Sustainable Product Profit Potential and Availability

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Abstract

In recent years, consumers have become more interested in purchasing products produced using more sustainable practices, with much of the recent growth in consumer packaged goods (CPGs) within the United States from products with clearly labelled sustainability claims on their packaging. However, many categories have low levels of sustainable product market share, with substantial geographic variation. This paper assesses the role of demographic variables on the relative "profit potential" for sustainable products (determined by equilibrium quantity and price, and price elasticity) and on their availability. To estimate profit potential, we estimate product and county-specific demand elasticities for six CPG subcategories in the grocery and mass merchandiser formats. A meta-analysis of the estimates show that the relative profit potential of sustainable products increases with income, Democratic vote share, and the fraction of the county that is college educated. These variables also lead to greater sustainable product availability, even after conditioning on profit potential. Furthermore, we find that fraction male and fraction white lead to higher sustainable product availability, indicating lower access for women and minority populations. This provides evidence that managers are likely using simple demographic heuristics to make product stocking decisions that do not necessarily reflect actual sustainable product preferences.

Keywords:
Sustainability, product availability, product demand, profits, retailing

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INTRODUCTION

Despite the growing consumer interest in sustainability and the substantial role sustainable products have on consumer packaged goods (CPG) product growth (Kronthal-Sacco et al. 2020), demand for sustainable products is vastly heterogeneous in the United States, both geographically and across product categories. This heterogeneity correlates highly with demographic factors such as income, political affiliation, and race. However, much like in the recent literature on healthy food purchases (Allcott et al. 2019; Hristakeva and Levine 2022), it is not clear the extent those differences are due to demand vs. supply side factors. While demand-side factors such as varying willingness to pay for socially responsible products (Tully and Winer 2014; Bastounis et al. 2021; Potter et al. 2021) can explain heterogeneity in shares conditional on availability, lack of sustainable product availability itself is one potential reason for lower shares in some markets.

Presumably, firms would like the availability of their sustainable products to reflect their profitability, given patronage and spending at stores are affected by product availability, in particular at grocery stores (Fox, Montgomery, and Lodish 2004). Thus, understanding the profitability of sustainable products given market (e.g. demographics, store format) and product (e.g. category, sustainability claim) characteristics is important for managers, given they are tasked with key decisions including 1) where to launch sustainable products, 2) within which product categories they should invest efforts in improving sustainability, and 3) along which dimensions of sustainability they should focus on, given consumer preferences.

In this paper, we take an empirics-first approach (Golder et al. 2023) to uncover patterns in sustainable product profitability and availability in three CPG categories across five years (2015 to 2019) in the US. Since the lack of marginal cost data limits our ability to directly make inferences about the profitability of different products across markets and brands, we instead measure the "profit potential" of individual products across markets (rather than actual profits) using a combination of observed equilibrium prices and quantities and estimated price elasticities, which determine the margin if prices were set optimally.

We address two main research questions related to our measure of profit potential. First, we investigate how demographics affect the profit potential of sustainable products relative to non-sustainable products. Second, as our primary focus, we examine what the direct effects of demographics are on the availability of sustainable products relative to non-sustainable ones, controlling for the relative profit potential of sustainable products. This second analysis isolates the role of demographics on availability and enables us to evaluate whether sustainable product profit potential explains the link between demographics and availability. Evidence to the contrary would suggest demographic factors may be over-utilized in deciding where to make sustainable products available, highlighting opportunities for firms to launch sustainable products in less-targeted markets.

To calculate profit potential, we need product-level measures of price, quantity, and price elasticity. To this end, we combine rich disaggregate sales and pricing data at the product-store-week level across the US from 2015 to 2019 across six subcategories within three CPG categories in both the grocery and mass merchandiser formats.[1] Starting with Label Insights data, we then hand-code information about on-package sustainability claims for every brand's product packaging (also used in Kronthal-Sacco et al. 2020). We define a product as being "sustainable" if it contains sustainability claims on its product packaging that highlight its influence on the health and/or welfare of humans, animals, or the environment, consistent with the United Nations Sustainable Development Goals. Examples of such claims include "Organic", "Non-GMO", "Plant-Based Ingredients", "Fair Trade", and so forth. We focus on packaging because it is ubiquitous and packaging claims have been shown to impact consumers at the point-of-purchase (Rao and Wang 2017). We then estimate over 180,000 flexible demand regressions (following Hitsch, Hortacsu, and Lin 2021) in order to obtain our estimates of price elasticity that enter the profit potential calculations, in conjunction with observed prices and quantities.

With estimates of profit potential in hand, we first examine the degree to which demographic factors of a market affect product-level profit potential for both sustainable and non-sustainable

[1]We also analyze the club format but limited availability of sustainable products limits our ability to make comparisons.

products. The demographic variables we examine (aggregated at the county level) are age, income, gender, education, race, political orientation, and population density. We find that profit potential is highest for the current set of sustainable products, in general, in areas with higher income, higher education, and higher Democratic vote share, as one might expect. However, the effects of population density, age, gender, and race on the relative profit potential of sustainable products vs. non-sustainable ones are largely inconclusive. Additionally, we note the size of the demographic effects for sustainable products are small relative to the main effect of these factors on profit potential for all products (both sustainable and non-sustainable), excepting education.

We then evaluate whether the heterogeneity in sustainable product availability can be simply attributed to the differences in profit potential, or whether demographic factors *directly* influence sustainable product availability after conditioning on profit potential. We find support for the latter — though profit potential of sustainable products positively predicts sustainable availability (with elasticities ranging from 0.05 to 0.15 in the grocery format and 0 to 0.05 in the mass merchandiser format, depending on the subcategory), demographic factors still influence availability even when accounting for their indirect effect via profit potential. After conditioning on profit potential, the availability of sustainable products increases with income, Democratic vote share, and the fraction of the county that is college educated, male, and white. Our findings suggest that these demographic factors may be over-utilized in deciding where to make sustainable products available, and the result highlights an opportunity for firms to launch sustainable products in markets with less stereotypical consumers of sustainable products (non-white, less college education, lower income, and Republican).

Our work makes several contributions to the rapidly growing literature in sustainability in marketing. While there is a large literature examining consumer demand for sustainable products, we note most studies use choice experiments (see the meta-analyses of e.g. Tully and Winer 2014, Bastounis et al. 2021, and Potter et al. 2021) and in some cases field experiments or observational studies (Aerni, Scholderer, and Ermen 2011; Hainmueller, Hiscox, and Sequeira 2015; Hainmueller and Hiscox 2015; Hallstein and Villas-Boas 2013; Kortelainen, Raychaudhuri, and

Roussillon 2016; Bezawada and Pauwels 2013; Ngobo 2011), with a majority of studies documenting increased willingness to pay or sales for sustainable products. These studies typically involve a single context in a controlled environment in which product availability is a given and other external factors are minimized. We add to the literature by employing a national scale dataset across five years, multiple product categories and store formats, and a large umbrella of sustainability claims to document empirical regularities related to sustainable products in the field rather than in more controlled settings.

Furthermore, our focus expands upon the existing research by not only measuring a demand-side primitive — price elasticity (which feeds into our measure for profit potential) — for sustainable products, but also exploring determinants of their availability, an element that is largely missing in the extant literature. While some studies highlight low *perceived* availability of sustainable products as a possible barrier to consumption (Vermeir and Verbeke 2006; Cerri, Testa, and Rizzi 2018) and one potential reason for the well-established "green gap" between consumers' stated willingness to pay (WTP) for sustainable products and actual product purchases (Auger 2007; Young et al. 2010; Prothero et al. 2011; Phipps et al. 2013; Johnstone and Tan 2015), we examine availability as a dependent variable in itself. In doing so, we document factors that influence the supply-side decisions for providing sustainable products across markets.

We also contribute to the literature on demographic variables that influence sustainable product outcomes. Much of the literature has shown that demographic variables explain little of the variance in consumer behavior towards sustainable products relative to consumer values (e.g. liberalism, collectivism) or attitudes (e.g. concerns towards the environment) (Diamantopoulos et al. 2003; Roberts 1996; Laroche, Bergeron, and Barbaro-Forleo 2001; Hornsey et al. 2016). Our results, however, show that, at least at an aggregate level, income, education, political affiliation, and race are still predictive of sustainable market shares, as well as product profit potential and availability, in different categories.

As demographic variables are among the more easily observed characteristics in a given market, our work lends support for managers to utilize low-cost information to determine which markets to supply sustainable products. In certain cases, we find a disconnect between demographic effects on profit potential and their effects on availability. Similar to Kwate et al. (2013) who study retail redlining in New York City and its potential consequences on ease of access to health products, our work shows that heterogeneity in availability of sustainable products cannot be fully explained by differing profit potential of sustainable products across demographic groups, highlighting markets in which there may be untapped opportunities for sustainable products.

EMPIRICAL ROADMAP

We map out the main empirical relationships explored in this paper in Figure 1. For a given store format, subcategory, and product or type of products (sustainable or non-sustainable), we show two pathways between demographics and availability, one indirect and the other direct. The upper path highlights the indirect pathway through profit potential as one possible determinant of availability. Profit potential is determined by price, demand (quantity), and price elasticity. This can easily be seen algebraically. The marginal profit for a product can be written as:

$$\pi = (p - c)q, \tag{1}$$

in which p is the price, c the marginal cost, and q the demand. Let us assume price competition with differentiated products (Bertrand). The first order pricing condition is:

$$p = c - \frac{q}{q'} = c - p\frac{1}{\alpha},$$

in which $q' \equiv dq/dp$ is the first derivative of demand with respect to price and α is the price elasticity, $\alpha \equiv (p/q)q'$. We can then write the optimal price as:

$$p = c\frac{\alpha}{1 + \alpha}. \tag{2}$$

Thus, the margin achievable by the firm with optimal pricing is determined by the elasticity of the marginal consumer. Who the marginal consumer is will depend on the underlying preference distribution of consumers in the market and the price level. For example, sustainable products in counties or categories that have low sustainable market shares serve a smaller segment of the population. Hence, the marginal consumers in these counties are more likely to be in the tail of the distribution of price sensitivity within the county (i.e. are less price sensitive), which leads to higher optimal margins, and thus prices, for sustainable products.

Although we do not observe marginal costs (which we note in Figure 1 to inform price in conjunction with price elasticity), which would enable direct cost comparisons for sustainable and non-sustainable products, we can rewrite profits (1) under optimal pricing (2) as:

$$\pi = \frac{p \cdot q}{-\alpha}.$$

That is, profits at optimal pricing can be expressed as a function of price, quantity, and the price elasticity of demand. The numerator is product revenue, and $-1/\alpha$ is the margin at the optimal price. We take logs on both sides of this expression to create our index of profit potential:

$$\log(\pi) = \log(p) + \log(q) - \log(-\alpha) \tag{3}$$

The profit potential of a product can increase via quantity, price, or elasticity (via a higher margin).

Completing the upper pathway of Figure 1, demographics likely affect both price elasticities and demand, which encapsulate revealed consumer preferences.[2]. Viewed from the perspective of sustainable vs. non-sustainable products, the upper path can be viewed as the demand-side explanations for differences in their respective availability. What remains, then, is the lower path, which links demographics directly to availability through managers' decisions. Whether there is a direct effect is an empirical question and is one of the focal points of this paper. The

[2]Although it is possible that demographics may also affect the realized price, the optimal price is determined by cost and these two demand factors.

conceptual framework outlined in Figure 1 highlights the fact that in order to examine the effect of demographic variables on availability, we need to control for the effect of the product's profit potential, which will also depend on demographic variables.

Insert Figure 1 here

Our empirical road-map adheres to the conceptual framework outlined in Figure 1 as follows:

1. First, we summarize our data and describe the associations between the demographic variables and multiple downstream outcomes including sustainable product market shares, availability, and price premiums.

2. We next estimate price elasticities for all available products at the product-county level, within store format and subcategory.

3. Using observed prices, observed quantities, and estimated price elasticites, we calculate profit potential at the product-county level, within store format and subcategory.

4. To address our first research question, we estimate the effect of demographic variables on profit potential of sustainable vs. non-sustainable products at the product-county level.

5. To address our second research question, and the primary focus of this paper, we estimate the effect of demographic variables on the relative availability of sustainable products, controlling for profit potential. Here, we aggregate our analysis to the county-level, using the average profit potential of sustainable vs. non-sustainable products within a county.

The empirical strategy we use differs from that used in Allcott et al. (2019) and Hristakeva and Levine (2022). Both of these papers use store openings to estimate the role of a new store location on consumer-level demand and the healthiness of products purchased, with the expectation that closer store proximity leads to more availability. In both papers, the dependent measure is an aggregation across many products. In contrast, we estimate product-level demand (with some limited aggregation in the definition of products) *conditional* on availability. Then, we calculate the average profit potential across sustainable and non-sustainable products at the county-week level and estimate the effect of profit potential and demographics on availability. This approach is similar to Kwate et al. (2013), who assess whether access to retailers is limited for certain populations even after controlling for both retail demand and relevant sociodemographic variables. In our analysis, the implicit assumption is that the average profit potential of the set of available products is indicative of the profitability of products that could enter the market. We also test an alternative measure, the minimum profit potential of sustainable and non-sustainable products at the county-week level (the underlying assumption being that the profit potential of a potential product entrant is more similar to the lowest profit potential of the set of products in the market already); our qualitative results are the same. As a further check, we find including the expected future profit potential (assuming firms make supply-side decisions not just on short-term profits but also long-term profits) also does not alter the main findings.

DATA

We collect three main sources of data: retail purchases in three CPG categories, sustainability claims information, and county demographic data. We describe each of these datasets below.

Retail Purchases

We obtain weekly store-level retail scanner data for products at the UPC (universal product code) level from Circana.[3]

Category Selection We select three CPG categories: coffee, laundry detergent, and yogurt.[4] These categories were chosen to 1) include both edible and non-edible categories as well as a variety of sustainability claims; 2) align with previously used typologies of product categories in the sustainability marketing literature; and 3) represent categories with low, medium, and high levels of sustainable market share. We expound on each of these reasons in Web Appendix 1.

[3] Circana was formerly Information Resources, Inc. and The NPD Group that merged in August 2022.
[4] We were limited to three categories at this level of disaggregation in our data sharing agreement.

Each category in the Circana data is further subdivided into subcategories. For the coffee category, which has several subcategories, we focus on the largest ones whose cumulative dollar spend make up at least 90% of total dollar spend in the category across all years in our data: single cup coffee, ground coffee, and instant coffee (43.9%, 39.9%, and 6.4% of total coffee dollar spend, respectively). In the laundry detergent category, we remove the two subcategories which have less than 1% of sales towards sustainable products (we discuss how we determine a product is sustainable below), leaving just the liquid laundry detergent subcategory. We include both yogurt subcategories, refrigerated yogurt and refrigerated yogurt drinks, which both command significant dollar shares of the yogurt category (90.5% and 9.5%, respectively). With limited ability to get more categories, we focused on the selection of three that are different across a range of factors, as mentioned above, in order to see if there are effects that still generalize across them.

Retail Variables For each UPC, we observe units sold and dollars spent for each week and store in the data. We compute average prices each week within a store for a UPC by dividing dollars spent by units sold. In addition to weekly purchases, the data include for each UPC its category, subcategory, brand, description, flavor or scent, volume in terms of a standard size (16 ounces), and an indicator for whether the product is organic. The organic indicator is present for both edible categories, coffee and yogurt, and we use it to supplement our sustainability claims data which we describe below. Among the three categories in our study, we observe over 27,000 unique UPCs from over 25,000 stores in the US. Table 1 shows the number of items (UPCs) and corresponding brands that are observed within each product category.

Insert Table 1 here

The retail data also include the state and county in which a store is located, as well as the store format (either club, grocery, or mass merchandiser) and an anonymized store identifier, though we do not observe the identity of each store nor the chain it belongs to. The sample of stores spans 2,445 counties in 52 states[5], which represents a significant portion of the total 3,242 counties in

[5]Including Washington D.C. and Puerto Rico.

the US. Table 2 shows the total number of stores of each format, the prevalence of each type within counties, and the average price (per 16 oz) of products sold in each of the three categories in our data. Grocery stores are the most common store format, consisting of 64.8% of all stores in our sample, followed by mass merchandiser stores (31.7%) then club stores (3.5%). Grocery and mass merchandiser stores both appear in over 1300 counties, while club stores only appear in over 400. Conditional on appearing in a county, there are on average about 12, 6, and 2 grocery, mass merchandiser, and club stores respectively per county. In terms of prices, club stores generally price lower than both grocery and mass merchandiser stores for all three categories. Due to the limited number of club stores and their low sustainable product shares, we focus our main paper on grocery and mass merchandiser stores (club store results are in Web Appendix 9).

Insert Table 2 here

It should be noted that the Circana scanner data retains records of purchases only when at least one unit of the product is sold in a store in a given week. As such, for product-store-week combinations with no observed purchases, we do not see the price of that product. Such an occurrence would occur if the product was not available in the store (i.e. a stock out) or if the product was available but no customers purchased it. We treat these observations as if the product were not available, though our analysis results are robust to alternative data specifications in which we impute prices for the week without an observation if there is an observed price for that product in a sufficiently "nearby" week within the store, within two weeks before or after.

Sustainability Claims

To assess whether a UPC was marketed as sustainable, we examined the 2018 packaging for all UPCs within the three categories of study (coffee, laundry detergent, and yogurt). As described earlier, we define a product as being "sustainable" if it contains any claims on its product packaging that highlight its influence on the health and/or welfare of humans, animals or the environment, thus taking a broad view of "sustainability". Label Insights data were used as a starting point but there were discrepancies between product content and what was claimed on the front-of-package. To address this and to fill in missing data, we hired four research assistants to code the sustainability claims.[6] In order to minimize coding errors, we 1) developed a codebook that identified which claims were considered sustainable per selected category; 2) coded whether the sustainability claim was present or absent; and 3) verified the results with a second coder. This resulted in a 97% agreement among coders. It is rare that the sustainability claims on packaging change over time; however, we updated the data using 2019 packaging for new UPCs that entered that year.

Table 3 displays the sustainability claims and the corresponding number of UPCs for the three categories of study. 32% and 46% of coffee and yogurt products respectively have sustainability claims, representing a significant portion of products within both edible categories. "Organic" and "Sustainably Sourced" claims are most prevalent in coffee, while "Organic" and "Non-GMO" are most prevalent in yogurt. On the other hand, laundry detergent has fewer products with sustainability claims, accounting for just 13% of the products in the category, with "Plant-based Ingredients" as the most common claim.

Insert Table 3 here

Product Definition

We aggregate UPCs in our definition of product, since characteristics such as flavor are not material for our analyses and we want to avoid missing data issues when specific UPCs may not have been purchased in any given week. We define a product j as a collection of UPCs that have the same brand[7], are of a similar size (which we refer to as being in the same "size bin", of which we specify six in each subcategory[8]), and are either sustainable or non-sustainable. We also define

[6]There were four coders: an undergraduate student, two graduate students, and one of this paper's authors.

[7]The brand names provided by Circana are fairly granular and we manually code a "parent" brand for each product (for example, the Circana dataset uses brand names such as "Starbucks", "Starbucks Coffee", "Starbucks Golden Smores", etc., which we group together under the parent brand "Starbucks") and use this as our brand definition instead of Circana's.

[8]We define products to be a "similar size" if they are classified within the same "size bins", which we construct using k-medoids clustering of the volume-equivalent sizes of all unique UPC's within the subcategory using six clusters.

a "product group" as the aggregation of both sustainable and non-sustainable products within the smallest three and the largest three size bins within each subcategory.

Geographic Heterogeneity and Trends

To summarize our retail data, we present geographic variation and trends in the market share, availability, and price premiums of sustainable products. To reduce the volume of figures, we aggregate products up to the category level. To compute market share of sustainable products, we use the total volume (in 16-oz units) of sustainable products within a category divided by the total volume of all products.[9] We construct an analogous measure of the relative availability of sustainable products, which replaces volume with an availability indicator equal to 1 if the product j was sold in store s in week t and 0 otherwise. For price premiums, we use a volume-weighted average of sustainable price premiums within each product group (as defined above) in the category, where the price premiums are in turn the percent difference in volume-weighted prices of sustainable vs. non-sustainable products within the product group.[10]

Figures 2 (grocery) and 3 (mass merchandiser) display the overall geographic time trends of the market share, availability, and price premiums of sustainable products, where each color represent a different US census division.[11] We aggregate each of these measures across counties within each census division[12], across weeks within each year of our data, and across product groups within each category. The figures show substantial geographic variation in sustainable product market shares. In addition to the cross sectional variation, there are clear upward trends for coffee and yogurt in all census divisions (roughly 5% and 10% increases in coffee and yogurt, respectively). On the other hand, only some census divisions have an upward time trend for

[9]One may also use the revenue or actual units sold instead of 16-oz volume-equivalent units sold to compute market share. The correlations between these three versions of "share" at the product group-county-week level are all greater than 0.96, a high enough figure that we view these metrics as interchangeable.

[10]Details on variable construction of these aggregate statistics can be found in Web Appendix 2.

[11]The Web Appendix show a series of maps displaying the market share (Figures W.1 and W.2), availability (Figures W.3 and W.4), and price premiums (Figures W.5 and W.6) of sustainable products in grocery and mass merchandiser stores at the county level for each product category in both 2015 and 2019, the first and last years of our sample period.

[12]There are 9 census divisions in the US. See `https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf` for details.

laundry detergent. In general, both the geographic variation and yearly time trends in sustainable market shares mirror the availability of sustainable products, shown in the second row of Figures 2 and 3. We note that the levels of sustainable availability are higher than the sustainable market share levels in the coffee and laundry detergent categories, while the levels are more similar in yogurt.

The third rows of Figures 2 and 3 show the relationship between price premium and market shares (and availability) are not as consistent. For the coffee category, the highest market share census division has the lowest price premium, which we might expect with price sensitive consumers. However, for laundry detergent, the highest price premiums are in areas with large sustainable market share, New England and the Pacific census divisions. For this category with much lower sustainable share, the price premiums are substantially lower.

County Demographics

Since our main objective is to link the large geographic heterogeneity in sustainable product outcomes to demographic heterogeneity in the US, we obtain county-level demographic data from the 2015-2019 five-year American Community Survey estimates. We first select variables that are frequently found in existing work linking demographics with sustainable consumption, including age, income, gender, and education (see e.g. Diamantopoulos et al. 2003; Grunert, Hieke, and Wills 2014; Roberts 1996; Verain, Dagevos, and Antonides 2015; Ngobo 2011; Kiesel and Villas-Boas 2007). While some of these factors are consistently shown to correlate more with greater sustainable behavior across studies, namely gender (female) and higher education, the existing literature is mixed regarding the effects of age and income. The extent to which these factors then influence profit potential and availability remains an open question, and so we include in our analyses each county's median age, median household income, fraction of the population who are female, and fraction of the population who are college educated.[13]

We also include political affiliation (which we measure using the Democratic vote share in

[13]Data on the fraction of the population who are college educated is conditional on the population within a county who are 25 or above in age.

the 2016 presidential election[14]) as one of the demographic variables in our study. Unlike the aforementioned demographics, political affiliation is strongly tied to political and personal values (Goren 2005; Schwartz, Caprara, and Vecchione 2010), which in turn influence environmental behavior (Karp 1996). Indeed, much of the literature finds more liberal political beliefs or affiliation to be correlated with sustainable intent, willingness to pay for sustainable products, and sustainable behavior (Roberts 1996; Mathur and Moschis 2022; Carlsson et al. 2021; Watkins, Aitken, and Mather 2016; Hornsey et al. 2016). Building on these findings, we argue that it is of substantial importance to firms to understand the relationship between a market's political leanings and sustainable product profitability as well as availability.

Lastly, we include two variables that have received less attention in the literature on sustainable consumption, which are population density and race. Regarding population density, existing work does show rural consumers state greater behavioral intent towards the environment compared to an urban sample (Berenguer, Corraliza, and Martín 2005), but industry reports in CPG link more urban consumers to an increased likelihood for purchasing sustainable products (Kronthal-Sacco and Whelan 2023). Given distribution and volume considerations when serving urban vs. rural markets, understanding sustainable product outcomes based on urbanicity is a managerially relevant avenue of research. To this end, we collect county-level measures of population density using total population divided by the county land area.

Regarding race, the relatively few studies investigating its role in consumer attitudes and behavioral intent regarding sustainability show a more consistent picture. Macias (2016) find greater likelihood in engaging in sustainable behaviors among minorities, Burt, Fera, and Lewin-Zwerdling (2021) show people of color have higher valuations for sustainable food, and Hornsey et al. (2016) link non-white consumers with greater beliefs in climate change (albeit a small effect). Race is also an important factor to examine given the historic issues with access to essential retail goods, specifically in the categories of health (Kwate et al. 2013) and food (Alkon and Agyeman 2011). Whether this lack of access in areas with larger populations of minorities similarly

[14] Data on Democratic vote share are from the US Census Bureau.

applies to sustainable products, despite their positive attitudes and intent towards sustainability, is an empirical question. Thus, to examine the degree to which the racial makeup of a county affects sustainable demand, profit potential, and availability, we collect data on the fraction of each county's population who are white.

A summary of the county demographics data we collect is provided in Table 4.

Insert Table 4 here

DEMOGRAPHIC PREDICTORS OF SUSTAINABLE PRODUCT OUTCOMES

Having summarized our data, we now explore associations between the demographics mentioned above and multiple downstream outcomes of sustainable products, namely market shares, availability, and price differences (to non-sustainable products). Unlike the yearly trends displayed in the previous section, since demographic variables could feasibly affect these outcomes differently within each subcategory, we run this and all subsequent analyses within a subcategory instead of the category level.

Specifically, we estimate the following descriptive regression, which we run separately for each subcategory and store format:

$$Y_{gmt} = \mathbf{Z}'_m \theta + \kappa_{gt} + \epsilon_{gmt}, \tag{4}$$

in which Y_{gmt} is either the log of sustainable market share, the log of sustainable product availability share, or the log ratio of sustainable vs. non-sustainable product volume-weighted price for product group g in county m at time t. For brevity, we show our results with log of sustainable market share as the dependent variable in the main text and present results for the other two dependent variables in Web Appendix 4. The $\mathbf{Z}_m$ are the county demographic variables described above, and the associated coefficients θ are estimated for each subcategory and store format. The κ_{gt} are product group-week fixed effects (recall that within each individual subcategory, there are two product groups, either large or small products in terms of actual product size within the subcategory). We run the sustainable market share regression both with and without controls for the log availability share and log price ratio. Standard errors are clustered by county and week. Summaries of the estimated effects in these regressions are shown in Figure 4, where dots and triangles represent point estimates (the triangles represent regressions which include the availability and price controls) and lines represent the 95% confidence intervals. The colors represent different product subcategories.[15]

As expected, there are positive effects of availability and negative effects of price premium on sustainable product market share. However, given the endogeneity of price and availability, we do not want to over-interpret the size of these coefficients. We expect the coefficients to be biased in the positive direction since availability and price should both increase with unobserved preferences for sustainable products.

In grocery stores, Democratic vote share in the 2016 presidential election is positively related to sustainable market share for four of the subcategories, and is negatively related for just one. In mass merchandiser stores, it is positively related for five subcategories, and four after controlling for availability and price. These results are indicative of stronger preferences for sustainable products by consumers who vote Democratic. Similarly, the effect of fraction college educated is positive and significant for five of the six subcategories and declines only slightly when controlling for availability and price. In sharp contrast, the large effects of age and the fraction of the population that is white are greatly reduced by the inclusion of the controls for availability and price, suggestive that a good portion of the reduced demand for sustainable products in counties with older and larger minority populations is due either to higher price premiums or limited availability. Tables W.7 and W.8 in the Web Appendix show price premiums and availability generally skew smaller with age, indicating that reduced availability is likely the reason for the large change in shares when controlling for these factors. Similarly, price premiums and availability generally are larger with the fraction of the population that is white, so again, lack of availability is a possible reason for reduced shares for sustainable products in counties with larger minority

[15] Full regression results are shown in the Web Appendix in Table W.1 for the grocery format and Table W.5 for the mass merchandiser format.

(smaller white) populations.[16]

The descriptive results outlined above hint at supply-side factors (e.g. price and availability) that potentially influence the heterogeneity in shares for sustainable products across markets. However, these descriptive regressions do not disentangle the causal relationships between market shares and either price or availability. We expect higher prices to lead to lower shares, but higher prices are also indicative of higher consumer willingness to pay and less elastic demand. Similarly, higher availability could lead to higher market shares, but it could also be driven by greater overall demand.

The preceding discussion underscores the importance of examining the underlying relationship between these factors. In what follows, we look to measure the profit potential of products, which incorporates the role of both demand and price, while also accounting for the price elasticity of demand, which determines optimal margins. Examining determinants of profit potential enables us to highlight markets that could benefit firms to introduce sustainable products in (our first research question). Investigating the determinants of availability of sustainable products, controlling for profit potential, then allows us to discern whether firms' provisioning of sustainable products is driven by the potential profitability of those products (which, again, incorporates consumer demand), or otherwise (our second research question).

PRICE ELASTICITIES

In order to estimate profit potential, we need estimates of price elasticity, which help determine a product's optimal margin, as described earlier. We estimate product-county-level price elasticities in two steps. First, we flexibly estimate price elasticities for each product within a county (within subcategory and store format) using a log-linear demand regression (Hitsch, Hortacsu, and Lin 2021). Second, recognizing these estimates are potentially imprecisely estimated, we conduct an empirical Bayes deconvolution to obtain posterior estimates of the price elastici-

[16] Some of the other demographic effects on sustainable market share are not consistent across subcategories (Figure 4). For example, while household income leads to higher sustainable share for ground and single cup coffee in grocery stores, it predicts no difference or a lower share for instant coffee, refrigerated yogurt drinks, and liquid laundry detergent. Other effects are more consistent.

ties. In this section, we detail both of these steps, then discuss the resulting estimates.

Demand Estimation

Following Hitsch, Hortacsu, and Lin (2021), we estimate the following log-linear demand regression for each product j within each store s at week t in market m (county) at the subcategory and store format level to obtain causal estimates of price elasticities:

$$\log(q_{jst}) = \alpha_{jm} \log(p_{jst}) + \mathbf{X}'_{jst}\boldsymbol{\beta}_{jm} + \eta_{js} + \tau^0_{st} + \tau^1_{st}\mathbb{1}\{Sus_j = 1\} + \epsilon_{jst}, \tag{5}$$

where q_{jst} is the quantity of product j sold in store s in week t, p_{jst} is the price index[17] of product j in store s in week t, and $\mathbf{X}_{jst}$ are a series of observed control variables that we describe below. Due to the log-log specification for quantity and price, α_{jm} is the price elasticity of demand for product j in market m over the support of the data. The $\boldsymbol{\beta}_{jm}$'s reflect the effects of the control variables on demand, while η_{js}, τ^0_{st}, and τ^1_{st} are fixed effects which we explain below.

Rather than assuming a particular functional form for demand, which imposes functional restrictions, we model the demand as flexibly as we can. We control for several product and store characteristics in $\mathbf{X}_{jst}$, including variables related to both the focal product itself as well as the competitive environment facing the focal product within the store. Variables related to the focal product are 1) an indicator for whether any underlying UPC was promoted that week, either as a display or feature; 2) a weighted price index of all other products within the same brand but not the same size bin as the focal product j, delineated by sustainable and non-sustainable if applicable, using the other own-brand products' yearly revenue in the store as weights, 3) a promotion indicator for whether any other products within the same brand but not the same size bin as the focal product j was promoted, delineated by sustainable and non-sustainable if applicable; and 4) the number of underlying UPCs within the product.

