Households under Economic Change: How Micro- and Macroeconomic Conditions Shape Grocery Shopping Behavior

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Abstract

Economic conditions may significantly affect households' shopping behavior and, by extension, retailers' and manufacturers' firm performance. By explicitly distinguishing between two basic types of economic conditions—micro conditions in terms of households' personal income and macro conditions in terms of the business cycle—this study analyzes *how* households adjust their grocery shopping behavior. The authors observe more than 5,000 households over eight years and analyze shopping outcomes in terms of *what*, *where*, and *how much* they shop and spend. Results show that micro and macro conditions substantially influence shopping outcomes, but in very different ways. Microeconomic changes lead households to adjust primarily their overall purchase volume—that is, after losing income, households buy fewer products and spend less in total. In contrast, macroeconomic changes cause pronounced structural shifts in households' shopping basket allocation and spending behavior. Specifically, during contractions, households shift purchases toward private labels while also buying and consequently spending more than during expansions. During expansions, however, households increasingly purchase national brands but keep their total spending constant. The authors discuss psychological and sociological mechanisms that can explain the differential effects of micro and macro conditions on shopping behavior and develop important diagnostic and normative implications for retailers and manufacturers.

Keywords: business cycle, income shocks, CPG market, private label, national brand, discounter, supermarket

Households are subjected to constantly changing economic conditions. These changes may take place at a personal, microeconomic level, such as if the main breadwinner receives a pay raise or a household member loses a job (micro conditions). Alternatively, changes may manifest at a macroeconomic level, in terms of the business cycle with its recurring expansions and contractions or in response to global events such as the Great Recession or the Covid-19 pandemic (macro conditions). These changing micro and macro conditions substantially affect household spending and, in turn, companies' profits. By one estimate, the Great Recession led to an average 8%, or $4,000, decrease in real annual spending among U.S. households, which amounts to $500 billion in foregone revenues (*The Economist* 2011).

While households tend to simply postpone purchases of durable goods to times of economic prosperity (Deleersnyder et al. 2004; Dutt and Padmanabhan 2011), they engage in a variety of adjustments when shopping consumer packaged goods (CPGs): switching from national brands (NBs) to cheaper brands or private labels (PLs), from supermarkets to discounters, from regular to promotional prices, or decreasing the amounts purchased altogether (e.g., Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007; Ma et al. 2011).

While research to date has focused intensively on how households adjust individual CPG shopping outcomes in response to changing macro conditions (e.g., Dubé, Hitsch, and Rossi 2018; Lamey 2014; Lamey et al. 2007), this work takes a holistic view on households' CPG shopping behavior uncovering how it is differentially affected by micro and macro conditions. This explicit distinction is important because changes in macro and micro conditions are not necessarily aligned. In fact, even the Great Recession, during which unemployment rates skyrocketed and housing prices and stock portfolios plummeted, did not equally affect the personal income and wealth of all demographic subgroups of the population (Kalleberg and Von Wachter 2017) or all geographical regions (Dubé, Hitsch, and Rossi 2018). Similarly, the economic downturn caused by the Covid-19 pandemic implies particularly severe microeconomic consequences for industry sectors that depend on tourism, events, or gastronomy, with less effect on banking or the public sector (OECD 2020). Of course, an income loss, for example as result of sudden unemployment, may as well occur during prosperous economic times and be no lesser of an individual hardship.

Furthermore, the consequences of changing micro and macro conditions differ considerably. While changing micro conditions directly affect households' *ability* to purchase, changing macro conditions, all else being equal, affect only households' *willingness* to purchase (Katona 1979). Accordingly, households' response to changing conditions depends on whether they are affected at a micro or macro level (or both) and may manifest in very different shopping outcomes. For example, households may alter what they purchase (e.g., NBs or PLs) and where they shop (e.g., in discounters or supermarkets), as well as how much they spend and purchase. Thus, to properly disentangle the distinct effects of micro and macro conditions and to provide differentiated implications for retailers and manufacturers, holistic observations of households' shopping behavior are crucial.

We analyze a total of seven measurable and managerially relevant shopping outcomes. These outcomes reflect *how* households allocate their budget across brand types and store formats—their *shopping basket allocation* (in terms of PL and NB spending in discounters and non-discounters)—as well as *how much* they spend and purchase—their *shopping basket value* (in terms of total spending, purchase volume, and an index of prices paid). Through the analysis, we uncover and characterize the differential effects of micro and macro conditions on households' shopping behavior by addressing the following research questions:

1. To what extent do micro (i.e., income) and macro conditions (i.e., the business cycle) affect households' CPG shopping behavior?
2. How do micro and macro conditions differ in terms of their effects on households' shopping basket allocation and shopping basket value?

3. Do asymmetries exist between negative (i.e., income losses/economic contractions) and positive conditions (i.e., income gains/economic expansions) and if so, do these asymmetries differ between micro and macro conditions?

We use a unique, comprehensive data set tailored to the research objectives. Drawing on the GfK Germany ConsumerScan panel, we obtain detailed information about daily CPG transactions for more than 5,000 households in Germany over a period of eight years including the Great Recession. Based on this, we identify what and where households shop, how much they purchase, what prices they pay, and how much they spend. Annual surveys administered to the panel provide us with longitudinal data on households' demographics and psychographics, including micro conditions in terms of household income. In addition, the panel data allows us to control for important marketing mix elements concerning prices, assortments, and promotional activities. We further enrich the data set with macroeconomic data from the German Federal Statistical Office and advertising data from the Nielsen Company on advertising spending by all manufacturers and retailers in the sample.

The analyses show that micro and macro conditions both have a substantial impact on households' shopping behavior. Importantly, households adjust their shopping behavior without a concrete change in their budget constraint. In addition, micro and macro conditions differ substantially in their effects on households' shopping behavior. Whereas micro conditions primarily have an impact on households' basket value, macro conditions not only affect households' basket value but also cause shifts in households' basket allocation. During adverse micro conditions, households buy lower volumes and spend substantially less in total but do not shift spending to other brands or store formats. In contrast, as macro conditions change, households shift spending to PLs (from both discounters and non-discounters) during contractions and to NBs during expansions. In addition, they increase their total spending and purchase volume during contractions. We argue that the shifts during macro conditions are driven by a greater society-wide acceptance of frugal consumption that does not emerge during changing micro conditions. These discrete effects of micro and macro conditions and the proposed underlying mechanisms have distinct managerial implications. The results also address some of the counterintuitive findings of earlier studies, such as increasing total spending and purchase volumes (Ma et al. 2011) as well as higher prices paid (Cha, Chintagunta, and Dhar 2015) during the Great Recession.

--- Insert Table 1 about here ---

Related Literature

Our study relates to business cycle research in marketing as summarized in Table 1. Pioneering studies in this stream show that during recessions, PL market shares (Lamey et al. 2007) and discounter market shares (Lamey 2014) increase, and some of these effects carry over into subsequent expansion periods. Dubé, Hitsch, and Rossi (2018) generally confirm these findings by analyzing PL demand at a household level accounting for heterogeneous income and wealth effects caused by the Great Recession. They find significant short- and long-term effects on PL demand, albeit with notably smaller elasticities. Cha, Chintagunta, and Dhar (2015) further extend the number of shopping behaviors observed. They find that unemployment caused by the Great Recession has led households to increasingly purchase products on price promotions, cheaper brands, and in cheaper store formats. Instead of traditional macroeconomic indicators, Gicheva, Hastings, and Villas-Boas (2007) and Ma and colleagues (2011) use gasoline prices to operationalize changing economic conditions. They show that gasoline prices relate to a multitude of shopping behaviors such as spending, prices paid, as well as store format and brand type shares.

Beside macro conditions, some of the studies in the field also observe households' micro conditions. However, they are either used as time-invariant demographic control variables

(Cha, Chintagunta, and Dhar 2015; Gicheva, Hastings, and Villas-Boas 2007; Ma et al. 2011) or conceptualized as direct consequences and part of macro conditions rather than distinct conditions with idiosyncratic effects (Dube, Hitsch, and Rossi 2018). Our study, thus, contributes to this literature stream by delineating the distinct effects of changing micro as well as macro conditions on households' shopping behavior. Importantly, we also account for different magnitudes and asymmetries between adverse and beneficial micro as well as macro conditions.

First insights into the differences between micro and macro conditions show that overall household spending on food products and alcoholic beverages increases during adverse macro conditions but decreases when micro conditions worsen (Kamakura and Du 2012). We complement these findings by analyzing a variety of shopping outcomes beyond overall spending, by using actual purchase data, thus increasing external validity, and by controlling for a large variety of confounding factors such as changes in the marketing mix that are associated with changes in macro conditions (Van Heerde et al. 2013).

Notably, studies to date either focus on individual shopping outcomes (e.g., Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007) or model several shopping outcomes independently from each other (Cha, Chintagunta, and Dhar 2015; Gicheva, Hastings, and Villas-Boas 2007; Ma et al. 2011). However, households have a variety of means to adjust their shopping behavior that are also highly interdependent—for example, discounters carry substantially more PLs and fewer NBs and usually feature fewer promotions in favor of an everyday low-price strategy. As such, when households switch store formats, it almost automatically also affects their brand type and promotion shares (Dekimpe and Deleersnyder 2018). Failing to account for these interdependencies can overestimate the effect of changing conditions on individual shopping outcomes. Hence, we analyze multiple shopping outcomes simultaneously, controlling for their interdependencies and, thereby, contribute to the literature by offering a holistic picture of micro and macro conditions' effects on households' shopping behavior.

Conceptual Framework

The conceptual framework (Figure 1) depicts the two main components of our study: micro and macro conditions and their effect on households' shopping behavior. We observe these behaviors through concrete and measurable shopping outcomes that, in essence, boil down to households' *shopping basket value,* or *how much* households purchase and at what price as well as their *shopping basket allocation,* or *how* households allocate their expenditures across brand types and store formats. To get a holistic picture of micro and macro conditions' effect on households' shopping behavior, we consider the various shopping outcomes simultaneously. We also control for household demographics and psychographics as well as manufacturer and retailer adjustments to the marketing mix.

--- Insert Figure 1 about here ---

Economic Conditions: Micro versus Macro

We analyze changing macro conditions in terms of the business cycle on the basis of gross domestic product (GDP) (e.g., Lamey et al. 2007; Van Heerde et al. 2013) and derive micro conditions in terms of households' income. While changing macro conditions are experienced by an entire region, nation, or even globally, they do not necessarily affect all households at a micro level. For example, not all households may experience income reductions, job loss, or shrinking wealth during a recession (Dubé, Hitsch, and Rossi 2018). Thus, by differentiating between micro and macro conditions, we isolate the distinct effects on shopping outcomes of changes in households' *ability to purchase* (micro level) and their *willingness to purchase* (macro level) (Katona 1979). A negative micro shock, for example, restricts some households' shopping budget, while households that face only adverse macro conditions lack this budget constraint. Importantly, whereas changing micro conditions are usually a personal matter, changing macro conditions affect a society at large. Thus, shifts in macro conditions can alter what type of shopping behavior is considered the norm. During recessions, for example, frugal consumption such as buying PLs or visiting discounters may become socially acceptable and even fashionable (Flatters and Willmott 2009; Kamakura and Du 2012).

In addition, beneficial and adverse economic conditions exercise asymmetric effects on consumers' shopping behavior for a number of possible reasons, such as general pessimism following a recession, inertia in maintaining newly adopted habits, or the need to pay off debts that have accrued during a period of lower income (Dekimpe and Deleersnyder 2018; Lamey et al. 2007). Thus, we investigate asymmetric effects by splitting micro and macro conditions into both adverse and beneficial changes.

Households' Shopping Outcomes

We distinguish between a household's *shopping basket value* and *shopping basket allocation*. We examine shopping basket value outcomes in terms of a household's total budget spent, total volume purchased, and an index of prices paid that indicates whether a household purchases products below average market prices of these products, for example, through temporary price promotions. In this way, we can differentiate to what degree households adjust how much they purchase and how much they spend. We discern shopping basket allocation outcomes by considering brand types and store formats jointly and differentiating between households' spending on i) PLs in discounters, ii) PLs in non-discounters (i.e., supermarkets, hypermarkets, etc.), iii) NBs in discounters, and iv) NBs in non-discounters. Prior research has taken a similar approach to households' budget allocation, with studies distinguishing between PLs and NBs as different *brand types* (e.g., Ailawadi, Neslin, and Gedenk 2001; Steenkamp and Geyskens 2014; Steenkamp, van Heerde, and Geyskens 2010) or discounters and non-discounters as different *store formats* (e.g., Cleeren et al. 2010; Lamey 2014; Hökelekli, Lamey, and Verboven 2017b). This approach has the following conceptual merits.

