1.3 (1.1), -46.44 (15.94), and -56.33 (20.94) for Models 1–3, respectively.

Table W8: Estimation results – Study 2.

	Model 1		Model 2		Model 3	
Parameter	**M**	**SD**	**M**	**SD**	**M**	**SD**
Levi's	6.18 [5.74, 6.63]	4.96 [4.51, 5.39]	6.48 [6.08, 6.89]	5.18 [4.79, 5.63]	6.62 [6.20, 7.04]	5.15 [4.72, 5.61]
C. Klein	5.42 [4.99, 5.85]	4.98 [4.56, 5.43]	5.68 [5.28, 6.09]	5.18 [4.81, 5.62]	5.80 [5.37, 6.23]	5.19 [4.77, 5.65]
T. Hilfiger	5.17 [4.74, 5.62]	5.06 [4.62, 5.50]	5.39 [4.99, 5.80]	5.19 [4.77, 5.64]	5.51 [5.09, 5.95]	5.22 [4.77, 5.70]
Wrangler	5.06 [4.60, 5.51]	5.29 [4.86, 5.71]	5.29 [4.87, 5.73]	5.51 [5.13, 5.94]	5.43 [5.00, 5.83]	5.48 [5.05, 5.94]
Mystery	5.54 [5.09, 5.98]	5.20 [4.79, 5.62]	–	–	–	–
Mystery L–C	–	–	5.94 [5.50, 6.40]	5.65 [5.18, 6.13]	6.05 [5.56, 6.52]	5.64 [5.20, 6.13]
Mystery L–T	–	–	5.74 [5.28, 6.19]	5.47 [5.04, 5.93]	5.87 [5.42, 6.32]	5.41 [4.87, 5.93]
Mystery L–W	–	–	5.84 [5.37, 6.31]	5.50 [5.08, 5.96]	5.97 [5.53, 6.43]	5.50 [5.05, 6.03]
Mystery C–T	–	–	5.69 [5.24, 6.15]	5.21 [4.79, 5.70]	5.83 [5.40, 6.30]	5.25 [4.81, 5.72]
Mystery C–W	–	–	5.77 [5.33, 6.25]	5.58 [5.16, 6.02]	5.88 [5.43, 6.34]	5.54 [5.08, 6.04]
Mystery T–W	–	–	5.64 [5.21, 6.06]	5.36 [4.97, 5.83]	5.78 [5.32, 6.25]	5.46 [5.00, 5.95]
Skinny	-3.28 [-3.85, -2.73]	7.72 [7.12, 8.31]	-3.45 [-3.98, -2.90]	8.12 [7.57, 8.72]	-3.51 [-4.03, -2.99]	7.55 [7.05, 8.05]
Wide	-4.80 [-5.28, -4.30]	4.98 [4.53, 5.44]	-5.01 [-5.49, -4.52]	5.20 [4.80, 5.66]	-5.18 [-5.73, -4.70]	5.24 [4.84, 5.70]
Slim	-0.68 [-1.02, -0.35]	5.08 [4.74, 5.44]	-0.72 [-1.05, -0.40]	5.32 [4.99, 5.66]	-0.75 [-1.11, -0.42]	5.18 [4.87, 5.51]
Light blue	-1.13 [-1.28, -0.97]	1.92 [1.76, 2.10]	-1.17 [-1.33, -1.01]	2.02 [1.86, 2.17]	-1.21 [-1.38, -1.05]	2.04 [1.87, 2.21]
Black	-0.07 [-0.23, .08]	2.02 [1.87, 2.18]	-0.08 [-0.23, .08]	2.12 [1.96, 2.29]	-0.08 [-0.24, .08]	2.16 [2.00, 2.32]
Price	1.21 [1.10, 1.30]	.93 [0.85, 1.01]	1.24 [1.14, 1.32]	.95 [0.88, 1.03]	1.27 [1.19, 1.35]	.93 [0.86, 1.01]
LMD	-7835.61		-7494.47		-7439.04	
Hit rate	0.825		0.832		0.834	
Hit probability	0.750		0.761		0.764	
RLH	0.668		0.679		0.681	