With respect to the competitive environment facing the focal product, we include indexes

[17] The price index is computed as a weighted average price across all UPCs that make up product j in store s at week t, where the weights are the total volume sold of the respective UPC in store s in the year that week t is in.

for competitor prices, promotions, and product mix. We define the competitor price index as the weighted average price of competing products within the set of sustainable (or non-sustainable) products in the store that week, using the competitor's yearly revenue in the store as weights to allow the prices of more "prevalent" products to have a greater impact on demand for the focal product. The competitor promotion index is computed as the proportion of products with any underlying UPC that is featured or displayed that week. Lastly, we include two types of product mix variables. First, we include the number of competing products in the store that week. In all cases, "competitor" products are those within the same size bin and subcategory as the focal product. Second, we allow an additional effect on demand if the product is a "monopolist" by including an indicator for whether the product is the only one within its size bin that is sold in the store in that week. To allow for differential effects of the control variables for both sustainable and non-sustainable products, all indexes are measured for the set of sustainable and non-sustainable competitors separately.[18].

To control for baseline product demand in each store, we include product-store fixed effects, η_{js}. We control for time-varying demand for products using store-week fixed effects, τ^0_{st}, which are common to the county and subcategory we run each regression in. These controls account for both product-varying sources of endogeneity (e.g. arising from product quality or different customer bases) and time-varying sources of endogeneity (e.g. seasonality). We include a separate set of store-week fixed effects for sustainable products, τ^1_{st} (which is "on" when the indicator for product j being sustainable, Sus_j, is equal to 1), allowing for time-varying baseline valuations of sustainability. These separate fixed effects for sustainable products are important to include in order to separately identify price elasticities from baseline preferences. For example, in our data we see price premiums for sustainable coffee products decrease while market shares increase. If we did not include separate store-week fixed effects for sustainable products, the increase in demand would be entirely attributed to the price elasticity term α_{jm}, resulting in a much higher (more negative) price elasticity estimate. By allowing the baseline demand for sustainable prod-

[18]Detailed descriptions of all variables used in our demand regressions are shown in Table W.13 in Web Appendix 5

ucts to differ from those of non-sustainable ones, we are able to estimate two sources of demand for sustainable products – both baseline preferences and price elasticity.

We apply two additional restrictions in terms of our data. To ensure less common UPCs do not spuriously affect a product's price index, we use only UPCs that appear in our data for greater than two years' (104 weeks') worth of periods in each store when aggregating to the product (brand-sustainable-size bin) level in our data. We further keep only stores that have both sustainable and non-sustainable sales such that our elasticity estimates reflect demand in stores where both sustainable and non-sustainable products are available. Despite these restrictions, our regressions use a subsample of UPCs and stores that cover roughly 70%-80% of revenue in most subcategories across both grocery and mass merchandiser store formats, for both sustainable and non-sustainable products alike (see Table W.9 in Web Appendix 5). Due to the former restriction, we are also able to ensure most of the products in our demand regressions are usually always available across weeks within the stores they are in, with the median product observed in over 90% of weeks[19] for most subcategories and store formats (see Table W.10 in Web Appendix 5). Additional estimation details and robustness checks are also described in Web Appendix 5. Our main specification consists of 22,917 total regressions and 565,563 product-county-specific own-price coefficient estimates.[20] We use two-way cluster-robust standard errors at the product and week levels for all regressions.

The main coefficients of interest are the own-price coefficients, α_{jm}'s, which represent own-price elasticities for each product j within a county m. We compute county-level (instead of store-level) elasticities for each product due to the fact that in some cases there is insufficient price variation within a single store to estimate sensible price elasticities, requiring us to pool our estimates at the next level of aggregation. With the set of fixed effects we utilize, identification results from comparing differences in demand for a product relative to the subcategory as a function of varying prices across time within a store.

[19] Proportion of store weeks a product is available in within a store is out of the total number of weeks between the first and last week the product was observed in the store.

[20] In total across all product categories and model specifications, we run over 180,000 regressions and obtain over 1.5 million own-price and competitor price elasticity estimates.

Empirical Bayes Deconvolution

Despite the advantages of the flexible demand system in removing functional assumptions in estimation, this flexibility results in a wide empirical distribution of price elasticities, some of which are imprecisely estimated when there is limited price variation within the county.

In order to address this imprecision, we conduct an empirical Bayes deconvolution of our elasticity estimates (Efron 2016; Wernerfelt et al. 2022). For all products j in a market m, our demand estimation yields the tuple $(\hat{\alpha}_{jm}, s_{jm}^2)$, the elasticity coefficient estimate and standard error, respectively, in our sample period. We model the elasticity estimates as realizations of a hierarchical Normal-Normal model:

$$\begin{aligned} \hat{\alpha}_{jm} &\sim N(\alpha_{jm}, s_{jm}^2), \\ \alpha_{jm} &\sim N(\mu_j + \mathbf{W}_{jm}'\boldsymbol{\gamma}_j, \sigma_j^2), \end{aligned} \tag{6}$$

in which the estimated elasticities $\hat{\alpha}_{jm}$ are assumed to be drawn from a Normal distribution centered around the true elasticity α_{jm} with variance s_{jm}^2, the standard error of the estimate. The true elasticity α_{jm} is modeled also as a Normal distribution centered around the expression $\delta_{jm} \equiv \mu_j + \mathbf{W}_{jm}'\boldsymbol{\gamma}_j$. We can interpret δ_{jm} as the *expected* elasticity of product j in market m, given a set of observed product and county covariates in $\mathbf{W}_{jm}$. The μ_j is the product "baseline" elasticity given zeros for all values in $\mathbf{W}_{jm}$ and $\boldsymbol{\gamma}_j$ is the product-specific effect of the covariates on the expected elasticity. The covariates we use in $\mathbf{W}_{jm}$ are all the market-level (county-level) demographic variables that are used in the earlier descriptive regressions as well as two competition variables: the average number of sustainable and non-sustainable competitors of product j within each store-week observation, across all weeks and stores within the county.[21]

For any product j in county m, we are interested in the posterior distribution of the true elasticity, conditional on the estimated elasticity coefficient and standard error, $f(\alpha_{jm}|\hat{\alpha}_{jm}, s_{jm}^2)$. Since we have assumed a normal likelihood and normal prior, the posterior is also normally

[21]Detailed definitions of the variables in the underlying empirical Bayes deconvolution in (6) are provided in Table W.14 in Web Appendix 5

distributed with expectation and variance as follows:

$$
\begin{aligned}
\mathbb{E}[\alpha_{jm}|\hat{\alpha}_{jm}, s_{jm}^2] &= \frac{\sigma_j^2}{\sigma_j^2 + s_{jm}^2}\hat{\alpha}_{jm} + \frac{s_{jm}^2}{\sigma_j^2 + s_{jm}^2}(\mu_j + \mathbf{W}'_{jm}\boldsymbol{\gamma}_j), \\
\mathrm{Var}[\alpha_{jm}|\hat{\alpha}_{jm}, s_{jm}^2] &= \frac{s_{jm}^2 \sigma_j^2}{\sigma_j^2 + s_{jm}^2}.
\end{aligned}
\tag{7}
$$

For every product j for which we observe estimated price elasticities (across counties), we obtain estimates of each of the hyperparameters μ_j, $\boldsymbol{\gamma}_j$, and σ_j^2 using maximum likelihood, then compute the posterior means and variances using (7).

Price Elasticity Results

Sustainable vs. Non-Sustainable Price Elasticities In Figure 5, we show the distributions of posterior mean estimates of own-price elasticities for the set of sustainable (in blue) and non-sustainable (in red) products in both grocery (Figure 5a) and mass merchandiser (Figure 5b) stores, in which the unit of observation is a product-county. We use counts along the y-axis in order to show the relative number of product-county estimates for each type of product within each subcategory. Dotted vertical lines show the median of the distributions, and the dotted lines of each color show the distributions of the subset of estimates which are statistically significant (the vast majority).

In the grocery store channel, the median sustainable product is roughly 10% to 25% less elastic than its median non-sustainable counterpart for ground coffee, instant coffee, and liquid laundry detergent. There are smaller differences in the same direction for single cup coffee and yogurt, while there is no discernible difference for yogurt drinks. A smaller (in magnitude) elasticity implies a higher optimal margin, and thus more profit potential at the same level of demand and price.

Insert Figure 5 here

In contrast to grocery stores, in mass merchandiser stores we find that the median sustainable ground coffee, single cup coffee, yogurt, and liquid laundry detergent products have price elasticities that are roughly the same as or to the left of (i.e. more elastic than) the median non-sustainable counterparts. Yogurt drinks is the only subcategory in which the difference in grocery and mass merchandiser goes in the opposite direction, with price elasticities of sustainable yogurt drink products being less elastic than non-sustainable ones.

We hesitate to draw broad conclusions about the heterogeneity in price elasticities, which show inconsistent differences between sustainable and non-sustainable products when comparing store formats. In line with this notion, boxplots of the hyperparameters (μ_j, γ_j) of the deconvolution estimates (which are at the product level) demonstrate no systematic effects of the number of sustainable or non-sustainable competitors or the demographic variables on the distribution of hyperparameters (and subsequently price elasticities), as reported in Web Appendix 6.2, Figures W.15 and W.16). This indicates the marginal utilities of sustainable vs. non-sustainable products are not the same across markets and store formats.

Price Elasticities by Sustainability Claim & Number of Claims Another source of heterogeneity in price elasticity might be through the type or number of claims. A benefit of estimating product (and county) specific elasticities is we can summarize the results based on specific product characteristics beyond just comparing sustainable to non-sustainable products, and we discuss here the distributions of elasticities along both of these aforementioned dimensions. In Web Appendices 6.3 and 6.4, we show the kernal densities of the price elasticities by type of claim and number of claims, respectively. We find evidence somewhat consistent with some of the prior literature showing that consumer willingness to pay for such products are highest when the beneficiary of the claim is humans and the lowest for the environment (Tully and Winer 2014).[22]

Additional Discussion on Price Elasticities Differences in price responses can be consistent with both heterogeneity in preferences (Blattberg and Wisniewski 1989; Johnson and Myatt 2006) and nonhomothetic choice models (Allenby and Rossi 1991; Allenby, Garratt, and Rossi 2010), in which demand for any given product depends on the level of possible utility from the

[22] We provide additional discussion and interpretation on these results in Web Appendices 6.3 and 6.4.

category.[23] Under nonhomothetic choice, a higher quality brand can have a higher price elasticity than a lower quality brand due to the interaction between income effects with product substitution effects, leading to rotations of consumer indifference curves. In our context, we note sustainable product demand tends to become more elastic as sustainable product market share increases across categories; for example, in grocery stores, laundry detergent has low sustainable market share and much lower sustainable price elasticity relative to non-sustainable products, compared to yogurt which has high sustainable market share and relatively similar price elasticities between the two types of products (see Figure 2 for market shares). This also suggests nonhomothetic demand, since substitution to the more sustainable products (from the non-sustainable products) will increase as the attainable utility increases (Allenby, Garratt, and Rossi 2010). While the increase in elasticity implies lower optimal margins, this should be more than offset by the increase in demand, since the rotation of the demand curve is outward under the assumption of nonhomothetic choice.

The elasticities also affect optimal pass through rates of cost changes. As noted by Butters, Sacks, and Seo (2022), the pass-through rate of a cost decline will depend on the curvature of the demand curve, $\zeta \equiv -p(q''/q') = -(q''/q)/(q')^2$, in which q'' is the second derivative of demand with respect to price. The pass through of a cost decline will be:

$$\rho \equiv \frac{dp}{dc} = \frac{1}{2 + \zeta/\alpha}. \tag{8}$$

With downward sloping demand, α is negative, and with convex demand, ζ is positive. The larger (in magnitude) the price elasticity (or the greater the curvature of the demand curve), the larger the pass-through rate of any costs associated with producing more sustainable products. If the costs of sustainable products can be reduced, either through economies of scale or other advances, these costs reductions will be reflected more in price when consumers are more price elastic. In other words, if cost declines lead sustainable products to appeal more to a broader set of more

[23] Unfortunately, it is difficult to distinguish between preference heterogeneity and nonhomothetic choice in our empirical setting.

price elastic consumers, optimal margins then decline, further broadening the set of consumers who might purchase sustainable products.

The potential link between demand and price elasticity highlights the importance of measuring not just price elasticity by itself. As alluded to in our empirical roadmap, our main measure of interest is profit potential, of which price elasticity is only one component, along with prices and quantities.

PROFIT POTENTIAL

With product-county level posterior estimates of price elasticity in hand, we are now able to compute the profit potential using observed prices, quantities, and estimated price elasticities, following (3). In this section, we first examine the distribution of sustainable and non-sustainable product-county level profit potential in each of the subcategories. We then examine demographic determinants of profit potential of sustainable vs. non-sustainable products.

Sustainable vs. Non-Sustainable Profit Potential

Product-county level profit potential following (3) is given as:

$$\log(\tilde{\pi}_{jm}) \equiv \log(\bar{q}_{jm}) + \log(\bar{p}_{jm}) - \log(-\tilde{\alpha}_{jm}), \tag{9}$$

where $\bar{q}_{jm}$ is the mean of weekly volume sold of product j in county m, $\bar{p}_{jm}$ is the weighted mean of store-week price index of product j in county m, where the weights are the total volume of product j sold within the year the week is in (the same as those used in the demand estimation regressions), and $\tilde{\alpha}_{jm}$ is the posterior expectation of product-county level price elasticity α_{jm}.[24]

Note that profit potential increases with all three of these components: the sum of the first two is log revenue and the third, $-\log(-\alpha_{jm})$, is log margin (with optimal pricing). As previously noted, equilibrium prices and quantities are jointly determined, with optimal pricing depending

[24]Both quantity and price measures are conditional on observing volume sales and prices respectively in the data.

on the elasticity of the marginal consumer at that price level. Some products may be more profitable because of high levels of demand, whereas others may be demanded by a smaller segment of very inelastic consumers, allowing firms to charge a higher margin.[25]

Insert Figure 6 here

Kernel densities of profit potential are shown in Figure 6 for grocery and mass merchandiser store formats respectively. Overall, sustainable products in both store formats have higher median profit potential compared to non-sustainable products, except for liquid laundry detergent, which has the lowest penetration of sustainable products. For most subcategories and in both store formats, the difference between the median profit potential of sustainable and non-sustainable products shows the same sign as the difference in the respective median price elasticities (Figure 5). Again, the only exception is liquid laundry detergent (in this case just within grocery), in which sustainable products are much less elastic but still have smaller profit potential due to their very low sales. In contrast, in the other subcategories in which sustainable products are less price elastic, the sustainable products are more profitable.

Profit Potential and Demographics

While sustainable products appear to exhibit larger profit potential on average than non-sustainable products in most subcategories, Figure 6 shows significant heterogeneity across product-county estimates. We investigate the demographic determinants of this heterogeneity using the following regression:

$$\begin{aligned} \log(\tilde{\pi}_{jm}) &\equiv \log(\bar{q}_{jm}) + \log(\bar{p}_{jm}) - \log(-\tilde{\alpha}_{jm}) \\ &= \mathbf{Z}_m'(\boldsymbol{\phi} + \boldsymbol{\phi}^S \mathbb{1}\{Sus_j = 1\}) + \psi_j + \epsilon_{jm}. \end{aligned} \tag{10}$$

We regress product-county-level profit potential in (9) on the same set of demographic variables, $\mathbf{Z}_m$, as in our earlier descriptive regressions, both with and without a control for product pene-

[25]In Web Appendix 7, we examine the tradeoff by showing the correlation between the three profit potential components for each of the subcategories in the grocery and mass merchandiser channels.

tration, which we define as the total number of store-week observations that specific product was available in stores within the county.[26] We allow these variables to be interacted with an indicator $\mathbb{1}\{Sus_j = 1\}$) for whether product j is sustainable. Thus, $\boldsymbol{\phi}$ captures the effect of demographics on product-county-level profit potential for all products, while $\boldsymbol{\phi}^S$ captures the additional effect of demographics on product-county-level profit potential for products that are sustainable. We include a product intercept ψ_j and perform two-way clustering by week and brand.

Insert Figure 7 here

Grocery Stores The results for the grocery store format are shown in Figure 7, with each point representing the coefficient point estimate and the vertical lines representing 95% confidence intervals. Each color represents a different subcategory. Triangular points represent the regression in (10) without controlling for product penetration, while circular points represent those with the additional control variable. Because the dependent variable is in logs, the effects can be interpreted as leading to a relative increase of that amount. A coefficient of one on Democratic vote share (in the 2016 presidential election) means that if the fraction of the zip code that voted Democrat increases by 0.1 (ten percentage points), it would increase profit potential by 10%. We first examine the top two rows in the figure, which shows the effects of each demographic variable on profit potential for the baseline (non-sustainable) products. Population density has a limited effect on profitability of products in general, after controlling for product penetration. Income predicts higher product profit potential for all six categories, and Democratic vote share and the fraction of the population that is white do so as well for five of six categories, with single cup coffee the lone exception. Effects of gender and college education are mixed. Higher median age leads to lower profits, and more product penetration leads to higher profits, as expected. Controlling for product penetration does not discernibly change the effects of the other demographic variables, excepting population density.

[26]Products with lower penetration may have more limited ability for consumers to purchase them, exhibit less loyalty, and have lower awareness.

The key estimates of interest are for the interactions of the demographic variables with the indicator for sustainable, shown in the bottom two rows of Figure 7. Income does appear to enhance the profit potential of sustainable products for four of the subcategories (one being marginally significant). Democratic vote share has positive and economically meaningful (larger than 0.25) effects as well, although the effects are imprecisely estimated in most of the subcategories. Fraction female and fraction college educated have positive and significant effects for two and three subcategories, respectively, with the opposite sign as their corresponding main effects. Race and age do not systemically predict profit potential in the same way across the subcategories, despite the fact that we observed county-level measures of product availability to be consistently lower in areas with smaller white and older populations (with yogurt drinks the exception for both).

Insert Figure 8 here

Mass Merchandiser Stores Figure 8 shows the effects of demographics on profit potential in the mass merchandiser store format are different to those for grocery stores. In the top two rows of the figure, we no longer observe the consistent positive effects of income, Democratic vote share, and fraction white on overall product profits, and in fact, Democratic vote share predicts lower profits for three of the subcategories.

Moving to the interaction terms in the bottom two rows, income and Democratic vote share does lead to higher profit potential for sustainable ground and instant coffee, relative to the non-sustainable alternatives. Fraction college educated increases the relative profits for sustainable products in every category but yogurt drinks. The size of these effects are substantially bigger than for grocery stores, with coefficients between 1 and 2. A coefficient of 2 on these interaction terms means that an increase of 10 percentage points in the Democratic vote share leads to a 20% increase in the profit potential for sustainable products (relative to non-sustainable). When controlling for the product penetration of a given product, the effects of household income and fraction of the population that is white are insignificant for every subcategory except ground coffee, with point estimates that are near zero or negative.

Some differences across store formats are to be expected. Carpenter and Moore (2006) show that different demographic groups frequent different types of stores, and thus we would expect the marginal sustainable consumer to be different in the two different formats. That said, we do still see some effects that appear systematic across categories, which we examine using a meta-analysis next.

Meta-Analysis We summarize the results of our regressions of product-county level profit potential on demographics using a random effects meta-analysis of each of the coefficients estimated from the twelve separate regressions across the six subcategories and two store formats. Figure 9 shows the pooled effect of each of the coefficients, with the middle of each diamond the estimated pooled effect and the length representing the 95% confidence interval.

Insert Figure 9 here

Profit potential irrespective of product type (the main coefficients) increases on average with product penetration, household income, and fraction of the population that is white, while it decreases with log of median age. When examining the incremental profit potential for sustainable products (the interaction coefficients), we see that profits are on average higher with household income, Democratic vote share, and fraction of the population that is college educated.

DEMOGRAPHIC EFFECTS ON SUSTAINABLE PRODUCT AVAILABILITY

Having estimated profit potential, we now estimate the effect of demographic variables on sustainable product availability, controlling for profit potential. Without this control, these effects could simply be reflective of the profit potential of the product which reflects the underlying demand conditions. With the control for profit potential, we are able to estimate the direct effect of demographics on the availability of sustainable products. For each subcategory and store format, we regress the relative availability of sustainable products (over non-sustainable products) within a product group g on the relative profit potential of sustainable products (over non-sustainable products) within that product group and the same county demographics $\mathbf{Z}_m$ as above, as follows:

$$\log\left(A^{S/NS}_{gmt}\right) = \omega \log\left(\tilde{\pi}^{S/NS}_{gmt}\right) + \mathbf{Z}'_m\theta + \kappa_{gt} + \epsilon_{gmt}. \tag{11}$$

The dependent variable, $\log\left(A^{S/NS}_{gmt}\right)$, is the ratio of sustainable product availability over non-sustainable product availability within product group g in market m at time t, where availability is defined as the total UPC-store-week observations within each group of products. $\tilde{\pi}^{S/NS}_{gmt}$ is the ratio of sustainable (over non-sustainable) product profit potential within product group g, county m and week t. To obtain the profit potential ratio, we first compute a weekly profit potential for each product within each county, $\log(\tilde{\pi}_{jmt}) = \log(q_{jmt}) + \log(\bar{p}_{jmt}) - \log(-\tilde{\alpha}_{jm})$, where q_{jmt} is the total volume for product j at the county level m within week t, $\bar{p}_{jmt}$ is the price index p_{jst} aggregated to the market level m using the same price index weights, and $\tilde{\alpha}_{jm}$ is the posterior expectation of product-county level price elasticity, as above. We then take the average of the weekly profit potential across products within either sustainable or non-sustainable. We denote these aggregated measures for sustainable and non-sustainable profit potential as $\tilde{\pi}^{S}_{gmt}$ and $\tilde{\pi}^{NS}_{gmt}$, respectively, where the ratio that we take to the regression is simply $\tilde{\pi}^{S/NS}_{gmt} = \tilde{\pi}^{S}_{gmt}$ / $\tilde{\pi}^{NS}_{gmt}$. The κ_{gt} term denotes a product group-week fixed effect. ω captures the effect of the relative profit potential of sustainable products on the relative availability of sustainable products, and θ shows the remaining demographic effects after profit potential is accounted for. We conduct two-way clustering of standard errors by county and week.

We restrict our sample to the set of counties for which we have profit potential estimates for both sustainable and non-sustainable products, since our profit potential measures rely on our estimates of price elasticity which we also estimate only using stores with both types of products present. However, as noted before, restricting to UPCs which are available for at least 104 weeks leads to very few observations in which products are not available in a given week, given they are available in the market at all. Table W.10 shows the median proportion of time the product is available per store – the lowest value is 82% of the time, and for most subcategory-store format combinations the number is over 95% of the time.

Insert Figure 10 here

The results of the analysis are shown in Figure 10 for both store formats.[27]

First, we examine the coefficients on the log of the profit potential ratio. The estimates range between 0.05 and 0.15 for grocery but just 0.00 and 0.05 for mass merchandiser. With the log-log specification, these coefficient estimates can be thought of as elasticities; a coefficient of 0.1 means that a 10% increase in the relative profit potential of sustainable products to non-sustainable products leads to a 1% increase in the availability of sustainable products. These results indicate the potential profitability of sustainable products is much more predictive of its availability in the grocery format compared to the mass merchandiser format.

While striking, this contrast becomes easier to interpret once we investigate the availability in different markets of different products in terms of whether they are local, regional, or national.[28] Table W.11 in Web Appendix 5 shows that in general, grocery stores have more local and regional products than mass merchandiser stores. We might expect that this indicates grocery store managers have or use more discretion in determining whether to stock a given product, in particular from non-national brands. This makes sense given the results of Fox, Montgomery, and Lodish (2004), who find that consumer perceptions of regional product assortment have a direct impact on a retailer's local image and consumer loyalty to the retailer, especially in grocery chains. As such, grocery managers may rely more on local demand to make product availability decisions, whereas mass merchandiser stores vary their product assortment less based on local demand conditions and primarily stock national products.

In addition, we see that local and regional brands stocked by grocery stores have a far greater share of their products that are sustainable relative to those stocked in mass merchandiser stores

[27] As before, the points denote the estimated coefficients with vertical lines showing their 95% confidence intervals, with each color representing a different subcategory. Circular points are for regressions that are run without profit potential as a control, while triangular points represent those with the control. Filled-in points show the results for grocery stores and unfilled points those for mass merchandiser stores.

[28] We define local products as those that appear in five or fewer states in our sample period and national products as those that appear in twenty or more states. Regional products are those that appear in between five and twenty states.

in four of the categories (with only slightly lower shares in the other two), as shown in Table W.12 in Web Appendix 5. This again helps explain the finding that the relative profit potential of sustainable products is more predictive of their availability in the grocery format — grocery stores tend to utilize underlying demand conditions of a local market more so than mass merchandisers, and so they are more likely to include a profitable local or regional sustainable product.

Next, we discuss the demographic effects on availability. While the inclusion of profit potential as a regressor shifts the demographic effects towards zero for the vast majority of estimates, this shift is small. We observe that some demographic variables are still predictive of availability, even after controlling for the relative profit potential of sustainable products. Fraction white and fraction college educated both lead to more availability after conditioning on profit potential in 9 of the 12 subcategory-store format combinations. Democratic vote share does so as well, for 10 of the 12 subcategory-format combinations (at the 5% significance level). In general, these results show reduced availability of sustainable products is partly responsible for the lower share in markets with lower incomes, smaller fractions of the population that are college educated and white, and lower Democratic vote share.

Meta-Analysis We summarize the results of the above regressions using a random effects meta-analysis across subcategories and store formats. The results are shown in Figure 11.

Insert Figure 11 here

On average, we find the availability of sustainable products increases with household income, Democratic vote share, and the fraction of the county that is white and college educated. Other than the fraction of the county that is white, these variables also increased the profit potential of sustainable products relative to non-sustainable products (Figure 9). However, given that we control for profit potential in these regressions, these results indicate that these demographic variables have a direct effect on the availability of sustainable products above and beyond their effect through consumer preferences.

In the case of the fraction of the county that is white, this variable did not systematically lead to higher relative profit potential for sustainable products, and yet we still find that sustainable products are more available in counties with larger white populations. The one other common predictor of availability in the meta-analysis is the fraction of the county that is female, which leads to lower sustainable product availability, but we did not find this variable to systematically lead to higher relative profit potential for sustainable products either.

Overall, our findings indicate that product stocking decisions are likely made with heuristics rather than being based solely on the actual product potential of the products, and that managers have beliefs which may lead to more limited access to sustainable products for women and minorities.

Robustness Checks We conduct two robustness checks for the regressions of demographics and profit potential on availability. An implicit assumption in the availability regression (11) is that the profit potential of new sustainable entrants is similar to the average profit potential of the set of available products. As a robustness check, we instead assume that that the profit potential of new sustainable entrants is more similar to the lowest profit potential of the set of products in the market instead of the average. To do so, we replace the average profit potential with the minimum profit potential of sustainable and non-sustainable products. Figure W.21 in Web Appendix 8 shows the qualitative results remain the same after making this change.

Another critique of the conclusion that managers are using heuristic decision-making given that demographic effects on availability cannot be fully explained by profit potential is that we are only using the current profit potential of products. Thus, we also test whether including the expected future profit potential alters the main findings. We assume rational expectations and compute the expected future profit potential using an average of the weekly profit potential of a product (in a county) over the 51 weeks following the focal week. This specification accounts for the possibility of firms making supply-side decisions not just considering short-term but also longer-term profits. Figure W.22 in Web Appendix 8 shows the results of this analysis, and we again find that the main qualitative results remain the same.

CONCLUSION

In this paper, we examine the role of availability and demographic variables on sustainable product demand and profit potential. Prices and quantities are equilibrium objects, and the optimal product margin is determined by the product's price elasticity. Using a rich fixed effects estimation approach, we flexibly estimate price elasticities for every product in every county in the United States, for which we have sufficient data, in different store formats. These elasticities reflect the demand response at the observed equilibrium levels of prices and quantities.

Although profit potential and availability of sustainable products increase together with some demographic variables, in other cases the availability of sustainable products does not reflect their profit potential. In particular, we find that the relative profit potential for sustainable products increases with income, Democratic vote share, and fraction of the population that is college educated. The relative availability of sustainable products also increase with these same demographic variables, above and beyond what can be explained by profit potential. Despite the effect of age on sustainable profit potential, we do not find an effect of age on sustainable profit availability. Instead, we find that the relative availability of sustainable products decreases with a higher fraction of the county that is female and non-white, but these variables do not systematically influence sustainable product profit potential.

Since profit potential reflects a short-term firm objective rather than a long-term one, we do not rule out the possibility that supply-side decisions are informed by the goal of managing, for instance, brand attitudes. Olsen, Slotegraaf, and Chandukala (2014) show that brands tend to conform to the level of sustainability in the product category, in turn fostering improved attitudes towards their brand, which may be one reason to focus sustainability in certain categories (or, in the same spirit, markets) more than others. Another potential alternative explanation is firms may face difficulties in introducing sustainable products in markets due to the large fixed costs of product introduction relative to the available demand (Waldfogel 1999).

Our findings contribute to previous findings that examine the role of access to different types of products as a determinant of demand (Kwate et al. 2013; Vermeir and Verbeke 2006; Cerri, Testa, and Rizzi 2018), as well as the literature examining predictors of sustainable product attitudes and preferences (Diamantopoulos et al. 2003; Roberts 1996; Laroche, Bergeron, and Barbaro-Forleo 2001; Hornsey et al. 2016). Given the disconnect between the effect of some demographic effects on profit potential vs. their effects on availability, there are profit opportunities for managers to make sustainable products more available in these under-indexed markets.

The main limitation of this study is that we use the presence of a sustainability claim as an indicator of being more sustainable. We have no specific measure of carbon footprint, for example, for these products, as is done in a new working paper (Bronnenberg et al. 2024). This is largely due to the fact that the range of sustainability claims encompass much more than simply carbon footprint, given the fact they relate to the entire range of the United Nation's Sustainable Development Goals. An accounting of how each label makes progress along each one of these goals would be a commendable exercise that is beyond the scope of this paper. We instead focus on the consumer demand conditions and the product availability decisions by managers, another critical dimension in determining the role sustainable products can have in improving outcomes for external stakeholders.

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TABLES AND FIGURES

Table 1: Number of Items and Brands

Product Category	Number of Items (UPCs)	Number of Brands
Coffee	13,939	1,311
Laundry Detergent	4,653	455
Yogurt	9,319	547

Table 2: Summary Statistics Across Store Types

		Club	Grocery	Mass Merchandiser
Total Stores		890	16493	8070
Counties with Store Type		420	1343	1342
Avg. Stores of Type Per County		2.12	12.28	6.01
Std. Dev. of Stores of Type		2.11	26.10	11.08
Min Stores of Type		1	1	1
Max Stores of Type		13	344	133
Avg. Price ($/lb)	Coffee	9.41	15.59	14.08
	Laundry Detergent	1.74	2.00	2.10
	Yogurt	1.80	2.66	2.40

Table 3: Sustainability Claims in Coffee, Laundry Detergent, and Yogurt

Coffee		**Laundry Detergent**		**Yogurt**	
Claim	**Products**	**Claim**	**Products**	**Claim**	**Products**
No Claim	**10,836**	**No Claim**	**4,100**	**No Claim**	**6,586**
With Claim	**3,103**	**With Claim**	**553**	**With Claim**	**2,733**
Organic	1,825	Plant Based Ingredients	358	Non-GMO	1,200
Sustainably Sourced	605	All Natural	69	Organic	1,111
Fair Trade	563	Cruelty Free	66	Hormones Free	659
Rainforest Alliance	166	Biodegradable/Biocompatible	60	B-Corp	414
Other Claims	101	Other Claims	228	Other Claims	107

Table 4: Demographic Variables

Statistic	N	Mean	St. Dev.	Min	Max
Median Household Income ($)	2,444	54,718.080	14,637.950	24,331	142,299
Population Density (Pop./Sq. Mi.)	2,444	343.336	2,024.646	0.270	71,484.580
Democratic Vote Share (2016 Presidential Election)	2,444	0.336	0.148	0.065	0.928
White (Only) Population Fraction	2,444	0.582	0.114	0.067	0.815
Female Population Fraction	2,444	0.502	0.019	0.340	0.572
College Educated Population Fraction	2,444	0.230	0.100	0.054	0.776
Median Age (Years)	2,444	40.702	5.071	22.300	67.400

Note. "Median Household Income" is the median household income in the past 12 months (in 2019 inflation-adjusted dollars). "Population Density" is the total population divided by the land area of the county, in square miles. "College Educated Population Fraction" refers to the fraction of the population who are 25 years of age or older that have received a Bachelor's degree. The data are from the ACS 5-Year Survey for 2015-2019, with supplemental information provided by the "socviz" R library, which sources the US Census Bureau, namely for the "Democratic Vote Share" variable and the land area of each county (which is used to construct the "Population Density" variable).

