Jeopardizing brand profitability by misattributing process heterogeneity to preference heterogeneity

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ABSTRACT

Brands develop strategies based on forecasts that allow for individual differences, usually attributed empirically to heterogeneity in consumers' preferences. Behavioral theories propose choice process heterogeneity as the conditioning stage for choice outcomes, and suggest that not accounting for it causes biases in parameters and policy measures. We conduct a Monte Carlo simulation to study how underlying choice process heterogeneity generates substantively significant biases in different market contexts if analysts (erroneously) channel heterogeneity solely into tastes. We extend the literature by using a game theoretical analysis, driven by the results from the demand simulation, to explore demand mis-specification effects on brands' profitability and market equilibrium. Through mixed strategies we examine necessary conditions for market equilibrium when managers have access to different demand representations but are uncertain about which is true. We demonstrate that biases generated by representing consumer response heterogeneity solely through preference heterogeneity are enough to significantly jeopardize brands' profits due to misalignment of firms' products and resources with demand. Our work forcefully demonstrates to both marketers and econometricians/data scientists the necessity of modeling choice process heterogeneity given its impacts on brands' performance.

1. Introduction

In the paradigmatic representation of competitive markets, product differentiation is a source of competitive advantage arising either from consumers' variety seeking across consumption occasions or from differences in tastes among consumers. In response to consumers' taste heterogeneity, brands choose the most profitable product assortment to offer and the market equilibrium reveals the product variety resulting from agents' behaviors in a given competitive structure (Lancaster, 1990). The identification of consumer response heterogeneity is the foundation for segmentation (where to compete) and positioning (how to compete). This implies that strategic decisions at the marketing level are outcomes of brand managers' understanding of consumers' preferences that would shape the market structure and competition patterns (Kamakura et al., 1996).

The complex decision environments encapsulated by modern markets are mentally costly for consumers: despite the enormous number of alternatives offered to consumers, they tend to make their choice among a small subset of the available options (i.e.,

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consumers seem to "screen" out large numbers of alternatives from consideration during choice). From 2008 to 2013 the number of TV channels received by the average American household escalated from 129 to 189, but the number of tuned channels stayed constant at 17 (Nielsen, 2014). Unobserved heterogeneity in subjective choice sets is a well-known phenomenon in consumer decision-making, with a major impact on the choice among alternatives (Hauser, 1978; Manski, 1977; Swait and Ben-Akiva, 1987), which arises as an adaptive response to the complexity of the decision-making environment when hierarchically superior psychological processes lead to the selection or elimination of alternatives in the available product assortment (Weber and Johnson, 2009). Hence, it is our argument that other such processes (what we collectively term *choice process heterogeneity*) are at work in consumers' choice processes conditioning the possible existence and impacts of taste heterogeneity.

This paper therefore studies the correctness of a brand's decision making (hence performance, and ultimately, profitability) in competitive markets in which consumer process heterogeneity occurs, but is empirically misattributed to taste heterogeneity. Our motivation behind targeting this particular directionality of misattribution (consumer process heterogeneity misattributed as taste heterogeneity) arises from (1) the central role that taste heterogeneity has in modern economics and marketing thought, (2) the statistical and computational advances that have greatly facilitated the estimation of demand representations that incorporate sophisticated and complex depictions of process heterogeneity (to illustrate, among others, see Aribarg et al., 2017; Dellaert et al., 2017; Hensher 2014), and (3) the pronounced tendency, among applied choice modelers and market analysts, to represent demand differences based solely on taste heterogeneity. Although the effects of econometric models' misspecification on measures describing demand are self-evident and well known, the magnitude of the resulting biases in model parameters (and derived quantities), and its consequences on brands' profitability have not been properly described and gauged. This paper addresses this gap in the literature from the viewpoint that ignoring the magnitude of such biases and the consequences on brands profitability leads to a lack of incentive to change modeling strategies. By deploying a Monte Carlo simulation (see Web Appendix A), we account simultaneously for variations in a focal brand's equity (Davcik et al., 2015; Erdem and Swait, 1998) and the extent of consumer choice process heterogeneity from a position of full knowledge; such would not be the case if we were to use market demand data from the real world. And given that in competitive markets there are multiple agents making decisions simultaneously, we further depart from extant literature by examining the possible effects of econometric modeling strategies on competitive reaction and market equilibrium. To make this latter extension, we connect the results from the Monte Carlo experiment (demand side) into a game-theoretical analysis (supply side).

In summary, we view markets as characterized by consumers aiming to balance utility maximizing choice while minimizing risks and cognitive effort, while on the supply side brands are searching for marketing strategies that lead to profit maximization. In this decision-making environment, our basic proposition is that when consumers choices are erroneously represented by misattributing choice process heterogeneity solely to preference/taste heterogeneity, it is likely that managers will make decisions leading brands away from profit maximization. We assert this based on the following logic: 1) a misrepresentation of demand will be expressed via the biased location of demand parameters, and through the potential (mis)identification of preference heterogeneity in the demand that may not actually be present in the marketplace, or at least not to the extent inferred by a mis-specified model; 2) biased demand measurements will lead to the adoption of incorrect policy measures due to mispredictions of brands' market shares and choice elasticities with respect to attributes; 3) consequently, brands will choose wrong quantities to offer in the marketplace from the biased choice probabilities and will operate with a suboptimal marginal cost (and profit) caused by the biased reading of demand price elasticities. Whilst it is likely that real markets are characterized by the co-existence of both choice process and preference heterogeneities, the empirical proclivity of market analysts to assume that only the latter is at work suggests to us that understanding the directional impacts of omitting the former will be most helpful in characterizing how the omission of process heterogeneity will lead to compromised performance on the part of the brand.

To our knowledge, this is the first research in the marketing, management and choice modeling literatures that attempts to investigate the impacts of misdiagnosing choice process heterogeneity as preference heterogeneity on brands' profitability and market equilibrium. Choice process heterogeneity has been a concern among some choice modelers who have been formalizing alternatives to the classical random utility models. However, the consequences of the proposed misspecification on brands' profitability is still a gap in the literature, perhaps justifying in the minds of many analysts the rare adoption of models that are harder to fit and to understand (as argued by Aribarg et al., 2017). To reinforce the focus of this paper on consequences of overlooking choice process heterogeneity and the importance of making room for it in modeling strategies, we (1) select and emphasize the focal bias directionality (misattribution of process heterogeneity as taste heterogeneity), and (2) extend the study of the consequences of model misspecification from parameters bias to brand financial performance.

To preview the structure of our paper, following this introduction we present the relevant literature about choice process heterogeneity, specifically focusing on two-stage consumer decision-making adopted in our data generation process. After this we offer a brief overview of the design of a Monte Carlo (MC) experiment embedding the true demand representation (i.e., existing choice process heterogeneity but no preference heterogeneity), then describe the experiment's main results. In the next section we describe the effects of the demand misrepresentation (i.e., no choice process heterogeneity, but assumed preference heterogeneity) on brands' profitability; we characterize market equilibria by "plugging in" the results from the MC simulation into the analytical solution to the proposed game. We conclude with a discussion and summary of our study's insights.

2. Literature review

The choice modeling literature generally attributes consumer response heterogeneity in multi-attribute decision-making to different tastes among people, i.e., random utility models have been extended to assume that people have dissimilar levels of preference for the various attributes or attribute levels involved in the choice, but follow a similar behavioral rule (usually random utility

maximization) to select one option among all those available (Rieskamp et al., 2006). This emphasis on preferences as a source of consumer response heterogeneity is evident in this excerpt: "Heterogeneity in preferences gives rise to differentiated product offerings, market segments and market niches. Differing sensitivities are the basis for targeted communication programs and promotions. As consumer preferences and sensitivities become more diverse, it becomes less and less efficient to consider the market in the aggregate." (Allenby and Rossi, 1998).

On the other hand, the behavioral decision theory literature reveals choice as a complex process driven by individuals' goals and the necessity of balancing the availability of cognitive resources and requirements of the context. Thus, a more encompassing perspective on judgment and decision-making is that different individuals follow different choice processes that, necessarily, shape the multi-attribute choice, i.e., process heterogeneity precedes taste heterogeneity. It has been said that heterogeneity results from "the individual differences consumers evince with respect to the judgments they make and the processes involved in making such judgments" (DeSarbo et al., 1997).

Altogether, choice process heterogeneity encompasses the unobserved sequence of cognitive events and decisions happening before the resulting observed choice (Swait and Feinberg, 2014). It describes differences between individuals or across purchase occasions related to balancing multiple goals (Dellaert et al., 2017; Swait and Marley, 2013; van Osselaer and Janiszewski, 2012; van Osselaer et al., 2005), selecting different behavioral rules (Bettman et al., 1998; Dana and Davis-Stober, 2016; Gigerenzer and Gaissmaier, 2011), screening or recruiting alternatives (Weber and Johnson, 2009), and perceptual processes conditioning the evaluation of alternatives (Swait et al., 2014), among other possibilities. One shared result of these various instances of psychological processes intervening in choice probabilities is choice set formation, i.e., the generation of subsets from the universal set of alternatives that contain only alternatives having a non-zero probability of being chosen in any specific purchase occasion (Swait and Feinberg, 2014). Choice sets can be formed, in any choice occasion, from the consideration sets containing salient or accessible brands apt to support a consumer in attaining a goal on a specific choice occasion (Shocker et al., 1991). The inclusion of brands in choice sets also results from strategic and tactical marketing activities (Kardes et al., 1993; Mitra, 1995; Priester et al., 2004; Shapiro et al., 1997), as well as from context (Chakravarti and Janiszewski, 2003; Kardes et al., 1993; Lehmann and Pan, 1994), and situational variables (Chakravarti and Janiszewski, 2003; Desai and Hoyer, 2000; Goodman and Reczek, 2020).

Gu et al. (2012) present strong empirical evidence for choice set formation, concluding that at least 78% of consumers purchasing online disregard alternatives displayed at the purchase occasion, even when choosing from a small number of products. Moreover, the identification of the correct set of alternatives having a non-zero probability of choice accounts for about 80% of the explained variance in probabilistic choice models (Hauser, 1978). And overlooking choice set heterogeneity in econometric models results in the biased estimation of model parameters, and multi-attribute and marketing activities sensitivities (Chiang et al., 1998; Li et al., 2015; Mehta et al., 2003; Swait and Ben-Akiva, 1985; Van Nierop et al., 2010).

We depart from this extant literature by focusing on the downstream consequences on firms' profitability of misattributing choice process heterogeneity solely to tastes differences between consumers. To attain our objective, we develop a (true) data generation process (*dgp*) based on a known choice set formation mechanism. The screening (initial) stage, resulting in a constrained choice set, precedes the selection of one alternative among those carried to the evaluative (second) step. Building the *dgp* on choice set formation, which could arise from multiple choice process mechanisms (e.g., goal selectivity, decision rule selection), implies that we are actually agnostic about the psychological process underlying the choice set formation. Rather than being restrictive, this allows us to (1) focus on the downstream consequences of overlooking the presence of unobserved choice sets when they occur, yet (2) to generalize the results to many instances of choice process heterogeneity that result in choice set formation impacts.

Given that different processes govern the different stages or that sensitivities can vary between stages (when the same underlying variable is involved in both), the proper identification of the bases for heterogeneity should shape the selection of the optimal marketing strategy by brand managers. Preference heterogeneity leads to product differentiation and market segmentation backed by marketing programs exploiting different multi-attribute sensitivities (Allenby and Rossi, 1998). Choice set formation impacts the market size for which a brand competes, and the fraction of the market excluding the brand in the choice set formation stage (by definition) does not respond to the appropriate strategies to address heterogeneity in preferences. To be included in choice sets, a brand needs to build trust (Liberali et al., 2013), to exploit hidden (by biased preference heterogeneity) sensitivity to in-store promotional activities (Chiang et al., 1998; Pires, 2016), and/or to morph online advertisement to match consumers cognitive styles (Urban et al., 2014). Thus, policies that impact only taste heterogeneity may or may not impact choice set formation, but conversely, policies that impact choice set formation will necessarily impact the role of taste heterogeneity.