Notes. M and SD denote the posterior mean and standard deviation of each parameter. Brackets report 95% credible intervals. The no-buy utility is normalized to zero, which allows us to estimate alternative-specific constants for all four brands and the mystery option across the six outcome sets. Reference levels are regular fit and blue color. The price coefficient is modeled as negative log-normal; the implied population mean (SD) of the price sensitivity is −5.14 (5.99), −5.43 (6.61), and −5.53 (6.53) for Models 1–3, respectively.

Web Appendix E: Post-Estimation Results

This Web Appendix describes our post-estimation simulations of market outcomes that propagate sampling and parameter uncertainty. For each of $R = 1{,}000$ MCMC draws, we generate a synthetic population of 10,000 individuals by resampling participant identifiers with replacement and carrying over their mean-centered covariates z_i. For each draw and simulated individual, we compute preference parameters via Equation 2 and map them into post-estimation quantities (e.g., WTP, elasticities, and optimal prices).

To isolate covariate effects (e.g., ambiguity vs. risk), we conduct one-at-a-time counterfactuals. For a focal covariate, we compare two scenarios: setting it to its maximum for all simulated individuals versus setting it to its minimum, holding all other covariates at their observed values. For each draw and scenario, we recompute preferences using Equation 2 and the corresponding post-estimation quantities; the covariate effect is the difference between the two scenarios.

E.1 Willingness-to-Pay

To express effects in monetary terms, we compute willingness-to-pay (WTP) as the price change that offsets a one-unit change in an attribute, i.e., the attribute coefficient divided by the absolute value of the price coefficient. Because the price coefficient is modeled as negative log-normal in both studies, WTP is well-defined for each simulated individual and for each posterior draw. Because the model is estimated in utility space and WTP distributions can be fat-tailed, we summarize central tendency using the median (Sonnier, Ainslie, and Otter 2007). Within each MCMC draw, we therefore take the median WTP across the 10,000 simulated individuals. Across the 1,000 draws, we report the posterior median and 95% highest-density intervals (HDIs). For covariate effects, we also report the probability of direction (PD), i.e., the posterior probability that the effect has the reported sign; we treat PD $\geq .95$ as reliable evidence. Full WTP summaries appear in Tables W9 and W10 for studies 1 and 2, respectively.

Table W9: WTP (difference) – Study 1.

					Observed heterogeneity													
	Overall				Condition		Gender		Age		Study		Mood		Frequency		Risk	
Parameter	**Median (£)**	**HDI (£)**	**MAD (£)**	**HDI (£)**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**
Value	104.08	[95.54, 113.72]	34.73	[28.29, 42.73]	2.05	0.59	4.92	0.69	1.23	0.54	1.55	0.57	−7.26	0.73	−0.12	0.51	1.93	0.60
Mystery obvious	1.99	[0.56, 3.44]	5.40	[3.94, 7.42]	1.25	0.80	−3.40	0.97	0.14	0.53	−2.11	0.92	0.51	0.64	−0.44	0.60	3.52	0.98
Mystery 20–40	34.06	[30.78, 37.36]	12.26	[9.82, 15.07]	0.62	0.57	3.36	0.82	−0.86	0.58	0.69	0.58	−4.03	0.84	−2.31	0.68	2.44	0.75
Mystery 20–60	42.20	[38.12, 46.49]	15.87	[12.70, 19.56]	0.84	0.58	−2.12	0.68	−1.42	0.60	2.69	0.73	−8.61	0.95	0.17	0.51	0.67	0.55
Mystery 20–80	52.11	[46.91, 57.43]	20.96	[17.10, 25.99]	2.10	0.66	−3.21	0.71	−1.87	0.62	1.70	0.61	−7.20	0.86	−2.22	0.62	8.25	0.90
Mystery 40–60	54.67	[50.10, 60.15]	18.78	[15.28, 23.08]	1.58	0.62	1.96	0.66	−0.38	0.53	0.51	0.55	−5.98	0.82	−0.96	0.55	3.36	0.74
Mystery 40–80	65.82	[60.00, 72.01]	23.50	[19.03, 28.87]	2.23	0.64	−0.76	0.54	−3.69	0.69	3.01	0.66	−1.06	0.55	0.09	0.51	4.54	0.74
Mystery 60–80	75.66	[68.71, 82.17]	25.96	[21.12, 32.14]	1.78	0.61	2.09	0.61	−0.81	0.54	0.33	0.52	−7.53	0.80	−0.78	0.53	2.79	0.65