Figure 1: Conceptual Framework

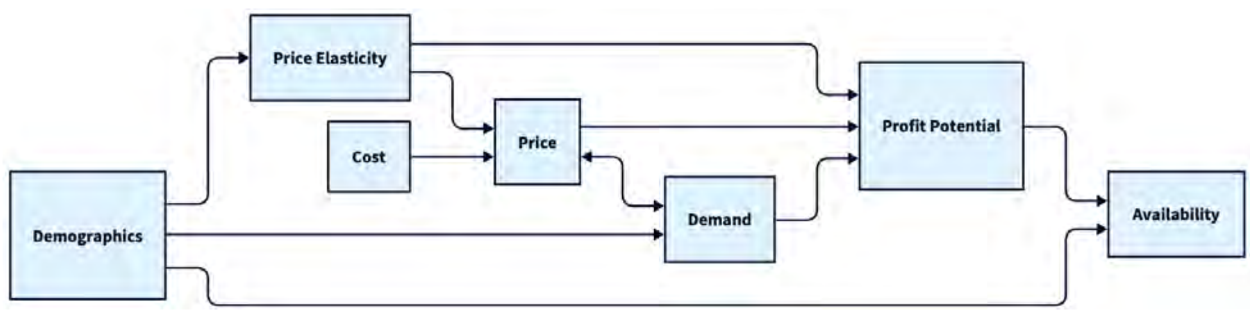


Figure 2: Yearly Trend of Sustainable Market Share, Product Availability, and Price Premium in Grocery Stores

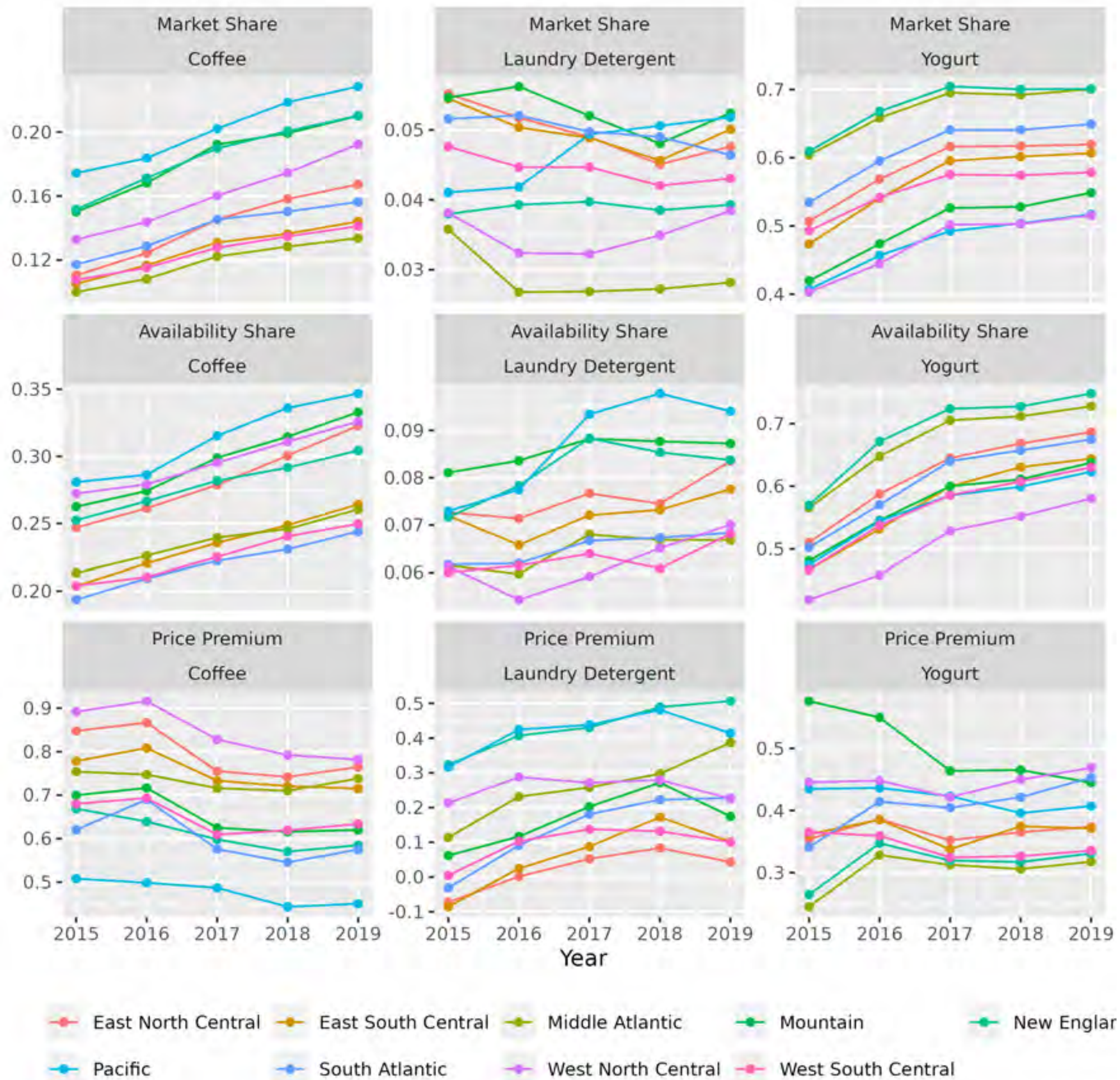


Figure 3: Yearly Trend of Sustainable Market Share, Product Availability, and Price Premium in Mass Merchandiser Stores

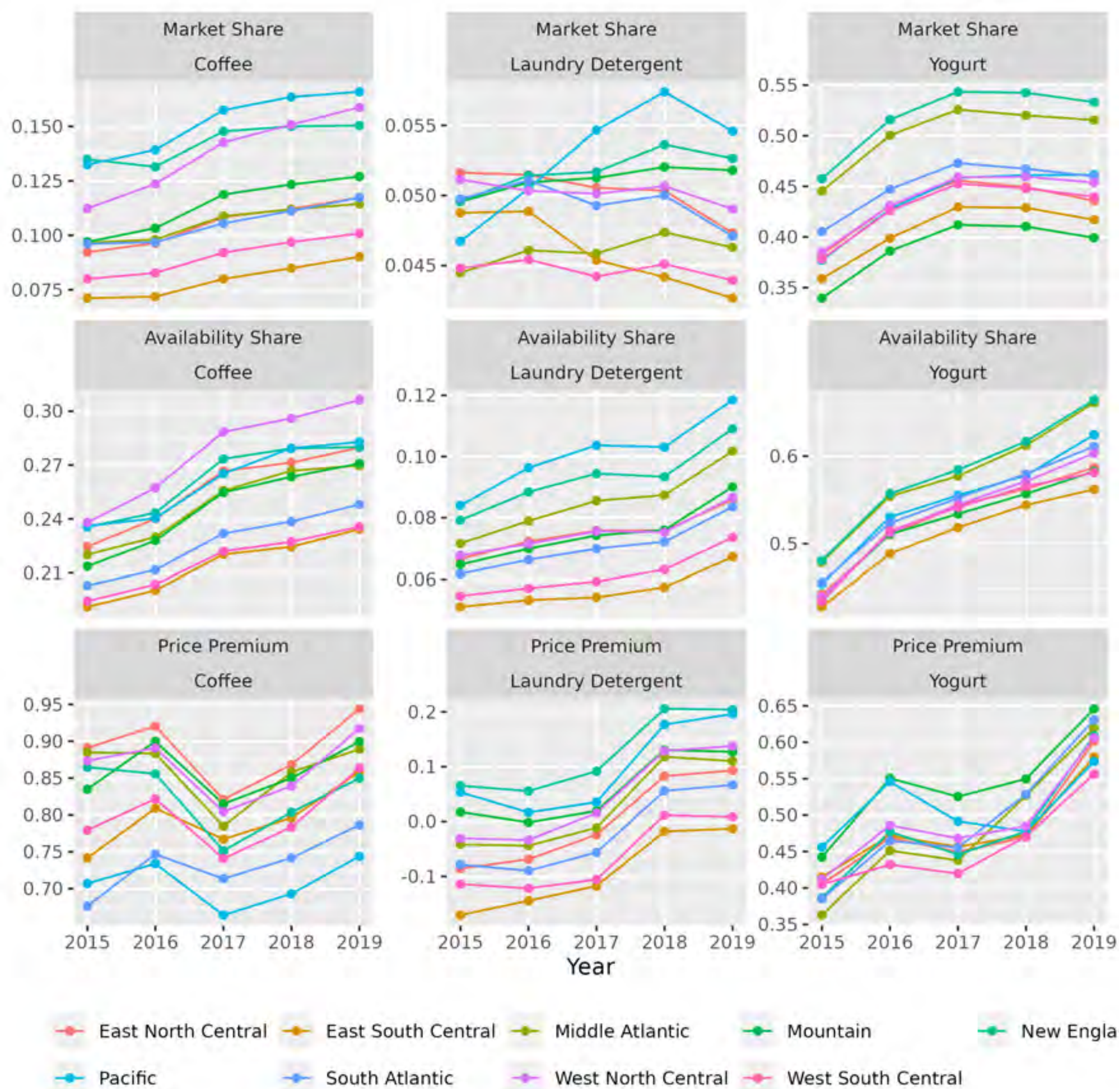
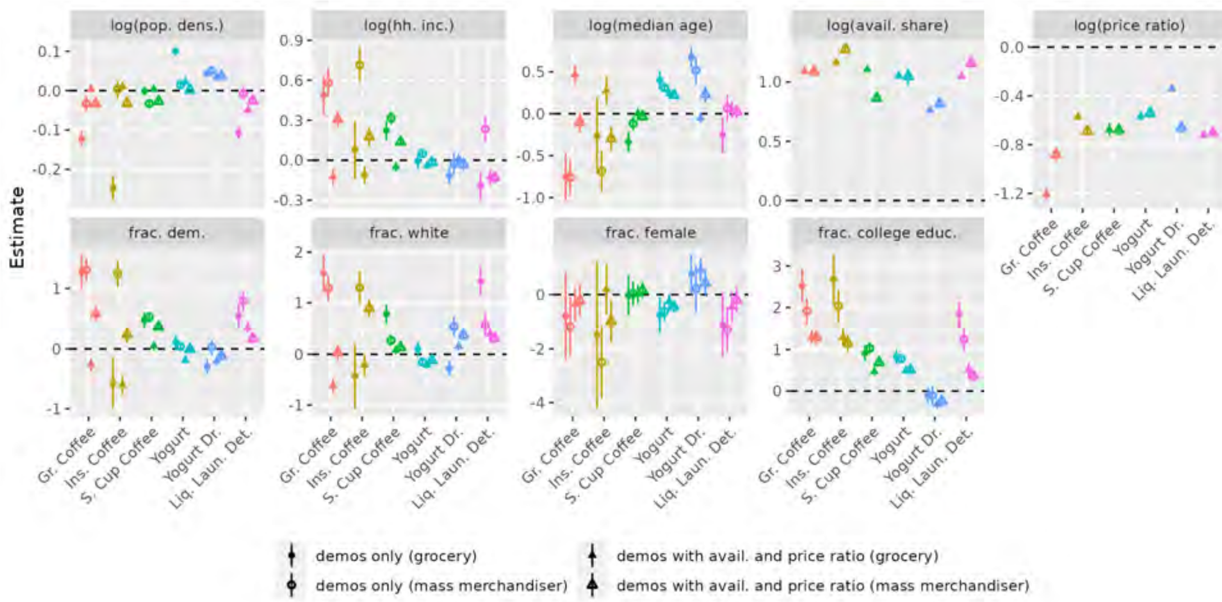
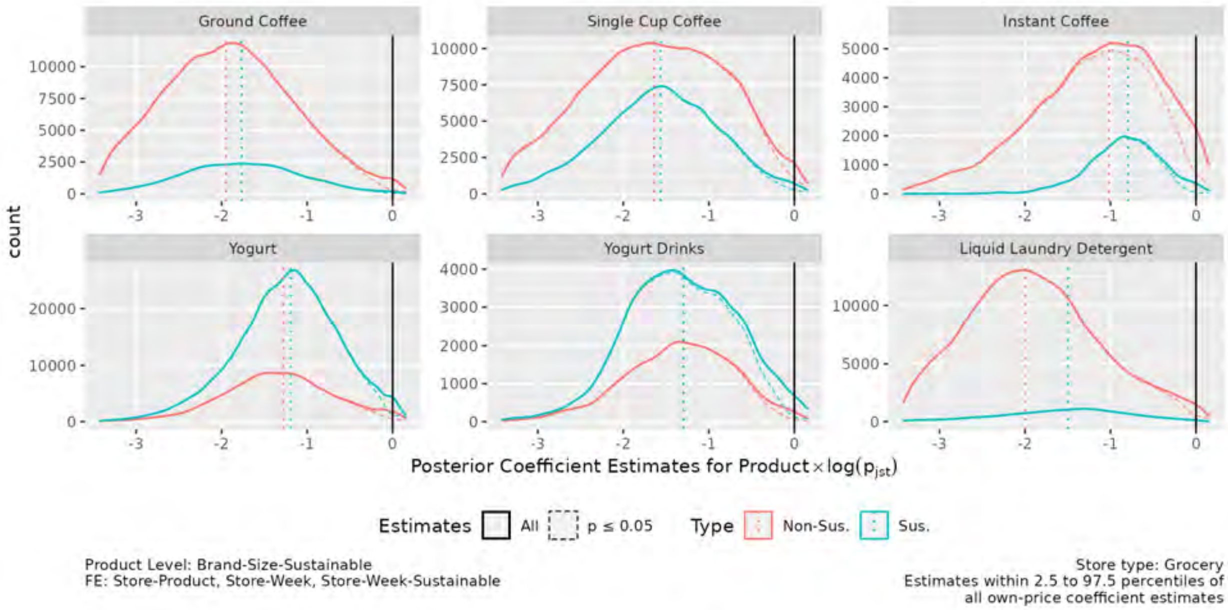


Figure 4: Demographic Predictors of Sustainable Product Market Share

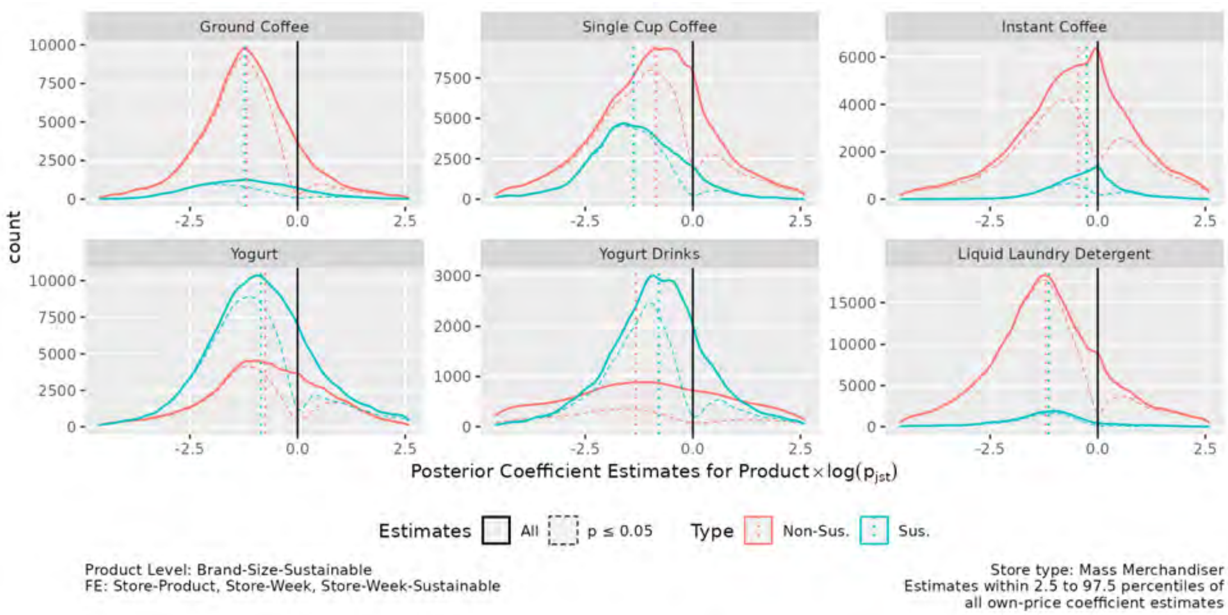


Notes. Points represent coefficient estimates of the variable named in each subplot title. Bars represent the 95% confidence interval of each coefficient estimate. Two-way clustered standard errors are conducted at the week and county levels. Fixed effects are included for each week and product size combination (size is defined as either large or small within the subcategory based on a median size split of all UPCs in the subcategory nationwide).

Figure 5: Density of Sustainable and Non-Sustainable Posterior Estimates of Product-County Elasticities

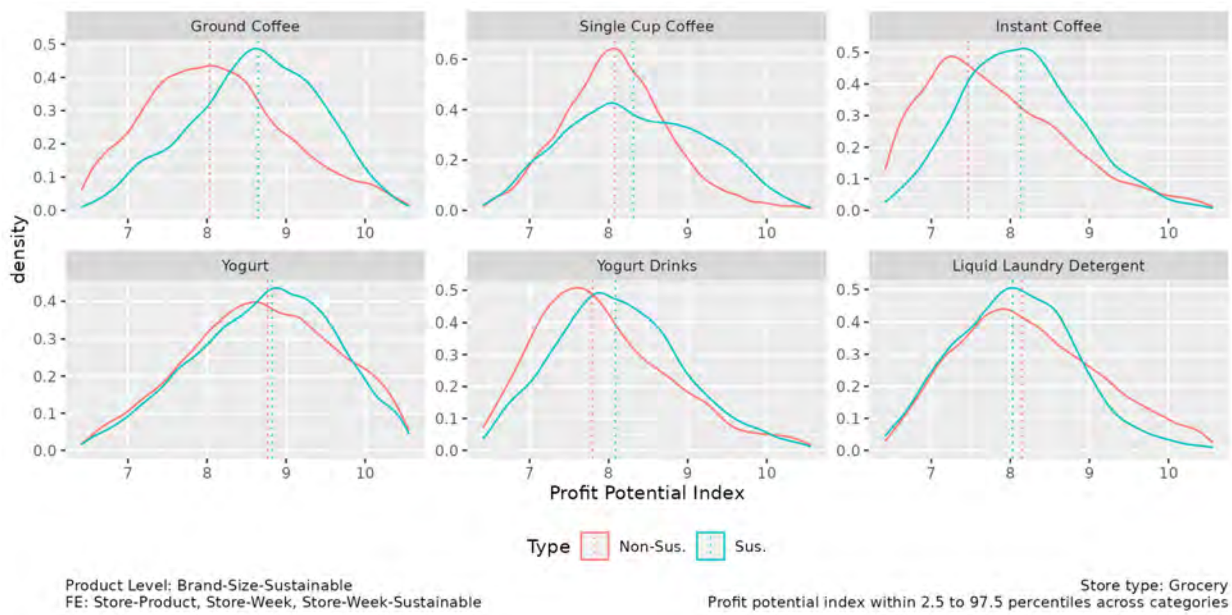


(a) Grocery

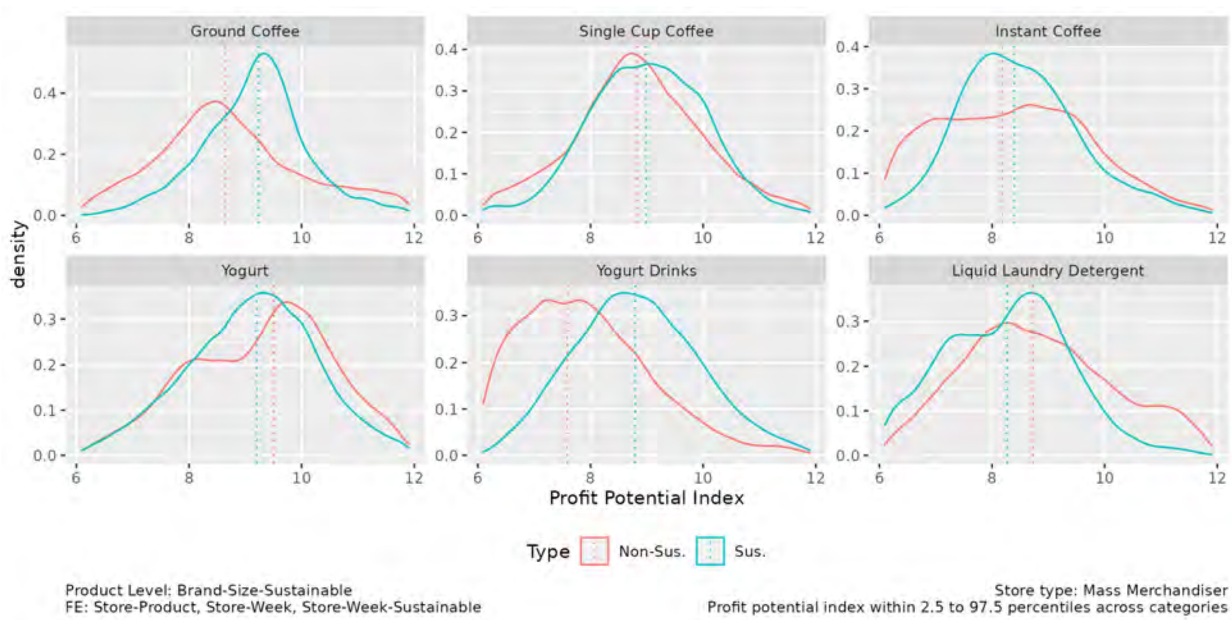


(b) Mass Merchandiser

Figure 6: Density of Sustainable and Non-Sustainable Product-County Profit Potential



(a) Grocery



(b) Mass Merchandiser

Figure 7: Average Demographic Effect on Product-Level Profit Potential Index: Grocery

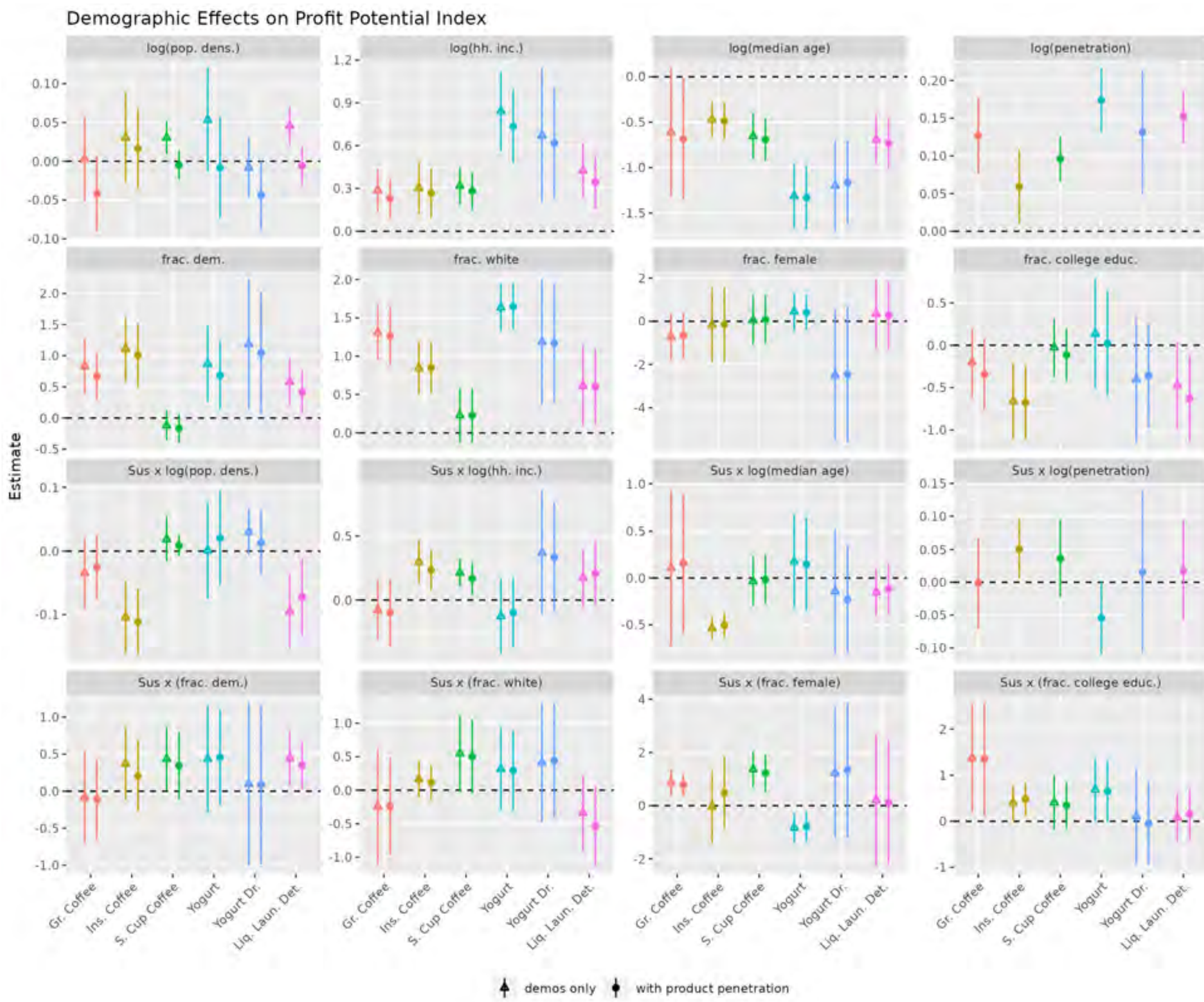


Figure 8: Average Demographic Effect on Product-Level Profit Potential Index: Mass Merchandiser

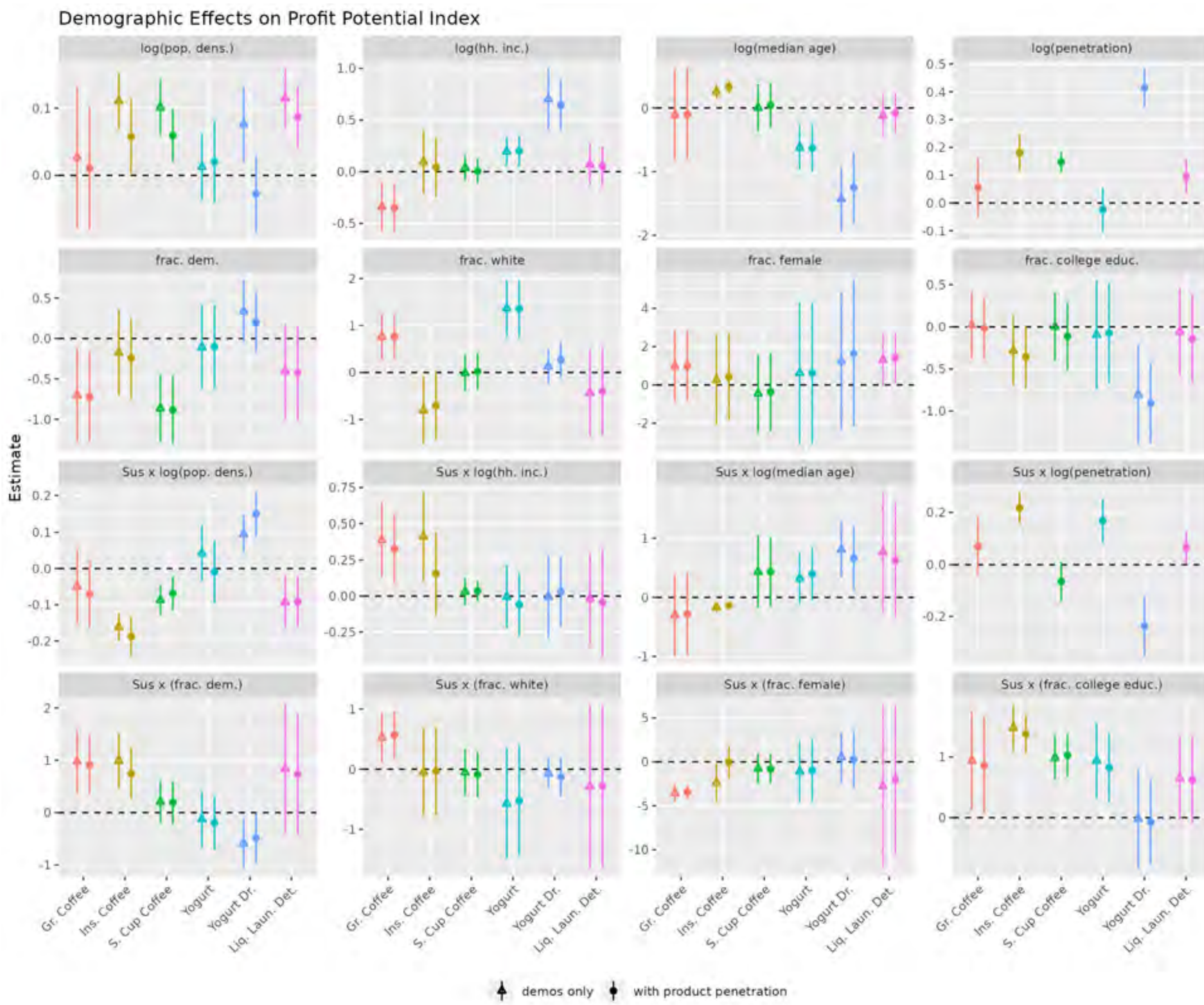


Figure 9: Meta-Analysis of Demographic Effects on Product-County Profit Potential

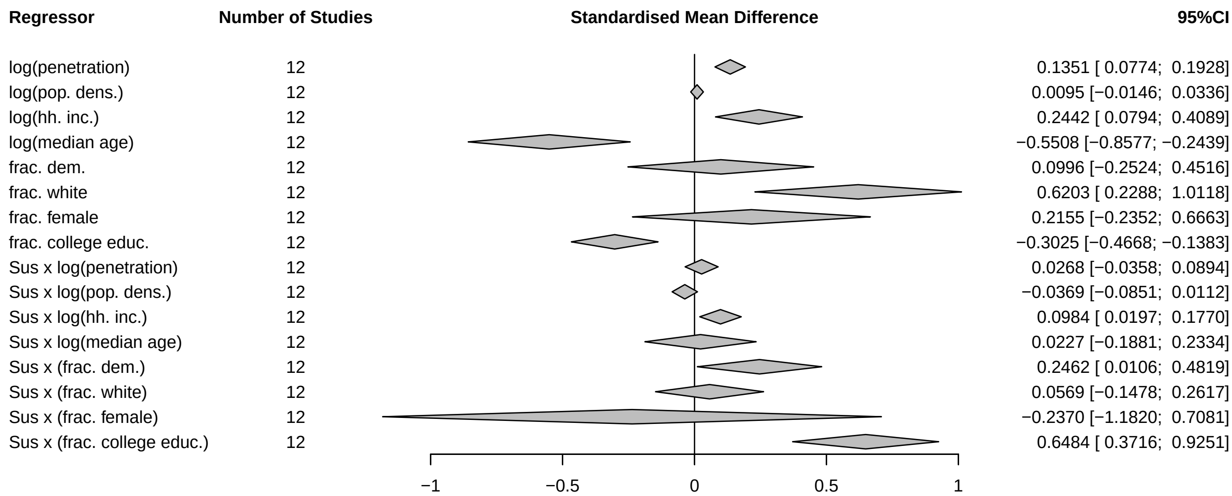
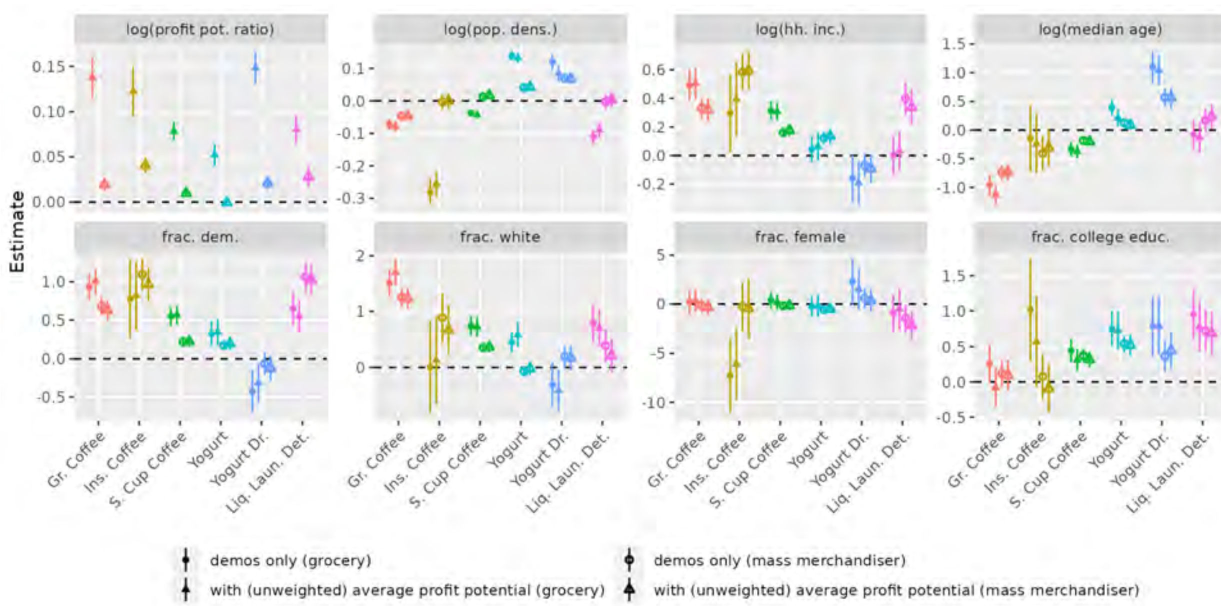
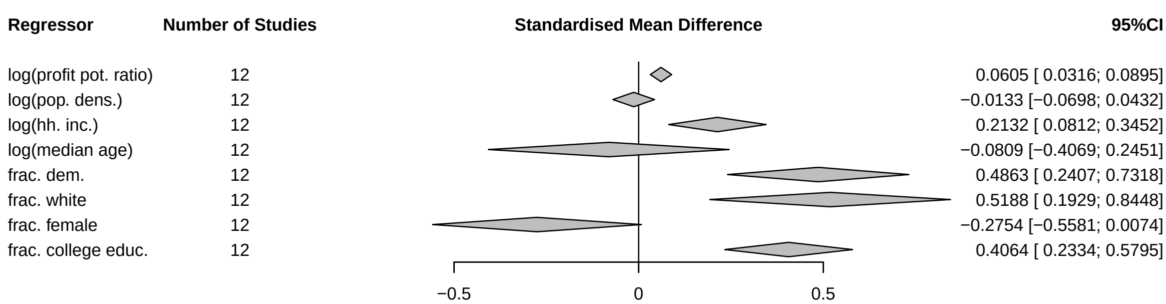


Figure 10: Demographic Effects on Sustainable Product Availability, Controlling for Profit Potential



Notes. Points represent coefficient estimates of the variable named in each subplot title. Bars represent the 95% confidence interval of each coefficient estimate. Two-way clustered standard errors are conducted at the week and county levels. Fixed effects are included for each week and product size combination (size is defined as either large or small within the subcategory based on a median size split of all UPCs in the subcategory nationwide).