Regardless of the wide variety of choice models investigating consumer response heterogeneity arising from other sources than preferences (e.g., goals, decision strategies, stochasticity), the adoption of these ideas as an alternative to the simplicity and parsimony of the representation of *homo economicus* in random utility models is still a challenge for the marketing discipline, as it has also been for other fields rooted in applied economics. This is the consequence of the complexity behind multi-stage models, which involve additional mathematical and statistical complexities and require additional information, compared to standard formulations. These give rise to practical issues like higher specification complexity, greater estimation time and costs, and thorny theoretical questions such as statistical and substantive identification (Aribarg et al., 2017; Dellaert et al., 2017; Hensher, 2014). In addition to complexity, evidence reporting the lack of noticeable superiority in statistical fit and/or the predictive ability of models accounting for choice process heterogeneity inhibits their adoption (Dieckmann et al., 2009).

To overcome such (reasonable) resistance from academics and practitioners, it is important to understand whether or not models that offer improved choice process representation will 1) have beneficial impacts on the decisions made by organizations, and 2) better enable organizations to meet their objectives compared with current standard models. The motivation for our empirical research is to investigate these downstream consequences of the focal econometric misspecification with the support of a data generation process

compatible with choice process heterogeneity.

3. Empirical (simulation) study

To give an overview of our research approach we formalize the behaviors of the relevant economic agents (consumers and brand managers) and describe the market equilibrium as an outcome of the strategy-driven interactions among these agents.

First, in section 3.1, we describe the choices faced by consumers and brand managers. A true data generation process (*dgp*) based on *choice set formation* represents consumer behavior and we populate market data using Monte Carlo techniques. This methodological choice carries the possibility of systematically varying market characteristics, allowing the study of the focal phenomenon in different settings. The data from the *dgp* are then modeled using one econometric model, which assumes no choice process homogeneity but allows for taste heterogeneity. This erroneous specification reflects the assumption usually made in empirical demand work. We also describe brand managers' choice between demand representations using information either from the *dgp* or the econometric model, in the specification of the market equilibrium (more on this later).

Second, in section 3.2, we investigate the decisions made by competing brands as a game, specifying players and their characteristics, the rules of the game, the informational structure and payoffs resulting from every interaction (Gintis, 2014; Grieco, 2014). Market equilibrium results from the choices made by players/brands between the two available demand representations, when the true one is uncertain and the choices made by one player affect the payoffs to other players, thus acknowledging the interdependence in players' strategy formulations. Examining the strategic interaction between non-cooperative agents as a game allows deeper understanding about the conditions that could result in a better market equilibrium when rational brand managers make decisions under the uncertainties encompassed by our research – to wit, (1) uncertainty about the nature of demand in terms of process vs preference heterogeneity, and (2) uncertainty about how competing brand managers will perceive the nature of demand. This general capability and use of the game theoretic approach is highlighted by Camerer (1991) and Di Benedetto (1987). Our use of game theory, then, does not imply that we assert that the assumptions of game theory will shape brands' decision making and market evolution, only that game theory constitutes a useful test-bed with the essential elements and decision-maker actions needed to evaluate the impact of decision-making under the aforementioned uncertainties.

While it may seem axiomatic that using the incorrect demand representation should result in the suboptimal formulation of brand strategy, we do not know a priori how sensitive brand strategies may be to the misspecification we examine. Importantly, to gain insights into strategy robustness and magnitudes of strategy-induced error, both issues that are not currently understood in marketing,
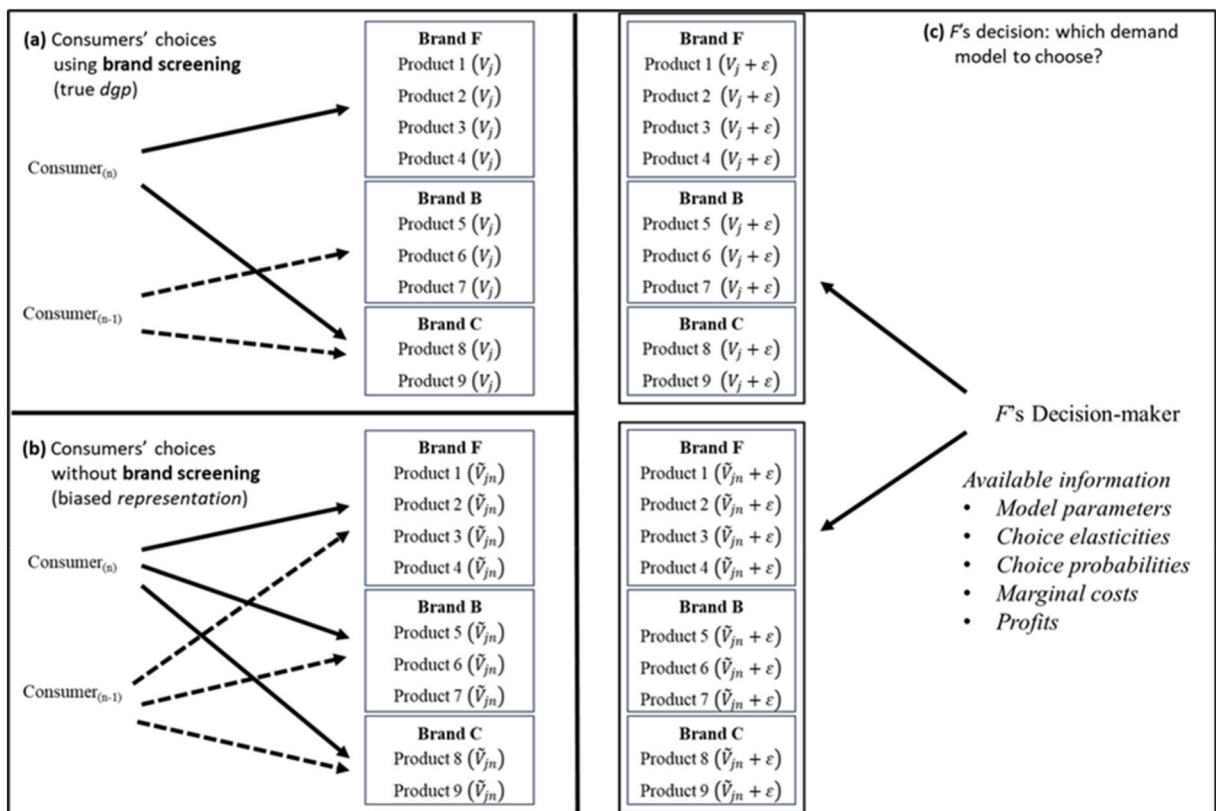

Fig. 1. Overview of the empirical approach.

we need to develop simulation studies (as contrasted with empirical ones). A question that arises from any experimental setting concerns the external validity of the results (or the degree of similarity between the experiment and the reality). To cope with this concern and given the novelty of the approach, we note the following: (1) our *dgp*, econometric model, and the interaction between competitive players are supported by widely accepted economic theories; (2) we define every building block (choice process heterogeneity *dgp*, taste heterogeneity econometric model and game settings) using as few variables and parameters as possible, while accounting for (i) the influence of context on consumer behavior; (ii) the dependency between the two-stages of the consumer choice process, but focusing it on choice set formation impacts; and (iii) the information asymmetry faced by brand managers when making decisions. Our methodological decision aims to facilitate the causal interpretation underlying our results and to study the focal phenomenon over its maximum range (varying only choice set formation across different levels, holding taste heterogeneity absent).

3.1. Consumers' and brand managers' decisions

Fig. 1 offers an overview of the consumer and brand managers' decision-making processes which will support the development of the subsequent sections of this paper. Panel (a) illustrates the demand data generation process (*dgp*) based on choice process heterogeneity. In this *dgp* a consumer n first screens out brand B from the offer set and selects one of the products from the assortment of brands F or C. A different consumer, say $n-1$, might instead have screened out brand F, thus forming a choice set with products from B and C. After forming these brand-level choice sets, both consumers choose the product with highest utility; the notation V_j (no "n" subscript) implies that preferences are the same for all individuals (i.e., there is *no* preference heterogeneity in the *dgp*). If the chosen alternatives happen to be different across individuals, this is partly explained by (i) the differences in (heterogeneous) choice sets and partly by (ii) the differences between products, but we emphasize that product differences are homogenously valued by individuals.

The bottom left panel (b) describes how a consumer makes choices according to the misspecified model by evaluating every product offered by every brand (i.e., no screening occurs). Moreover, the notation U_{nj} implies that different choices among different consumers are explainable by differences in utilities across consumers. Thus, this model has no consumer process heterogeneity, in the form of choice set formation, but does contain taste heterogeneity.

The right panel (c) describes the brand manager's decision problem. We now make explicit necessary agent behaviors that underlie the assumed information environment. The first observation we make is that a stochastic term (ε) is added to every product utility, suggesting that consumers' choices can be predicted by the analyst up to a probability. This uncertainty emerges from the fact that the analyst observes consumers' choices but does not observe the data generation process. As a result, brand managers develop two plausible demand generation models, one based on choice set formation - Fig. 1, panel (a) - and the other based on taste heterogeneity - panel (b). A brand manager, say brand F's, knows its own payoffs in both demand representations and can also estimate competitors' payoffs (see details in Appendix B). But F's brand manager needs to define a strategy leading to market equilibrium while not knowing which is the true demand representation nor which representation will be used by B and C (these competitors will collectively be denoted by the mnemonic *NF*) to support *their* strategies.

Different demand representations might imply different decisions in terms of product configuration, pricing and quantities offered by every brand, and if the market does not clear due to brand managers' decisions, additional welfare losses may be incurred by the brands. Examples of such losses are out-of-stock items (or excessive storage costs); necessity of increasing (or reducing) costs for clearing the market or setting the production function targeting an inefficient marginal cost. In summary, brands need to grapple with two sources of uncertainties, the true demand representation and competitors' behavior, while exploring future possible states of the market that will orient their strategies.

3.2. Market equilibrium

Informed by the possible existence of these two demand representations, a brand decides on its marketing mix, while considering the competitor's choice of strategy (i.e., demand representation). We use the normal form of game theory to study the outcomes of these decisions in a conflict situation (i.e., brands in market competition) in which a brand partially controls the decision process through its optimal choice and players' payoffs result through each player's choice from a set of possible strategies (Wang and Parlar, 1989). Given the need of strategic commitments to support players' choices, we start from a static game of complete information as per Gibbons (1997), complementing it with mixed strategies to cope with the information asymmetries in our conceptualization. Relaxing the strict assumption of complete information makes our setting more realistic, since there are quantities that need to be estimated from other sources than choice models; further, even when brands adopt the same market research methodologies, their sources of data differ and can lead to information asymmetries. The normal form representation of this game specifies the m players in the game, the strategies $S_1, \ldots, S_m$ available to each player and the payoffs $\mu_1, \ldots, \mu_m$ received by each player for each combination of strategies that could be chosen by the players.

Rational players $\boldsymbol{F}$ and $\boldsymbol{NF}$ (i.e., focal firm F and all other firms NF) choose their strategies, the true or the biased demand representation, without knowledge about other players' choices. In our setting, brand managers have invested on two different demand representations, each one signaling different market equilibria resulting from different choice elasticities to price, attributes and other elements of the marketing mix. This means that the strategy space is the choice of one demand representation, considering that the brand managers do not know which is true. There will be a Nash Equilibrium (NE) if every player chooses a strategy that is the best response to the predicted strategy of other players, meaning that no player wants to deviate from its chosen strategy.

If the competing firms have the same information, they would both believe in the superiority of the econometric demand representation with best goodness-of-fit and they would both make the same choice (resulting in a pure strategy solution). If both make the

wrong decision, they will have the chance to learn and adjust their pure strategy since they have the same information.

However, there are uncertainties about competitors' behavior even if brand managers see the same data and the same types of demand representations, calling for some enrichment in this game of complete information. Consider that each player knows its own information exactly but is only capable of estimating the competitor's profit, given a demand representation. Or, given the knowledge about expected choice probabilities, they do not know the size of the potential market and how it varies between demand representations represented in Fig. 1. This means that each player needs to estimate the difference $(\widehat{Q} - \widetilde{Q})$, where $\widehat{Q} = \widehat{Q}\widehat{P}_F + \widehat{Q}\widehat{P}_{NF}$ and $\widetilde{Q} = \widetilde{Q}\widetilde{P}_F + \widetilde{Q}\widetilde{P}_{NF}$, the first representing the expectation of market quantity for the true *dgp* and the second that of the erroneous *dgp*. Additionally, players may use proprietary data to model the same types of demand representation, and select different models induced by statistical goodness of fit criteria. These ex-post uncertainties about other players' choices prevent market equilibrium in the absence of a pure strategy solution, and require the deployment of mixed strategies working as a randomization device over the strategy space (Wang and Parlar, 1989).

