Effects of Income Distribution Changes on Assortment Size in the Mainstream Grocery Channel

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ABSTRACT

The authors study the effect of changes in the U.S. income distribution on assortment size in the mainstream grocery channel. Census demographics for 1,711 counties are matched to local assortment data from Nielsen in 944 grocery product categories from 2007 to 2013. The authors show that – holding other demographics constant – assortment size increases with higher average income but decreases with greater income dispersion. This pattern holds for several specifications of assortment at the local level: the number of category UPCs, the number of brands, the number of products per brand, as well as both horizontal and vertical dimensions of assortment. The results suggest that increased income dispersion (holding other factors constant) reduces both horizontal and vertical differentiation. The effect sizes are similar for private labels and branded products, but large brands lose proportionally more UPCs than small brands when income dispersion rises. Potential mechanisms underlying the results are also explored, with evidence that a hollowing out of the middle class along with Engel's law of expenditure explain a significant portion of this effect. The findings also offer insights for CPG manufacturers that might help them allocate resources to expand shelf presence or defend current positions.

Keywords: Income distribution, Census Bureau data, consumer packaged goods, retailing, assortment decisions

1. Introduction

National and international policymakers, economists, management consultants, and the media have recently drawn increased attention to changes in the distribution of income over the past several decades (e.g., Dabla-Norris et al. 2015; Derby 2015). Census Bureau data show that inflation-adjusted income has oscillated widely: for example, median income in 2012 dropped 9% from a high in 2007, before recovering to its 2007 level in 2016. Income dispersion has risen significantly in the U.S., with the Gini index moving from .40 in 1980 to .48 in 2017, a 20% increase. Figure 1 shows Census data for incomes at various percentiles from 1967 to 2017; incomes of the top earning households expanded dramatically, while those of the lower tiers have remained relatively flat. Such shifts in the distribution of income can lead to changes in aggregate consumer spending (e.g., Krueger and Perri 2006; Kamakura 2014) with implications for firms and marketing strategies.

Industry experts have expressed conflicting views about how firms should respond to changes in the income distribution, with some advocating that companies should target the pressing needs of low-income consumers (e.g., Simanis and Duke 2014) and others advising that high-income consumers should be targeted with premium products (e.g., Lodd 2016). Reflecting these views, the high-end grocery retailer Whole Foods entered low-income markets seeking to find new ways to sustain growth (Berman 2014), whereas many mass-market retailers have tried to attract high-income consumers with upscale merchandise and nicer store layouts (Ries 2013).

The issue of how to react to changes in local income and spending patterns may be especially important for consumer packaged goods (CPG) manufacturers, who have to constantly fight for shelf space. Since retailers frequently add and subtract products from their assortments, manufacturers need to understand what factors drive these shifts so resources can be allocated to either defend distribution coverage in contracting markets or seek new shelf space in expanding markets. Understanding which products are most affected by changes in the income distribution is also valuable for CPG manufacturers, e.g., large- versus small-share brands or private labels versus national brands.

In this paper, we focus on the effect that changes in the distribution of income have on assortment size in the mainstream grocery channel. As the income distribution changes – and with that, consumer spending in the food retailing industry – retailers may alter the amount of space they allocate to CPG products (compared to deli, bakery, meats, and other non-CPG categories) and change the mix of the products they offer within each category. For these reasons, assortment size – within each store but also across stores within a market – is likely to vary as the income distribution changes.

To conduct our analysis, we draw upon Nielsen and the U.S. Census Bureau as sources to assemble a large-scale dataset that describes both demographic characteristics and market outcomes in 944 CPG product categories across 1,711 U.S. counties over a period of seven years (2007-2013). We examine how the sizes of local assortments change with local average income and income dispersion, holding constant a range of demographic factors. We use the Gini index to represent dispersion, noting that the Gini index is the classic measure for inequality (e.g., Cowell and Flachaire 2013; Leigh 2007).[1] A Gini close to zero represents that households earn equal incomes, whereas a Gini close to one indicates that nearly all income is received by one household. An important feature of the data is that U.S. counties varied substantially in the income distribution changes they experienced during this period. In particular, although the distribution became more unequal in the majority of counties, income dispersion actually fell in a large fraction of counties. Our basic measure of assortment size is the number of UPCs available in each county, a metric well suited for the large-scale analysis we conduct and one that has been widely used by both industry and academics (e.g., Salazar 2014; Watson 2014; Draganska, Klapper, and Villas-Boas 2010; Hwang, Bronnenberg, and Thomadsen 2010; Ren et al. 2011; Jaravel 2018).[2] In addition to the number of UPCs, we also look at number of brands, number of products per brand, and vertical and horizontal dimensions of assortment.

[1] We use income dispersion and inequality interchangeably.

[2] We also note that more complex measures designed to capture the variety in an assortment are often highly correlated with the count-based measure of assortment size (see, e.g., Van Herpen and Pieters 2002).

We find that increases in average income and decreases in income inequality lead to larger assortments. This result is robust to a recession; specifically, the effects are similar for the periods 2007-2010 and 2010-2013. We then consider additional aspects of the relationship between assortment size and changes in the income distribution.

First, we consider several different dimensions of assortment size. We find that the results also hold for both the number of brands and the product line length within brands. Indeed, the effect of income distribution changes is larger on the number of brands than on the number of UPCs per brand. We also find that both vertical and horizontal differentiation change in the same direction as the income distribution changes. Further, the impact on UPC counts is similar for private labels and national brands, but more income dispersion (higher Gini index) results in large brands losing a fraction of their UPCs greater than the fraction of UPCs lost by small brands.

Second, we break down the Gini index into the income shares of different income groups, represented by the income quintiles reported by the Census Bureau. We find that the overall effect can be attributed primarily to changes in the income shares of the third income quintile (40^{th} to 60^{th} percentile) and the fourth income quintile (60^{th} to 80^{th} percentile), which are arguably associated with the lower middle and upper middle class. A decline in these quintiles, which occurs more often at the county-level than an increase does, is consistent with a hollowing out of the middle class.

While the principal objective of this paper is to document the empirical connection between changes in the income distribution and assortment, we extend our main findings to briefly explore what theories are consistent with our results. We find that most of the effects can be explained by the greater consumer spending that occurs when average income increases and income dispersion decreases, consistent with Engel's Law for expenditure. Interestingly, when we control for consumer spending in the analysis, a smaller negative relationship between assortment and the Gini index persists. This suggests that multiple mechanisms may be at work in how income distribution shifts drive changes in assortment.

Our findings offer guidance to CPG manufacturers on how to manage trade marketing. The relationship between changes in the income distribution and assortment sizes provides CPG managers with a new metric to help prioritize markets according to the distribution opportunities – or challenges – they may provide. Even when average incomes are constant, our results show that markets with rising income inequality experience assortment pruning by the grocery channel and markets with falling inequality see expansion. With data on local changes in the Gini index, managers may be better able to guide either defensive actions to retain shelf space or offensive actions to acquire it. We also briefly discuss potential implications that our findings may have for policy makers.

Our paper is related to research that studies how retailers – or retailers and manufacturers jointly – rely on local consumer demographics to plan their assortments (Grewal et al. 1999; Kadiyali, Chintagunta, and Vilcassim 2000; Israilevich 2004; Rosenblum and Rowen 2008; Dukes, Geylani, and Srinivasan 2009). For example, Hwang et al. (2010) show that high-end regional brands of cereal and toothpaste were more likely to be carried by retailers in areas with high proportions of high-income households, demonstrating an empirical link between income and retail assortment decisions. As in their study, we do not attempt to formally model retailer or manufacturer behaviors but rather seek to understand equilibrium outcomes.

Our topic is also related to the literature on the “poverty penalty,” which examines how low-income consumers may face higher food prices (e.g., Kunreuther 1973; Talukdar 2008) and may reside in areas with limited access to groceries (so-called “food deserts”). More recently, Orhun and Palazzolo (2019) find that liquidity constraints can inhibit the ability of low-income households to buy large packages of non-perishable goods, so they are less likely to benefit from quantity discounts. Allcott et al. (2019) look at how the mix of stores affects the nutrition of consumers in poorer neighborhoods. They note that different stores offer wider or narrower selections, and that poorer areas have more stores with limited selection (e.g., dollar stores). Allcott et al. then use changes in the presence of stores to measure whether the supply of different UPCs affects the nutritional value of the choices by poorer consumers, and find that supply has only a small effect. Our research question differs in that we focus on how assortment changes as the overall distribution of income shifts over time. Allcott et al. do raise another potential mechanism for our result, which is that the mix of stores could shift as the income distribution changes. Our main analysis examines the assortment of products in a market – either across stores or within stores – but we also find that changes in income dispersion affect the product assortment within stores. Indeed, the majority of the market-level effect can be explained by changes in the sizes of store assortments rather than by changes in store presence and changes in the similarity of assortments across stores in the market. We also note that much of the previous literature has focused on what happens with the lowest income brackets; instead, we are concerned with the assortment of products offered to consumers in all income brackets.

The balance of this paper is structured as follows. Section 2 provides a detailed description of our data. Section 3 presents our model and empirical strategy. Our estimation results appear in Section 4. Section 5 presents several robustness checks. Section 6 explores theoretical underpinnings of our results. Finally, Section 7 discusses implications of the results and concludes.

2. Data

Most of the income and demographic information we use comes from the U.S. Census Bureau. Though the decennial census covers the entire U.S. population, it does not provide the longitudinal data we need because it is conducted only once every 10 years. The American Community Survey (ACS) samples 3 million addresses in the U.S. every year, and the Census Bureau uses the survey to create population estimates. These population estimates are available at the levels of county, county subdivision, place, congressional district, school district, and larger areas. Until 2013, the Census Bureau also provided annual estimates that pool data for 3-year and 5-year rolling periods to reduce sampling error. The pooled estimates are based on a larger number of respondents per geographic area and also are reported for a much larger number of counties than the individual-year estimates. We use the annually reported 3-year rolling-sample estimates and select the county as the geographic unit of analysis. In total, we compile data for 1,711 counties that consistently appear in the 3-year estimates of the American Community Survey from 2007 to 2013. These counties correspond to 204 Designated Market Areas (DMAs) and account for 94% of the U.S. population in the 48 contiguous states.[3] Although an effort could be made to work with data at the county

[3] The 3-year estimates of the American Community Survey are reported for a total of 1,846 (59%) of the 3,141 counties and county equivalents in the U.S. (We select 1,711 on the basis of consistent reporting.) These estimates correspond

subdivision level to increase granularity, the sample would be limited because the Census does not report subdivision data for many areas.

Our dependent variables are derived from the Nielsen Retail Scanner dataset covering the 2007-2013 period, as distributed by the Kilts Center for Marketing. The dataset reports weekly unit sales and average prices from about 35,000 stores belonging to approximately 90 participating retail chains operating in the 48 contiguous states.[4] The location of each store is reported in terms of its Federal Information Processing Standard (FIPS) county and state codes, DMA code, and the first three digits of its ZIP code, but the identity of the store is not revealed. The dataset includes approximately 2.6 million UPCs within 1,075 product modules (categories) in 10 departments. The all-commodity volume (ACV) by channel is 53% of grocery stores, 55% of drugstores, 32% of mass merchandisers, 1% of liquor stores, and 2% of convenience stores.

We use the following departments for analysis: Frozen Foods, Health and Beauty Care, Dry Grocery, Non-Food Grocery, and General Merchandise. Other departments for which data were available include Alcohol, Dairy, Deli, Packaged Meat, and Fresh Produce. We exclude Alcohol because the industry is highly regulated at the state level. We do not include perishables because their assortment is strongly affected by difficult-to-control factors such as the quality of distribution-related infrastructure and the distance between retailers and producers. We also drop categories that do not appear to be available consistently in each county every year. Altogether, these steps yielded a total of 944 product categories for analysis. To match with the Census data at the county level, we aggregate the product-category information across stores within each county and within each year. The variables used in the main analysis are described in the Appendix. Descriptive statistics and correlations appear in Tables 1 and 2. From Table 2, we note that average income and the Gini index are weakly and negatively correlated in the data ($\rho = -0.11$).