Figure 11: Meta-Analysis of Demographic Effects on Sustainable Product Availability, Controlling for Profit Potential



Sustainable Product Profit Potential and Availability

WEB APPENDIX

These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

Contents

CATEGORY SELECTION

First, a majority of the literature studying consumer response to sustainable products focuses on food categories and the environmental dimension of sustainability (see reviews of, e.g. Tully and Winer 2014; Bangsa and Schlegelmilch 2020; Bastounis et al. 2021; Potter et al. 2021; Asioli et al. 2017; Schleenbecker and Hamm 2013). For breadth of both product category and sustainability claim types, we look to include edible (coffee, yogurt) and non-edible (laundry detergent) categories that provide a variety of claims that focus not only on environmental sustainability (e.g. "Organic", "Rainforest Alliance", "Plant-Based Ingredients"), but also on social and economic dimensions of sustainability (e.g. "Fair Trade", "B-Corp"). Certain sustainability claims for edible products also have an added health implication (e.g. "Organic" or "Non-GMO") that could affect consumer demand differently to sustainability claims of non-edible products (Verain et al. 2012; Hughner et al. 2007), reinforcing the inclusion of a non-edible category.

Second, we choose categories that fit into existing typologies which have been shown to exhibit differing effects of sustainability on product consumption outcomes. A stream of literature classifies products as belonging to "virtue" (associated with healthful and long-term benefits) or "vice" (associated with less healthful benefits and immediate gratification) categories (Wertenbroch 1998; Hui, Bradlow, and Fader 2009), with work showing mixed effects of sustainability on these types of products. Sustainable products in higher virtue categories are associated with higher quality associations and willingness to pay (van Doorn and Verhoef 2011), but they are shown to have greater long-term elasticities implying more frequent optimal reductions in prices (Bezawada and Pauwels 2013). Olsen, Slotegraaf, and Chandukala (2014) also find less positive effects of green new product introductions on brand attitudes for virtue categories compared to vice ones. The categories in this study fall into either category — specifically, using the classification in Hui, Bradlow, and Fader (2009), yogurt and laundry detergent are considered virtue categories, while coffee is considered a vice category.[29]

Luchs et al. (2010) provides another typology, namely the "gentleness" vs. "strength" of products, for which we also use to motivate our selection of categories. Gentleness in a product is related to words such as "safe", "healthy", "soft", while strength is related to words such as "powerful", "gets the job done", and "effective". In their work, Luchs et al. (2010) highlight the negative effect of including sustainability or eco-friendly claims on "strong" products, such as cleaning products, on consumer preferences (the "sustainability liability"), due to the association of sustainability with more gentle rather than strong product attributes. We thus select laundry detergent as a "strong" category due to the importance of cleaning and effectiveness, yogurt as a "gentle" category due to its associations with healthiness, and coffee as somewhere in between.

Third, we focus our attention on categories that represent those with low, medium, and high levels of sustainable market share. Doing so allows us to discern whether there are differences in sustainable product outcomes based on how prevalent sustainability is within a category. Indeed, (Olsen, Slotegraaf, and Chandukala 2014) shows that green new product introductions increase brand attitudes and are more prevalent in categories with already higher levels of sustainability within the category.

[29]The virtue-vice scores of the three categories in our study according to Table 4 from Olsen, Slotegraaf, and Chandukala (2014) indicate yogurt to be the highest virtue category (4th of 22 categories), followed by household cleaners (11th) then coffee (13th).

CONSTRUCTION OF SUMMARY STATISTICS

Let q_{jst} denote the volume sold of product j (in group g), store s, and week t. Let $\mathcal{J}^{l}_{gs}$ denote the set of products sold in store s in group g with sustainability label $l \in \{0, 1\}$, where $l = 0$ denotes non-sustainable products and $l = 1$ denotes sustainable products, and let $\mathcal{S}_{mf}$ denote the set of all stores within a market (county) m of store format $f \in$ {Club, Grocery, Mass Merchandiser}. Let $\mathcal{G}_c$ be the set of product groups within category c. Denoting the volume sold of product j in store s in period t as v_{jst}, the market share of sustainable products within a county m within all stores of format f within a given week t is computed by taking the total volume on sustainable products over the total volume on all products within the category:

$$\text{Market Share}_{cmft} = \frac{\sum_{s\in\mathcal{S}_{mf}} \sum_{g\in\mathcal{G}_c} \sum_{j\in\mathcal{J}^{1}_{gs}} q_{jst}}{\sum_{s\in\mathcal{S}_{mf}} \sum_{g\in\mathcal{G}_c} \sum_{j\in\mathcal{J}^{1}_{gs}\cup\mathcal{J}^{0}_{gs}} q_{jst}} \tag{12}$$

in which the product subscript j is subsumed by group subscript g which is subsumed by category subscripts c. We construct an analogous measure of the relative availability of sustainable products, which uses expression (12), replacing q_{jst} with an availability indicator $\mathbb{1}(q_{jst} > 0)$ which equals to 1 if the product j was sold in store s in week t and 0 otherwise.

To compute the price premium, we first compute a weighted average price (per 16-oz) for either sustainable or non-sustainable products sold each week in each product group, market, and store format. Let p_{jst} be the price (per 16-oz) of product j in store s in week t. Let w_{jst} denote the weights used for product j sold in store s in period t, which we set equal to the total store-level volume of product j sold in store s in the full year that period t belongs to. These weights allow the relative prominence of a product, but not its contemporaneous demand, to affect its contribution to the overall price index for sustainable and non-sustainable products. Then, the volume-weighted price of products with label $l \in \{0, 1\}$ within a product group g, market m, store format f, and week t is:

$$\bar{p}^{l}_{gmft} = \frac{\sum_{s\in\mathcal{S}_{mf}} \sum_{j\in\mathcal{J}^{l}_{gs}} w_{jst} p_{jst}}{\sum_{s\in\mathcal{S}_{mf}} \sum_{j\in\mathcal{J}^{l}_{gs}} w_{jst}}. \tag{13}$$

The volume-weighted price premium Δ_{gmft} is then:

$$\Delta_{gmft} = \frac{\bar{p}^{1}_{gmft} - \bar{p}^{0}_{gmft}}{\bar{p}^{0}_{gmft}} \tag{14}$$

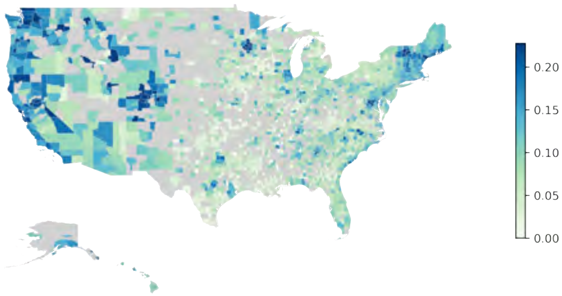
i.e. the ratio of the difference in the volume-weighted price of sustainable to non-sustainable products over the volume-weighted price of non-sustainable products, for the product group g in market m in store format f in period t.

To aggregate market share and availability for the summary statistics, we use the denominator in (12) (using the corresponding v_{jst} or $\mathbb{1}(v_{jst} > 0)$) as weights to aggregate the measures to the category, year, and census division levels. For the volume-weighted price premiums, we first aggregate the volume-weighted prices (13) of sustainable and non-sustainable products to the year and census division levels (but not category) using the denominator in (13) as weights. We then compute the price premium within the product group for the year and census division in the same way as in (14). This price premium measure is then aggregated across categories by taking the weighted average using the total volume sold of the product group within the year and census division as weights.

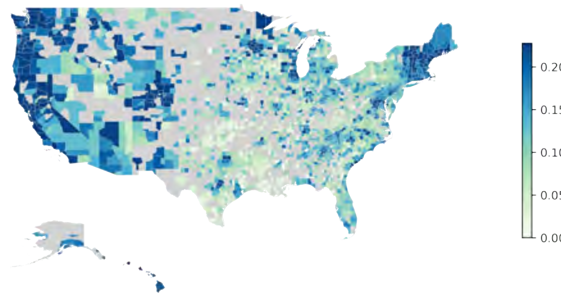
MAPS

Market Share Maps: Grocery

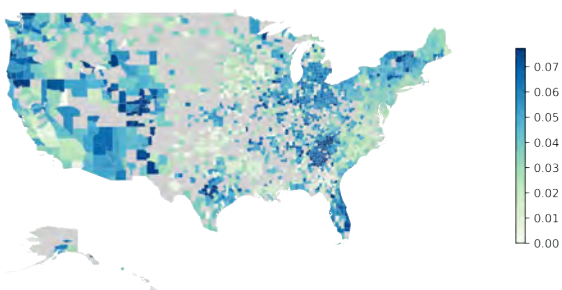
Figure W.1: Sustainable Product Market Share: Grocery



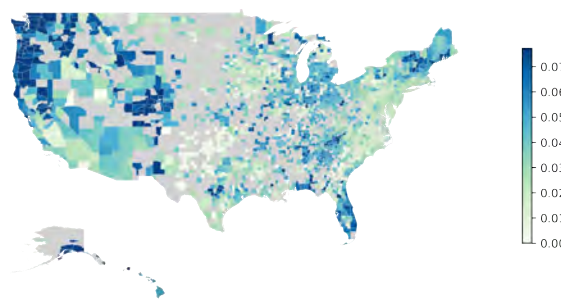
(a) Coffee 2015



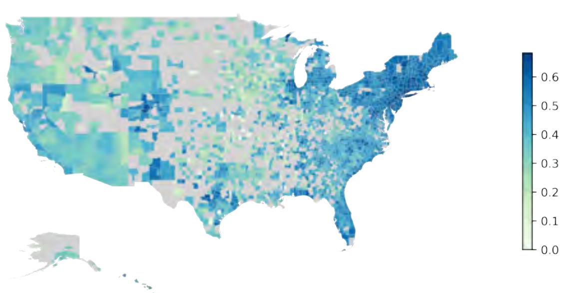
(b) Coffee 2019



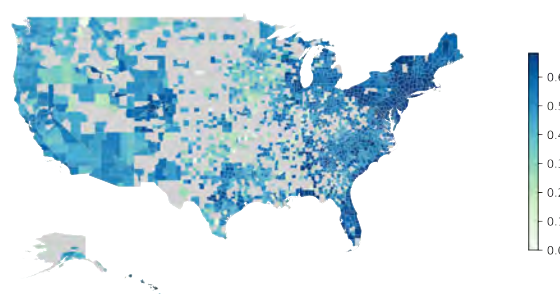
(c) Detergent 2015



(d) Detergent 2015



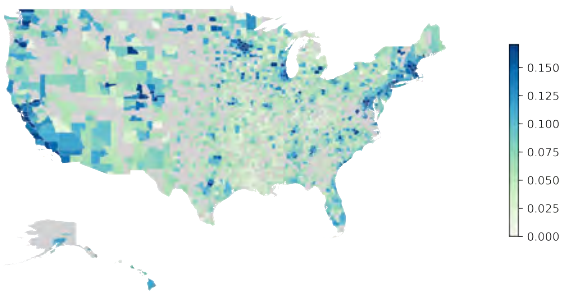
(e) Yogurt 2015



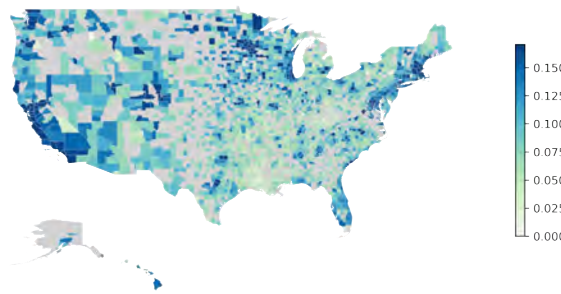
(f) Yogurt 2019

Market Share Maps: Mass Merchandiser

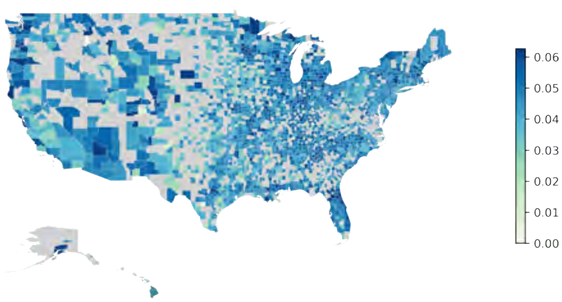
Figure W.2: Sustainable Product Market Share: Mass Merchandiser



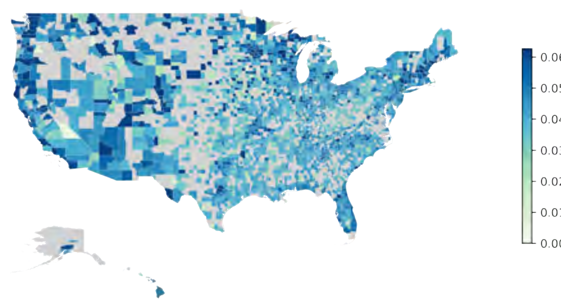
(a) Coffee 2015



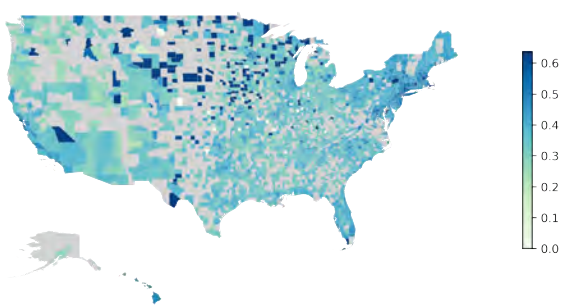
(b) Coffee 2019



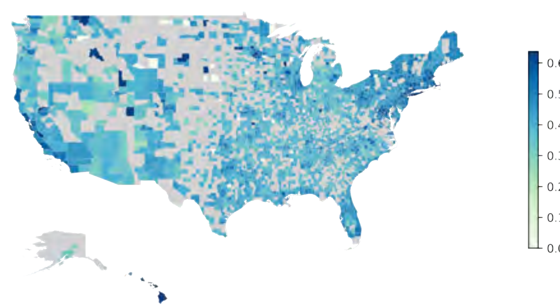
(c) Detergent 2015



(d) Detergent 2015



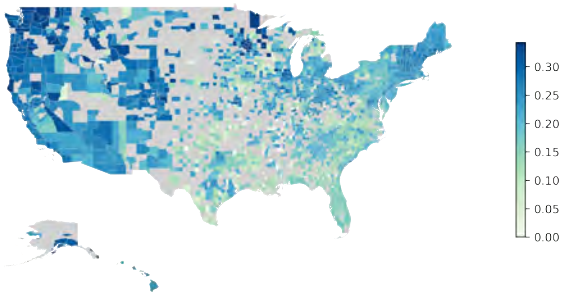
(e) Yogurt 2015



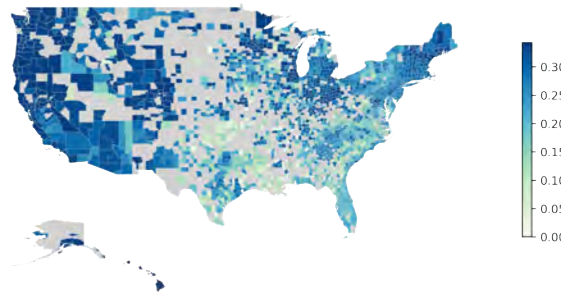
(f) Yogurt 2019

Availability Maps: Grocery

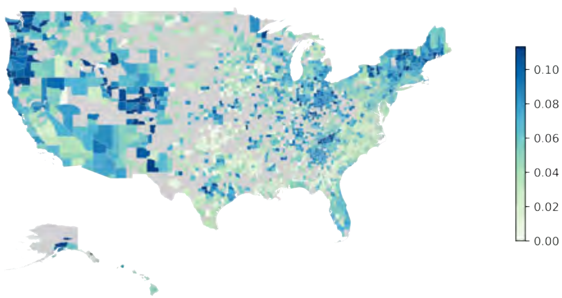
Figure W.3: Sustainable Product Availability: Grocery



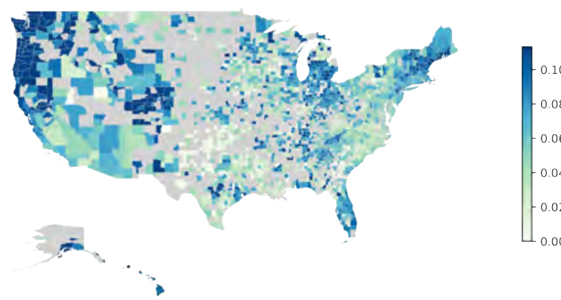
(a) Coffee 2015



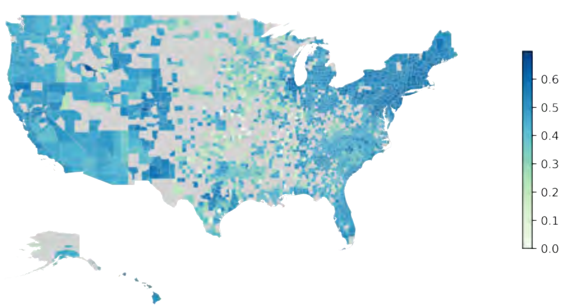
(b) Coffee 2019



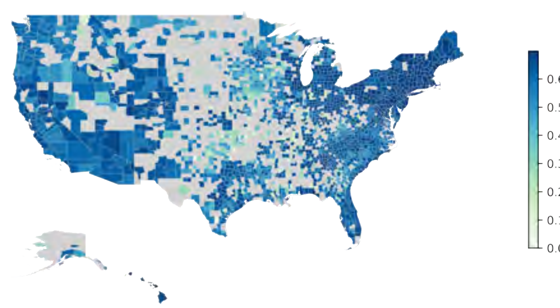
(c) Detergent 2015



(d) Detergent 2019



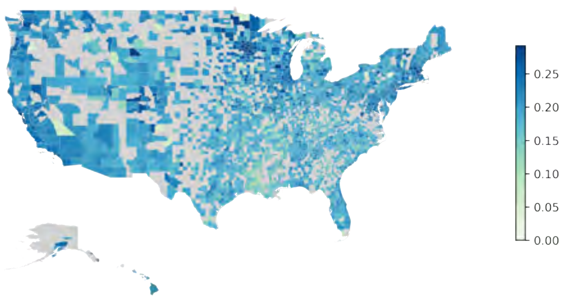
(e) Yogurt 2015



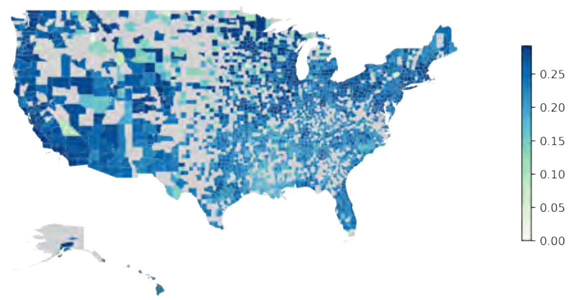
(f) Yogurt 2019

Availability Maps: Mass Merchandiser

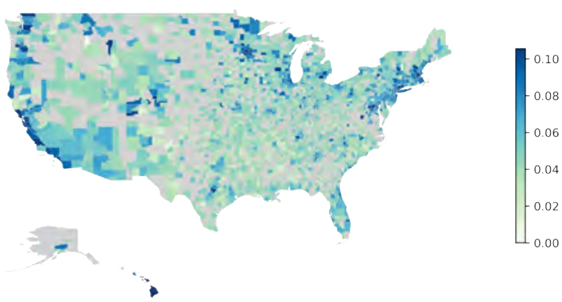
Figure W.4: Sustainable Product Availability: Mass Merchandiser



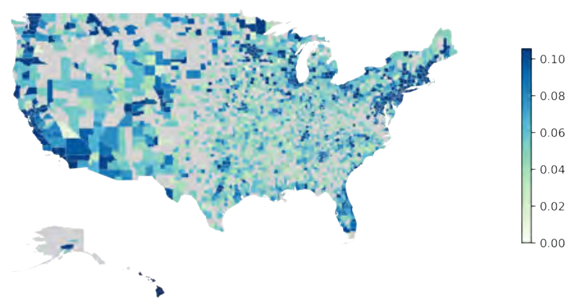
(a) Coffee 2015



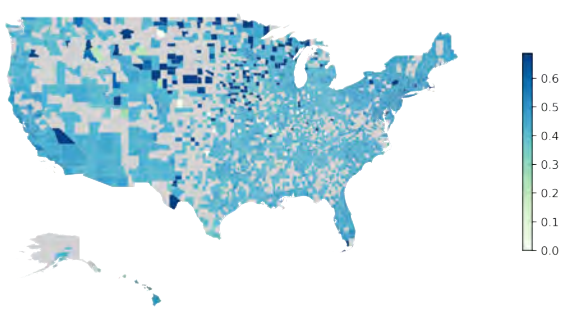
(b) Coffee 2019



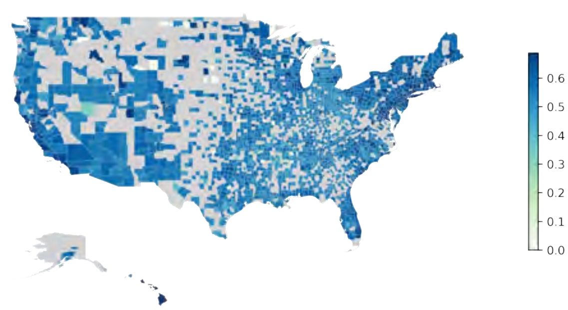
(c) Detergent 2015



(d) Detergent 2019



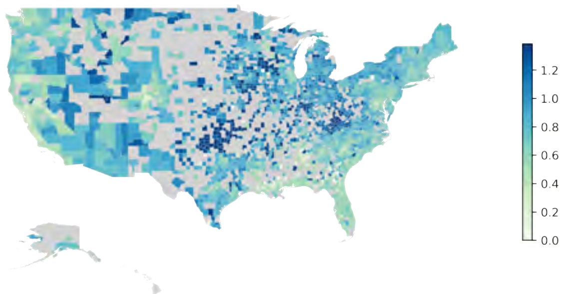
(e) Yogurt 2015



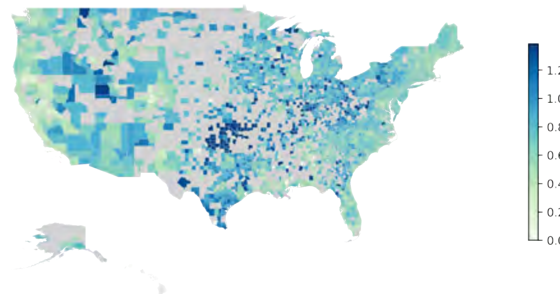
(f) Yogurt 2019

Price Premium Maps: Grocery

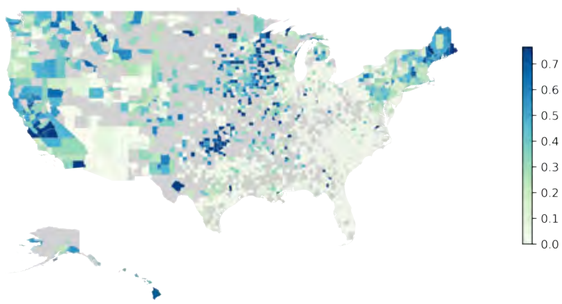
Figure W.5: Sustainable Product Price Premium: Grocery



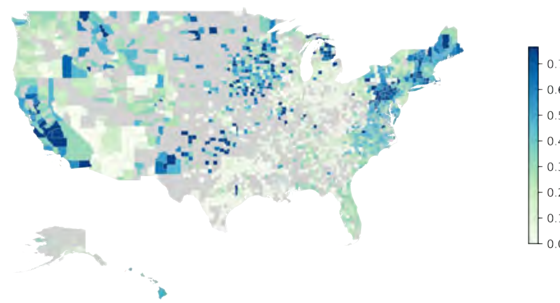
(a) Coffee 2015



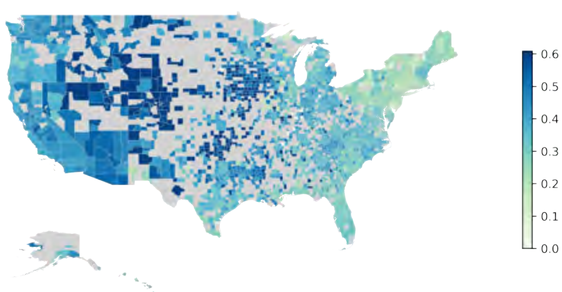
(b) Coffee 2019



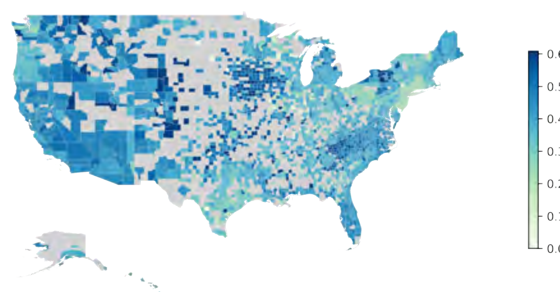
(c) Detergent 2015



(d) Detergent 2015



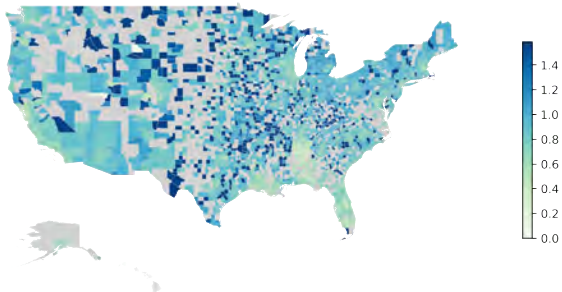
(e) Yogurt 2015



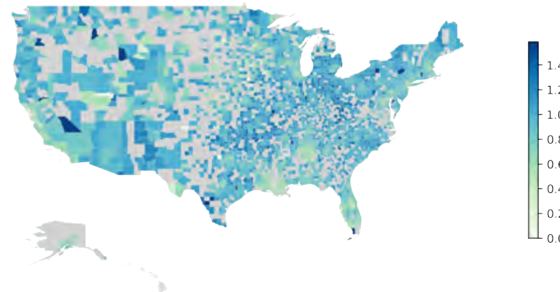
(f) Yogurt 2019

Price Premium Maps: Mass Merchandiser

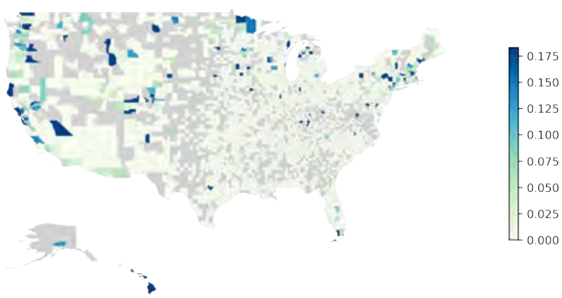
Figure W.6: Sustainable Product Price Premium: Mass Merchandiser