Through this randomization mechanism, we allow players to have a small amount of private information, thus reducing the information asymmetry to a game of complete information regardless of players' intentions to use the strategies available in the strategy space with the prescribed probabilities (Harsanyi, 1973).

The mixed strategy solution calls for the additional specification of the set of beliefs describing the firms' proclivities towards the two possible strategies as $\{\theta_F, \theta_{NF}\}$. Given that players are aware of the two possible demand representations but do not know which one is the true, *F*(or *NF*)'s proclivity towards any strategy arises from the knowledge of *F*(*NF*) about both payoffs and from its consideration of *NF*(*F*)'s best response to this information. From payoffs and best responses, we can explore different plausible market equilibria (details about the settings of the game are available in Web Appendix B). Let *F*'s payoff (or profit) from the true demand representation be $\widehat{\mu}_F$ and the same quantity from the misspecified demand representation be $\widetilde{\mu}_F$. The analogous quantities for *NF* are $\widehat{\mu}_{NF}$ and $\widetilde{\mu}_{NF}$. Also, let the *sgn(x)* function define the sign of a real number *x*, so that $sgn(x) = -1$ if $x < 0$, $sgn(x) = 0$ if $x = 0$, and $sgn(x) = +1$ if $x > 0$. The pair $\{sgn(\widehat{\mu}_F - \widetilde{\mu}_F), sgn(\widehat{\mu}_{NF} - \widetilde{\mu}_{NF})\}$ results in nine possible realizations of firms' best responses to the other firm decision, but for our purpose it is sufficient to consider the product $delta = sgn(\widehat{\mu}_F - \widetilde{\mu}_F) \times sgn(\widehat{\mu}_{NF} - \widetilde{\mu}_{NF})$, delta in the set $\{1, 0, -1\}$, to support our analysis. For example, $delta = 1$ means that a pure strategy will clear the market, with either brand predicting higher payoffs from the same demand representation, either the true or the misspecified one. On the other hand, $delta = -1$ implies that each brand predicts higher payoffs from a different demand representation, raising the uncertainty about the competitor's behavior and calling for a mixed strategy to explain market equilibrium. We ignore the $delta = 0$ case since it did not happen in our data (if it had, it would be equivalent to one of the pure strategies). Moreover, pure strategies are special cases of mixed strategies, which we represent by the set of players' beliefs $\{\theta_F, \theta_{NF}\}$, such that $\theta_F \to 1$ when $sgn(\widehat{\mu}_F - \widetilde{\mu}_F) = 1$, meaning that *F* tends to choose the true demand representation (choice process heterogeneity) compared to the misspecified demand representation (taste heterogeneity), and $\theta_F \to 0$ when $sgn(\widehat{\mu}_F - \widetilde{\mu}_F) = -1$; the same logic applies to θ_{NF}. If both payoffs are larger in the true demand representation ($sgn(\widehat{\mu}_F - \widetilde{\mu}_F) = sgn(\widehat{\mu}_{NF} - \widetilde{\mu}_{NF}) = 1$), thus so is the market level payoff ($\widehat{\mu} > \widetilde{\mu}$) and the mixed strategy simplifies to the pure strategy $\{\theta_F, \theta_{NF}\} = \{1, 1\}$. This condition offers an ideal market equilibrium, which happens only when both players know the true demand structure and behave in consonance with these signals. If both payoffs are larger in the biased model ($sgn(\widehat{\mu}_F - \widetilde{\mu}_F) = sgn(\widehat{\mu}_{NF} - \widetilde{\mu}_{NF}) = -1$), thus at the market level ($\widehat{\mu} < \widetilde{\mu}$) and the mixed strategy simplifies to the pure strategy $\{\theta_F, \theta_{NF}\} = \{0, 0\}$. This condition offers a sub-optimal market equilibrium since both players follow the same biased signal. Whenever brands' payoff differences between demand representations differ in sign, the mixed strategy solves to $0 < \theta_F, \theta_{NF} < 1$.

In summary, by estimating payoffs through the demand simulation, we are conditioning the supply-side investigation on the information that brands have acquired by previously considering alternative demand representations and strategically selecting the most plausible one. Calculating profits (from the demand) as the payoff, we thus account for unit profits and market share, two usual goals pursued by firms. And through mixed strategies, we explore the effects of remaining ex-post uncertainties that a brand may have about the knowledge that a competitor has acquired during its demand forecast. Emphasizing this methodological choice, we adopt game theory as an analytical instrument, without prescriptive pretension, that allows the researcher to understand possible market equilibria from information that brands use to make decisions.

To study the model misspecification illustrated in Fig. 1, and to establish the causal link between such misspecification and the market equilibrium described in our non-cooperative game, we need to overcome the unobservability of the true *dgp* either by researchers or by brand managers. Certainty about the true *dgp* is required to study the downstream consequences of model misspecifications, as well as to qualify these consequences as functions of varying market contexts and consumer behaviors. Our solution is to conduct a MC simulation, which permits (a) the true *dgp* to be known; (b) the robustness of results to be tested via replication; and (c) increased generalizability of results via deployment of a multiple-cell experiment compared to single cell real data applications (Andrews and Currim, 2005; Li et al., 2015). Our MC experiment has a noteworthy difference from the usual approach of deploying the method to assess the ability of statistical models to recover any specific data generation process. Here, the experiment is used to study the consequences on brands managers' decisions of having more than one plausible statistical model to explain the unobservable *dgp*. The experiment is designed to (1) generate product purchasing data using precisely specified consumer behavior based on choice process heterogeneity, known by us as researchers; (2) compute two relevant sets of information, one through the true *dgp* and the other through a model that misspecifies the *dgp*, posing to the brand managers the problem of choosing one of them given that the data generation process is unobservable to them; and (3) use the results to study brand' payoffs given the correct and the misspecified demand representations and the consequent market equilibrium from a game theoretical perspective.

3.3. The Monte Carlo experiment

Two different general market contexts were simulated: the first represents a fast-moving consumer good (*fmcg*), such as product categories found in supermarkets, for which it is reasonable to assume that in the short term the environment is constant and brand managers have some degree of control over it. These conditions imply that consumers find a largely common assortment of products in different retail chains, either across points of sale or occasions (like supermarkets), and the quality (as described by the levels of their attributes) and the price of products are stable across purchase occasions. The second market context represents *services*, such as may be found in fast food chains, laundry services or personal services, among others. In such contexts, any brand plans to deliver a standardized service, but consumers can experience varying levels of quality across occasions or points of sale. When evaluating alternatives consumers incorporate this characteristic observed in any service as a time- and space-varying expected quality level. Our motivation to include these contexts is to represent the two prototypical markets that have historically been of interest to the marketing discipline. In our study, the *services* context offers insights of adding variability to the expected level of quality, which supports the estimation of random taste parameters, and thus may affect (even exacerbate) the pattern of the biases that we anticipate observing in the *fmcg* context.

Assortments are composed by supply from three brands, each one presenting a different number of products (or alternatives). Products are described by two dummy variables as brand-specific constants (BSCs) defining the three brands (one dummy variable omitted for identification); two generic attributes, indexed by *k,* allowing for product differentiation; and, based on Erdem et al. (2002) three brand-specific price variables, allowing for brand-specific price sensitivity. Generic attributes and brand-specific price levels are random variables such that $l_k \sim U(1,6)$, where l_k represents the quality level that brands plan to deliver. In the *services* market context, a random variable $v_k \sim U(-0.5,0.5)$ was further added to each generic attribute to represent the consumer's expected service level, so that l_k+v_k represents the consumer's expectation across occasions or points of sales. BSCs permit the econometric model to capture the effects of brand equity on consumers choices. Brand-specific prices imply that each brand can set different prices, even for the same product, and that each brand has its own demand price elasticities. In the utility function, brand-specific constants and brand-specific prices are elements that encapsulate the brand equity of a firm in monopolistic competition, which best characterizes most consumption markets (Davies and Cline, 2005). A larger brand-specific constant and a smaller price elasticity of the demand (compared to competitors) result from the cumulative impact of prior marketing activities and allow greater flexibility to brand managers to execute current strategies.

Taking brand *F* as the focal point of analysis, we studied the effects of misattributing process heterogeneity (i.e., screening activity, or choice set formation) as taste heterogeneity, as our MC experiment systematically varied (i) the size of the focal brand's assortment; (ii) the relative price elasticity of the focal; and (iii) the extent of choice set formation and how it distributes across brands. Choice set formation is operationalized via brand screening, which implies the existence of: (a) captivity or choice sets containing only one brand, which is compatible with habitual or loyalty consumer decision-making; (b) choice sets containing any two brands, which is compatible to consumers rejecting the omitted brand; (c) the complete choice set including all 3 brands, leading to full information decision-making on the part of consumers. Given the random allocation of each observation to one of the choice sets, the focal brand *F* may, also randomly, be included or not in the choice set. A main effects experimental design, combined with the purchase occasion generation algorithm previously exposited, fully specifies the MC simulation setting. In total, for each market context (*fmcg* and *services*) our experimental setup generated 6,250 data sets (250 replications for each of the 25 experimental conditions), each set including 1,000 consumers attending to eight choice scenarios (a total of 8,000 purchase occasions).

In the following sections we describe the MC experiment results, and the consequences of misattributing choice process heterogeneity as tastes on model parameters, policy measures, brand profits and market equilibrium. Since the extant literature have already
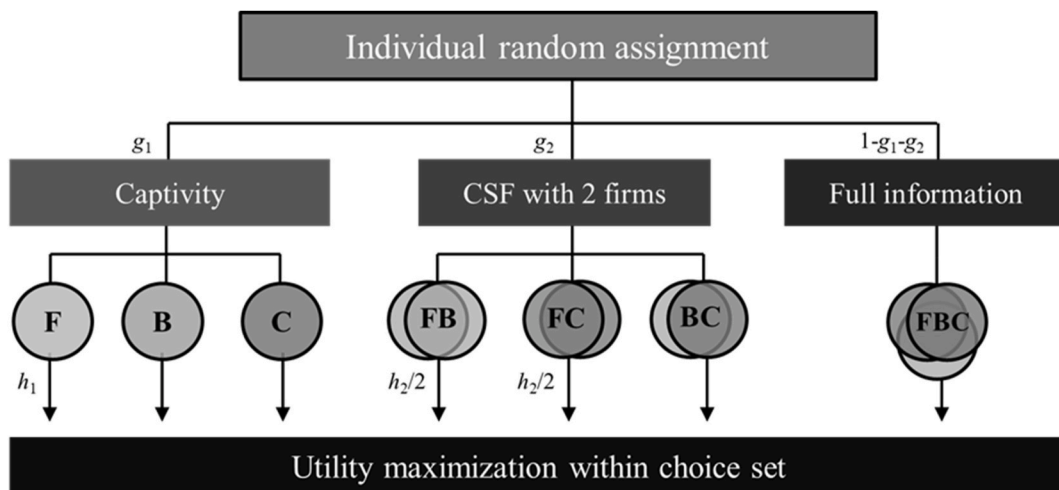

Fig. 2. Description of the true consumers' choice process.

examined the proposed misspecification effects on model parameters and choice elasticities, we describe these results briefly and connect then to such literature.

   True Data Generation Process: Choice Process Heterogeneity, Taste Homogeneity. The true *dgp* is based on the total absence of taste heterogeneity and on the presence of process heterogeneity, specifically through choice set formation. The true consumers' decision-making process is semi-compensatory, with a first non-compensatory stage reducing the number of brands prior to the second compensatory stage in which alternatives' evaluations result in the observed choice (see Fig. 1, panel a). This conforms to the two-stage choice process outlined in the previous section, thus generating choice set heterogeneity. Details of the screening process are illustrated in Fig. 2. In the first stage of the decision-making a consumer selects the brands that will have their products evaluated in the second stage. The consumer's probability of a subjective choice set having one, two or three brands is given by $0 \leq g_1, g_2 \leq 0.5$ and the probability of including the focal brand in the subjective choice set is given by $0 \leq h_1, h_2 \leq 1$.

   Once the first stage of choice ends, the products offered by the brands included in the second stage are evaluated through a decision rule that maximizes the expected utility of the chosen alternative. In this stage the utility of alternative i in each choice task (scenario) is:

$$U_{in} = V_{in} + \varepsilon_i; V_{in} = \beta_b BSC_b + \sum_{k=1}^{K} \beta_k X_{ikn} + \beta_{bsp} p_i , \tag{1}$$

where the systematic portion of this utility function for product i has three components: (a) its brand identifier (BSC) weighted by a brand-specific taste parameter β_b, (b) $X_{i1n}, ..., X_{ikn}$ are levels of K attributes describing alternative i, the subscript n applies only to the varying attributes in the *services* context, and $\beta_1, ..., \beta_k$ are K taste parameters that apply to all consumers since there is taste homogeneity in the true *dgp*; and (c) a price p_i weighted by a taste parameter which is specific to the brand offering alternative i. Moreover, ε_i is an independent identically distributed stochastic term with Gumbel distribution, leading to an MNL choice probability model. In the *services* context, U and V are also indexed by n because of varying quality attributes.