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to geographic areas with at least 20,000 inhabitants. We examined the differences between the 1,846 included counties and the 1,295 excluded ones using data from the year 2000 decennial census. With the exception of population size, we found that the two sets of counties differ only slightly in terms of their demographics, such as average income. Unfortunately, even the decennial census does not report income dispersion in small-population counties, so assessing how they might differ from the counties we analyze in this respect is not possible.

[4] Nielsen does not report data from all affiliated retailers, and on rare occasions, a few stores may be excluded from the sample because of confidentiality concerns.

We next illustrate the variation in the data that allows us to empirically identify the effect of changes in income distributions on changes in product assortment. The top row of Figure 2 presents the mean, across counties, of the county-level, real average income, Gini index, and average (across categories) number of UPCs for each year in the sample, together with their 95% confidence intervals. These data show that real incomes fell and average income inequality increased during our sample period. The bottom row of Figure 2 presents histograms of the changes for the same variables between 2007 and 2013. While average real income decreased and income inequality increased in the U.S. overall, significant variation exists at the county level; average income actually rose and income inequality actually fell for a significant number of counties. Like average income and the income Gini, changes in county-level assortments also vary significantly in the data.

The plot on the left side of Figure 3 depicts the changes in UPCs between 2007 and 2013. We plot these changes separately for counties with decreased average income and those with increased average income over the same time span. For counties with increased average income, the gains in product assortment are significantly higher than the gains in counties with decreased average income ($p < .01$). The plot on the right side of Figure 3 depicts the changes in UPC per $10,000 of local average income between 2007 and 2013; that is, we divide the local number of UPCs by the local average income, expressed in units of 10,000 dollars.[5] We compute these changes separately for counties with decreased and increased Gini index values. For counties with an increase in the Gini, the gains in product assortment are significantly lower than the gains in counties with a decrease in the Gini ($p < .05$). We also ran Fisher Exact Tests, which reject the hypotheses that changes in product assortment are independent of changes in average income and of changes in the Gini index ($p < .001$). This model-free evidence suggests that an increase in average income will be associated with an enlargement of grocery product assortment, while an increase in the Gini index will be associated with a reduction.

[5] The division by average income is done for graphic purposes as a way to control for average income, because the relationship between income inequality and spending (and therefore assortment size) is only hypothesized to exist when average income is held constant. However, as we show in Table 2, higher Gini indices are correlated with lower average incomes.

3. Empirical Model and Estimation

Model

We now introduce our econometric approach to estimate the relationship between changes in the income distribution and changes in product assortment size. In contrast with recent work that has used cross-sectional regressions to study the effects of demographics on product assortment (Hwang et al. 2010) and product availability (Handbury and Weinstein 2014), we use panel regressions to explain the geographic variation of changes in product assortment over time in response to changes in the income distribution over time. Our analysis thus focuses on variation that is both cross-sectional and longitudinal, effectively controlling for variation that is purely longitudinal (e.g., the 2008 recession) or purely cross-sectional (e.g., climate differences and constant supply factors such as distance to producers). Because we observe the income distribution values at the county-year level, we regard counties as the main observational units and changes in average income and Gini as treatments that can vary across units. We capitalize on the three-dimensional nature of our dataset (counties, years, categories) to improve statistical power by treating product categories as repeated observations for each county-year combination while controlling for category-specific intercepts and trends. We identify the effects of *changes* in the income distribution on product assortment across counties by exploiting the heterogeneous variation in the direction and magnitude of the *changes* in average income, the Gini index, and product assortment size across counties.

Let $nUPCs_{ict}$ denote the number of distinct UPCs offered in category *i* by stores in county *c* and year *t*. We express the log of this measure of assortment as a linear function[6] of average income ($AVGINCOME_{ct}$) and the Gini index ($GINI_{ct}$), such that

(1) $$\log(nUPCs_{ict}) = \beta_1 AVGINCOME_{ct} + \beta_2 GINI_{ct} + X_{ct}\boldsymbol{\omega} + \tau_{it} + \gamma_{ic} + \varepsilon_{ct} + u_{ict},$$

where X_{ct} includes a set of control variables for county *c* and year *t*, τ_{it} and γ_{ic} are category-time and category-county fixed effects respectively, and ε_{ct} and u_{ict} are error terms assumed to satisfy $E[\varepsilon_{ct}] = 0$ and

[6] Although this log-linear functional form can be derived from aggregating Engel curves, we also analyzed other nonlinear functions as a robustness check. Please see Web Appendix W4.

$E[u_{ict}|\theta, \varepsilon_{ct}] = 0$, where $\theta \equiv [\beta_1, \beta_2, \tau, \gamma, \omega^T]^T$.[7] The term ε_{ct} represents unobserved factors specific to each county-year combination – such as county-level trends – and the term u_{ict} represents category-specific deviations from the county-year averages in ε_{ct}. This two-term representation of the error facilitates the exposition of the estimation approach (described below).

The coefficients of main interest are β_1 and β_2, which measure the magnitude of the effects that county-level changes in average income and income Gini have on local assortments in *equilibrium*. Changes in the income distribution may influence assortments directly through changes in consumer demand but also indirectly because retailers and manufacturers may respond to those changes in demand by adjusting other elements of the marketing mix (e.g., prices and store format) and these adjustments may further affect demand and assortments. We do not seek to explain these other changes in the marketing mix. Rather, we focus purely on understanding how changes in the income distribution affect the equilibrium size of the assortments offered in local markets.

Estimation

Because we consider a wide set of product categories with different characteristics such as sales volumes, we expect that u_{ict} and ε_{ct} might exhibit heteroscedasticity. In addition, the unobservables ε_{ct} might be serially correlated. Finally, different retailers serve different regions. Thus, their actions might lead to spatially correlated residuals (Bronnenberg and Mahajan 2001). Spatially correlated residuals may also arise if consumers shop at stores in counties different from where they live. Because heteroscedasticity, serial correlation, and spatial correlation may induce biases in the estimates of the standard errors (e.g., Barrios, Diamond, Imbens, and Kolesár 2012), we utilize an FGLS approach. We estimate several different

[7] Note that full statistical independence between u_{ict} and x_{ct} is not required to identify average treatment effects (Athey and Imbens 2006). A sufficient condition for $E[u_{ict}|\theta,\varepsilon_{ct}] = 0$ to hold is that u_{ict} be statistically independent of group and time (Santos Silva and Tenreyro 2006). This condition implies that $VAR[nUPCs_{ict}|\theta]$ is a function of the variance of u_{ict}; that is, average income, income inequality, and the controls may shift not only the conditional mean but also the conditional variance. To account for potential deviations from this assumed correlational structure, we use estimation methods robust to heteroscedasticity and serial correlation.

specifications of residual correlation, including (1) no correlation, (2) spatial correlation, (3) county-clustered errors and serial correlation, and (4) county-clustered errors, serial, and spatial correlation.

Estimating models with flexible error structures on very large datasets is, however, not straightforward. Researchers have proposed iterative projection methods to estimate linear models with clustered errors on datasets similar to ours (e.g., Correia 2017), but these methods have not yet been extended to account for serially or spatially correlated errors. Because allowing errors to be clustered does not address the problem of unobserved spatial correlation (Barrios et al. 2012), FGLS methods are needed. Implementing FGLS involves computing the disturbance covariance matrix $\Omega = u_{ict}u_{ict}^T$. Because our sample includes 11,306,288 observations, storing the 1×10^{13} elements of this matrix would require 354TB of memory (in single precision). Thus, given the large scale of our study, directly implementing FGLS for the proposed model in (1) is not computationally possible. To address this challenge, we turn to a two-step procedure that yields consistent estimates (as described by Hansen 2007). To understand this approach, we rewrite equation (1) as

(2) $$\log(nUPCs_{ict}) = \beta_1 AVGINCOME_{ct} + \beta_2 GINI_{ct} + X_{ct}\boldsymbol{\omega} + (\tau_t + \tilde{\tau}_{it}) + (\gamma_c + \tilde{\gamma}_{ic}) + \varepsilon_{ct} + u_{ict},$$

where we decompose $\tau_{it} = \tau_t + \tilde{\tau}_{it}$ so that $\tau_t = E_i[\tau_{it}]$. We decompose γ_{ic} in a similar manner. We implement the first step of this procedure using ordinary least squares (OLS) to estimate the fixed-effects regression

(3) $$\log(nUPCs_{ict}) = \delta_{ct} + \tilde{u}_{ict},$$

where $\delta_{ct} = \beta_1 AVGINCOME_{ct} + \beta_2 GINI_{ct} + X_{ct}\boldsymbol{\omega} + \tau_t + \gamma_c + \varepsilon_{ct}$ and $\tilde{u}_{ict} = u_{ict} + \tilde{\tau}_{it} + \tilde{\gamma}_{ic}$, with $E[\tilde{u}_{ict}|\boldsymbol{\theta}, \varepsilon_{ct}] = 0$. Note that even though the fixed effects τ_{it} and γ_{ic} are included to account for unobservable effects that might be correlated with both $\log(nUPCs_{ict})$ and the income variables, because $E_i[\tilde{\tau}_{it}] = 0 \; \forall \; t$ and $E_i[\tilde{\gamma}_{ic}] = 0 \; \forall \; c$, neither $\tilde{\tau}_{it}$ nor $\tilde{\gamma}_{ic}$ can be correlated with any variables that are observed at the county-time level (i.e., $AVGINCOME_{ct}$, $GINI_{ct}$, and X_{ct}). Rather, only the projections of τ_{it} and γ_{ic} on t and c (i.e., τ_t and γ_c), respectively, can be correlated with these variables, and these variables are included in the δ_{ct} terms.

Even with this simplification, our model includes 11,977 fixed effects, δ_{ct}, one for each county-year combination. With a model of this size, classical estimation methods impose very taxing computational requirements. For instance, OLS would compute the model parameters $\boldsymbol{\delta} = (D^T D)^{-1} D^T Y$ by storing and manipulating in memory a covariate matrix D with 1.35×10^{11} elements (504GB of memory). The burden of the operations involved can be significantly alleviated using partitioned regression methods and parallel computing. In these methods, a master computing node coordinates K slave nodes. The master partitions the D and Y matrices into K pairs of smaller submatrices D_k and Y_k, k=1...K. Each slave node k computes the products $D_k^T D_k$ and $D_k^T Y_k$ and returns them to the master node, which uses them together with special (sometimes iterative) algorithms to compute $D^T D$, $D^T Y$, and $\hat{\delta}_{ct}$.

