Markups Across the Income Distribution: Measurement and Implications

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Abstract

The Law of Diminishing Elasticity of Demand (Harrod 1936) conjectures that price elasticity declines with income. I provide empirical evidence in support of Harrod's conjecture using data on household transactions and wholesale costs. Over the observed set of purchases, high-income households pay 9pp higher retail markups than low-income households. Half of the differences in markups paid across households is due to differences in markups paid at the same store. Conversely, products with a high-income customer base charge higher markups: a 10pp higher share of customers with over $100K in income is associated with a 2.5–5.2pp higher retail markup. A search model in which households' search intensity depends on their opportunity cost of time can replicate these facts. Through the lens of the model, changes in the income distribution since 1950 account for a 9pp rise in retail markups, with one-third of the increase due to growing income dispersion. This rise in markups consists of within-firm markup increases as well as a reallocation of sales to high-markup firms, which occurs without any changes to the nature of firm production or competition.

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1 Introduction

There is growing evidence that average markups in the U.S. economy have been rising (De Loecker et al. 2020, Barkai 2020, Autor et al. 2020, Gutiérrez 2017). A number of mechanisms put forward to explain this phenomenon relate the rise in markups to changes in the supply side of the economy, such as a decline in antitrust enforcement (Gutiérrez and Philippon 2018), the rise of superstar firms (Autor et al. 2017), and structural technological change (De Loecker et al. 2021).

How changes in the demand side of the economy may contribute to the rise in markups is less studied. Under Harrod's (1936) conjecture that price sensitivity declines in income, the price elasticities facing firms—and hence the optimal markups charged by firms—depend on the level and distribution of income. In particular, a shift in the composition of demand toward high-income households leads to a decline in aggregate price sensitivity and hence a rise in markups. This paper provides empirical evidence that the behavior of retail markups is consistent with Harrod's conjecture and explores the implications of this pattern for the evolution of markups over time.

This paper starts by establishing that higher-income households systematically pay higher retail markups. I construct a measure of retail markups by pairing Nielsen Homescan data on purchases by a panel of households with wholesale cost data from PromoData Price-Trak, which monitors weekly changes to prices charged by wholesalers to retailers across the U.S. The merged panel covers 23.6 million transactions made in a single year, accounting for 42 percent of transactions and 37 percent of expenditures in the Nielsen Homescan data. Relative to using data from a single retailer, this merged panel has two advantages: (1) since we observe all household expenditures in Nielsen-tracked categories, we capture patterns of substitution across retailers; and (2) we observe detailed demographic information for households, typically not available in standalone retailer data. As argued by Gopinath et al. (2011), since rent, capital, and labor are fixed at short horizons, it is natural to interpret the wholesale cost as the marginal cost facing the retailer. Hence, I calculate retail markups—hereafter referred to as markups for brevity—as the ratio of the transaction price to the product's wholesale cost in the month of purchase.

The data indicate stark differences in markups paid by income. Over the observed set of purchases, the average markup paid by households increases from 28 percent for households with $10,000 in annual income to 37 percent for households with over $200,000 in annual income. The difference in markups paid between high- and low-income households is robust to the inclusion of demographic controls including household size, age group, and race/ethnicity.

To relax the assumption that local inputs, transport costs, or store-specific factors do not affect marginal cost, I explore differences in markups paid within county and within store. Interestingly, over half of the gap in markups paid by high- and low-income households (5pp) persists within store. Measures of the elasticity of markups paid with respect to household income yield a similar conclusion: the elasticity of markups paid to household income within store is 0.017, over half of the unconditional elasticity of markups to household income (0.026). The elasticity of markups to household income is 2–2.5 times larger than the elasticity of prices paid for identical products to household income measured by Broda et al. (2009). Differences in prices paid for identical products underestimate true differences in price sensitivity across households because high-income households opt to buy other, high-markup substitutes.

Next, I show that products purchased by high-income households have higher retail markups, and that the link between product markups and buyer income is not explained by supply-side factors such as differences in the products' market shares, differences in brand market share, differences in product market concentration, or whether the product category is a necessity or luxury. In magnitudes, a 10pp increase in the share of purchases of a product coming from households with over $100,000 in income is associated with a 2.5–5.2pp increase in the product's retail markup. Similar results obtain using other measures of the income of a product's consumer base, such as the average income of a product's buyers or the share of purchases coming from households with less than $50,000 in income.

These two facts provide empirical support for Harrod's (1936) Law of Diminishing Elasticity of Demand: less price-sensitive, high-income households pay higher retail markups over the goods purchased, and firms charge optimally higher markups on products purchased by high-income households. The implication of this analysis is that markups set by firms depend on the composition of demand and thus on the income distribution.

To investigate this mechanism formally, I develop a model of consumer search building on the nonsequential search model of Burdett and Judd (1983).[1] The key innovation in the model is that households have heterogeneous labor and shopping productivities, leading to different opportunity costs of time across households. The household decision on shopping effort parallels the canonical model of price search by Aguiar and Hurst (2007), but the returns to shopping effort are determined in equilibrium by the search behavior of all other households and by firm profit-maximization. As a result, households' search

[1] Appendix E shows that a sequential search model à la Burdett and Mortensen (1998) generates similar qualitative and quantitative results.

decisions and the distribution of markups charged by firms are endogenous outcomes affected by changes to the income distribution.

Cross-sectional analysis of household search behavior across U.S. counties provides suggestive evidence for the model mechanism. The model predicts that search intensity is decreasing with income but that all households optimally search more in high-income areas. (The latter prediction arises because household search decisions are strategic substitutes in equilibrium.) In keeping with this prediction, search intensity—measured as the number of shopping trips or unique retailers visited per dollar spent—is decreasing in income (as previously documented by Pytka 2018), but conditional on income is increasing in the average county income.

The model allows me to derive comparative statics of the aggregate markup with respect to the distribution of household income. These comparative statics depend crucially on how labor productivity and shopping productivity vary with household income. I show that a first-order stochastic shift in the income distribution increases the aggregate markup if shopping productivity increases less than one-for-one with labor productivity over the income distribution. A mean-preserving spread in the income distribution increases the aggregate markup if the rate at which labor productivity rises in income is faster than the rate at which shopping productivity rises in income.

To understand whether these conditions on labor and shopping productivity hold in the data, I calibrate the model to match differences in the retail markups paid by different income groups. The estimated search intensities are decreasing in income, with high-income households retrieving on average 30 percent fewer price quotes per purchase than low-income households. Shopping productivity increases less than one-for-one with labor productivity and at a decreasing rate in income, satisfying both conditions above.

The calibration suggests significant externalities that the search behaviors of some households impose on others. Low-income (high-income) households retrieve 6 percent more (3 percent fewer) price quotes on average than they would in an economy of homogeneous households of their income level. In terms of markups paid, low-income households pay 7pp higher markups on average than they would in an economy populated only by low-income households. In contrast, high-income households save 10pp in average markups paid due to the presence of low-income shoppers. In other words, the search effort exerted by low-income households generates a significant positive externality for high-income households.[2] Accordingly, the "macro" elasticity of markups paid to

[2]These externalities are distinct from the shopping externalities modeled by Kaplan and Menzio (2016). There, shopping externalities operate through employment, since unemployed shoppers search more and therefore reduce revenues for all firms.

household income is nearly three times larger than the micro elasticity documented in the cross-section.[3]

I use the model to return to the question that opens this paper: How do changes in the income distribution affect the aggregate markup? I consider the U.S. distribution of post-tax real income from 1950–2018 documented by Saez and Zucman (2019). Holding all other factors constant, these changes in the income distribution predict a 9pp rise in the aggregate markup from 1950 to 2018 through the lens of the model. Increases in the aggregate markup are moderate before 1980, but accelerate from 1980–2018 due both to the rising level and rising dispersion of incomes. Of the 9pp predicted rise in the aggregate markup, one-third (3pp) is attributed to changes in income dispersion since 1950. The rise in the aggregate markup predicted by the model occurs due to both a rise in markups charged by individual firms as well as a reallocation of sales to high-markup firms. Changes to the composition of demand can therefore be a potent force in increasing markups over time.

Related literature. This paper contributes to a robust literature documenting differences in prices paid by income. Aguiar and Hurst (2007), Broda et al. (2009), Kaplan and Menzio (2015), and Handbury (2021) show that prices paid for identical products systematically rise with household income.[4,5] The empirical evidence in this paper augments the literature by showing that the elasticity of markups paid to household income is 2–2.5 times greater than the elasticity of prices paid for identical products to income. I build upon the insight by Aguiar and Hurst (2007) that search plays an important role in prices paid.[6]

A related trade literature explores why export prices are correlated with per-capita income in the export destination. Using data from an online retailer, Simonovska (2015) shows that the price of identical goods across export destinations correlates with per-capita income, and that this pattern is not explained by shipping costs or local inputs. Alessandria and Kaboski (2011) argue that households' comparative advantage in search in low-income countries can explain differences in markups across export destinations. The link between per-capita income, search, and prices is similar to the one developed here,

[3]The macro elasticity of markups paid to household income (the percent change in average markups that would result if the income of a representative household doubles) in the model is 0.082. This accounts for 30–60 percent of the elasticity of markups to per-capita income across countries estimated in the trade literature by Simonovska (2015).

[4]These studies define identical products by product barcode or, in the case of Handbury (2021), as products with the same brand sold in the same disaggregated product category.

[5]Kaplan and Menzio (2015) do not explicitly consider how prices paid vary with income but do find a significant relationship with employment status.

[6]See also subsequent empirical work on search effort and the use of savings technologies including Griffith et al. (2009), Aguiar et al. (2013), Coibion et al. (2015), Pytka (2018), and Nevo and Wong (2019).

though households within an economy are homogeneous in Alessandria and Kaboski (2011). The robust relationship between markups and per-capita income suggest that markups need not follow a balanced growth path, a finding replicated in the present model.[7]

A key contribution of this paper is to document that the behavior of retail markups is consistent with Harrod's conjecture. Several papers offer complementary evidence. Lach (2007) finds that the arrival of price-sensitive immigrants from the Soviet Union led to a decrease in prices in Israeli neighborhoods where they moved and provides reduced-form evidence that these immigrants spent more time shopping. Stroebel and Vavra (2019) show that retail prices and markups increase when homeowners' housing wealth rises. Anderson et al. (2018) find that markups charged by a single retail chain covary with local income due to product assortment but not product prices. By regressing changes in product sales on instrumented price changes, DellaVigna and Gentzkow (2019) find that demand elasticities are lower for stores in higher-income areas, and Faber and Fally (2017) find that higher quantiles of household income have small but statistically significant differences in price elasticities. Handbury (2021) finds that non-homotheticities in the elasticity of demand and valuation of quality are important to match observed market shares. Most recently, Auer et al. (2022) identify differences in the elasticities of substitution of high- and low-income Swiss households using exchange rate shocks. Relatedly, a marketing literature explores how income and other customer characteristics covary with a household's likelihood to be "coupon-prone" (Narasimhan 1984, Dickson and Sawyer 1990, Hoch et al. 1995, Allenby and Rossi 1999).

A recent literature explores trends in markups over time by structurally estimating markups in Nielsen scanner data. I view the retail markup measures in this paper as complementary to those estimated with IO techniques. Döpper et al. (2021) attribute rising markups measured in Nielsen scanner data to declining consumer price sensitivity, echoing the mechanism developed in this paper, combined with falling marginal costs. Brand (2021) and Neiman and Vavra (2019) explore rising differentiation in products and idiosyncratic tastes. A link between finicky tastes, income, and price elasticity is formalized by Hummels and Lugovskyy (2009).

Finally, the theoretical analysis in this paper relates to studies that link the income distribution to markups using non-homothetic preferences, such as Fajgelbaum et al.

[7] Relatedly, Menzio (2021) explores how a balanced growth path may be compatible with declining search frictions due to increasing (endogenous) specialization by sellers. This paper makes the complementary point that rising shopping productivity need not result in lower markups. Instead, it is the race between two productivities—the relative growth rates of labor and shopping productivity—that matters for the evolution of markups in the model.

(2011) and Bertoletti and Etro (2017).

2 Data construction

In this section, I describe two data sources—Nielsen Homescan data and PromoData Price-Trak—that I use to construct measures of retail markups paid by households. Appendix A provides a detailed description of the process used to clean the data and merge the two datasets.

2.1 Data sources

Consumer panel data. To measure how markups paid vary with household income, I use Nielsen Homescan data. The panel contains transaction data for a nationally representative group of households over the period 2004–2019. In the main text, I present results using data from 2009, which covers 57 million transactions by over 60,000 households in about 2,700 counties.[8] The product categories tracked by Nielsen cover about 30 percent of all expenditure on goods in the consumer price index.[9]

Panelists in the Nielsen Homescan data use in-home scanners or a mobile application to record all purchases intended for personal, in-home use. The data include all Nielsen-tracked categories of food and non-food items purchased at any retail outlet. In addition to reporting the date and the store location of a shopping trip, panelists scan the universal product code (UPC) of each item purchased, report the number of units purchased, and record savings from coupons. While Nielsen does not pay panelists, it offers households a variety of incentives to accurately report data, such as monthly prize drawings and redeemable gift points. Nielsen monitors household reporting levels and filters out households that are poor reporters.

Nielsen collects annual demographic data on panelists including the age of each household member, race, employment status, household size, and household income. Panelists report household income for the full calendar year prior to the start of the panel year (i.e., households in the 2009 panel report income from the full 2007 calendar year). As in Handbury (2021), I exclude households with below $10K income or missing income data from my analysis.

[8] From 2006-2009, Nielsen Homescan separately identifies households with $100K, $125K, $150K, and $200K+ in household income. These distinctions are not available prior to 2006 or after 2009. As we will see, markups paid across households vary significantly in this income range, so I report results for 2009, the most recent year where this breakdown is available. Results from other years are similar and are available upon request.

[9] See Broda and Weinstein (2010) for a detailed description of the Nielsen Homescan data.

I make use of Nielsen's product hierarchy, which organizes products into product groups and modules. There are about 125 product groups and just over 1,000 highly disaggregated product modules. For example, "jams, jellies and spreads" is a product group, which consists of nine product modules for jams, jelly, marmalade, preserves, honey, fruit spreads, peanut butter, fruit and honey butters, and garlic spreads.

Wholesale costs. I use data on wholesale costs from PromoData Price-Trak, a weekly monitoring service that tracks wholesale prices for over 100,000 UPCs. The PromoData comes from 12 grocery wholesaler organizations that sell products to retailers across the U.S. and covers the period 2006–2012.[10] On a weekly basis, wholesalers send PromoData order prices and promotional discounts that they make available to their customers.[11] Previously studies using this data include Nakamura and Zerom (2010), Stroebel and Vavra (2019), and Afrouzi et al. (2021).

The wholesale cost data include both base prices and "deal prices." Deal prices are discounts offered to retailers during promotions. These deal prices are only available to retailers during windows scheduled by the wholesaler and may require retailers to provide proof of promotion in order to redeem the discounted price. I present results using base prices as the measure of retailers' wholesale costs. However, the differences in markups paid across income groups are similar using either base or deal prices as the measure of wholesale costs.

Consistent with Stroebel and Vavra (2019), I show in Table A.1 that wholesale costs are surprisingly similar across markets: over 80 percent of items available in a market in a given month have a wholesale cost equal to the modal wholesale cost observed across markets. Hence, I calculate a national wholesale price for each UPC in each month. In all, about 66,000 UPCs purchased by Homescan panelists in 2009 are matched to wholesale costs from Promodata. These UPCs constitute 42 percent of transactions and 37 percent of expenditures in the 2009 panel. Table A.3 shows that the match rate of wholesale costs to Homescan purchases is similar across income groups and that the relative prices of unmatched products covary with income in the same direction as matched products.

Constructing retail markup estimates. I calculate the retail markup on product g purchased by household i in month t as the price paid by i over the wholesale cost of product

[10] A significant portion of grocery retail sales pass through wholesalers. In 2009, total sales by merchant wholesalers in grocery and related products was $475B according to the Census of Manufacturers. Retailers typically constitute about half of grocery wholesalers' sales to non-wholesalers (2012 Economic Census). Total retail sales by grocery stores in 2009 were $510B according to the Census of Retail Trade.

[11] The prices reported to PromoData are inclusive of wholesaler markups, which PromoData estimates are 2-5% of list price.

g in month t,

$$\text{Retail Markup}_{i,g,t} = \frac{\text{Price}_{i,g,t}}{\text{Wholesale cost}_{g,t}}.$$

This approach is similar to Gopinath et al. (2011) and Anderson et al. (2018), who measure retail markups as price over replacement costs for a single retailer.[12]

Wholesale costs serve as a reasonable proxy for marginal cost for two reasons. First, according to the Census's Annual Retail Trade Statistics, wholesale costs account for three-fourths of total retail costs (including operating expenses and overhead) and constitute the largest portion of cost of goods sold. Annual reports from public grocery companies record a similar proportion of total costs coming from wholesale costs.[13] Second, as argued by Gopinath et al. (2011), since rent, capital, and labor are fixed at short horizons, it is natural to understand the replacement cost as the full marginal cost faced by the retailer.

Nevertheless, the wholesale cost data may mismeasure the marginal costs faced by retailers for three reasons: (1) true wholesale costs may vary across retailers due to retailer-wholesaler deals, such as negotiated rebates or volume discounts, (2) true replacement costs may differ from wholesale costs due to other components of replacement costs, such as freight and transportation costs, and (3) true marginal costs may differ from replacement costs due to local inputs (such as labor for shelving and inventory management). The empirical analysis in Section 3 seeks to control for each of these potential sources of mismeasurement—for example, by comparing markups paid by households within a specific store location—to ensure that the results are robust to each.

Retail markups are winsorized at the 1 percent level for all analyses. The sales-weighted average markup in the merged Homescan-PromoData data is 31 percent. This is moderately lower than the average markup of 39 percent reported by the Census Annual Retail Trade Statistics in 2009.

3 Empirical Evidence

This section presents two sets of analyses. First, I show that high-income households pay higher retail markups on average over the observed set of purchases. At a descriptive

[12]The replacement costs used by Gopinath et al. (2011) include wholesale costs and total allowances (which include freight and transportation costs and subtract net rebates) from a single retailer. I observe only listed wholesale costs, and not transportation or rebate allowances. Industry reports suggest freight costs constitute 3-5% of costs of good sold.

[13]For example, in 2019, Kroger Co. reported merchandise costs—which include "product costs net of discounts and allowances; advertising costs; inbound freight charges; warehousing costs including receiving and inspection costs; transportation costs; and food production costs"—of $95.2M. Operating, general, and administrative expenses, which consist primarily of employee-related costs, and rent expense were $22.1M.

level, the sales-weighted markup paid increases from 28 percent for households earning \$10–12K per year to 37 percent for households earning over \$200K per year. Differences in markups paid within store—which plausibly control for idiosyncratic differences in marginal costs due to labor or rent—account for over half of the overall effect. Similar results follow from estimating the elasticity of markups to household income. I show that the difference in markups paid by households is not driven by retailer-product specific deals (such as quantity discounts received by large retailers on a subset of products) and further decompose the differences in markups paid by households within store.

Second, I show that products consumed by high-income households tend to have higher markups. In the cross-section, a 10pp increase in the share of consumers with over \$100K in household income is associated with a 2.5–5.2pp increase in the product's markup. The relationship between retail markups and the income composition of buyers remains stable after accounting for supply-side factors such as product market share and module concentration that lead to heterogeneous markups in representative household models.

3.1 Fact 1. High-income households pay higher markups

Figure 1 plots the (unconditional) sales-weighted average markup paid by households over the income distribution for the set of products matched to wholesale costs. The average sales-weighted markup paid by households increases from 28 percent for households with \$10–12K in annual income to 37 percent for households with over \$200K in annual income.

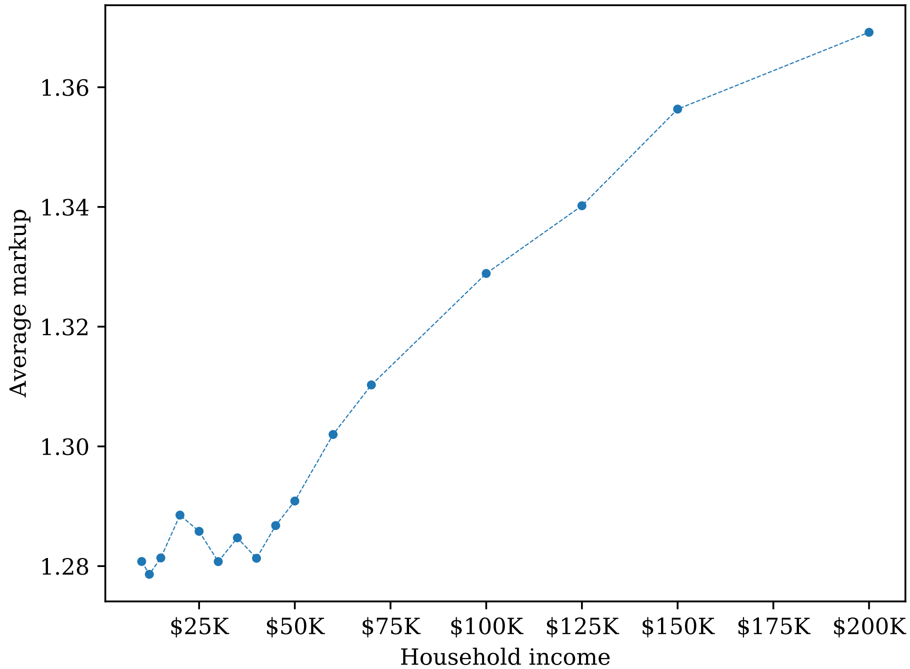
To address concerns about mismeasurement of marginal cost mentioned above, I document the difference in markups paid between low- and high-income households within county and within store. Adding successive sets of controls absorbs factors that may lead to systematic differences in marginal cost across counties or across stores, such as differences in transportation costs or local input costs, thus isolating the differences in markups.