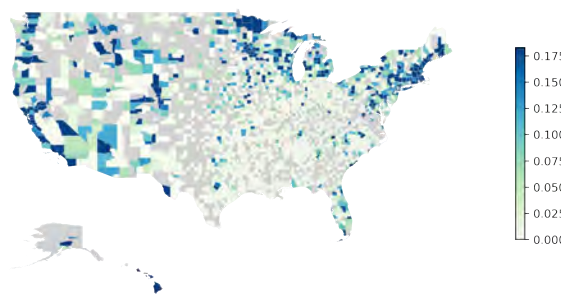
(a) Coffee 2015



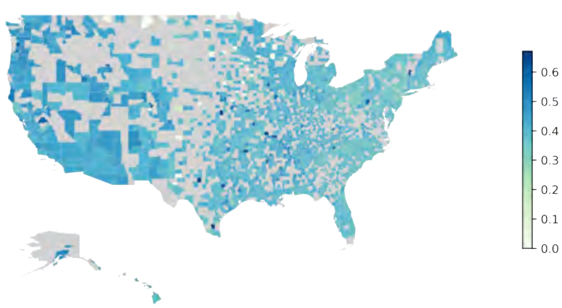
(b) Coffee 2019



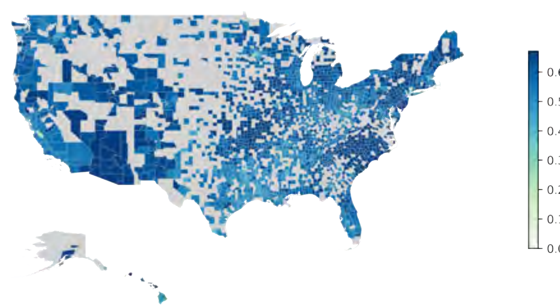
(c) Detergent 2015



(d) Detergent 2015

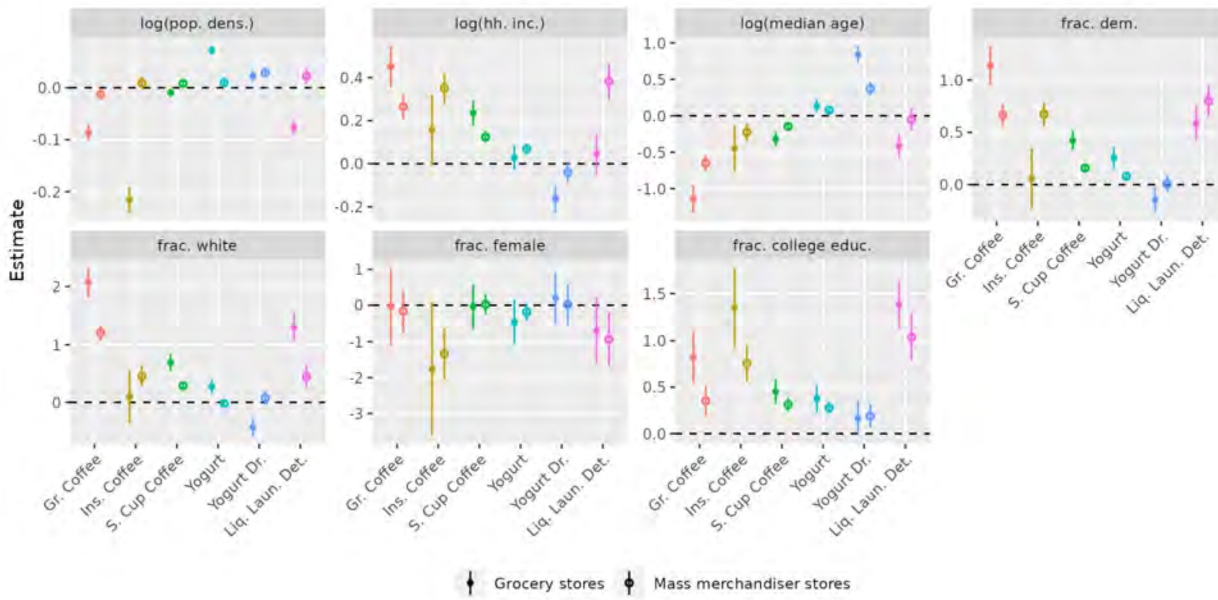


(e) Yogurt 2015



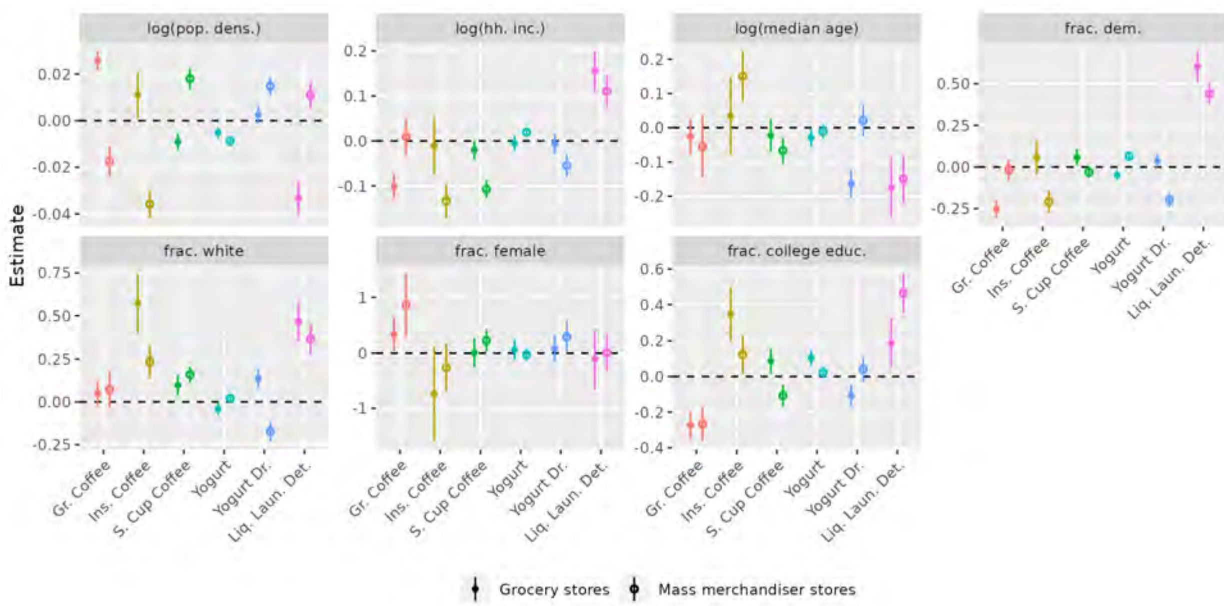
(f) Yogurt 2019

Figure W.7: Demographic Predictors of Sustainable Product Availability Share



Notes. Points represent coefficient estimates of the variable named in each subplot title. Bars represent the 95% confidence interval of each coefficient estimate. Two-way clustered standard errors are conducted at the week and county levels. Fixed effects are included for each week and product size combination (size is defined as either large or small within the subcategory based on a median size split of all UPCs in the subcategory nationwide).

Figure W.8: Demographic Predictors of Sustainable Product Price Premium



Notes. Points represent coefficient estimates of the variable named in each subplot title. Bars represent the 95% confidence interval of each coefficient estimate. Two-way clustered standard errors are conducted at the week and county levels. Fixed effects are included for each week and product size combination (size is defined as either large or small within the subcategory based on a median size split of all UPCs in the subcategory nationwide).

Table W.1: Demographic Effects on County-Level Sustainable Market Share - Grocery Format

Dependent Variable:	Log of Sustainable Market Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.4874***	0.2232***	0.0775	-0.0068	-0.1169***	-0.1925***
	(0.0732)	(0.0373)	(0.1124)	(0.0319)	(0.0329)	(0.0562)
Log(Pop. Density)	-0.1223***	-0.0013	-0.2475***	0.1004***	0.0435***	-0.1066***
	(0.0109)	(0.0053)	(0.0162)	(0.0052)	(0.0050)	(0.0083)
Frac. Dem. Vote 2016	1.280***	0.4779***	-0.5716***	0.1116*	-0.2944***	0.5404***
	(0.1466)	(0.0614)	(0.2178)	(0.0650)	(0.0635)	(0.1069)
Frac. White Pop.	1.582***	0.7794***	-0.4319	0.0972	-0.2692***	1.430***
	(0.1883)	(0.0923)	(0.3256)	(0.0747)	(0.0737)	(0.1465)
Frac. Female Pop.	-0.7963	-0.0302	-1.492	-0.7645**	0.7698**	-1.105*
	(0.8310)	(0.3771)	(1.396)	(0.3362)	(0.3692)	(0.6079)
Frac. College Educ.	2.527***	0.9129***	2.681***	0.8310***	-0.1051	1.834***
	(0.2107)	(0.0918)	(0.3035)	(0.0901)	(0.0985)	(0.1527)
Log(Median Age)	-0.7525***	-0.3357***	-0.2620	0.3998***	0.6742***	-0.2532**
	(0.1443)	(0.0622)	(0.2337)	(0.0565)	(0.0613)	(0.1100)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	894,058	907,730	580,350	1,047,172	947,886	810,430
R^2	0.35822	0.15638	0.53897	0.30852	0.20524	0.14570
Within R^2	0.19778	0.10679	0.13035	0.22610	0.07017	0.07896

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable market share is the sustainable volume-equivalent units sold divided by the total, in the focal county and week.

Table W.2: Demographic Effects on County-Level Sustainable Availability Share - Grocery Format

Dependent Variable:	Log of Sustainable Availability Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.4505***	0.2353***	0.1575*	0.0285	-0.1621***	0.0450
	(0.0494)	(0.0285)	(0.0831)	(0.0277)	(0.0332)	(0.0479)
Log(Pop. Density)	-0.0869***	-0.0097**	-0.2159***	0.0719***	0.0222***	-0.0768***
	(0.0075)	(0.0041)	(0.0125)	(0.0045)	(0.0050)	(0.0067)
Frac. Dem. Vote 2016	1.138***	0.4233***	0.0578	0.2578***	-0.1471**	0.5856***
	(0.0968)	(0.0463)	(0.1489)	(0.0534)	(0.0616)	(0.0872)
Frac. White Pop.	2.067***	0.6912***	0.0956	0.2743***	-0.4298***	1.304***
	(0.1299)	(0.0735)	(0.2345)	(0.0632)	(0.0756)	(0.1213)
Frac. Female Pop.	-0.0353	-0.0365	-1.767*	-0.4555	0.2007	-0.6874
	(0.5464)	(0.3088)	(0.9427)	(0.3087)	(0.3592)	(0.4769)
Frac. College Educ.	0.8212***	0.4540***	1.353***	0.3758***	0.1673*	1.383***
	(0.1427)	(0.0672)	(0.2156)	(0.0769)	(0.0959)	(0.1291)
Log(Median Age)	-1.143***	-0.3204***	-0.4503***	0.1344***	0.8414***	-0.4096***
	(0.0959)	(0.0495)	(0.1620)	(0.0463)	(0.0611)	(0.0899)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	894,058	907,730	580,350	1,047,172	947,886	810,430
R^2	0.27596	0.19037	0.55274	0.33487	0.28414	0.15266
Within R^2	0.20042	0.11322	0.16950	0.19014	0.06621	0.12375

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable availability share is the number of sustainable UPC-store-level observations divided by the total, in the focal county and week.

Table W.3: Demographic Effects on County-Level Sustainable vs. Non-Sustainable Price Ratio - Grocery Format

Dependent Variable:	Log of Sustainable vs. Non-Sustainable Price Ratio					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	-0.1008***	-0.0202*	-0.0105	-0.0051	-0.0059	0.1545***
	(0.0148)	(0.0113)	(0.0328)	(0.0081)	(0.0116)	(0.0233)
Log(Pop. Density)	0.0258***	-0.0090***	0.0111**	-0.0051***	0.0026	-0.0333***
	(0.0021)	(0.0019)	(0.0050)	(0.0012)	(0.0019)	(0.0037)
Frac. Dem. Vote 2016	-0.2514***	0.0580**	0.0576	-0.0491***	0.0362*	0.6019***
	(0.0281)	(0.0254)	(0.0515)	(0.0137)	(0.0199)	(0.0486)
Frac. White Pop.	0.0480	0.0971***	0.5732***	-0.0411**	0.1354***	0.4681***
	(0.0379)	(0.0307)	(0.0884)	(0.0184)	(0.0299)	(0.0587)
Frac. Female Pop.	0.3399**	0.0089	-0.7455*	0.0597	0.0766	-0.1096
	(0.1568)	(0.1371)	(0.4351)	(0.0934)	(0.1231)	(0.2822)
Frac. College Educ.	-0.2742***	0.0866**	0.3467***	0.1041***	-0.1082***	0.1868***
	(0.0408)	(0.0357)	(0.0783)	(0.0215)	(0.0308)	(0.0711)
Log(Median Age)	-0.0256	-0.0225	0.0344	-0.0295**	-0.1630***	-0.1744***
	(0.0268)	(0.0244)	(0.0593)	(0.0139)	(0.0205)	(0.0457)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	892,578	906,477	578,021	1,046,246	749,763	810,411
R^2	0.31359	0.10040	0.26501	0.42246	0.48195	0.26820
Within R^2	0.08490	0.00692	0.02622	0.00722	0.00692	0.07740

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The price ratio takes the across-stores and across-UPCs weighted average price of sustainable and non-sustainable UPCs, respectively, using each UPC's total volume-equivalent units sold in the focal store and year as weights. This price ratio is computed at the county-week level.

Table W.4: Demographic, Availability, and Price Effects on County-Level Sustainable Market Shares - Grocery Format

Dependent Variable:	Log of Sustainable Market Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	-0.1258***	-0.0507***	-0.1108***	-0.0394***	0.0091	-0.1284***
	(0.0318)	(0.0169)	(0.0339)	(0.0119)	(0.0182)	(0.0295)
Log(Pop. Density)	0.0036	0.0034	0.0107*	0.0219***	0.0333***	-0.0499***
	(0.0045)	(0.0027)	(0.0056)	(0.0021)	(0.0029)	(0.0044)
Frac. Dem. Vote 2016	-0.2634***	0.0491	-0.6043***	-0.1873***	-0.2059***	0.3599***
	(0.0546)	(0.0345)	(0.0804)	(0.0264)	(0.0355)	(0.0507)
Frac. White Pop.	-0.6169***	0.0813*	-0.2089*	-0.2138***	0.1593***	0.4003***
	(0.0757)	(0.0433)	(0.1062)	(0.0305)	(0.0419)	(0.0672)
Frac. Female Pop.	-0.3543	0.0171	0.1962	-0.2495*	0.9270***	-0.4627
	(0.3149)	(0.1728)	(0.4807)	(0.1326)	(0.2237)	(0.2861)
Frac. College Educ.	1.306***	0.4708***	1.303***	0.4950***	-0.3121***	0.5187***
	(0.0815)	(0.0498)	(0.1071)	(0.0362)	(0.0559)	(0.0791)
Log(Median Age)	0.4655***	0.0031	0.2774***	0.2413***	-0.0495	0.0506
	(0.0538)	(0.0319)	(0.0840)	(0.0244)	(0.0331)	(0.0484)
Log(Avail. Share)	1.090***	1.105***	1.163***	1.052***	0.7604***	1.048***
	(0.0085)	(0.0074)	(0.0086)	(0.0106)	(0.0114)	(0.0067)
Log(Price Ratio)	-1.207***	-0.6765***	-0.5723***	-0.5671***	-0.3418***	-0.7201***
	(0.0261)	(0.0269)	(0.0103)	(0.0188)	(0.0125)	(0.0130)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	892,578	906,477	578,021	1,046,246	749,763	810,411
R^2	0.84480	0.74472	0.90861	0.83170	0.65077	0.69907
Within R^2	0.80673	0.72922	0.82795	0.81171	0.60829	0.67553

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable market share is the sustainable volume-equivalent units sold divided by the total, in the focal county and week. Sustainable availability share is the number of sustainable UPC-store-level observations divided by the total, in the focal county and week. The price ratio takes the across-stores and across-UPCs weighted average price of sustainable and non-sustainable UPCs, respectively, using each UPC's total volume-equivalent units sold in the focal store and year as weights. This price ratio is computed at the county-week level.

Table W.5: Demographic Effects on County-Level Sustainable Market Share - Mass Merchandiser

Dependent Variable:	Log of Sustainable Market Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.5836***	0.3175***	0.7158***	0.0505***	-0.0250	0.2341***
	(0.0567)	(0.0245)	(0.0679)	(0.0176)	(0.0423)	(0.0460)
Log(Pop. Density)	-0.0328***	-0.0330***	0.0031	0.0151***	0.0501***	-0.0084
	(0.0088)	(0.0044)	(0.0119)	(0.0033)	(0.0067)	(0.0082)
Frac. Dem. Vote 2016	1.307***	0.5262***	1.244***	0.0431	0.0281	0.7920***
	(0.1052)	(0.0399)	(0.1180)	(0.0296)	(0.0687)	(0.0900)
Frac. White Pop.	1.282***	0.2735***	1.306***	-0.1530***	0.5429***	0.5744***
	(0.1328)	(0.0549)	(0.1604)	(0.0391)	(0.0932)	(0.1140)
Frac. Female Pop.	-1.167**	0.0326	-2.509***	-0.6321***	0.2183	-1.283***
	(0.5509)	(0.2331)	(0.6945)	(0.1791)	(0.4512)	(0.4195)
Frac. College Educ.	1.912***	1.032***	2.037***	0.7845***	-0.1066	1.242***
	(0.1587)	(0.0699)	(0.1970)	(0.0471)	(0.1175)	(0.1399)
Log(Median Age)	-0.7604***	-0.1146***	-0.6875***	0.3116***	0.5170***	0.0695
	(0.1110)	(0.0433)	(0.1246)	(0.0294)	(0.0819)	(0.0876)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	823,162	1,048,946	792,411	985,562	962,620	769,443
R^2	0.44761	0.42834	0.58681	0.56296	0.38800	0.23069
Within R^2	0.25420	0.19357	0.26245	0.24058	0.09214	0.12085

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable market share is the sustainable volume-equivalent units sold divided by the total, in the focal county and week.

Table W.6: Demographic Effects on County-Level Sustainable Availability Share - Mass Merchandiser

Dependent Variable:	Log of Sustainable Availability Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.2631***	0.1242***	0.3512***	0.0691***	-0.0397	0.3825***
	(0.0294)	(0.0131)	(0.0362)	(0.0114)	(0.0244)	(0.0438)
Log(Pop. Density)	-0.0129***	0.0081***	0.0084	0.0096***	0.0293***	0.0221***
	(0.0047)	(0.0026)	(0.0059)	(0.0021)	(0.0039)	(0.0074)
Frac. Dem. Vote 2016	0.6641***	0.1584***	0.6746***	0.0798***	0.0070	0.8023***
	(0.0539)	(0.0231)	(0.0590)	(0.0175)	(0.0430)	(0.0767)
Frac. White Pop.	1.208***	0.2853***	0.4542***	-0.0214	0.0760	0.4467***
	(0.0711)	(0.0313)	(0.0899)	(0.0252)	(0.0565)	(0.1047)
Frac. Female Pop.	-0.1719	0.0201	-1.333***	-0.1926	0.0213	-0.9347**
	(0.2967)	(0.1448)	(0.3607)	(0.1183)	(0.2804)	(0.3860)
Frac. College Educ.	0.3522***	0.3133***	0.7567***	0.2775***	0.1907***	1.036***
	(0.0837)	(0.0366)	(0.0997)	(0.0302)	(0.0659)	(0.1290)
Log(Median Age)	-0.6501***	-0.1464***	-0.2261***	0.0780***	0.3706***	-0.0530
	(0.0569)	(0.0241)	(0.0643)	(0.0184)	(0.0476)	(0.0795)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	823,162	1,048,946	792,411	985,562	962,620	769,443
R^2	0.51091	0.52863	0.69297	0.59501	0.66472	0.32985
Within R^2	0.13540	0.07260	0.21903	0.16579	0.04992	0.25633

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable availability share is the number of sustainable UPC-store-level observations divided by the total, in the focal county and week.

Table W.7: Demographic Effects on County-Level Sustainable vs. Non-Sustainable Price Ratio - Mass Merchandiser

Dependent Variable:	Log of Sustainable vs. Non-Sustainable Price Ratio					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.0096	-0.1074***	-0.1334***	0.0198***	-0.0547***	0.1105***
	(0.0215)	(0.0106)	(0.0194)	(0.0052)	(0.0129)	(0.0190)
Log(Pop. Density)	-0.0174***	0.0180***	-0.0358***	-0.0087***	0.0147***	0.0110***
	(0.0033)	(0.0023)	(0.0031)	(0.0009)	(0.0021)	(0.0030)
Frac. Dem. Vote 2016	-0.0172	-0.0304*	-0.2087***	0.0650***	-0.1991***	0.4407***
	(0.0317)	(0.0180)	(0.0349)	(0.0090)	(0.0213)	(0.0326)
Frac. White Pop.	0.0716	0.1592***	0.2341***	0.0215*	-0.1723***	0.3683***
	(0.0526)	(0.0237)	(0.0490)	(0.0116)	(0.0294)	(0.0466)
Frac. Female Pop.	0.8593***	0.2278**	-0.2604	-0.0277	0.2947**	0.0118
	(0.2930)	(0.1053)	(0.2227)	(0.0549)	(0.1418)	(0.1790)
Frac. College Educ.	-0.2656***	-0.1070***	0.1228**	0.0227	0.0395	0.4657***
	(0.0501)	(0.0306)	(0.0552)	(0.0149)	(0.0358)	(0.0559)
Log(Median Age)	-0.0551	-0.0672***	0.1500***	-0.0111	0.0211	-0.1502***
	(0.0467)	(0.0194)	(0.0379)	(0.0102)	(0.0238)	(0.0348)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	822,731	1,047,446	792,090	975,696	941,827	768,501
R^2	0.29299	0.36121	0.52255	0.36787	0.32145	0.73387
Within R^2	0.02263	0.05308	0.10182	0.02416	0.02632	0.17289

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The price ratio takes the across-stores and across-UPCs weighted average price of sustainable and non-sustainable UPCs, respectively, using each UPC's total volume-equivalent units sold in the focal store and year as weights. This price ratio is computed at the county-week level.

Table W.8: Demographic, Availability, and Price Effects on County-Level Sustainable Market Shares - Mass Merchandiser

Dependent Variable:	Log of Sustainable Market Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.3059***	0.1364***	0.1767***	-0.0151	-0.0308	-0.1310***
	(0.0292)	(0.0146)	(0.0355)	(0.0101)	(0.0260)	(0.0210)
Log(Pop. Density)	-0.0337***	-0.0272***	-0.0320***	0.0021	0.0368***	-0.0255***
	(0.0049)	(0.0024)	(0.0061)	(0.0017)	(0.0040)	(0.0033)
Frac. Dem. Vote 2016	0.5705***	0.3675***	0.2393***	-0.0086	-0.1147***	0.1745***
	(0.0567)	(0.0254)	(0.0678)	(0.0187)	(0.0415)	(0.0412)
Frac. White Pop.	0.0320	0.1337***	0.8886***	-0.1195***	0.3773***	0.3182***
	(0.0739)	(0.0343)	(0.0883)	(0.0248)	(0.0558)	(0.0545)
Frac. Female Pop.	-0.2267	0.1644	-0.9902**	-0.4524***	0.4266*	-0.1966
	(0.3016)	(0.1510)	(0.3968)	(0.1013)	(0.2539)	(0.2453)
Frac. College Educ.	1.297***	0.6886***	1.158***	0.5065***	-0.2393***	0.3710***
	(0.0875)	(0.0406)	(0.1058)	(0.0267)	(0.0728)	(0.0640)
Log(Median Age)	-0.1025*	-0.0335	-0.2962***	0.2216***	0.2300***	0.0236
	(0.0593)	(0.0256)	(0.0728)	(0.0188)	(0.0480)	(0.0398)
Log(Avail. Share)	1.087***	0.8646***	1.275***	1.045***	0.8147***	1.155***
	(0.0107)	(0.0101)	(0.0094)	(0.0350)	(0.0145)	(0.0093)
Log(Price Ratio)	-0.8804***	-0.6806***	-0.6893***	-0.5408***	-0.6621***	-0.7017***
	(0.0282)	(0.0196)	(0.0116)	(0.0209)	(0.0214)	(0.0142)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	822,731	1,047,446	792,090	975,696	941,827	768,501
R^2	0.77538	0.70236	0.82167	0.81682	0.64748	0.75130
Within R^2	0.69658	0.57659	0.68151	0.66121	0.47734	0.71306

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable market share is the sustainable volume-equivalent units sold divided by the total, in the focal county and week. Sustainable availability share is the number of sustainable UPC-store-level observations divided by the total, in the focal county and week. The price ratio takes the across-stores and across-UPCs weighted average price of sustainable and non-sustainable UPCs, respectively, using each UPC's total volume-equivalent units sold in the focal store and year as weights. This price ratio is computed at the county-week level.

DEMAND ESTIMATION DETAILS

Estimation Details & Robustness Checks

Since we estimate product-specific own-price elasticities α_{jm} in each regression, it becomes infeasible to include every product sold in the regression when there are many brands that make up the available products within a county. To aid in estimation, we group the smallest brands (in terms of total revenue in the county across all years of our sample) that cumulatively contribute up to 10% of market share within the county as a single brand named "small brands" (delineated by sustainable and non-sustainable), which are then split into size bins to fit our product definition. The other brands that make up the remaining greater-than-90% of market share are unchanged.

We note our econometric specification in (5) also allows product-specific effects β_{jm} for all the control variables. Owing to the number of parameters this introduces to the model even when smaller brands are grouped together, we only estimate product-specific coefficients for the control variables that are related to the focal product itself, keeping common county-level coefficients for those variables related to the product's competitive environment. We do allow, however for sustainable and non-sustainable products to have differing county-level effects by including a sustainable interaction term on the competitive mix control variables.

We apply two additional restrictions in terms of our data. To ensure less common UPCs do not spuriously affect a product's price index, we use only UPCs that appear in our data for greater than two total years' (104 weeks') worth of periods in each store when aggregating to the product (brand-sustainable-size bin) level in our data. We further keep only stores that have both sustainable and non-sustainable sales such that our elasticity estimates reflect demand in stores where both sustainable and non-sustainable products are available.

We also estimate the model with two modifications for robustness and an additional modification for parsimony. First, we test robustness of our results to a different specification of the time fixed effects. While our main model (5) uses store-week fixed effects for both non-sustainable and sustainable products, τ_{st} and τ^1_{st}, we run a separate version using county-week fixed effects (τ^0_{mt} and τ^1_{mt}) restricting time varying demand shocks to be common to the whole subcategory within a county. Second, we test whether a more aggregated product definition, which uses just the brand and a sustainability claim indicator, changes our results. This modification enforces own-price elasticities to be common for all size bins within a brand. Lastly, for parsimony, we run a separate version of the model that only estimates common county-level effects for all the variables, including the own-price elasticities, allowing for a baseline (non-sustainable) effect and a sustainable interaction.

The robustness checks described above do not meaningfully impact our key takeaways from the paper and are available from the authors upon request. Results and discussion pertaining to the version where we estimate common county-level effects for own-price elasticities are given in Web Appendix 6.1.

Table W.9: Percentage of Total Revenue Used in Demand Estimation

	Ground Coffee	Instant Coffee	Single Cup Coffee	Yogurt	Yogurt Drinks	Laundry Detergent
Grocery						
All	76.4%	53.8%	71.6%	80.3%	69.0%	72.2%
Non-Sustainable	75.5%	51.3%	71.5%	76.0%	58.8%	72.8%
Sustainable	80.4%	68.1%	71.9%	82.4%	74.9%	60.6%
Mass Merchandiser						
All	78.1%	78.9%	71.0%	81.4%	73.6%	82.1%
Non-Sustainable	78.5%	80.5%	73.6%	79.2%	63.0%	82.6%
Sustainable	75.5%	63.2%	65.2%	83.2%	82.3%	71.7%

Table W.10: Median Proportion of Weeks Each Product Is Observed Per Store

	Ground Coffee	Instant Coffee	Single Cup Coffee	Yogurt	Yogurt Drinks	Laundry Detergent
Grocery						
Non-Sustainable	0.950	0.904	0.916	0.996	0.979	0.969
Sustainable	0.950	0.840	0.927	0.996	0.992	0.815
Mass Merchandiser						
Non-Sustainable	0.989	0.970	0.955	1	0.995	0.992
Sustainable	0.981	0.817	0.962	0.996	1	0.918

Notes. Within-store availability for a product is computed as the number of weeks a product was observed (i.e. non-zero sales) within a store divided by the total number of weeks the product is in that store (e.g. for a product in the store for the entire sample period, this value is the number of weeks in the sample period). The values in this table show the average of product-store availability within a store format, subcategory, and set of products that are sustainable vs. non-sustainable. The products represented in this table are the ones used in the demand regressions in Section 5.

Table W.11: Average Available Products Per Store, by Local, Regional, or National

	Ground Coffee	Instant Coffee	Single Cup Coffee	Yogurt	Yogurt Drinks	Laundry Detergent
Grocery						
Local	0.39	0.03	0.10	0.13	0.05	0.002
Regional	0.82	0.19	0.34	0.59	0.17	0.04
National	25.58	13.95	25.23	36.91	6.88	23.57
Mass Merchandiser						
Local	0.06	0	0.003	0.02	0.03	0.003
Regional	0.39	0.04	0.11	0.18	0.01	0.01
National	22.15	15.90	29.05	35.61	9.64	38.72

Table W.12: Average Proportion of Sustainable Products Per Store, by Local, Regional, or National

	Ground Coffee	Instant Coffee	Single Cup Coffee	Yogurt	Yogurt Drinks	Laundry Detergent
Grocery						
Local	0.28	0.14	0.17	0.15	0.002	0.54
Regional	0.27	0.04	0.42	0.14	0.13	0.12
National	0.15	0.16	0.31	0.66	0.64	0.14
Mass Merchandiser						
Local	0.02		0	0.73	0	0
Regional	0.34	0.06	0.10	0	0	0
National	0.15	0.15	0.23	0.63	0.53	0.15

Variable Definitions

Demand Estimation Variables Table W.13 describes the variables used in our demand regressions in equation (5), reproduced here for reference.

$$\log(q_{jst}) = \alpha_{jm}\log(p_{jst}) + \mathbf{X}'_{jst}\boldsymbol{\beta}_{jm} + \eta_{js} + \tau^0_{st} + \tau^1_{st}\mathbb{1}\{Sus_j = 1\} + \epsilon_{jst},$$

Table W.13: Variable Definitions for Demand Regressions

Symbol	Variable	Definition
$\log(q_{jst})$	Quantity (logged)	The total standardized volume sold of product j in store s in week t, logged.
$\log(p_{jst})$	Price index (logged)	The log of the weighted average volume-equivalent price (dollars/standard volume) across all UPCs that make up product j in store s in week t. The weights are the total volume sold of the respective UPC in store s in the year that week t is in.
$\mathbf{X}_{jst}$	Promotion indicator	An indicator for whether any underlying UPC in product j was promoted (either featured or displayed) in store s in week t.
	Number of UPCs	The number of underlying UPCs within the product j that are observed in store s during week t.
	Own-brand price index of other non-sustainable products (logged)	The log of the weighted average price index of all non-sustainable products other than product j that are within the same brand (i.e. not in the same size bin) in store s in week t. The weights are the total volume sold of the respective products in store s in the year that week t is in. 0 if the brand has no other products that are non-sustainable available within j's brand in store s during week t.
	Own-brand price index of other sustainable products (logged)	The log of the weighted average price index of all sustainable products other than product j that are within the same brand (i.e. not in the same size bin) in store s in week t. The weights are the total volume sold of the respective products in store s in the year that week t is in. 0 if the brand has no other products that are sustainable available within j's brand in store s during week t.
	Own-brand promotion indicator of other non-sustainable products	An indicator for whether any non-sustainable products within the same brand but not the same size bin as the focal product j was promoted (either feature or display). 0 if the brand has no other products that are non-sustainable available within j's brand in store s during week t.
	Own-brand promotion indicator of other sustainable products	An indicator for whether any sustainable products within the same brand but not the same size bin as the focal product j was promoted (either feature or display). 0 if the brand has no other products that are sustainable available within j's brand in store s during week t.
	Indicator for no other non-sustainable products within the same brand	An indicator that equals 1 if there are no other non-sustainable products available within j's brand in store s during week t.
	Indicator for no other sustainable products within the same brand	An indicator that equals 1 if there are no other sustainable products available within j's brand in store s during week t.
	Price index of non-sustainable competitor products (logged)	The log of the weighted average price index of all non-sustainable products from competitor brands that share the same size bin as product j in store s in week t. 0 if there are no competing non-sustainable products in the same size bin as product j.