Brand types. Regarding brand types, PLs and NBs and their competition have received ample attention from both academics and practitioners (Kumar and Steenkamp 2007). PLs have evolved from pure economic options to covering all price tiers and even special segments like organic foods (Gielens et al. 2021; Hökelekli, Lamey, and Verboven 2017a). They have thus developed into major competitors for NBs, for example in Germany gaining a market share of 41% with 95% of consumers buying PLs (GfK 2019; Ipsos 2016). The competition between NBs and PLs is distinct in that PLs are managed by retailers and, thus, they introduce an aspect of competition into their otherwise collaborative relationship with manufacturers through downward price pressure. However, at the same time, NBs and PLs benefit each other by increasing store traffic and reinforcing quality disparities (Geyskens, Gielens, and Gijsbrechts 2010; Pauwels and Srinivasan 2004). From a consumer perspective, NBs and PLs differ substantially. First, consumers perceive PLs as inexpensive and as a good value for money. Further, while NBs are generally still better known and are perceived as being of higher quality, PLs are catching up in terms of quality perception (Ipsos 2016). These differences in terms of price and quality perceptions generally suggest households will switch between these two brand types in response to changing micro or macro conditions. Thus, the explicit distinction between NBs and PLs is relevant for our research.

Store formats. In terms of store formats, past research has contrasted discounters with "traditional retailers" (Hökelekli, Lamey, and Verboven 2017b; Lamey 2014), supermarkets (Cleeren et al. 2010), and large retail formats (Gijsbrechts, Campo, and Nisol 2008; Gonzalez-Benito, Munoz-Gallego, and Kopalle 2005). In contrast to other formats, discounters are highly optimized for cost efficiency resulting in a substantially different retail marketing mix: Store design and product presentation are austere, consumer services are reduced to a minimum, and serviced fresh foods and baked goods counters are lacking. The assortment is typically limited, especially in terms of produce, shallow with few alternatives in each product category, and dominated by PLs featuring relatively few NBs. As such, discounters are able to offer substantially lower prices than other store format at the cost of service quality (Lamey 2014; Steenkamp and Sloot 2019).

In contrast to that, the major non-discount store formats, such as supermarkets, superstores, and hypermarkets, vary in floor size and assortments offered beyond CPGs (e.g., clothing, home décor, or hardware) but are similar to each other in terms of prices, service quality, and CPG assortments (Hökelekli, Lamey, and Verboven 2017b; Lamey 2014; Steenkamp and Sloot 2019). This is also evident from Table 2 in which we contrast market data from discount and non-discount store formats in Germany. Therefore, distinguishing between discounters and non-discounters is most obvious from a retailer as well as consumer perspective. Despite their distinct characteristics, however, discounters and non-discounters do not merely address different target groups but also compete directly with each other for the same consumers as consistently argued and shown in past research (e.g., Cleeren et al. 2010; Haucap et al. 2013).

Brand type and store format combinations. Importantly, we do not consider the defined brand types (NBs and PLs) and store formats (discounters and non-discounters) in isolation but in combination. This combined view is important because the brand choice decision cannot be seen independently of the underlying store format. For example, as discounters carry a larger PL share than non-discounters, PLs are more visible to households at discounters and also compete with fewer NBs. At the same time, non-discount formats usually offer more price tiers (e.g., economy, standard, and premium) and variants (e.g., organic, locally-produced, or diet) for NBs as well as PLs within a product category than discounters (Gielens et al. 2021; Hökelekli, Lamey, and Verboven 2017a). As such, PL and NB assortments differ structurally between discounters and non-discounters and we account for these differences by the combined consideration of these brand types (PLs and NBs) and store formats (discounter and non-discounters). Thus, by crossing the two brand types and store formats, we obtain a parsimonious, mutually exclusive, collectively exhaustive, and meaningful conceptualization of households' shopping basket allocation. Altogether, the three shopping basket value outcomes and the four shopping basket allocation outcomes holistically cover the essence of households' CPG shopping behavior.

--- Insert Table 2 about here ---

Control Variables

We control for household demographics, which play an important role in explaining differences in shopping baskets (e.g., Ma et al. 2011). In addition, we control for a set of household psychographics: price and quality consciousness, deal proneness, and out-of-home consumption preference. Psychographics control for household heterogeneity that is not necessarily captured by demographics because, for example, even households with high income may be deal-savvy or highly price-conscious (Ailawadi, Pauwels, and Steenkamp 2008). Such psychographics strongly resemble consumer traits that are largely stable in short-term environmental changes but also reflect long-term societal trends, cultural developments, and the process of consumer aging (Steenkamp and Maydeu-Olivares 2015).

As prior research has shown, retailers and manufacturers also react to macro conditions by adapting their marketing mix (e.g., Deleersnyder et al. 2009; Lamey et al. 2012). We are less concerned with this relationship per se but control for adjustments in the marketing mix owing to their substantial influence on households' shopping behavior.

Data

Research Context

As presented in Table 2, the German CPG retail market is split rather evenly between discounters and non-discounters, with discounters accounting for 45% of revenues and 43% of stores. [1] Discounters in Germany are usually located in easily accessible and densely populated areas (Steenkamp and Sloot 2019) and have an average sales area of 779 m² which is slightly smaller than a typical supermarket (982 m²) and substantially smaller than superstores (3,461 m²) and hypermarkets (7,051 m²) (EHI 2017). However, they carry far fewer stock-keeping units (SKUs) and offer a much larger PL share (65.6%) that typically outweighs NBs (GFK 2019). Discounters' PL shares may vary by retailer (e.g., Aldi 96%, Lidl 61%), but even discounters with a relatively strong focus on NBs have a substantially larger PL share than non-discounters (e.g., Penny 42%, Netto Marken-Discount 40% on the basis of our own data versus 21.2% in non-discounters). Discounters offer substantially lower prices but also limited service, as is evident from a study by the German Institute for Service Quality (DISQ 2018), which scores stores on the basis of their prices and service (higher scores mean better prices/service). The tested discounters received substantially higher (lower) price (service) scores than their non-discounter counterparts. Discounters' focus on functionality rather than service is also reflected in their high space productivity (i.e., revenues per store space). Similarly, annual revenues per SKU are considerably higher in discounters (€30.4 million) than in non-discounters (€3.6 million) (EHI 2017).

As such, this data underlines the similarity of the non-discount store formats and their dissimilarity to discounters for the German market from both, a retailer as well as consumer perspective. It, thus, corroborates the previously introduced conceptual distinction between these two groups. Interestingly, this distinction is also reflected in the branding of different retail store formats in the German CPG market. For example, two major German retail companies—the REWE Group and the EDEKA Group—operate both regular supermarkets and superstores under their REWE and EDEKA umbrella brands. Their hypermarkets (REWE Center and E-Center) also incorporate many of the same brand cues. In contrast, their discounters—Penny and Netto Marken-Discount—carry retail brands that are completely distinct from their respective umbrella brand.

Data Sources

To reflect the particularities of the German CPG market, the data set draws on several sources and combines information across distinct aggregation levels. The primary data source is the ConsumerScan panel provided by GfK Germany, which includes transaction and survey data for panelists at the individual household level. As a major advantage, the ConsumerScan panel covers private consumption comprehensively and representatively, spanning all German CPG retailers, including discounters that typically do not offer data for market research purposes through retail panels.[2] This data availability is particularly crucial, considering the substantial market share of discount stores in Germany (see Table 2). The panel also contains survey data for all panelists, based on self-reported annual demographic information (age, household size, income) and psychographic measures (e.g., price and quality consciousness). In addition, we obtain data on weekly advertising spending that covers all major channels as well as all manufacturers and retailers from the Nielsen Company. Finally, we add publicly available GDP data from the Federal Statistical Office that indicate the aggregate economic condition. We thus build a unique, encompassing data set that combines behavioral measures with survey-based household demographics and psychographics, macroeconomic measures, and brand- and store-level advertising spending.

Data Preparation

The initial raw data set from the ConsumerScan panel is composed of household characteristics and purchase decisions by 85,428 unique households—with 24,000 to 37,000 in any given year—that made more than 13 million shopping trips and 48 million purchases between 2006 and 2013. Purchase information is available at the SKU level for 39 product categories from 467 retailers, most of which maintain multiple stores. These products include alcoholic and non-alcoholic beverages (e.g., beer, fruit juice) and food (e.g., cereals, pasta, ice cream) as well as non-food items (e.g., deodorants, detergents, toilet paper). For each purchased item, we have access to the unique product code, date and place of purchase, price paid, identifiers for store format, brand type, and temporary price reductions as well as specific product characteristics like brand and manufacturer name and package size. In preparing these data, we took several cleaning and filtering steps at the purchase record and household levels. In particular, we eliminated inconsistent transaction records and households that did not remain in the panel for the entire period. This procedure is conservative and in line with prior literature (e.g., Dubé, Hitsch, and Rossi 2018). Data cleaning involved the following steps:

1. Removal of all cases with missing values.
2. Removal of all cases with unusually large (more than four times the median price) or unusually small (less than one-fourth the median price) prices at the SKU level.
3. Removal of all cases with SKUs purchased fewer than 25 times in the entire period.

These data-cleaning steps preserved 97.4% of all observations and 96.1% of all expenditures. To exploit the analytical potential of panelists with long purchase histories and extensive survey information, we retain only households with at least one transaction per quarter (7,441 households) and full survey information from 2006 to 2013, leaving 5,101 unique households.

To avoid structural differences between samples, we compared the filtered households with the remaining households in terms of shopping outcomes and demographics. Overall, we find only marginal deviations in purchase behaviors and demographic composition. Hence, we assume that the selected households with complete purchase histories are not structurally different from households with shorter or incomplete purchase histories. We also compare the filtered sample with information from the 2006 Microcensus (Destatis 2008). As in other studies using this type of data (e.g., Dubé, Hitsch, and Rossi 2018), our sample is only slightly older, with higher income, fewer single and more two-person households, and fewer children. However, we find a sizeable overlap in the distributions of the demographic variables and we control for these demographics at the individual household level throughout the empirical analyses. Therefore, a lack of sample representativeness is not an issue. Detailed comparisons of the raw, filtered, and remaining household samples are available in Web Appendix A.

Variable Operationalization

Shopping basket value. In line with the conceptual framework, we consider multiple dependent variables to capture the two domains of shopping outcomes as exhaustively as possible. The first domain relates to a household's shopping basket value—that is, *how much* is spent by the focal household, as represented by three dependent variables. $\text{TotalSpending}_{ht}$ relates to the total CPG spending of household h at time t, measured in euros. PurchaseVol_{ht} refers to the total CPG purchase volume of household h at time t, again measured in euros. Note that a household's shopping basket typically contains products with different volume units (e.g., liters, grams, pieces) that cannot directly be combined into a total volume measure. Therefore, we follow Ma et al. (2011) and use an average category price per volume unit from a one-year (here: 2006) initialization period and multiply it by the total equivalent volume units purchased in each category. This enables us to aggregate the purchase volume across categories. Accordingly, the resulting variable is expressed in euros. It should be noted that any variations in this variable are only caused by changes in volume and not changes in prices being paid that may result from switching between brand types and store formats. Therefore, we are able to clearly disentangle households' consumption (volume) from households' spending (value) of CPG purchases. Finally, PriceIndex_{ht} is constructed as an index (Aguiar and Hurst 2007) and compares, for household h at time t, the costs of the shopping basket at average market prices to the actual costs incurred by the household. These price differentials are considered for identical goods identified at the SKU level. As such, they do not reflect differences in the quality of goods purchased but whether specific SKUs in the basket were purchased at cheaper prices e.g., through temporary price promotions. An index greater than one implies that a household paid more than average for the specific goods in its basket and a value of less than one implies the household paid less than average. This variable, therefore, reflects households' cherry-picking behavior (Fox and Hoch 2005) and is not related to households' switching behavior between different brand or price tiers. We provide further details on the construction of purchase volume and the price index in Web Appendix B.