The first specification adds demographic controls and county fixed effects:

$$\text{Markup}_{i,g} = \sum_{\ell} \beta_{\ell} 1\{i \text{ has income level } \ell\} + \gamma' X_i + \delta_{\text{County}} + \epsilon_{i,g}. \tag{1}$$

Demographic controls X_i include fixed effects for race, ethnicity, household size, presence of a female head of household, and the age group of the female head of household; δ_{County} are county fixed effects; and $\epsilon_{i,g}$ is a mean-zero error. I leave out the income level indicator

Figure 1: Sales-weighted average markup paid by income group.



for households with \$10–12K income, so that the coefficients β_ℓ are differences relative to the \$10–12K income group.

Figure 2a plots the coefficients β_ℓ for specification (1) with and without county fixed effects. After accounting for demographic controls, the fixed effect on income for the highest-income group is 11pp, which is moderately larger than the unconditional difference of 9pp. After adding county fixed effects, the fixed effect on income for the highest-income group is 8pp. Hence, over 70 percent of the difference in retail markups paid between the highest and lowest income groups in the sample is due to differences in markups paid within-county.[14] To the degree that freight and transportation costs or the cost of local inputs (such as labor) vary across counties but are constant within county, this result bounds the extent to which these factors drive the effect.

For just over half of the sample, Nielsen provides store IDs that identify the specific store outlet where the purchases were made. For example, unique store IDs would be assigned to the CVS in Harvard Square and the Walgreens in Central Square. The second

[14] I use the retail markup in levels as the dependent variable for all regression results presented in the main text. If we want to control for a county having, say, a 10 percent premium on all wholesale costs, then using the log retail markup is more appropriate. I replicate all analyses using the log retail markup in Appendix B.1. The quantitative results are nearly identical.

specification adds store fixed effects for this subsample:

$$\text{Markup}_{i,g} = \sum_{\ell} \tilde{\beta}_{\ell} 1\{i \text{ has income level } \ell\} + \tilde{\gamma}' X_i + \alpha_{\text{Store}} + \epsilon_{i,g}. \quad (2)$$

Figure 2b plots the coefficients on income level for specification (2) with and without store fixed effects for the subsample of 12.8 million transactions where a unique store ID is available. For the subsample of transactions made at an identified store outlet, the fixed effect on income for the highest-income group is moderately smaller than in the full sample at 7.5pp.[15] Adding store fixed effects brings the difference in markups paid by the lowest and highest-income households to 5pp. Accordingly, for the sample of transactions made at a Nielsen-identified store, two-thirds of the difference in markups paid by low- and high-income households is due to differences in markups paid within store.

Elasticity of markups to household income. An alternative way to measure the link between retail markups paid and household income is to estimate the elasticity of markups to household income. This approach closely mirrors Broda et al. (2009), who estimate the elasticity of prices paid for identical UPCs to household income in Nielsen data from 2005.

As noted by Broda et al. (2009), Nielsen reports income in discrete categories, and thus a continuous measure of household income is not available. For this analysis, I follow Broda et al. (2009) and recode each household's income as the midpoint of the income bracket. For example, a household earning \$13,000 is part of the \$12,000-\$15,000 income group and is assigned an income equal to \$13,500. For the group with over \$200,000 in annual income, I assign an income of \$225,000.

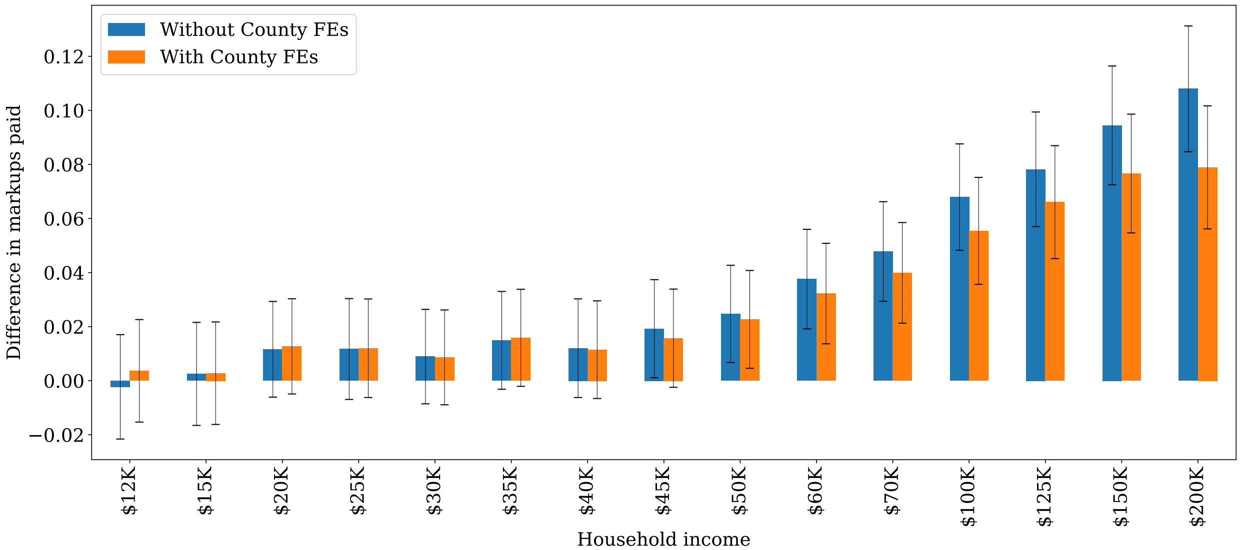
Table 1 reports the results from regressing the log of retail markups on log household income. The elasticity of markups to household income is 0.026 unconditionally (column 1) and 0.032 after controlling for demographic characteristics (column 2). The parallel estimates in Broda et al. (2009) are 0.011 and 0.013. Hence, the elasticity of markups to household income is 2.3–2.5 times larger than the elasticity of prices paid per identical product.[16]

Controlling for county income (column 3) and county fixed effects (column 4) reduces the estimated elasticity of markups to income by up to 15 percent, which is consistent with the degree to which the income level fixed effects estimated above decline after adding

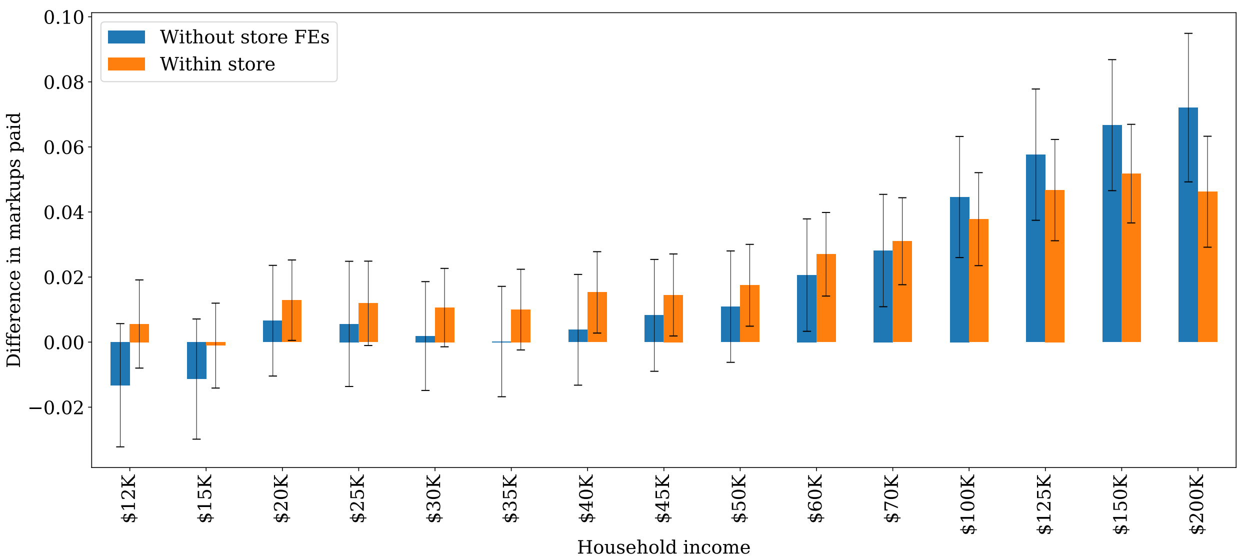
[15]Nielsen store IDs are available for the subset of retailers that also participate in Nielsen's retailer scanner data program. One reason the difference in markups paid between low- and high-income groups within these retailers is smaller could be these retailers are more homogeneous than retailers in the full sample.

[16]Table B.2 replicates the analysis from Broda et al. (2009) for the 2009 Homescan panel and yields nearly identical estimates.

Figure 2: Difference in markups paid relative to households with $10–12K income.



(a) With and without county fixed effects (N = 23.6 million).



(b) With and without store fixed effects (store transactions only, N = 12.8 million).

Notes: These figures plot the coefficients β_ℓ on household income dummies in a regression of the markup paid by a household on demographic controls (race, ethnicity, household size, and presence and age of female head of household) weighted by sales. Income levels on the y-axis are the minimum of the income bracket provided by Nielsen (e.g., $12K includes households reporting income between $12–15K). Standard errors are two-way clustered by UPC and household. Figure (a) shows β_ℓ with and without county fixed effects (specification (1)), and (b) shows $\tilde{\beta}_\ell$ with and without store fixed effects for the sample of transactions where the unique store ID is observed (specification (2)).

Table 1: Impact of income on markups paid.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Household Income	0.026**	0.032**	0.029**	0.026**	0.022**	0.017**	0.012**	0.010**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Log Avg. County Income			0.074**						
			(0.005)						
Household Size		−0.006**	−0.006**	−0.006**	−0.006**	−0.006**	−0.004**	−0.003**	−0.001**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Demographic Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs				Yes	Yes	Yes	Yes	Yes	Yes
Store FEs						Yes	Yes	Yes	Yes
Store-Group FEs							Yes		
Store-Module FEs								Yes	
Store-UPC FEs									Yes
N (millions)	23.6	23.6	18.1	23.6	12.8	12.8	12.8	12.8	12.8
R^2	0.00	0.00	0.01	0.02	0.02	0.09	0.40	0.60	0.92

Notes: The log of household income is calculated using the midpoint of the range provided by Nielsen (e.g., a household with an income of $13K would be in the range $12–15K and would be assigned a value of $13.5K). Demographic controls include race, ethnicity, presence of female head of household, and age group of female head of household. Regression weighted by sales, and standard errors two-way clustered by UPC and household. * indicates significance at 10%, ** at 5%.

county fixed effects. A significant and positive coefficient on the average county income in column 3 suggests that markups paid increase when a household is surrounded by other high-income households.

Columns 5-9 focus on the subsample with store IDs, which constitutes just over half of the full sample. The elasticity of markups to household income in this subsample (column 4) is slightly smaller than the elasticity of markups to household income in the full sample (0.022 versus 0.026). After accounting for store fixed effects (column 6), the elasticity of markups to household income is 0.017, which is over half of the overall elasticity estimated in column 2 and over three-quarters of the elasticity estimated in the identified-store subsample.[17] This result parallels the finding in Kaplan and Menzio (2015) that half of the variance in relative prices paid by households is due to differences in the choice of stores to frequent, and the remaining half is due to choices about which good to buy from which store and transaction timing.

Decomposing differences within store. We can further decompose the differences in markups paid within store. The remaining columns of Table 1 explore the elasticity of markups to household income within store-product group (column 7), within store-product module (column 8), and within store-UPC. One-half (two-thirds) of the link between markups and household income at the store level is attributed to differences in markups paid within product modules (product groups). At the finest level of disaggregation, differences in markups paid for the same UPC at the same store constitute about one-fourth of the within-store elasticity and one-sixth of the total difference.

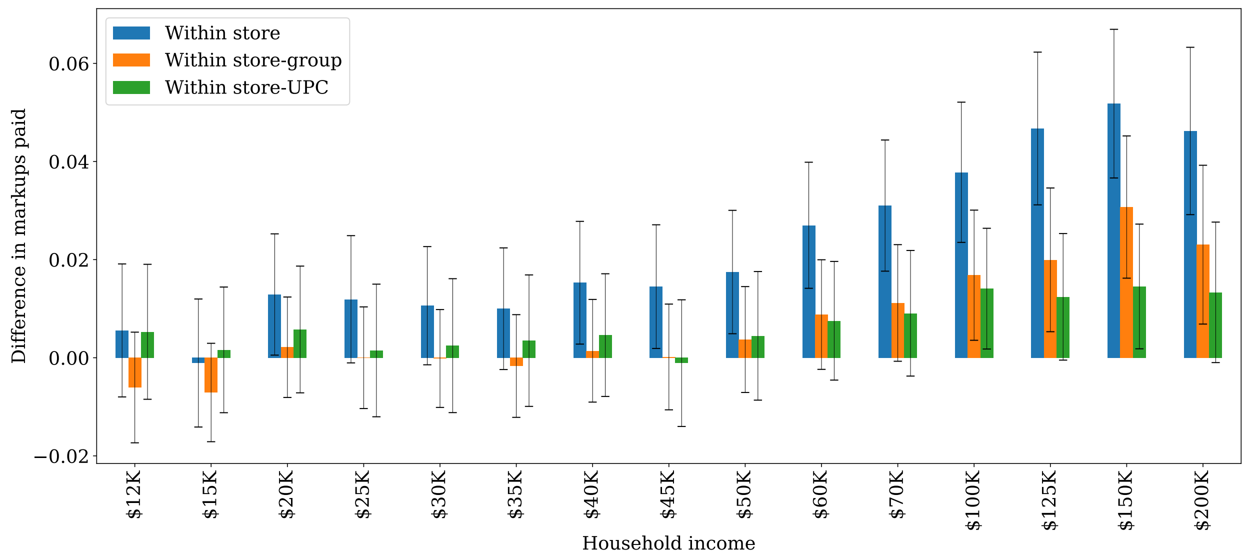
Similar results obtain if we take the approach of estimating markups within store-product group and within store-UPC with fixed effects by income level:

$$\text{Markup}_{i,g} = \sum_{\ell} \beta_\ell 1\{i \text{ has income level } \ell\} + \gamma' X_i + \alpha_{\text{Store}} + \tilde{\alpha}_{\text{Store-Group}} + \hat{\alpha}_{\text{Store-UPC}} + \epsilon_{i,g}. \quad (3)$$

Figure 3 plots the coefficients on income level for specification (3) with and without store-product group and store-UPC fixed effects. About half of the difference in markups paid by the lowest- and highest-income households within store is due to differences paid within product group. Differences in markups paid for the same UPC within store are about one-fourth percent of the total within-store effect and in general are not statistically

[17] The closest parallel in Broda et al. (2009) adds retail chain (but not individual store) fixed effects. The reported elasticity from this regression is 0.009; hence, the elasticity of markups to household income within store is 2 times larger than the elasticity of prices paid per identical product within retail chain (which is an upper bound of the elasticity of prices paid within store).

Figure 3: Difference in markups paid within store (blue), within store-product group (orange), and within store-UPC (green) relative to households with $10–12K income.



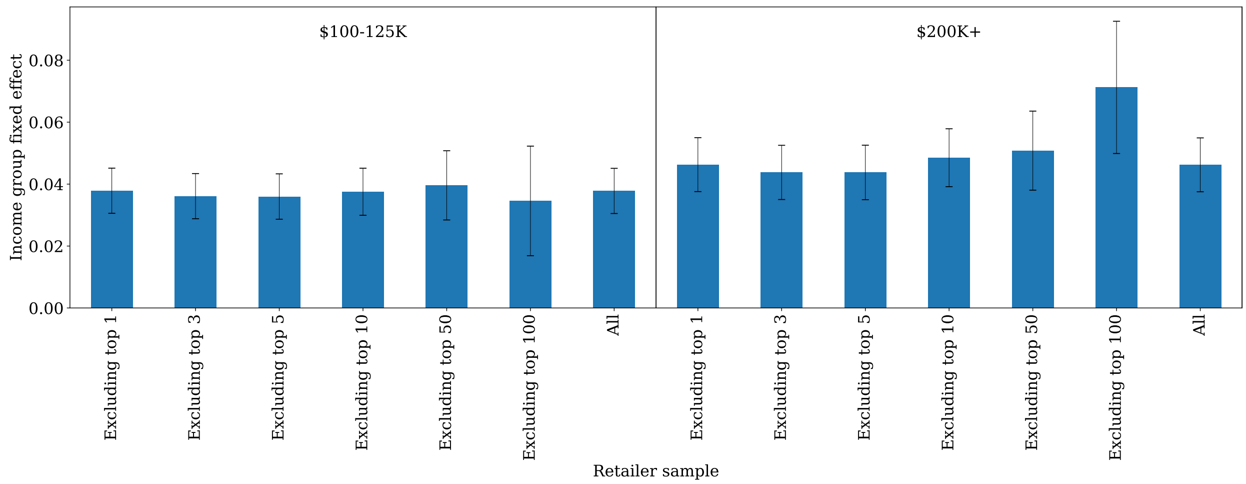
Notes: This figure plots the coefficients β_ℓ on household income dummies in a regression of the markup paid by a household on demographic controls (race, ethnicity, household size, and presence and age of female head of household) and store fixed effects weighted by sales. Income levels on the y-axis are the minimum of the income bracket provided by Nielsen (e.g., $12K includes households reporting income between $12–15K). Standard errors are two-way clustered by UPC and household. The orange bars add store-product group fixed effects, and the green bars add store-UPC fixed effects, following specification (3).

significant.[18]

Differential volume discounts by retailer size. While store fixed effects in specification (2) and Table 1 column 6 absorb systematic differences in wholesale costs, transport costs, and local input costs that cause marginal costs to differ by store, they will not absorb heterogeneity in marginal costs by product-store pair. For example, suppose large retailers are able to lower marginal costs by negotiating volume discounts and that these volume discounts are steeper on a subset of products (e.g., on commodity items compared to luxury items). In this case, our data would overstate the marginal cost and understate the markup on commodity items sold at large retailers. If low-income households buy more commodity items at large retailers than high-income households, this would lead us to overestimate the difference in markups paid across income groups.

[18]To see the elasticity of markups paid with respect to household income within retail chain, see Table B.3. To see the elasticity of markups paid with respect to household income within product group and within product module, see Table B.4.

Figure 4: Stability of markup gap excluding largest retail chains.



I address this concern by testing whether the difference in markups paid by low- and high-income households is driven by large retailers in the sample. I rank retailers by total sales in the Homescan data. Then, I test specification (2) for the subsample of transactions excluding the largest retailer, excluding the largest three retailers, excluding the largest five retailers, and so on. If mismeasurement of marginal costs at large retailers is driving the effect, then the coefficients on income should diminish as we remove large retailers.

Figure 4 plots the fixed effect coefficient on two of the highest income groups as we successively remove large retailers from the sample. The coefficient on income group is relatively stable and slightly grows as we exclude top retailers. These results suggest that the difference in markups paid by low- and high-income households is not driven by differential quantity discounts at large retailers.

Robustness. Figure B.1 shows that regressions of log markups on household income level dummies, household demographic controls, and county and store fixed effects yield results nearly identical to those presented above, which instead use the markup level. Figure B.2 and Table B.1 replicate the analyses above using Price-Trak deal prices (rather than base prices) as the measure of marginal costs and produce similar results.

Discussion. To contextualize the differences in markups across household income levels, it is helpful to relate the observed markups to price-elasticities in a back-of-the-envelope analysis. Suppose that products are perfectly price-discriminated across customers, so that the markups paid by each income group exactly represent price elasticities of demand across groups. (Since consumption bundles of income groups overlap, this analysis is a lower bound for true differences in price elasticities of demand across households.) The markups plotted in Figure 1 imply price elasticities that decrease from 4.57 for the lowest-income households in the sample to 3.70 for the highest-income households.

This 0.87 difference in price elasticities is somewhat higher than differences in price elasticity measured by Faber and Fally (2017), who find that price elasticities for the two lowest-income quintiles are only 0.4 higher than that of the richest quintile. However, this difference is broadly consistent with Auer et al. (2022), who find that elasticities of substitution for low-income households are about 2.1–2.4 higher than than those of high-income households, and with the range of price sensitivity differences across income groups estimated by Handbury (2021).

3.2 Fact 2. Products with high-income consumers have higher markups

The previous section showed that high-income households pay higher markups. In this section, I show the converse: products bought by high-income consumers have systematically higher retail markups.