	Price index of sustainable competitor products (logged)	The log of the weighted average price index of all sustainable products from competitor brands that share the same size bin as product j in store s in week t. 0 if there are no competing sustainable products in the same size bin as product j.
	Promotion indicator of non-sustainable competitor products	The proportion of non-sustainable products from competitor brands that share the same size bin as product j for which any underlying UPC is promoted (featured or displayed) in store s in week t. 0 if there are no competing non-sustainable products in the same size bin as product j.
	Promotion indicator of sustainable competitor products	The proportion of sustainable products from competitor brands that share the same size bin as product j for which any underlying UPC is promoted (featured or displayed) in store s in week t. 0 if there are no competing sustainable products in the same size bin as product j.
	Number of non-sustainable competitors	Number of non-sustainable products from competitor brands that share the same size bin as product j in store s in week t.
	Number of sustainable competitors	Number of sustainable products from competitor brands that share the same size bin as product j in store s in week t.
	Monopolist indicator, non-sustainable	An indicator for whether product j is the only non-sustainable product available in its size bin in store s in week t.
	Monopolist indicator, sustainable	An indicator for whether product j is the only sustainable product available in its size bin in store s in week t.
η_{js}	Product-store fixed effect	
τ^0_{st}	Store-week fixed effect	
τ^1_{st}	Store-week fixed effect for sustainable products	

Empirical Bayes Variables Table W.14 describes the variables used in the empirical Bayes deconvolution in equation (6), reproduced here.

$$\hat{\alpha}_{jm} \sim N(\alpha_{jm}, s_{jm}^2)$$
$$\alpha_{jm} \sim N(\mu_j + \mathbf{W}'_{jm}\gamma_j, \sigma_j^2)$$

Table W.14: Variable Definitions for Empirical Bayes Deconvolution

Symbol	Variable	Definition
μ_j	Product intercept	A constant term for the product j, i.e. the "baseline" elasticity of the product given zeros for all values in $\mathbf{W}_{jm}$.
$\hat{\alpha}_{jm}$	Price elasticity estimate	The estimated price elasticity of product j in county m from the demand regressions in (5).
s_{jm}	Standard error	The standard error of the estimated price elasticity of product j in county m from the demand regressions in (5).
$\mathbf{W}_{jm}$	Average number of non-sustainable competitors	The average number of of non-sustainable products from competitor brands that share the same size bin as product j, across stores s in county m and across all weeks t in the sample period for which product j is observed in county m.
	Average number of sustainable competitors	The average number of of sustainable products from competitor brands that share the same size bin as product j, across stores s in county m and across all weeks t in the sample period for which product j is observed in county m.
	Median household income (logged)	The log of the median household income in the past 12 months (in 2019 inflation-adjusted dollars) for county m.
	Population density (logged)	The log of the total population of county m divided by the land area (in square miles) of the county.
	Median age (logged)	The log of the median age (years) of the population of county m.
	Democratic vote share (2016 presidential election)	The percent of the population of county m that voted for the Democratic presidential candidate in the 2016 presidential election.
	White (only) population fraction	Fraction of the population of county m who are white (only).
	Female population fraction	Fraction of the population of county m who are female.
	College educated population fraction	Fraction of the population of county m who are 25 years of age or older that have received a Bachelor's degree.

Note. The data are from the ACS 5-Year Survey for 2015-2019, with supplemental information provided by the "socviz" R library, which sources the US Census Bureau, namely for the "Democratic vote share" variable and the land area of each county, which is used to construct the "population density" variable.

ADDITIONAL DEMAND ESTIMATION RESULTS

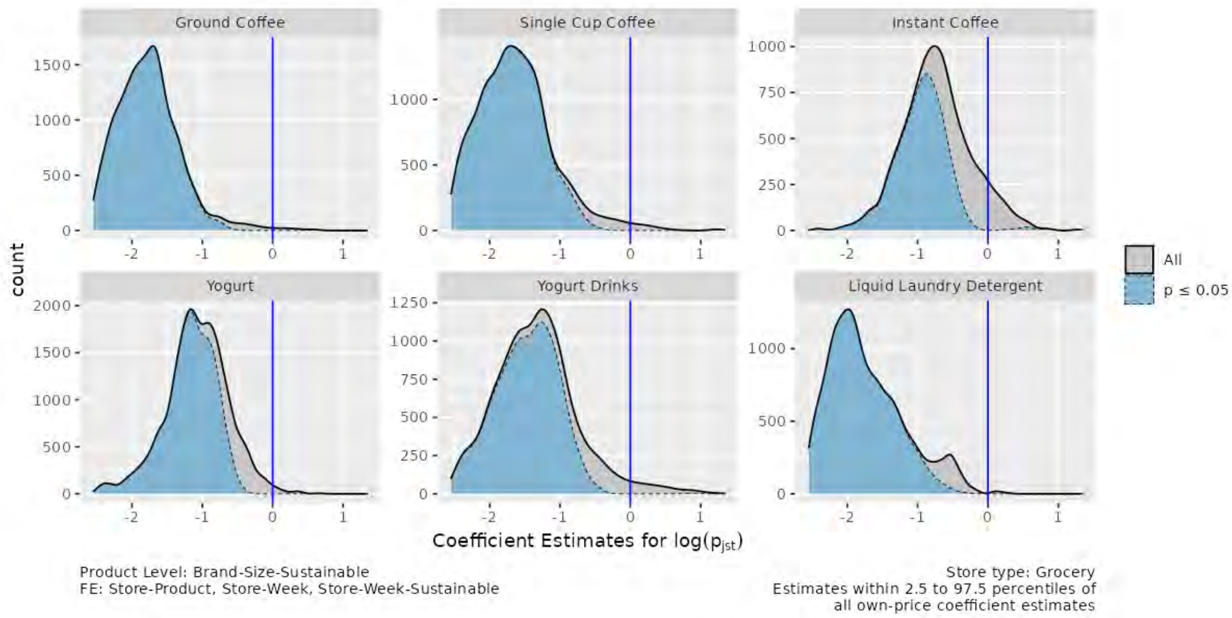
Homogeneous Price Elasticities

Here, we estimate a simpler version of the model in which price elasticities are the same within a county for all non-sustainable and sustainable products, respectively. Figure W.9a shows the distribution of county-level estimates for the baseline price coefficient as well as the county-level estimates for the coefficient on price interacted with an indicator variable for being a sustainable product. The blue shaded part of the density are for estimates with $p < .05$. As expected, the vast majority of price coefficients are significant and negative. There is also considerable variation in whether sustainable products within the county exhibit larger or smaller elasticities, as shown in Figure W.9b. For ground coffee, instant coffee, yogurt, and liquid laundry detergent, sustainable products typically exhibit smaller price elasticities in magnitude.

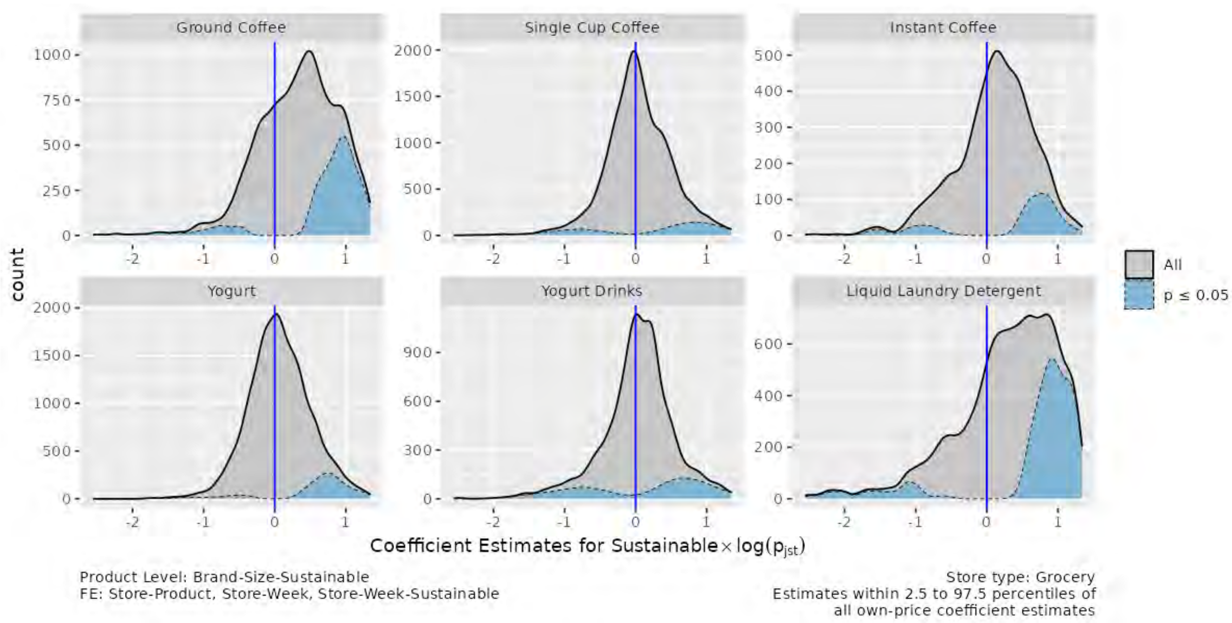
For the mass merchandiser format, estimates of homogeneous price elasticities for sustainable vs. non-sustainable products are displayed in Figure W.10. Compared to the grocery store format, mass merchandiser stores show more mixed sustainable interactions. Instant coffee, yogurt, and yogurt drinks typically exhibit smaller price elasticities in magnitude, while ground coffee, single cup coffee, and liquid laundry detergent typically exhibit larger price elasticities in magnitude.

The cross price effects (for the sustainable and non-sustainable competitor price indexes) are shown in the Web Appendix in Figures W.11 and W.12. The prices of competing sustainable products do not systematically affect demand differently than competing non-sustainable products.

Figure W.9: Distribution of County-Level Average Own-Price Elasticities: Grocery

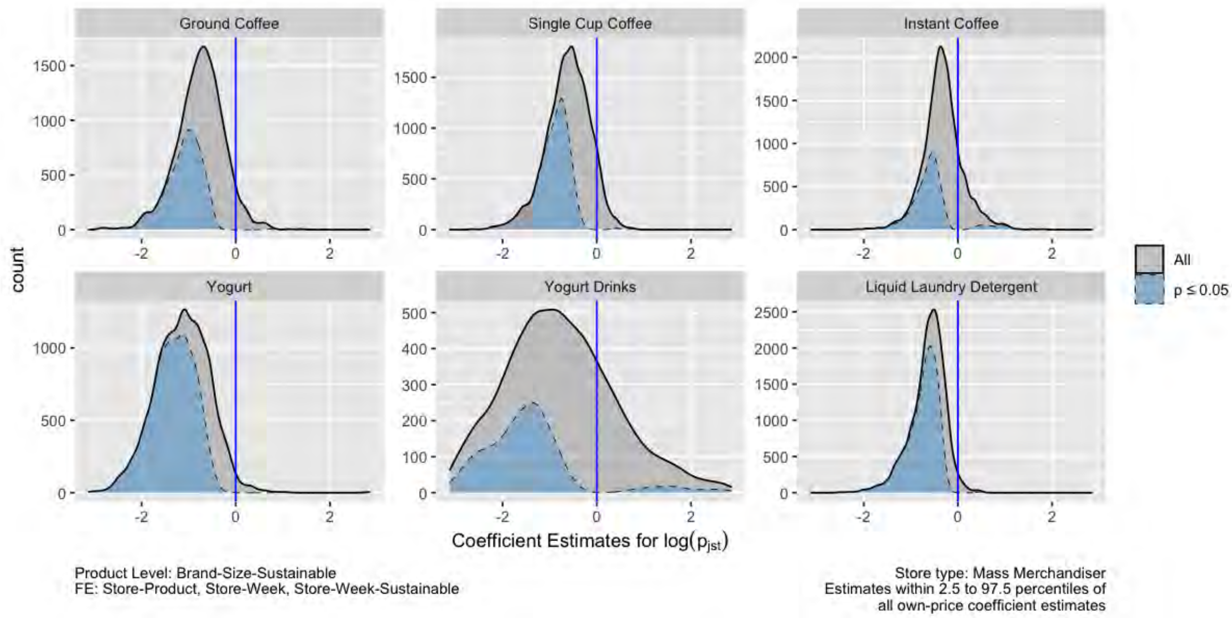


(a) Non-Sustainable Baseline

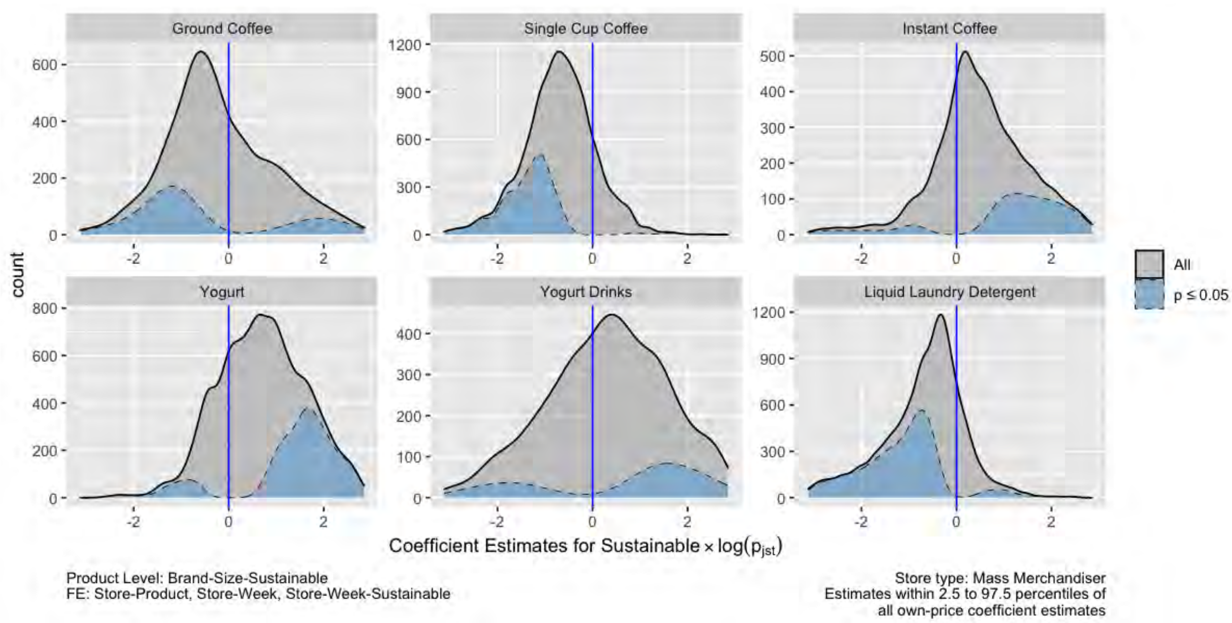


(b) Sustainable Interaction

Figure W.10: Distribution of County-Level Average Own-Price Elasticities: Mass Merchandiser

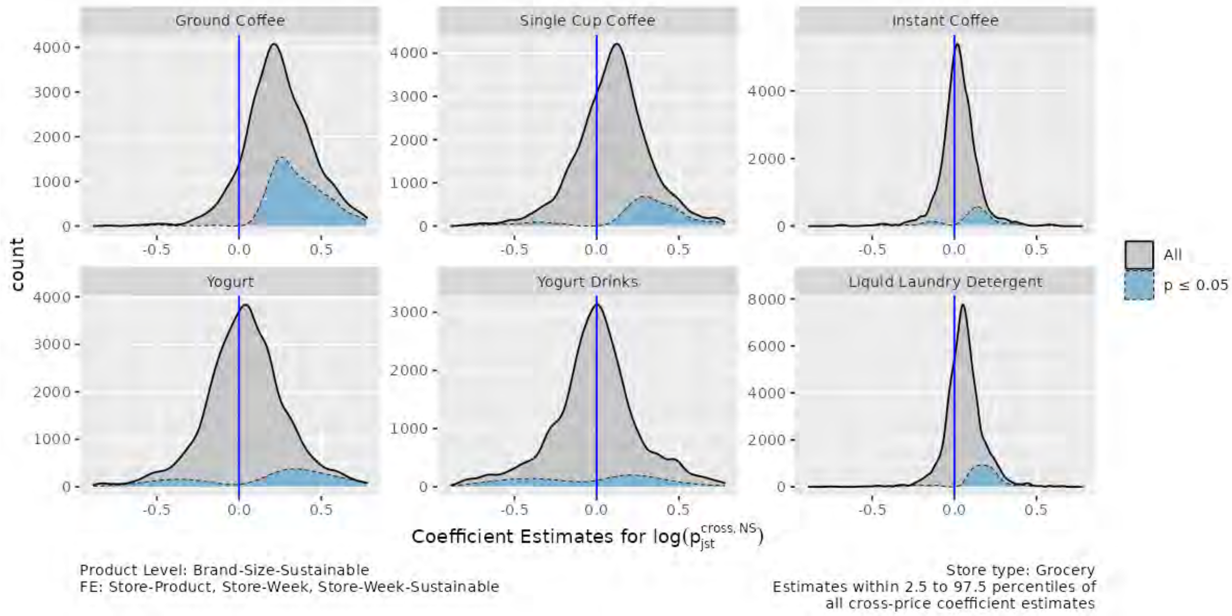


(a) Non-Sustainable Baseline

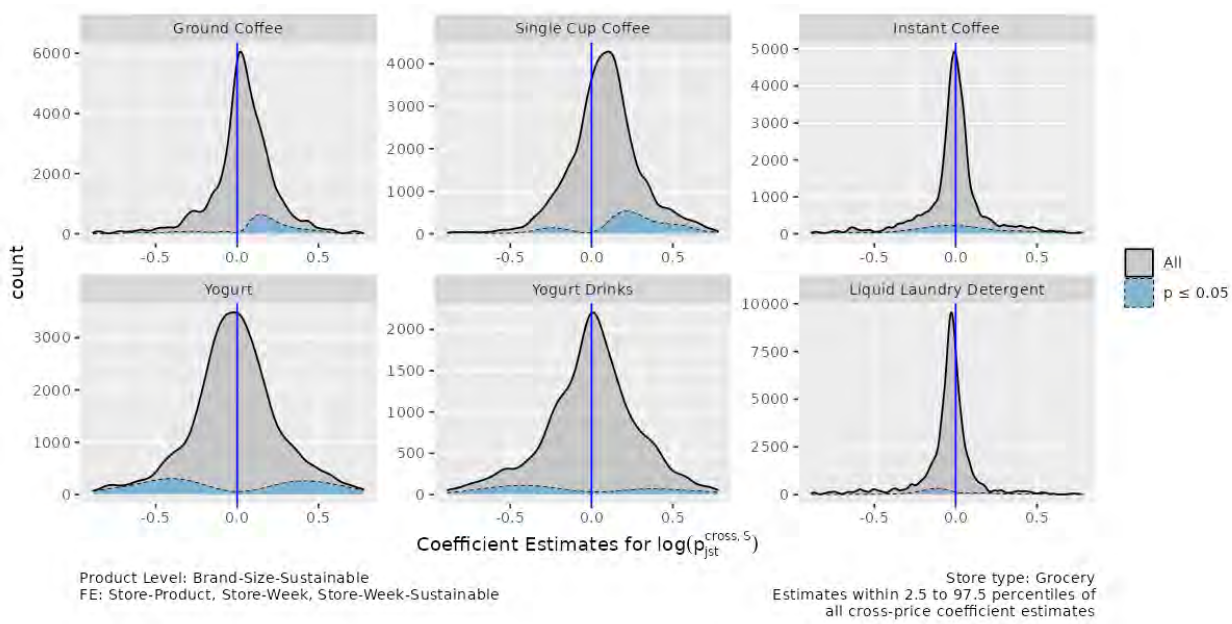


(b) Sustainable Interaction

Figure W.11: Distribution of County-Level Average Cross Price Elasticities on Non-Sustainable Product Demand: Grocery

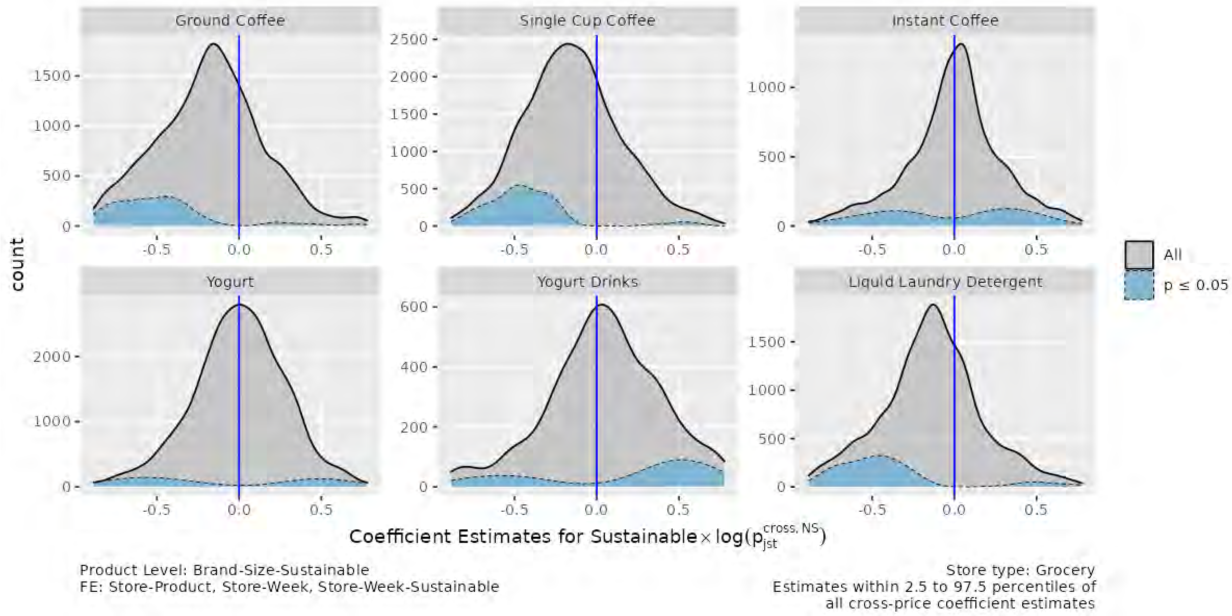


(a) Baseline Cross Price Elasticity of Non-Sustainable Demand

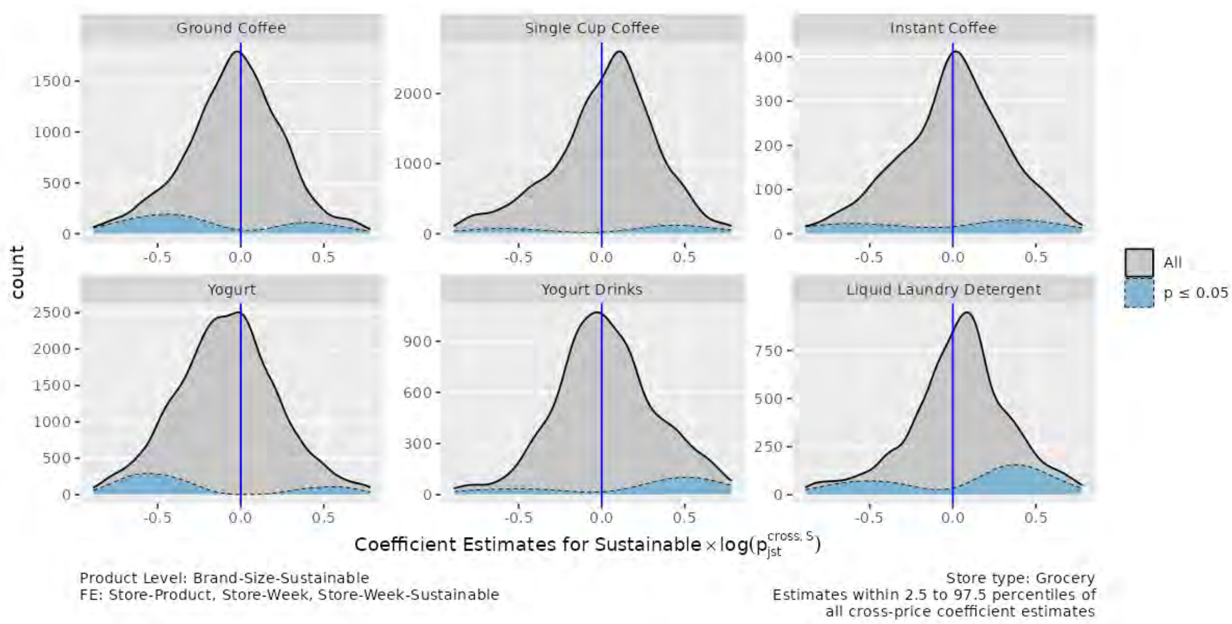


(b) Sustainable Interaction

Figure W.12: Distribution of County-Level Average Cross Price Elasticities on Sustainable Product Demand: Grocery

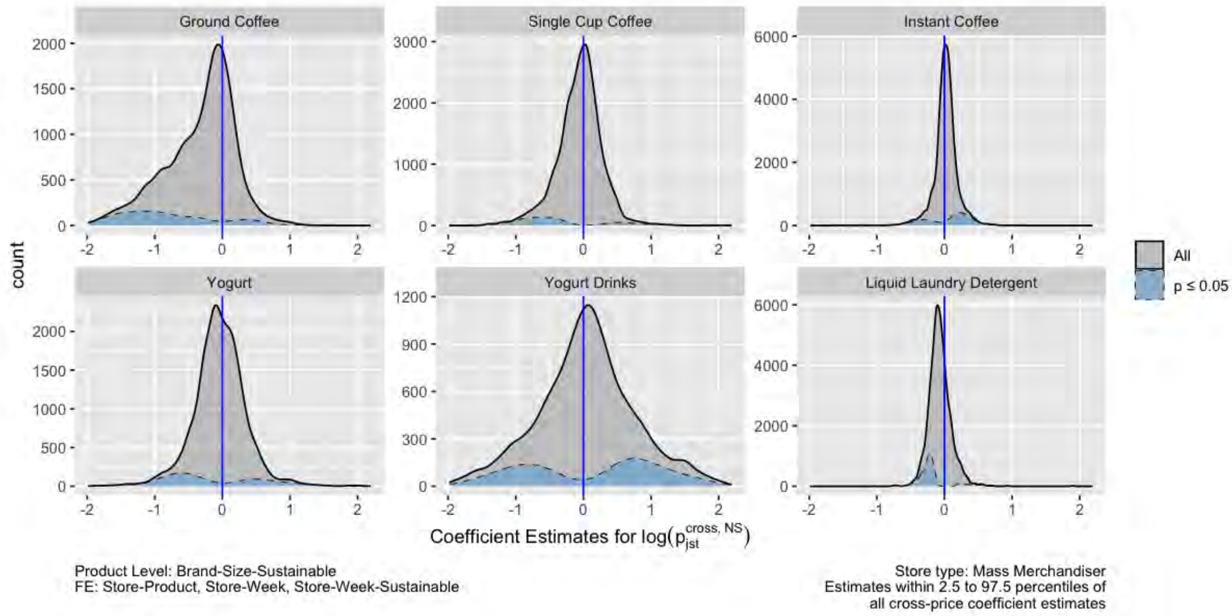


(a) Baseline Cross Price Elasticity of Sustainable Demand

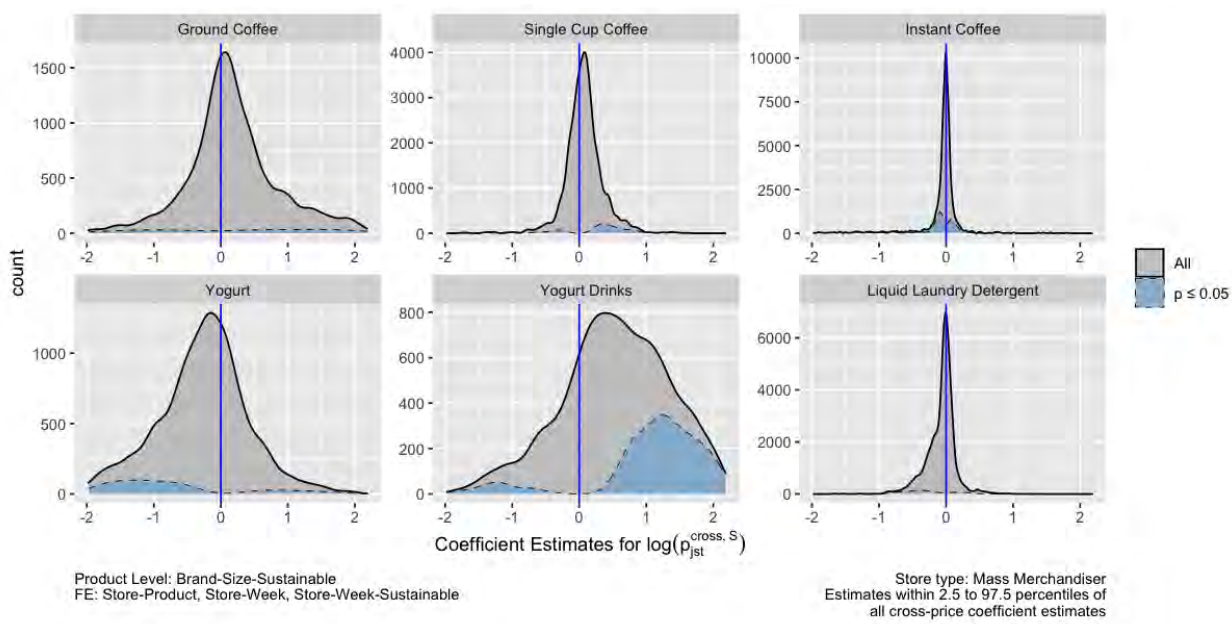


(b) Sustainable Interaction

Figure W.13: Distribution of County-Level Average Cross Price Elasticities on Non-Sustainable Product Demand: Mass Merchandiser

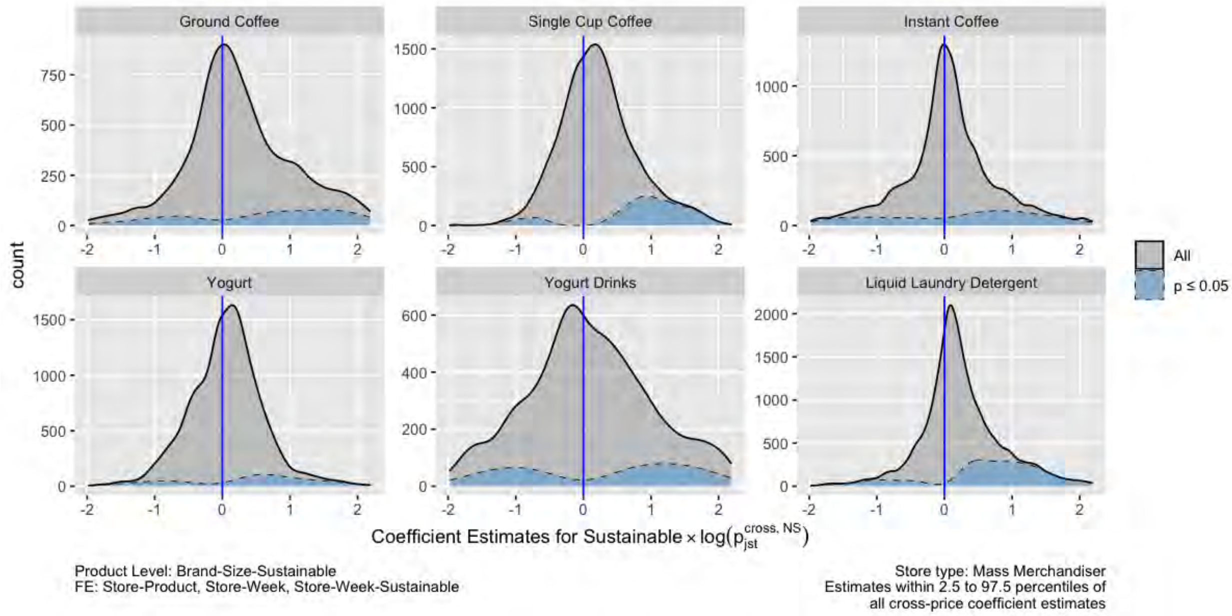


(a) Baseline Cross Price Elasticity of Non-Sustainable Demand

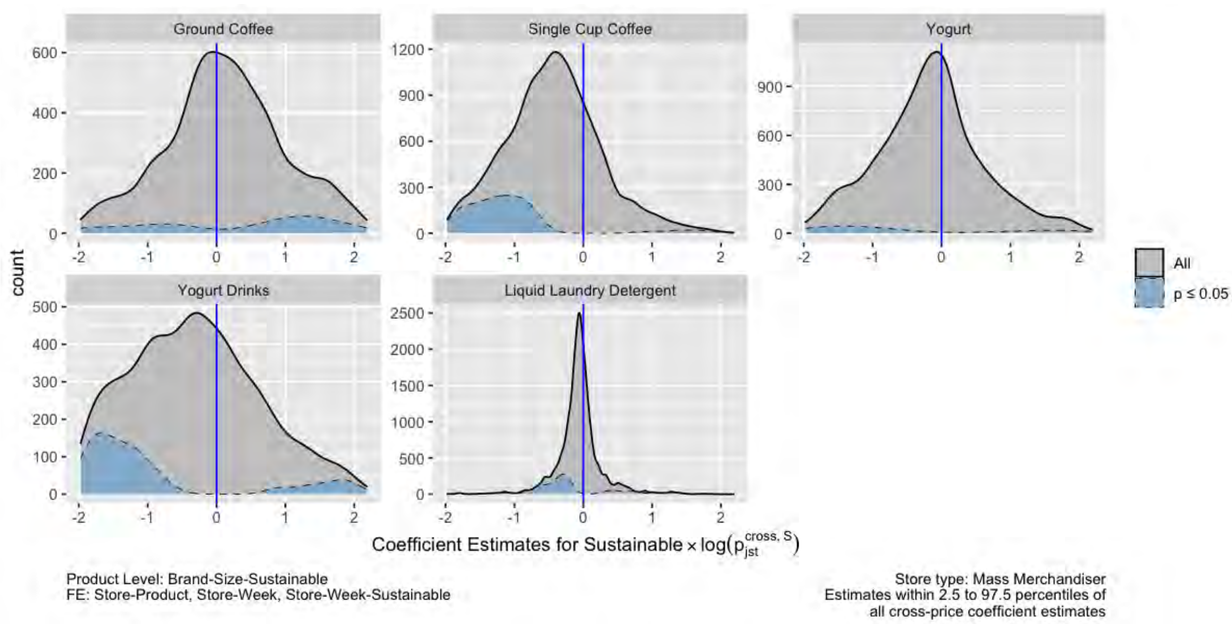


(b) Sustainable Interaction

Figure W.14: Distribution of County-Level Average Cross Price Elasticities on Sustainable Product Demand: Mass Merchandiser