Shopping basket allocation. The second domain of shopping outcomes relates to a household's shopping basket allocation between combinations of brand types and store formats—that is, it captures *how* the household is allocating its budget. We measure this allocation with the dependent variable Spending_{bht} in terms of household h's total spending (in euros) at time t on the respective brand type-store format combination b: (b = 1) PLs in discounters (PLDisc), (b = 2) NBs in discounters (NBDisc), (b = 3) PLs in non-discounters (PLNonDisc), and (b = 4) NBs in non-discounters (NBNonDisc). Altogether, these four spending variables encompass each household's total spending.[3]

Macro conditions. The focal explanatory variables represent a household's individual micro conditions and the overall macro conditions. At the macro level, we first apply the Christiano-Fitzgerald random-walk filter (Christiano and Fitzgerald 2003) to the log-transformed quarterly GDP data to assess the general state of the economy itself. The extracted cyclical component of the GDP series constitutes the deviation from the economy's underlying long-term growth trend. Thus, periods with increases in the cyclical component indicate economic expansions, whereas periods with decreases indicate economic contractions. However, it is important to not only account for different phases of the business cycle but also the severity that comes with the depth of up- and downturns (e.g., Steenkamp and Fang 2011). To do so, we follow prior research (Lamey et al. 2007; Van Heerde et al. 2013) and define the magnitude of an expansion (contraction) period relative to the prior trough (peak) of the cyclical series, or the point in the cyclical component at which the quarter-on-quarter growth turns from negative to positive (from positive to negative). Therefore, we operationalize the symmetric measure of the business cycle ($BCycle_t$) as changes in the cyclical component of GDP at time t relative to the prior peak or trough. Additionally, to study potential asymmetries of macro conditions, we use the same operationalization to construct two semi-dummy variables that separately capture periods with an increase in the cyclical component relative to the prior trough as expansions ($Expansion_t$) and periods with a decrease relative to the prior peak as contractions ($Contraction_t$) of the economy. That is, $Expansion_t$ ($Contraction_t$) takes values increasing with economic expansion (contraction) and 0 values during contractions (expansions).[4]

Micro conditions. At the individual level, micro conditions reflect a household’s financial situation, captured by the household’s monthly net income. The original income data included in the ConsumerScan panel are at a yearly aggregation level and are measured in 16 income brackets.[5] We construct a continuous income variable by taking midpoint values of these brackets in euros and transform the resulting series to a quarterly sequence (the aggregation level of the shopping outcomes variables) by applying linear interpolation for each household.[6] We adjust income for inflation using the consumer price index. In line with the operationalization of macro conditions, we define micro conditions as a household’s income change ($IncomeChange_{ht}$) relative to its previous income peak or trough. This step allows us to not only capture income changes from one period to another, but also to take the higher magnitude into account, which results from income changes along consecutive periods. Furthermore, we construct semi-dummy variables for positive ($IncomeGain_{ht}$) and negative ($IncomeLoss_{ht}$) income changes that are equivalent to the operationalization of asymmetric measures at the macro level. Thus, $IncomeGain_{ht}$ ($IncomeLoss_{ht}$) is defined as the difference of the log-transformed net income at time t and the prior log-transformed income trough (peak), allowing us to account for the accumulated magnitude of income gains and losses over time. IncomeLoss_{ht} and Contraction_{t} are converted to positive values for easier interpretation.

Control variables. As control variables, we include a household's value of the dependent variable from a one-year (here: 2006) initialization period t0 ($\text{TotalSpending}_{ht0}$, PurchaseVol_{ht0}, PriceIndex_{ht0}, and Spending_{bht0}). In addition, we include demographics to control for household heterogeneity regarding household size (HhSize_{ht}), age of a household head (Age_{ht}), presence of children (Kids_{ht}), and employment status (Unemployed_{ht}). We also include psychographic variables to control for heterogeneity in shopping-related traits and preferences in terms of quality (QualCons_{ht}) and price consciousness (PriceCons_{ht}), deal proneness (DealProne_{ht}), and preferences for eating out (EatOut_{ht}). While QualCons_{ht} and PriceCons_{ht} are based on fixed constructs provided by the GfK, we construct DealProne_{ht} and EatOut_{ht} from several survey questions. The associated items, factor loadings, and Cronbach's alphas appear in Web Appendix B, Table WB1. Demographic and psychographic controls are measured at an annual level and we transform the psychographics to a quarterly series using linear interpolation.

Finally, we include controls for the marketing mix. We compute this group of variables at different levels of aggregation as appropriate for each set of models and use households-specific product category weights to incorporate household heterogeneity (Ma et al. 2011). Except for the advertising measures, marketing mix controls are based on transaction information from the ConsumerScan panel. Because we construct the marketing mix controls based on observed household transactions, we use only transaction information (e.g., prices, SKUs, price-promoted SKUs) of households that are not part of the analysis sample. Thereby, we avoid potential biases resulting from nesting the transactions of these focal households into the marketing mix controls. For the basket value models, we construct absolute measures for price (Price_{ht}), assortment size (Assort_{ht}), price promotions (Promo_{ht}), PL share in assortments (PctPL_{ht}), and advertising spending of NBs (AdvNB_{t}) and of store format j (with j=1 for discounters and j=2 for non-discounters) ($AdvStore_{jt}$), which includes advertising spending on retailer brands as well as their PLs. For the basket allocation models, the marketing mix variables for each brand type-store format combination are computed relative to the average across all brand type-store format alternatives. Thereby, we parsimoniously account for potential cross-effects. In particular, we construct relative measures for price ($RelPrice_{bht}$), assortment size ($RelAssort_{bht}$), price promotions ($RelPromo_{bht}$), PL share in assortments ($RelPctPL_{jht}$), and advertising spending at the store level ($RelAdvStore_{jt}$). As advertising spending at the brand level refers to NBs only, we use it as an absolute measure.

We adjust all spending and price variables for inflation using the consumer price index and advertising spending using the GDP deflator. Table 3 presents an overview of all variables and their operationalization, while Web Appendix B shows the detailed construction of the marketing mix variables. Tables 4 and 5 provide the descriptives and correlations for variables in the shopping basket value models and shopping basket allocation models, respectively. Note the small correlations between micro and macro conditions supporting the conceptualization of differential effects.

--- Insert Tables 3, 4 and 5 about here ---

Model

We define regression models for the individual shopping outcomes and estimate them jointly in a system of seemingly unrelated regressions. To control for unobserved household heterogeneity, we use a random intercept specification. The three shopping basket value equations for total spending, purchase volume, and price index as well as the four basket allocation equations for spending across four brand type-store format combinations are specified in log-log form (excluding the dummy variables $Kids_{ht}$, $Unemployed_{ht}$, and $Quarter_{qt}$). This approach allows for an interpretation of coefficients as elasticities and accounts for the fact that households vary substantially in magnitudes of the dependent variables (Ma et al. 2011).[7] We first assume symmetry in each model and subsequently introduce asymmetric effects with regard to the focal micro- and macroeconomic measures. The focal micro- and macroeconomic variables are specified across models as follows:

(1) $\text{MacroEcon}_t = \delta_1 \text{BCycle}_t$ and

(2) $\text{MicroEcon}_{ht} = \delta_2 \text{IncomeChange}_{ht}$ in the case of symmetry, and

(3) $\text{MacroEcon}_t = \gamma_1 \text{Expansion}_t + \gamma_2 \text{Contraction}_t$ and

(4) $\text{MicroEcon}_{ht} = \gamma_3 \text{IncomeGain}_{ht} + \gamma_4 \text{IncomeLoss}_{ht}$ in the case of asymmetry.

The individual models in the system are formulated as follows.

Shopping basket value models. The three shopping basket value models are defined as:

$$
\begin{aligned}
(5)\quad \ln(\text{TotalSpending}_{ht}) = {} & \alpha_h^1 + \text{MacroEcon}_t + \text{MicroEcon}_{ht} \\
& + \alpha_2^1 \ln(\text{TotalSpending}_{ht0}) + \alpha_3^1 \ln(\text{Price}_{ht}) + \alpha_4^1 \ln(\text{Assort}_{ht}) + \alpha_5^1 \ln(\text{Promo}_{ht}) \\
& + \alpha_6^1 \ln(\text{PctPL}_{ht}) + \alpha_7^1 \ln(\text{AdvStore}_t) + \alpha_8^1 \ln(\text{AdvNB}_t) \\
& + \alpha_9^1 \ln(\text{HhSize}_{ht}) + \alpha_{10}^1 \ln(\text{Age}_{ht}) + \alpha_{11}^1 \text{Kids}_{ht} + \alpha_{12}^1 \text{Unemployed}_{ht} \\
& + \alpha_{13}^1 \ln(\text{QualCons}_{ht}) + \alpha_{14}^1 \ln(\text{PriceCons}_{ht}) \\
& + \alpha_{15}^1 \ln(\text{DealProne}_{ht}) + \alpha_{16}^1 \ln(\text{EatOut}_{ht}) \\
& + \alpha_{17}^1 \ln(\text{Time}_t) + \textstyle\sum_2^4 \kappa_{q-1}^1 \text{Quarter}_{qt} + \sum_k \omega_k^1 \text{Copula}_{kht} + \varepsilon_{ht}^1,
\end{aligned}
$$

$$
\begin{aligned}
(6)\quad \ln(\text{PurchaseVol}_{ht}) = {} & \alpha_h^2 + \text{MacroEcon}_t + \text{MicroEcon}_{ht} \\
& + \alpha_2^2 \ln(\text{PurchaseVol}_{ht0}) + \alpha_3^2 \ln(\text{Price}_{ht}) + \alpha_4^2 \ln(\text{Assort}_{ht}) + \alpha_5^2 \ln(\text{Promo}_{ht}) \\
& + \alpha_6^2 \ln(\text{PctPL}_{ht}) + \alpha_7^2 \ln(\text{AdvStore}_t) + \alpha_8^2 \ln(\text{AdvNB}_t) \\
& + \alpha_9^2 \ln(\text{HhSize}_{ht}) + \alpha_{10}^2 \ln(\text{Age}_{ht}) + \alpha_{11}^2 \text{Kids}_{ht} + \alpha_{12}^2 \text{Unemployed}_{ht} \\
& + \alpha_{13}^2 \ln(\text{QualCons}_{ht}) + \alpha_{14}^2 \ln(\text{PriceCons}_{ht}) \\
& + \alpha_{15}^2 \ln(\text{DealProne}_{ht}) + \alpha_{16}^2 \ln(\text{EatOut}_{ht}) \\
& + \alpha_{17}^2 \ln(\text{Time}_t) + \textstyle\sum_2^4 \kappa_{q-1}^2 \text{Quarter}_{qt} + \sum_k \omega_k^2 \text{Copula}_{kht} + \varepsilon_{ht}^2,
\end{aligned}
$$

$$
\begin{aligned}
(7)\quad \ln(\text{PriceIndex}_{ht}) = {} & \alpha_h^3 + \text{MacroEcon}_t + \text{MicroEcon}_{ht} \\
& + \alpha_2^3 \ln(\text{PriceIndex}_{ht0}) + \alpha_3^3 \ln(\text{Price}_{ht}) + \alpha_4^3 \ln(\text{Assort}_{ht}) + \alpha_5^3 \ln(\text{Promo}_{ht}) \\
& + \alpha_6^3 \ln(\text{PctPL}_{ht}) + \alpha_7^3 \ln(\text{AdvStore}_t) + \alpha_8^3 \ln(\text{AdvNB}_t) \\
& + \alpha_9^3 \ln(\text{HhSize}_{ht}) + \alpha_{10}^3 \ln(\text{Age}_{ht}) + \alpha_{11}^3 \text{Kids}_{ht} + \alpha_{12}^3 \text{Unemployed}_{ht} \\
& + \alpha_{13}^3 \ln(\text{QualCons}_{ht}) + \alpha_{14}^3 \ln(\text{PriceCons}_{ht}) \\
& + \alpha_{15}^3 \ln(\text{DealProne}_{ht}) + \alpha_{16}^3 \ln(\text{EatOut}_{ht})
\end{aligned}
$$

$$+ \alpha^3_{17}\ln(\text{Time}_t) + \textstyle\sum_2^4 \kappa^3_{q-1}\, \text{Quarter}_{qt} + \sum_k \omega^3_k \text{Copula}_{kht} + \varepsilon^3_{ht},$$

where $\alpha_h = \alpha_0 + \mu_h$, $\mu_h \sim N(0, \sigma^2_\mu)$, and k is marketing mix variable k, q is quarter q in a given year (q = 1, …, 4), and t is time period t at a quarterly level (t = 1, …, T).