Notes. The reported values correspond to the median of posterior draw–specific medians (or median absolute deviations, MADs) across 10,000 simulated individuals. Columns under *Overall* report WTP in £ across the full sample, with 95% HDIs (highest density intervals) summarizing uncertainty across 1,000 draws. Columns under *Observed Heterogeneity* show the marginal effect of each covariate on WTP in £, defined as the difference between the focal and reference group, together with the corresponding probability of direction (PD), which reflects the posterior certainty about the sign of the effect. Specifically, *Condition* compares ambiguity to risk; *Gender* compares female to male; *Age*, *Mood*, and *Risk* (Dohmen et al. 2011) compare individuals above or equal to vs. below the sample median on each measure; *Study* compares those studying Economics and Social Sciences to all others; and *Frequency* contrasts participants who had taken part in more than five prior experiments with those who had participated five times or fewer.

Table W10: WTP (difference) – Study 2.

	Overall				Observed heterogeneity													
					Condition		Gender		Age		Income		Occupation		Education		Risk	
Parameter	**Median (£)**	**HDI (£)**	**MAD (£)**	**HDI (£)**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**	**Median (£)**	**PD**
Levi's	138.47	[129.78, 148.29]	117.43	[105.52, 129.13]	−17.00	0.97	−21.00	0.98	2.38	0.61	1.94	0.61	−13.99	0.93	17.10	0.96	−15.90	0.94
C. Klein	117.66	[108.85, 125.37]	108.84	[97.59, 119.21]	−14.85	0.98	−19.16	0.99	0.24	0.52	3.08	0.66	−10.00	0.87	9.07	0.88	−23.45	0.99
T. Hilfiger	110.95	[102.36, 119.15]	109.52	[98.68, 120.46]	−11.71	0.94	−22.85	0.99	−5.67	0.75	5.40	0.79	−11.13	0.91	16.95	0.98	−27.65	1.00
Wrangler	107.85	[100.16, 116.37]	114.17	[104.04, 126.82]	−16.55	0.98	−25.86	1.00	16.25	0.98	−6.12	0.74	−10.69	0.88	16.58	0.97	−30.82	1.00
Mystery L–C	121.93	[112.64, 131.57]	116.58	[104.55, 128.99]	−17.53	0.98	−25.21	0.99	−1.76	0.58	4.46	0.70	−15.55	0.93	21.00	0.98	−26.71	1.00
Mystery L–T	118.67	[109.43, 127.88]	115.13	[102.73, 127.31]	−17.51	0.97	−25.34	0.99	−5.79	0.74	3.64	0.66	−9.97	0.84	14.17	0.93	−32.73	1.00
Mystery L–W	120.50	[111.80, 129.38]	113.74	[101.60, 125.72]	−26.35	1.00	−29.29	1.00	2.57	0.62	−7.81	0.80	−5.38	0.70	20.44	0.98	−28.45	1.00
Mystery C–T	118.14	[109.25, 127.10]	107.39	[97.11, 119.18]	−7.24	0.81	−16.96	0.95	5.30	0.75	−1.42	0.56	−17.11	0.94	20.19	0.98	−26.06	0.99
Mystery C–W	118.10	[109.80, 128.45]	115.38	[104.52, 128.19]	−18.29	0.97	−23.91	0.99	1.12	0.56	−10.32	0.82	−11.62	0.87	13.76	0.94	−23.36	0.99
Mystery T–W	116.09	[108.07, 125.47]	109.82	[97.73, 121.77]	−11.37	0.92	−21.08	0.98	−4.10	0.69	−2.69	0.61	−14.17	0.93	16.24	0.96	−30.69	1.00
Skinny	−69.30	[-83.38, -55.64]	215.22	[194.58, 236.22]	27.71	0.97	127.50	1.00	−109.18	1.00	−7.02	0.68	63.00	1.00	−20.81	0.93	28.06	0.97
Wide	−112.93	[-130.61, -99.06]	161.84	[140.91, 184.77]	−1.44	0.54	38.40	0.99	−53.81	1.00	−22.39	0.93	11.63	0.81	9.31	0.77	−10.10	0.77
Slim	−13.63	[-21.18, -6.99]	137.86	[124.54, 152.18]	28.03	1.00	46.08	1.00	−62.93	1.00	0.64	0.54	34.15	1.00	−2.98	0.69	20.17	0.99
Light blue	−25.76	[-30.86, -20.98]	57.21	[50.68, 63.54]	0.93	0.59	−2.88	0.75	−11.14	0.99	−5.76	0.88	10.36	0.97	−9.40	0.95	11.22	0.98
Black	−1.42	[-4.59, 1.77]	54.47	[48.29, 60.10]	2.00	0.71	0.56	0.58	−11.06	1.00	−3.41	0.80	3.51	0.82	0.89	0.61	5.16	0.90