(a) Baseline Cross Price Elasticity of Sustainable Demand



(b) Sustainable Interaction

Distribution of Hyperparameter Estimates

Figure W.15: Distribution of Empirical Bayes Deconvolution Hyperparameter Estimates Across Products: Grocery

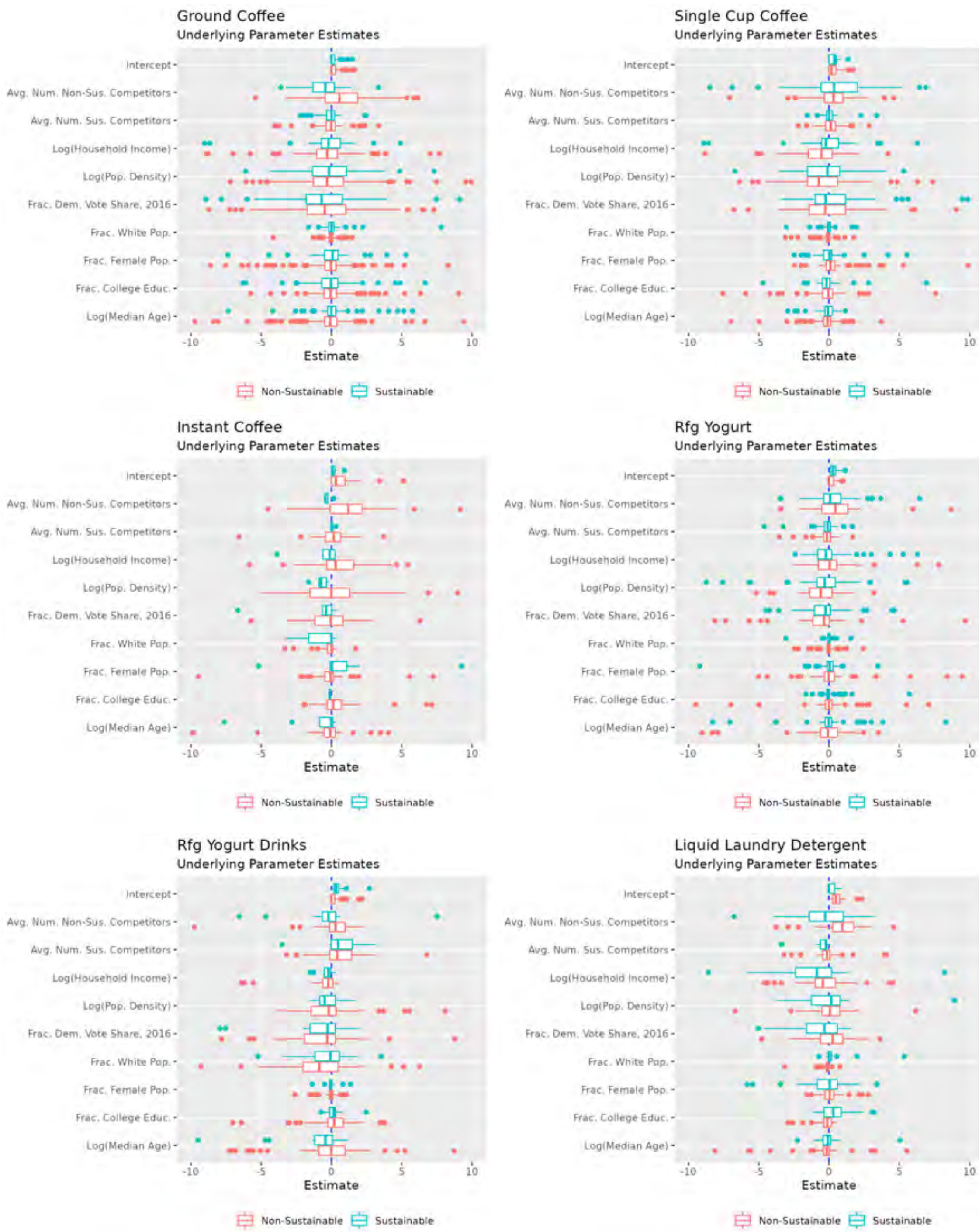
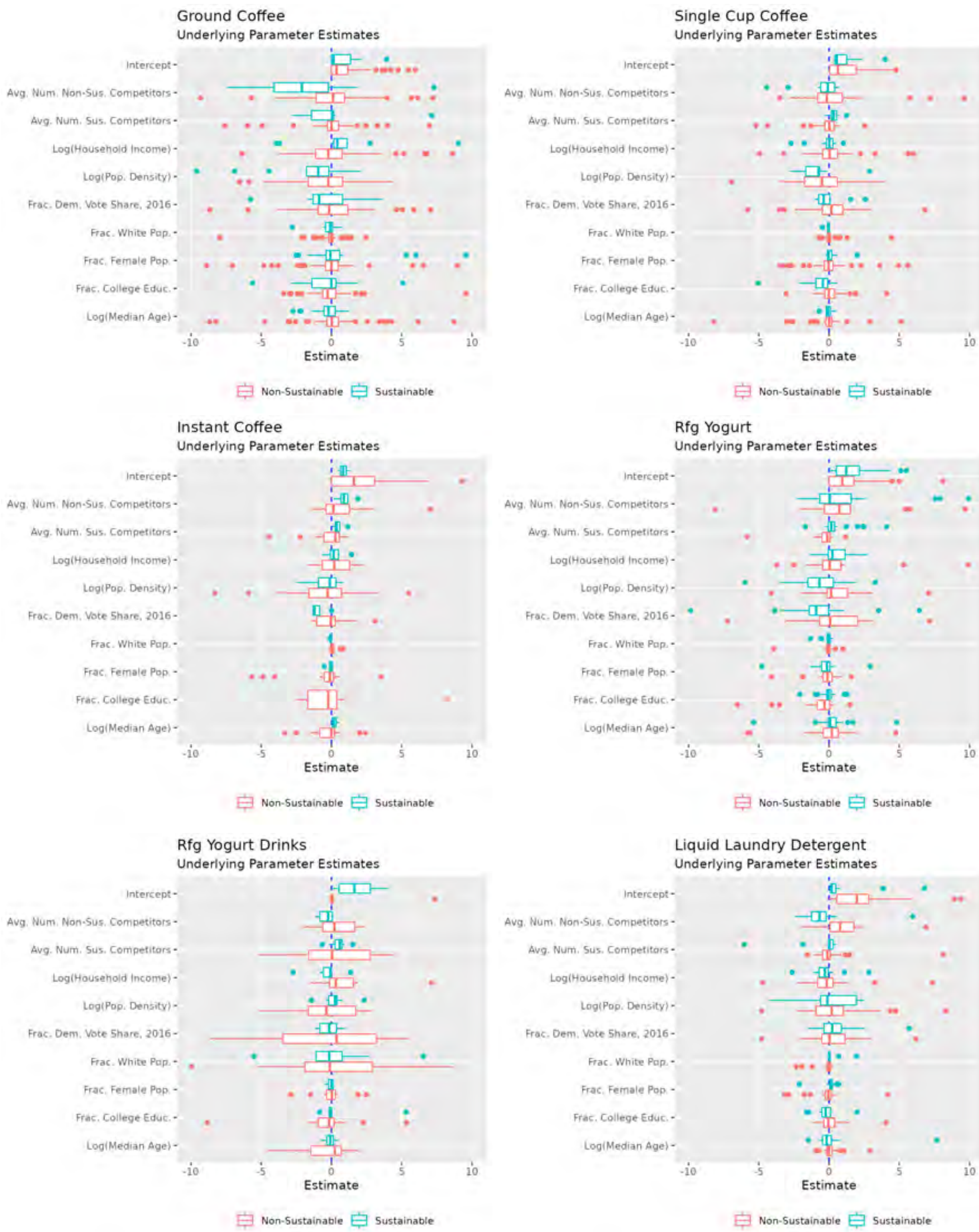


Figure W.16: Distribution of Empirical Bayes Deconvolution Hyperparameter Estimates Across Products: Mass Merchandiser



Posterior Price Elasticity Estimates by Sustainability Claim

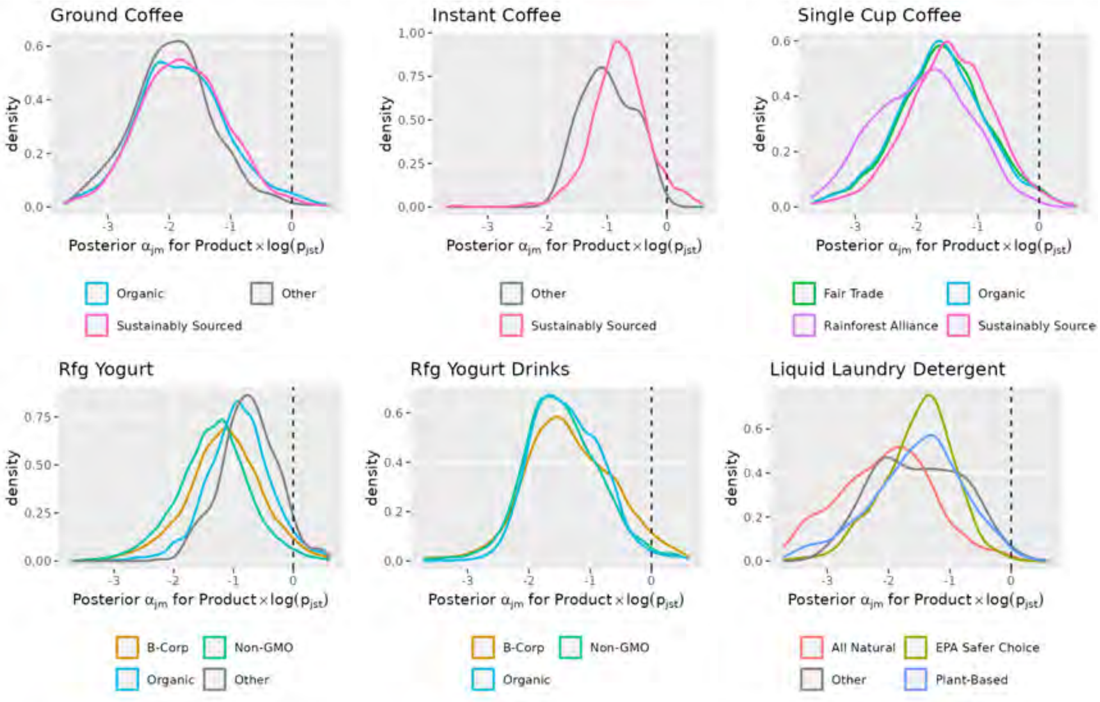
Figure W.17 6.3 shows the kernel densities for the different types of claims used (a product may appear in multiple distributions if it has multiple claims). In all three coffee subcategories, we note the distribution of elasticities for the "Sustainably Sourced" claim is shifted to the right compared to the other claims (in ground coffee, the "Organic" claim is fairly similar), indicating more inelastic responses to price for products with that claim. Within the single cup coffee subcategory, we find products with the "Rainforest Alliance" claim to have higher elasticities compared to the others, including "Fair Trade" and "Organic", which are similar in elasticity, and "Sustainably Sourced" which again has the lowest elasticities. In yogurt, "Organic" claims, as well as "Other" claims in grocery stores (which consist mostly of "Plant Based" claims), are less elastic than "Non-GMO" and "Certified B Corporation" claims. Elasticities are fairly similar across different types of claims in yogurt drinks, while products with the "All Natural" claim in the liquid laundry detergent subcategory are generally more price elastic than "EPA Safer Choice" and "Plant Based" claims.

We leverage insights from two existing studies to interpret our results on the price elasticities of products with different claims. First, Tully and Winer (2014) study the role of the beneficiary of socially responsible claims on products and find consumer willingness to pay for such products are highest when the beneficiary of the claim is humans and the lowest for the environment. Among the prominent claims in our study, "Fair Trade" has a clear human benefit, while "Sustainably Sourced" and "Rainforest Alliance" have more clear-cut environmental benefits (others, such as "Organic", "EPA Safer Choice" have both human/health as well as environmental benefits). Our results partially align with Tully and Winer (2014), with price elasticities for products with a "Fair Trade" claim being lower on average than those with the "Rainforest Alliance" claim. However, as mentioned, the "Sustainably Sourced" claim has the lowest price elasticities among the coffee subcategories.

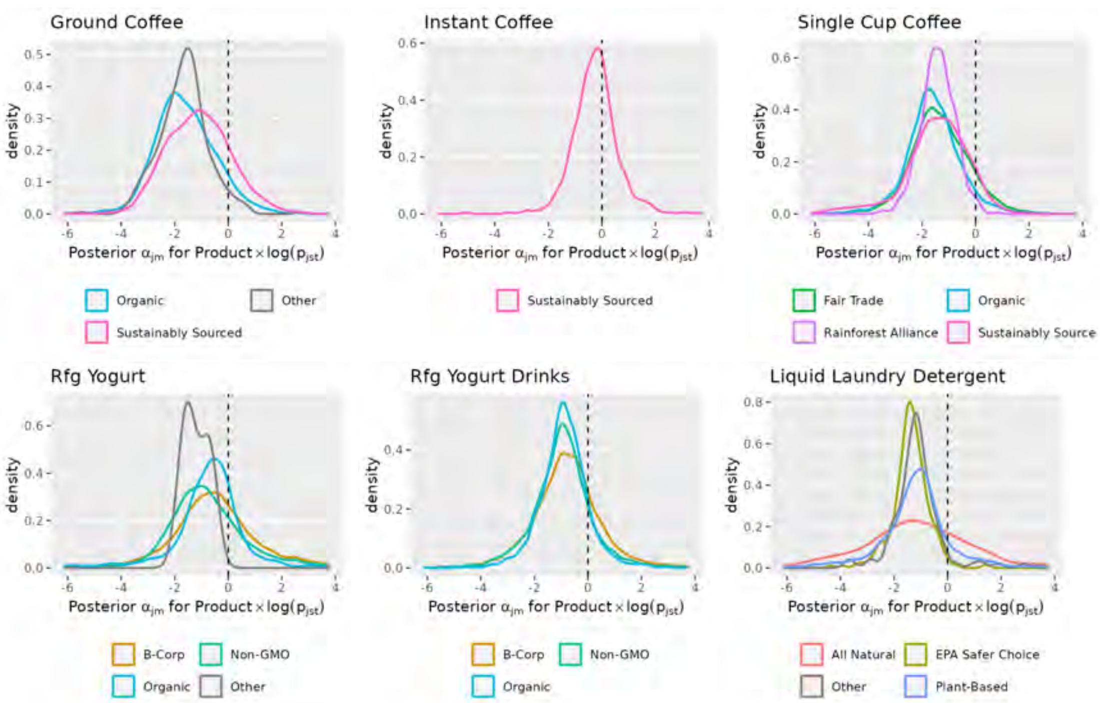
Second, André and Chandon (2019) study perceptions of food products with health claims along two dimensions, namely nature (not adjusting ingredients) vs. science (adjusting ingredients) and presence (not removing or adding ingredients) vs. absence (not adding or removing ingredients). They find products with science-based claims are perceived as healthier than nature-based ones. Among the claims in our study, ones such as "EPA Safer Choice" and "Plant-Based Ingredients" in laundry detergent fall under science-based claims, since they involve the added use of safe or plant-based ingredients, while "All Natural" would fall under nature-based. We find that the science-based claims have lower price elasticities than the nature-based claim in the laundry detergent category, possibly due to the greater perceptions of healthiness which were reported in André and Chandon (2019) for products with science-based claims. We also see this pattern for yogurt, where "Plant Based" claims (which are the most prominent claim within the "Other" claims in grocery stores) have lower overall price elasticities than the nature-based claims in "Organic" and "Non-GMO".[30]

[30] André and Chandon (2019) also find among products with nature-based claims, the ones with a presence focus (e.g. "Organic") are perceived to be healthier than those with an absence focus (e.g. "Non-GMO") — there, our results align again, with yogurt products containing the "Organic" claim showing slightly lower elasticities compared to those with the "Non-GMO" claim.

Figure W.17: Distribution of Posterior Estimates By Sustainability Claim



(a) Grocery

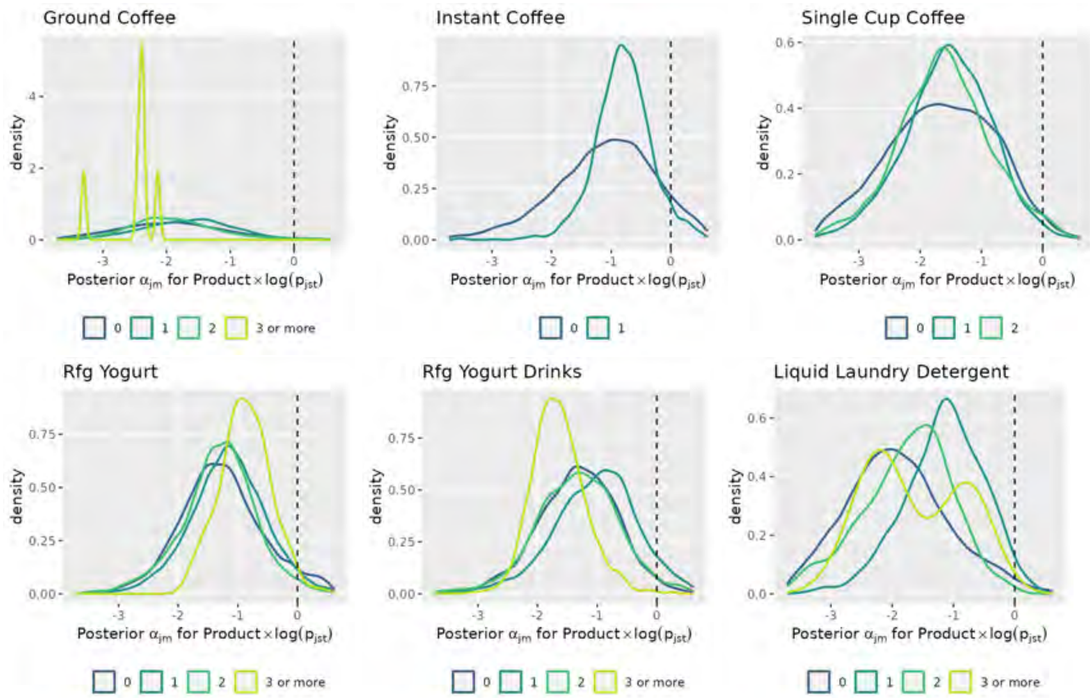


(b) Mass Merchandiser

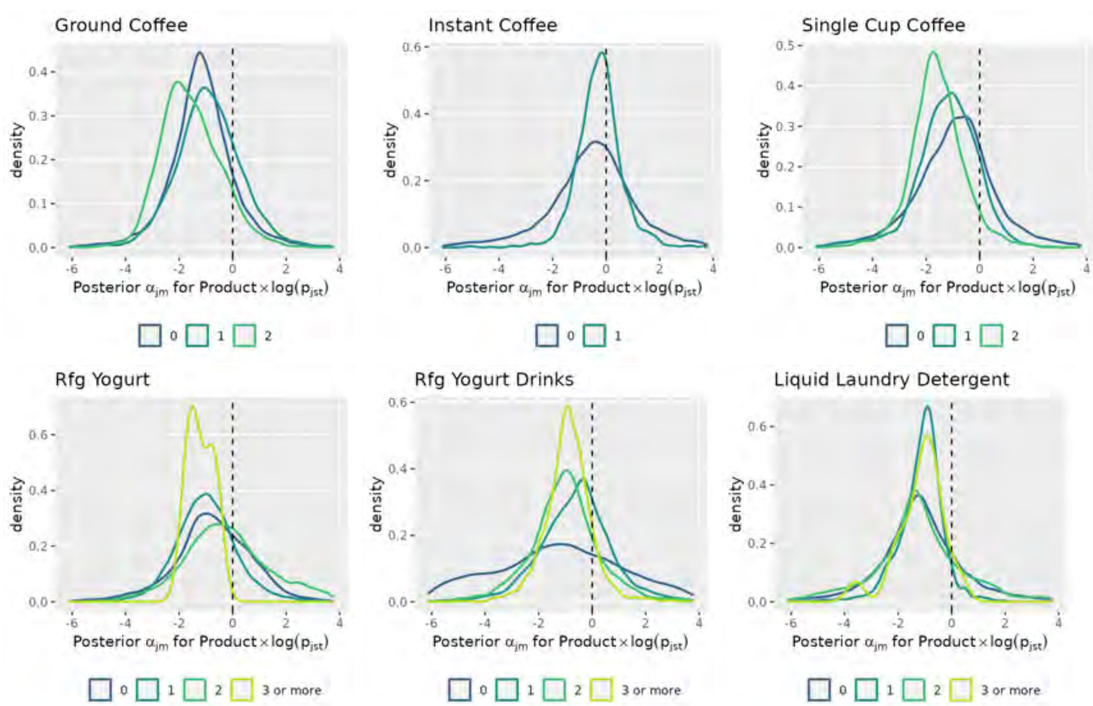
Posterior Price Elasticity Estimates by Number of Sustainability Claims

Here, we examine the distribution of price elasticity estimates by the number of claims, which we report in Figure W.18 in Web Appendix 6.4. Similar to Olsen, Slotegraaf, and Chandukala (2014) who show green message quantity to negatively influence brand attitudes, we find for most subcategories we study, more sustainability claims (conditional on at least one claim) leads to larger elasticities in grocery stores (the results for mass merchandiser are less clear). The exception is yogurt, where products with more sustainability claims tend to have smaller elasticities in magnitude (implying the ability to charge higher margins). Olsen, Slotegraaf, and Chandukala (2014) do show a positive interaction of the number of green claims and being a high virtue category, which could explain this result (among the categories we study, yogurt has the highest virtue score in their paper). Another possibility is that since yogurt has the highest market share of sustainable products out of the subcategories we study, the additional sustainability claims add to the legitimacy of sustainable yogurt products, but not for the other subcategories in which sustainable products are still not mainstream.

Figure W.18: Distribution of Posterior Estimates By Number of Sustainability Claims



(a) Grocery



(b) Mass Merchandiser

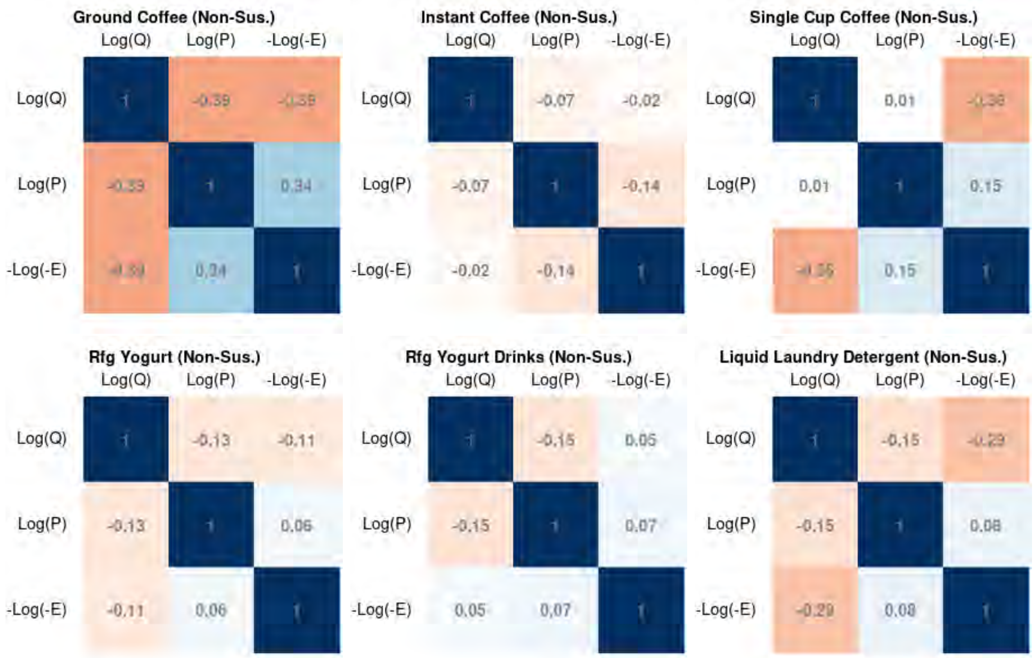
CORRELATIONS OF PROFIT POTENTIAL COMPONENTS

In this Appendix, we analyze the correlations between its three components, $\log(\bar{q}_{jm})$, $\log(\bar{p}_{jm})$, and $-\log(-\tilde{\varepsilon}_{jm})$, where $\bar{q}_{jm}$, $\bar{p}_{jm}$, and $\tilde{\varepsilon}_{jm}$ are the average quantity (in units) sold across the full panel, the average price (per 16oz), and the posterior mean own-price elasticity estimate, respectively, for a product j within a market m for the different subcategories in each store format.

Figures W.19 and W.20 show these correlations, which we compute within the set of either sustainable or non-sustainable products, for the grocery and mass merchandiser store formats, respectively. In some product categories, the trade-off is larger than others. For non-sustainable ground coffee in both the grocery and mass merchandiser formats, for example, products with higher demand are priced substantially lower with lower margin, whereas for non-sustainable instant coffee, margins and prices are only very slightly negatively correlated with demand. In some sustainable product subcategories (instant coffee in both store formats, for example), there is a positive correlation between prices and quantities, i.e. those products that have higher demand are also priced higher, possibly due to higher quality or quality perceptions. In both those examples, there is a slight negative correlation between price and possible margin, indicating that the higher prices are likely due to higher costs. In contrast, for sustainable liquid laundry detergent, there is a very strong positive correlation between price and possible margin in the grocery format, indicative of firms charging higher prices due to their ability to extract surplus from less price sensitive consumers.