We control for potential endogeneity in the marketing mix variables resulting from unobserved shocks by including Gaussian copulas (Park and Gupta 2012), which directly model the joint distribution of the potentially endogenous regressor and the error term through control function terms. An advantage of this method is that it does not require instrumental variables that may, as in our case given the number of marketing mix variables across brand type-store format combinations, be difficult to find (Rossi 2014). A requirement is that the endogenous regressor is not normally distributed. Anderson-Darling tests and Kolmogorov-Smirnov tests confirm this non-normality for all marketing mix variables at $p < .001$. Given the large size of the sample, we also visually inspect quantile–quantile plots, which confirm non-normality for all marketing mix variables. The Gaussian copula for each marketing mix variable X_{ht} for household h at time t is defined as follows:

$$\text{(8)}\quad \text{Copula}_{ht} = \Phi^{-1}[H(X_{ht})],$$

where Φ^{-1} is the inverse distribution function of the standard normal and $H(\cdot)$ is the empirical cumulative distribution function of X_{ht}.

Shopping basket allocation models. We define the four models as:

$$\begin{aligned}
\text{(9)}\quad \ln(\text{Spending}_{bht}) = {} & \beta^b_h + \text{MacroEcon}_t + \text{MicroEcon}_{ht} \\
& + \beta^b_2\ln(\text{Spending}_{bht0}) + \beta^b_3\ln(\text{RelPrice}_{bht}) + \beta^b_4\ln(\text{RelAssort}_{bht}) + \beta^b_5\ln(\text{RelPromo}_{bht}) \\
& + \beta^b_6\ln(\text{RelPct.PL}_{jht}) + \beta^b_7\ln(\text{RelAdvStore}_{jt}) + \beta^b_8\ln(\text{AdvNB}_t) \\
& + \beta^b_9\ln(\text{HhSize}_{ht}) + \beta^b_{10}{+}\ln(\text{Age}_{ht}) + \beta^b_{11}\text{Kids}_{ht} + \beta^b_{12}\text{Unemployed}_{ht} \\
& + \beta^b_{13}\ln(\text{QualCons}_{ht}) + \beta^b_{14}\ln(\text{PriceCons}_{ht}) + \beta^b_{15}\ln(\text{DealProne}_{ht}) + \gamma^b_{16}\ln(\text{EatOut}_{ht}) \\
& + \beta^b_{17}\ln(\text{Time}_t) + \textstyle\sum_2^4 \kappa^b_{q-1}\,\text{Quarter}_{qt} + \sum_k \omega^b_k\text{Copula}_{kbht} + \gamma^b_{18}\text{InvMills}_{bht} + \varepsilon_{bht},
\end{aligned}$$

where $\beta_h = \beta_0 + \mu_h$, $\mu_h \sim N(0, \sigma^2_\mu)$, and the subscripts are as defined before.

One issue with Equation (9) is that expenditures are zero where a household does not patronize a specific brand type-store format combination during a period. Considering only those observations with existing expenditures or adding a small constant may lead to biased estimates (Leenheer et al. 2007). This bias may be quite substantial in our case, where zero expenditures make up between 2.6% for NBs in non-discounters and 20.8% for NBs in discounters of all the observations. To solve this issue appropriately, we follow the procedure for type II Tobit models (Wooldridge 2002, pp. 560-566). In a first step, we apply a probit model with a random intercept specification and pooled coefficients for brand type-store format choice. This approach allows for the fact that households may patronize multiple brand type-store format combinations. We use the same set of independent variables as in the basket allocation models and additional instrumental variables (average number of shopping trips and unique retailers visited, share of CPG spending on income overall and per person) for identification purposes. In a second step, we compute the inverse Mills ratio, $InvMills_{bht}$, based on the probit model results for each brand type-store format combination as follows:

$$InvMills_{bht}=\frac{\varphi(X_{bht}'\eta)}{\Phi(X_{bht}'\eta)}, \tag{10}$$

where φ is the standard normal density function, Φ is the standard normal cumulative distribution function, and η is the vector of parameters from the probit model. The inverse Mills ratio is then added for each brand type-store format combination as an additional independent variable in the basket allocation model to correct for interrelations between brand type-store format choice and spending. As before, we also add Gaussian copulas for all brand type-store format combination specific marketing mix variables to account for potential endogeneity issues.

Results

Model Estimation and Validation

We use Latent GOLD 5.1 (Vermunt and Magidson 2016) for estimating the seemingly unrelated regression system consisting of seven equations with a maximum likelihood approach. All the models converged before reaching the maximum number of iterations. As we use data from 2006 for parts of the variable operationalization, we run the model on data from 2007–2013. For hold-out validation, we randomly sample 500 households from the filtered data set and run the final estimations on the remaining 4,601 households. Starting with an intercept, time, and sample selection control model (Model 1), we sequentially add the dependent variable from the initialization period (Model 2), marketing mix variables and endogeneity controls (Model 3), demographic (Model 4), psychographic (Model 5), and symmetric micro and macro variables (Model 6). Finally, we replace the symmetric with the asymmetric micro and macro variables (Model 7). Table 6 provides an overview of the model-building process and fit statistics. Relying on Akaike's and the Bayesian information criteria, Model 7 offers the best fit. We further scrutinize Model 7 for overfitting. We compare Model 7's mean squared errors and mean absolute errors between the estimation and hold-out sample and find that they are very similar, showing no sign of potential overfitting.

--- Insert Table 6 and 7 about here ---

Symmetric Effects of Micro and Macro Conditions on Shopping Outcomes

Although the asymmetric model (Model 7) shows the best fit, we briefly present the results from the symmetric model specification (Model 6) to check for internal consistency across the two models. Table 7 provides an overview of all significant elasticities of micro and macro conditions on basket value and basket allocation measures. The complete results of the symmetric model are available in Web Appendix C, Table WC1. Overall, we find significant influences on household shopping behavior for changes in micro and macro conditions of households. However, the nature of these influences clearly varies.

Micro conditions. In line with economic theory, we find significant positive elasticities of income change on shopping basket value, namely total spending ($\delta = .07$, $p < .01$) and purchase volume (δ = .06, $p < .01$). Given that these elasticities are very similar in size and both variables are representations of a household's shopping basket in euros featuring comparable means, we can deduce that the majority of the expenditure effect is merely driven by volume adjustments. In fact, these volume adjustments are mainly attributable to purchases of NBs in non-discounters, as indicated by the significant positive elasticity of income change on NB spending in non-discounters (δ = .08, $p < .01$). Importantly, we do not find any structural shifts in households' basket allocation in that households increase (decrease) spending for a specific brand type-store format combination and simultaneously decrease (increase) spending for another.

Macro conditions. Under changing macro conditions, the results are different. We find marginally significant negative elasticities of the business cycle on shopping basket value dimensions; i.e., total spending (δ = -.06, $p < .1$), purchase volume (δ = -.06, $p < .1$), and price index (δ = -.01, $p < .1$). While intuitively surprising, the results confirm earlier studies that already found countercyclical CPG spending behavior of households (in value and volume) along the business cycle (e.g., Ma et al. 2011). In addition, we also find several significant elasticities of the business cycle on households' shopping basket allocation. In particular, the elasticity of the business cycle on PL spending in discounters (δ = -.70, $p < .01$) and non-discounters (δ = -.63, $p < .01$) is significantly negative, respectively, while it is significantly positive on NB spending in non-discounters (δ = .27, $p < .01$). This finding indicates that, to some degree, households shift from PLs in discounters and non-discounters to NBs in non-discounters—and vice versa—when macro conditions change. Moreover, when shifting their basket allocation across brand types-store format combinations, households also tend to purchase items at lower prices, for example, through temporary price promotions, as indicated by the negative effect of macro conditions on price index.

Asymmetric Effects of Micro and Macro Conditions on Shopping Outcomes

Table 8 shows the estimation results of the asymmetric model. For better comparability of the impact of micro and macro conditions, Figure 2 provides an overview of the asymmetric effects of micro and macro conditions on basket allocation and basket value at their respective mean values—specifically, 2.42 (1.37) for $Expansion_t$ ($Contraction_t$) and €176.70 (€124.77) for $IncomeGain_{ht}$ ($IncomeLoss_{ht}$), which translates to 7.8% (5.5%) of mean income. The findings from the symmetric model are confirmed by the asymmetric model, although the asymmetric estimation results show that the underlying effects are not symmetric, but differ strongly in terms of size as well as significance between beneficial and adverse conditions.

Micro conditions. Regarding micro conditions, we again find that micro conditions primarily have an impact on households' shopping basket value but do not cause shifts in households' shopping basket allocation. However, the results reveal substantial asymmetries between beneficial and adverse micro conditions. Most notably, income gains have no effect on households' basket value or basket allocation; only income losses show significant effects. More precisely, a 1% loss in income decreases total spending and purchase volume by .12% ($p < .01$) and .11% ($p < .01$), respectively. Owing to the similar size of the elasticities, we can again assume that expenditure reductions are largely driven by volume reductions.[8] Given that income losses show no effect on households' price index, we can rule out that expenditure reductions stem from households' shopping for lower prices.

Importantly in the context of income losses, we also see no evidence that households shift their basket allocation to less expensive brand type-store format combinations. Rather, we find significant negative elasticities of income losses only on NB spending in non-discounters ($\gamma = -.16$, $p < .01$) and PL spending in discounters ($\gamma = -.10$, $p < .05$), respectively. Thereby, we can conclude that the adjustments in purchase volume, and subsequently total spending, predominantly stem from abandoning NBs in non-discounters and PLs in discounters when income losses occur. Thus, instead of shifting to cheaper store formats, brand types, or both when income losses occur, households give up the relatively more expensive NBs in non-discounters without substituting them with cheaper alternatives such as NBs in discounters or PLs in general. This lack of substitution is also true for PLs in discounters but in this case options for shifting to even cheaper alternatives to reduce spending are limited and therefore volume adjustments are households' "last resort". That is, households' primary means of coping with adverse micro conditions is to reduce expenditures on specific brand types and store formats and thereby reduce shopping basket value (i.e., spending less by purchasing lower volumes) rather than adjusting basket allocation by shifting to cheaper brand types or store formats.

Macro conditions. In contrast to adverse micro conditions (i.e., income losses), *economic contractions* not only have an impact on households' shopping basket value but also cause shifts in basket allocation. With regard to basket value, we find a significant increase in total spending and a marginally significant increase in purchase volume when the economy contracts: a 1% decrease in GDP compared to its prior peak increases total spending by .14% ($p < .05$) and purchase volume by .11% ($p < .1$). As already indicated for the symmetric model, earlier studies also find countercyclical buying behavior of households during adverse macro conditions (Ma et al. 2011).[9] The results confirm and extend these findings by showing that increased total spending and purchase volume are not the only effects during economic downturns, as contractions also cause shifts of households' shopping basket allocation. In particular, we find significantly positive elasticities of contractions on PL spending in discounters ($\gamma = .36$, $p < .05$) and non-discounters ($\gamma = .51$, $p < .01$), respectively; as well as a marginally significant negative elasticity of contractions on NB spending in discounters ($\gamma = -.32$, $p < .1$). These findings suggest that households shift from NBs to PLs during unfavorable macro conditions. Although previous studies also find comparable changes (e.g., Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007), the combined results further illustrate one important phenomenon: Even though households purchase PLs to a greater extent, they actually increase total spending and purchase volume. Moreover, the results suggest that by switching from NBs to PLs, NBs are not affected by economic downturns per se, but only in the context of discounters. That is, we only find the contraction elasticity of NB spending in discounters to be marginally significant and negative.

The estimated elasticities during *economic expansions* further substantiate that changing macro conditions cause shifts in households' shopping basket allocation. Inversely to contractions, we find significant negative elasticities of expansions on PL spending in discounters (γ = -.94, p < .01) and non-discounters (γ = -.71, p < .01), respectively. At the same time, we find a significant positive effect on NB spending in non-discounters when the economy expands (γ = .52, p < .01). Additionally, the results show a marginally significant and negative elasticity of an expansion on the price index (γ = -.01, p < .1). This result complements the findings on households' shifts from PLs in discounters and non-discounters to NBs in non-discounters during favorable economic times. In fact, to keep their purchase volume and total expenditures steady while shifting to more expensive NBs, households seem to actively seek price-promoted items to keep the prices they pay low.

Overall, the results show major differences in the effects of micro and macro conditions on households' shopping behavior. While favorable micro conditions show no effect at all, adverse micro conditions lead households to reduce expenditures for specific brand types and store formats, resulting in lower total spending and purchase volumes. In contrast, favorable and unfavorable macro conditions primarily result in shifts of shopping basket allocation. These results highlight the importance to separate micro from macro conditions to identify their unique properties, effects, and implications.

--- Insert Table 8 and Figure 2 about here ---

Effects of Control Variables on Shopping Outcomes

Although the control variables included in the asymmetric Model 7 are not of primary interest, they are important to rule out rival explanations and thus to support the causal interpretability of the main results. Therefore, we briefly summarize them here; a more detailed discussion can be found in Web Appendix C. For the most part, when significant, the effects of the included control variables are intuitive and in line with prior research.