The second step involves using robust methods to regress the fixed effects δ_{ct} on the covariates of interest. Specifically, we next estimate

(4) $$\delta_{ct} = \beta_1 AVGINCOME_{ct} + \beta_2 GINI_{ct} + X_{ct}\boldsymbol{\omega} + \tau_t + \gamma_c + \varepsilon_{ct}.$$

The estimation of the first stage with OLS and the second stage with robust methods then yields consistent estimates in the face of clustering, serial correlation, and uncertainty in the estimation of $\hat{\delta}_{ct}$. Hansen (2007) shows that when the number of categories is large, as is the case in our application with 944 categories, the estimates $\hat{\delta}_{ct}$ can be treated as data. Further, the estimates of β_1, β_2, and $\boldsymbol{\omega}$ are unbiased and consistent even if the sample is not that large.[8] By following this two-step procedure, we reduce the computational scale of the estimation problem from 11,306,288 observations to 11,977, so we can accommodate a non-i.i.d. error structure in the second step. Nevertheless, estimating the second stage model with county and year fixed effects would still involve estimating 1,718 fixed effects [7 year fixed effects (τ_t) plus 1,711 county fixed effects (γ_c)]. Instead, we implement the covariance estimator (Hsiao 2014, p. 62) by first computing

[8] While the sample is large enough for the standard errors of $\hat{\delta}_{ct}$ to be very small, we replicate the analysis using a computationally-intense bootstrap method to account for the uncertainty in the estimates $\hat{\delta}_{ct}$ and find that the results are essentially unaffected (see Web Appendix W1).

$$\Delta\Delta\hat{\delta}_{ct} = \hat{\delta}_{ct} - \bar{\hat{\delta}}_{\cdot t} - \bar{\hat{\delta}}_{c\cdot} + \bar{\bar{\hat{\delta}}}_{\cdot\cdot},$$

$$\Delta\Delta AVGINCOME_{ct} = AVGINCOME_{ct} - \overline{AVGINCOME}_{\cdot t} - \overline{AVGINCOME}_{c\cdot} + \overline{\overline{AVGINCOME}}_{\cdot\cdot},$$

$$\Delta\Delta GINI_{ct} = GINI_{ct} - \overline{GINI}_{\cdot t} - \overline{GINI}_{c\cdot} + \overline{\overline{GINI}}_{\cdot\cdot},$$

$$\Delta\Delta\varepsilon_{ct} = \varepsilon_{ct} - \bar{\varepsilon}_{\cdot t} - \bar{\varepsilon}_{c\cdot} + \bar{\bar{\varepsilon}}_{\cdot\cdot},$$

and

$$\Delta\Delta X_{ct} = X_{ct} - \bar{X}_{\cdot t} - \bar{X}_{c\cdot} + \bar{\bar{X}}_{\cdot\cdot},$$

where single bars denote an average along one dimension and double bars denote an average along two dimensions. The dot in the subindex denotes the dimension along which the averaging takes place.

Finally, we use FGLS to estimate

(5) $$\Delta\Delta\hat{\delta}_{ct} = \beta_0 \Delta\Delta AVGINCOME_{ct} + \beta_1 \Delta\Delta GINI_{ct} + \sum_d \omega_d \Delta\Delta X_{ct,d} + \Delta\Delta\varepsilon_{ct}.$$

The smaller number of explanatory variables and the reduction in the number of observations to 11,977 make the estimation of (5) computationally tractable.[9]

Identification

Our identification strategy relies on the main assumption that, conditional on all of our time- and geography-specific controls X_{ct}, category specific time trends τ_{it}, and county and category-specific fixed effects γ_{ic}, geographic differences in the annual changes of the income distribution are uncorrelated with geographic differences in the annual changes of unobserved factors that could affect local assortment sizes.[10]

[9] As an alternative to the two-stage approach, we could estimate a simplified version of the model in (1) for each product category in one single stage and obtain category-specific estimates. Such an approach, however, is demanding of the data because it involves estimating the roughly 1.5×10^6 distinct elements of the Ω matrix on the 11,977 observations of each category. The estimates of the Ω matrices and the standard errors may thus be inaccurate and lead to incorrect inferences. Furthermore, not all categories are present in all counties, and thus the statistical power may not be sufficient to estimate the model parameters for a number of categories. As a robustness check, we obtained single-stage estimates for 20 randomly selected categories within the Dry Grocery department and find that the results for *GINI* are consistent with our main results though significantly noisier. Of the coefficients of *GINI* in these 20 regressions, 12 are negative and significant, one was positive and marginally significant, and the remaining seven were not significant.

[10] If this main assumption holds and the β coefficients are to be interpreted as average treatment effects, one also needs to assume that the changes in average income and income Gini (i.e., the treatments) are homogeneous. Otherwise the coefficients should be interpreted as weighted treatment effects (Angrist 1998). We thank the Associate Editor for this observation.

Analogous to the main assumption of Dubé, Hitsch, and Rossi (2018), this assumption implies that counties that would have experienced larger decreases in assortment sizes (relative to other counties) for reasons other than larger changes in the income distribution and larger changes in the controls X_{ct}, did not systematically experience larger decreases in average income and larger increases in income inequality than other counties. Mathematically, this implies that

$$log(nUPCs_{ict}(avgincome_{ct}, gini_{ct})) \perp\!\!\!\perp (AVGINCOME_{ct}, GINI_{ct}) | X_{ct}, \tau_{it}, \gamma_{ic} \quad \forall (avgincome_{ct}, gini_{ct}),$$

where $nUPCs_{ict}(avgincome_{ct}, gini_{ct})$ is the assortment size evaluated at any potential values of average income and income inequality, $avgincome_{ct}$ and $gini_{ct}$, instead of their realized values, given by $AVGINCOME_{ct}$ and $GINI_{ct}$ (we use lowercase to denote random variables and uppercase to denote their realized values). The reader is referred to Dubé, Hitsch, and Rossi (2018) for a similar example or Imbens and Rubin (2015) for more details on the underlying theory. The control variables, X_{ct}, described in the Appendix, exhibit both longitudinal and cross-sectional (geographic) variation. The fixed effects, described above, mitigate the potential effects of other omitted variables that could explain assortment size and might be correlated with the distribution of income.

Among possible omitted variables, unobserved consumer preferences may be of particular concern. As noted by Dubé, Hitsch, and Rossi (2018), households with stronger preferences for branded products could self-select into careers associated with high income. Likewise, households with weak preferences for CPGs and strong preferences for prepared meals could self-select into high-paying careers. We note that the county-level fixed effects control for this type of self-selection (Dubé, Hitsch, and Rossi 2018). Because they control for the fixed portion of consumer preferences, any unobserved aspects of preferences would have to evolve over time to create biases in our analysis. In a study that tracked the behavior of consumers who relocated across state boundaries, Bronnenberg, Dubé, and Gentzkow (2012) showed that, even after large changes in supply-side factors (operationalized in their study as the relocations), preferences for favored brands changed very slowly. Hence, we expect that the observed changes in assortment size will be more heavily influenced by changes in income than by changes in innate preferences over the seven years we study. We also obtain similar results when we estimate our model on shorter time periods, as reported below. More generally, the fixed effects τ_{it} and γ_{ic} control for possible category-specific trends (e.g., a category's demand may be weaker in early stages of the category's life cycle) and county-level preferences for specific categories (e.g., demand for mosquito repellent may be stronger in Alabama counties than in California counties).

In addition to potential correlation with unobserved consumer preferences, the income distribution could also be correlated with local and national unobserved supply factors that determine retailer and manufacturer decisions to offer certain products. Two considerations mitigate this concern here. First, we seek to describe equilibrium outcomes – which might include retailer self-selection in terms of which markets the retailers should enter – rather than to separate the diverse effects of the income distribution on demand and/or supply. Second, the category-county fixed effects γ_{ic} account for retailer considerations, such as self-selection and distribution costs, which are local but largely constant. Likewise, the category-time fixed effects τ_{it} account for manufacturer supply considerations, such as manufacturing costs and factor inputs, which are largely national in nature.

Because our identification strategy relies on variation that is both cross-sectional and longitudinal, we acknowledge that our estimates may be contaminated by changes in supply factors that are both year and county specific. For example, local producers and retailers could open or close down their establishments, simultaneously affecting the assortments of locally-sourced products and the incomes of the local population. We mitigate potential biases that could arise from ignoring these unobserved county-year factors in three ways. First, we exclude from our analysis categories where local changes in supply factors and regulations might have a strong effect on locally available assortment (e.g., highly perishable products, which are often produced by local manufacturers, and alcohol). Second, we directly control for factors that are likely to correlate with these unobserved shocks, such as unemployment and trade (see our robustness tests below). Third, we allow for a spatially-correlated error structure, which helps account for unobserved retailer actions that may be correlated across counties (e.g., Bronnenberg and Mahajan 2001).[11]

4. Estimation Results

Main Results

We evaluate several estimation approaches to handle the potential correlation and clustering of the model residuals in equation (5) and present the results in Table 3. We use (i) OLS, (ii) FGLS with heteroscedasticity-robust standard errors (Greene 2003, p. 314) and serially correlated errors, (iii) FGLS with only spatially correlated errors, and (iv) FGLS combining (ii) and (iii). For serial correlation, we consider an autoregressive structure of order one (AR1) (implemented as in Hsiao 2014, p. 66). For spatial correlation, we adopt an error structure of the form $\boldsymbol{\varepsilon} = \rho W \boldsymbol{\varepsilon} + \boldsymbol{\eta}$, where W is a matrix of adjacencies (see Anselin 1988, chapter 8). For the models without spatially correlated errors (i and ii), the z-score of the standardized Moran I statistic is greater than 1.96, suggesting that spatial correlation is indeed present. In addition, accounting for spatial effects reduces the magnitude of the coefficients of the statistically significant terms.

We note that the signs, significance levels, and orders of magnitude are stable for the coefficients on average income and Gini across each of these specifications, with positive coefficients for average income and negative coefficients for Gini. Thus, we observe that assortment size increases with increasing average income and decreases with greater income dispersion. The consistency of the results across the columns provides evidence that our main findings are robust to different error specifications.

We also note that while we include demographic controls, the results of our analysis are virtually unchanged if we do not include them [see Column (5) of Table 3]. This is likely because the county (and perhaps time) fixed effects capture most of the assortment decisions that are driven by demographics. The

[11] An alternative approach to accounting for supply-side or cost factors that are likely to affect manufacturer and retailer decisions would be to model these decisions explicitly. Given the national scale and the local emphasis of our study, such a modeling effort is beyond the scope of this paper.

coefficients of the control variables in the specifications that include them are all intuitive except those of population size and educational diversity. A negative effect of population size could be consistent with previous findings that market size correlates with competition intensity and higher competition intensity may lead manufacturers and retailers to supply only their best performing products (Mayer, Melitz, and Ottaviano 2014). The negative effect of educational diversity could be explained by more educated households demanding more variety (Conklin et al. 2014) and educational diversity being positively correlated with the proportion of population with high school degrees only (ρ = .88, p < .0001).[12] In the analysis that follows, we elect to use the results from Column (4), the spatial-heteroscedastic-AR1 FGLS specification, because it is the most conservative approach.[13]

We compare the size of the impact of average income on assortment with the size of the effect of the Gini by computing the elasticities of UPC counts with respect to changes in average income and changes in Gini. Evaluating at the county-level Gini average of .435 yields an elasticity of assortment size with respect to Gini of -.131,[14] while the elasticity with respect to average real income (evaluated at the county-level mean of $45,456) is .164. This indicates that the sensitivity of UPC counts with respect to changes in the Gini index is of the same order of magnitude as the impact of changes in the average income level, though changes in average income are a more important driver of changes in product assortment.[15]

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[12] Some readers may also wonder whether the results could be driven by international trade shocks that may affect both assortment and the income distribution. We procure import and export data at the state level from the U.S. Census Bureau and export data at the county level from the Brookings Metropolitan Policy Program (imports data at the county level are not available). We estimate models that include these variables and find that our main results are unaffected, as reported in Columns (3) and (4) of Table W1-1 of the Web Appendix.

[13] As a robustness check, we consider the impact of the uncertainty of the $\hat{\delta}_{ct}$ terms in the first stage of the estimation through a bootstrapping process. The results are presented in the second column of Table W1-1 in the Web Appendix. The coefficient estimates are slightly different due to the randomness in the specific draws from the bootstrapping procedure. Nevertheless, the results are essentially unchanged, and the standard errors are only slightly larger. We use the procedure described in Section 3 instead of the bootstrapping approach due to the computational burden of estimating all of our results with bootstrapping.