Notes. The reported values correspond to the median of posterior draw–specific medians (or median absolute deviations, MADs) across 10,000 simulated individuals. Columns under *Overall* report WTP in £ across the full sample, with 95% HDIs (highest density intervals) summarizing uncertainty across 1,000 draws. Columns under *Observed Heterogeneity* show the marginal effect of each covariate on WTP in £, defined as the difference between the focal and reference group, together with the corresponding probability of direction (PD), which reflects the posterior certainty about the sign of the effect. Specifically, *Condition* compares ambiguity to risk; *Gender* compares female to male; *Age*, *Income*, and *Risk* compare individuals above or equal to vs. below the sample median on each measure (with *Risk* measured as perceived risk of the mystery product; Thelen, Yoo, and Magnini 2011); *Occupation* compares those employed for wages to all others; and *Education* contrasts participants with an undergraduate or graduate degree against those without.

E.2 Study 2: Price Elasticities

Elasticities summarize how choice probabilities for the two brands, the mystery jeans (which resolves to one of those brands), and the no-buy option respond to price changes (all alternatives are regular-fit, blue jeans). In the elasticity matrix, diagonal elements are own-price elasticities and off-diagonal elements are cross-price elasticities. Each entry reports the percent change in the *column* alternative's choice probability associated with a 1% change in the *row* alternative's price. Table W11 reports elasticity estimates by outcome set and condition.

Table W11: Own- and cross-price elasticities across brand-pair sets.