Marketing mix variables. As expected, we find a marginally significant positive effect of assortment size (in terms of unique SKUs) on total spending and a significant positive effect on NB expenditures in non-discounters. We also find several effects of promotion activity (in terms of unique SKUs sold on promotion): a negative effect on the price index; a marginally significant positive effect on NB spending in non-discounters; as well as a positive effect on PL spending in discounters and—marginally significant—on non-discounters, respectively. It is noteworthy that the effects for PLs are of smaller magnitude and confirm prior research showing that retail promotions are less positive for PLs than for NBs (Sethuraman and Gielens 2014). We also find that the share of unique PL SKUs in the total SKU assortment has a negative effect on total spending and purchase volume, suggesting that focusing too strongly on PLs can have unfavorable consequences for retailers (e.g., Ailawadi, Pauwels, and Steenkamp 2008). Finally, advertising at the store level has the expected positive effect on total spending, purchase volume, and PL spending in non-discounters, while NB advertising has an expected positive effect on NB spending in discounters.

However, we also have to note that some of the effects are counterintuitive. This is particularly true for the negative effects of assortment size and PL share in assortments, negative own and positive cross advertising effects as well as the absence of significant price effects. Varying perceptions of PLs and NBs in assortments (e.g., Briesch, Chintagunta, and Fox 2009; Deleersnyder and Koll 2012; Hoch, Bradlow, and Wansink 1999), underlying advertising spillover effects (Anderson and Simester 2013), or potential difficulties when measuring advertising effects (Sethuraman, Tellis, and Briesch 2011; Shapiro, Hitsch, and Tuchman 2021) may provide reasonable explanations for these findings. Counterintuitive marketing mix coefficients may, however, also be caused by the aggregation level of the data (quarterly, national-level aggregation across many individual brands, retailers, and product categories).

Demographic variables. As expected, we find that larger households tend to spend more across all four brand type-store format combinations, spend more in total, purchase larger volumes, and maintain a lower price index. Older households typically spend less on PLs in general as well as spend marginally significantly less on NBs in discounters, but more on NBs in non-discounters while exhibiting a higher price index. Furthermore, the results suggest that households with children spend less on NBs in non-discounters and marginally significantly less on NBs in discounters, respectively. Households that suffer from unemployment of the main breadwinner tend to spend less in total, corresponding to fewer expenditures on both NBs in non-discounter and PLs in discounters.

Psychographic variables. In terms of psychographics, the analyses reveal many significant effects, generally underscoring the importance of accounting for such types of consumer characteristics (Ailawadi, Pauwels, and Steenkamp 2008). In particular, we find that quality-conscious households tend to spend more in total, more on NBs but less on PLs in non-discounters. In comparison, price-conscious households typically spend more on PLs and less on NBs in general, spend less overall, and exhibit a lower price index. Deal-prone households, furthermore, spend more in total, purchase larger volumes, exhibit a lower price index, spend less on PLs in non-discounters but significantly more on NBs in discounters and marginally significantly more in non-discounters. Finally, households with preferences for eating out tend to spend less overall, purchase lower volumes but exhibit a higher price index and typically show lower spending for PLs in discounters.

Robustness Checks

We perform several robustness checks to confirm the validity of the findings by applying alternative measures and indicators for micro and macro conditions. First, we use the growth rate of real GDP (e.g., Kamakura and Du 2012; Ma et al. 2011) and an index of consumer confidence (e.g., Allenby, Lichung, and Leone 1996) to assess the general state of the economy. To a large extent, the results are consistent in significance, direction, and magnitude with the main symmetric model (Model 6). Second, we use first-difference specifications of micro conditions rather than differences relative to prior income peaks and troughs as in the main asymmetric model (Model 7). We can confirm all effects to be consistent in significance and direction, even though the elasticities are of a higher order of magnitude. Third, we introduce an individual-level measure of a household's perceived financial situation into both main models. This measure captures changing perceptions of micro conditions that are not reflected in household income, for example, wealth. Controlling for individual financial perceptions does not alter the findings regarding income and we can confirm all effects to be consistent in terms of significance, direction, and the order of magnitude. All significant effects of the financial perception measure itself are in line with economic theory. We present and discuss these results in greater detail in Web Appendix C.

Discussion

Micro and macro conditions have significant effects on households' shopping behavior and outcomes that, by extension, may affect firm performance of retailers and manufacturers. By observing shopping basket allocation across brand types and store formats as well as shopping basket value in terms of total spending, purchase volume, and an index of prices paid, this research provides an extensive analysis of *how* (through shopping basket allocation) and *how much* (through shopping basket value) households adjust the various facets of their CPG shopping behavior. Thereby, we distinguish the effects caused by micro conditions in terms of income and macro conditions in terms of the business cycle. In addition, we account for possible asymmetries between adverse and beneficial conditions. These findings, based on a rigorous modeling approach and longitudinal field data, have important diagnostic and normative value for managers and contribute to past research on business cycle effects. We provide an overview of the results for each shopping outcome and associated implications in Table 9.

The results uncover and juxtapose the specific effects of micro and macro conditions on shopping behavior. We find that both micro and macro conditions have pronounced effects on households' shopping behavior that are distinct from one another and asymmetric for positive versus negative conditions. Some findings are especially intriguing: micro conditions only affect households' overall consumption levels whereas macro conditions additionally lead to structural shifts in households' budget allocation across brand types and store formats. In addition, during changing macro conditions, household adjust their shopping behavior even though they are not affected financially (as we control for income). In the following, we first summarize the results and, subsequently, discuss potential underlying psychological and sociological mechanisms, before turning the attention to interaction effects and asymmetries.

--- Insert Table 9 about here ---

Micro Conditions

While for income gains no significant adjustments in shopping basket allocation or value emerge, income losses lead to a general decline in CPG expenditures. This drop is largely driven by households purchasing less and thus spending less. The overall decrease in consumption specifically affects PLs purchased in discounters and NBs purchased in non-discounters. These findings show that, rather intuitively, budgetary constraints lead to decreased consumption adding to extant research which has mostly taken a spending perspective (e.g., Kamakura and Du 2012). However, the absence of structural shifts in households' budget allocation is noteworthy. Theoretically, households could also reduce spending by switching to a cheaper store format or brand type, but instead they generate savings primarily through volume reductions.

Macro Conditions

In contrast, changing macro conditions evoke structural shifts in households' basket allocation. During *contractions*, we see expenditures for NBs purchased in discounters being reallocated to PLs purchased in discounters and non-discounters. While this seems intuitive, it is interesting to note that this shift is accompanied by a general *increase* in total spending driven by households buying more. In other words, even though households switch to PLs during contractions, they end up spending more in total.

During *expansions* households reallocate their purchases from PLs (purchased in non-discounters as well as discounters) to NBs purchased in non-discounters. Interestingly, we also find that total spending and volumes purchased remain unaffected at the same time since households focus more on getting deals, as indicated by a decline of the index for prices paid. As such, households switch to a more expensive brand type during expansions although their budget remains constant (as we control for income), which seems to be feasible as they increasingly purchase products on price promotion.

Plausible Mechanisms Underlying Micro and Macro Effects

Several theoretical mechanisms can explain our findings. First, the findings suggest that adverse macro conditions may have a societal impact that trickles down to individual households even though they are not affected at a financial level. In trying times, frugal consumption, such as buying PLs or visiting discounters, seems to become more socially acceptable and even fashionable (Flatters and Willmott 2009; Kamakura and Du 2012), which is in line with the shifts of budgets toward PLs in (non-)discounters that we observe during contractions. Just as much as frugal consumption may become increasingly commonplace during contractions, purchasing NBs may become a societal norm and is required if households want to maintain their social standing during expansions (Kamakura and Du 2012). In accordance with that norm, households seem to drop PLs in favor of NBs in non-discounters even though they have no increase in budgets as we see in the results. They seem to accommodate this shopping behavior by being price-savvy, shopping products on price promotion. Price promotions may also offer a welcome justification for households to abandon the PLs they have adopted during prior contractions in favor of NBs.

This reasoning is also consistent with the lack of shifts in the face of adverse micro conditions, as described above. An income loss, independent of macro conditions, is first a personal hardship rather than one shared by society. Therefore, there is not a general move to and acceptance of PLs and discounters as in the case of adverse macro conditions (Flatters and Willmott 2009; Kamakura and Du 2012)—households do not switch to these cheaper brand types or store formats but instead reduce their overall consumption. In addition, income losses may weaken self-confidence and, thus, awaken a desire to bolster one’s social status (Hamilton et al. 2019; Sivanathan and Pettit 2010) which may lead households to keep buying NBs while economizing on volume to accommodate their lower income.

Another explanation for these findings may lie in households’ perception of the nature of micro and macro conditions. While nationwide or global contraction is beyond households’ direct control, personal income can be influenced through concrete actions. This discrepancy in the “mutability” of the conditions leads to different reactions in households: while high mutability conditions (here: micro conditions) result in high self-regulation, planning, and prioritizing, low mutability conditions (here: macro conditions) elicit a desire for restoration of control (Cannon, Goldsmith, and Roux 2019; Hamilton et al. 2019). Adverse micro conditions lead households to self-regulate by reducing their overall consumption, whereas adverse macro conditions result in a desire to restore control through actions that are perceived as more frugal—that is, purchasing PLs. Control-restoration behaviors are also associated with compensatory consumption, such as in the form of overspending and higher food intake (Cannon, Goldsmith, and Roux 2019; Laran and Salerno 2013), which may explain the overall increase in household spending and which is potentially aggravated by the lack of a budgetary constraint that would limit this behavior (Watson et al. 2020).

Other explanations of the increased consumption may lie in households' shift to PLs, which usually are associated with larger package sizes and lower product prices and which have been shown to increase consumption (Cakir et al. 2019; Wansink 1996). Similarly, these factors contribute to households' purchase of increased quantities when shopping in warehouse club stores (Ailawadi, Ma, and Grewal 2018). In addition, adding discounter visits to a shopping trip may increase households' spending owing to self-licensing and self-control depletion (Gijsbrechts. Campo, and Vroegrijk 2018).

Asymmetries and Interactions

Like past studies in the field, we find asymmetries between adverse and beneficial conditions for both micro and macro conditions. In the case of micro conditions, we find that income gains generally have no significant effects on shopping outcomes whereas income losses do. This finding suggests that households are quick to decrease spending when income decreases but are slow to respond when income increases, potentially because they need to compensate for postponed purchases of durables or paying off debts (Dekimpe and Deleersnyder 2018). While contractions affect households' shopping basket value more extensively than expansions, the expansion elasticities for shopping basket allocation are mostly larger than during contractions. This response seems reasonable, as failing to keep up with one's surroundings during an expansion would translate into a loss of status whereas not adopting a more frugal shopping behavior during a contraction implies an increase in status (Kamakura and Du 2012). In addition, we find more pronounced asymmetries between adverse and beneficial conditions at the macro level than at the micro level. Thus, adjustments in shopping behaviors may reverse more quickly when they are caused by changing micro conditions compared to macro conditions. Given that adverse macro conditions shift the societal acceptance of certain brand types and store formats, households' attitudes may change (Hampson and McGoldrick 2013). This reasoning implies that macro conditions' effects on shopping outcomes linger longer than micro conditions, during which households engage in status-maintaining shopping behaviors. Therefore, the adjustment may be a means to an end rather than an attitudinal shift that households would quickly discard once conditions improve.

Finally, we investigate whether micro and macro conditions and the underlying mechanisms that affect households' shopping behavior moderate each other. Hence, we perform a post-hoc analysis to test for possible interactions effects for which we present complete results in Web Appendix C, Table WC3.[10] Interestingly, the main effects remain unchanged while all interaction effects are insignificant which suggests that micro and macro conditions do not moderate each other. Thus, the results indicate that the effects and mechanisms that micro and macro conditions elicit occur independently from each other. That is, if both conditions change simultaneously, their individual effects on households' shopping outcomes work in parallel.