[14] The elasticity estimated directly from the log-log specification is -0.133 [see Column (7) in Table W4-1, Web Appendix 4].

[15] These estimates are consistent with Cirera and Masset (2010), who conducted a simulation analysis to relate changes in the Gini index to changes in food demand based on Engel-curve estimates. They estimate an elasticity of food demand with respect to Gini of -.20. Our results may be lower because Cirera and Masset (2010) used data from India to guide their simulation, whereas we study the U.S. Also, we include food and non-food items; indeed, when we run the analysis only on the Dry Grocery department, we get an elasticity of -0.15, which is closer to Cirera and Masset's

Exploring Aspects of Assortment

We now explore which aspects of assortment are most affected by changes in the income distribution. We begin by investigating the effect of changes in average income and the income Gini on the number of brands and the average number of UPCs per brand (which represents product line length) [16]. The results appear in Columns (1) and (2) of Table 4. We find the effects of average income to be positive and the effects of income inequality to be negative in both cases, though the effect of the income distribution – both average income and income dispersion – is larger for the regression of the number of brands [in Column (1)] than for the regression of the number of UPCs per brand [in Column (2)]. While declines in average income and increases in inequality are associated with fewer offerings of each brand's least popular flavors and sizes, more of the effect stems from removing niche brands.

Next, we break down assortment size into its horizontal and vertical dimensions. We follow Jaravel (2018) in using unit price to determine the vertical quality of UPCs and segment each product category into 12 quality tiers, while controlling for geographic and temporal variation in prices as described in Web Appendix W2. This effectively assumes a significant correlation between product prices and quality and a monotonic relationship between unit prices and quantity discounts. We then propose two rough measures of differentiation: the number of non-empty tiers in each category, *nTIERs*, and the average number of UPCs per tier across non-empty tiers, *AVGTIERUPCs*. *nTIERs* is intended to proxy for the extent of vertical differentiation in the category, while *AVGTIERUPCs* is meant to proxy for the extent of horizontal differentiation. We then replicate the main analysis using log(*nTIERs*) and log(*AVGTIERUPCs*) as the dependent variables instead log(*nUPCs*). The estimated coefficients of average income, presented in Columns (3) and (4) of Table 4, are positive and significant, indicating that greater average income increases both horizontal and vertical differentiation. The estimated coefficients of income Gini are negative and significant, suggesting that dispersion reduces both horizontal and vertical differentiation.

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estimate. To the extent that income elasticities for food and non-food categories in the U.S. are higher than food in India (i.e., necessity categories play a smaller role), we may expect an attenuated relationship between changes in Gini and category demand and therefore smaller shifts in UPC and brand availability by manufacturers and retailers.

[16] We use Nielsen's definition of brands for these analyses.

We also explore which brands win or lose when the income distribution shifts. We first test whether private label or branded products gain or lose more products. We run separate analyses using the number of private-label UPCs or the number of branded UPCs. (All products in the Nielsen data are classified as either branded or private label.) The results are reported in Columns (1) and (2) of Table 5. We find that the coefficients for average income and Gini are very similar in magnitude and statistical significance in both columns. Thus, changes in average income and Gini affect the assortment of private labels and branded products to about the same extent. The parallel result may reflect the comparable market shares that private labels now command versus many branded products and the improvements in quality that have broadened the appeal of private labels to a wide range of income levels.

We next examine whether large or small brands (brands with market shares above or below the median share in their categories) lose more UPCs when average income decreases and income dispersion increases. The results appear in Columns (3) and (4) of Table 5. We observe larger coefficients on average income and Gini for large brands versus small brands. Because the dependent variables are logs of the number of products, the coefficients can be interpreted as percentage changes in the number of UPCs. Thus, we observe that large brands lose a greater share of UPCs than small brands.

Exploring Dimensions of the Gini Index

In the foregoing analyses, we explored a series of different aspects of the dependent variable in our regressions of assortment on average income and Gini. We now pursue a similar inquiry for the Gini index for income. Specifically, we examine which quintiles of the income distribution drive the results for Gini. To do this, we decompose the Gini index by replacing it with the income shares of the income quintiles reported by the U.S. Census Bureau.[17] Note that the income shares of the five quintiles add to one. Thus, at minimum, one of the quintiles must be dropped from the regression. Also, the income shares of the different quintiles are highly correlated (see Table 2), so running a regression that keeps the income shares of four of the quintiles still leads to severe multicollinearity. To address this multicollinearity, we collapsed the

[17] Alvaredo (2011) shows how the Gini index can be expressed as a function of income shares.

five quintiles into three groups (low, middle, and high income) and included the two lower groups in our model. Of the 24 possible ways to group five quintiles into three groups, six combinations produce contiguous groups. Estimating models for these six combinations yields stable, interpretable results, which we report in Table 6. The income shares of the lowest group are not significant in any model except marginally for the case where the lower group includes Quintile 3 [see Column (1)]. The income shares of the middle group are significant as long as they include Quintile 3 or Quintile 4, with significance greatest when Quintile 4 is included. Thus, we conclude that the income share of Quintile 4, and to some degree Quintile 3, drives most of our main result for overall income dispersion or Gini. Quintile 4 roughly corresponds to the upper middle class and in what follows we will refer to it as "the middle" of the distribution. Our main results thus indicate that the effect of inequality on product assortments is caused by a "hollowing of the middle class."

Exploring Store-Level Changes in Assortment

In this subsection, we investigate the extent to which assortments shift within stores in response to changes in the income distribution of their customers and discuss the implications of the findings. To do this, we use demographic and purchase data in the Nielsen Homescan panel to construct measures of the income distribution and demographics of the patrons of individual stores.[18] We likewise use store-specific data to compute store-level measures of product assortment. Details about the specific variables we use and summary statistics for those variables appear in Web Appendix W3. We run regressions like those for our main model and report the results in Table 7. The results show that store-specific assortment size increases with average income and decreases with Gini, paralleling our findings above. We estimate that the elasticity

[18] Changes in the county-level income distribution may also shift store patronage as the observed income distribution of a given store's customers also reflects the store choices made by different income groups. In our analysis, we use the store-level income distribution to explain store-level assortments and do not attempt to separately address store choice. Alternatively, one could use county-level measures of the income distribution to explain store-level assortments, but these measures will include consumers outside of the stores' trading areas. Indeed, Gini index values are higher at the county-level than for store trading areas. Replicating our store-level analysis with county-level demographics gives coefficients (standard errors) on average income of 6.10 (2.60) and Gini of -0.44 (0.37). Note that standard errors become very large in this case.

of store-specific assortment with respect to the store-level Gini index is -0.160. This is larger than the county-level elasticity for Gini of -0.131 reported earlier, although the difference is not statistically significant. Thus, at least a significant amount of our main results are driven by changes of assortment within the stores rather than being driven only by changes in the composition and differentiation of stores serving the county. One implication of this is that researchers studying the consequences of local product availability for different income groups (e.g. Allcott et al. 2019) also might analyze the availability effects of within-store assortment changes in addition to the effects of store openings and closures.

We can also get some insight into whether stores are deleting products that other stores also are deleting or whether stores are becoming more differentiated with greater income dispersion. To glean this insight, we consider three hypothetical scenarios. In the first scenario, all stores within a county respond to increasing income dispersion by delisting exactly the same products so that differentiation does not increase and the effect on assortment size is the same at the store and county levels. In this scenario, the elasticities satisfy $E^{County}_{nUPCs,Gini} = E^{Store}_{nUPCs,Gini} < 0$. In the second scenario, stores react to increases in Gini by delisting entirely non-overlapping sets of UPCs. In this situation, the county-level assortment size is unaffected but the store-level effect is negative: $E^{County}_{nUPCs,Gini} = 0$, $E^{Store}_{nUPCs,Gini} < 0$. The third scenario falls between the two extremes: stores react by delisting both common and unique products. Here, the elasticities will have the following relationship: $E^{Store}_{nUPCs,Gini} < E^{County}_{nUPCs,Gini} < 0$. For our data, the point estimates of the elasticities are -0.16 (store) and -0.11 (county), which is consistent with the third scenario. However, these elasticities are not statistically different from each other, consistent with the first scenario. This suggests that the results are at least somewhat driven by stores delisting overlapping UPCs.

5. Robustness

In this subsection we investigate the robustness of our results to a series of issues. In particular, we examine the role of the 2008-09 recession, chain ownership, different functional specifications for average income and income dispersion, and possible migration of patronage to stores outside the Nielsen sample.

First, we consider whether the 2008-09 economic recession affects the findings. To do so, we conduct separate analyses for the 2007-10 and 2010-13 periods. The results appear in Table 8. The coefficients for average income and the Gini index are very close across the two time periods. Thus, the main effects are not driven by the presence (or absence) of a recession. Further, the similarity in the coefficients of average income and the Gini index across the time periods suggests that the effect is unlikely to be driven by changes in the distribution of consumer preferences over time because preference changes are less likely to occur in shorter periods (Bronnenberg, Dubé, and Gentzkow 2012). We also explored whether the similarity of the coefficients in the two time periods could occur because counties experience a common trend in UPC counts and income across the two time periods. The correlation of the change in UPC counts in 2007-2010 with the change in UPC counts in 2010-2013 is close to zero (-0.06), indicating that a common trend is not present.[19] Thus, the effects of the changes in average income and the Gini index on changes in UPC counts must be due to a different pattern of changes in the two time periods. Nonetheless, the estimates of the effects are almost the same, which further supports the results.

Table 8 also presents estimates for a model controlling for the number of retailer parent companies operating locally, *NPARENTS*, for years 2010-2013. (This variable is not included in the main analysis presented above because it is available from Nielsen only for these latter years.) Hwang et al. (2010) report that retail assortment is largely set at the chain level. Thus, one might wonder if our results are due to a correlation between ownership structure and income distributions. As Table 8 shows, the coefficient on *NPARENTS* is statistically significant, but its inclusion does not significantly affect the coefficients of our variables of interest.

We next explore how different functional specifications for Gini may affect our results. We estimate seven models, each including all of the control variables, as reported in Table W4-1 of Web Appendix W4. We consider models where the Gini enters with a linear effect, a quadratic effect, a linear effect with an interaction of Gini with average income, a logarithmic effect of Gini, and a linear effect of Gini plus

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[19] The correlation in the changes in the Gini index in each time period is -0.43, reflecting a reversion toward the long-term Gini trend after the recession.

polynomial effects of average income. Overall, the similarity in the estimated coefficients of average income and Gini across columns and the results of the heteroscedasticity-robust Wald and Lagrange multiplier (LM) tests (Wooldridge 2010, p. 62) suggests that the linear model performs well and that the Gini does not proxy for higher-order terms of average income. As a further robustness check on Gini as a measure of income dispersion, we also compute Palma-type measures (Palma 2011). These are defined as the ratios of the income shares of high earners over the income shares of low earners. The results for the Palma measures are very similar to those for Gini (see Table W4-2 in Web Appendix W4).

Some readers may wonder whether our results may be due to consumers shifting their patronage to stores outside the dataset, such as dollar stores, whose footprint increased during the time period analyzed. We assess this possibility by using Nielsen's Homescan panel data to analyze household-level expenditures across stores. Households in the Homescan panel report all purchases across all stores, whether or not the store collaborates with Nielsen. This enables us to assess whether households shifted their expenditure to stores outside the sample. For each household, we computed the proportion of spending at Nielsen stores for the years in our main analysis, 2007-13, and then averaged across households. The results, depicted in Figure 4, suggest that consumers did not migrate their spending to stores outside the sample. Likewise, we note that during the period of study online grocers accounted for a very small share of the market. Even after several years of rapid growth, online shopping accounted for less than 2% of the grocery market even by 2018 (e.g., Rogers 2018). Thus, migration to online channels is unlikely to explain our findings.