   Let $\widehat{P}_i$ be the choice-set-conditional MNL choice probabilities estimated from the data generated using the true *dgp* (which has choice set heterogeneity but no preference homogeneity), and $Q\widehat{P}_i$ be alternative i's expected demand, thus:

$$Q\widehat{P}_{Fn} = g_1 h_1 + g_2 \frac{h_2}{2} \sum_{i \in F} \frac{e^{V_i}}{\sum_{j \in F, B} e^{V_j}} + g_2 \frac{h_2}{2} \sum_{i \in F} \frac{e^{V_i}}{\sum_{j \in F, C} e^{V_j}} + (1 - g_1 - g_2) \sum_{i \in F} \frac{e^{V_i}}{\sum_{j \in F, B, C} e^{V_j}}. \tag{2}$$

   The expected demand for brands B and C is calculated in the same way, with adjustments in the choice set formation parameters. Notice that the quantities in equation (2) are computed from the *dgp*, which populates market data based on the stochastic choice set formation described in Fig. 2 and on the true taste parameters. The only source of uncertainty is the random term added to the Vs, per Fig. 1.

   Traditional Choice model – Choice Process Homogeneity, Taste Heterogeneity. The commonly mis-specified model based on choice process homogeneity (expected utility maximization) is obtained by setting the parameters controlling choice set formation (g_1, g_2) to zero, which implies that every individual always considers all brands, i.e., they are all assigned to the full information condition in Fig. 2.

   Moreover, we relax the assumption of taste homogeneity to allow for heterogeneous preferences across consumers (U_{in}), described by a multivariate distribution $f()$. The resulting decision-making process leads to the mixed logit model (Train, 2009 p. 135), so that choice probabilities, for brand F for instance, are given by:

$$\widetilde{P}_F = \sum_{i \in F} \int_B \frac{e^{V_i(x_i|\widetilde{\beta}_i)}}{\sum_j e^{V_j(x_j|\widetilde{\beta}_j)}} \varphi(\widetilde{\beta}|\widetilde{b}, \widetilde{W}) d\beta, \tag{3}$$

where $\varphi(\widetilde{\beta}|\widetilde{b}, \widetilde{W})$ is the multivariate normal density with mean $\widetilde{b}$ and covariance $\widetilde{W}$. In this simulation, covariances are constrained to zero and the diagonal of $\widetilde{W}$ is populated by free parameters representing taste variances.

   The difference between expected demands derived from the true model in expression (2) and the expected demand derived from the incorrect model in formula (1), is given by:

$$Q\widehat{P}_F - Q\widetilde{P}_F = \left(g_1 h_1 + g_2 \frac{h_2}{2} \sum_{i \in F} \frac{e^{V_i}}{\sum_{j \in F, B} e^{V_j}} + g_2 \frac{h_2}{2} \sum_{i \in F} \frac{e^{V_i}}{\sum_{j \in F, C} e^{V_j}} + (1 - g_1 - g_2) \sum_{i \in F} \frac{e^{V_i}}{\sum_{j \in F, B, C} e^{V_j}} \right) - \sum_{i \in F} \int_B \frac{e^{V_i(x_i|\widetilde{\beta}_i)}}{\sum_j e^{V_j(x_j|\widetilde{\beta}_j)}} \varphi(\widetilde{\beta}|\widetilde{b}, \widetilde{W}) d\beta. \tag{4}$$

   The derivation of equation (4) allows the study of the difference in the left side of the expression as a function of the parameters controlling the consumers' choice process. Because the biased probabilities are expressed as a distribution over the experimental cells and across replications within cell, the differences also can be represented in terms of their mean and variance. In this study, however, due to the difficulties of calculating (4) analytically, we instead use the MC experiment to map these differences empirically by employing the choice probabilities computed from the true and from the estimated (mixed logit) models.

   Results. It is important to first notice that payoffs are standardized through the weighted product of each alternative's marginal profit and its choice probability. For each brand, the payoff is this sum product of its alternatives; for the aggregated market, all alternatives are considered. For every brand, the payoff varies as the net effect of changes in its choice probability and in its marginal
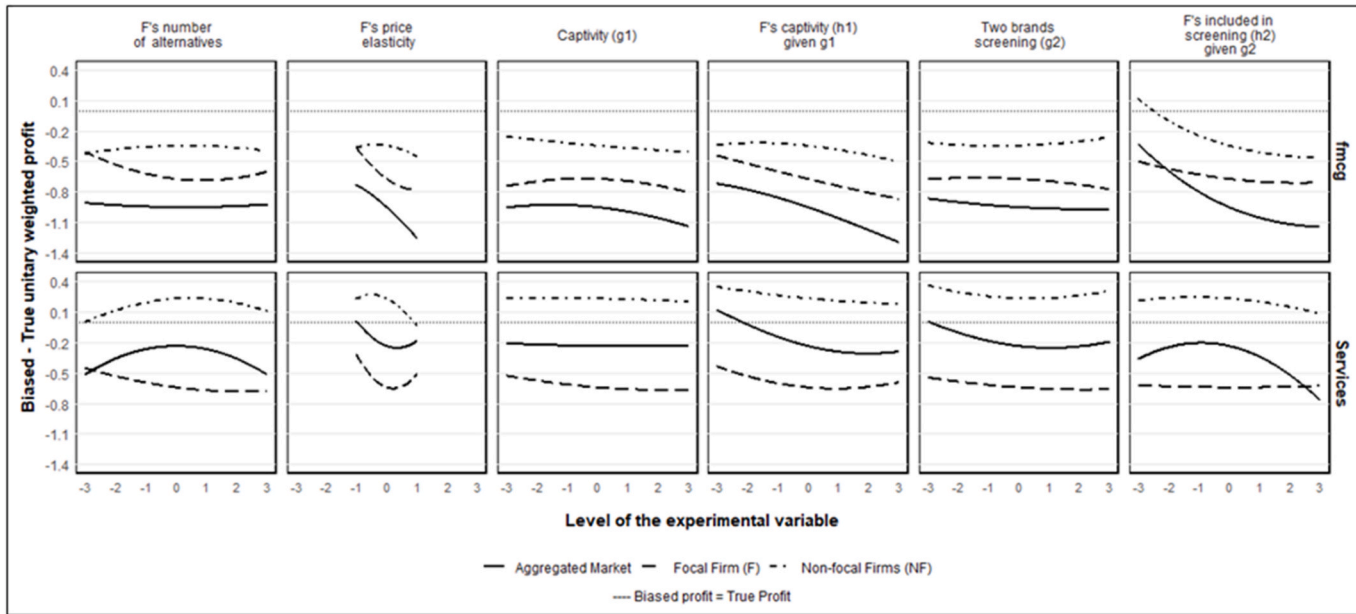
Fig. 3. Differences in profits due to model misspecification.

profit. After the payoffs analysis reported below, we aggregate the profitability of brands B and C, and refer to this quantity as competitors' profits (***NF***), before populating the game theoretical model with this information. This simplification keeps the derivation and the study of the market equilibrium as straightforward as possible, although the solution developed in the Web Appendix B is extensible to three or more brands.

Fig. 3 depicts the main results of the effects of our MC experiment design factors on the differences in payoffs between demand representations. At the market level, the expected profitability is reduced by model misspecification in both market contexts. The magnitude of this effect varies by market context, with the reduction in the total market's payoff being attenuated in the *services* context compared to the *fmcg*. The market level difference between market contexts is explained by different effects of the experimental design on brands, which can be tracked from parameters' biases through to brands' outcomes.

Relevant to this study, in the *fmcg* context the three brand-specific price parameters are overestimated by the misspecified econometric model (preference heterogeneity only), prompting all price elasticities of choice probabilities to exceed the true ones. But when adding variability in the *services* context to the generic attributes, we observe the *under*estimation of the three brand-specific price parameters. This reversal in the parameters' bias direction points to an increased overestimation of the price elasticity of F's choice probability while diminishing the overestimation for B and eliminating it for C. This result conforms to previous empirical evidence (Chiang et al., 1998; Mehta et al., 2003; Pires, 2016; Van Nierop et al., 2010), which indicates from empirical studies that price elasticities differ between models accounting for choice set formation, compared to those based on preference heterogeneity only. But the sign and the magnitude of the discrepancies are brand specific. Our study, which in contrast to past empirical work features certainty of the *dgp* and wide variation in the market context variables and the extent of choice process heterogeneity, enriches past findings (reproducing them in some of the experimental conditions) and suggests that the variables manipulated in our design give room to the observation of different patterns in the brand-specific price elasticities of choice probabilities. The direction and magnitude of price elasticities is an empirical matter, conditioned by the extent of choice set formation, the brand's choice probability, and the frequency of its inclusion in the latent choice set. Pires (2016) explains this phenomenon by two counteracting forces: 1) a non-reaction distortion leading to deflation of the focal price elasticity due to price changes only affecting some choice sets; and 2) a competitive distortion leading to inflation of the price elasticity because choice sets explicitly condition the scope of competition. Empirically, directionality and magnitude of bias in price elasticities will result from the dominance of one or the other of these effects. These are relevant remarks since these quantities obtained from the utility function allow a novel fusion between the traditional approach of demand forecasting and the profitability and strategic interactions between competing brands, proposed in our research.

Following, Fig. 3 portrays the sensitivity of the predicted profitability for each brand between demand representations, conditioned on the experimental independent variables (the profit difference is calculated on the basis of the demand difference given by Equation (4)). In every panel, we learn the effect of varying the level of the focal IV (the horizontal axis), while keeping the other IVs at their mean levels represented at the zeros shown on the horizontal axis (see Web Appendix A for details on the experimental design). For instance, in the *fmcg* context (row 1 of the figure), the discrepancy in profits between demand representation (for both players and aggregated market) increases when we increase the probability of benefiting ***F*** by this choice set formation rule (column 4).

The decline in *F*'s expected payoff between demand representations is qualitatively similar (although numerically different) in the two market contexts (as evidenced by the comparison across the two rows of graphs), despite the different bias pattern in *F*'s BSC and price parameter, in its choice probabilities, and in its price elasticity. Next, we summarize these biases (note that there is a more exhaustive and thorough analysis available upon request from the authors). In both market contexts, *F*'s BSC is underestimated (the sign is reversed), thus shifting down *F*'s choice probability curves, and the magnitude of this error is larger in the *services* context. Also, *F's* price elasticity of choice probability (averaged across experimental conditions) is larger in the *fmcg* (biased elasticity is ±2x the true one) compared to the *services* context (biased elasticity is ±1.5x the true one). The combined effects of the model misspecification drive *F*'s share down to 36%–33% of the true value in *fmcg* and to 30% in the *services* context (averaged across experimental conditions). Facing higher choice price elasticity when adopting the biased demand representation (process homogeneity, preference heterogeneity), *F* maximizes profits targeting a higher marginal cost (compared to price) than when adopting the true one. Additionally, it targets a higher marginal cost in the *fmcg* than in the *services* context. The smaller (larger) choice probability reduction in the *fmcg* (*services*) context is combined with a larger (smaller) choice price elasticity, leading the analyst to observe substantively similar expected reduction in *F*'s payoffs across market contexts.

Brand *B* has similar results in terms of parameters' biases compared to *F*, except that choice probabilities are always smaller. *B*'s choice probabilities drop from 9% in the *dgp* to nearly 1% (0%) when model misspecification occurs in the *fmcg* (*services*) context. Given the pattern in the price parameters, the underestimation in the price elasticity of *B*'s choice probability is sharply diminished (reversed in some experimental conditions) in the *services* context (compared to the *fmcg*). However, given its consistent loss in choice probabilities, brand *B* always experiences reduced profitability under the misspecified econometric model.

Finally, the econometric misspecification drives *C*'s choice probability up, from 57% to 67% (*fmcg*) and 70% (*services*). The combination of a significant gain in the brand's choice probability allied to an estimate of its price elasticity close to the true one, leads the observed profit to be larger in the misspecified econometric model than in the true *dgp* (process heterogeneity, taste homogeneity). Given the overestimation of the price elasticity, the profit averaged across experimental conditions is slightly lower when forecasted from the misspecified model (choice homogeneity, taste heterogeneity), but this pattern is reversed depending on the experimental condition.