Managerial Implications

Micro Conditions

Changing micro conditions affect shopping outcomes only when households suffer income losses rather than gains, leading to a decrease in PLs purchased in discounters and NBs purchased in non-discounters. To buffer the negative effects of when and where they expect wages to decrease, manufacturers as well as discounters can profit from listing NBs in discounters. Especially hard discounters like Aldi and Lidl, whose overwhelming majority of revenues stem from their own PLs, may profit from this strategy. Thus, we provide a further perspective to the literature investigating the role of NBs in discounters (e.g., Deleersnyder et al. 2007). If households indeed suffer from weakened self-confidence and desire to bolster their social status as a result of adverse micro conditions (Hamilton et al. 2019; Sivanathan and Pettit 2010), NB manufacturers and non-discounters may leverage this reaction by using status appeals in their advertising. As adverse micro conditions lead to a general decline in consumption, retailers and manufacturers may target those product categories with marketing mix actions that are affected the most. Changing micro conditions may be especially hard for manufacturers and retailers to identify, but with increasing availability of data through loyalty cards and online shopping, managers may detect the specific shopping outcomes associated with these changes and address those households through personalized coupons and deals.

Macro Conditions

Changing macro conditions substantially affect households' shopping basket allocation as well as value. Given the increased acceptance of PLs, retailers can use the opportunity to extend their PL portfolio into higher price tiers and product categories with high involvement and complexity (Steenkamp, van Heerde, and Geyskens 2010). In addition, they may narrow their price gap to NBs and strengthen their branding to preemptively counteract households' shifts back to NBs during subsequent expansions. During expansions, they can then offer more attractive and profitable price promotions. Especially non-discounter PLs may get away with raising prices as they are unaffected by increasing budgetary constraints. Given the countercyclical susceptibility of PLs, retailers should adjust their assortment accordingly, reducing their PL share in expansions and increasing it in contractions. While hard discounters are especially susceptible to adverse micro conditions, soft discounters (i.e., discounters with a relatively low PL assortment share) should be aware of contractions owing to the substantial negative effect of NBs purchased in discounters and their comparatively low share of PLs that may compensate the losses.

As we control for micro conditions, the reallocation of budgets to PLs that we observe during adverse macro conditions is apparently not driven by monetary factors but instead may result from changing attitudes toward frugal consumption across society (Kamakura and Du 2012) and a desire to restore control (Cannon, Goldsmith, and Roux 2019). If this reasoning holds, it has important implications for managers. NBs and retailers can avoid costly price reductions that are ineffective given the lack of a more constrained budget and instead use measures that provide a perception of frugality.[11] These measures may allow households to engage in behaviors that they associate with economizing but at the same time are economical for the retailer or manufacturer. For example, loyalty programs can offer low price discounts and small rewards, giving households the perception that they engage in frugal consumption (Leenheer et al. 2007). Distribution of (digital) store fliers may create a sense of greater control over the planned shopping trip. In addition, communication may highlight the quality and reliability of products to reduce uncertainty and increase compensatory consumption. NB managers may also consider increasing package size, as larger package size is often associated with a lower per-unit price (Cakir et al. 2019). Finally, NB managers and retailers can leverage the higher cognitive load and depletion of self-control resulting from switching stores and/or brands (Vohs and Faber 2007), rendering shoppers more susceptible to in-store promotions (Gijsbrechts, Campo, and Vroegrijk 2018).

Limitations and Directions for Future Research

When individual income is controlled for, the changes of observed shopping behaviors resulting from macro conditions clearly have to be linked to households' willingness rather than ability to purchase. Potential underlying changes in attitudes and societal acceptance of certain shopping behaviors provide a conclusive basis for our argumentation. However, we do not observe these changes of attitudes in the data directly. Therefore, we encourage field experiments and laboratory studies to dive deeper into the underlying psychological and sociological mechanisms that might drive these findings. These insights can be crucial in predicting how households will change their CPG shopping in reaction to other types of macro conditions, such as a worldwide pandemic.

Including demographics and psychographics, we control for household characteristics but do not account for heterogeneity in households' reaction to changing conditions which should be addressed by future research. Heterogeneity may originate, for example, from households' differing preferences for high-quality products, with those preferring high-quality potentially opting for volume adjustments and prices paid for identical goods over switches to low-tier NBs and PLs. Alternatively, heterogeneity may stem from households' usual "baseline" shopping behavior because it influences whether and how they are able to economize during adverse conditions.

Future analyses may also differentiate among different product categories, especially relating to the reduction in consumption levels caused by adverse micro conditions. Some product categories may be more essential than others and, hence, consumption may not simply be reduced (Kamakura and Du 2012). Some product categories may even see increasing consumption, for example as households shift from soft drinks and juices to plain water.

Finally, previous research has shown that macro conditions affect marketing mix decisions (van Heerde et al. 2013). Hence, future research may take a corporate rather than household perspective, investigating how managers detect and react to changes in micro conditions.

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Footnotes

[1] We consider non-discounters as comprised of small retailers (<400 m² sales area), supermarkets (400-2,500 m²), superstores (2,500-5,000 m²), and hypermarkets (>5,000 m²) (EHI 2017). The classification of discounters is based on retail brands and is highly consistent within the industry; we follow this industry convention.

[2] The data set covers the discounters Penny, Norma, Lidl, Plus, Aldi (Nord and Süd), Netto (Nord), Netto Marken-Discount (Süd), and several smaller, more regional discounters. In terms of non-discounters, the data set covers Edeka, Rewe, Rewe Center, E-Center, Edeka Neukauf, Nah und Gut, Ihr Platz, Markant, Marktkauf, Kaufland, Hit, Real, Globus, Tengelmann Kaisers, Metro, DM, Rossmann, Müller, Budnikowski, Schlecker, and multiple smaller, more regional non-discount retailers.

[3] An alternative approach is to use a market-share model specification with shares-of-wallets (SOW) as dependent variables. We refrain from this approach as elasticities are not easily comparable across models since the elasticities in the SOWs models depend on total spending (e.g., Van Heerde 2005). Also, the elasticities may be misleading as they may show, for example, positive effects on SOWs while the total market size is shrinking and actual spending levels are decreasing. We thank the reviewing team for pointing us in this direction.

[4] Please note that the business cycle variable BCycle does not solely represent the cyclical component extracted from a GDP series as used e.g., by Deleersnyder et al. (2004). It rather is a combination of expansion and contraction variables as used e.g., by Lamey et al. (2007) and Van Heerde et al. (2013). We use this operationalization to achieve comparability between the symmetric and asymmetric models.

[5] The income brackets are: (1) <€500, (2) €500–749, (3) €750–999, (4) €1,000–1,249, (5) €1,250–1,499, (6) €1,500–1,749, (7) €1,750–1,999, (8) €2,000–2,249, (9) €2,250–2,499, (10) €2,500–2,749, (11) €2,750–2,999, (12) €3,000–3,249, (13) €3,250–3,49, (14) €3,500–3,749, (15) €3,750–3,999, and (16) ≥€4,000.

[6] We use €499 as a proxy for the lowest income bracket and €4,000 for the highest income bracket. Potential biases inferred by this approach should be minimal as the relative number of households falling into these two brackets over the observation period combined is only 7%.

[7] The cyclical component is extracted from a log-transformed GDP series and thus expresses percentage deviations (Lamey et al. 2007). Hence, the coefficients associated with macro variables are elasticities, too.

[8] We also test this more formally through an alternative model specification. It uses average price paid by households ($AvgPrice_{ht}$) in lieu of households' total spending. $AvgPrice_{ht}$ is defined as $TotalSpending_{ht}$ divided by $PurchaseVol_{ht}$ and in contrast to $PriceIndex_{ht}$, it captures whether households switch to different cheaper or more expensive products. All coefficients of the focal independent variables in the $AvgPrice_{ht}$ model are insignificant, supporting the interpretation that total spending indeed increases due to volume adjustments rather than due to switches to differently priced products. We thank the Area Editor for pointing us in this direction.

[9] Also, the total spending elasticities for micro and macro conditions match the direction found by Kamakura and Du (2012) but are substantially lower, which may stem from the use of field data alongside a variety of control variables rather than survey data. Kamakura and Du (2012) estimate an income elasticity of -1.0% and .9% for a reduction in GDP for food at home, whereas we find -.121% for income losses and .235 for contractions.

[10] As interactions in the asymmetric model would necessitate four interaction effects leading to a complex interpretation and a high potential for multicollinearity (especially given the limited variance in the macro conditions specified as semi-dummies), we used the symmetric model to test for interaction effects.

[11] While this may seem to contradict earlier findings on stronger price elasticities during adverse macro conditions (Gordon, Goldfarb, and Li 2013; van Heerde et al. 2013), these studies have not controlled for income but assumed that an associated decrease in income would lead to greater price sensitivity (see, e.g. van Heerde et al. 2013, p. 179). In this way, our study nicely supports, complements, and concretizes these earlier findings.

TABLE 1
Literature Overview

Authors	Macro conditions	Micro conditions	Shopping behavior(s)	Data basis
Gicheva, Hastings, and Villas-Boas 2007	Gasoline prices		Spending share of income, out-of-home consumption, promotion (individually)	Weekly, household-level consumption surveys, repeated cross-section, two U.S. regions from 2000 to 2004
Lamey et al. 2007	Business cycle (asymmetries)		PL share	Annual, country-level longitudinal data, four countries spanning multiple decades
Lamey et al. 2012	Business cycle		PL share	Annual, category-level longitudinal data, U.S. from 1985 to 2005
Ma et al. 2011	Gasoline prices, GDP growth rate		Shopping trips, total spending, purchase volume, store format, brand type, price tier, and promotion shares (individually)	Monthly, household-level longitudinal panel data, U.S. metropolitan area from 2006 to 2008
Kamakura and Du 2012	GDP growth	Household budget	Spending share of budget	Annual, household-level consumption surveys, repeated cross-section, U.S. from 1989 to 2003
Lamey 2014	Business cycle (asymmetries)		Discounter share	Annual, country-level longitudinal data, 15 countries, spanning 17 years
Cha, Chintagunta, and Dhar 2015	Regional unemployment level		Total spending, purchase volume, prices paid, store format, brand type, price tier, and promotion shares (individually)	Annual, household-level panel data, repeated cross-section, U.S. from 2006 to 2011
Dube, Hitsch, and Rossi 2018	(Post-)Recession phase	Income, wealth	PL share	Monthly, longitudinal household-level panel data, U.S. from 2004 to 2012
This paper	Business cycle (asymmetries)	Income (asymmetries)	Total spending, purchase volume, price index paid, brand type and store format shares (simultaneously)	Quarterly, longitudinal household-level panel data, Germany from 2007 to 2013

Notes: Gicheva, Hastings, and Villas-Boas (2007) and Ma et al. (2011) argue that changes in gasoline prices reflected changes in household budgets. We regard gasoline prices as macro effects because they are experienced simultaneously but not necessarily equally by all households as some households may rely on their car more than others. As such, they are more similar to macro rather than micro events.

TABLE 2
Store Format Characteristics

Store format	Nr. of stores[1]	Sales area (m²/store)[1]	Revenues (€ mil.)[1]	Market share[1]	Space prod. (€/m²)	Nr. of SKUS[1]	SKU prod. (€ mil./SKU)	PL share[2]	Service score[3]	Price score[3]
1) Discounters	16,054	779	69,800	45.44%	5,584	2,295	30.4	65.6%	67.1	82.9
2) Small retailers	8,750	297	4,800	3.13%	1,846	—	—	—	—	—
3) Supermarkets	10,900	982	44,900	29.23%	4,196	11,830	3.8	21.6%	82.0	73.6
4) Superstores	1,127	3,461	15,200	9.90%	3,897	25,005	.6		84.5	74.0
6) Hypermarkets	851	7,051	18,900	12.30%	3,150	48,870	.4	19.6%	79.1	77.9
Discounters (1)	16,054	779	69,800	45.44%	5,584	2,295	30.4	65.6%	67.1	82.7
Non-Discounters (2-5)	21,628	1,073	83,800	54.56%	3,612	23,226	3.2	21.2%	82.5	74.7

Notes: Data based on the German market, [1] based on 2016, [2,3] based on 2018. Aggregated values for non-discounters based on sums or averages weighted by market shares. Service and price scores are indexes (0-100), scores for store formats are aggregates from the twelve major retail brands that were tested. We assigned retail brands to their primary store format based on industry convention and average store size: small retailers < 400 m², supermarkets 400 – 2,500 m², superstores 2,500 – 5,000 m², hypermarkets > 5.000 m² average sales area.
Sources: [1] EHI 2017; [2] GfK 2019; [3] DISQ 2018