6. Exploring Explanations for the Effects of Income Dispersion on Assortment

Our principal objective has been to describe the equilibrium relationship between changes in the income distribution and changes in assortment size. Having established the robustness of our main findings, we now explore why changes in income dispersion may affect the size of local assortments. Specifically, we consider various theoretical reasons and discuss evidence supporting the feasibility of different theories.

We first consider Engel's law for expenditure. If grocery categories are, for the most part, necessities, category spending will rise less than proportionally with income (Engel 1857; Du and Kamakura 2008;

Cirera and Masset 2010), producing a concave relationship between household incomes and spending on groceries. At the aggregate level, the concavity implies that an increase in income dispersion – holding average income constant – decreases grocery expenditures, because high-income households will not increase their spending as much as low-income households decrease theirs. This is shown in a stylized fashion in the top panel of Figure 5. The lower panel of Figure 5 shows the actual income and grocery expenditure levels of the households in the Nielsen Homescan sample, along with the fitted mean relationship, which is concave. Engel's law of expenditure could imply that greater income dispersion leads to lower assortment (holding average income constant) if the lower spending due to more income dispersion means that only a smaller number of products can be supported.[20]

To examine whether Engel's law of expenditure could be a potential mechanism, we begin by testing whether category sales (*CATEGORYSALES*) change with Gini after controlling for average income. Specifically, using the same two-stage procedure as before, we estimate

$$\text{(6)} \qquad \log(CATEGORYSALES_{ict}) = \lambda_{ic} + \lambda_{it} + \alpha_1 AVGINCOME_{ct} + \alpha_2 GINI_{ct} + X_{ct}\boldsymbol{\varphi} + \tilde{\xi}_{ict}.$$

where X_{ct} are demographic controls and λ_{ic} and λ_{it} are category-county and category-year fixed effects. Estimation results for this model appear in Table 9, with and without fixed effects. Consistent with Engel's law for expenditure, increases in Gini, holding average income constant, lead to decreased spending. We next investigate the extent to which Engel's law of expenditure explains the results for assortment. If Engel's law of expenditure is the only explanation for our results, there should be no effect of changes in the income distribution on assortment size once we control for category sales in the assortment regression. To assess this, we estimate

$$\text{(7)} \quad \log(nUPCs_{ict}) = \beta_1 AVGINCOME_{ct} + \beta_2 GINI_{ct} + \beta_3 \log(CATEGORYSALES_{ict}) + X_{ct}\boldsymbol{\omega} + \tau_{it} + \gamma_{ic} + \varepsilon_{ct} + u_{ict}.$$

In this specification, we use $\log(CATEGORYSALES_{ict})$ to control for category sales but note that results also very similar when we use 2nd and 3rd order polynomials of category sales instead. Estimates for

[20] We also tested for the concavity of Engel curves at the level of the different grocery departments by using Nielsen's consumer panel data. We found that logarithmic specifications fit the data better than linear specifications, consistent with concavity.

model (7) appear in Column (2) of Table 10.[21] Wald and Lagrange Multiplier tests support the model that includes average income and Gini (reported at the bottom of Table 10). Note that the coefficients on average income and Gini retain the signs from Table 3, but the magnitudes here are less than half of those in Table 3. This suggests that most of the effect that income distribution changes have on assortment occurs through changes in spending.

We also note that Li (forthcoming) and Carlson et al. (2015) show that an Engel Curve for Variety also exists: consumers consume more variety as the level of their expenditures increases. This is similar to findings that increasing incomes lead to higher within-household tastes for consumption variety (Chai, Rohde, and Silber 2015). The positive coefficient of average income reported in Table 10 is consistent with this theory, though the theory does not explain the negative coefficient for income dispersion.

Since expenditure and demand for variety may not account for all of the negative effects that income dispersion has on assortment, we consider another explanation based on theoretical models of vertical differentiation (e.g., Gabszewicz and Thisse 1979; Shaked and Sutton 1983). Conventionally, vertical differentiation theories suggest that income dispersion could lead to a broader offering of products in the market, contrary to the results in Table 10. There are important caveats with this conventional wisdom as applied to our empirical setting. In particular, most of these theories assume that consumers buy at most one product and that incomes are uniformly or log-normally distributed, which gives rise to three caveats. First, in the context of consumer packaged goods, shoppers often buy multiple varieties and may buy multiple units of each. Second, in the cases of the uniform and log-normal distributions, the variance is an exact and increasing function of the mean; in our data, however, average income and dispersion are negatively and weakly correlated.

A third caveat with respect to the vertical differentiation theories is more nuanced. In the two parametric distributions that are commonly used, uniform and log-normal, greater income dispersion implies greater consumer heterogeneity, which in turn leads to the provision of greater vertical assortment.

[21] Table W5-2 of Web Appendix W5 reports equivalent results with a control function approach that addresses the potential simultaneity between assortment size and category sales. The results are largely unchanged.

Another possibility, however, is that greater income inequality could arise from a "hollowing out" of middle-income consumers, leaving higher concentrations of lower-income and upper-income households (Alichi, Mariscal, and Muhaj 2017; Foster and Wolfson 2010). Such a shift towards the extremes actually would make the population more homogenous on the low end (due to floor effects), leading to an overall decline in consumer heterogeneity as income inequality rises. This could produce a result that greater income dispersion leads to smaller assortments, consistent with our findings. The results for the decomposition of Gini in Table 6, discussed above, provide some evidence that this may be taking place. There, we found that the principal driver of assortment change due to changes in income dispersion was the income shares of Quintile 4 and, to a lesser degree, Quintile 3. Thus, the shrinkage (or "hollowing out") of the middle class could indeed lead to reductions in assortment sizes.

Because of these mismatches between the assumptions of vertical differentiation theories and the features of our empirical setting, we note that our results neither confirm nor contradict these theories. We also acknowledge that other theories may be consistent with our empirical findings. While we believe that our results support the likelihood of an important role for Engel's Law in the relationship between income distribution and assortment size, we leave detailed exploration of these mechanisms to future research.

7. Discussion and Conclusion

The purpose of this paper has been to study the empirical relationship between changes in the distribution of incomes and changes in the assortment size of grocery products, captured at the local level. We examined 944 product categories in 1,711 U.S. counties (which account for 94% of the U.S. population) over seven years (from 2007 to 2013). We employed a two-step econometric approach to obtain FGLS estimates using more than 11 million observations. The results provide strong empirical evidence that decreases in average income and increases in income dispersion lead to decreases in assortments, holding constant demographics and other factors. Our findings are also robust to the recession of 2008-09.

Our primary metric for assortment was the number of UPCs per category at the county level. We also examined a series of additional dependent variable specifications to capture different dimensions of product assortment. These included the number of brands per category, the number of UPCs per brand, and measures of vertical and horizontal differentiation within each category. The results suggest that more of the variation in assortment stems from adding or delisting brands as opposed to changes in product line length and that average income and Gini changes have a significant effect on both horizontal differentiation and vertical differentiation. Little difference in effect sizes was found for private labels versus national brands, but the available product lines for large brands shifted more due to income and Gini than the product lines for small brands. Turning to predictors, we also decomposed the Gini index into the income shares of income quintiles. That analysis revealed that shifts in Quintile 4, and to a lesser extent Quintile 3, (upper middle and lower middle income groups, respectively) are largely responsible for the effects that Gini has on assortment in the mainstream grocery channel. Thus, our findings appear to be caused to a great extent by a "hollowing out" of the middle class. We also demonstrated that a significant fraction of the effects we show are due to within-store shifts versus the entry or exit of stores. The evidence also suggests that when stores remove products, they are likely to remove the same products that other stores cut.

We also briefly explored why these effects occur. In particular, we found that most of the effect occurs through the changes in overall category spending, consistent with Engel's law for expenditure. Even when average income levels are constant, the concavity of the Engel curve means that rising income inequality leads consumers with falling incomes to reduce grocery spending more than rising inequality leads consumers with rising incomes to increase their spending. The net reduction in spending leads retailers to reduce the assortment available to consumers. While our analysis suggests that the concavity of the Engel curve is the largest mechanism for our effects, the main effects persist even after we control for expenditure, suggesting that other mechanisms are at play as well. We leave deeper theoretical development for future research.

Managerial Implications

We believe that our findings are relevant for CPG manufacturers in supporting their efforts to manage distribution coverage for their products in the mainstream grocery channel. In particular, by linking changes in assortment at the local (and store level) to changes in the local (and store patron) income distribution, we show how challenges in seeking and retaining shelf space may be, at least in part, driven by changes in not only income levels but also income dispersion. This may enable manufacturers to better understand why reductions or expansions in assortment may be taking place in their categories and to forecast where this may occur, providing an “early warning” system. Moreover, by highlighting the role of income dispersion, we also show how changes in assortment can take place even if average income levels remain the same. While income dispersion grew nationally during the time span of our data, the Gini index actually fell in about one-third of U.S. counties and numerous local areas had assortments increase. With an understanding of these differences and their implications, managers may be able to develop promotional strategies and targeting efforts designed to expand distribution where possible or to defend it where necessary.

Besides the implications of our basic findings, the additional analyses we present also offer insights to CPG manufacturers. For example, we find that category offerings are more likely to shrink via the addition or deletion of brands versus UPCs within a brand. To the extent changes occur in product line lengths, large brand lines fluctuate more than small brands. Further, the magnitudes of our results suggest that expansion and contraction of category offerings is also more common along the horizontal dimension than the vertical dimension. This indicates that retailers tend to favor preserving vertical differentiation in categories while making adjustments at existing price points.

A potential concern in using our results prescriptively is that our analysis examines the equilibrium relationship between income inequality and assortment supply. It may seem then that we are just describing manufacturers’ actions back to themselves. The ability to provide guidance to manufacturers is based on the assumption that, while the numbers and extent of variety is important for retailer profits, the retailer has the choice of which manufacturer to use to supply those products. Ultimately, switching between one manufacturer and another for similar marginal products that are added or subtracted is likely to have relatively small effects on the profits of the retailer, but large effects on the profits of the winning (or losing) manufacturer. Numerous papers examining slotting allowances or category captainship have noted such a dynamic (e.g., Marx and Shaffer 2010, Subramanian et al. 2010, Nijs et al. 2014). In sum, this means that we assume that the equilibrium assortment offerings are the results of retailer choices but not the direct effects of manufacturer choices. In this case, our study may benefit manufacturers.

Policy Implications

Our analysis sheds light on the potentially unintended consequences of policy interventions. For example, the U.S. government recently increased the minimum number of offerings per category required for retailers to participate in the food stamp program (London 2017). A long-term implication of our results is that consumers' ability to use food stamps may decline in areas where falling average income and rising income dispersion leads retailers to reduce their assortments and possibly stop participating in the food stamp program.[22]

Further, the increase or decrease in assortment that arises from changes in the income distribution can also have implications for consumer welfare (see Israilevich 2004; Dukes et al. 2009; Jaravel 2018). In particular, consumers who lose access to their preferred items may be most adversely affected (Broniarczyk, Hoyer, and McAlister 1998). Broniarczyk et al. (1998) also show that consumer perceptions of assortment attractiveness fall with reductions in the count of stock keeping units but that the continued presence of favorite items and the maintenance of similar category space can mitigate this effect. While our county-level measures of assortment size are imprecise measures of product availability because not all stores in a county are accessible to all of its inhabitants, our store-level analysis indicates that a great part of the effect happens within stores so that the effects of changes in income distribution on consumer welfare are real.