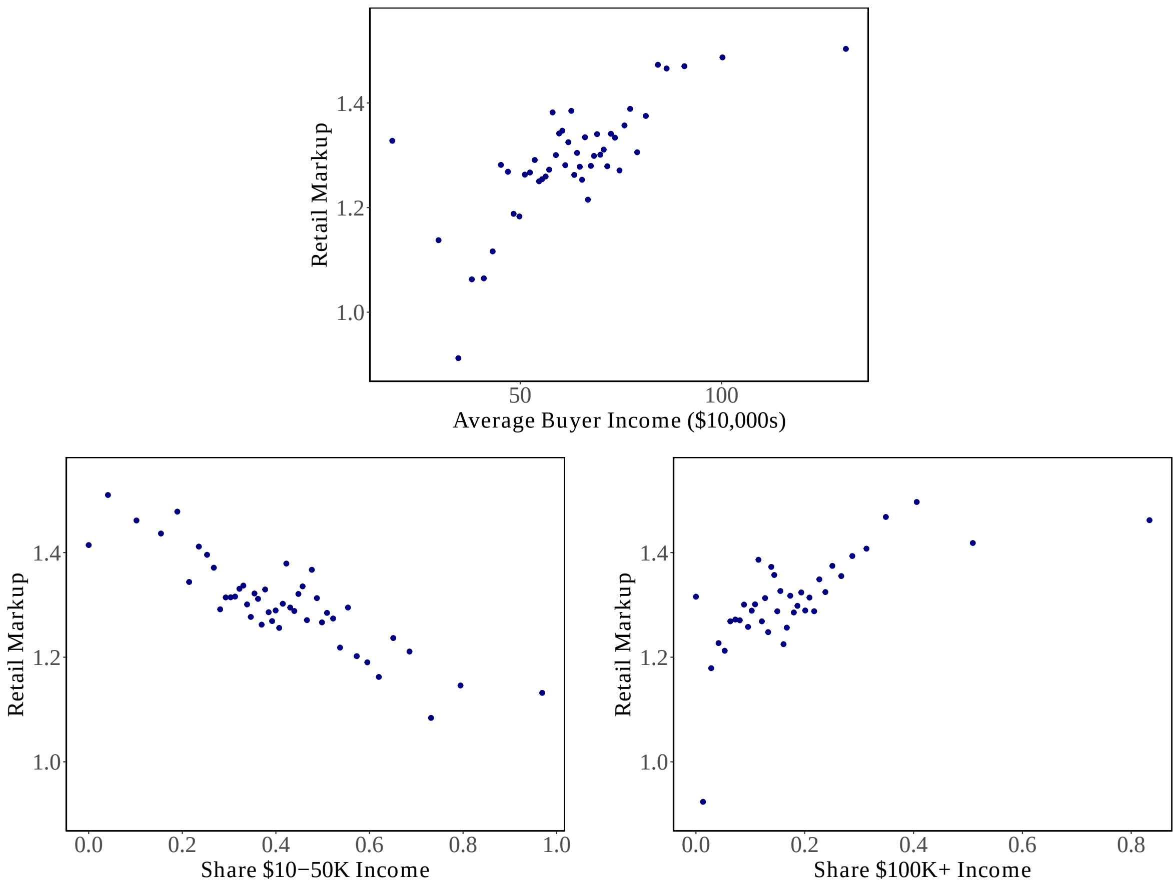
I construct an average markup for each product barcode (UPC) in the Homescan data as the sales-weighted average markup over all observed transactions of the product. I also construct three measures of the income of a product's buyers: (1) the average income of households buying the product (weighted by each household's expenditure on the product), (2) the share of purchases coming from households with over $100K in income, and (3) the share of purchases coming from households with $10–50K in income.[19]

Figure 5 shows binned scatterplots of UPC retail markups against these three measures of buyer income. Retail markups appear positively correlated with average buyer income and the share of high-income buyers and negatively correlated with the share of low-income buyers.

Table 2 tests this correlation. In columns 1, 3, and 5, I test whether these three measures of buyer income are associated with UPC retail markups. Consistent with the observed visual correlation, I find that a UPC's retail markup is positively associated with average buyer income and the share of high-income buyers and negatively associated with the share of low-income buyers. A 10pp increase in the share of purchases coming from households with over $100K in income is associated with a 5.2pp increase in a product's retail markup. While these associations are statistically significant, the R-squared of these regressions is only 1 percent, which suggests that most of the variation in UPC retail

[19]Since income levels provided by Nielsen are bucketed into discrete categories, the average income of households buying a product is constructed by recoding each household's income as the midpoint of the bracket provided by Nielsen.

Figure 5: UPC retail markup and buyer income.



Note: The unit of observation is a UPC. The UPC retail markup is calculated as the sales-weighted average markup over all observed transactions. Graphs show a binned scatter weighted by UPC sales.

Table 2: Relationship between buyer income and UPC retail markup.

	(1)	(2)	(3)	(4)	(5)	(6)
Average Income (10,000s)	0.041**	0.023**				
	(0.005)	(0.005)				
Share \$100K+ income			0.521**	0.276**		
			(0.066)	(0.061)		
Share \$10-50K income					−0.335**	−0.183**
					(0.048)	(0.051)
Product Module FEs		Yes		Yes		Yes
N	66 033	66 033	66 033	66 033	66 033	66 033
R^2	0.01	0.31	0.01	0.31	0.01	0.31

Notes: The unit of observation is a UPC. The dependent variable is the UPC retail markup, which is the sales-weighted average of markups at which the UPC was sold. Regression weighted by UPC sales, and robust standard errors in parentheses. * indicates significance at 10%, ** at 5%.

markups is due to other factors.

Columns 2, 4, and 6 add product module fixed effects. All three measures of buyer income remain significantly associated with UPC retail markups, though the magnitudes shrink by half. Accordingly, for two products in the same product module, a 10pp increase in the share of purchases coming from households with over \$100K in income is associated with a 2.8pp increase in the product's retail markup. (In Figure B.3, I show suggestive evidence that households substitute across product modules, and that product modules with more high-income consumers have higher markups.)

Supply-side factors. In representative household models, firms may charge heterogeneous markups due to differences in the representative household's elasticity of demand across goods, differences in market power across firms (as in the nested oligopoly model of Atkeson and Burstein 2008), and/or differences in industrial concentration or conduct. In Table 3, I test whether the association between retail markups and demand composition is robust to including these supply-side factors. I use the share of consumers with over \$100K in income as the measure of buyer income in Table 3; similar results using average buyer income and the share of low-income buyers are available in Appendix B.2.

Column 1 of Table 3 regresses the UPC retail markup on the share of households with over \$100K in income (this is identical to column 3 in Table 2). In column 2, I add a proxy for whether a product module is a necessity. This measure of necessity is the share of households in the consumer panel that purchase any product from the module in the

Table 3: Relationship between buyer income and UPC retail markup.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share $100K+ income	0.521**	0.560**	0.532**	0.526**	0.247**	0.248**	0.263**	0.266**	0.276**	0.282**
	(0.066)	(0.067)	(0.065)	(0.065)	(0.068)	(0.068)	(0.066)	(0.066)	(0.061)	(0.061)
Necessity		−0.086**				−0.131**				
		(0.025)				(0.029)				
UPC Sales Share			0.634**	0.422**			0.267**	0.248*		−0.117
			(0.178)	(0.201)			(0.129)	(0.143)		(0.136)
Brand Sales Share				0.166**				0.149**		0.174**
				(0.045)				(0.048)		(0.042)
Module HHI				−0.023				−0.216**		
				(0.051)				(0.067)		
Product Group FEs					Yes	Yes	Yes	Yes	Yes	Yes
Product Module FEs									Yes	Yes
N	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033
R^2	0.01	0.01	0.02	0.02	0.15	0.15	0.15	0.15	0.31	0.31

Notes: The unit of observation is a UPC. The dependent variable is the UPC retail markup, which is the sales-weighted average of markups at which the UPC was sold. Regression weighted by UPC sales, and robust standard errors in parentheses. Share $100K+ income is the share of sales for a UPC made by households with $100K or more in reported household income. Necessity is measured as the share of households in the Homescan panel that purchase at least one good from that module in the year. UPC sales share, brand sales share, and the product module Herfindahl-Hirschman index are all calculated using sales in the Homescan data. * indicates significance at 10%, ** at 5%.

year. Product modules that rank high on this necessity index include fresh bakery bread, refrigerated dairy milk, and toilet tissue, each of which are purchased at least once by over 90 percent of households. Hair nets and caps, dishwashing accessories, and hair accessories are a few of the modules scoring low on this measure, with fewer than one percent of households buying a product from that module within the year. Surprisingly, this proxy of necessity appears (mildly) negatively correlated with UPC markups, and the coefficient on the share of high-income buyers is similar.[20]

Columns 3 and 4 add measures of the product's market share, the brand's market share (using brand codes provided by Nielsen), and the Herfindahl-Hirschman index of concentration within the product module. While both measures of market share are positively correlated with UPC retail markups, as the Atkeson and Burstein (2008) oligopoly model would suggest, the coefficient on buyer income remains stable.

Columns 5-8 replicate this analysis after adding product group fixed effects, and columns 9-10 replicate the analysis with product module fixed effects. (I do not include module HHI as a regressor in column 10 since it is collinear with product module fixed effects.) Across these regressions, the coefficient on the share of high-income buyers is stable after the inclusion of supply-side factors. While this is not an exhaustive exploration of all potential supply-side mechanisms, it suggests that the effects of demand composition on markups are not driven by a spurious correlation with supply-side factors.

Retailer-UPC markups. An alternative to taking a UPC as a unit of observation is to take each retail chain-UPC pair as a distinct observation. DellaVigna and Gentzkow (2019) show that UPC prices are close to uniform within a retail chain at a point in time.

Table 4 replicates the analysis using each retail chain-UPC as a distinct observation. I use only retailers that are uniquely identified in the Nielsen data (see Appendix A for details). Columns 1-3 find that a 10pp increase in the share of consumers with over $100K in income is associated with a 1.3–1.7pp increase in retail markups for a UPC at a given retail chain. This coefficient is moderately smaller than the specification at the UPC level. Adding UPC fixed effects (column 4) greatly increases the explanatory power of the regression, but surprisingly does not lead to much attenuation in the association between retail markups and the share of high-income buyers.

On the other hand, accounting for retailer characteristics or retailer fixed effects (columns 5-7) reduces the magnitude of the coefficient on buyer income. One plausible explanation is that the share of high-income buyers that a UPC has covaries significantly

[20]This finding is in contrast to models that generate heterogeneous markups by bounding marginal utility for a product from above, such as Neiman and Vavra (2019). Those models predict that "cutoff" products consumed by the fewest households have low, rather than high, markups.

Table 4: Effect of buyer and retailer characteristics on retailer-UPC markup.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share $100K+ income	0.170**	0.131**	0.132**	0.114**	0.060**	0.050**	0.026**
	(0.048)	(0.045)	(0.043)	(0.036)	(0.017)	(0.015)	(0.005)
Retailer Price Index					0.217**		
					(0.066)		
Log Retailer Sales					−0.025**		
					(0.004)		
Product Group FEs		Yes	Yes	Yes	Yes	Yes	Yes
Product Module FEs			Yes	Yes	Yes	Yes	Yes
UPC FEs				Yes	Yes		Yes
Retailer FEs						Yes	Yes
N	1 753 374	1 753 374	1 753 374	1 753 374	1 753 374	1 753 374	1 753 374
R^2	0.00	0.13	0.27	0.87	0.88	0.31	0.91

Notes: The unit of observation is a retail chain-UPC pair. The dependent variable is the retailer-UPC markup, which is the sales-weighted average of markups at which the UPC was sold within a retail chain. Regression weighted by retailer-UPC sales, and standard errors two-way clustered by product group and retailer. * indicates significance at 10%, ** at 5%.

with the retail chain at which it is sold. For example, a product sold at a Whole Foods may tend to have higher-income buyers than the same product when sold at a Stop & Shop, since the set of buyers a UPC has at a retail chain naturally depends on the overall composition of buyers at that retail chain. It is worth noting that this result is not necessarily at odds with the finding in Kaplan and Menzio (2015) that price differences across retail chains constitute a small part of overall price dispersion: the explanatory power of the regression including retail chain fixed effects (column 6, $R^2 = 0.31$) is only moderately higher than that without retail chain fixed effects (column 3, $R^2 = 0.27$). An interesting result in column 5 is that markups appear negatively correlated with retailer size (as measured in log sales). Yet, the magnitude of this coefficient is small: for uniquely identified retailers in the Nielsen sample, the difference in log sales between the largest retailer and a retailer at the 10th percentile of sales is 12, so the coefficient on log retailer sales implies that moving from a retailer at the 10th percentile of sales to the largest retailer leads to a 0.3pp reduction in markup.

Robustness. Table 3 showed that the relationship between buyer income and UPC retail markups is robust to controlling for supply-side factors. Table B.5 and Table B.6 replicate this analysis using two other measures of buyer income: the average income of a product's buyers and the share of buyers with $10-50K in income. These alternatives yield similar conclusions. Table B.7 replicates the analysis using PromoData Price-Trak deal prices (rather than base prices) as the measure of wholesale costs and finds similar results.

4 A Search Model of Income and Markups

I now develop a model in which households search for goods. The model builds upon the Burdett and Judd (1983) model of nonsequential search. The key innovation is that households endogenously choose search intensities depending on heterogeneous costs of time. As I show below, the model delivers an equilibrium in which the search decisions of households are strategic substitutes. I then derive conditions under which a first-order stochastic shift and a mean-preserving spread in the income distribution lead to an increase in the aggregate markup.

I show in Appendix E that a sequential search model yields similar results qualitatively and quantitatively.

4.1 Households

There is a unit measure of households indexed by type $i \in [0, \infty)$. Types are distributed in the population according to the density $dH(i)$, where $H(i)$ is the share of households with type less than or equal to i. Households search for an identical good sold by a unit measure of firms. All households are risk-neutral. As in canonical models of search frictions, households know the distribution of prices offered by firms, $F(p)$, but do not know which retailer sells at which price. Denote $\underline{p}$ and $\bar{p}$ as the infimum and supremum of the support of F.

Household i draws a number of price quotes independently from the distribution of prices F. The number of price quotes observed by i is a random variable with probability mass function $\langle q_{i,n} \rangle_{n=1}^{\infty}$. That is, with probability $q_{i,1}$, the household only observes a single price quote, with probability $q_{i,2}$, the household observes two independently drawn price quotes, and so on. (As we will see later, the distribution of price quotes $\langle q_{i,n} \rangle_{n=1}^{\infty}$ is a result of i's endogenous choice of search intensity.) Households compare the minimum price quote received to a reservation price, R, and buy one unit of the good from the retailer with the lowest price quote p as long as $p \leq R$.

Household i's utility is

$$u_i = \begin{cases} z_i(T - t_i) + R - p_i & \text{if } i \text{ purchases good at price } p_i \\ z_i(T - t_i) & \text{otherwise} \end{cases}$$

where t_i is the time i spends shopping and $T - t_i$ is the time i spends working with wage equal to i's labor productivity z_i.

Denote household i's shopping intensity by s_i,

$$s_i = a_i t_i,$$

where a_i is shopping productivity that may vary across households. The function $\mathcal{S}$ maps shopping intensity s_i to the distribution of price quotes received $\langle q_{i,n} \rangle_{n=1}^{\infty}$. Let $Q_{i,n}$ be the cumulative mass function associated with $\langle q_{i,n} \rangle_{n=1}^{\infty}$. Assumption 1 puts constraints on the mapping function $\mathcal{S}$.

Assumption 1. The function $\mathcal{S} : s_i \mapsto \langle q_{i,n} \rangle_{n=1}^{\infty}$ is such that:

(A). If $s_i = 0$, $Q_{i,n} = 1$ for all n.
(B). $Q_{i,n}(s_i)$ is weakly decreasing in s_i for all n and strictly decreasing for $n = 1$.
(C). $Q_{i,n}(s_i)$ is C^{∞} for all n and all $s_i \geq 0$.

Assumption 1(A) means that if a household spends no time searching, it will always receive exactly one price quote. Under Assumption 1(B), an increase in s_i leads to a first-order stochastic shift in the number of price quotes received. Under these conditions, the expected price paid by i, $\mathbb{E}[p_i | s_i, F]$, is decreasing in search intensity s_i. Assumption 1(C) is made for convenience, since it is satisfied by common parameterizations of the Burdett and Judd (1983) model.

Households allocate time t_i to shopping to maximize expected utility. The household's first-order condition equates the marginal benefit from increasing searching intensity to the opportunity cost of i's time:

$$-\frac{\partial \mathbb{E}[p_i | s_i, F]}{\partial s_i} = \frac{z_i}{a_i}. \tag{4}$$

If gains from search at any search level are too small—or conversely, if the cost of i's time is too high—a household will choose the corner case $s_i = 0$. For the remainder of the text, I focus on the case where each household has an internal solution for s_i.

4.2 Firms

A measure M of ex ante identical firms with marginal cost mc set prices to maximize profits. The demand that a firm faces depends on its price, the distribution of prices charged by other firms, and the aggregate search behavior of households.

Denote aggregate search behavior by $\bar{q}$:

$$\langle \bar{q}_n \rangle_{n=1}^{\infty} = \left\langle \int_0^{\infty} q_{i,n} dH(i) \right\rangle_{n=1}^{\infty}. \tag{5}$$

With this description of aggregate search behavior in hand, proving the existence of a dispersed-price equilibrium follows closely from Burdett and Judd (1983); I relegate the details to Appendix C. Given $\langle \bar{q}_n \rangle_{n=1}^{\infty}$ with $\bar{q}_1 \in (0,1)$, the unique equilibrium price distribution $F(p)$ is

$$F(p) = \begin{cases} 0 & \text{if } p < \underline{p} \\ 1 - \Phi\left[\left(\frac{R-mc}{p-mc}\right)\bar{q}_1\right] & \text{if } \underline{p} \leq p \leq R \\ 1 & \text{if } p > R \end{cases} \tag{6}$$

where the lowest price $\underline{p}$ is

$$\underline{p} = mc + \frac{\bar{q}_1}{\sum_{n=1}^{\infty} n\bar{q}_n}(R - mc), \tag{7}$$

and $\Phi(\cdot)$ is the inverse of the strictly increasing, C^{∞} function $y(x) = \sum_{n=1}^{\infty} n\bar{q}_n x^{n-1}$.

Free entry and exit determines the mass of firms M. Firms pay a fixed entry cost f_e. In equilibrium, the zero profit condition yields

$$\pi(p) - f_e = 0 \qquad \text{for all} \qquad p \in (\underline{p}, R), \tag{8}$$

where $\pi(p)$ are the variable profits earned by a firm charging price p.[21]

4.3 Equilibrium

An equilibrium is a tuple $\left(\{s_i\}_{i=0}^{\infty}, F, \pi, M\right)$ where each household's search intensity s_i maximizes its expected utility given F, all firms choosing a price $p \in \text{supp}(F)$ have variable profits π given the prices charged by other firms F, any price $p \notin \text{supp}(F)$ results in variable profits that are strictly less than π, and the mass of firms M is such that firms make zero profits net of the entry cost. Equivalently, s_i satisfies (4) for all i, $F(p)$ is given by (6), and $\pi = f_e$.

[21]Whether we assume free entry or an exogenous mass of firms has no effect on the level of markups in this model. As shown in Appendix C, markups are pinned down by consumer search behavior, and the free entry condition is cleared by changes in the mass of firms M. This would also be the case in a CES model where the elasticity of substitution changes: a reduction in the elasticity of substitution would result in higher equilibrium markups, and an increase in the number of firms is required to maintain the zero profit condition.

Aggregating households' first-order conditions in (4) yields:[22]

$$\underbrace{\sum_{n=1}^{\infty}\left(\int_0^{\infty}\frac{-dQ_{i,n}}{ds_i}dH(i)\right)\left[\mathbb{E}\left[p|n\right]-\mathbb{E}\left[p|n+1\right]\right]}_{\text{Aggregate returns to search}} = \underbrace{\int_0^{\infty}\frac{z_i}{a_i}dH(i)}_{\text{Aggregate cost of time}}\quad, \tag{9}$$

where $\mathbb{E}[p|n]$ is the expected price paid after receiving n price quotes from F.

Consider how the aggregate returns to search (the left-hand side in (9)) change with $\bar{q}_1$. When $\bar{q}_1 = 1$, all households search only once, and hence firms identically set the monopoly price, $p = R$. Since the price distribution is degenerate, the returns to search are zero. Similarly, when $\bar{q} = 0$, all households retrieve at least two price quotes, and hence no firm can be incentivized to set a price above all other firms. Hence, all firms price at marginal cost, and returns to search are again zero. For any intermediate value of $\bar{q}_1 \in (0,1)$, however, the left-hand side of (9) is strictly positive by Assumption 1(B).

Hence, if there exists a value of $\bar{q}_1$ such that the aggregate equilibrium condition (9) holds, there must be at least one value of $\bar{q}_1$ where the left-hand side of (9) is weakly increasing in $\bar{q}_1$. See Appendix C.3 for a formal discussion.