TABLE 3
Variable Operationalization

Variable Group	Variable	Operationalization
Shopping Outcomes	$TotalSpending_{ht}$	Total spending (in euros) by household h at time t.
	$PurchaseVol_{ht}$	Total purchase volume by household h at time t measured in constant euros.
	$PriceIndex_{ht}$	Index of prices paid by household h at time t.
	$Spending_{bht}$	Spending (in euros) by household h at time t for brand type-store format combination b.
Micro- and Macro Conditions	$BCycle_{t}$	Difference between the cyclical GDP component at time t and the prior trough/peak.
	$Expansion_{t}$	Difference between the cyclical GDP component at time t and the prior trough.
	$Contraction_{t}$	Difference between the cyclical GDP component at time t and the prior peak.
	$IncomeChange_{ht}$	Difference between the log-transformed monthly net income (in euros) of household h at time t and the prior income trough/peak.
	$IncomeGain_{ht}$	Difference between the log-transformed monthly net income (in euros) of household h at time t and the prior income trough.
	$IncomeLoss_{ht}$	Difference between the log-transformed monthly net income (in euros) of household h at time t and the prior income peak.
Marketing Mix Controls	$Price_{ht}$	Net price facing household h at time t.
	$RelPrice_{bht}$	Relative net price of brand type-store format combination b facing household h at time t.
	$Assort_{ht}$	Number of unique SKUs facing household h at time t.
	$RelAssort_{bht}$	Relative number of unique SKUs of brand type-store format combination b facing household h at time t.
	$Promo_{ht}$	Number of price-promoted SKUs facing household h at time t.
	$RelPromo_{bht}$	Relative number of price-promoted SKUs of brand type-store format combination b facing household h at time t.
	$PLPct_{ht}$	Percentage share of PL SKUs in the assortment facing household h at time t.
	$RelPLPct_{jht}$	Relative share of PL SKUs in assortment of store format j facing household h at time t.
	$AdvStore_{t}$	Store-level advertising spending (in million euros) at time t.
	$RelAdvStore_{jt}$	Relative store-level advertising spending (in million euros) of store format j at time t.
	$AdvNB_{t}$	Advertising spending (in million euros) of NBs at time t.
Demographic Controls	$HhSize_{ht}$	Number of persons in household h at time t.
	Age_{ht}	Age of the leading person in household h at time t.
	$Kids_{ht}$	Dummy variable, 1 if children are present in household h at time t, 0 otherwise.
	$Unemployed_{ht}$	Dummy variable, 1 if principal earner of household h is unemployed at time t, 0 otherwise.
Psychographic Controls	$QualCons_{ht}$	Scale indicating quality consciousness of household h at time t; provided by GfK.
	$PriceCons_{ht}$	Scale indicating price consciousness of household h at time t; provided by GfK.
	$DealProne_{ht}$	Five-item scale indicating deal proneness of household h at time t.
	$EatOut_{ht}$	Three-item scale indicating preference for eating out of household h at time t.
Time Controls	$Time_{t}$	Continuous variable for time t.
	$Quarter_{qt}$	Indicator variable for quarter q of the year at time t.
Other Controls	$Copula_{kht}$	Gaussian copula for marketing mix variable k to account for potential endogeneity.
	$InvMill_{bht}$	Inverse Mills ratio to account for potential selection effects.

Notes: Items, factor loadings and Cronbach's alphas for DealProne and EatOut are presented in Table WB1 of Web Appendix B.

TABLE 4

Descriptive Statistics and Correlation Matrix for Variables in the Shopping Basket Value Models

		M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	TotalSpending	184.44	114.40	1																							
2	PurchaseVol	183.06	115.62	.94	1																						
3	PriceIndex	.99	.05	-.02	-.15	1																					
4	BCycle	1.05	4.50	.00	.01	-.01	1																				
5	Expansion	2.42	2.69	.01	.02	.00	.87	1																			
6	Contraction	1.37	2.53	.01	.01	.01	-.85	-.49	1																		
7	IncomeChange	51.93	510.04	.03	.03	-.01	-.01	-.02	-.01	1																	
8	IncomeGain	176.70	341.42	.00	.01	-.01	-.01	-.05	-.04	.80	1																
9	IncomeLoss	124.77	315.41	-.05	-.04	.00	.01	-.02	-.03	-.74	-.19	1															
10	Price	.99	.06	-.11	-.16	.02	-.13	-.10	.11	.02	.02	-.01	1														
11	Assort	444.89	113.02	.15	.13	-.01	.03	-.03	-.09	.02	.06	.03	.08	1													
12	Promo	217.65	55.96	.04	.02	-.01	.05	-.08	-.17	.04	.14	.08	.07	.86	1												
13	PLPct	.33	.04	-.17	-.24	.05	-.03	-.06	.00	.01	.02	.00	.72	.17	.18	1											
14	AdvStore	254.98	27.22	.03	.02	.00	.02	.17	.15	.00	-.02	-.01	-.02	-.03	-.03	-.04	1										
15	AdvNB	294.83	46.12	.00	.00	.00	.13	.08	-.15	.01	.04	.04	-.02	.05	.10	-.01	.25	1									
16	HhSize	2.33	1.13	.49	.52	-.14	.00	.01	.01	.07	.05	-.07	.18	.06	-.01	.03	.01	.00	1								
17	Age	54.36	12.07	-.12	-.13	.07	-.01	-.04	-.02	-.10	-.14	.01	-.18	.02	.10	-.08	-.02	.01	-.37	1							
18	Kids	.18	.38	.19	.21	-.08	.00	.02	.01	.07	.06	-.04	.25	.03	-.03	.12	.01	.00	.56	-.54	1						
19	Unemployed	.06	.24	-.06	-.01	-.01	.01	.01	.00	-.05	.01	.09	-.01	.00	-.03	-.02	-.01	-.01	-.04	-.07	.02	1					
20	QualCons	2.94	.86	.03	-.07	.12	.00	.00	-.01	.01	-.01	-.03	.03	-.01	.03	.05	-.01	.01	-.04	.11	-.07	-.10	1				
21	PriceCons	3.14	.93	.00	.13	-.28	.00	.00	.01	-.01	.02	.03	.02	.02	-.01	-.03	.01	.00	.14	-.11	.11	.08	-.39	1			
22	DealProne	11.26	2.47	.10	.18	-.28	.00	.01	.01	.02	.02	-.01	-.02	.00	-.04	-.04	.01	.00	.18	-.10	.11	.03	-.10	.38	1		
23	EatOut	5.41	2.38	-.07	-.10	.05	.01	.01	-.01	.05	.07	.00	-.02	-.01	-.02	-.01	-.01	.00	-.07	-.32	.09	.03	.03	-.05	-.01	1	
24	Time			-.05	-.05	-.01	-.16	-.27	.00	.06	.20	.12	.05	.25	.61	.05	.08	.19	-.04	.13	-.05	-.04	.04	-.02	-.03	-.01	1

Notes: M = mean; SD = standard deviation. Means and standard deviations are based on untransformed values, correlations are based on log-transformed variables except dummy variables. BCycle, Expansion, and Contraction are multiplied by 100 to be expressed in percentage deviations.

TABLE 5
Descriptive Statistics for Variables in the Shopping Basket Allocation Models

	PLDisc		**NBDisc**		**PLNonDisc**		**NBNonDisc**	
	M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Spending	45.47	46.10	23.64	33.29	12.98	16.91	102.35	93.18
Price	.76	.03	1.17	.04	.73	.04	1.34	.04
Assort	.74	.12	.66	.05	.46	.08	2.15	.17
Promo	.65	.13	.72	.05	.43	.08	2.20	.18
Pct.PL	1.46	.04	1.46	.04	.54	.04	.54	.04
Adv.Store	1.09	.07	1.09	.07	.91	.07	.91	.07
Adv.NB	294.83	46.12	294.83	46.12	294.83	46.12	294.83	46.12

Notes: M = mean; SD = standard deviation. PLDisc = private labels in discounters; NBDisc = national brands in non-discounters; PLNonDisc = private labels in non-discounters; NBNonDisc = national brands in non-discounters.

TABLE 6
Model Building and Fit Statistics

		Estimation-Sample			
Model	Components	LL	BIC	AIC	Parameters
M1	Intercept + Time + Sample Selection Controls	-395,450	791,524	791,048	74
M2	M1 + Dependent Variable from Initialization Period	-287,496	575,674	575,153	81
M3	M2 + Marketing Mix + Copulas	-281,705	564,801	563,739	165
M4	M3 + Demographics	-273,889	549,407	548,165	193
M5	M4 + Psychographics	-270,205	542,273	540,852	221
M6	M5 + Symmetric Economic Conditions	-270,034	542,051	540,539	235
M7	M6 + Asymmetric Economic Conditions	-269,968	542,036	540,434	249

Notes: LL = log-likelihood; BIC = Bayesian information criterion; AIC = Akaike's information criterion. Note that only models M3 to M7 can be compared against each other as they incorporate the same set of instruments (copulas and inverse Mills ratio) and vary only by their exogenous variables (Ebbes, Papies, and van Heerde 2011).

TABLE 7
Overview of Significant Elasticities

		Basket Allocation				*Basket Value*		
	Variable	**PLDisc Spending**	**NBDisc Spending**	**PLNonDisc Spending**	**NBNonDisc Spending**	**Total Spending**	**Purchase Volume**	**Price Index**
Asymmetric Model (M6)	BCycle	-.70***		-.63***	.27***	-.06*	-.06*	-.01*
	IncomeChange				.08***	.07***	.06***	
Symmetric Model (M7)	Expansion	-.94***		-.71***	.52***			-.01*
	Contraction	.36**	-.32*	.51***		.14**	.11*	
	IncomeGain							
	IncomeLoss	-.10**			-.16***	-.12***	-.11***	

Notes: Illustrated are only significant elasticities at **p* < .1; ***p* < .05; ****p* < .01. PLDisc = private labels in discounters; NBDisc = national brands in non-discounters; PLNonDisc = private labels in non-discounters; NBNonDisc = national brands in non-discounters. Complete results of the asymmetric Model 7 are provided in Table 8. Complete results of the symmetric Model 6 are provided in Table WC1 of Web Appendix C.