A final remark is that the analyst's arbitrary decision about which brand to omit from the vector of BSCs results in the firm with the omitted constant having its choice probability curve shifted upwards, and this effect is stronger in the *services* context. Given that predicted profitability is driven both by the location and inclination of the demand curve, the arbitrary decision of omitting one brand from the vector of BSCs has a substantive impact on the analysis, when a misspecified econometric model is adopted.
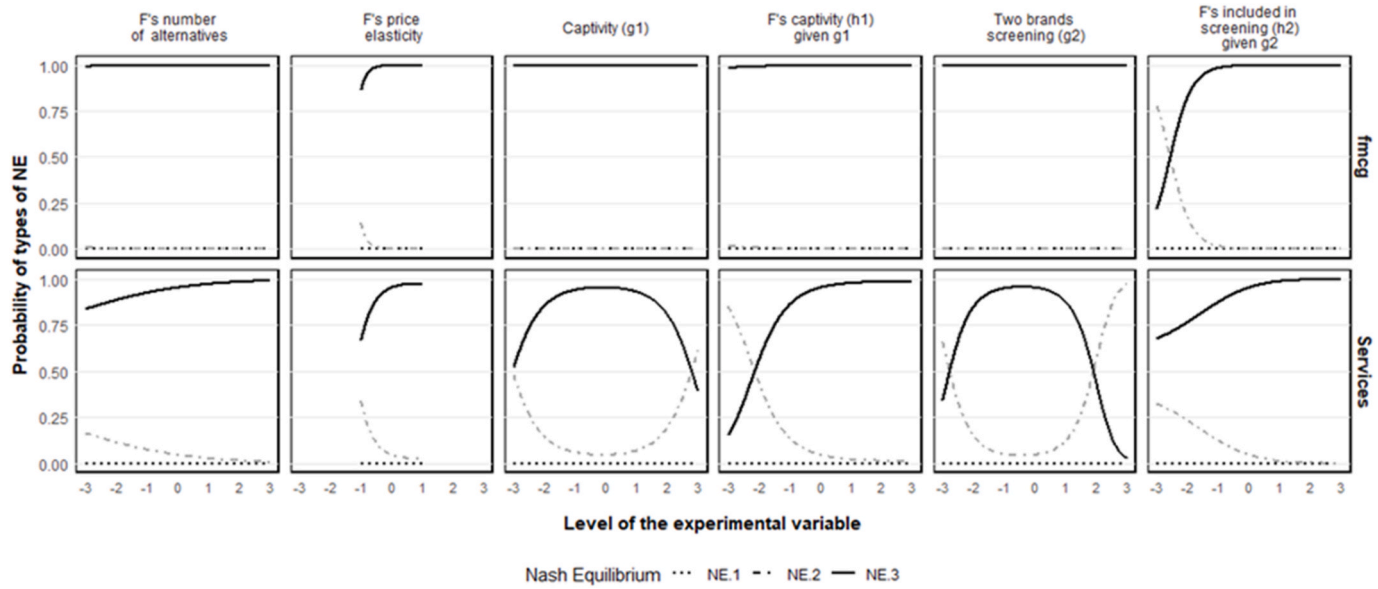
Fig. 4. Conditional probabilities of types of Nash Equilibrium.

In summary, not accounting for choice set formation and allowing solely for preference heterogeneity leads not only to the emergence of context dependent counterfeit preference heterogeneity but also affects the location of taste parameters, including for generic attributes, which naturally flows downstream to policy/strategy measures (choice probabilities and attribute choice probability elasticities) and payoffs both at brand and market levels. Confirming our hunch, biases in parameters and policy/strategy measures are larger in the *services* context than in the *fmcg* context, revealing that adding product-level attribute variation leads the biased model to perform even worse compared to the *dgp*. The effects of misspecification of the econometric model are also dependent on brands' characteristics (specific constants and specific prices), on the extent of choice process heterogeneity (here choice set formation), and on the extent that the focal brand is included on the choice sets (detailed results available from the authors). Moreover, the effects of the model misspecification are qualitatively different for the different brands given that choice probabilities result in a zero-sum game, while brands' payoffs result in a non-zero-sum game as a function of choice probabilities and demand price elasticities.

These results confirm what we already knew would arise from *dgp* mis-specification (e.g., Swait and Ben-Akiva 1987) as far as parameter and figure-of-merit biases is concerned, albeit in far more detail than previously available. In several comments above, we noted that the brand manager decision would thus certainly be affected by the mistake. However, considering that brand managers do not actually have access to the true data generation process and do not know what model adoption decision competitors will make, we are left to wonder: how would the brands interact to produce market equilibrium and how would this process be affected by different market contexts and by the process heterogeneity underlying consumer behavior?

In the game theoretical approach previously presented, we described possible Nash Equilibrium solutions for market clearance, which can be summarized in 1) an ideal pure strategy with both players choosing the correct demand representation; 2) a mixed strategy with players randomizing over the strategy space; and 3) a pure strategy with both players choosing the mis-specified demand representation, which we would argue is the current dominant practice In what follows, we investigate how the likelihood of each of these NE solutions responds to the factors included in the Monte Carlo simulation study. This represents the core results (and contribution) of our research.

We first sort each type of NE by its proximity to the true NE. This normative NE is described by the choice of the true demand representation (based on the brand screening process) by both brands, i.e., $\{\theta_F, \theta_{NF}\} = \{1, 1\}$. When this solution emerges from the data, the signal emitted by the true demand representation is strong enough to drive both brands to behave according to the true model (in other words, both F and NF avoid the costly mistake of not allowing for choice process heterogeneity). This normative NE may result either from both brands having only the true model available or due to the model accounting for choice process heterogeneity predicting higher payoffs or performing better in the goodness of fit measures (even if their sources of data are different). Next in proximity to the normative NE is the set of mixed strategies represented by $0 < \theta_F, \theta_{NF} < 1$, and the closer the solution is to unity, the closer it is to the normative NE, while the closer it is to 0 the more distant it is from the normative NE. Finally, the most distant solution from the normative NE happens when both brands choose the pure strategy favoring the biased model (preference heterogeneity only), i.e. $\{\theta_F, \theta_{NF}\} = \{0, 0\}$. This equilibrium may result either from both brands considering only the biased model, or due to both brands predicting higher payoffs, or observing superior goodness of fit favoring the biased model (even if they are using different data sources).

Fig. 4 describes the sensitivity of the conditional probabilities of each possible NE to the experimental variables' values. The figure is based on an ordered logistic model, in which the dependent variable is the Monte Carlo payoff estimates, defining the ordered alternatives as:

$$\begin{cases} Y = 1 \leftrightarrow \widehat{\mu}_F - \widetilde{\mu}_F < 0 \cdot \widehat{\mu}_{NF} - \widetilde{\mu}_{NF} < 0 \ (see \ delta = 1 \ in \ section \ 3.2) \\ Y = 2 \leftrightarrow \widehat{\mu}_F - \widetilde{\mu}_F < 0 \ OR \ \widehat{\mu}_{NF} - \widetilde{\mu}_{NF} < 0 \ (see \ delta = -1 \ in \ section \ 3.2) \\ Y = 3 \leftrightarrow \widehat{\mu}_F - \widetilde{\mu}_F > 0 \cdot \widehat{\mu}_{NF} - \widetilde{\mu}_{NF} > 0 \ (see \ delta = 1 \ in \ section \ 3.2) \end{cases}$$

The first important outcome of this model is that in the *fmcg* context (first row of graphs in Fig. 4) the pure strategy based on the true demand representation (choice set formation) emerges as a dominant strategy in almost every experimental condition. (The exceptions happen when *F*'s price elasticity is smaller than its competitors' price elasticities – second column, row 1 - or when *F* is excluded from brand screening when it happens including two brands – last column, row 1.) Overall, the signal produced by the correct model (here choice process heterogeneity) is strong enough to elicit a normative market equilibrium, thus disregarding the traditional choice model based purely on preference heterogeneity.

In the *services* context (second row in the figure), the results described in Fig. 4 portray a more complex pattern. Although the pure strategy solution based on the true demand representation is still dominant when the independent variables are at their average levels (zeroes on the horizontal axis), there is a small probability that a mixed strategy better describes the market equilibrium. When the independent variables deviate from their intermediate levels the normative Nash Equilibrium becomes less likely to be observed. This means that the likelihood of a solution being better described through mixed strategies increases when the number of alternatives (second row, first column) offered by *F* is reduced or when its price elasticity (second row, second column) is smaller than its competitors' price elasticity. The chance of observing mixed strategies increases when the frequency of captivity (second row, third column) deviates from average values either up or down, while the change of observing the normative pure strategy increases when choice set formation includes *F* (second row, fourth column). We observe the same pattern we vary the probability of choice set formation with two brands (second row, fifth column), and when we include *F* in the choice set (second row, sixth column). In some extreme situations, the conditional probability of a NE being represented by mixed strategies becomes dominant. These insights stress the power of simulation to identify variations in the expected quality levels, typical of *services* context, as the causal variable for the contrasts in results between rows 1 and 2 in Fig. 4.

It should be noted that, in practice, brand managers usually consider only one demand representation in the decision-making

process. This representation may even have been selected among different statistical models (based on goodness of fit criteria) specifying alternative taste heterogeneity possibilities (like continuous versus discrete mixtures, or the use of systematic sources). Our approach suggests that in both market contexts and across the experimental conditions, the consideration of different demand representations through competitors' reactions (assuming that the truth is unobservable) by brand managers will, eventually, reveal the true demand generation process and maximize supplier surplus.

We close our game theory analysis noting that not accounting for choice set formation, whatever its origin among alternative choice process heterogeneity mechanisms, significantly reduces both individual brand profits and aggregated profits, even if market equilibrium is achieved. The magnitude of this reduction of brands' performance depends on the context and market structure but in our experiment is shown that it can be as large as 80% of the potential profit when the brands jointly read the demand correctly. The challenge for brand managers is that the *dgp* is unobserved, i.e., consumers' actual choice processes are not fully accessible to brands. However, when knowledge about an alternative demand representation (here choice set formation) is presented to brand managers (with the currently common representation based on taste heterogeneity alone, when in truth choice process heterogeneity is also at work), and when the analysis is extended beyond model parameters and elasticities, our simulation study demonstrates that the NE moves towards the true demand representation. Even in contexts or conditions in which the convergence to the true demand representation is not immediate, the learning opportunities from consecutive rounds of decision-making should point brand managers towards the proper direction after a few periods. Also, between rounds, exogenous shocks (e.g., changes in consumer behavior or costs structures) tend to perturb markets, and it would be valuable to comprehend such effects on market equilibrium. Thus, a dynamic game would enrich our results by studying the path that would lead to the market equilibrium around the *dgp*, either in stable or revolving conditions. However, despite this self-correcting tendency, we must reiterate that the losses suffered by brands and markets will be *very significant* compared to full adoption of the true *dgp* by all brand agents. We also note that we have ignored potential consumer welfare losses that might result from poor brand manager decision-making, e.g., insufficient production of preferred product variants, out-of-stock situations, and so forth.

4. General discussion

Behavioral decision theories have a long tradition of studying choice process heterogeneity as a source of violations to normative rationality. Among choice modelers, the most common solution to unobserved choice heterogeneity is the use of random taste parameter models. Yet the urgency of exploring other sources of heterogeneity than preferences and to formalize choice models capable of more rigorous representations of consumers' decision-making is a challenge (e.g., Hensher 2014; Swait and Feinberg 2014). Despite the existence of papers exploring the biases in demand representation when choice process heterogeneity is (mis)channeled into tastes (e.g., Li et al., 2015), to our best knowledge this is the first effort to explore the phenomena in the management/marketing literature and, most importantly, to connect demand model misrepresentation to the consequences on brand managers decisions.

Broadly speaking, we have demonstrated the universally prejudicial consequences of ignoring choice process heterogeneity – here choice set formation – by showing that market equilibrium is thereby impaired due to sub-optimal brand manager decision-making. We base this assertion on an extensive MC experiment we conducted to study the effects on brand managers decisions of misattributing choice process heterogeneity to taste heterogeneity alone. The known data generation process was based on the existence of choice set formation built into the data generation process (i.e., process heterogeneity, but taste homogeneity). In contrast, the generated data was used to estimate a biased choice model (no process heterogeneity but allowing taste heterogeneity) to describe demand.