	Ambiguity				**Risk**			
	Brand 1	**Brand 2**	**Mystery**	**No-buy**	**Brand 1**	**Brand 2**	**Mystery**	**No-buy**
Levi's (Brand 1)	−2.25	1.04	1.02	0.35	−2.16	1.03	1.00	0.37
C. Klein (Brand 2)	0.76	−2.64	1.02	0.39	0.73	−2.57	0.99	0.41
Mystery	0.82	1.13	−2.63	0.35	0.83	1.16	−2.49	0.38
Levi's (Brand 1)	−2.15	0.79	0.88	0.29	−2.04	0.82	0.88	0.32
T. Hilfiger (Brand 2)	0.70	−2.02	1.11	0.51	0.65	−2.03	1.02	0.51
Mystery	0.67	0.95	−2.53	0.27	0.69	1.02	−2.37	0.30
Levi's (Brand 1)	−2.02	0.55	0.68	0.23	−1.97	0.50	0.60	0.22
Wrangler (Brand 2)	0.60	−1.38	1.05	0.54	0.55	−1.40	0.95	0.54
Mystery	0.54	0.76	−2.35	0.26	0.62	0.91	−2.07	0.32
C. Klein (Brand 1)	−2.53	0.73	0.65	0.22	−2.34	0.81	0.73	0.26
T. Hilfiger (Brand 2)	0.94	−2.11	0.95	0.41	0.92	−2.01	0.97	0.43
Mystery	0.93	1.07	−2.16	0.43	0.82	0.95	−2.20	0.39
C. Klein (Brand 1)	−2.11	0.44	0.52	0.20	−2.03	0.42	0.50	0.21
Wrangler (Brand 2)	0.64	−1.52	1.01	0.48	0.62	−1.45	0.98	0.49
Mystery	0.69	0.93	−2.04	0.30	0.70	0.94	−1.91	0.32
T. Hilfiger (Brand 1)	−1.96	0.46	0.65	0.21	−1.87	0.44	0.63	0.21
Wrangler (Brand 2)	0.60	−1.61	0.95	0.38	0.62	−1.45	0.99	0.41
Mystery	0.83	0.95	−2.06	0.39	0.78	0.87	−2.02	0.37

E.3 Study 2: Optimal Prices and Profits

Lastly, we compute Bertrand–Nash equilibrium prices for counterfactual markets with and without a mystery option, separately by outcome set and condition. Firms are profit maximizers and compete in prices in a market with four branded products (and, when applicable, a mystery alternative). Following Allenby et al. (2014), we solve for equilibrium via fixed-point iteration of best responses (Morrow and Skerlos 2011), $\mathbf{p} = \mathbf{c} - \left(\Omega \circ \Delta(\mathbf{p})\right)^{-1}\mathbf{s}(\mathbf{p})$, where $\mathbf{s}(\mathbf{p})$ are model-implied choice shares, $\Delta(\mathbf{p}) = \partial \mathbf{s}(\mathbf{p})/\partial \mathbf{p}$ is the share Jacobian with respect to prices $\mathbf{p}$, and Ω is an ownership/profit-sharing matrix.

Without a mystery option, this reduces to the standard single-product-per-firm case (Allenby et al. 2014). With a mystery option, we assume the two brands in the relevant outcome set share the mystery option's profit with a mystery retailer (an independent seller). Each participating brand receives a fixed share ϕ of mystery profit (set *ex ante*). For example, when Levi's and Wrangler participate, we have the following set of profit functions:

$$
\begin{aligned}
\pi_L(\mathbf{p}) &= (p_L - c_L) \cdot s_L(\mathbf{p}) \; + \; \phi_L \cdot (p_M - c_M) \cdot s_M(\mathbf{p}), \\
\pi_C(\mathbf{p}) &= (p_C - c_C) \cdot s_C(\mathbf{p}), \\
\pi_T(\mathbf{p}) &= (p_T - c_T) \cdot s_T(\mathbf{p}), \\
\pi_W(\mathbf{p}) &= (p_W - c_W) \cdot s_W(\mathbf{p}) \; + \; \phi_W \cdot (p_M - c_M) \cdot s_M(\mathbf{p}), \\
\pi_M(\mathbf{p}) &= (1 - \phi_L - \phi_W) \cdot (p_M - c_M) \cdot s_M(\mathbf{p}).
\end{aligned}
\tag{W1}
$$

Because $(1 - \phi_L - \phi_W)$ is a constant factor in the retailer's profit, it does not affect the retailer's pricing FOC; in contrast, ϕ_L and ϕ_W enter the participating brands' incentives by linking their prices to the mystery option's profit through the shares. The resulting best-response system is shown below.