Figure W.19: Correlation of Sales (Volume), Price, and Elasticity (Posterior Estimates): Grocery

(a) Non-Sustainable Products



(b) Sustainable Products

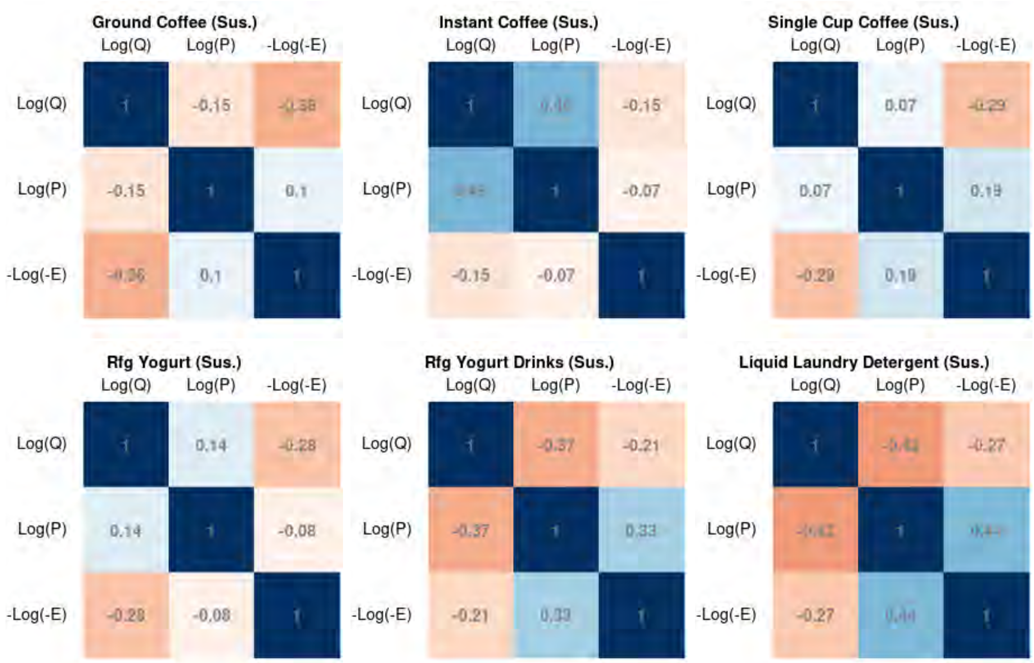
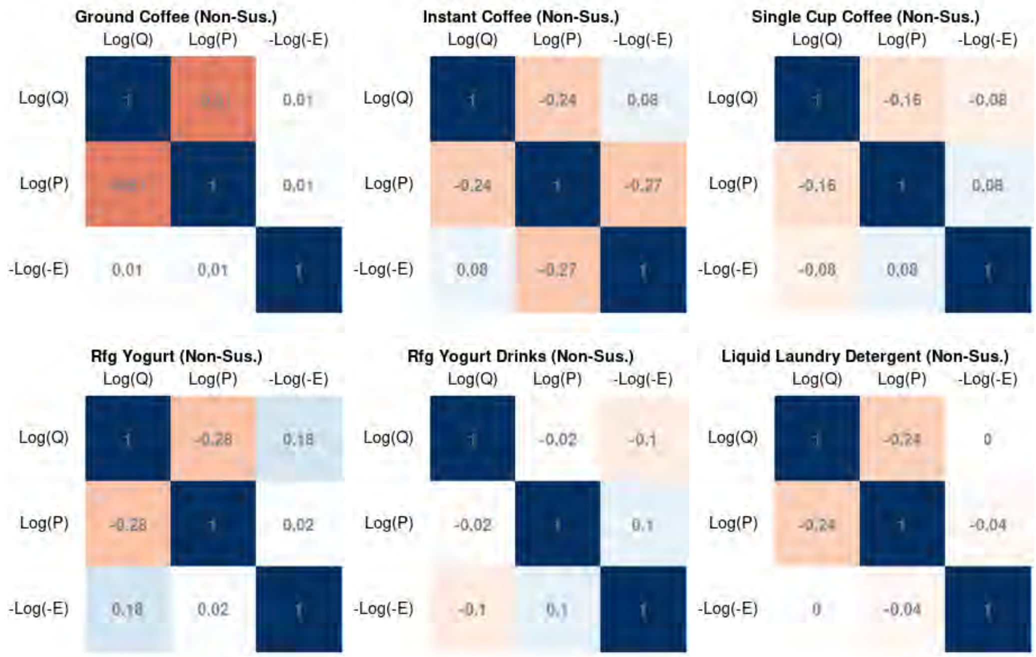
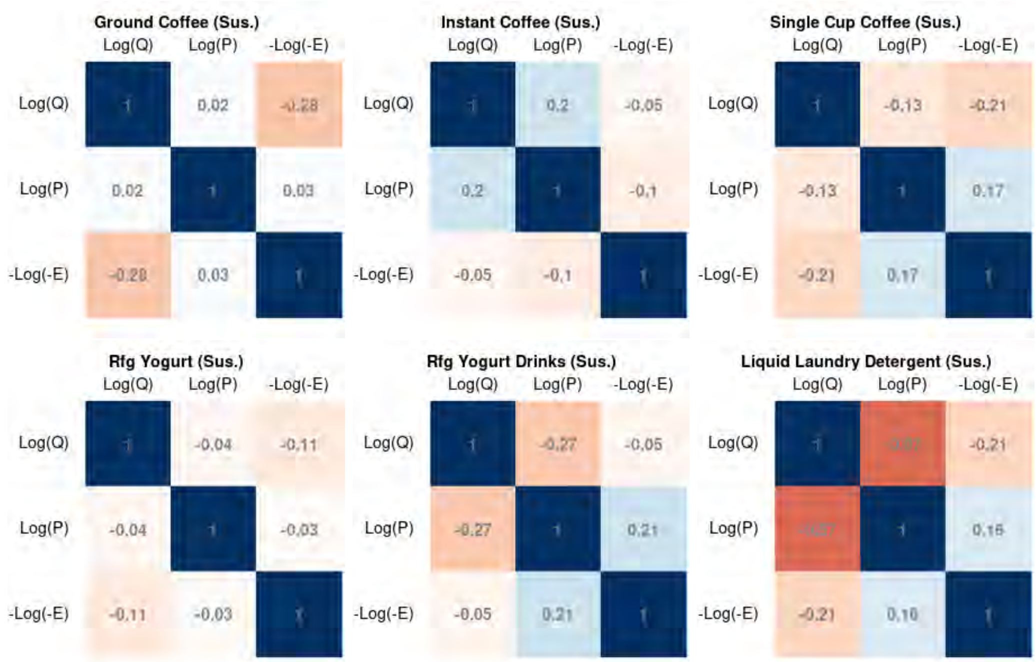


Figure W.20: Correlation of Sales (Volume), Price, and Elasticity (Posterior Estimates): Mass Merchandiser

(a) Non-Sustainable Products



(b) Sustainable Products



DEMOGRAPHIC EFFECTS ON SUSTAINABLE PRODUCT AVAILABILITY: ROBUSTNESS CHECKS

Figure W.21: Demographic Effects on Sustainable Product Availability, Controlling for Minimum Profit Potential

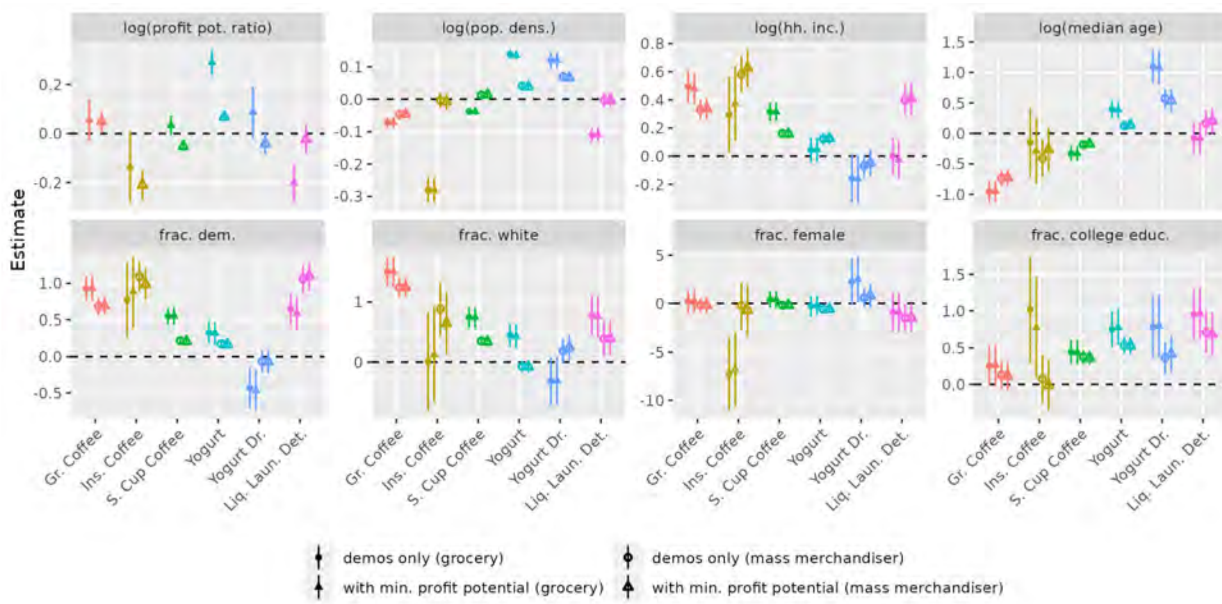
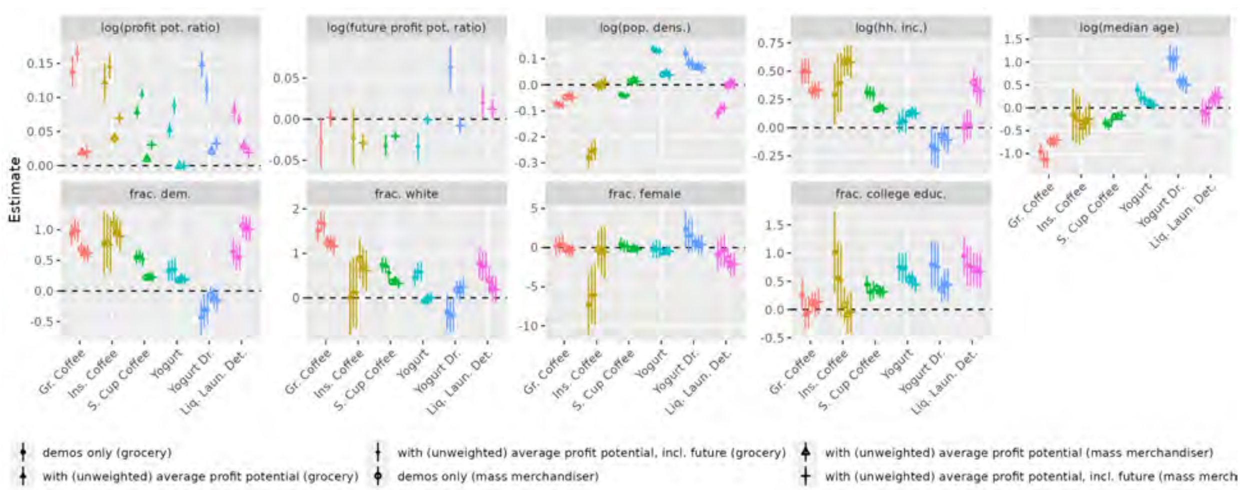


Figure W.22: Demographic Effects on Sustainable Product Availability, Controlling for Current & Future Profit Potential



CLUB STORE FORMAT RESULTS

Table W.15: Demographic Effects on County-Level Sustainable Market Share - Club Format

Dependent Variable:	Log of Sustainable Market Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.5433***	0.2379***	0.1091	-0.1283***	-0.1117	-0.8434***
	(0.1656)	(0.0609)	(0.2902)	(0.0368)	(0.0766)	(0.1536)
Log(Pop. Density)	-0.0043	-0.0184*	-0.1356***	0.0169**	0.0246**	-0.1244***
	(0.0258)	(0.0101)	(0.0497)	(0.0065)	(0.0123)	(0.0250)
Frac. Dem. Vote 2016	1.545***	0.7380***	-1.601***	-0.0151	-0.1920	-0.8905***
	(0.2918)	(0.1057)	(0.4423)	(0.0553)	(0.1190)	(0.2201)
Frac. White Pop.	1.503***	0.5200***	1.411**	0.2887***	0.1311	-0.6672**
	(0.4760)	(0.1493)	(0.5839)	(0.0745)	(0.1717)	(0.3033)
Frac. Female Pop.	-8.354**	-1.799	20.87***	0.4049	1.447	-1.448
	(3.264)	(1.140)	(5.072)	(0.7354)	(1.409)	(2.114)
Frac. College Educ.	1.819***	0.6909***	-0.1436	0.4507***	0.2189	2.302***
	(0.4494)	(0.1537)	(0.6861)	(0.0918)	(0.1998)	(0.3510)
Log(Median Age)	0.3561	0.0442	-0.6539	0.3999***	0.2973*	0.3080
	(0.4039)	(0.1233)	(0.4820)	(0.0730)	(0.1615)	(0.2572)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	117,411	126,357	3,039	132,145	118,856	105,584
R^2	0.54994	0.36900	0.44487	0.60771	0.13151	0.40969
Within R^2	0.26811	0.26534	0.09009	0.20583	0.04373	0.12662

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable market share is the sustainable volume-equivalent units sold divided by the total, in the focal county and week.

Table W.16: Demographic Effects on County-Level Sustainable Availability Share - Club Format

Dependent Variable:	Log of Sustainable Availability Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.0148	0.0065	-0.3933*	-0.0153	-0.2298*	-0.4002***
	(0.0917)	(0.0307)	(0.2020)	(0.0247)	(0.1194)	(0.1193)
Log(Pop. Density)	0.0130	0.0021	-0.1715***	0.0125***	0.0202	-0.0845***
	(0.0151)	(0.0052)	(0.0292)	(0.0041)	(0.0179)	(0.0174)
Frac. Dem. Vote 2016	0.4566***	0.1975***	-1.170***	0.0437	-0.2193	-0.6712***
	(0.1619)	(0.0543)	(0.2644)	(0.0366)	(0.1854)	(0.1550)
Frac. White Pop.	0.7999***	0.0744	0.6942	0.1669***	0.1560	-0.2800
	(0.2747)	(0.0814)	(0.4619)	(0.0580)	(0.2675)	(0.2300)
Frac. Female Pop.	-3.229*	-0.6609	8.131**	0.3038	0.8622	2.284
	(1.851)	(0.6119)	(3.818)	(0.5406)	(2.107)	(1.407)
Frac. College Educ.	0.3524	0.2144***	0.7261	0.0931	0.4808	0.4681*
	(0.2599)	(0.0735)	(0.5093)	(0.0612)	(0.3044)	(0.2573)
Log(Median Age)	-0.1864	0.1413*	-0.4484	0.1706***	0.7492***	-0.5449***
	(0.2312)	(0.0721)	(0.3752)	(0.0504)	(0.2518)	(0.1805)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	117,411	126,357	3,039	132,145	118,856	105,584
R^2	0.41084	0.24547	0.37112	0.58549	0.26187	0.48111
Within R^2	0.05217	0.06065	0.33882	0.09803	0.06000	0.19144

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable availability share is the number of sustainable UPC-store-level observations divided by the total, in the focal county and week.

Table W.17: Demographic Effects on County-Level Sustainable vs. Non-Sustainable Price Ratio - Club Format

Dependent Variable:	Log of Sustainable vs. Non-Sustainable Price Ratio					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.0511**	-0.1013***	-0.6112***	0.0176	-0.2782***	0.0206
	(0.0247)	(0.0150)	(0.1410)	(0.0111)	(0.0449)	(0.0144)
Log(Pop. Density)	-0.0123***	-0.0030	-0.0796***	0.0026	0.0062	-0.0016
	(0.0038)	(0.0024)	(0.0204)	(0.0019)	(0.0067)	(0.0024)
Frac. Dem. Vote 2016	0.0978**	-0.0947***	-0.8614***	0.0146	-0.3555***	0.0594***
	(0.0383)	(0.0245)	(0.1983)	(0.0177)	(0.0571)	(0.0183)
Frac. White Pop.	-0.0206	-0.0433	0.5769*	0.0635***	-0.1935**	0.0458*
	(0.0582)	(0.0350)	(0.3192)	(0.0211)	(0.0870)	(0.0273)
Frac. Female Pop.	0.0123	-0.2323	-1.756	0.0813	2.105**	-0.0159
	(0.5857)	(0.2558)	(2.598)	(0.1799)	(0.8439)	(0.2344)
Frac. College Educ.	-0.2035***	0.1391***	0.9624***	-0.0199	0.5618***	-0.0071
	(0.0589)	(0.0381)	(0.3247)	(0.0276)	(0.1025)	(0.0290)
Log(Median Age)	-0.0368	-0.0727**	-0.2095	-0.0214	0.1211	0.0607**
	(0.0548)	(0.0285)	(0.2670)	(0.0193)	(0.0778)	(0.0257)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	114,081	126,333	3,025	126,332	77,814	104,182
R^2	0.24850	0.29469	0.76586	0.61777	0.26745	0.37196
Within R^2	0.02258	0.13165	0.35896	0.01039	0.09323	0.01890

Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The price ratio takes the across-stores and across-UPCs weighted average price of sustainable and non-sustainable UPCs, respectively, using each UPC's total volume-equivalent units sold in the focal store and year as weights. This price ratio is computed at the county-week level.

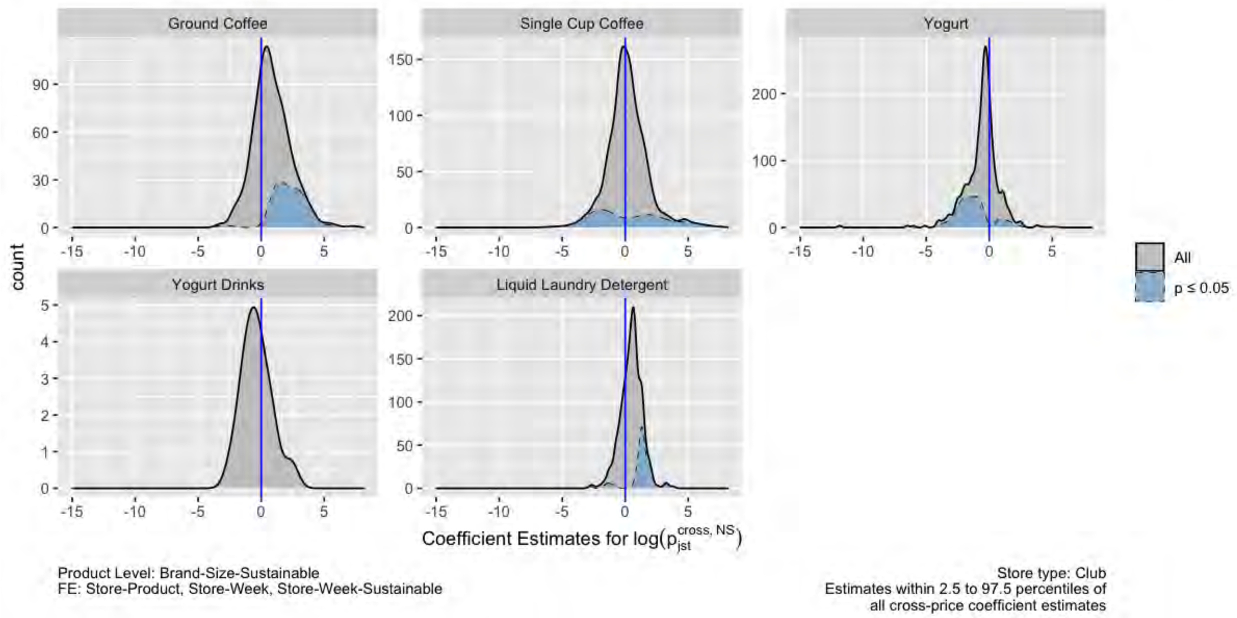
Table W.18: Demographic, Availability, and Price Effects on County-Level Sustainable Market Shares - Club Format

Dependent Variable:	Log of Sustainable Market Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subcategory	Ground Coffee	Single Cup Coffee	Instant Coffee	Rfg Yogurt	Rfg Yogurt Drinks	Liquid Laundry Detergent
Log(Household Income)	0.5598***	0.1586***	0.0658	-0.1086***	0.0099	-0.4629***
	(0.1160)	(0.0437)	(0.2197)	(0.0203)	(0.0408)	(0.1046)
Log(Pop. Density)	-0.0229	-0.0226***	0.0073	0.0067	0.0221***	-0.0555***
	(0.0193)	(0.0069)	(0.0348)	(0.0042)	(0.0067)	(0.0198)
Frac. Dem. Vote 2016	1.121***	0.4767***	-0.9050***	-0.0488	-0.1204**	-0.2003
	(0.1939)	(0.0757)	(0.2965)	(0.0331)	(0.0515)	(0.1570)
Frac. White Pop.	0.6518**	0.4161***	0.8584*	0.1830***	0.0638	-0.3343
	(0.2905)	(0.1072)	(0.4360)	(0.0452)	(0.0820)	(0.2287)
Frac. Female Pop.	-5.033**	-1.320*	10.04**	0.1908	1.527*	-3.490*
	(2.177)	(0.7092)	(4.135)	(0.3783)	(0.8164)	(1.781)
Frac. College Educ.	1.402***	0.5816***	-0.1479	0.3721***	-0.0514	1.913***
	(0.3045)	(0.1132)	(0.5038)	(0.0527)	(0.0976)	(0.2561)
Log(Median Age)	0.5440**	-0.1463*	-0.3172	0.2370***	-0.1358*	0.9100***
	(0.2439)	(0.0842)	(0.3995)	(0.0397)	(0.0738)	(0.2063)
Log(Avail. Share)	1.077***	0.9773***	1.186***	0.9174***	0.4944***	0.8621***
	(0.0370)	(0.0424)	(0.0791)	(0.0274)	(0.0152)	(0.0443)
Log(Price Ratio)	-0.3678***	-0.7204***	-0.7029***	-0.5920***	-0.0023	-2.008***
	(0.1244)	(0.1137)	(0.1095)	(0.0450)	(0.0285)	(0.1778)
Fixed-effects						
Week-Size	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	114,081	126,333	3,025	126,332	77,814	104,182
R^2	0.66003	0.64194	0.57073	0.72989	0.52665	0.55690
Within R^2	0.60151	0.58419	0.27123	0.60991	0.50307	0.49983

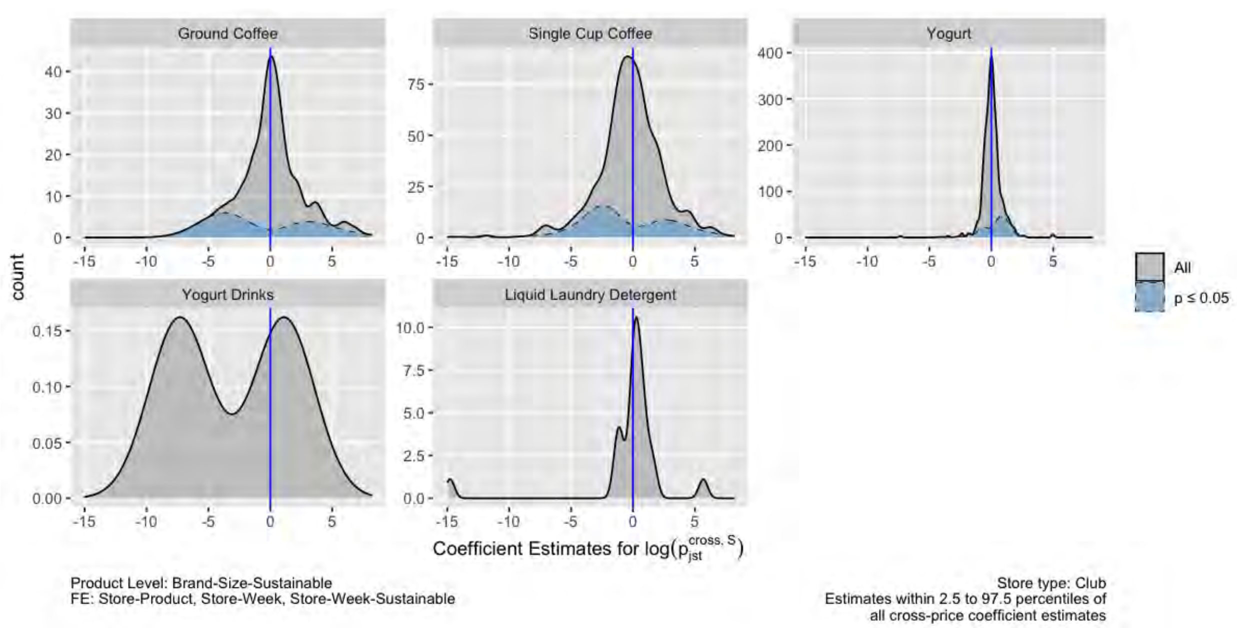
Clustered (Week & County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Sustainable market share is the sustainable volume-equivalent units sold divided by the total, in the focal county and week. Sustainable availability share is the number of sustainable UPC-store-level observations divided by the total, in the focal county and week. The price ratio takes the across-stores and across-UPCs weighted average price of sustainable and non-sustainable UPCs, respectively, using each UPC's total volume-equivalent units sold in the focal store and year as weights. This price ratio is computed at the county-week level.

Figure W.23: Distribution of County-Level Average Cross Price Elasticities on Non-Sustainable Product Demand: Club

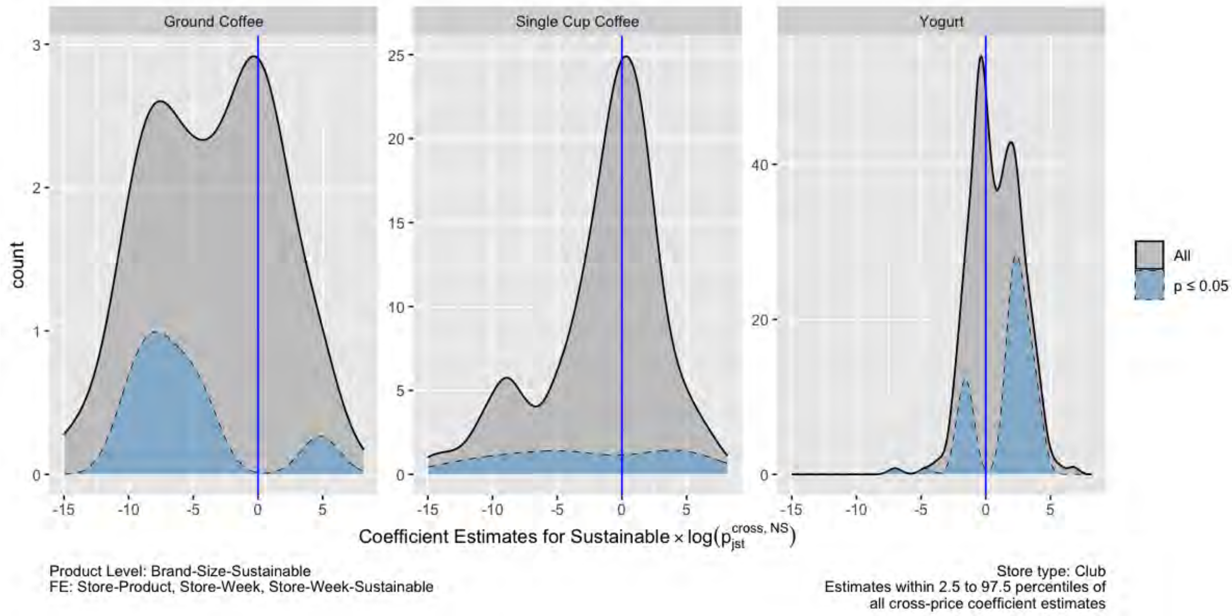


(a) Baseline Cross Price Elasticity of Non-Sustainable Demand

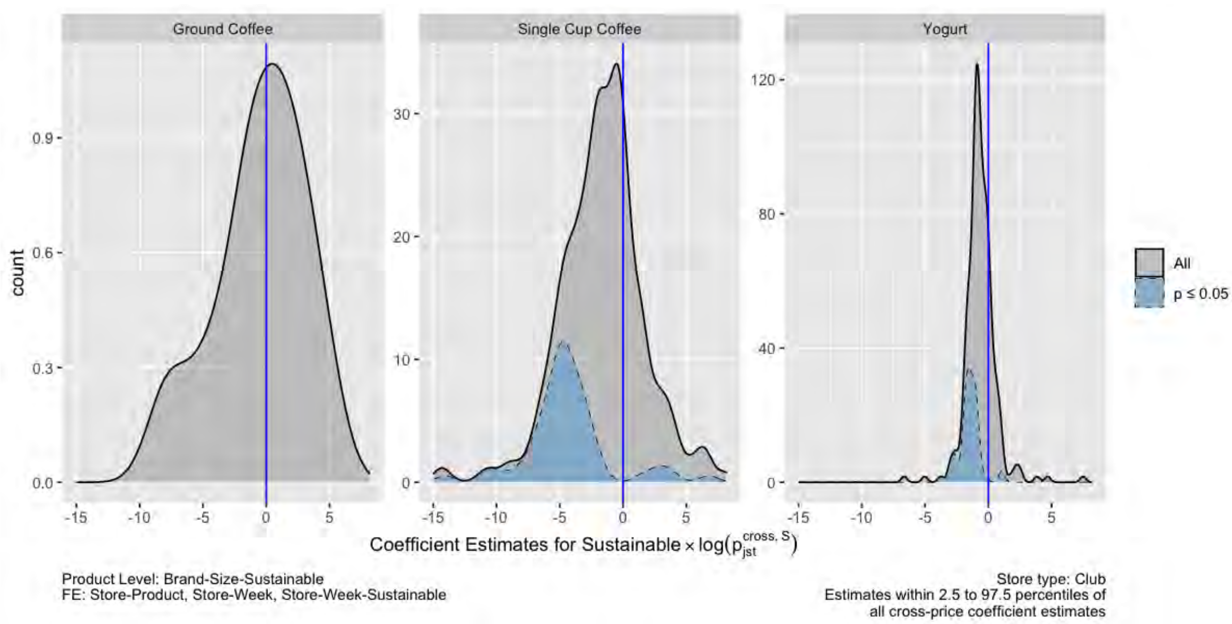


(b) Sustainable Interaction

Figure W.24: Distribution of County-Level Average Cross Price Elasticities on Sustainable Product Demand: Club



(a) Baseline Cross Price Elasticity of Sustainable Demand



(b) Sustainable Interaction

Figure W.25: Density of Sustainable and Non-Sustainable Posterior Estimates of Product-County Elasticities: Club

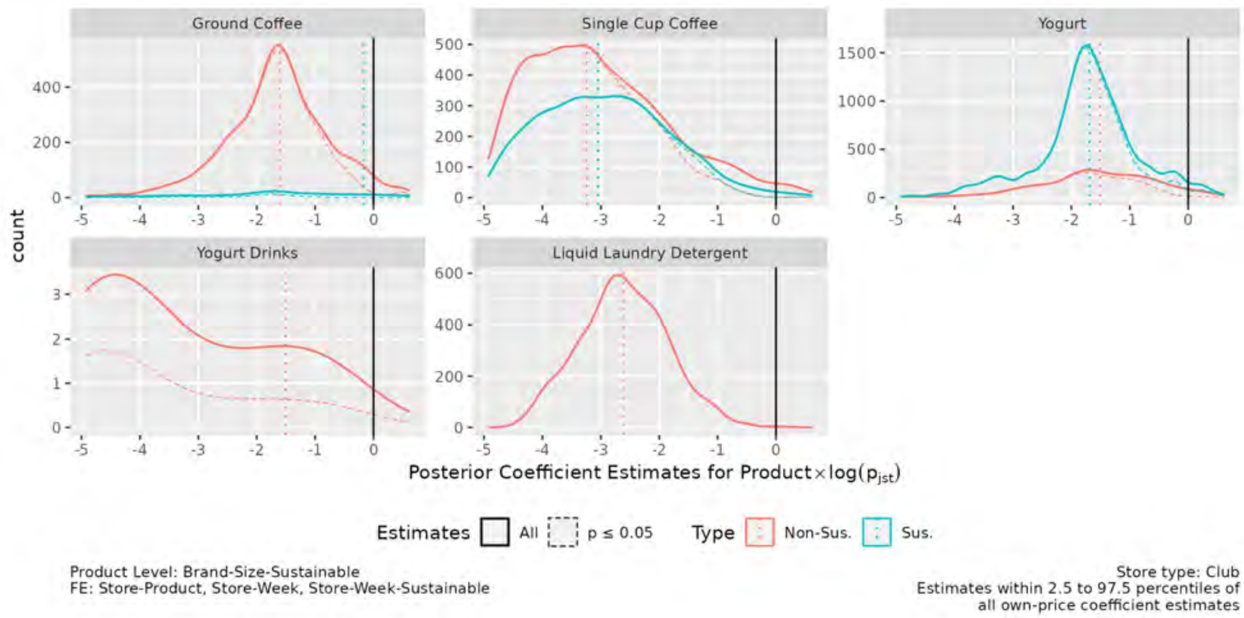


Figure W.26: Density of Sustainable and Non-Sustainable Product-County Profit Potential: Club

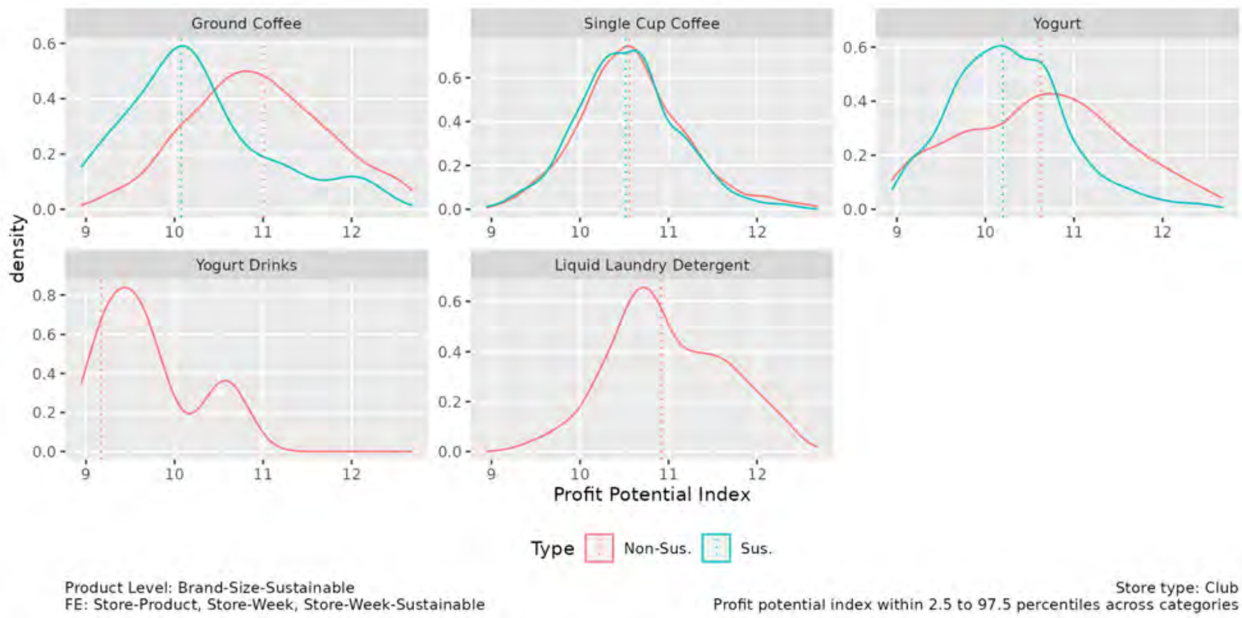


Figure W.27: Distribution of Empirical Bayes Deconvolution Hyperparameter Estimates Across Products: Club

Figure W.28: Average Demographic Effect on Product-Level Profit Potential Index: Club