The Nash Equilibrium resulting from a static game of complete information (but allowing for information asymmetry) was analyzed and the results reveal that brands will move towards and eventually achieve full profit maximization when brands have the knowledge about demand representation based on process heterogeneity; the intensity/magnitude of the phenomenon is context dependent, but its occurrence is not. To quantify this discrepancy, under the conditions of our MC experiment the average profit under-realization at the market level (focal brand), when ignoring choice set formation, is 27% (43%) in the *fmcg* context and 9% (31%) in the *services* context. The process happens through: (i) generalized biased estimation of preference parameters; (ii) biased formulation of policy measures, here choice probabilities and attributes' choice elasticities; (iii) brand managers decisions producing a Nash Equilibrium in which the focal and the aggregate market ends up worse off than if choice set formation had been correctly accounted for.

The biases from process misspecification propagate to all parameters: brand-specific constants and price sensitivities, as well as generic attributes. The bias distribution among brand-specific constants and price specific constants is dependent on the BSC parametrization, which is an arbitrary choice to be made by the econometrician/data scientist. This implies that a seemingly innocuous mathematical decision about the base brand when defining identification conditions for brand constants suddenly takes on great importance when choice set formation is present in the data generation process. More research is needed to clarify this phenomenon and (hopefully) establish market structure sensitive guidelines for econometricians. In our experiment, except for the focal brand *F*'s BSC, the parameters were estimated with the correct sign, but were over-estimated in the *fmcg* context and under-estimated in the *services* context (except for one generic attribute which was over-estimated).

The downstream consequence of biased parameters is the biased estimation of policy measures that are inputs for brand managers. Brand *F*'s choice probabilities are systematically lower in the true demand representation, an outcome related to the reversed sign of its brand-specific constant. While in the true *dgp F*'s specific constant is the largest among the brands, meaning that it can capture a premium price, the use of the mis-specified model (in which this parameter's sign is reversed) suggests that *F* should give a discount to make consumers buy its products if they have the same attribute configuration compared to brand *C*. Moreover, in the *fmcg* context elasticities are overestimated in the mis-specified model, informing brands that consumers are more price and quality sensitive than they really are. The rational brand using this information offers more and charges less from its consumers, operating with gross

margins below achievable levels if it had the correct information. In the *services* context, demand price elasticities are under-estimated, which will also lead rational brands to make wrong decisions.

In both contexts, profits at market level are under-realized when brands use a misspecified model. At the brand level, *F*'s profits are lower in the biased demand representation in both contexts, and *NF*'s profits are lower in the *fmcg* and higher in the *services* context. All the observed effects are stronger when choice set formation is more intense and are also dependent on the market structure (the true pattern of BSCs and brand-specific price attributes).

5. Conclusion

The game theoretic analysis reveals that the mere possibility of a demand representation considering choice set formation, along with the dominant approach considering taste heterogeneity, elicits a market equilibrium that is closer to the ideal. The final market equilibrium depends on the context and on the market structure, but in most cases the NE will be described by pure strategies accounting for choice set formation or will move towards it by using mixed strategies. This finding suggests that the analyst should develop multiple representations of an unobservable data generation process in a quest to discover the true (or, perhaps more realistically, the best) *dgp* to describe market demand. Our results reveal within the scope of our simulations the severe under realization of profit arising from mischaracterizing the true *dgp*; conversely, they also reveal the substantive potential for improving brand managers decisions and market performance. Moreover, as the results of our Monte Carlo simulation indicate the importance of this phenomenon to the marketer and to the econometrician/data scientist, the results of the game further reveal the importance of studying different demand representations to the business strategist.

To cope with the comprehensiveness of our experimental design and with the novelty of connecting the results of demand estimation to brand performance and the strategic interaction between competitors, we made important methodological choices during the course of developing our study, which leaves ample room for improvements and extensions to our efforts. On the demand side, preferences were held homogeneous when it is well established that tastes vary between consumers and across occasion, along with other components of the choice process. At this point, it is worth noting that the econometrician facing the uncertain *dgp* from empirical data (either from stated or revealed preferences) has challenges that differ from the ones we needed to address. Modeling such empirical data requires recognizing the coexistence of process and taste heterogeneity, which is the central takeaway from this project for the empirical modeler. We suggest that future simulation studies should also permit tastes to vary in the data generation process containing none, one, or more forms of process heterogeneity. These more flexible *dgps* allow for more realistic and interesting cross-substitution patterns to study the effects of reversing the directionality of the misattribution focused on by this paper. (We make this observation with the caveat that the conclusion that tastes vary empirically *might* be at least partly an artifact of ignoring other aspects of process heterogeneity, as empirically suggested by Chiang et al., 1998.) Also, different market contexts may be studied with suitable variability added to the attributes, including prices. A multitude of market characterizations can be explored in terms of the nature of products and competitive structures, including a numeraire alternative that would explicitly allow consumers to exit the marketplace if proper conditions arise (i.e., if none of the alternatives reach a threshold utility).

At the brand level, there are also interesting opportunities. We have derived the analytical market equilibrium conditions for each player, and our solution is extensible for three or more players. We have studied a static Nash Equilibrium in a game of complete information, where mixed strategies allowed some players to retain some proprietary knowledge to cope with the uncertainties inherent in the game context. In the future the assumptions of this kind of game can be further relaxed to add greater realism. It is particularly desirous to consider that complete information is not available, i.e., in real markets information is usually incomplete, often asymmetric, and usually dynamic, which motivates the study of Bayesian Nash Equilibria. Allowing for sequential decision iterations, this setting can illustrate the path towards equilibrium as new plausible demand representations arise and the effects of exogenous shocks that usually impact competitive markets play out. Additionally, brands may strive for optimization of other goals than profit (like market share) or even to simultaneously maximize multiple goals that can be represented in the payoff function.

There are likely to be other consequences of this misattribution of choice process heterogeneity to taste heterogeneity, affecting both consumers and governments. We have not specifically studied these in this research since our focus was on brand managers' decisions, but we offer some reasonable speculations about wider impacts. Our archetypal misspecification of demand may lead brands to offer cheaper products with lower quality due to incorrect inferences of high price demand elasticities, which perversely prevents consumers from fulfilling their needs. On the other hand, brands may increase prices due to inferring lower than true price demand elasticities, which may alienate consumers from the marketplace since they may perceive that their needs cannot be fulfilled. Additionally, lower profits captured by brands (compared to the potential given a correct understanding about demand) result in lower taxes collected by governments, preventing them from executing relevant public policies and improving overall population welfare.

To model choice process heterogeneity requires more data and/or more complex models. In our paper, we represented choice set generation through a 2-stage choice process involving a first step of screening alternatives followed by a second phase of evaluation and choice among the alternatives that survived choice set formation. Brand managers and econometricians have a variety of models accounting for this structure, which can support the development of empirical models. The Independent Availability Model (Swait and Ben-Akiva, 1987) uses exogenous variables to estimate the likelihood of every (potential) choice set based on individual characteristics or task and context properties, and estimates the alternatives' choice probabilities given the latent choice set. While this approach is the most complete for describing our focal *dgp*, it involves enumeration of unobserved choice sets and the computational effort increases rapidly in the number of alternatives. In practice, its application is limited by the size of the problem at hand, by the available processing power and the time available for analysis. An alternative to complete enumeration of choice sets is to adopt a model allowing partial representations of the choice set space. For example, the GenL model (Swait, 2001a) presents an endogenous choice

set generation function permitting the analyst to restrict the choice set space based on other sources of information than choice data, that may suggest a maximum size of choice set that consumers are willing to consider. Such a restriction is useful if it results in a number of choice sets much smaller than $(2^{|J|} - 1)$. The empirical applications used to assess (Chiang et al., 1998; Mehta et al., 2003; Van Nierop et al., 2010) the consistency of our simulation results are based on econometric models that infer latent choice set from observed choice data and in store marketing activities, available in consumer panel datasets. These models do not require individual consumer information other than the observed choice, and they can handle large amounts of data, either in terms of number of alternatives, number of individuals, or number of observations per individual. Finally, returning to our original main argument to favor choice process heterogeneity, other forms of the phenomena are well-known and Aribarg et al. (2017) present an extensive survey of non-compensatory or multiple stages choice models available to brand managers, econometricians and data scientists to represent consumer behavior.

As a final remark on modeling strategies, the usual approach to model selection is the assessment of goodness of fit measures, which tends to maximize internal consistency and to explain the pattern in the data used to develop the model. However, given the proposition that choice behavior is conditioned by consumer, task and context characteristics, modelers should test alternative models for ecological validity. This can be done using independent samples and different methods (such as presenting choice scenarios in different formats, with different number of alternatives, or use alternatives actually available to consumers) to assess the predictive power of the competing models (Swait et al., 2018).

The initial motivation behind this study was to build a compelling "call to action" directed at brand managers, business strategists and the choice modeling community to recognize the existence of choice process heterogeneity (such as choice set formation) in choice data. In stated preferences studies, where the number of alternatives is usually small (say, less than 12), we feel that there are no compelling reasons to avoid facing the challenge of modeling choice set formation, preferably using latent enumeration strategies. In revealed preference situations the issue can be far more complex, but implicit choice set generation models (see Cascetta and Papola 2001; Martínez et al. 2009; Paleti 2015; Swait 2001b) may prove a viable route to represent consumer behavior in a more ecologically valid way.

Our study shows that the business consequences of ignoring potential confounds can be observed as large profit under-realization, both at the market level and at brand level. On the other hand, this underperformance can be overcome by investments in developing different demand representations, including those based on choice process heterogeneity. Every possible demand representation, true or biased, represents a different market equilibrium, and the availability of more than one representation increases the likelihood of brands matching the naturally unobservable true demand structures. Our results show that strategic interactions, like those described by mixed strategies, permits the learning about demand structures from consumer behavior and from signals by competitors' strategic choices. Through these competitive interactions the market equilibrium shifts towards the optimal one, thereby improving business strategy efficacy.

Credit statement

Luis Pilli: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Visualization, Project administration, Funding acquisition.

Joffre Swait: Conceptualization, Methodology, Validation, Resources, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

José Afonso Mazzon: Supervision, Project administration, Funding acquisition.

Funding

Declaration of competing interest

None.

Appendix A. Design of the Monte Carlo Experiment

The two demand representations, each emulating different market contexts, are portrayed in utility functions detailed by brand-specific constants, generic attributes, and brand-specific prices. One demand representation describes many fast-moving consumer goods (*fmcg*) categories and the other describes consumers' experiences with services, which also is a usual domain of consumption. Taking one of the brands as the focal point of analysis, an experimental design supports the study of the effects of misattributing process heterogeneity as taste heterogeneity by systematically varying these factors: the relative size of the focal brand's portfolio, the relative price elasticity of the focal brand, the extent of choice set formation and how it distributes across brands. Thus, demand arises through a mixture of choice set formation rules. Furthermore, the true data generation process has *taste homogeneity*. A mixed logit model, allowing *taste heterogeneity*, is used to estimate the consumers' preferences and to identify the market structure.

1. Demand data generation process

The demand representation is grounded on consumers making choices based on homogeneous preferences, however, due to the differences in the process of judgment and decision making, each consumer maximizes expected utility within a latent choice set.

The two data generation processes are planned to reproduce common characteristics in the proposed competitive market contexts, and some characteristics of the consumer choice process that may trigger the focal phenomena being studied, i.e., the misattribution of process heterogeneity to tastes.

The scenarios are composed by offers from three brands, each presenting a different number of products (or alternatives). Product attributes (k_s) are two dummy variables as brand-specific constants defining three brands (one dummy variable omitted for identification); two generic attributes allowing for product differentiation; and three brand-specific price variables.

The generic and specific attributes levels, for every product, are random variables such that $l_k \sim U(1,6)$. To represent the variation in the level of the service experienced by the consumer in the services market context, a random variable $v_k \sim U(-0.5, 0.5)$ is added to each generic attribute; in the fmcg context, no perturbation is added to l_k. The draw of l_k represents the level of quality the brand plans to deliver and the draw of v_k represents the variation that consumers expect to experience across occasions or points of sales. Finally, the brand-specific prices mean that each brand can set different prices, even for the same product, and that each one has its own demand price elasticities. For the analytical purposes, brands will be named F (for Focal), B and C.

The consumer decision-making process is based on a dual stage process. At the initial stage (choice set formation) consumers select brands that will have the products evaluated in the second stage. After choice set formation ends, utility maximization drives choice.