$$
\underbrace{\begin{bmatrix} p_L \\ p_C \\ p_T \\ p_W \\ p_M \end{bmatrix}}_{\mathbf{p}} = \underbrace{\begin{bmatrix} c_L \\ c_C \\ c_T \\ c_W \\ c_M \end{bmatrix}}_{\mathbf{c}} - \underbrace{\begin{bmatrix} \frac{1}{\Delta_{LL}} & 0 & 0 & 0 & -\frac{\phi_L \Delta_{ML}}{\Delta_{LL}\Delta_{MM}} \\ 0 & \frac{1}{\Delta_{CC}} & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{\Delta_{TT}} & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{\Delta_{WW}} & -\frac{\phi_W \Delta_{MW}}{\Delta_{WW}\Delta_{MM}} \\ 0 & 0 & 0 & 0 & \frac{1}{\Delta_{MM}} \end{bmatrix}}_{\left(\Omega \circ \Delta(\mathbf{p})\right)^{-1}} \underbrace{\begin{bmatrix} s_L \\ s_C \\ s_T \\ s_W \\ s_M \end{bmatrix}}_{\mathbf{s}(\mathbf{p})}
\tag{W2}
$$

The off-diagonal terms in $\left(\Omega \circ \Delta(\mathbf{p})\right)^{-1}$ are central: Δ_{ML} and Δ_{MW} capture how Levi's and Wrangler prices affect the mystery option's share, and therefore enter their pricing incentives through the profit-sharing rule. Tables W12, W13, W14, and W15 report equilibrium prices for alternative values of ϕ.

Additional scenarios. The paper reports results for symmetric profit sharing at 80% ($\phi = .4$). Here we compute three counterfactual scenarios to examine the robustness of those results: (1) Letting ϕ denote each brand's share of the mystery product's profit, lowering symmetric profit sharing from 80% to 50% ($\phi = .25$) reduces how much participating brands internalize cannibalization from the mystery product. With less internalization, competition intensifies, pushing each participating brand to lower prices, resulting in a decline in profits relative to the 80% case (see Table W13). The mystery retailer retains a larger margin share, but this does not offset the intensified competition, resulting in a decline in total channel profit. Moreover, brand profits (both participating and non-participating) are below the baseline with no mystery channel.

(2) Removing profit sharing ($\phi = 0$) fully externalizes cannibalization, so the mystery product is treated as a pure competitor rather than a partially internalized outlet. Participating brands cut prices further and profits decline below the 50% case, while price changes for non-participants are near zero (see Table W14). Although the mystery product retains the diverted margin, this gain does not offset brand losses, so total channel profit decreases and remains below the no-mystery baseline.

(3) Holding profit sharing at 80% and adopting asymmetric sharing ($\phi_1 = .5,\ \phi_2 = .3$) allocates 50% of mystery profit to the more-preferred brand (by model-estimated preferences) and 30% to the other. This leaves the mystery price and profits close to the symmetric benchmark and primarily redistributes profits across participating brands (see Table W15). Relative to the no-mystery baseline, both participating brands are better off, though the more-preferred brand gains more. Relative to symmetric sharing, the effect is purely distributional: the more-preferred brand gains while the less-preferred brand loses by a similar magnitude. The more-preferred brand internalizes more cannibalization, raises price, and captures additional profit, while the less-preferred brand

internalizes less, lowers price, and cedes profit to its partner. Overall, the asymmetric scenario's primary effect is distributional: profit shifts toward the more preferred brand, with virtually no change in total channel profit.

Table W12: Optimal prices and profits; symmetric profit sharing ($\phi = .4$).