I refer to an equilibrium in which aggregate returns to search are weakly increasing in $\bar{q}_1$ as a *stable* equilibrium and conduct all comparative statics locally around such an equilibrium. The intuition for stability is as follows. Suppose instead that aggregate returns to search are decreasing in $\bar{q}_1$. Then, an idiosyncratic increase in the search effort exerted by any household leads to a decrease in $\bar{q}_1$, which increases returns to search for all other individuals. Hence, a perturbation in search effort by any household kicks off changes in search effort by all households that lead away from the equilibrium point. The opposite is true for a stable equilibrium: when aggregate returns to search are increasing in $\bar{q}_1$, household search decisions are strategic substitutes, and hence an idiosyncratic increase in search effort exerted by one household is counteracted by decreases in search effort by all other households.

4.4 Comparative statics: Changes to income distribution

Define the aggregate markup as total sales over total (variable) costs. Lemma 1 shows that the fraction of households receiving only one price quote is a sufficient statistic for

[22] I use the assumption here that all households have an internal solution for s_i. If the aggregate cost of time in (9) is too high, it is evident that no dispersed-price equilibrium exists, and the sole equilibrium is the monopoly price equilibrium in which all households choose $s_i = 0$ and firms choose $p = R$. See the discussion in Appendix C.3.

the aggregate markup in the model.

Lemma 1. *In equilibrium, the aggregate markup is*

$$\bar{\mu} = 1 + \left(\frac{R}{mc} - 1\right)\bar{q}_1.$$

Intuitively, since firms must make identical profits at all prices in the support of F, and the only customers of a firm charging the highest price R are those that receive no other price quotes, $\bar{q}_1$ pins down the profits of all firms and hence the aggregate markup.

To characterize how changes in the income distribution affect the aggregate markup, we need to define two additional conditions on the mapping $\mathcal{S}$ from search intensity to the distribution of price quotes received.

Condition 1. The mapping $\mathcal{S} : s_i \mapsto \langle q_{i,n} \rangle_{n=1}^{\infty}$ satisfies

$$\sum_{n=1}^{\infty} \frac{d^2 Q_{i,n}}{ds_i^2} \left[\mathbb{E}\left[p|n;F\right] - \mathbb{E}\left[p|n+1;F\right]\right] > 0,$$

for any non-degenerate distribution F, where $Q_{i,n}$ is the cumulative mass function of $\langle q_{i,n} \rangle_{n=1}^{\infty}$ and where $\mathbb{E}[p|n;F]$ is the expected value of the minimum of n independent draws from the distribution F.

Condition 2. The mapping $\mathcal{S}$ satisfies

$$\sum_{n=1}^{\infty} \left(\frac{d^2 q_{i,1}}{ds_i^2}\frac{d^2 Q_{i,n}}{ds_i^2} - \frac{dq_{i,1}}{ds_i}\frac{d^3 Q_{i,n}}{ds_i^3}\right) \left[\mathbb{E}\left[p|n;F\right] - \mathbb{E}\left[p|n+1;F\right]\right] \geq 0,$$

for any non-degenerate distribution F, where $Q_{i,n}$ and $\mathbb{E}[p|n;F]$ are as defined above.

These two conditions may appear technical. However, I show in Appendix C.4 that both conditions are satisfied by the two most common parameterizations of the Burdett and Judd (1983) model: (1) a version in which households receive only one or two quotes (e.g., Alessandria and Kaboski 2011 and Pytka 2018), and (2) a version in which the number of price quotes received by households is drawn from a Poisson distribution (e.g., Albrecht et al. 2021 and Menzio 2021).

The main results follow: Proposition 1 provides sufficient conditions for a first-order stochastic shift in the income distribution to increase the aggregate markup. Proposition 2 does the same for a mean-preserving spread in the income distribution.

Proposition 1 (First-Order Shift in the Income Distribution)**.** *Suppose $\widetilde{H}(i)$ first-order stochastically dominates $H(i)$. Then, the aggregate markup in an economy with income distribution $\widetilde{H}(i)$ is weakly greater than the markup under $H(i)$ (holding all other parameters fixed) if:*

1. *Condition 1 holds, and*
2. *The ratio of labor to shopping productivity, z_i/a_i, is weakly increasing in i.*

Proposition 2 (Mean-Preserving Spread in the Income Distribution)**.** *Suppose $\widetilde{H}(i)$ is a mean-preserving spread of $H(i)$. Then, the aggregate markup in an economy with income distribution $\widetilde{H}(i)$ is weakly greater than the markup under $H(i)$ (holding all other parameters fixed) if:*

1. *Conditions 1 and 2 hold, and*
2. *The ratio of labor to shopping productivity, z_i/a_i, is weakly increasing and convex in i.*

All proofs are in Appendix C. A brief sketch of the intuition follows.

Since the aggregate markup is determined by $\bar{q}_1$, the first-order response of the aggregate markup to a change in the distribution $dH(i)$ depends on whether $q_{i,1}$ is increasing (for Proposition 1) and convex (for Proposition 2) in i. The stability of the equilibrium then ensures that all second-order responses (i.e., the adjustment each household type i makes to its search decision) do not overwhelm the first-order response.

Condition 1 is a sufficient condition for search intensity s_i to be decreasing in the opportunity cost of time z_i/a_i. Given that search intensity is decreasing in z_i/a_i, it is sufficient for z_i/a_i to be increasing in i for $q_{i,1}$ to also be increasing in i. Analogously, Condition 2 ensures that the probability of receiving exactly one price quote, $q_{i,1}$, is weakly convex in z_i/a_i. Once this is established, then the convexity of $q_{i,1}$ in i is guaranteed when z_i/a_i is convex in i.

4.5 Discussion

Balanced growth. Proposition 1 implies that income growth leads to an unbalanced growth path in markups if labor productivity grows at a faster rate than shopping productivity. If labor productivity growth outpaces shopping productivity growth, search intensity tends toward zero, and the economy tends toward the monopoly price equilibrium. Of course, a balanced growth path is achieved in this model if labor productivity and shopping productivity grow at the same rate for all i over time (and the ratio of households' valuations to marginal costs, R/mc, remains fixed).

Menzio (2021) develops conditions under which Stiglerian growth (a decline in search frictions) is consistent with a balanced growth path in price dispersion, due to endogenous specialization by sellers. This paper makes the complementary point that increases in shopping productivity may not lead to a decline in prices toward the monopoly price equilibrium if labor productivity is also growing. In fact, differences in the rates of growth in these two productivities can lead shopping productivity growth to coincide with *increasing* average markups.

Given robust evidence from the trade literature (see Simonovska 2015 and references therein) that high per-capita income countries pay systematically higher markups, I view the ability to generate a positive correlation between growth and markups as a feature, rather than a bug, of the model.

Limitations. It is worth noting some limitations of the model. The model isolates the endogenous choice of search intensity and the effect of search behavior on the distribution of markups charged by firms. As a result, it silences some dimensions of consumer and firm heterogeneity that may be important in understanding markups.

On the household side, all households are identical in their valuation of the good (R). Previous work by Faber and Fally (2017) and Handbury (2021) suggests that under non-homothetic CES preferences, differences in the valuation of goods is important to match product markups measured using demand estimation. Neiman and Vavra (2019) also find that idiosyncratic differences in tastes across consumers may be important to match opposing trends in the concentration of individual and aggregate expenditures. To the degree that valuations across consumers are positively correlated with consumer income (which is the case if heterogeneity in valuations is determined by differences in the marginal value of money), heterogeneous valuations are likely to amplify the effect of a rightward shift in the income distribution on markups.[23]

The simplifications made on the firm side of the model—that all products are identical, and that all firms have identical marginal costs—are perhaps more limiting. In particular, quality segmentation of the market may lead to downward pressure on markups in product categories consumed by high-income households as incomes rise. Jaravel (2019) provides intertemporal evidence for this mechanism, finding that product categories consumed disproportionately by high-income households experienced increases in product variety and lower inflation. In the cross-section, Handbury (2021) finds that products consumed by high-income households are relatively more expensive in low-income areas. One way to understand how the phenomenon described by Jaravel (2019) and Handbury (2021) is reflected in this model is that a rightward shift in the income

[23]The dispersed-price equilibrium of the nonsequential search model here can be fragile to such heterogeneity in reservation prices. However, a similar sequential search model developed in Appendix Section E can admit such heterogeneity in valuations.

distribution leads to a greater density of firms at high markup levels. This entry at the top end of the distribution reduces the sales of each high-markup firm compared to the sales it would have if the markup distribution did not adjust. However, in this model the first-order reallocation of expenditures toward high-markup products always dominates any pro-competitive effects on markups.

5 Suggestive Evidence

This section provides suggestive evidence for the search mechanism in the model. In particular, measures of shopping intensity in the Nielsen data are consistent with two predictions of the model: (1) search intensity (measured as shopping trips or unique retailers visited per dollar spent) is decreasing in household income, and (2) conditional on income, search intensity is increasing in high-income areas.

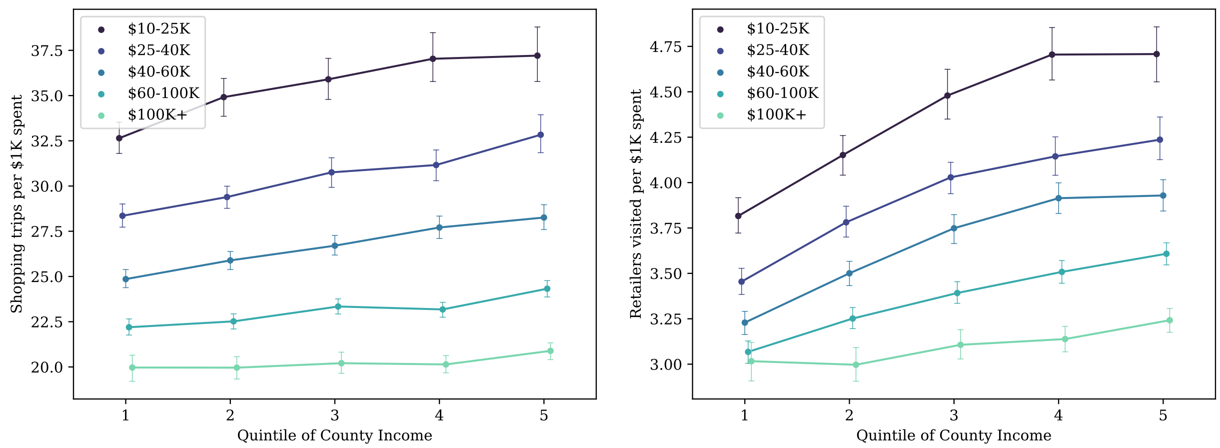
I use two measures of shopping intensity: the number of shopping trips a household makes per dollar spent and the number of unique retailers visited per dollar spent. The normalization by dollar spent reflects the insight by Pytka (2018) that search time reflects both search intensity and the size of the consumption basket; our objective is to isolate the former. Nevertheless, using expenditures to control for the size of the consumption basket risks confounding our results with differences in prices paid by income. Appendix B.3 replicates the analysis instead normalizing by households' total number of transactions, number of unique UPCs purchased, or number of unique brands purchased. All three alternatives yield similar results to the ones presented here.

Figure 6 plots shopping intensity, as measured by the number of shopping trips a household makes per \$1,000 expenditures (left panel) or the number of unique retailers visited per \$1,000 expenditures (right panel), across five income groups. The x-axis splits these income groups by the quintile of the average income in the county in which the household is based.

Two patterns emerge. First, across all county quintiles, high-income households exert less search intensity per dollar spent. This fact has been previously established by Pytka (2018). Second, conditional on income, households exert greater search intensity in high-income counties. This finding is novel and is consistent with the model prediction that households optimally search more when the search intensity of surrounding households decreases.

Table 5 formally tests this relationship. Columns 1 and 4 report the link between shopping intensity and household income with county fixed effects. Both measures indicate that shopping intensity is decreasing in income: a \$10,000 increase in household

Figure 6: Shopping intensity by income group and county income.



(a) Shopping trips per $1K expenditures.

(b) Unique retailers visited per $1K expenditures.

income is associated with making 1.3 fewer shopping trips per $1,000 spent and with visiting 0.12 fewer retail chains. Columns 2 and 5 add average county income from the BEA. Since county income is collinear with county fixed effects, I instead use state fixed effects in these regressions. The coefficient on a household's income remains stable, and we find that shopping intensity is increasing in average county income conditional on household income.

One concern is that a household's shopping productivity may vary across counties, since some counties may have a higher density of stores or better transportation. Columns 3 and 6 control for the log number of grocery establishments in each county from the Census Business Patterns.[24] While the coefficient on county income attenuates, it remains positive and significant. This finding is consistent with the model prediction that a given household will search more when surrounded by higher-income households, since households' search decisions are strategic substitutes.

6 Calibration

In this section, I calibrate the model developed in Section 4. Calibrated parameters suggest significant externalities across households from shopping behavior. Finally, I simulate the model under different income distributions.

[24]Grocery establishments count all NAICS 445 code establishments, which include grocery stores, liquor stores, and specialty food stores. All counties in the sample have at least one grocery establishment, so we do not have to include any correction for zeroes.

Table 5: Effect of income and county income on shopping intensity.

	Shopping trips per \$1K			Retailers visited per \$1K		
	(1)	(2)	(3)	(4)	(5)	(6)
Income (\$10,000s)	–1.13**	–1.14**	–1.15**	–0.10**	–0.10**	–0.10**
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Avg. County Income		1.06**	0.54*		0.20**	0.06**
		(0.21)	(0.29)		(0.02)	(0.02)
Log(Grocery Estabs.)			0.80**			0.21**
			(0.08)			(0.01)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	60 506	60 002	59 997	60 506	60 002	59 997
R^2	0.12	0.07	0.08	0.10	0.05	0.06

Notes: Household income is calculated using the midpoint of the range provided by Nielsen (e.g., a household with an income of \$13K would be in the range \$12–15K and would be assigned a value of \$13.5K). Average county income in 2009 is from the BEA Personal Income by County Area release. Grocery Estabs. are a count of NAICS 445 establishments from Census Business Patterns (includes grocery stores, supermarkets, liquor stores, and specialty food stores). BEA and Census Business Pattern data is not available for a small number of counties in the Homescan sample. Standard errors clustered by county. * indicates significance at 10%, ** at 5%.

6.1 Calibration procedure

I normalize firms' marginal costs to one and set the reservation price $R = 3$, which is the 98th percentile of markups in the data. (Decreasing R tends to moderately increase the predicted change in markups over time, so setting $R = 3$ is conservative.) I use data on the U.S. income distribution over 1950–2018 from Saez and Zucman (2019). I set $dH(i)$ equal to the density of post-tax income in 2010; the densities are plotted in Figure D.1.

I assume that the mapping function $\mathcal{S} : s_i \mapsto \langle q_{i,n} \rangle_{n=1}^{\infty}$ is Poisson as in Albrecht et al. (2021) and Menzio (2021), so that

$$q_{i,n+1} = \frac{s_i^n \exp(-s_i)}{n!}.$$

The remaining parameters, $(\{s_i, a_i\}_{i=0}^{\infty}, F)$, are calibrated within the model. The calibration proceeds in two steps.

Step 1. Offer distribution F and search intensities s_i. Given an offer distribution F, I choose search intensities s_i to match the average markup paid by each income group in 2009 (as reported in Figure 1). Define $s(i)$ as a linear interpolation of income i to s_i. I set the search behavior of any household with income over \$200K to the search behavior of the \$200K income group, so that our results are not influenced by extrapolation beyond the sample of observed incomes. The aggregate search parameter is then

$$\bar{s} = \int_0^{\infty} s(i) dH^{2010}(i),$$

where $dH^{2010}(i)$ is the post-tax income-weighted density of households across income levels in 2010 from Saez and Zucman (2019).[25] Since Poisson distributions are additive, this expression is equivalent to constructing the aggregate search behavior using (5).

Given aggregate search behavior parameterized by $\bar{s}$, the unique equilibrium price distribution F is pinned down by (6). This yields a new offer price distribution F given s_i.

I iterate these calculations to find a fixed point for F and $\{s_i\}_{i=0}^{\infty}$. In the calibration, I find that the fixed point for F and $\{s_i\}_{i=0}^{\infty}$ appears to be unique and does not depend on the initial conditions provided.

[25]This is a departure from the unitary demand assumed in Section 4, which is made to reflect that demand elasticities facing firms depend on the expenditure-weighted average of demand elasticities of their consumers. We can integrate this into the model by assuming that amount purchased by i, n_i, varies across i, and using $dH(i) = n_i d\hat{H}(i)$, where $d\hat{H}(i)$ is the household density by income.

Step 2. Search productivities a_i. Given F and s_i, shopping productivities are identified from households' first-order condition (4). I calculate $\partial\mathbb{E}[p_i|s_i, F]/\partial s_i$ using the offer distribution F and validate that $\partial\mathbb{E}[p_i|s_i, F]/\partial s_i$ is negative and increasing. I set z_i equal to i's post-tax income as an approximation of each type's labor productivity.

6.2 Results

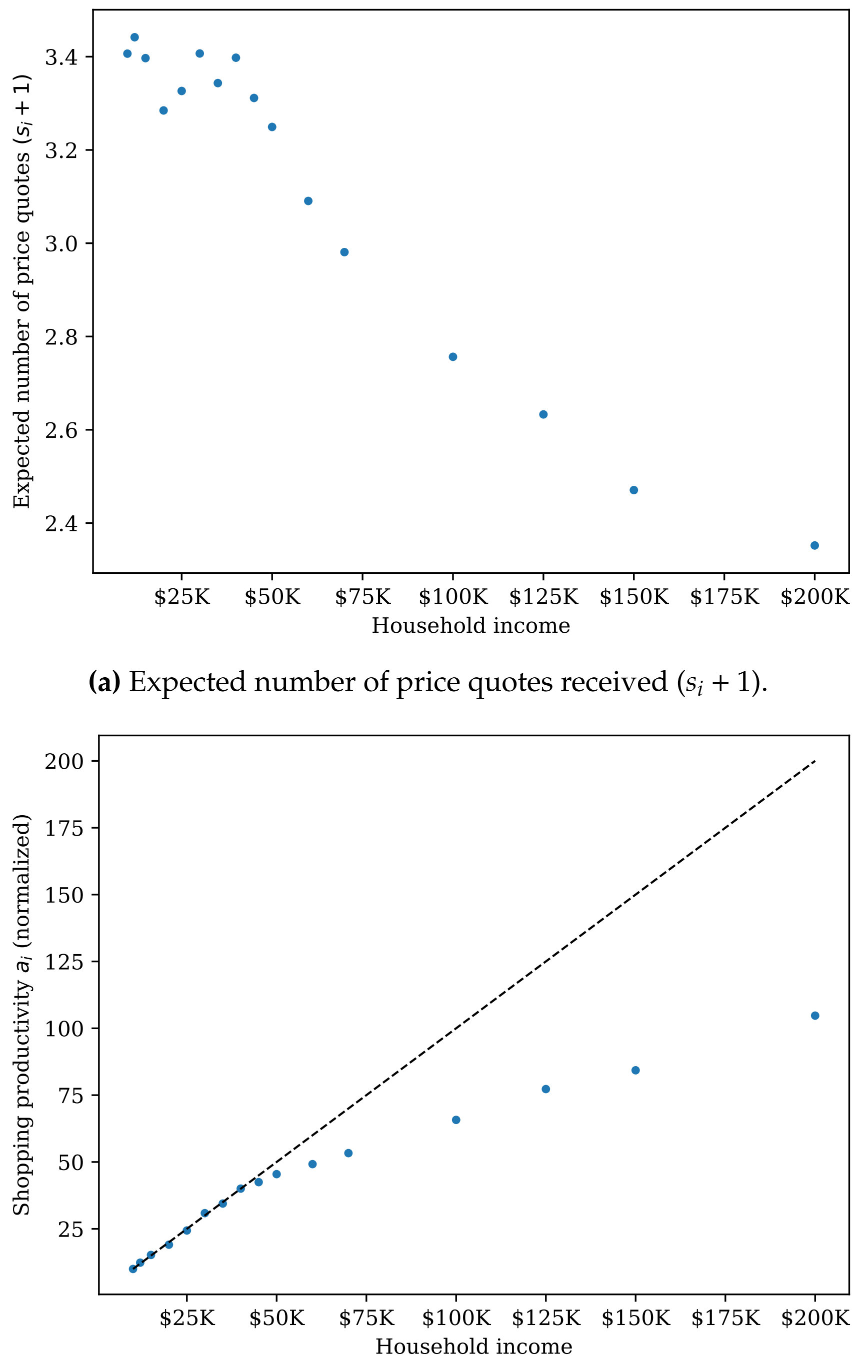
The top panel of Figure 7 plots the expected number of price quotes ($s_i + 1$) received by household i. Search intensity is highest for the lowest-income households in the sample, at around $s_i = 2.4$. As income increases, search intensity falls to under $s_i = 1.3$ for the highest income households in the sample. The result is that households with $200K+ in income expect to receive about 30% fewer price quotes than low-income households.

The lower panel of Figure 7 shows the calibrated shopping productivities a_i. Shopping productivity initially increases one-for-one with income, but becomes concave for incomes over $40K. The calibrated shopping productivities satisfy both hypotheses in Propositions 1 and 2—shopping productivity increases at a slower rate in i than labor productivity z_i, and the ratio z_i/a_i is increasing and convex in i.