2. Experimental plan

The experimental plan is the same for both marketing contexts and involves characteristics of choice tasks and consumers' choice process, and it is explained from a general overview of the building blocks of the experiment, followed by the description of variables' manipulation. Building blocks of the experiment were: (a) the utility parameters; (b) the number of SKUs in the choice task, attribute levels and the number of choice tasks; (c) the rules for choice set formation and the attribution of consumers to rules; (d) the experimental design.

2.1. Utility parameters

The utility function has seven utility parameters: two for brand-specific constants, two for generic attributes and three for brand-specific prices. The known/true utility parameters, for the systematic term of the utility function, are presented in Table A1.

Table A.1
True utility function parameters

Variables	BSCs		Generic attributes		Brand-specific attributes		
	F (focal)	B	I	II	F (focal)	B	C
Parameters β_k	0.5	−0.5	−1.0	1.0	−0.5 −1.0 −1.5	−1.0	−1.0

The only parameter that varies across the experimental conditions is the brand-specific price for the focal brand. It has three levels representing the focal branding facing price elasticities lower, equal or higher than competitors.

2.2. Number of SKUs, attribute levels, and choice task

F's number of alternatives varies across the experimental conditions while competitors offer a fixed number of alternatives, as described in Table A2. Brand B offers four and brand C offers seven SKUs, allowing F's product line length to be shorter than both competitors, equal to brand B but shorter than brand C, larger that brand B and equal to brand C and larger than both competitors.

Table A.2
Number of SKUs per brand

BRAND	F	B	C
Product line length	2	4	7
	4		
	7		
	10		

Attribute levels for generic attributes and specific prices, of the 21 SKUs are drawn as $x_{kj} \sim U(1,6)$. These product profiles, defined as the universal choice set (M), are kept constant across experimental conditions and replications.

In the service context the generic attributes are drawn as $x_k \sim U(1,6)_j + U(-0.5, 0.5)_{entj}$. Expected quality levels varying across consumers n and choice occasions t, are consistent with the definition of services. The draw of the of the portion that adds variability to the quality level of the service is done for each experimental condition e from $1, …, E$. We acknowledge that the variability could have

been included at the replication level, but then it could also be confounded with the disturbance term ε, described below, and to avoid this confound the decision was made to keep it at the experimental condition level.

The fixed universal choice set is described in Table A3 and the last column is the value of the systematic part of the utility (*V*) for each product profile when the price parameter for the focal brand is set to −1.

Table A.3
The universal choice set (M) for the fmcg context

Alternative ID	Brand-specific constant		Generic attributes		Brand-specific prices			V
	F	B	I	II	F	B	C	
1	1	0	5.5	4.6	1.6	0	0	−4.7
2	1	0	3.2	4.8	1.4	0	0	−2.3
3	1	0	5.2	1.7	2.3	0	0	−1.2
4	1	0	1.0	4.3	3.1	0	0	−5.7
5	1	0	3.0	3.3	5.8	0	0	−5.1
6	1	0	5.9	5.9	4.5	0	0	−1.7
7	1	0	1.7	5.3	3.6	0	0	−5.6
8	1	0	1.6	2.0	4.5	0	0	−9.3
9	1	0	2.5	5.6	3.0	0	0	0.9
10	1	0	1.2	4.0	3.1	0	0	−3.2
11	0	1	4.6	2.9	0	2.7	0	−1.9
12	0	1	1.9	3.5	0	2.0	0	−5.9
13	0	1	5.5	3.3	0	4.7	0	−1.0
14	0	1	2.9	5.3	0	4.6	0	−3.0
15	0	0	4.8	2.3	0	0	2.4	−2.2
16	0	0	3.4	2.8	0	0	3.4	−4.8
17	0	0	3.7	5.4	0	0	1.3	0.0
18	0	0	4.9	3.9	0	0	1.8	−1.1
19	0	0	5.3	2.3	0	0	3.2	−3.0
20	0	0	1.1	5.9	0	0	1.8	−1.8
21	0	0	2.1	4.4	0	0	1.6	−1.4

F's alternatives, in the experimental conditions where its product line is shorter than 10, is a subset of *M* and the alternatives kept are those with the highest *V* for the condition, i.e., when *F* offers two products, those with the highest *V*, in the *F*'s portfolio, are kept and the others are dropped from the choice task.

To add stochasticity to the utility function, the random term is drawn from an identical and independent distributed (i.i.d) Gumbel distribution with scale equal to one. The random term ε_{erntj} varies across alternatives *j*, choice scenarios *t*, individuals *n*, replication *r*, and experimental conditions *e*, acknowledging that unobservable variables may have a different effect on consumers' choice on different occasions.

Number of choice scenarios per consumer is fixed at eight for every experimental condition and replication. This decision has ecological validity, since consumers make sequential choices in fixed scenarios in many *fmcg* categories and varying scenarios in different kind of services, the sequential decision-making allows the introduction of variance at the individual level (trough ε) and eight choice tasks is a common number for discrete choice experiments.

2.3. Rules for choice set formation

Considering three brands in the experiment there are seven possible choice sets. In any real sample of observed choices, through real or stated preferences, the true data generation process is an unknown mixture of the possible choice sets. The mixture is controlled in the experiment to understand effects of the intensity of choice set formation or process heterogeneity.

The experimental manipulation was designed in two steps. A variable G_g defines the relative size of consumer groups allocated to: (i) captivity or choice sets formed by products from only one brand; (ii) choice sets formation including products from two brands; and (iii) full information processing, i.e., consideration of all the three brands' products. A second variable H_h defines the distribution of consumers allocated to the choice sets containing or not the focal brand within each g. Given that for g = 3 all brands are included in the choice set, there is no associated *h* and the choice is fully compensatory. Table A4 describes the allocation process and informs the levels adopted for *g* and *h*.

One additional criterion to operationalize the process detailed in Table A4 is that for captivity (condition *i* above) consumers assigned to the choice set rules excluding the brand *F* are equally distributed between other two brands. Likewise, consumers assigned to choice set formation with any two brands (condition *ii*), are equally distributed across the two considered brands.

The values of G_g and H_h defines the proportion of the sample across the choice set formation rules, and individuals are assigned to a specific rule through a random draw following a cumulative uniform distribution.

Table A.4
Assignment to the choice set formation rules.

Number of brands in the choice set formation rule	Assignment to CSF rules		CSF rules	Assignment to rules including focal brand		
	Variable	Levels		Variable	Levels	
1	g_1	0 0.17 0.34 0.5	F	h_1	0 / 0.25 / 0.75 / 1	
			B		$(1 - h_1) / 2$	
			C		$(1 - h_1) / 2$	
2	g_2	0 0.17 0.34 0.5	FB	h_2	0 0.25	$(h_2 / 2)$
			FC		0.75 1	$(h_2 / 2)$
			BC		$(1 - h_2)$	
3	g_3	$(1 - g_1 - g_2)$	FBC			

2.4. Experimental design

The factors and its levels experimentally manipulated are summarized in Table A5 and the full factorial of this experiment would result in 3072 (3*45) conditions.

Table A.5
Experimental factors and factor levels

Factors	Levels			
	1	2	3	4
Focal brand number of SKUs	2	4	7	10
Focal brand price parameter	−0.5	−1.0	−1.5	
g_1	0	0.17	0.34	0.5
g_2	0	0.17	0.34	0.5
h_1	0	0.25	0.75	1
h_2	0	0.25	0.75	1

To maintain the simulation tractable, from the perspective of the Monte Carlo simulation, a main effects experimental design is used, and its 25 conditions are presented in Table A6. These 25 conditions define the cells of the experiment.

Finally, within each cell, each data set is generated with 1,000 respondents, which is a common sample size in market research studies among heterogeneous populations. To obtain a distribution of parameters (tastes and standard deviations) every experimental condition was replicated 250 times, providing sufficient power to detect the relationship between any level of any independent variable and the deviation from the estimated to the true parameters.

Table A.6
Experimental design

Condition	Factor levels					
	Number of SKUs	Price parameter	g_1	g_2	h_1	h_2
1	2	−1.0	0.17	0.17	1	1
2	10	−0.5	0.17	0	0.75	0
3	4	−1.0	0	0.34	0	0
4	10	−1.0	0	0	0	0.25
5	10	−1.5	0.34	0.17	0	0.75
6	7	−0.5	0.17	0.34	0	0.75
7	7	−1.0	0	0.17	0.25	0
8	2	−0.5	0	0	0	0
9	4	−0.5	0	0.5	1	0.75
10	10	−0.5	0	0.5	0.25	1
11	2	−0.5	0.34	0	1	0

(continued on next page)

Table A.6 (*continued*)

Condition	Factor levels					
	Number of SKUs	Price parameter	g_1	g_2	h_1	h_2
12	7	−0.5	0.5	0	0	1
13	2	−1.0	0	0	0.75	0.75
14	2	−0.5	0.34	0.34	0.25	0.25
15	2	−1.0	0.17	0.5	0	0.25
16	2	−0.5	0	0.17	0	0
17	4	−1.5	0.17	0	0.25	0
18	4	−1.0	0.34	0	0	1
19	10	−1.0	0.5	0.34	1	0
20	2	−1.0	0.5	0	0.25	0.75
21	7	−1.0	0.34	0.5	0.75	0
22	2	−1.5	0	0.34	0.75	1
23	2	−1.5	0.5	0.5	0	0
24	7	−1.5	0	0	1	0.25
25	4	−0.5	0.5	0.17	0.75	0.25

Table A7 summarizes the settings for the Monte Carlo simulation. In total, there are 6,250 (the number of experimental conditions times the number of replications) data sets, for each market context, each one with 8,000 choice scenarios (the number of observations per data set times the number of choice tasks per observation).

Table A.7

Setting for the data generation process – for each market context

Variable	Notation	Value
Number of experimental conditions	C	25
Number of replications	R	250
Number of observations per data set	N	1.000
Number of choice tasks per observation	T	8
Number of alternatives per choice task	J	13/15/18/21
Number of taste parameters	K	7

Appendix B. Static Game of Complete Information

The non-cooperative static game of complete information is detailed, starting from definitions offered by Gibbons (1997) and Wang and Parlar (1989). The normal formal representation of an n-players game specifies players' strategy spaces $S_1, ..., S_n$ and their payoff functions $\mu_1, ..., \mu_n$. The following set defines the game:

$$G = \{S_1, ..., S_n; \mu_1, ..., \mu_n\} \tag{B.1}$$

Players choose their strategies without knowledge about other players' choices, they are rational (in the sense that they do not choose strictly dominated strategies) and they know that other players are rational. There will be a unique equilibrium to this game if every player chooses a strategy that is the best response to the predicted (by the theory) strategy of the other players. This solution is a Nash Equilibrium, meaning that no player wants to deviate from her predicted strategy which is expressed as:

$$(NE) : \mu_i(\dot{s}_1, ..., \dot{s}_{i-1}, \dot{s}_i, \dot{s}_{i+1}, ..., \dot{s}_n) \geq \mu_i(\dot{s}_1, ..., \dot{s}_{i-1}, \dot{s}_i, \dot{s}_{i+1}, ..., \dot{s}_n) \tag{B.2}$$

Consider the **focal** firm (**F**) and the **non-focal** firms (**NF**) as the two players in this game. First, the **strategy space** is defined as $S_F = S_{NF} = \{\widehat{Q}\widehat{P}_i\widehat{\mu}_i, \widetilde{Q}\widetilde{P}_i\widetilde{\mu}_i\}$. $\widehat{Q}$ is the active number of consumers in the market, $\widehat{P}$ is the i's conditional choice probability, and $\widehat{\mu}_i$ is i's profit resulting from the true demand representation (choice process heterogeneity, preference homogeneity). $\widetilde{Q}, \widetilde{P}, \widetilde{\mu}_i$ are equivalent quantities resulting from the biased demand representation (choice process homogeneity, preference heterogeneity).