		Price in £					Profit in £				
Set	**Framing**	**Levi's**	**C. Klein**	**T. Hilfiger**	**Wrangler**	**Mystery**	**Levi's**	**C. Klein**	**T. Hilfiger**	**Wrangler**	**Mystery**
L–C	Ambiguity	106.11	94.65	92.48	93.97	93.52	10.24	6.65	4.11	4.21	1.20
	Risk	109.07	96.54	92.84	96.04	95.68	11.35	7.40	4.13	4.83	1.38
L–T	Ambiguity	104.98	90.58	95.57	93.77	92.74	10.03	4.56	6.03	4.27	1.03
	Risk	107.74	91.97	96.45	95.64	94.81	11.13	4.99	6.32	4.88	1.18
L–W	Ambiguity	106.07	91.06	92.97	98.25	91.06	10.09	4.63	4.25	6.17	1.00
	Risk	108.75	91.86	92.87	100.95	95.91	11.31	4.87	4.11	7.35	1.40
T–C	Ambiguity	100.97	93.88	96.19	93.53	92.09	8.14	6.46	6.10	4.21	1.06
	Risk	104.19	95.68	96.97	96.17	91.37	9.35	6.90	6.12	5.02	0.97
C–W	Ambiguity	100.80	94.27	92.43	96.95	92.45	8.11	6.49	4.14	6.04	1.05
	Risk	102.70	96.01	92.72	99.30	94.68	8.87	7.23	4.15	6.94	1.22
T–W	Ambiguity	102.32	91.00	96.73	98.16	90.69	8.31	4.58	6.01	6.13	1.02
	Risk	105.18	92.73	97.68	100.77	91.34	9.37	5.12	6.16	6.90	1.04
w/o	Ambiguity	104.65	93.18	94.73	96.74		10.12	5.74	5.29	5.36	
	Risk	107.11	94.76	95.34	99.06		11.23	6.38	5.38	6.21	

Notes. All products are regular-fit blue jeans. The set "w/o" indicates markets without the mystery product.

Table W13: Optimal prices and profits; symmetric profit sharing ($\phi = .25$).

		Price in £					Profit in £				
Set	**Framing**	**Levi's**	**C. Klein**	**T. Hilfiger**	**Wrangler**	**Mystery**	**Levi's**	**C. Klein**	**T. Hilfiger**	**Wrangler**	**Mystery**
L–C	Ambiguity	104.15	92.88	92.40	93.84	93.21	9.23	5.68	4.01	4.11	2.93
	Risk	106.96	94.40	92.88	96.01	95.37	10.22	6.26	4.00	4.69	3.35
L–T	Ambiguity	103.42	90.46	93.90	93.62	92.51	9.19	4.45	5.20	4.19	2.52
	Risk	105.81	91.77	94.58	95.64	94.64	10.15	4.87	5.37	4.79	2.90
L–W	Ambiguity	104.23	91.00	93.03	96.34	90.86	9.25	4.52	4.15	5.32	2.45
	Risk	106.40	91.75	92.95	98.34	95.52	10.13	4.73	4.01	6.18	3.41
T–C	Ambiguity	101.01	92.37	94.43	93.57	91.96	8.03	5.61	5.24	4.14	2.61
	Risk	104.28	94.15	95.31	96.26	91.26	9.21	6.12	5.32	4.95	2.39
C–W	Ambiguity	100.80	92.97	92.53	95.10	92.27	7.97	5.67	4.07	5.21	2.56
	Risk	102.75	94.52	92.72	97.31	94.54	8.70	6.26	4.06	5.96	2.99
T–W	Ambiguity	102.31	91.01	95.03	96.44	90.52	8.17	4.48	5.21	5.32	2.51
	Risk	105.14	92.68	95.88	98.91	91.07	9.22	5.02	5.34	6.06	2.54
w/o	Ambiguity	104.65	93.18	94.73	96.74		10.12	5.74	5.29	5.36	
	Risk	107.11	94.76	95.34	99.06		11.23	6.38	5.38	6.21	

Notes. All products are regular-fit blue jeans. The set "w/o" indicates markets without the mystery product.

Table W14: Optimal prices and profits; no profit sharing ($\phi = 0$) .