Given that search intensities across income groups are calibrated to match the average markup paid by income group, it is worthwhile to ask how well the implied distribution of markups predicted by the model fits the data. Table 6 compares various percentiles of the markup distribution in the data and predicted by the model for four levels of household income. The model appears to fit the data reasonably well, but there are some systematic differences of note. First, for all four income groups, more than 10 percent of purchases are made at markups below one. The model, on the other hand, does not admit prices below marginal cost. A richer model could account for the role of habit formation in generating sales below marginal cost, but this is beyond the scope of the current paper. As such, the 10th and 25th percentiles of markups predicted by the model are higher than their empirical counterparts. At the top of the markup distribution, the model predicts predicts the 90th and 95th percentiles of markups paid by the highest-income households well, but slightly overstates the these quantiles of the distribution for lower-income households.

Another way to assess the validity of the model predictions is to compare statistics within the model to those documented by previous work. Figure D.2 plots the expected price paid against search intensity and shows that the elasticity of prices paid to search time is 11.0–11.6 percent. This estimate is roughly in line with Aguiar and Hurst (2007), who estimate that doubling shopping frequency lowers prices paid by 7–10 percent.

Figure 7: Calibrated shopping intensity $(s_i + 1)$ and shopping productivity a_i.



(a) Expected number of price quotes received $(s_i + 1)$.

(b) Shopping productivity a_i.

Table 6: Comparison of markup distribution in data to model.

Percentile of markup distribution	\$20–\$25K Data	\$20–\$25K Model	\$50–\$60K Data	\$50–\$60K Model	\$100–\$125K Data	\$100–\$125K Model	Over \$200K Data	Over \$200K Model
10	0.82	1.12	0.83	1.12	0.87	1.12	0.89	1.13
25	1.01	1.14	1.01	1.14	1.04	1.15	1.07	1.15
50	1.21	1.19	1.21	1.19	1.24	1.21	1.28	1.23
75	1.44	1.31	1.44	1.31	1.47	1.36	1.53	1.42
90	1.74	1.56	1.74	1.57	1.80	1.69	1.86	1.82
95	2.07	1.82	2.07	1.83	2.12	2.01	2.18	2.17

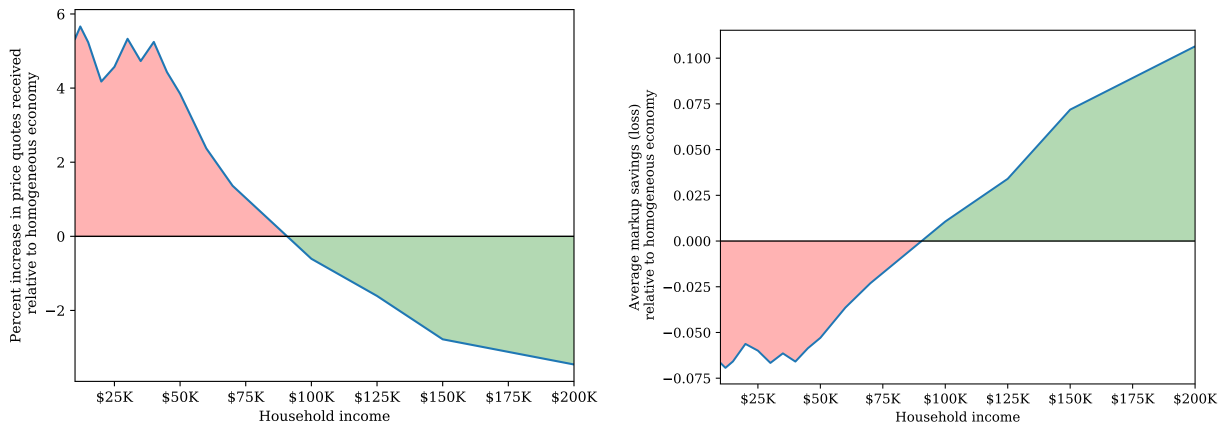
Macro vs. micro elasticities of markups to household income. A key implication of the model is that the markup distribution and household search decisions are affected by the composition of households in the economy. In particular, the search decision and aggregate markup paid by household i is different than what it would be in an economy where all households had the same characteristics (labor and shopping productivity) as i. As a result, micro estimates of the elasticity of markups to household income in the cross-section differ from the "macro" elasticity of markups to income that would result if the incomes of all households changed by some amount.

To show this quantitatively, for each income level, I consider an economy in which there is a single representative household with labor productivity z_i and shopping productivity a_i, and calibrate the representative household's search intensity and the markup distribution charged by firms. Figure 8 shows how search behavior and average markups differ between the baseline calibration with heterogeneous households and these representative household economies.

The left panel shows the percent difference in the average number of price quotes $\mathbb{E}[n] = s_i + 1$ retrieved by households in the baseline calibration compared to an economy with a representative household with z_i and a_i. Because of the presence of high-income households in the baseline calibration, low-income households search more than they would in an economy with other low-income households. In particular, households with \$10K retrieve about 6 percent more price quotes on average than in the baseline calibration.

The right panel shows the resulting difference in average markups paid. The results are large in magnitude: low-income households would pay 7pp lower markups on average in an economy populated with only low-income households. On the other hand, households with over \$200K in income save over 10pp on markups due to the greater search intensity of lower-income households. These results suggest the search behavior of low-income

Figure 8: Differences in search behavior and markups paid relative to economies with homogeneous income.



(a) Percent increase in price quotes received ($s_i + 1$) relative to homog. income economy.

(b) Savings (losses) in average markup paid relative to homog. income economy.

households generate a significant positive externality for high-income households.

In terms of the elasticity of markups paid to household income, a simple (unweighted) regression of markups paid on log household income leads to an estimate of 0.082 across economies with homogeneous income, compared to only 0.029 in the cross-section of incomes in the baseline calibration (similar to the empirical estimates from Section 3.1). In words, the macro elasticity of markups to household income is nearly three times larger than the micro elasticity.[26]

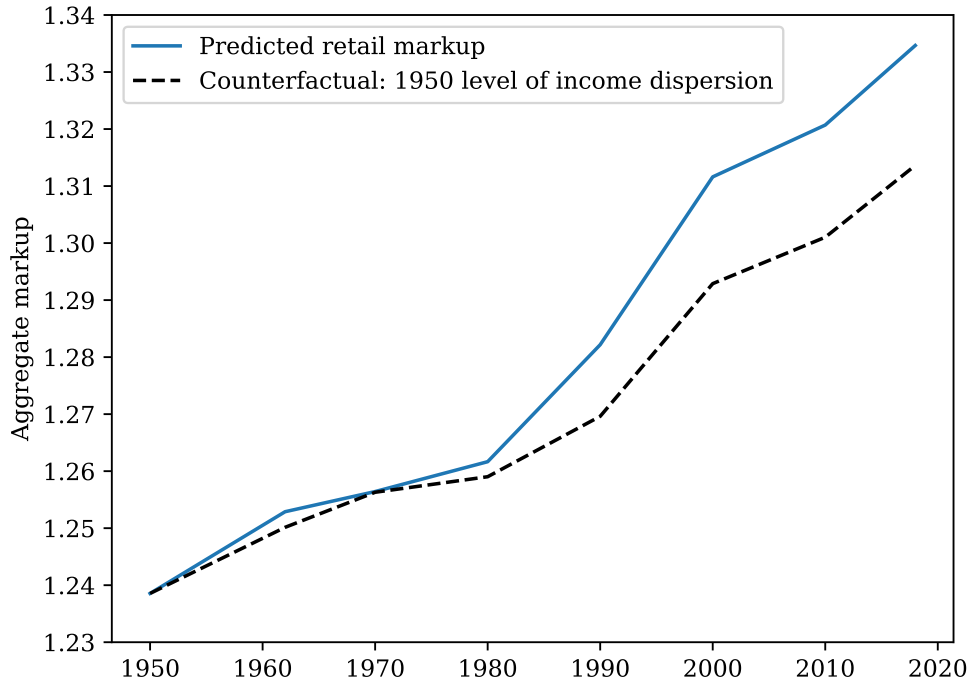
6.3 Counterfactuals: Income distribution from 1950–2018

How do changes in the income distribution affect the aggregate retail markup? In this subsection, I consider how changes to the income distribution $dH(i)$ affect the distribution of prices charged by firms, F, and households' shopping behavior, $\{s_i\}_{i=0}^{\infty}$, holding other parameters constant. The purpose of this exercise is to isolate how the composition of demand affects markups charged in equilibrium.

The procedure for calibrating to a new income distribution $d\widetilde{H}(i)$ follows. I assume types i map to post-tax income in 2009 USD. Hence, for each i, I set shopping productivity a_i equal to the search intensity of a household with the same real post-tax earnings in 2009. Now, as in Step 1 of the calibration procedure above, I search for a fixed point in the offer distribution F and in search intensities $\{s_i\}_{i=0}^{\infty}$. Since labor productivities and shopping

[26]Simonovska (2015) finds that the elasticity of markups to a country's per-capita income (for identical products, and controlling for differences in shipping costs) is 0.12–0.24. Hence, the estimates generated by the model account for between 30 and 60 percent of the cross-country elasticity she documents.

Figure 9: Predicted aggregate retail markup under income distributions from 1950–2018.



productivities are now known for all types, given an offer distribution F, search intensities s_i are identified from households' first-order conditions in (4) (whereas before they were calibrated to match average markups paid in the data). I find that the fixed point of F and $\{s_i\}_{i=0}^{\infty}$ does not depend on the initial values provided.

The solid blue line in Figure 9 plots the predicted retail markup over time using the income distributions from 1950–2018 from Saez and Zucman (2019). The rightward shift in the income distribution over this period leads to a 9pp increase in the aggregate retail markup predicted by the model. The rise in predicted retail markups is mild from 1950–1980 but accelerates significantly from 1980–2000.

To understand the degree to which the predicted increase in retail markups is due to changes in the dispersion, rather than the level, of income, I simulate the model using counterfactual income distributions, holding the shape of the income distribution constant from 1950 but increasing incomes of all households at the rate of average per capita income growth. The dotted black line in Figure 9 plots the predicted retail markups holding income dispersion constant at 1950 levels. The change in predicted markups before 1980 is nearly identical to the change predicted under the realized income distribution. However, the two series diverge in 1980 as income dispersion rises. In 2018, the predicted markup under the 1950 level of income dispersion is 3pp lower than at the 2018 level of income dispersion.

Figure 10(a) plots search intensities of households at different income levels over time. We see a pattern resembling the cross-sectional differences in search behavior across counties from Figure 6: as the income distribution shifts rightward over time, households at each income level are surrounded by higher-income households, and thus exert more search effort.

Within-firm changes vs. cross-firm reallocations. Changes in the aggregate markup may reflect both changes in the markups set by individual firms and a compositional shift reallocating sales toward high-markup firms. Autor et al. (2020) and Kehrig and Vincent (2021) suggest that reallocation across firms has played the dominant role in increasing markups (and decreasing the labor share) in the U.S. economy. On the other hand, Döpper et al. (2021) find that an increase in markups estimated using structural techniques in Nielsen scanner data is driven primarily by changes within products over time.

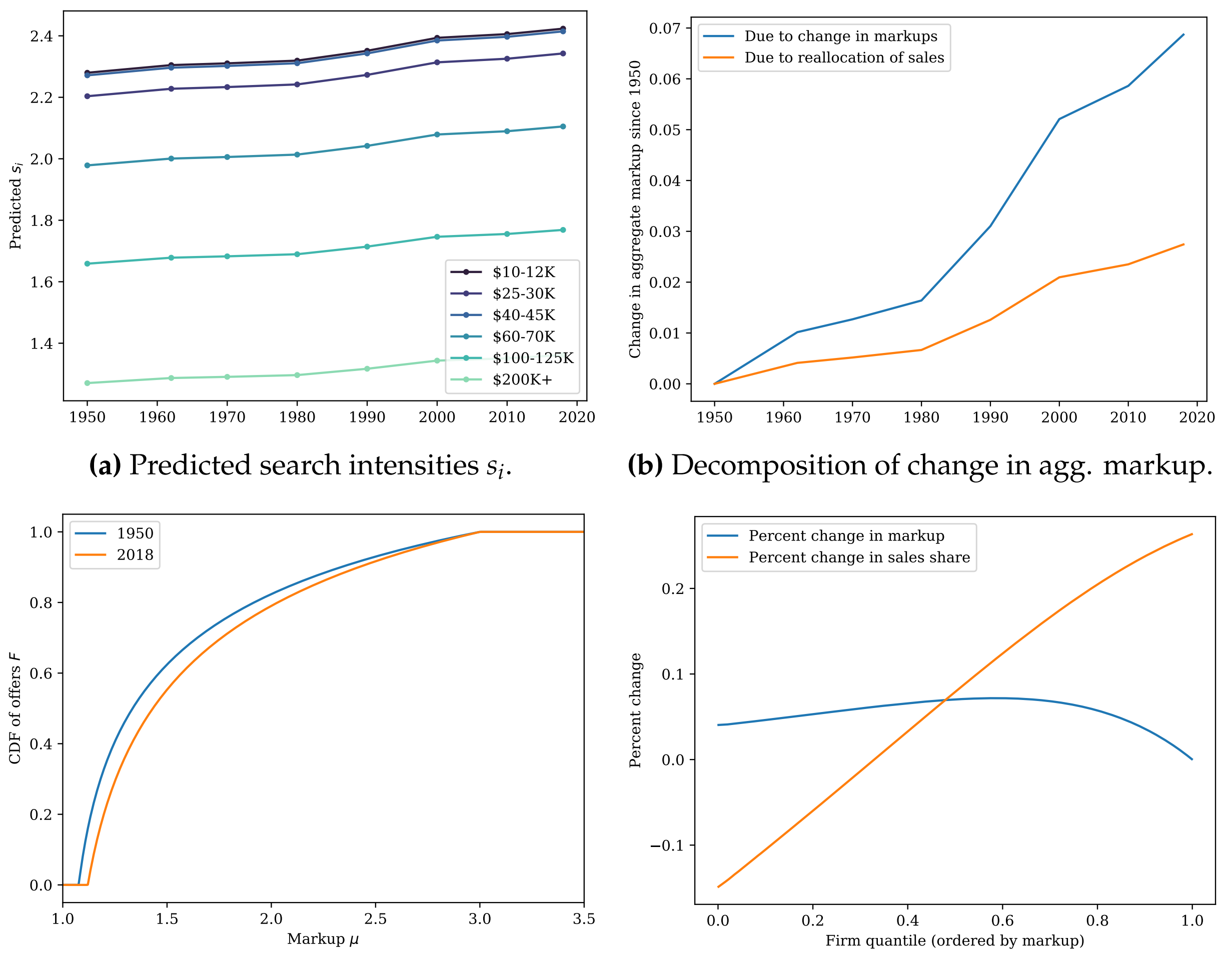
Figure 10(b) decomposes the change in markups from 1950–2018 predicted by the model into these two channels. In particular, the blue line in Figure 10(b) is the increase in the aggregate markup due to an increase in markups at each quantile of the markup distribution, while the orange line is the increase in the aggregate markup due to a reallocation of sales to firms at higher quantiles of the distribution.[27] Both effects play an important role in this calibration, with about two-thirds of the change over time coming from within-firm changes and one-third from cross-firm reallocations. Panel (c) plots the model-predicted offer distribution in 1950 and 2018, depicting the rightward shift in markups at all quantiles of the distribution. In panel (d), this rightward shift in markups at all points of the distribution is illustrated in the blue line, which plots the percent change in markups for a firm at each quantile of the distribution from 1950 to 2018. The orange line plots the percent change in sales at each quantile of the distribution. The reallocations are significant: firms at the lowest end of the markup distribution lose 12 percent in sales, while the sales of firms at the top of the markup distribution grow more than 20 percent.

6.4 Discussion

Döpper et al. (2021) estimate markups in Nielsen retail data and find that average markups

[27]Formally, the aggregate markup is the sales-weighted harmonic average of all firm markups, $\bar{\mu} = \mathbb{E}[\lambda_i/\mu_i]^{-1}$, where λ_i is the sales share of firm i. The change in the aggregate markup from $\bar{\mu}_0$ to $\bar{\mu}_1$ is decomposed as the change in within-firm markups ($\mathbb{E}[\lambda_{0,i}/\mu_{1,i}]^{-1} - \mathbb{E}[\lambda_{0,i}/\mu_{0,i}]^{-1}$) and the change due to reallocations across firms ($\mathbb{E}[\lambda_{1,i}/\mu_{1,i}]^{-1} - \mathbb{E}[\lambda_{0,i}/\mu_{1,i}]^{-1}$).

Figure 10: Predictions of search model under counterfactual income distributions.



(a) Predicted search intensities s_i.

(b) Decomposition of change in agg. markup.

(c) Offer distribution F in 1950 and 2018.

(d) Percent change in markups and sales shares by quantile from 1950 and 2018.

increased from 63% to 100% from 2006 to 2019.[28] The increase in markups predicted in the model is an order of magnitude more moderate. One reason for this difference is that markups calculated by Döpper et al. (2021) are identified by profit-maximization, and thus include manufacturer and wholesaler markups, while this paper has focused exclusively on retail markups. A second reason is that marginal costs estimated by Döpper et al. (2021) are falling over time. In the model presented above, a decrease in marginal costs holding customers' reservation prices constant is isomorphic to increasing R, and increases in R over time can generate large increases in the aggregate markup.

Despite these quantitative differences, the qualitative predictions of the model align closely with Döpper et al. (2021). The mechanism driving the increase in markups is decreasing average consumer price sensitivity. The increase in aggregate is driven by both a rightward shift in the full distribution of markups, as in Döpper et al. (2021), and by a reallocation of sales toward high-markup products.

Two broader insights emerge from this exercise. First, individual shopping decisions result in quantitatively significant externalities on other households that operate through the price distribution. These externalities share a resemblance with the shopping externalities explored by Kaplan and Menzio (2016), though shopping intensity in Kaplan and Menzio (2016) changes due to employment status rather than returns to search. Relatedly, Nevo and Wong (2019) find that returns to shopping declined during the Great Recession; this is consistent with the model prediction that increases in household shopping intensity decrease all households' returns to search.

The second insight is that changes in the composition of demand do not operate exclusively through changing the price elasticity faced by a given firm. Instead, the composition of demand both affects price elasticities for individual firms and reallocates sales across firms. The latter implies that market concentration and structure can be an outcome of demand composition. Of course, both effects of the changing composition of demand are absent in models that assume a representative household with homothetic preferences.

7 Conclusion

This paper explores the link between the income distribution and markups charged by firms. Empirical evidence from retail markups paid by households across the income distribution lends support to the Law of Diminishing Elasticity of Demand (Harrod 1936), which conjectures a decreasing relationship between income and price elasticity. This

[28] In price-cost margins reported by Döpper et al. (2021), this is a change from 0.39 to 0.50.

non-homotheticity suggests that markups are not purely a supply-side phenomenon: rather, the composition of demand can have significant effects on the distribution of firm markups.

This paper's focus is on the time series of the U.S. aggregate markup. Differences in the level and distribution of income across geographies or over the business cycle may also affect markups across locations and over cycles. I am pursuing these extensions in ongoing work.

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Appendix A Data Cleaning and Construction

A.1 Nielsen Homescan

Following the Nielsen data manual, I exclude magnet products (fresh produce and other items without barcodes) from my analysis.

Construction of relative price indices. I construct a relative price index for each transaction for some analyses in the main text. I calculate the price index for a transaction g as the log ratio of the unit price paid for transaction g to the average price paid for all transactions in the same product module measured in the same units (such as ounces, pounds, or count):

$$\hat{p}_g = \log\left(\frac{\text{Price}(g)}{\text{Units}(g)}\right) - \log\left(\frac{\sum_{g' \in \text{Module}(g)} \text{Price}(g')}{\sum_{g' \in \text{Module}(g)} \text{Units}(g')}\right). \tag{10}$$

In the above expression, Module(g) is the subset of products in the same product module as g measured in the same units as g, Price(g) is the price paid in transaction g, and Units(g) are the total units purchased in transaction g (the quantity of items sold times the ounces/pounds/count/etc. per item). Products with a high price index $\hat{p}$ are those that sell at higher unit prices than the average product in their product module.

Treatment of retailer IDs. Nielsen provides a retailer code for each transaction in the data, which designate retail chains (the identities of the retailers are anonymized for privacy reasons). Some retailer IDs, however, are catch-all IDs meant capturing all remaining retail chains not uniquely coded by Nielsen. For the purpose of all analyses at the retailer level (e.g., the retailer-UPC markup analysis in Section 3.2), I exclude retail IDs that do not uniquely identify a retail chain.

For the robustness analysis removing the largest retailers from the sample in Section 3.1, I rank uniquely identified retail chains by total sales observed in the Nielsen Homescan data. All retail chains that are not uniquely identified in the Nielsen data are assumed to be smaller than those uniquely identified.

The retailer price indices used in Section 3.2 Table 4 are calculated as the sales-weighted average retail price index for all products purchased from a retail chain. I.e., the retailer price index for retail chain k is

$$\text{Price Index}(k) = \sum_{g \in \mathcal{G}(k)} \frac{\text{Price}(g)}{\sum_{g' \in \mathcal{G}(k)} \text{Price}(g')} \cdot \hat{p}_g,$$

where $\mathcal{G}(k)$ is the set of all observed transactions made at retail chain k and $\hat{p}_g$ is the relative price index for transaction g as defined in (10).