Firm's choice probabilities are described in the paper. Profits are maximized when the firm's marginal cost equals its marginal revenue, so that:

$$MC_i = MR_i = pr_i + pr_i\left(\frac{1}{E_{pr}^i}\right) \tag{B.3}$$

In expression (B.3), *MC* is marginal cost, *MR* is marginal revenue, pr is price and E_{pr}^i is the demand price elasticity of alternative *i*. Choice elasticities are estimated at the firm level, and prices are averaged as:

$$pr_f = \sum_{i \in f} P_i.pr_i \tag{B.4}$$

Equation (B.4) states that the average price of *f* is the price of every alternative offered by the firm weighted by its choice probability. Firm *f* maximizes its payoff when:

$$MC_f = MR_f = pr_f + pr_f \left(\frac{1}{E_{pr}^f} \right) \tag{B.5}$$

Marginal costs are estimated from the demand Monte Carlo simulation, to understand the overall impact of the bias. And, finally, firms' payoff, or profit, is given by:

$$\mu_f = QP_f (pr_f - MC_f) \tag{B.6}$$

where μ_f is firm f's profit, Q is the number of active consumers in the market, P_f is firm f's choice probability, pr_f is firm f's weighted price, and MC_f is firm f's marginal cost. Q is unknown, since we have created the conditional demand functions in the data generation process. From dropping Q from equation (B.6), it is possible to conclude that $\mu \pi_f$ is increasing both in the choice probability and in the unit profit, and it is capturing the net effect of the variation in the choice probabilities and in the marginal costs across experimental conditions. The market level profit is the sum of the firms' unit profits weighted by the respective choice probabilities, i.e.:

$$\mu = Q \sum_f P_f (pr_f - MC_f); \mu_F = \mu - Q \sum_{f-F} P_f (pr_f - MC_f) \tag{B.7}$$

The difference $\widehat{Q} - \widetilde{Q}$ is not public and we assume that it is privately estimated by players. Now, players are uncertain about competitors' choice of demand representations, and they also have some private information. A mixed strategy is a randomization device that allows players to couple with these uncertainties and it reduces a game incomplete information to a game of complete information regardless the players' intentions to use the strategies available in the strategy space with the prescribed probabilities (Harsanyi, 1973).

Formally, a **mixed strategy** for player i is a probability distribution over the **pure strategies** in her S. A pure strategy is a mixed strategy that places a probability 1 (0) to one of the options in the strategy spaces (to the set of all remaining options). In the normal form game $G = \{S_1, \ldots, S_n; \mu_1, \ldots, \mu_n\}$, let $S_i = \{s_{i1}, \ldots, s_{iK}\}$. A **mixed strategy** for player i is a probability distribution $p_i = \{p_{i1}, \ldots, p_{iK}\}$, for which

$$0 \leq p_{ik}; p_{i1} + \ldots + p_{iK} = 1; for \ k = 1, \ldots, K \tag{B.8}$$

The players mixed strategies $(\dot{p}_1, \dot{p}_2)$ are a NE if each player's mixed strategy is a best response to the strategy of the other player. In the normal form $G = \{S_F, S_{NF}; \mu_F, \mu_{NF}\}$: $S_F = S_{NF} = \{\widehat{Q}\widehat{P}_i\widehat{\mu}_i, \widetilde{Q}\widetilde{P}_i\widetilde{\mu}_i\}$, **F(NF)**'s uncertainty about **NF(F)**'s strategy is:

$$p_F = \{\theta_{F,} 1 - \theta_{F,}\}; \ p_{NF} = \{\theta_{NF,} 1 - \theta_{NF,}\} \tag{B.9}$$

And **F**'s best response to **NF's** mixed strategy is:

$$\dot{s}_F = \theta_F (\widehat{Q}\widehat{\mu} - \widehat{Q}\widehat{P}_{NF}\widehat{\mu}_{NF}) + (1 - \theta_F)(\widetilde{Q}\widehat{\mu} - \widetilde{Q}\widetilde{P}_{NF}\widehat{\mu}_{NF}) \tag{B.10}$$

Likewise, the **NF**'s best response to **F**'s mixed strategy is:

$$\dot{s}_{NF} = \theta_{NF} (\widehat{Q}\widehat{\mu} - \widehat{Q}\widehat{P}_F\widehat{\mu}_F) + (1 - \theta_{NF})(\widetilde{Q}\widehat{\mu}_F - \widetilde{Q}\widetilde{P}_F\widehat{\mu}_{NF}) \tag{B.11}$$

The Nash Equilibrium requires a simultaneous solution to the first order conditions, given by (10) and (11), subject to the constraint $\dot{s}_F + \dot{s}_{NF} = \dot{Q}\mu$.

Now, (10) can be rewritten as:

$$\begin{aligned}
\dot{s}_F &= \theta_F (\widehat{Q}\widehat{\mu} - \widehat{Q}\widehat{P}_{NF}\widehat{\mu}_{NF}) + (1 - \theta_F)(\widetilde{Q}\widetilde{\mu} - \widetilde{Q}\widetilde{P}_{NF}\widetilde{\mu}_{NF}) \\
\dot{s}_F &= (\widetilde{Q}\widetilde{\mu} - \widetilde{Q}\widetilde{P}_{NF}\widetilde{\mu}_{NF}) + \theta_F (\widehat{Q}\widehat{\mu} - \widehat{Q}\widehat{P}_{NF}\widehat{\mu}_{NF} - \widetilde{Q}\widetilde{\mu} - \widetilde{Q}\widetilde{P}_{NF}\widetilde{\mu}_{NF}) \\
\dot{s}_F &= (\widetilde{Q}\widetilde{\mu} - \widetilde{Q}\widetilde{P}_{NF}\widetilde{\mu}_{NF}) + \theta_F [(\widehat{Q}\widehat{\mu} - \widehat{Q}\widehat{P}_{NF}\widehat{\mu}_{NF}) - (\widetilde{Q}\widetilde{\mu} - \widetilde{Q}\widetilde{P}_{NF}\widetilde{\mu}_{NF})] \\
\dot{s}_F &= \widetilde{Q}\widetilde{P}_F\widetilde{\mu}_F + \theta_F (\widehat{Q}\widehat{P}_F\widehat{\mu}_F - \widetilde{Q}\widetilde{P}_F\widetilde{\mu}_F)
\end{aligned} \tag{B.12}$$

Likewise:

$$\dot{s}_{NF} = \widetilde{Q}\widetilde{P}_{NF}\widetilde{\mu}_{NF} + \theta_{NF} (\widehat{Q}\widehat{P}_{NF}\widehat{\mu}_{NF} - \widetilde{Q}\widetilde{P}_{NF}\widetilde{\mu}_{NF}) \tag{B.13}$$

Given that mixed strategies reduce the game to a game of complete information, we drop Q from expressions above, and write the following pair of mixed strategies representing firms' best responses when two demand representations are available:

$$\{\theta_F, \theta_{NF}\} = \left\{ \begin{aligned} &\theta_{NF} + \frac{\theta_{NF}(\dot{\mu} - \widehat{\mu}) + (1 - \theta_{NF})(\dot{\mu} - \widetilde{\mu})}{\widehat{P}_F\widehat{\mu}_F - \widetilde{P}_F\widetilde{\mu}_F}, \\ &\theta_F + \frac{\theta_F(\dot{\mu} - \widehat{\mu}) + (1 - \theta_F)(\dot{\mu} - \widetilde{\mu})}{\widehat{P}_{NF}\widehat{\mu}_{NF} - \widetilde{P}_{NF}\widetilde{\mu}_{NF}} \end{aligned} \right\} \tag{B.14}$$

F's best response to the **NF**'s mixed strategy in Nash Equilibrium is proved as follows:

$$\widetilde{P}_F\widetilde{\mu}_F + \theta_F(\widehat{P}_F\widehat{\mu}_F - \widetilde{P}_F\widetilde{\mu}_F) + \widetilde{P}_{NF}\widetilde{\mu}_{NF} + \theta_{NF}(\widehat{P}_{NF}\widehat{\mu}_{NF} - \widetilde{P}_{NF}\widetilde{\mu}_{NF}) = \dot{\mu}$$

$$\theta_F(\widehat{P}_F\widehat{\mu}_F - \widetilde{P}_F\widetilde{\mu}_F) + \theta_{NF}(\widehat{P}_{NF}\widehat{\mu}_{NF} - \widetilde{P}_{NF}\widetilde{\mu}_{NF}) = \dot{\mu} - \widetilde{\mu}$$

$$\theta_F(\widehat{P}_F\widehat{\mu}_F - \widetilde{P}_F\widetilde{\mu}_F) = \dot{\mu} - \widetilde{\mu} - \theta_{NF}[(\widehat{\mu} - \widehat{P}_F\widehat{\mu}_F) - (\widetilde{\mu} - \widetilde{P}_F\widetilde{\mu}_F)]$$

$$\theta_F = \frac{\theta_{NF}(\dot{\mu} - \widehat{\mu}) + (1 - \theta_{NF})(\dot{\mu} - \widetilde{\mu}) + \theta_{NF}(\widehat{P}_F\widehat{\mu}_F - \widetilde{P}_F\widetilde{\mu}_F)}{\widehat{P}_F\widehat{\mu}_F - \widetilde{P}_F\widetilde{\mu}_F} \tag{B.15}$$

$$\theta_F = \theta_{NF} + \frac{\theta_{NF}(\dot{\mu} - \widehat{\mu}) + (1 - \theta_{NF})(\dot{\mu} - \widetilde{\mu})}{\widehat{P}_F\widehat{\mu}_F - \widetilde{P}_F\widetilde{\mu}_F}$$

And **NF**'s best response to **F**'s mixed strategy is:

$$\theta_{NF} = \theta_F + \frac{\theta_F(\dot{\mu} - \widehat{\mu}) + (1 - \theta_F)(\dot{\mu} - \widetilde{\mu})}{\widehat{P}_{NF}\widehat{\mu}_{NF} - \widetilde{P}_{NF}\widetilde{\mu}_{NF}} \tag{B.16}$$

This pair of mixed strategies solves into specific firms' behaviors depending on the market level and on each firm's payoff in the two demand representations. An illustration of three possible generic conditions $\{\dot{\mu} > \widetilde{\mu}; \widehat{\mu} = \dot{\mu}; \dot{\mu} < \widetilde{\mu}\}$ and nine unfolding specific behaviors is presented in Figure B1.

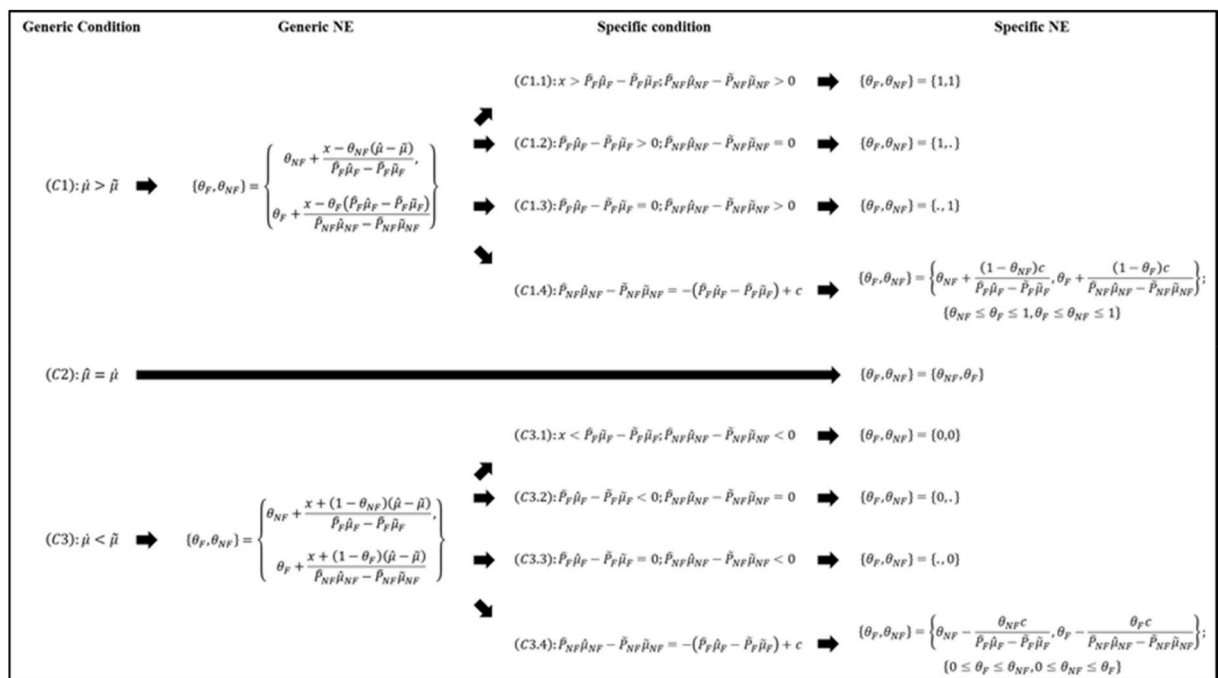The formal description, and proofs, represented in this figure is available upon request from the authors.

Fig. B.1. Nash Equilibrium under different conditions.

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