Set	Framing	Price in £ Levi's	C. Klein	T. Hilfiger	Wrangler	Mystery	Profit in £ Levi's	C. Klein	T. Hilfiger	Wrangler	Mystery
L–C	Ambiguity	101.05	89.94	92.39	93.83	92.72	7.63	4.10	3.83	3.94	5.64
	Risk	103.53	91.16	92.83	95.87	94.94	8.39	4.47	3.83	4.51	6.41
L–T	Ambiguity	100.76	90.20	91.30	93.59	92.30	7.84	4.28	3.85	4.05	4.84
	Risk	103.06	91.52	91.62	95.44	94.40	8.57	4.67	3.85	4.60	5.58
L–W	Ambiguity	101.45	90.94	93.07	93.33	90.45	7.91	4.37	4.03	4.00	4.71
	Risk	102.95	91.73	93.00	94.62	95.05	8.24	4.53	3.83	4.37	6.53
T–C	Ambiguity	101.31	89.96	91.83	93.71	91.82	7.84	4.24	3.88	4.06	5.06
	Risk	104.47	91.90	92.80	96.52	91.11	9.01	4.85	4.08	4.85	4.63
C–W	Ambiguity	100.91	90.91	92.61	92.45	92.04	7.78	4.34	3.95	3.89	4.98
	Risk	102.91	92.21	92.87	94.26	94.37	8.48	4.70	3.95	4.41	5.80
T–W	Ambiguity	102.36	90.92	92.33	93.61	90.13	7.96	4.34	3.90	4.02	4.84
	Risk	105.33	92.62	92.99	96.10	90.74	8.99	4.86	4.01	4.73	4.92
w/o	Ambiguity	104.65	93.18	94.73	96.74		10.12	5.74	5.29	5.36	
	Risk	107.11	94.76	95.34	99.06		11.23	6.38	5.38	6.21	

Notes. All products are regular-fit blue jeans. The set "w/o" indicates markets without the mystery product.

Table W15: Optimal prices and profits; asymmetric profit sharing ($\phi_1 = .5, \phi_2 = .3$).

Set	Framing	Price in £ Levi's	C. Klein	T. Hilfiger	Wrangler	Mystery	Profit in £ Levi's	C. Klein	T. Hilfiger	Wrangler	Mystery
L–C	Ambiguity	107.45	93.55	92.44	94.10	93.47	10.80	6.11	4.11	4.22	1.21
	Risk	110.73	95.25	92.81	96.21	95.70	11.97	6.78	4.12	4.85	1.38
L–T	Ambiguity	106.14	90.60	94.58	93.80	92.73	10.50	4.56	5.54	4.29	1.03
	Risk	108.99	91.94	95.16	95.80	94.88	11.69	5.00	5.78	4.89	1.19
L–W	Ambiguity	107.19	91.11	93.12	97.20	91.13	10.56	4.63	4.25	5.69	1.00
	Risk	110.51	91.95	92.90	99.54	95.99	11.95	4.89	4.12	6.73	1.41
T–C	Ambiguity	100.96	94.80	94.95	93.59	92.10	8.15	6.96	5.60	4.21	1.06
	Risk	104.08	96.60	95.94	96.24	91.35	9.33	7.35	5.67	5.02	0.97
C–W	Ambiguity	100.81	95.22	92.46	95.74	92.36	8.10	6.98	4.15	5.55	1.04
	Risk	102.66	97.02	92.80	97.91	94.70	8.84	7.78	4.15	6.36	1.22
T–W	Ambiguity	102.22	91.11	98.10	97.05	90.71	8.31	4.58	6.50	5.64	1.02
	Risk	105.14	92.80	98.92	99.58	91.30	9.36	5.13	6.66	6.41	1.04
w/o	Ambiguity	104.65	93.18	94.73	96.74		10.12	5.74	5.29	5.36	
	Risk	107.11	94.76	95.34	99.06		11.23	6.38	5.38	6.21	

Notes. All products are regular-fit blue jeans. The set "w/o" indicates markets without the mystery product. ϕ_1 denotes the higher-preferred brand's share of the mystery product's profit.

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