A.2 PromoData Price-Trak

Wholesale costs provided by PromoData include a list of active categories and inactive categories (which PromoData uses to update an internal product encyclopedia). Following the data manual, I use both the active and inactive databases and drop duplicated observations in the inactive database. The database includes about 114,000 UPCs that also show up in the Nielsen Homescan data. Each UPC may be listed multiple times since it is available in different pack sizes to retailers; I call each unique UPC-pack size available to a retailer an "item" in the following description.

Data cleaning and construction. I construct the monthly wholesale base price and deal price for each item-market pair as the minimum reported base and deal prices for the item in the market in each month. Of about 230,000 items, wholesale prices for about 62,000 items are observed at least two markets in a given month. Let $w^{\text{base}}_{i,m,t}$ and $w^{\text{deal}}_{i,m,t}$ be the wholesale base price and deal price of item i in market m in month t. I calculate the relative price $\hat{w}^{x}_{i,m,t}$ as the ratio of the price of i in market m to the modal price for i across markets in t. Consistent with Stroebel and Vavra (2019), I find that wholesale prices are surprisingly uniform across markets: Table A.1 shows that over 80 percent of items in a given month in 2009 have a wholesale cost exactly equal to the modal price across markets.[29]

I assume that retailers purchase UPCs at the minimum price available to them, and so I calculate wholesale base and deal prices for each UPC in each month by taking the minimum price at which the UPC is offered across items (pack sizes) in that month. Since the PromoData lack information on the quantities of each item sold, this is a more principled approach than taking an unweighted average across items.

Merge with Nielsen Homescan. I merge these monthly wholesale costs into the Homescan data using the date of the shopping trip recorded by the panelist and the scanned UPC. As a check, I calculate the sales-weighted average markup for each UPC over all purchases observed in the Homescan data. Table A.2 shows summary statistics on the distribution of UPC markups. Over 90 percent of UPCs have markups that lie between one and 2.3, and the fraction of products with a markups below one is under 10 percent.

[29]Stroebel and Vavra (2019) conduct a similar analysis at a quarterly level across all years using a subset of 32 markets in the wholesale cost data, and find a similar figure of 78 percent.

Table A.1: Uniformity of wholesale prices across markets.

	Measure of wholesale cost	
	Base Price	Deal Price
Percent of items sold:		
At modal price ($\hat{w}^x_{i,m,t} = 1$)	84.5	82.9
Within 5% of modal price ($\lvert\hat{w}^x_{i,m,t} - 1\rvert \leq 0.05$)	91.8	88.3
Within 10% of modal price ($\lvert\hat{w}^x_{i,m,t} - 1\rvert \leq 0.10$)	95.7	92.7

Table A.3 reports the match rate of wholesale cost data by income group. The percent of transactions matched to wholesale cost data increases slightly with income, and the share of expenditures matched to wholesale cost data decreases slightly with income.

To check whether transactions matched to wholesale cost data are similar to the unmatched transactions, I compare the average of the relative price indices (as defined in (10)) for matched and unmatched transactions by income group. The final two columns of Table A.3 show the average price index for matched and unmatched products by income group. We see that for middle-income groups, the average price index on unmatched products is similar to the average price index on matched products. For the lowest and highest income groups, however, the two values differ: unmatched products consumed by low-income households tend to have lower price indices than those matched to the wholesale cost data, and unmatched products consumed by high-income households tend to have higher price indices than those matched to the wholesale cost data. To the degree that the price index of a product covaries positively with its markup, this means that differences in markups calculated for our matched sample will be conservative relative to the true differences in markups across these income groups.

Table A.2: Summary statistics for markup distribution.

	Measure of wholesale cost	
	Base Price	Deal Price
Percentiles of distribution:		
10	1.033	1.099
25	1.185	1.260
50	1.364	1.443
75	1.593	1.667
90	1.918	1.970
Percent below $\mu = 1$:		
By count	7.95	5.31
By sales	12.63	5.26
N UPCs matched	66033	66033

Table A.3: Coverage of UPC wholesale costs data by income level.

	Percent matched to wholesale cost data		Average price index ($\hat{p}$)	
Income group	Transactions	Expenditures	Matched	Unmatched
\$10–25K	41	38	-0.02	-0.04
\$25–40K	42	38	0.00	-0.01
\$40–60K	42	38	0.03	0.03
\$60–100K	43	36	0.08	0.08
Over \$100K	43	34	0.14	0.16
All	42	37	0.05	0.05

Appendix B Robustness

B.1 Fact 1. High-income households pay higher markups

Figure B.1 shows that regressions of log markups on household income level dummies, household demographic controls, and county and store fixed effects yield results similar to those in the main text, which instead use the level of the markup as the dependent variable. The quantitative results are nearly identical. Using the log markup as the dependent variable may be preferred if idiosyncracies to marginal cost across counties or across stores exist on a percent basis rather than level basis.

In the main text, I use list prices from Promodata Price-Trak as the measure of wholesale costs. Results are quantitatively similar instead using deal prices from Price-trak as the measure of marginal costs. Figure B.2 replicates Figure 2 from the main text instead using Price-Trak deal prices as the measure of marginal cost. Table B.1 measures the elasticity of markups to household income as in Table 1, but instead using Price-Trak deal prices as the measure of marginal costs.

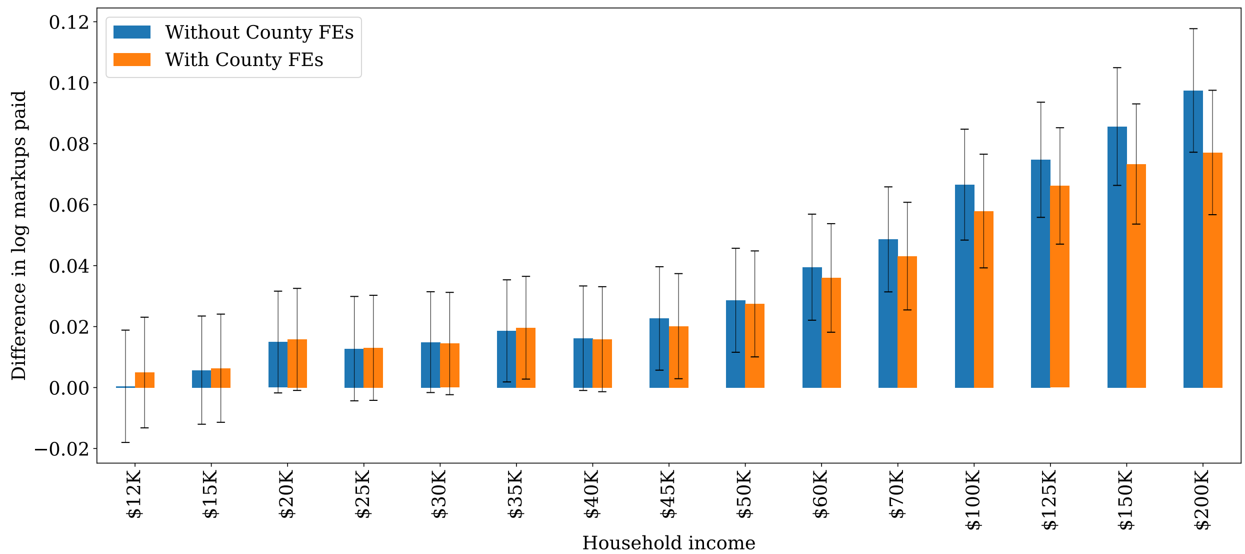
Table B.2 replicates the analysis from Broda et al. (2009) using the 2009 Homescan sample and using the same procedures and demographic controls as used in the main text in this paper. The results are quantitatively similar to the Broda et al. (2009) estimates. The differences in the procedures relative to Broda et al. (2009) are: (1) Broda et al. (2009) uses the 2005 Nielsen Homescan panel, while this analysis uses the 2009 data; (2) demographic controls included by Broda et al. (2009) also include marital status and city controls rather than the county controls used here; (3) Broda et al. (2009) drops the highest income group with over \$100K income and does not exclude income groups with below \$10K in income; and (4) the regressions in Broda et al. (2009) are not weighted by sales.

Finally, Table B.3 and Table B.4 provide two alternate views of how the elasticity of markups paid with respect to household income varies as we include successive controls. Table B.3 clicks in on the relationship between markups paid and household income at the retail chain and retail chain-county level. Rather than initially control for county and store, Table B.4 instead looks at differences in markups paid by income within product group and product module.

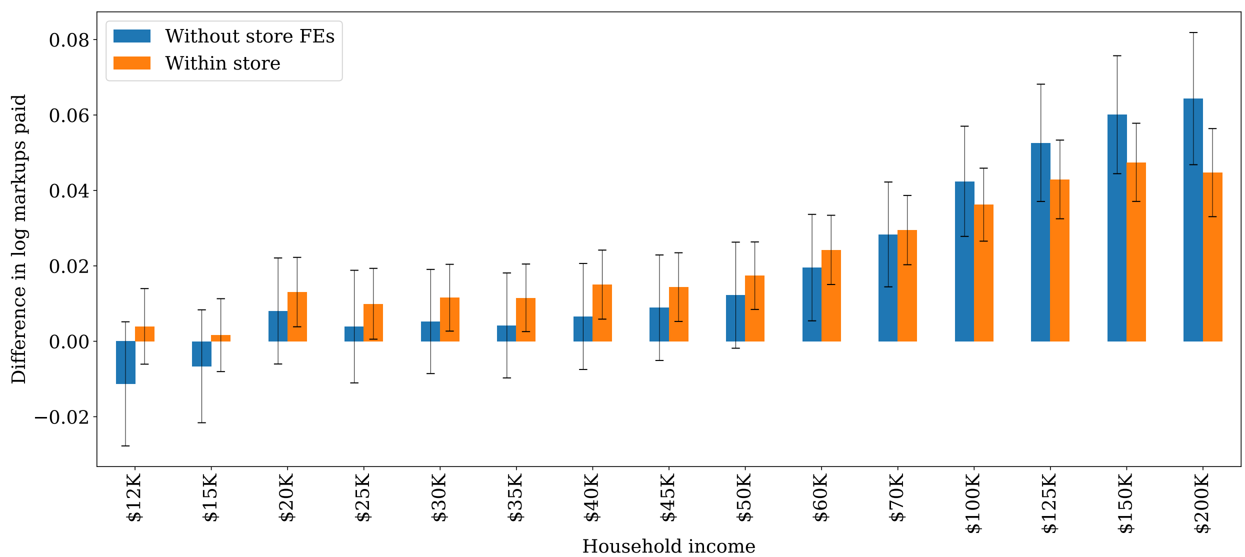
B.2 Fact 2. Products consumed by high-income have higher markups

As discussed in the main text, the coefficient on buyer income on a product's retail markup decreases in magnitude once we include product module fixed effects (see Table 2). Product module fixed effects may control for confounders that covary with both buyer

Figure B.1: Difference in log markups paid relative to households with $10-12K income.



(a) With and without county fixed effects (N = 23.6 million).



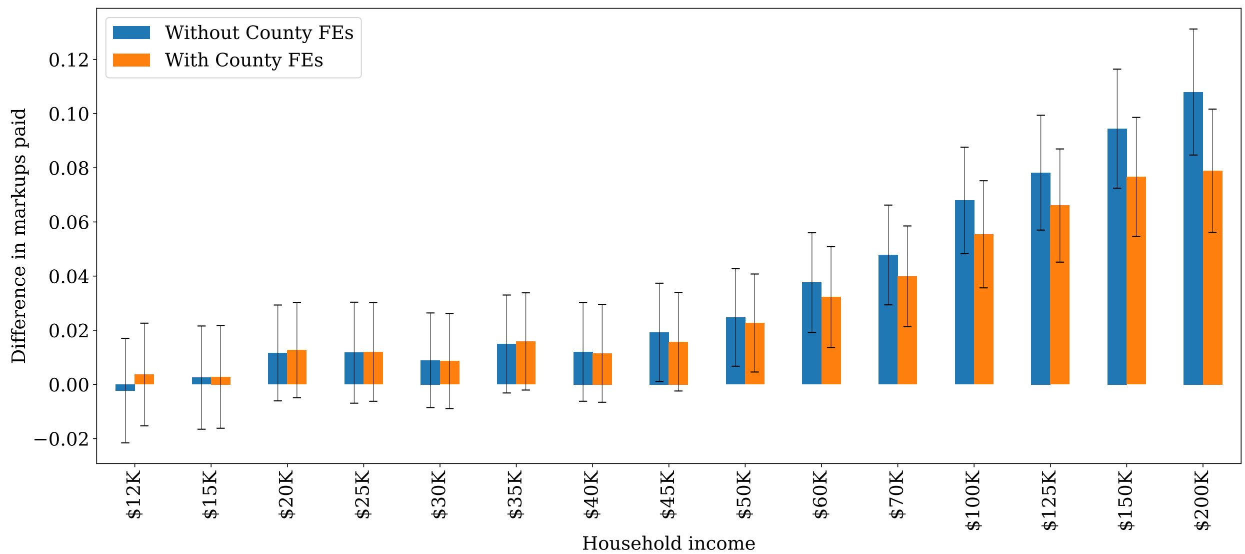
(b) With and without store fixed effects (store transactions only, N = 12.8 million).

Notes: These figures plot the coefficients β_ℓ on household income dummies in a regression of the log markup paid by a household on demographic controls (race, ethnicity, household size, and age of female head of household) weighted by sales. Income levels on the y-axis are the minimum of the income bracket provided by Nielsen (e.g., $12K includes households reporting income between $12–15K). Standard errors are two-way clustered by UPC and household. Figure (a) shows β_ℓ with and without county fixed effects, and (b) shows $\tilde{\beta}_\ell$ with and without store fixed effects for the sample of transactions where the unique store ID is observed.

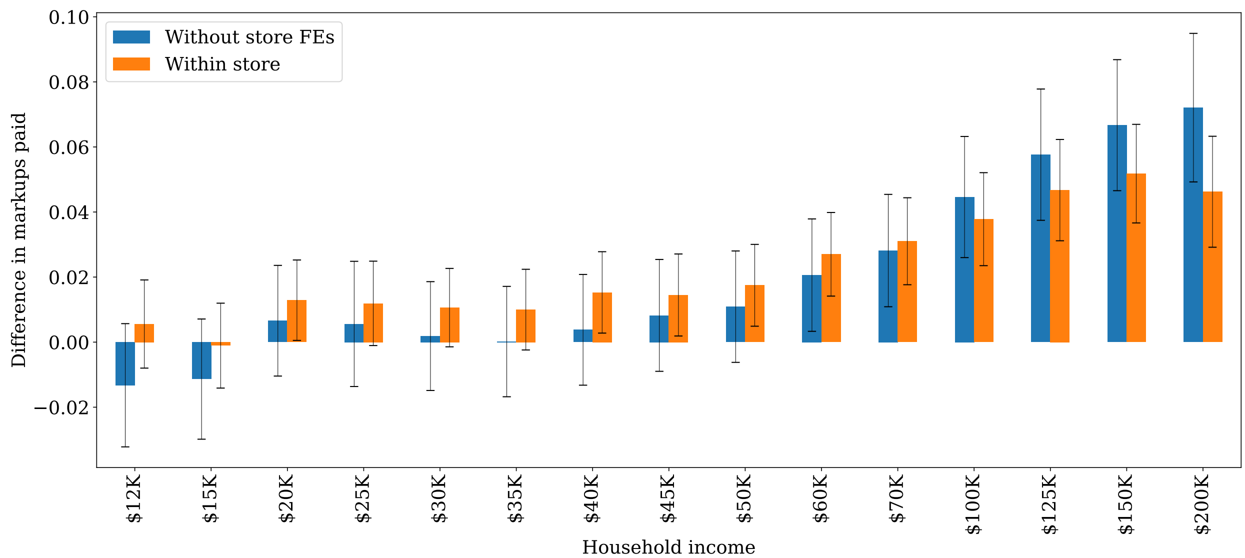
$$\text{(a)} \qquad \log(\text{Markup})_{i,g} = \sum_\ell \beta_\ell 1\{i \text{ has income level } \ell\} + \gamma' X_i + \delta_{\text{County}} + \epsilon_{i,g}.$$

$$\text{(b)} \qquad \log(\text{Markup})_{i,g} = \sum_\ell \tilde{\beta}_\ell 1\{i \text{ has income level } \ell\} + \tilde{\gamma}' X_i + \alpha_{\text{Store}} + \epsilon_{i,g}.$$

Figure B.2: Difference in markups paid relative to households with $10-12K income (using Price-Trak deal prices as measure of wholesale costs).



(a) With and without county fixed effects (N = 23.6 million).



(b) With and without store fixed effects (store transactions only, N = 12.8 million).

Notes: These figures plot the coefficients β_ℓ on household income dummies in a regression of the markup paid by a household on demographic controls (race, ethnicity, household size, and age of female head of household) weighted by sales. Income levels on the y-axis are the minimum of the income bracket provided by Nielsen (e.g., $12K includes households reporting income between $12–15K). Standard errors are two-way clustered by UPC and household. Figure (a) shows β_ℓ with and without county fixed effects (specification (1)), and (b) shows $\tilde{\beta}_\ell$ with and without store fixed effects for the sample of transactions where the unique store ID is observed (specification (2)).

Table B.1: Impact of income on markups paid (using Price-Trak deal prices as measure of wholesale costs).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Household Income	0.027**	0.032**	0.029**	0.026**	0.020**	0.015**	0.010**	0.008**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Log Avg. County Income			0.074**						
			(0.005)						
Household Size		−0.004**	−0.004**	−0.003**	−0.003**	−0.003**	−0.003**	−0.003**	−0.001**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Demographic Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs				Yes	Yes	Yes	Yes	Yes	Yes
Store FEs						Yes	Yes	Yes	Yes
Store-Group FEs							Yes		
Store-Module FEs								Yes	
Store-UPC FEs									Yes
N (millions)	23.6	23.6	18.1	23.6	12.8	12.8	12.8	12.8	12.8
R^2	0.00	0.00	0.01	0.02	0.02	0.10	0.39	0.59	0.91

Notes: The log of household income is calculated using the midpoint of the range provided by Nielsen (e.g., a household with an income of $13K would be in the range $12–15K and would be assigned a value of $13.5K). Demographic controls include race, ethnicity, presence of female head of household, and age group of female head of household. Regression weighted by sales, and standard errors two-way clustered by UPC and household. * indicates significance at 10%, ** at 5%.

Table B.2: Impact of income on prices paid.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Household Income	0.012**	0.014**	0.012**	0.010**	0.012**	0.012**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Avg. County Income			0.069**			
			(0.003)			
Household Size		−0.003**	−0.003**	−0.003**	−0.003**	−0.002**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UPC FEs	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls		Yes	Yes	Yes	Yes	Yes
County FEs				Yes	Yes	Yes
Store FEs						Yes
N (millions)	23.6	23.6	18.1	23.6	12.8	12.8
R^2	0.96	0.96	0.96	0.96	0.95	0.95

Notes: The log of household income is calculated using the midpoint of the range provided by Nielsen (e.g., a household with an income of \$13K would be in the range \$12–15K and would be assigned a value of \$13.5K). Demographic controls include race, ethnicity, presence of female head of household, and age group of female head of household. Regression weighted by sales, and standard errors two-way clustered by UPC and household. * indicates significance at 10%, ** at 5%.

income and UPC markups. Nevertheless, it is important to note that isolating our analysis to differences in markups charged between products in the same product module excludes household patterns of substitution across product modules that may affect markups at a module level.

Figure B.3 provides suggestive evidence of such substitution patterns for two pairs of product modules. The left panel plots the ratio of household expenditures on butter to margarine over the income distribution. High-income households appear to systematically spend more on butter than margarine compared to low-income households. The sales-weighted average of markups in the butter product module is 46 percent, compared to 18 percent for the margarine product module. In this case, it is plausible that part of the difference in markups across the butter and margarine categories is due to buyer income (just as markup for products within these categories are associated with buyer income). The right panel shows a similar pattern for tortilla chips and potato chips: relative expenditures on tortilla chips compared to potato chips increase with household income, and tortilla chips charge a higher markup on average (35 percent) compared to potato chips (21 percent).