Scope of Findings

Our findings are limited to non-perishable categories of consumer packaged goods distributed in the mainstream grocery channel, as captured by the Nielsen data. While these products are important to the overall economy, it would be of interest to explore the relationship between average income, Gini, and

[22] We make no judgment about whether the current level of assortment offerings is too high, too low, or just right. Rather, our goal is simply to demonstrate the link between income distribution changes and assortment. While changes in assortment may have welfare implications (both positive and negative), we do not interpret any set of results in a normative way.

assortment size in other product classes. Indeed, taking a broader view of food and grocery consumption to include non-necessities outside the Nielsen data could potentially reverse the direction of the effects we find for Gini. We hope that the modeling approach we developed and the connections we have drawn to relevant theory will motivate further research into the relationships among income distribution changes and marketing outcomes.

Appendix: Variable Descriptions

Dependent Variables

We use the Nielsen data to construct our dependent variables. We define the following variables for each product category i that is available in county c anytime during year t:

- $nUPCs_{ict}$ is the number of distinct products in category i at time t and county c.
- $nBRANDS_{ict}$ is the number of distinct brands in category i at time t and county c.
- $AVGBRANDUPCs_{ict}$ is the average across brands of the number of UPCs of each brand in category i
- $CATEGORYSALES_{ict}$ is the dollar revenue of all stores for category i at time t and county c.
- $nTIERs_{ict}$ is the number of quality tiers with at least one UPC in category i at time t and county c (refer to Web Appendix W2 for details).
- $AVGTIERUPCs_{ict}$ is the average, across quality tiers, of the number of UPCs in each non-empty tier of category i at time t and county c (refer to Web Appendix W2 for details).

Explanatory Variables

The following demographic variables were obtained from the American Community Survey (ACS):

- $AVGINCOME_{ct}$ is the average household income in county c at time t, given in thousands of dollars, adjusted for inflation (using weights provided by the Bureau of Labor Statistics).
- $GINI_{ct}$ is the Gini index of income inequality in county c at time t.
- *INCOME SHARE QTL*a_{ct} is the percent income share of the a=1,…,5 quintile of the income distribution (a=1 is the lowest income group, a=5 is the highest income group).
- $POPULATION_{ct}$ is the population size of county c at time t in millions of inhabitants.
- $UNEMPLOYMENT_{ct}$ is the percentage of unemployed members of the labor force aged 16 and over in county c at time t.
- $HOMEVALUE_{ct}$ is the median home value as reported by the ACS respondents, in thousands of dollars, in county c at time t.
- $HIGHSCHOOL_{ct}$ is the percentage of the population over 25 years old who completed high-school in county c at time t
- $HISPANIC_{ct}$ is the proportion of the population who identify as Hispanic in county c, time t.
- $EDUCDVRSTY_{ct}$ is the Simpson index of diversity of education levels, for county c, time t. It is defined as $EDUCDVRSTY_{ct} = \Sigma_{e \in E}\ POPULATION_{ect}^2$, where e indexes the three education levels (individuals without high school education, individuals with high school education only, individuals with higher education) and $POPULATION_{ect}$ is the proportion of inhabitants with education level e.
- $AGEDVRSTY_{ct}$ is the Simpson index of diversity of population ages, for county c, time t. It is reported in terms of a set A of 18 age brackets of five years each. It is defined as $AGEDVRSTY_{ct} = \Sigma_{a \in A}$ $POPULATION_{act}^2$, where a indexes the 18 age brackets and $\mathrm{POPULATION}_{act}$ is the proportion of inhabitants whose age falls within bracket a.
- $HHSIZEDVRSTY_{ct}$ is the Simpson index of diversity of household sizes for county c, time t. It is reported in terms of a set S of 8 household size brackets. The index is defined as $HHSIZEDVRSTY_{ct} =$

$\Sigma_{s \in S}$ *POPULATION*$_{sct}^{2}$, where s indexes the S size brackets and *POPUPLATION*$_{sct}$ is the proportion of households with sizes within bracket s.

- *ETHNICDVRSTY*$_{ct}$ is the Simpson index of ethnic diversity for county c at time t. Ethnicity is defined by the following four racial groups: White, Black, Asian, others. The index is defined as *ETHNICDVRSTY*$_{ct}$ = $\Sigma_{r \in R}$ *POPULATION*$_{rct}^{2}$, where r indexes the four racial groups and *POPULATION*$_{rct}$ is the proportion of inhabitants of race r.
- *FOREIGN*$_{ct}$ is the proportion of the population born overseas in county c, time t.

The following retailing measure was based on information from the Nielsen dataset:

- *NPARENTS*$_{ct}$ is the number of unique retailer parents associated with the stores that reported positive sales in county c, time t. Retailer parents are either corporate parents or retail banners.

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Table 1

SUMMARY STATISTICS

	Mean	St. Dev.	Min.	Median	Max.
log(*nUPCs*)	3.01	0.78	-0.17	3.12	4.72
AVGINCOME ($100000)	0.45	0.11	0.23	0.43	1.05
GINI	0.44	0.03	0.33	0.44	0.60
INCOME SHARE QTL1	3.86	0.64	0.00	3.90	6.00
INCOME SHARE QTL2	9.49	1.01	5.20	9.50	13.10
INCOME SHARE QTL3	15.58	1.03	10.70	15.61	18.80
INCOME SHARE QTL4	23.78	0.95	16.95	23.83	27.30
INCOME SHARE QTL5	47.29	3.05	38.10	47.10	63.20
log(*CATEGORYSALES*)	8.90	1.52	4.39	8.80	14.12
UNEMPLOYMENT (10)	0.01	0.003	0.00	0.01	0.03
HOMEVALUE ($1000000)	0.12	0.07	0.02	0.10	0.72
HIGHSCHOOL (10)	0.03	0.01	0.01	0.03	0.06
POPULATION (1000000)	0.17	0.41	0.02	0.06	9.95
HISPANIC	0.05	0.11	0.00	0.00	1.00
EDUCDVRSTY	0.12	0.04	0.03	0.12	0.32
AGEDVRSTY	0.06	0.005	0.06	0.06	0.13
HHSIZEDVRSTY	0.12	0.02	0.05	0.12	0.34
ETHNICDVRSTY	0.77	0.17	0.29	0.81	1.00
FOREIGN	0.01	0.05	0.00	0.00	0.48

Note: Detailed variable descriptions appear in the Appendix

Table 2

CORRELATIONS

	log(*nUPCs*)	*AVGINCOME*	*GINI*	*INCOME SHARE QTL1*	*INCOME SHARE QTL2*	*INCOME SHARE QTL3*	*INCOME SHARE QTL4*	*INCOME SHARE QTL5*	log(*CATEGORYSALES*)	*UNEMPLOYMENT*	*HOMEVALUE*	*HIGHSCHOOL*	*POPULATION*	*HISPANIC*	*EDUCDVRSTY*	*AGEDVRSTY*	*HHSIZEDVRSTY*	*ETHNICDVRSTY*	*FOREIGN*
log(*nUPCs*)	1																		
AVGINCOME	0.35	1																	
GINI	0.14	-0.11	1																
INCOME SHARE QTL1	-0.14	0.16	-0.87	1															
INCOME SHARE QTL2	-0.08	0.24	-0.95	0.87	1														
INCOME SHARE QTL3	-0.11	0.12	-0.94	0.70	0.88	1													
INCOME SHARE QTL4	-0.16	-0.28	-0.54	0.18	0.32	0.61	1												
INCOME SHARE QTL5	0.14	-0.06	0.99	-0.79	-0.91	-0.97	-0.66	1											
log(*CATEGORYSALES*)	0.35	0.39	0.17	-0.14	-0.11	-0.15	-0.20	0.18	1										
UNEMPLOYMENT	0.15	-0.39	0.24	-0.27	-0.29	-0.24	0.05	0.22	-0.01	1									
HOMEVALUE	0.33	0.79	0.00	0.03	0.10	0.02	-0.24	0.03	0.42	-0.21	1								
HIGHSCHOOL	-0.49	-0.44	-0.31	0.27	0.24	0.29	0.27	-0.32	-0.31	-0.08	-0.44	1							
POPULATION	0.31	0.33	0.19	-0.16	-0.13	-0.17	-0.19	0.19	0.96	0.02	0.38	-0.28	1						
HISPANIC	0.22	0.20	0.13	-0.12	-0.10	-0.13	-0.12	0.14	0.31	0.08	0.27	-0.38	0.36	1					
EDUCDVRSTY	-0.38	-0.11	-0.31	0.29	0.28	0.30	0.17	-0.31	-0.16	-0.27	-0.18	0.88	-0.17	-0.36	1				
AGEDVRSTY	0.07	0.16	0.11	-0.21	-0.09	-0.06	0.03	0.09	0.05	-0.10	0.16	-0.34	0.05	0.13	-0.20	1			
HHSIZEDVRSTY	0.16	-0.05	0.46	-0.48	-0.47	-0.41	-0.11	0.43	0.23	0.12	0.04	-0.19	0.24	0.14	-0.14	0.11	1		
ETHNICDVRSTY	-0.28	-0.20	-0.31	0.37	0.28	0.26	0.10	-0.29	-0.32	-0.17	-0.22	0.41	-0.34	-0.37	0.39	-0.18	-0.33	1	
FOREIGN	0.25	0.44	0.18	-0.16	-0.14	-0.17	-0.19	0.20	0.65	-0.02	0.55	-0.28	0.68	0.34	-0.12	0.06	0.26	-0.36	1

Table 3

MAIN RESULTS AND SELECTION OF RESIDUAL SPECIFICATION

	Dependent variable: log(*nUPCs*)				
Residual specification	OLS	FGLS het, AR(1)	FGLS SP	FGLS het, SP, AR(1)	FGLS het, SP, AR(1)
	(1)	(2)	(3)	(4)	(5)
UNEMPLOYMENT	-9.800	-2.582	-3.017	3.603	
	(6.967)	(7.349)	(6.923)	(7.302)	
HOMEVALUE	1.827**	2.608***	1.480*	2.071***	
	(0.775)	(0.547)	(0.840)	(0.624)	
HIGHSCHOOL	8.511***	6.404***	8.022***	5.698***	
	(1.362)	(1.504)	(1.352)	(1.470)	
POPULATION	-3.956***	-3.862***	-4.633***	-4.499***	
	(1.028)	(0.456)	(1.025)	(0.507)	
HISPANIC	3.963	-0.840	3.684	-3.947	
	(27.528)	(34.598)	(26.529)	(32.902)	
EDUCDVRSTY	-12.949***	-9.581***	-12.728***	-8.826***	
	(1.848)	(2.029)	(1.844)	(2.014)	
AGEDVRSTY	-6.329	1.992	-3.830	4.501	
	(9.164)	(6.244)	(8.947)	(5.882)	
HHSIZEDVRSTY	-13.950	-7.011	-16.524	-9.172	
	(13.163)	(15.774)	(12.711)	(14.647)	
ETHNICDVRSTY	8.507***	4.358**	7.585***	3.581**	
	(1.710)	(1.808)	(1.653)	(1.711)	
FOREIGN	1.131	0.916***	1.010	0.815***	
	(0.826)	(0.236)	(0.799)	(0.219)	
AVGINCOME	6.587***	5.213***	5.323***	4.010***	4.385***
	(0.688)	(0.713)	(0.682)	(0.687)	(0.642)
GINI	-0.377***	-0.373***	-0.307***	-0.301***	-0.309***
	(0.075)	(0.084)	(0.073)	(0.080)	(0.079)
Category-County, Category-Year Fixed Effects	Included	Included	Included	Included	Included
Observations	11,977	11,977	11,977	11,977	11,977
Moran I Z	Inf.	Inf.	1.793	1.793	1.765
Within Adjusted R^2	0.023	0.014	0.018	0.009	0.005

Notes: *p<0.10; **p<0.05; ***p<0.01; het - heteroscedasticity-consistent standard errors; AR(1) - estimates corrected for serial correlation of order 1; SP - estimates corrected for spatial correlation.