TABLE 8: Results of Asymmetric Model 7

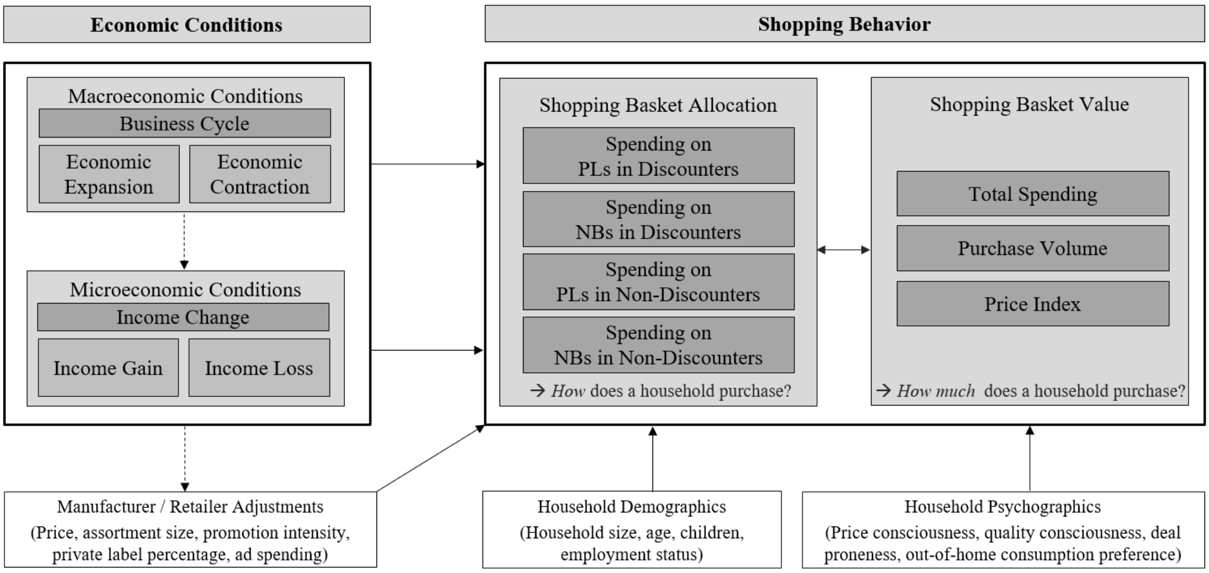
	Basket Allocation								*Basket Value*					
Variable	**PLDisc Spending**		**NBDisc Spending**		**PLNonDisc Spending**		**NBNonDisc Spending**		**TotalSpending**		**PurchaseVolume**		**PriceIndex**	
Intercept	2.6310**	(1.3047)	-4.4137*	(2.3163)	-2.0639	(1.3452)	4.6453***	(1.0345)	-1.0209	(2.6274)	.4872	(2.6826)	.0460	(.1136)
Random Intercept	-.4634***	(.0131)	-.1435***	(.0308)	.1604***	(.0241)	.2319***	(.0260)	.0279***	(.0107)	-.0194*	(.0103)	-.0006	(.0006)
Micro and Macro Conditions														
Expansion	-.9387***	(.1925)	-.0063	(.2001)	-.7139***	(.1816)	.5186***	(.1132)	.0198	(.0546)	.0024	(.0548)	-.0083*	(.0048)
Contraction	.3578**	(.1496)	-.3242*	(.1968)	.5068***	(.1602)	.0485	(.1198)	.1357**	(.0605)	.1086*	(.0600)	.0015	(.0050)
IncomeGain	-.0341	(.0413)	.0479	(.0471)	.0284	(.0428)	.0112	(.0352)	.0183	(.0206)	.0153	(.0205)	.0011	(.0014)
IncomeLoss	-.0977**	(.0447)	.0124	(.0532)	-.0508	(.0463)	-.1567***	(.0380)	-.1208***	(.0224)	-.1053***	(.0219)	-.0005	(.0017)
Controls														
DV(t=0)	.3535***	(.0245)	.2117***	(.0116)	.3187***	(.0135)	.5997***	(.0207)	.5910	(.0148)	.5719***	(.0152)	.7263	(.0162)
(Rel)Price	-.6183	(1.2878)	1.8388	(2.1456)	-1.5194	(1.7101)	-.2376	(1.5296)	.3850	(.7840)	.0194	(.8050)	-.0384	(.0863)
(Rel)Assort	-.4142**	(.1789)	.4310	(1.1226)	-.2307	(.2178)	1.5306***	(.3764)	.4395*	(.2495)	.1980	(.2603)	.0239	(.0169)
(Rel)Promo	.1519**	(.0725)	1.2602	(3.2248)	.4613*	(.2525)	.8275*	(.4941)	-.4199	(.2621)	-.2884	(.2691)	-.0300**	(.0141)
(Rel)PLPct	-7.0982***	(2.0868)	5.3710*	(2.9790)	-1.4206**	(.6413)	-.1210	(.2981)	-.5991***	(.0864)	-.5763***	(.0930)	-.0025	(.0096)
(Rel)AdvStore	-.2452**	(.1031)	.0052	(.1281)	.5303***	(.1342)	-.2811***	(.0778)	.1275***	(.0173)	.1022***	(.0194)	.0005	(.0022)
AdvNB	.1265***	(.0453)	.2301***	(.0763)	.1619***	(.0594)	-.2903***	(.0418)	-.0396*	(.0223)	-.0488**	(.0230)	-.0008	(.0022)
HhSize	.3706***	(.0479)	.4305***	(.0297)	.3406***	(.0272)	.3722***	(.0276)	.3077***	(.0154)	.3250***	(.0164)	-.0018**	(.0008)
Age	-.1958***	(.0689)	-.1135*	(.0632)	-.1397**	(.0543)	.1270***	(.0491)	.0078	(.0228)	-.0085	(.0224)	.0039**	(.0019)
Kids	-.0057	(.0308)	-.0594*	(.0334)	-.0104	(.0298)	-.0593**	(.0234)	-.0148	(.0133)	-.0086	(.0135)	-.0002	(.0010)
Unemployed	-.0617**	(.0274)	-.0092	(.0364)	.0563	(.0342)	-.1157***	(.0278)	-.0533***	(.0167)	-.0169	(.0165)	-.0010	(.0012)
QualCons	-.0224	(.0262)	.0286	(.0278)	-.1167***	(.0253)	.0860***	(.0200)	.0291***	(.0109)	-.0175	(.0108)	.0012	(.0008)
PriceCons	.0654***	(.0216)	-.0814***	(.0275)	.0516**	(.0231)	-.1366***	(.0177)	-.0583***	(.0109)	.0018	(.0110)	-.0098***	(.0009)
DealProne	.0196	(.0349)	.2549***	(.0402)	-.1277***	(.0349)	.0485*	(.0268)	.0499***	(.0153)	.0830***	(.0152)	-.0158***	(.0012)
EatOut	-.0581**	(.0243)	-.0373	(.0258)	-.0100	(.0232)	-.0282	(.0186)	-.0273**	(.0107)	-.0360***	(.0105)	.0017**	(.0008)
Time	-.0197	(.0121)	.0781***	(.0112)	.0382***	(.0123)	-.0425***	(.0090)	-.0233***	(.0051)	-.0270***	(.0056)	-.0001	(.0006)
Quarter 2	.0327*	(.0188)	-.0842***	(.0310)	-.0355	(.0220)	.1078***	(.0174)	.0379***	(.0098)	.0440***	(.0102)	.0005	(.0010)
Quarter 3	.0154	(.0134)	-.0695***	(.0219)	-.0559***	(.0157)	.0260**	(.0102)	.0002	(.0066)	.0089	(.0070)	.0005	(.0007)
Quarter 4	-.0026	(.0136)	-.0076	(.0231)	-.0193	(.0168)	.1187***	(.0113)	.0258***	(.0063)	.0228***	(.0065)	-.0001	(.0006)
Copula (Rel)Price	.0483	(.0587)	-.0626	(.0717)	.0594	(.0937)	.0506	(.0458)	-.0243	(.0446)	-.0255	(.0459)	.0019	(.0049)
Copula (Rel)Assort	.0010	(.0284)	.0143	(.0742)	.0191	(.0317)	-.1207***	(.0297)	-.0719	(.0603)	-.0222	(.0629)	-.0041	(.0041)
Copula (Rel)Promo	.0785***	(.0136)	-.0515	(.2441)	-.0289	(.0420)	-.0212	(.0414)	.0829	(.0659)	.0607	(.0676)	.0051	(.0036)
Copula (Rel)PL.Pct	.2990***	(.0623)	-.0955	(.0824)	.1306***	(.0470)	.0149	(.0228)	.0431***	(.0103)	.0201*	(.0109)	.0015	(.0012)
Copula (Rel)AdvStore	.0063**	(.0028)	.0001	(.0048)	-.0330***	(.0061)	.0074**	(.0033)	-.0017	(.0012)	-.0023*	(.0014)	.0003**	(.0001)
Copula AdvNB	-.0057*	(.0031)	-.0018	(.0047)	-.0124***	(.0045)	.0027	(.0028)	-.0042***	(.0016)	-.0031**	(.0015)	.0001	(.0001)
Inv.Mills	.1907	(.1656)	-.2506***	(.0703)	-.0832	(.0734)	-.0260	(.2121)						
N	131,566		113,092		121,787		139,163		142,828		142,828		142,828	
Pseudo-R^2	.59													

Notes: PLDisc = private labels in discounters; NBDisc = national brands in non-discounters; PLNonDisc = private labels in non-discounters; NBNonDisc = national brands in non-discounters. Standard errors are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

TABLE 9
Overview of Results and Implications

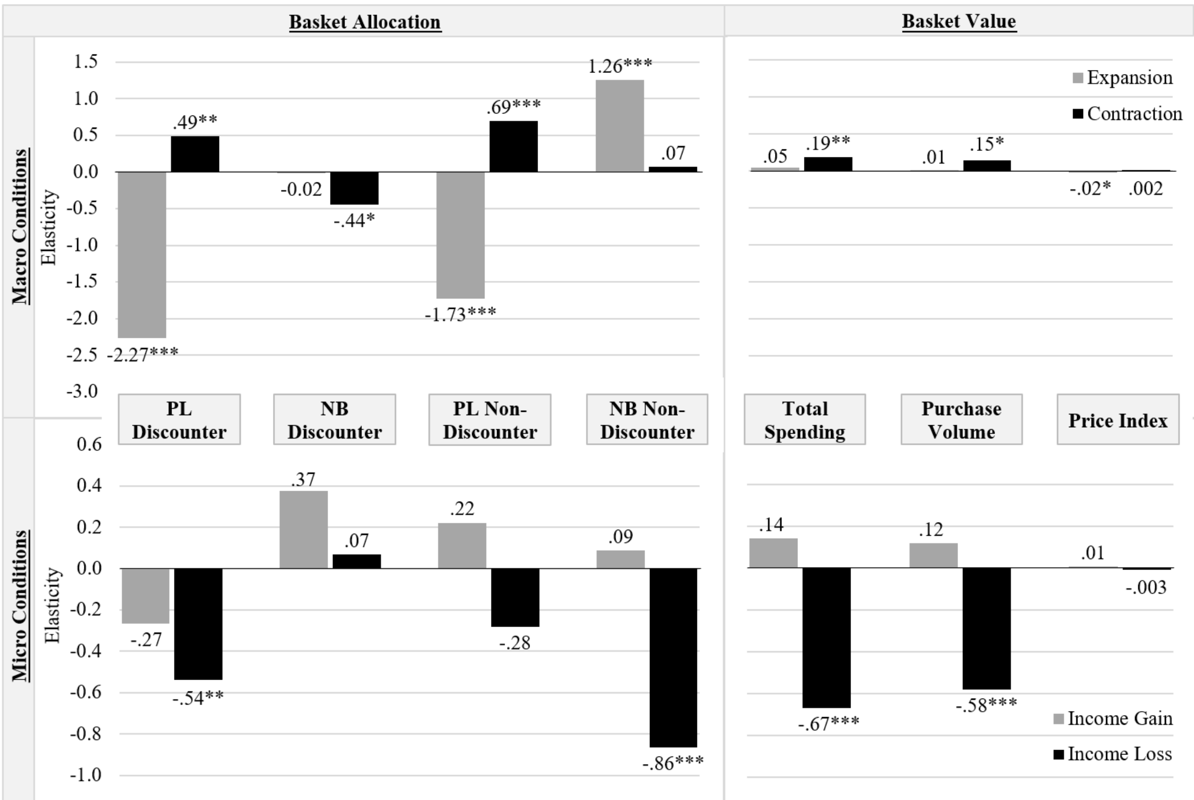
Outcomes		Main findings	Interpretation and Implications
Shopping Basket Allocation	PL Discounter Spending	Moves countercyclically with macro conditions, decreasing in expansions and increasing in contractions. Decreases with adverse micro conditions.	As social acceptance of and demand for PLs increase during contractions, discounters can narrow their price gap to NBs. This allows for more profitable price reductions that discounters should deploy cyclically to counteract shifts to non-discounters and NBs during expansions and adverse micro conditions. Soft discounters should extend their PL portfolio during contractions.
	NB Discounter Spending	Moves cyclically with macro conditions, decreasing substantially in contractions.	Buffer discounters' and manufacturers' revenue losses during adverse micro conditions. Brand managers should extend their portfolio to discounters in these conditions to counteract losses from NBs sold in non-discounters. Especially hard discounters may profit from a larger NB portfolio.
	PL Non-Discounter Spending	Moves countercyclically with macro conditions, decreasing in expansions and increasing in contractions.	Allow non-discounters to grow revenues even during contractions. Non-discounters can use this opportunity to extend their PL portfolios to new product categories and price-tiers and strengthen their branding to counteract shifts back to NBs during expansions. As they are unaffected by increasing budget constraints, non-discounters may adjust prices countercyclically to reap additional revenues during contractions and defend against NBs by deploying price reductions during expansions.
	NB Non-Discounter Spending	Moves cyclically, increasing during expansions. Decreases with adverse micro conditions.	Are affected the strongest by adverse micro conditions. Manufacturers and non-discounters can react to this through status appeals in their communication. As households do not switch due to budget constraints, marketers should not waste budgets on price promotions but provide "cheap" mechanisms that provide consumers with a sense of control and frugality such as loyalty and reward programs or (digital) store fliers.
Shopping Basket Value	Total Spending	Grows with adverse macro conditions. Shrinks with adverse micro conditions.	As long as households are not affected at a micro level, they increase their purchased volumes and total spending during contractions. Managers can leverage households' increased consumption and cognitive load from shifts in spending through larger package sizes and in-store promotions. Measures that provide a sense of control and frugality such as loyalty programs or quality and status appeals may further increase compensatory consumption. During expansions, retailers and manufacturers should utilize the increased deal proneness and price savviness through price promotions and couponing.
	Purchase Volume	Grows with adverse macro conditions. Shrinks with adverse micro conditions.	
	Price Index	Grows with adverse macro conditions.	

FIGURE 1
Conceptual Framework



Notes: PL = private label, NB = national brand.

FIGURE 2
Asymmetric Elasticities at Mean Values for Micro and Macro Conditions



Notes: Upper (lower) plots show elasticities for mean expansion (income gain) values in grey and elasticities for mean contraction (income loss) values in black from the basket allocation (left) and basket value (right) models. *$p < .1$; **$p < .05$; ***$p < .01$.