Table 3 showed that the link between UPC retail markups and buyer income (as measured by the share of buyers with over \$100K in income) is robust to the inclusion of

Table B.3: Impact of income on markups paid: Decomposition by retail chain and county.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Household Income	0.032**	0.026**	0.023**	0.018**	0.017**	0.021**	0.017**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Household Size	−0.006**	−0.006**	−0.006**	−0.005**	−0.005**	−0.006**	−0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs		Yes	Yes		Yes	Yes	Yes
Retail Chain FEs				Yes	Yes	Yes	Yes
Store FEs							Yes
Sample	All	All	Retail Chain	Retail Chain	Retail Chain	Store	Store
N (millions)	23.6	23.6	22.8	22.8	22.8	12.8	12.8
R^2	0.00	0.02	0.02	0.06	0.07	0.04	0.09

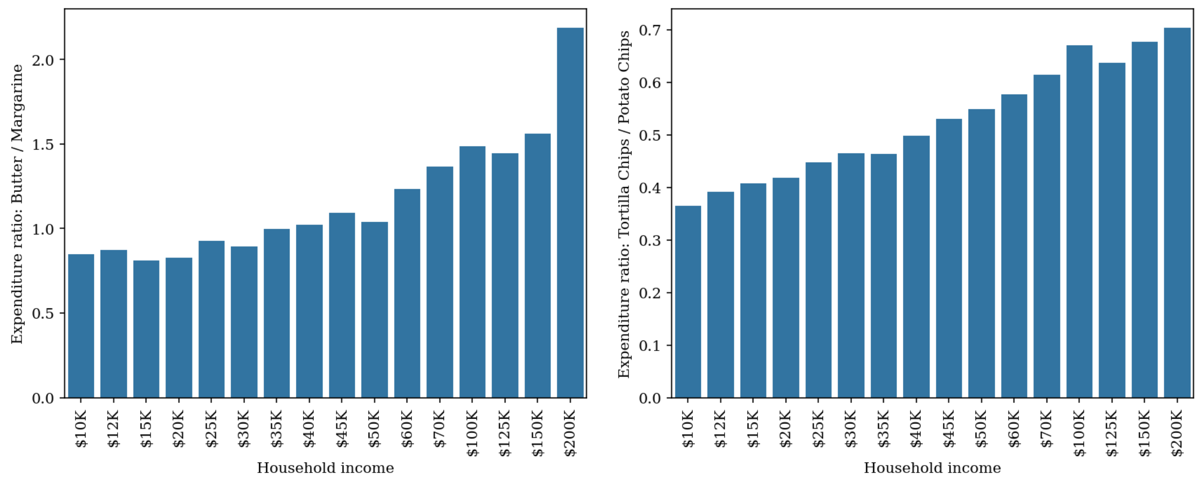
Notes: The log of household income is calculated using the midpoint of the range provided by Nielsen (e.g., a household with an income of $13K would be in the range $12–15K and would be assigned a value of $13.5K). Demographic controls include race, ethnicity, presence of female head of household, and age group of female head of household. Samples indicate the full wholesale cost-matched dataset ("All"), the dataset where retail chains are uniquely identified ("Retail Chain"), and the dataset where stores are unique identified ("Store"). Regression weighted by sales, and standard errors two-way clustered by UPC and household. * indicates significance at 10%, ** at 5%.

Table B.4: Impact of income on markups paid: Decomposition by products.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Household Income	0.032**	0.022**	0.021**	0.014**	0.011**	0.011**	0.004**	0.005**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Household Size	−0.006**	−0.006**	−0.006**	−0.004**	−0.004**	−0.003**	−0.001**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product Group FEs		Yes						
Product Module FEs			Yes					
UPC FEs				Yes				
County-UPC FEs					Yes	Yes		
Retail Chain-UPC FEs							Yes	
Retail Chain-County-UPC FEs								Yes
Sample	All	All	All	All	All	Retail Chain	Retail Chain	Retail Chain
N (millions)	23.6	23.6	23.6	23.6	23.6	22.8	22.8	22.8
R^2	0.00	0.11	0.21	0.64	0.82	0.81	0.77	0.89

Notes: The log of household income is calculated using the midpoint of the range provided by Nielsen (e.g., a household with an income of $13K would be in the range $12–15K and would be assigned a value of $13.5K). Demographic controls include race, ethnicity, presence of female head of household, and age group of female head of household. Samples indicate the full wholesale cost-matched dataset ("All") and the dataset where retail chains are uniquely identified ("Retail Chain"). Regression weighted by sales, and standard errors two-way clustered by UPC and household. * indicates significance at 10%, ** at 5%.

Figure B.3: Ratio of expenditures on (a) butter versus margarine and (b) tortilla chips versus potato chips by household income group. The sales-weighted average of markups on butter UPCs is 46% compared to 18% for margarine UPCs, and 35% for tortilla chips compared to 21% for potato chips.



(a) Expenditures on butter (avg. markup 46%) vs. margarine (avg. markup 18%).

(b) Expenditures on tortilla chips (avg. markup 35%) vs. potato chips (avg. markup 21%).

various supply-side factors. Table B.5 and Table B.6 show that this is true using the other two measures of income explored in the main text, the average income of a product's bueyrs and the share of buyers with $10-50K in income. Finally, Table B.7 shows that the analysis in Table 3 is robust to instead using Promodata Price-trak deal prices as the measure of wholesale costs (rather than the Price-trak list prices used for analyses in the main text).

B.3 Shopping intensity and income

Section 5 shows that two measures of shopping intensity—the number of shopping trips a household makes per dollar spent, and the number of unique retailers visited per dollar spent—are decreasing in income, but conditional in income are increasing in average county income. The normalization by dollars spent is made to control for differences in the size of the consumption basket, since Pytka (2018) shows that search time reflects both search intensity (our object of interest) and the size of the consumption basket.

Scaling by expenditures to control for the size of the consumption basket risks conflating basket size with average prices paid, which we have shown are increasing in income. In this appendix, I show that the findings are robust to instead normalizing by a number of alternative measures of consumption basket size: (1) a household's total number of

Table B.5: Relationship between buyer income (measured using average buyer income) and UPC retail markup.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average Income (10,000s)	0.041**	0.045**	0.041**	0.041**	0.021**	0.022**	0.022**	0.022**	0.023**	0.023**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Necessity		−0.092**				−0.133**				
		(0.025)				(0.029)				
UPC Sales Share			0.634**	0.427**			0.270**	0.252*		−0.118
			(0.178)	(0.201)			(0.128)	(0.142)		(0.136)
Brand Sales Share				0.163**				0.147**		0.172**
				(0.045)				(0.049)		(0.042)
Module HHI				−0.023				−0.214**		
				(0.051)				(0.067)		
Product Group FEs					Yes	Yes	Yes	Yes	Yes	Yes
Product Module FEs									Yes	Yes
N	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033
R^2	0.01	0.01	0.02	0.02	0.15	0.15	0.15	0.15	0.31	0.31

Notes: The unit of observation is a UPC. The dependent variable is the UPC retail markup, which is the sales-weighted average of markups at which the UPC was sold. Regression weighted by UPC sales, and robust standard errors in parentheses. Average buyer income is an expenditure-weighted average of buyers' incomes, recoding households' incomes as the bottom of the range provided by Nielsen. Necessity is measured as the share of households in the Homescan panel that purchase at least one good from that module in the year. UPC sales share, brand sales share, and the product module Herfindahl-Hirschman index are all calculated using sales in the Homescan data. * indicates significance at 10%, ** at 5%.

Table B.6: Relationship between buyer income (measured using the share of low-income buyers) and UPC retail markup.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share \$10-50K income	−0.335**	−0.366**	−0.342**	−0.332**	−0.186**	−0.191**	−0.195**	−0.191**	−0.183**	−0.179**
	(0.048)	(0.048)	(0.047)	(0.048)	(0.050)	(0.050)	(0.049)	(0.049)	(0.051)	(0.050)
Necessity		−0.089**				−0.133**				
		(0.025)				(0.029)				
UPC Sales Share			0.633**	0.425**			0.267**	0.250*		−0.120
			(0.179)	(0.201)			(0.129)	(0.143)		(0.136)
Brand Sales Share				0.158**				0.144**		0.169**
				(0.045)				(0.049)		(0.042)
Module HHI				−0.014				−0.212**		
				(0.050)				(0.067)		
Product Group FEs					Yes	Yes	Yes	Yes	Yes	Yes
Product Module FEs									Yes	Yes
N	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033
R^2	0.01	0.01	0.01	0.02	0.15	0.15	0.15	0.15	0.31	0.31

Notes: The unit of observation is a UPC. The dependent variable is the UPC retail markup, which is the sales-weighted average of markups at which the UPC was sold. Regression weighted by UPC sales, and robust standard errors in parentheses. Share \$10–50K income is the share of sales for a UPC made by households with between \$10–50K in reported household income. Necessity is measured as the share of households in the Homescan panel that purchase at least one good from that module in the year. UPC sales share, brand sales share, and the product module Herfindahl-Hirschman index are all calculated using sales in the Homescan data. * indicates significance at 10%, ** at 5%.

Table B.7: Relationship between buyer income and UPC retail markup (using Price-Trak deal prices as measure of wholesale costs).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share $100K+ income	0.611**	0.596**	0.622**	0.617**	0.170**	0.170**	0.189**	0.191**	0.171**	0.183**
	(0.064)	(0.063)	(0.064)	(0.063)	(0.060)	(0.060)	(0.059)	(0.059)	(0.054)	(0.054)
Necessity		0.032*				−0.083**				
		(0.019)				(0.027)				
UPC Sales Share			0.647**	0.447**			0.331**	0.361**		0.282**
			(0.150)	(0.167)			(0.121)	(0.137)		(0.130)
Brand Sales Share				0.165**				0.151**		0.150**
				(0.037)				(0.041)		(0.038)
Module HHI				−0.033				−0.286**		
				(0.046)				(0.059)		
Product Group FEs					Yes	Yes	Yes	Yes	Yes	Yes
Product Module FEs									Yes	Yes
N	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033	66 033
R^2	0.01	0.01	0.02	0.02	0.15	0.15	0.15	0.15	0.31	0.32

Notes: The unit of observation is a UPC. The dependent variable is the UPC retail markup, which is the sales-weighted average of markups at which the UPC was sold. Regression weighted by UPC sales, and robust standard errors in parentheses. Share $100K+ income is the share of sales for a UPC made by households with $100K or more in reported household income. Necessity is measured as the share of households in the Homescan panel that purchase at least one good from that module in the year. UPC sales share, brand sales share, and the product module Herfindahl-Hirschman index are all calculated using sales in the Homescan data. * indicates significance at 10%, ** at 5%.

Table B.8: Effect of income and county income on shopping intensity (measured per transaction).

	Shopping trips per 1k txns			Retailers visited per 1k txns		
	(1)	(2)	(3)	(4)	(5)	(6)
Income ($10,000s)	−4.83**	−4.78**	−4.87**	−0.19	−0.14	−0.18
	(0.84)	(0.78)	(0.78)	(0.15)	(0.14)	(0.14)
Avg. County Income		11.75**	8.74**		1.91**	0.70
		(3.42)	(3.55)		(0.44)	(0.48)
Log(Grocery Estabs.)			4.63**			1.85**
			(2.34)			(0.38)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	60 502	59 999	59 994	60 502	59 999	59 994
R^2	0.06	0.00	0.00	0.06	0.00	0.00

Notes: Household income is calculated using the minimum of the range provided by Nielsen (e.g., a household with an income of $13K would be in the range $12–15K and would be assigned a value of $12K). Average county income in 2009 is from the BEA Personal Income by County Area release. Grocery Estabs. are a count of NAICS 445 establishments from Census Business Patterns (includes grocery stores, supermarkets, liquor stores, and specialty food stores.) BEA and Census Business Pattern data is not available for a small number of counties in the Homescan sample. Standard errors clustered by county. * indicates significance at 10%, ** at 5%.

transactions (Table B.8), (2) the number of unique UPCs purchased (Table B.9), or (3) the number of unique brands purchased (Table B.10). In all three cases, we get qualitatively very similar results to those presented in the main text.

Table B.9: Effect of income and county income on shopping intensity (measured per unique UPCs purchased).

	Shopping trips per 100 UPCs			Retailers visited per 100 UPCs		
	(1)	(2)	(3)	(4)	(5)	(6)
Income ($10,000s)	−0.91**	−0.91**	−0.93**	−0.04**	−0.03*	−0.03**
	(0.11)	(0.10)	(0.11)	(0.02)	(0.02)	(0.02)
Avg. County Income		2.42**	1.81**		0.34**	0.15**
		(0.53)	(0.59)		(0.06)	(0.07)
Log(Grocery Estabs.)			0.93**			0.28**
			(0.34)			(0.05)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	60 502	59 999	59 994	60 502	59 999	59 994
R^2	0.06	0.00	0.00	0.06	0.00	0.00

Notes: Household income is calculated using the minimum of the range provided by Nielsen (e.g., a household with an income of $13K would be in the range $12–15K and would be assigned a value of $12K). Average county income in 2009 is from the BEA Personal Income by County Area release. Grocery Estabs. are a count of NAICS 445 establishments from Census Business Patterns (includes grocery stores, supermarkets, liquor stores, and specialty food stores.) BEA and Census Business Pattern data is not available for a small number of counties in the Homescan sample. Standard errors clustered by county. * indicates significance at 10%, ** at 5%.

Table B.10: Effect of income and county income on shopping intensity (measured per unique brand purchased).

	Shopping trips per 100 brands			Retailers visited per 100 brands		
	(1)	(2)	(3)	(4)	(5)	(6)
Income ($10,000s)	−1.21**	−1.22**	−1.24**	−0.04**	−0.03*	−0.04**
	(0.12)	(0.12)	(0.12)	(0.02)	(0.02)	(0.02)
Avg. County Income		3.30**	2.42**		0.46**	0.22**
		(0.62)	(0.73)		(0.06)	(0.07)
Log(Grocery Estabs.)			1.35**			0.37**
			(0.38)			(0.05)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	60 502	59 999	59 994	60 502	59 999	59 994
R^2	0.06	0.00	0.00	0.06	0.00	0.01

Notes: Household income is calculated using the minimum of the range provided by Nielsen (e.g., a household with an income of $13K would be in the range $12–15K and would be assigned a value of $12K). Average county income in 2009 is from the BEA Personal Income by County Area release. Grocery Estabs. are a count of NAICS 445 establishments from Census Business Patterns (includes grocery stores, supermarkets, liquor stores, and specialty food stores.) BEA and Census Business Pattern data is not available for a small number of counties in the Homescan sample. Standard errors clustered by county. * indicates significance at 10%, ** at 5%.

Appendix C Proofs

C.1 Firms

Given $\langle \bar{q}_n \rangle_{n=1}^{\infty}$, recall that $\bar{q}_1$ quotes are retrieved by households receiving only one quote, $2\bar{q}_2$ quotes are retrieved by households receiving two quotes, $3\bar{q}_3$ quotes are retrieved by households receiving three quotes, and so on. Hence, the demand facing a firm charging price $p \leq R$ is

$$
\begin{aligned}
D(p) &= \frac{1}{M}\left[\bar{q}_1 + 2\bar{q}_2\left(1 - F(p)\right) + 3\bar{q}_3\left(1 - F(p)\right)^2 + ...\right] \\
&= \frac{1}{M}\sum_{n=1}^{\infty} n\bar{q}_n\left(1 - F(p)\right)^{n-1},
\end{aligned}
$$

and zero for any firm charging a price $p > R$. Accordingly, variable profits at any price $p \leq R$ are

$$
\pi = \frac{1}{M}\left(p - mc\right)\sum_{n=1}^{\infty} n\bar{q}_n\left(1 - F(p)\right)^{n-1}.
$$

Our equilibrium condition for the offer price distribution $F(p)$ is that all firms charging $p \in \text{supp}(F)$ make equal profits π, and any firm charging some $p \notin \text{supp}(F)$ will make profits strictly less than π. A firm charging the maximum price in the support of p (assuming $\bar{p} \leq R$) makes profits

$$
\pi(\bar{p}) = \frac{1}{M}(\bar{p} - mc)\bar{q}_1.
$$

As long as $\bar{q}_1 > 0$, profits of this firm are monotonically increasing in the price it charges in the region $p \leq R$, so it is clear that $\bar{p} = R$ as long as $\bar{q} > 1$. Hence, profits of all firms must be

$$
\pi = \frac{1}{M}\left(R - mc\right)\bar{q}_1.
$$

Accordingly, the distribution $F(p)$ is pinned down by the condition

$$
\frac{R - mc}{p - mc}\bar{q}_1 = \sum_{n=1}^{\infty} n\bar{q}_n\left(1 - F(p)\right)^{n-1}.
$$

Solving yields the expression for F (6) and for the minimum price $\underline{p}$ (7).

The aggregate markup (total sales over total costs) for firms in this economy can be represented as

$$\bar{\mu} = 1 + \frac{\int_{\underline{p}}^{R} (p - mc)\, D(p) \cdot MdF(p)}{\int_{\underline{p}}^{R} mcD(p) \cdot MdF(p)} = 1 + \int_{\underline{p}}^{R} \frac{\pi}{mc} \cdot MdF(p) = 1 + \left(\frac{R}{mc} - 1\right)\bar{q}_1. \qquad (11)$$

Hence, given R/mc (i.e., the maximum markup in the support of F), the fraction of households getting only one price quote $\bar{q}_1$ is a sufficient statistic for the aggregate markup in the model. We can confirm this intuition by considering the two edge cases: when $\bar{q}_1 = 1$, no consumers search, resulting in the monopoly price equilibrium (Diamond 1971), and when $\bar{q}_1 = 0$, all consumers search, and we obtain competitive marginal cost pricing.

C.2 Household utility maximization

Given the distribution of prices offered by firms $F(p)$, the distribution of prices paid by household i is:

$$G_i(p) = \underbrace{q_{i,1}F(p)}_{\substack{\text{Receives one} \\ \text{price quote}}} + \underbrace{q_{i,2}(1 - (1 - F(p))^2)}_{\substack{\text{Receives two} \\ \text{price quotes}}} + \ \dots = \sum_{n=1}^{\infty} q_{i,n}(1 - (1 - F(p))^n).$$

The expected price paid by household i is then $\mathbb{E}[p_i|s_i, F] = \int_{\underline{p}}^{R} pdG_i(p)$. Equivalently, the expected price can be written as

$$\mathbb{E}[p_i|s_i, F] = \sum_{n=1}^{\infty} q_{i,n}\mathbb{E}[p|n],$$

where

$$\mathbb{E}\,[p|n] = \int_{\underline{p}}^{R} pn\,(1 - F(p))^{n-1}\, dF(p)$$

is the expected price paid having received n independent price quotes. It is easy to verify that $\mathbb{E}[p|n]$ is decreasing in n and that the returns to an additional price quote $(-\partial\mathbb{E}[p|n]/\partial n)$ are also decreasing in n. I.e., $\mathbb{E}[p|n]$ is decreasing and convex in n.

Using the above expression for $\mathbb{E}[p_i|s_i, F]$ and the fact that $q_{i,n} = Q_{i,n} - Q_{i,n-1}$ (where $Q_{i,0} = 0$), we can rewrite the household first-order condition (4) as

$$\frac{z_i}{a_i} = -\sum_{n=1}^{\infty} \frac{dQ_{i,n}}{ds_i}\left[\mathbb{E}\,[p|n] - \mathbb{E}\,[p|n+1]\right].$$

Assumption 1(B) guarantees that $dQ_{i,n}/ds_i < 0$ for all n, thus guaranteeing that the right-hand side of this expression is positive (strictly when F is non-degenerate).

It will be helpful below to calculate the first and second derivatives of s_i with respect to z_i/a_i. Again using the household first-order condition, we get:

$$\frac{ds_i}{d\left(\frac{z_i}{a_i}\right)} = \frac{1}{\frac{-d^2\mathbb{E}[p_i]}{ds_i^2}}, \qquad \text{and} \qquad \frac{d^2 s_i}{d\left(z_i/a_i\right)^2} = \frac{\frac{d^3\mathbb{E}[p_i]}{ds_i^3}}{\left(\frac{-d^2\mathbb{E}[p_i]}{ds_i^2}\right)^3}.$$

C.3 Equilibrium stability

In equilibrium, for each household we must have (assuming all households have an internal solution for s_i):

$$\frac{z_i}{a_i} = -\sum_{n=1}^{\infty} \frac{dQ_{i,n}}{ds_i}\left[\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right]\right].$$

Taking the integral of both sides with respect to the type distribution $dH(i)$, we get:

$$\underbrace{\int_0^{\infty} \frac{z_i}{a_i} dH(i)}_{\text{Aggregate opportunity cost of time}} = \underbrace{\sum_{n=1}^{\infty}\left(\int_0^{\infty} \frac{-dQ_{i,n}}{ds_i} dH(i)\right)\left[\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right]\right]}_{\text{Aggregate returns to search}}. \tag{12}$$

In equilibrium, the "aggregate opportunity cost of time"—the sum of the marginal cost of increasing search intensity across all households—must equal the "aggregate returns to search"—the sum of the incremental benefits that households get from searching more.

The right-hand side of (12) depends crucially on the fraction of households getting exactly one price quote, $\bar{q}_1$. To see why, note that when $\bar{q}_1 = 1$, all firms set the monopoly price, and hence the distribution F is degenerate with all firms setting $p = R$. When $\bar{q}_1 = 0$, all consumers get at least two price quotes, and therefore no firm is willing to take a higher price than all other firms. Hence, all firms price at marginal cost, and the distribution F is again degenerate at $p = mc$.

This means that, for both $\bar{q}_1 = 0$ and $\bar{q}_1 = 1$, the right-hand side of (12) is zero. For any intermediate value of $\bar{q}_1 \in (0, 1)$, the right-hand side of (12) is strictly positive by Assumption 1(B).