Table 4

ANALYSES OF ADDITIONAL ASSORTMENT SIZE MEASURES

	Dependent variable:			
	log(*nBRANDs*)	log(*AVG BRAND UPCs*)	log(*nTIERs*)	log(*AVG TIERUPCs*)
	(1)	(2)	(3)	(4)
UNEMPLOYMENT	3.800	0.456	1.554	1.635
	(4.813)	(1.856)	(2.061)	(4.403)
HOMEVALUE	1.109***	0.665***	0.478***	1.360***
	(0.419)	(0.172)	(0.173)	(0.390)
HIGHSCHOOL	2.974***	1.803***	1.923***	3.046***
	(0.961)	(0.378)	(0.404)	(0.898)
POPULATION	-2.462***	-1.518***	-1.735***	-2.081***
	(0.353)	(0.140)	(0.164)	(0.306)
HISPANIC	-1.360	-2.768	1.002	-4.286
	(21.875)	(7.896)	(9.361)	(19.547)
EDUCDVRSTY	-4.826***	-2.659***	-3.125***	-4.592***
	(1.315)	(0.524)	(0.555)	(1.231)
AGEDVRSTY	2.465	1.023	0.617	3.439
	(4.029)	(1.456)	(1.620)	(3.674)
HHSIZEDVRSTY	-7.847	-0.312	-1.088	-7.532
	(9.625)	(3.619)	(4.102)	(8.800)
ETHNICDVRSTY	2.318**	0.772*	1.048**	2.135**
	(1.122)	(0.426)	(0.489)	(1.015)
FOREIGN	0.634***	0.102**	0.400***	0.292**
	(0.165)	(0.052)	(0.069)	(0.139)
AVGINCOME	2.467***	0.965***	1.208***	2.259***
	(0.451)	(0.176)	(0.189)	(0.419)
GINI	-0.186***	-0.074***	-0.088***	-0.173***
	(0.052)	(0.020)	(0.022)	(0.049)
Category-County, Category-Year Fixed Effects	Included	Included	Included	Included
Observations	11,977	11,977	11,977	11,977
Within Adjusted R^2	0.007	0.010	0.013	0.010

Notes: *p<0.10; **p<0.05; ***p<0.01.

Table 5

FURTHER ANALYSES OF ADDITIONAL ASSORTMENT SIZE MEASURES

	Dependent variable:			
	log(*nUPCs*) private	log(*nUPCs*) national	log(*nUPCs*) small brands	log(*nUPCs*) large brands
	(1)	(2)	(3)	(4)
UNEMPLOYMENT	1.343	4.728	3.346	3.756
	(6.028)	(6.983)	(4.562)	(8.265)
HOMEVALUE	0.879	1.796***	1.709***	2.268***
	(0.604)	(0.610)	(0.408)	(0.700)
HIGHSCHOOL	6.045***	4.315***	3.267***	6.744***
	(1.240)	(1.408)	(0.914)	(1.670)
POPULATION	-7.657***	-2.847***	-2.819***	-5.188***
	(0.573)	(0.474)	(0.349)	(0.565)
HISPANIC	-3.762	-1.945	0.484	-5.830
	(25.790)	(31.600)	(20.638)	(37.349)
EDUCDVRSTY	-8.631***	-7.056***	-5.253***	-10.338***
	(1.709)	(1.932)	(1.251)	(2.288)
AGEDVRSTY	3.686	3.433	2.912	4.723
	(5.238)	(5.692)	(3.803)	(6.656)
HHSIZEDVRSTY	8.501	-13.413	-7.262	-8.740
	(11.523)	(14.034)	(9.135)	(16.606)
ETHNICDVRSTY	1.504	3.458**	2.327**	3.990**
	(1.356)	(1.637)	(1.067)	(1.937)
FOREIGN	0.793***	0.715***	0.645***	0.824***
	(0.248)	(0.211)	(0.161)	(0.243)
AVGINCOME	3.461***	3.558***	2.548***	4.597***
	(0.571)	(0.659)	(0.428)	(0.779)
GINI	-0.271***	-0.260***	-0.194***	-0.345***
	(0.064)	(0.077)	(0.050)	(0.091)
Category-County, Category-Year Fixed Effects	Included	Included	Included	Included
Observations	11,977	11,977	11,977	11,977
Within Adjusted R^2	0.013	0.007	0.010	0.009

Notes: *p<0.10; **p<0.05; ***p<0.01.

Table 6

ANALYSIS BY INCOME QUINTILE (GINI INDEX COMPONENTS)

	Dependent variable: log(nUPCs)					
Income quintiles in lower group	1 to 3	1 to 2	1	1 to 2	1	1
Income quintiles in middle group	4	3 to 4	2 to 4	3	2 to 3	2
	(1)	(2)	(3)	(4)	(5)	(6)
UNEMPLOYMENT	3.468	3.064	3.189	2.150	2.168	1.485
	(7.338)	(7.328)	(7.329)	(7.307)	(7.309)	(7.324)
HOMEVALUE	1.934***	2.022***	2.038***	2.220***	2.244***	2.370***
	(0.619)	(0.612)	(0.613)	(0.614)	(0.615)	(0.617)
HIGHSCHOOL	6.045***	5.904***	5.829***	5.674***	5.611***	5.498***
	(1.483)	(1.482)	(1.487)	(1.481)	(1.487)	(1.486)
POPULATION	-4.638***	-4.567***	-4.550***	-4.541***	-4.524***	-4.496***
	(0.502)	(0.496)	(0.495)	(0.497)	(0.496)	(0.498)
HISPANIC	-4.060	-4.194	-4.352	-3.904	-3.981	-3.621
	(33.339)	(33.332)	(33.322)	(33.317)	(33.291)	(33.222)
EDUCDVRSTY	-9.318***	-9.152***	-9.049***	-8.870***	-8.772***	-8.606***
	(2.025)	(2.022)	(2.034)	(2.023)	(2.035)	(2.037)
AGEDVRSTY	3.132	3.622	3.827	3.599	3.655	3.298
	(5.966)	(5.948)	(5.935)	(5.951)	(5.948)	(5.943)
HHSIZEDVRSTY	-10.206	-9.180	-8.447	-10.466	-10.260	-12.060
	(14.874)	(14.859)	(14.850)	(14.839)	(14.828)	(14.821)
ETHNICDVRSTY	3.686**	3.632**	3.593**	3.575**	3.546**	3.530**
	(1.738)	(1.732)	(1.730)	(1.732)	(1.730)	(1.728)
FOREIGN	0.817***	0.839***	0.833***	0.815***	0.808***	0.790***
	(0.220)	(0.220)	(0.219)	(0.219)	(0.219)	(0.219)
AVGINCOME	4.517***	4.391***	4.282***	3.723***	3.610***	3.251***
	(0.734)	(0.718)	(0.711)	(0.669)	(0.666)	(0.654)
INCOME SHARE LOWER	2.476**	2.887	5.347	3.092	5.742	6.660
	(1.242)	(1.958)	(4.266)	(2.150)	(4.538)	(5.081)
INCOME SHARE MIDDLE	5.978***	4.046***	3.404***	4.907*	3.351**	4.026
	(2.090)	(1.291)	(1.033)	(2.701)	(1.596)	(3.587)
Category-County, Category-Year Fixed Effects	Included	Included	Included	Included	Included	Included
Observations	11,977	11,977	11,977	11,977	11,977	11,977
Within Adjusted R^2	0.010	0.010	0.010	0.009	0.009	0.009

Notes: $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7

STORE-LEVEL ANALYSIS

	Dependent variable: log(*nUPCs*)			
Residual specification	OLS	FGLS het, AR(1)	FGLS SP	FGLS het, SP, AR(1)
	(1)	(2)	(3)	(4)
HISPANIC	0.213***	0.213***	0.221***	0.221***
	(0.050)	(0.077)	(0.050)	(0.079)
HHSIZEDVRSTY	-7.178*	-7.178	-9.123**	-9.123
	(3.715)	(7.922)	(3.757)	(8.108)
HHCOMPDVRSTY	-3.607	-3.607	-3.069	-3.069
	(2.840)	(5.007)	(2.860)	(5.154)
ETHNICDVRSTY	9.719***	9.719**	10.789***	10.789**
	(2.677)	(4.874)	(2.721)	(5.081)
ZIPDVRSTY	-1.735	-1.735	-2.177	-2.177
	(1.605)	(2.602)	(1.627)	(2.338)
FHEMPDVRSTY	3.332	3.332	3.779*	3.779
	(2.101)	(3.433)	(2.101)	(3.442)
MHEMPDVRSTY	2.259*	2.259	2.504**	2.504
	(1.241)	(2.686)	(1.236)	(2.663)
MARSTATDVRSTY	-7.168	-7.168	-8.760*	-8.760
	(5.285)	(9.301)	(5.321)	(9.637)
POPULATION	-0.221***	-0.221***	-0.250***	-0.250***
	(0.046)	(0.059)	(0.055)	(0.079)
AVGINCOME	1.203***	1.203***	1.134***	1.134***
	(0.258)	(0.346)	(0.261)	(0.353)
GINI	-0.110**	-0.110**	-0.112***	-0.112**
	(0.043)	(0.052)	(0.043)	(0.053)
Store-Category, Year-Category Fixed Effects	Included	Included	Included	Included
Observations	3,066	3,066	3,066	3,066
Moran I Z	4.094	4.094	1.749	1.749
Within Adjusted R^2	0.027	0.027	0.030	0.030

Notes: *p<0.10; **p<0.05; ***p<0.01; het - heteroscedasticity-consistent standard errors; AR(1) - estimates corrected for serial correlation of order 1; SP - estimates corrected for spatial correlation.

Table 8

TESTS OF ROBUSTNESS TO RECESSION PERIOD

	Dependent variable: log(*nUPCs*)		
Time Period	2007-2010	2010-2013	2010-2013
	(1)	(2)	(3)
UNEMPLOYMENT	4.551	23.007***	23.482***
	(10.114)	(8.087)	(7.338)
HOMEVALUE	1.907**	3.260**	1.591
	(0.748)	(1.462)	(1.338)
HIGHSCHOOL	9.734***	-0.394	-1.110
	(1.881)	(2.428)	(2.065)
POPULATION	-4.435***	-3.557***	-3.091***
	(0.637)	(0.734)	(0.796)
HISPANIC	-59.778	29.218	10.305
	(49.367)	(38.292)	(30.849)
EDUCDVRSTY	-13.069***	-1.621	0.525
	(2.500)	(3.989)	(3.367)
AGEDVRSTY	3.672	27.594*	25.185*
	(6.696)	(15.196)	(14.312)
HHSIZEDVRSTY	-0.179	-12.601	-5.090
	(20.712)	(16.416)	(14.566)
ETHNICDVRSTY	-1.063	7.151***	3.790
	(2.119)	(2.633)	(2.313)
FOREIGN	1.078***	0.099	0.779**
	(0.249)	(0.318)	(0.339)
AVGINCOME	2.941***	3.267***	2.897***
	(0.921)	(0.841)	(0.749)
GINI	-0.337***	-0.223**	-0.217**
	(0.121)	(0.093)	(0.087)
NPARENTS			0.283***
			(0.018)
Category-County, Category-Year Fixed Effects	Included	Included	Included
Observations	6,844	6,844	11,977
Within Adjusted R^2	0.008	0.010	0.163

Notes: *p<0.10; **p<0.05; ***p<0.01.

Table 9

EFFECT OF CHANGES IN INCOME AND GINI ON CATEGORY SALES

	Dependent variable: log(*CATEGORYSALES*)	
	(1)	(2)
Constant	8.741***	
	(0.298)	
UNEMPLOYMENT	284.181***	-11.071
	(34.720)	(12.645)
HOMEVALUE	22.217***	6.840***
	(2.457)	(1.297)
HIGHSCHOOL	-74.255***	6.851***
	(4.387)	(2.531)
POPULATION	12.540***	-3.651***
	(0.323)	(0.940)
HISPANIC	669.066***	-49.625
	(98.526)	(38.705)
EDUCDVRSTY	84.963***	-12.153***
	(7.228)	(3.556)
AGEDVRSTY	-201.124***	-20.169*
	(21.276)	(11.000)
HHSIZEDVRSTY	1,271.570***	-27.471
	(69.235)	(23.241)
ETHNICDVRSTY	-130.163***	9.212***
	(6.797)	(2.829)
FOREIGN	-35.142***	1.342***
	(2.991)	(0.368)
AVGINCOME	38.085***	3.957***
	(1.766)	(1.170)
GINI	-0.693**	-0.343**
	(0.331)	(0.136)
Category-County, Category-Year Fixed Effects	Not Included	Included
Observations	11,977	11,977
Adjusted R^2	0.549	
Within Adjusted R^2		0.007

Notes: *p<0.10; **p<0.05; ***p<0.01.

Table 10

EFFECT OF CHANGES IN INCOME AND GINI ON ASSORTMENT SIZE CONTROLLING FOR CATEGORY SALES

	Dependent variable: log(*nUPCs*)	
	(1)	(2)
UNEMPLOYMENT	9.755*	13.660***
	(5.157)	(5.193)
HOMEVALUE	-1.663***	-2.355***
	(0.378)	(0.404)
HIGHSCHOOL	1.384	1.657*
	(0.919)	(0.921)
POPULATION	-4.064***	-4.049***
	(0.432)	(0.429)
HISPANIC	-1.771	-3.539
	(23.235)	(23.192)
EDUCDVRSTY	-2.347*	-2.561**
	(1.251)	(1.250)
AGEDVRSTY	12.995***	14.162***
	(4.893)	(4.924)
HHSIZEDVRSTY	-8.603	0.141
	(10.026)	(10.080)
ETHNICDVRSTY	-1.481	-1.549
	(1.421)	(1.421)
FOREIGN	0.176	0.227
	(0.196)	(0.196)
log(*CATEGORYSALES*)	0.442***	0.441***
	(0.008)	(0.008)
AVGINCOME		1.864***
		(0.476)
GINI		-0.148***
		(0.057)
Category-County, Category-Year Fixed Effects	Included	Included
Observations	11,977	11,977
Within Adjusted R^2	0.581	0.581
Wald test p-value		0.0002
LM test p-value		0

Notes: $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$.

Figure 1

LOWER INCOME LIMITS FOR U.S. INCOME QUINTILES OVER TIME

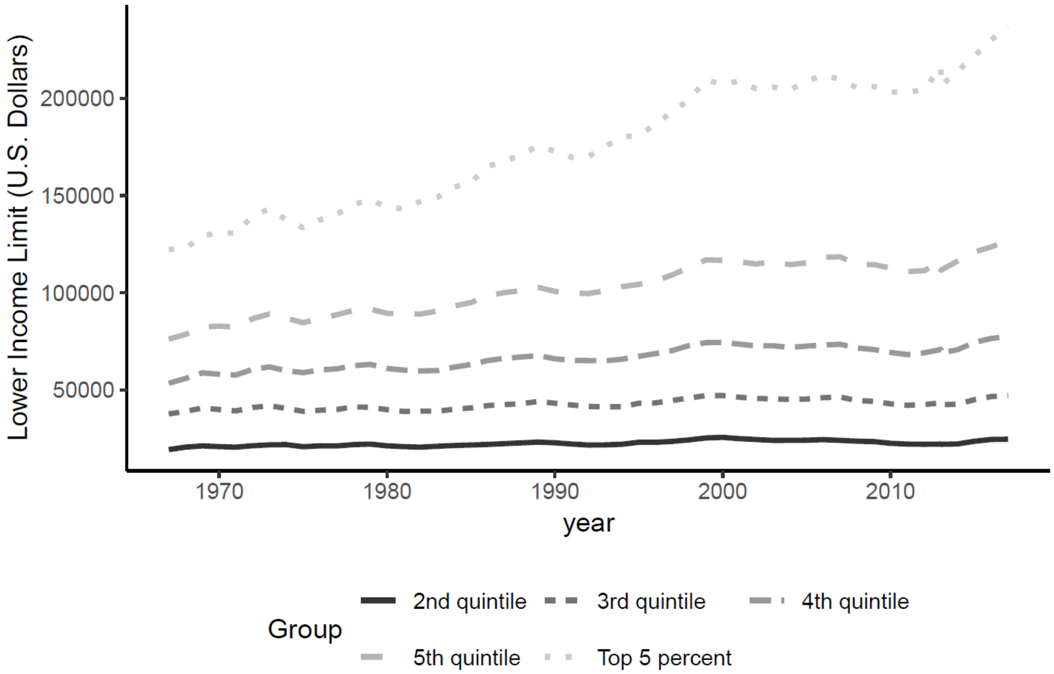

Figure 2

SAMPLE VARIATION OF AVERAGE REAL INCOME, GINI, AND UPC COUNT

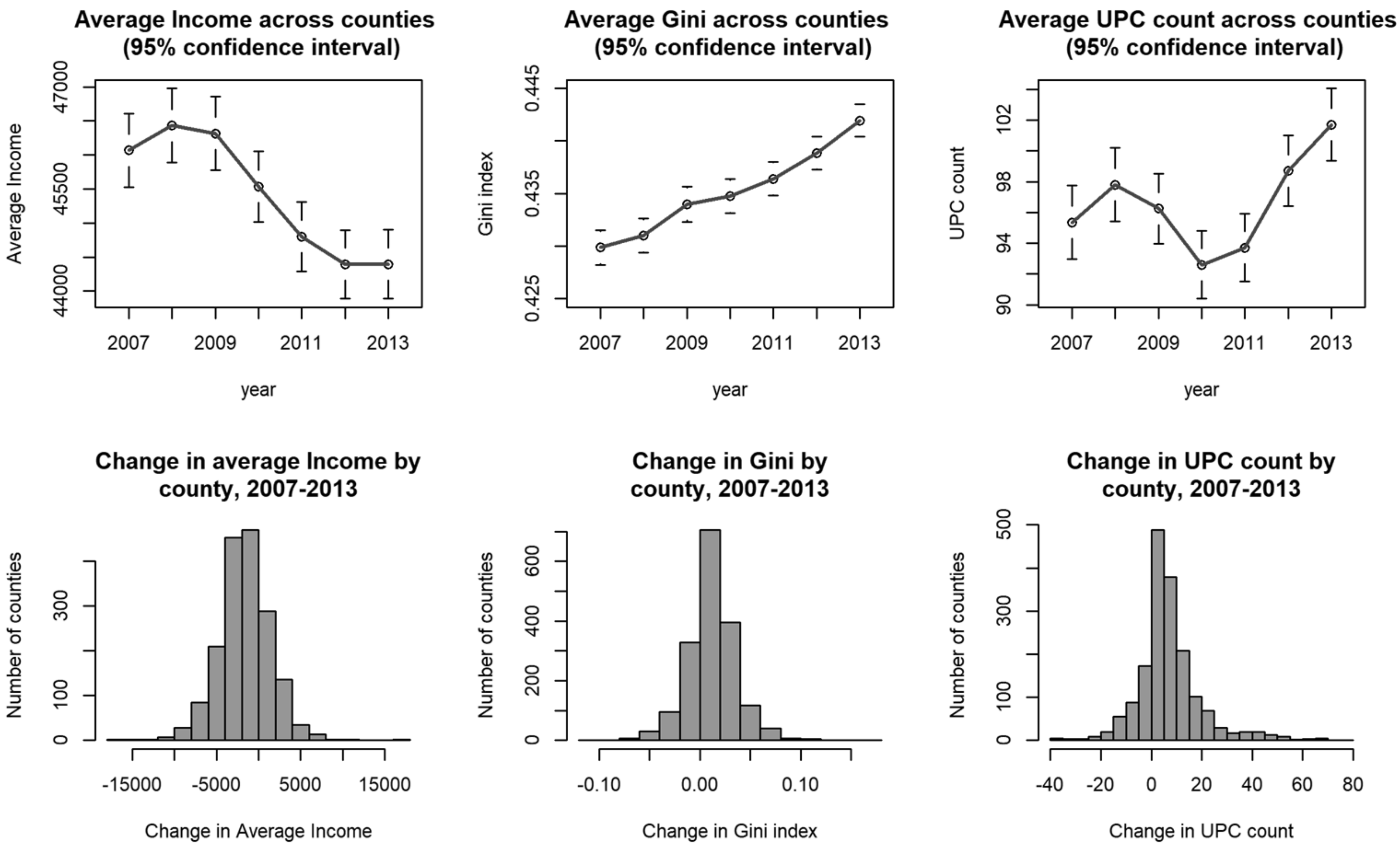

Figure 3

CHANGES IN UPC COUNTS AND UPC COUNTS PER 10,000 DOLLARS IN INCOME FOR COUNTIES WITH DECREASED AND INCREASED AVERAGE INCOME AND INCOME GINI, 2007 TO 2013

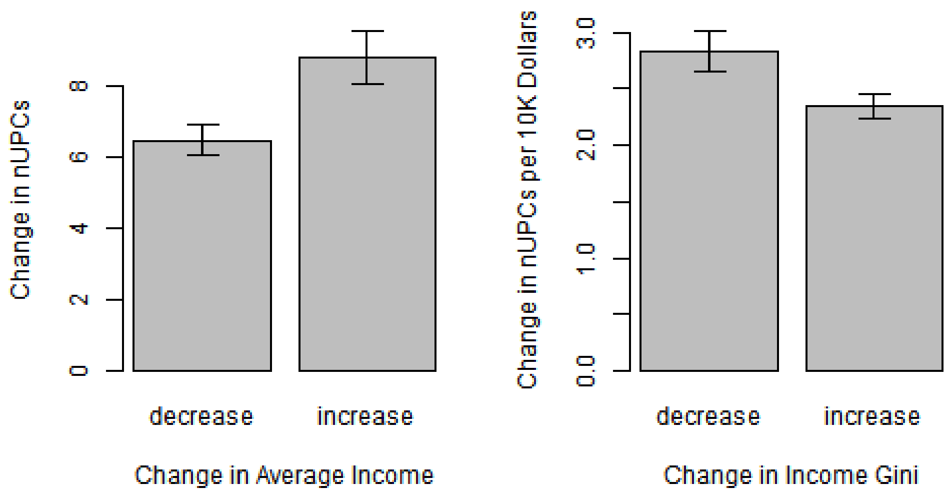

Figure 4

PROPORTION OF HOUSEHOLD EXPENDITURE IN NIELSEN STORES 2007-2013

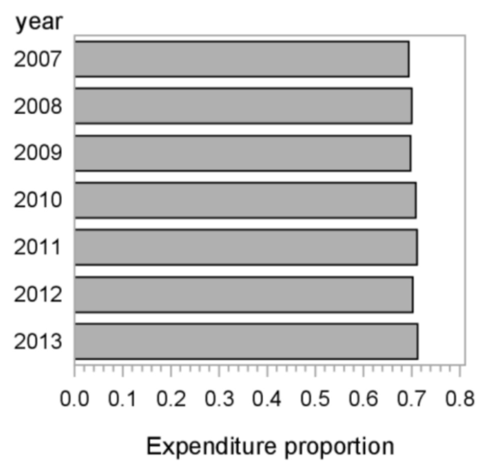

Figure 5

INCOME, EXPENDITURE, AND THE ENGEL CURVE. PANEL (a) PORTRAYS A STYLIZED MODEL. PANEL (b) DEPICTS DATA FROM THE NIELSEN HOMESCAN PANEL AND THEIR SMOOTHED CONDITIONAL MEAN