Hence, if there is exists at least one value of $\bar{q}_1$ for which (12) holds, then there must exist at least one value of $\bar{q}_1$ where (12) holds *and* the right-hand side of (12) is weakly increasing in $\bar{q}_1$ (by Assumption 1(C)). I refer to such an equilibrium in which (12) holds and in which the right-hand side is weakly increasing in $\bar{q}_1$ as a *stable equilibrium*.

Why? Suppose the right-hand side of (12) is instead weakly decreasing in $\bar{q}_1$. Then, consider an idiosyncratic decrease in the search intensity by any one household. A decrease in any s_i increases $\bar{q}_1$. Since the right-hand side of (12) is decreasing in $\bar{q}_1$, the returns to search each individual household decrease, and this leads to further decreases in search intensity by all households. Hence, the equilibrium in which the right-hand side of (12) is decreasing in $\bar{q}_1$ is unstable to any perturbations.

For intuition, I consider the two-quote and Poisson distribution cases.

C.3.1 Two-quote case

Suppose that households always receive only one or two quotes, and that the probability of receiving two quotes is increasing in i's effort according to $q_{i,2} = 1 - \exp(-s_i)$. Thus

$$Q_{i,1} = \exp(-s_i),$$
$$Q_{i,2} = 1.$$

In this case, (12) becomes

$$\left(\int_0^\infty q_{i,1} dH(i)\right)(\mathbb{E}[p|1] - \mathbb{E}[p|2]) = \int_0^\infty \frac{z_i}{a_i} dH(i). \tag{13}$$

With some algebra, we can show that the price distribution $F(p)$, the minimum price $\underline{p}$, the expected price from one and two searches $\mathbb{E}[p|1]$ and $\mathbb{E}[p|2]$, and the returns to search $\mathbb{E}[p|1] - \mathbb{E}[p|2]$ are given by:

$$\begin{aligned}
F(p) &= 1 - \frac{1}{2}\frac{\bar{q}_1}{1-\bar{q}_1}\frac{R-p}{p-mc}, \\
\underline{p} &= mc + \frac{\bar{q}_1}{2-\bar{q}_1}(R-mc), \\
\mathbb{E}[p|1] &= mc + \frac{1}{2}\frac{\bar{q}_1}{1-\bar{q}_1}(R-mc)\log\left(\frac{2-\bar{q}_1}{\bar{q}_1}\right), \\
\mathbb{E}[p|2] &= mc + \frac{q_1}{1-\bar{q}_1}(R-mc) - \frac{1}{2}\left(\frac{q_1}{1-\bar{q}_1}\right)^2(R-mc)\log\left(\frac{2-\bar{q}_1}{\bar{q}_1}\right), \\
\mathbb{E}[p|1] - \mathbb{E}[p|2] &= \frac{\bar{q}_1}{1-\bar{q}_1}(R-mc)\left[\frac{1}{2}\frac{1}{1-\bar{q}_1}\log\left(\frac{2-\bar{q}_1}{\bar{q}_1}\right) - 1\right].
\end{aligned}$$

So, we can rewrite (13) as

$$\underbrace{\frac{\bar{q}_1^2}{1-\bar{q}_1}(R-mc)\left[\frac{1}{2}\frac{1}{1-\bar{q}_1}\log\left(\frac{2-\bar{q}_1}{\bar{q}_1}\right)-1\right]}_{\text{Aggregate returns to search}} = \underbrace{\int_0^\infty \frac{z_i}{a_i}dH(i)}_{\text{Aggregate cost of time}} \quad .$$

Figure C.4a illustrates this aggregate equilibrium condition (using the exact functional form above). We can see that there is some threshold c such that (1) if the aggregate opportunity cost of time is greater than c, no dispersed-price equilibrium exists and the sole equilibrium is the monopoly-price equilibrium (all households choose $s_i = 0$); (2) if the aggregate opportunity cost of time is equal to c, there is exactly one value of $\bar{q}_1$ delivering a dispersed-price equilibrium, and (3) if the aggregate opportunity cost of time is less than c, there are two values of $\bar{q}_1$ with corresponding dispersed-price equilibria.

The arrows indicate how the equilibrium responds to a perturbation. We see that only the left-hand side equilibrium, where aggregate returns to search are increasing in $\bar{q}_1$, is a stable equilibrium. In this equilibrium, household decisions are strategic substitutes: an idiosyncratic increase in one household's search intensity decreases the returns to search and leads all other households to decrease search effort.

C.3.2 Poisson case

Under the Poisson distribution, the mapping from s_i to the probability mass function of price quotes is

$$q_{i,n+1} = e^{-s_i}\frac{s_i^n}{n!}.$$

Note the index $n+1$, so that the support of the distribution starts from one.

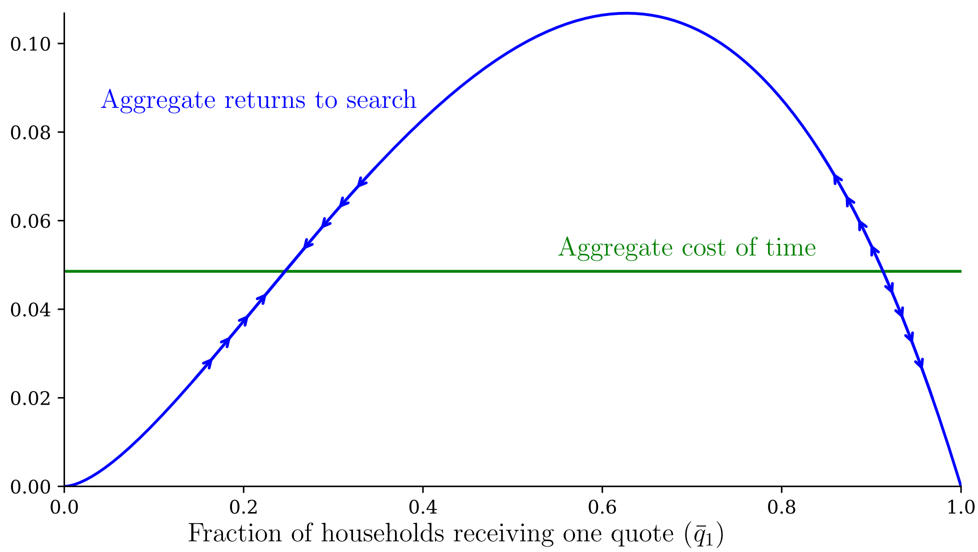
We can rewrite the household first-order condition as:

$$\sum_{n=1}^{\infty} -\frac{dq_{i,n}}{ds_i}\mathbb{E}\left[p|n\right] = \frac{z_i}{a_i}.$$

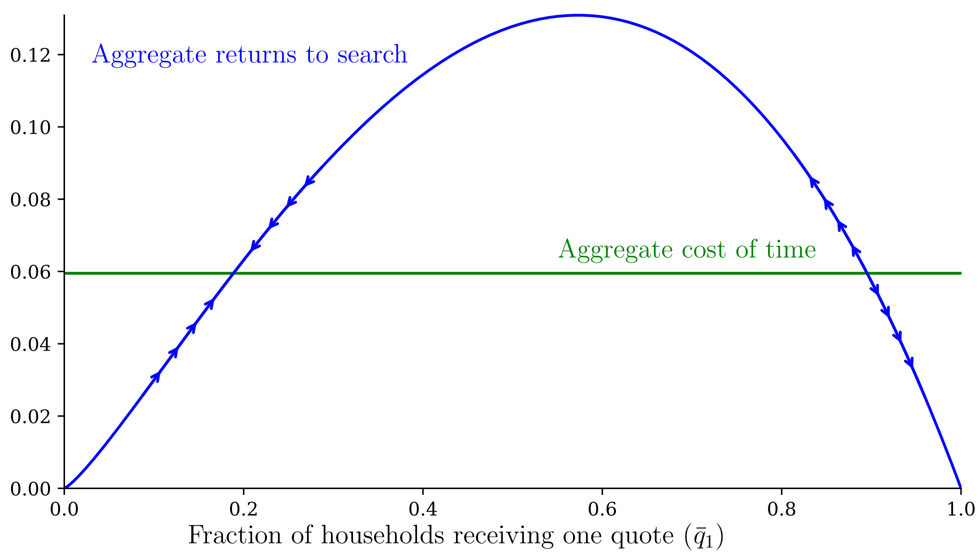
With some algebra, we can simplify this as:

$$\begin{aligned}\frac{z_i}{a_i} &= \sum_{n=1}^{\infty} -\frac{d}{ds_i}\left[\left(\frac{s_i^{n-1}\exp\left(-s_i\right)}{(n-1)!}\right)\right]\mathbb{E}\left[p|n\right] \\ &= \sum_{n=1}^{\infty} \frac{s_i^{n-1}\exp\left(-s_i\right)}{(n-1)!}\left(\mathbb{E}\left[p|n\right]-\mathbb{E}\left[p|n+1\right]\right)\end{aligned}$$

Figure C.4: Stable and unstable equilibria in two parameterizations of the nonsequential search equilibrium.



(a) Two-quote parameterization.



(b) Poisson parameterization.

$$= \sum_{n=1}^{\infty} q_{i,n} \left(\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right] \right).$$

So, the aggregate equilibrium condition is simply

$$\sum_{n=1}^{\infty} \bar{q}_n \left(\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right] \right) = \int_0^{\infty} \frac{z_i}{a_i} dH(i).$$

Clearly, the left-hand side only depends on $\bar{q}_1$. Figure C.4b illustrates this aggregate equilibrium condition (again using the exact functional form above). The implications are identical to those in the two-quote case.

C.4 Comparative statics of markups to the income distribution

Recall from (11) that the aggregate markup in the economy is

$$\bar{\mu} = 1 + \left(\frac{R}{mc} - 1 \right) \int_0^{\infty} q_{i,1} dH(i).$$

A first-order stochastic dominant shift to $H(i)$ increases $\bar{\mu}$ if $q_{i,1}$ is increasing in i, and a mean-preserving spread in $H(i)$ increases $\bar{\mu}$ if $q_{i,1}$ is increasing and convex in i. So, conditions that guarantee $q_{i,1}$ is increasing and convex in i are sufficient to deliver increasing markups in response to either a first-order stochastic shift or a mean-preserving spread in the income distribution $H(i)$.

We can write (noting that $q_{i,1} = Q_{i,1}$),

$$\frac{dQ_{i,1}}{di} = \underbrace{\frac{dQ_{i,1}}{ds_i}}_{(-) \text{ by Assumption 1(B)}} \frac{ds_i}{d\left(z_i/a_i\right)} \frac{d\left(z_i/a_i\right)}{di}.$$

If z_i/a_i is increasing in i, then showing that $\frac{ds_i}{d(z_i/a_i)} < 0$ is sufficient to show that $\frac{dQ_{i,1}}{di} > 0$. Recall that

$$\frac{ds_i}{d\left(\frac{z_i}{a_i}\right)} = \frac{1}{\frac{-d^2\mathbb{E}[p_i]}{ds_i^2}} \qquad \text{and} \qquad \frac{d^2\mathbb{E}\left[p_i\right]}{ds_i^2} = \sum_{n=1}^{\infty} \frac{d^2 Q_{i,n}}{ds_i^2} \left[\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right] \right].$$

Hence we arrive at condition 1:

Condition 1.

$$\sum_{n=1}^{\infty} \frac{d^2 Q_{i,n}}{ds_i^2} \left[\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right]\right] > 0.$$

To review the logic, Condition 1 guarantees that $\frac{ds_i}{d(z_i/a_i)} < 0$, which in turn guarantees that $\frac{dQ_{i,1}}{di} > 0$ when $d(z_i/a_i)/di > 0$.

The second derivative of $Q_{i,1}$ with respect to i is more complicated:

$$\frac{d^2 Q_{i,1}}{di^2} = \frac{d^2 Q_{i,1}}{ds_i^2} \underbrace{\left(\frac{ds_i}{d\left(z_i/a_i\right)} \frac{d\left(z_i/a_i\right)}{di}\right)^2}_{(+)} + \frac{d^2 s_i}{d\left(z_i/a_i\right)^2} \underbrace{\frac{dQ_{i,1}}{ds_i} \left(\frac{d\left(z_i/a_i\right)}{di}\right)^2}_{(-)} + \underbrace{\frac{dQ_{i,1}}{ds_i} \frac{ds_i}{d\left(z_i/a_i\right)}}_{(+)} \frac{d^2\left(z_i/a_i\right)}{di^2}.$$

where the indicated signs presuppose that Condition 1 holds. If z_i/a_i is increasing and convex in i, then for $\frac{d^2 Q_{i,1}}{di^2}$ to be increasing and convex in i, it is sufficient to show that

$$\frac{d^2 Q_{i,1}}{ds_i^2} \underbrace{\left(\frac{ds_i}{d\left(z_i/a_i\right)}\right)^2}_{(+)} + \frac{d^2 s_i}{d\left(z_i/a_i\right)^2} \underbrace{\frac{dQ_{i,1}}{ds_i}}_{(-)} \geq 0.$$

By plugging in the expressions above for $ds_i/d(z_i/a_i)$, we get Condition 2.

Condition 2.

$$\sum_{n=1}^{\infty} \left(\frac{d^2 Q_{i,1}}{ds_i^2} \frac{d^2 Q_{i,n}}{ds_i^2} - \frac{dQ_{i,1}}{ds_i} \frac{d^3 Q_{i,n}}{ds_i^3}\right) \left[\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right]\right] \geq 0.$$

Again, Condition 1 and Condition 2 are sufficient to conclude that $\frac{d^2 Q_{i,1}}{di^2} > 0$ if $\frac{d^2(z_i/a_i)}{di^2} > 0$.

C.4.1 Application to two-quote case

Suppose that households always receive only one or two quotes, and that the probability of receiving two quotes is increasing in i's effort according to $q_{i,2} = 1 - \exp(-s_i)$. Thus

$$Q_{i,1} = \exp\left(-s_i\right),$$
$$Q_{i,2} = 1.$$

I show that both Condition 1 and Condition 2 hold for this mapping $\mathcal{S}$.

Condition 1 becomes:

$$\exp(-s_i)\left[\mathbb{E}[p|1] - \mathbb{E}[p|2]\right] > 0,$$

which is trivially true since $\exp(-s_i) > 0$ and since $\mathbb{E}[p|n]$ is strictly decreasing in n when F is non-degenerate.

Condition 2 becomes:

$$\left((-\exp(-s_i))^2 - (\exp(-s_i))^2\right)\left[\mathbb{E}[p|1] - \mathbb{E}[p|2]\right] = 0 \geq 0.$$

So, we verify that the two-quote mapping satisfies both conditions.

C.4.2 Application to Poisson distribution

Under the Poisson distribution, the mapping from s_i to the probability mass function of price quotes is

$$q_{i,n+1} = e^{-s_i}\frac{s_i^n}{n!}.$$

Note the index $n+1$, so that the support of the distribution starts from one. Accordingly,

$$Q_{i,n+1} = \sum_{k=0}^{n} e^{-s_i}\frac{s_i^k}{k!}.$$

For convenience in the below derivations, I drop the i subscripts. The first derivative with respect to s is

$$\begin{aligned}
\frac{dQ_{n+1}}{ds} &= -e^{-s}\left(1 + \sum_{k=1}^{n}\frac{s^k}{k!}\right) + e^{-s}\left(\sum_{k=1}^{n}\frac{ks^{k-1}}{k!}\right)\\
&= -e^{-s}\left(1 + \sum_{k=1}^{n}\frac{s^k}{k!}\right) + e^{-s}\left(1 + \sum_{k=1}^{n-1}\frac{s^k}{k!}\right)\\
&= -e^{-s}\frac{s^n}{n!}.
\end{aligned}$$

Consequently,

$$\begin{aligned}
\frac{d^2Q_{n+1}}{ds^2} &= e^{-s}\frac{s^{n-1}}{n!}(s-n) && \text{for } n \geq 1,\\
\frac{d^3Q_{n+1}}{ds^3} &= -e^{-s}\frac{s^{n-2}}{n!}\left((s-n)^2 - n\right) && \text{for } n \geq 2.
\end{aligned}$$

For Q_1 and Q_2, we can explicitly write

$$\frac{d^2Q_1}{ds^2} = e^{-s}$$
$$\frac{d^3Q_1}{ds^3} = -e^{-s},$$
$$\frac{d^2Q_2}{ds^2} = e^{-s}(s-1),$$
$$\frac{d^3Q_2}{ds^3} = -e^{-s}(s-2).$$

Now we are ready to simplify Condition 1:

$$\sum_{n=1}^{\infty} \frac{d^2Q_{i,n}}{ds_i^2} \left[\mathbb{E}[p|n] - \mathbb{E}[p|n+1]\right] > 0$$

$$e^{-s}\left[\mathbb{E}[p|1] - \mathbb{E}[p|2]\right] + \sum_{n=1}^{\infty} \frac{d^2Q_{i,n+1}}{ds_i^2} \left[\mathbb{E}[p|n+1] - \mathbb{E}[p|n+2]\right] > 0$$

With some algebra, this condition simplifies to:

$$\sum_{n=0}^{\infty} e^{-s}\frac{s^n}{n!}\left(\left[\mathbb{E}[p|n+1] - \mathbb{E}[p|n+2]\right] - \left[\mathbb{E}[p|n+2] - \mathbb{E}[p|n+3]\right]\right) > 0$$

Since $\exp(-s)$ is strictly positive and $\mathbb{E}[p|n]$ is decreasing and convex in n, we verify this condition holds.

Now, for Condition 2. Again, some algebra reveals:

$$\sum_{n=1}^{\infty}\left(\frac{d^2Q_{i,1}}{ds_i^2}\frac{d^2Q_{i,n}}{ds_i^2} - \frac{dQ_{i,1}}{ds_i}\frac{d^3Q_{i,n}}{ds_i^3}\right)\left[\mathbb{E}[p|n] - \mathbb{E}[p|n+1]\right] \geq 0.$$

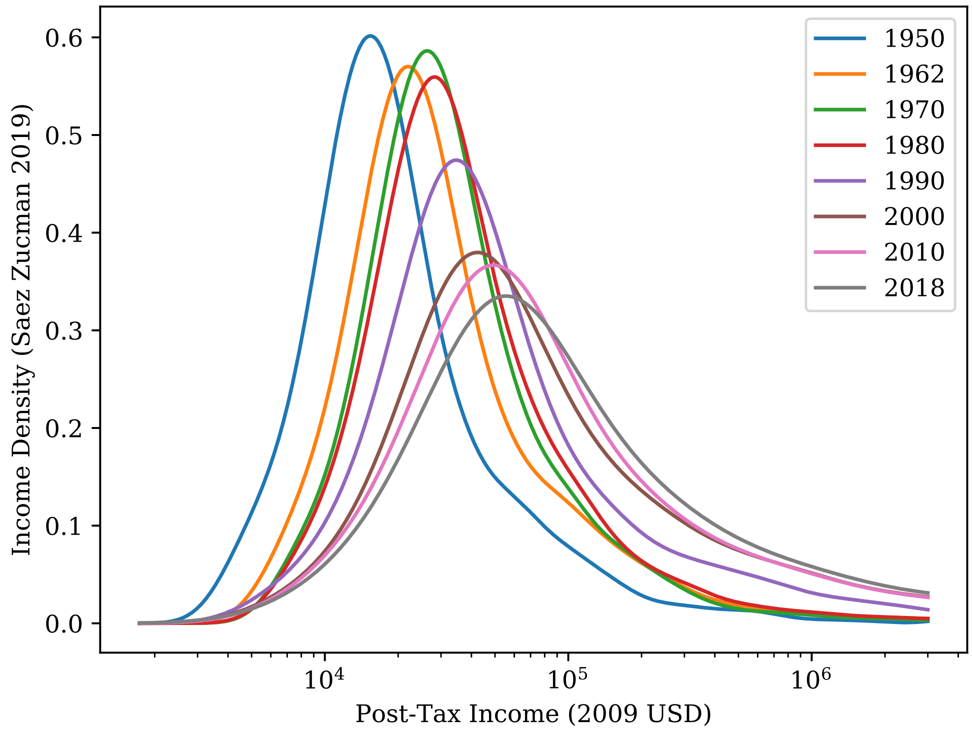
$$\sum_{n=1}^{\infty} e^{-s}\left(\frac{d^2Q_{i,n}}{ds_i^2} + \frac{d^3Q_{i,n}}{ds_i^3}\right)\left[\mathbb{E}[p|n] - \mathbb{E}[p|n+1]\right] \geq 0.$$

$$\left[\mathbb{E}[p|2] - \mathbb{E}[p|3]\right] + \sum_{n=2}^{\infty}\left(\frac{s^{n-1}}{(n-1)!} - \frac{s^{n-2}}{(n-2)!}\right)\left[\mathbb{E}[p|n+1] - \mathbb{E}[p|n+2]\right] \geq 0.$$

$$\sum_{n=0}^{\infty} \frac{s^n}{n!}\left(\left[\mathbb{E}[p|n+2] - \mathbb{E}[p|n+3]\right] - \left[\mathbb{E}[p|n+3] - \mathbb{E}[p|n+4]\right]\right) \geq 0.$$

Again, since $\mathbb{E}[p|n]$ is decreasing and convex in n, we verify this condition holds.

Figure D.1: Density $dH(i)$, constructed from data by Saez and Zucman (2019).



Appendix D Calibration: Additional Figures

This section includes backup figures for the calibration in the main text.

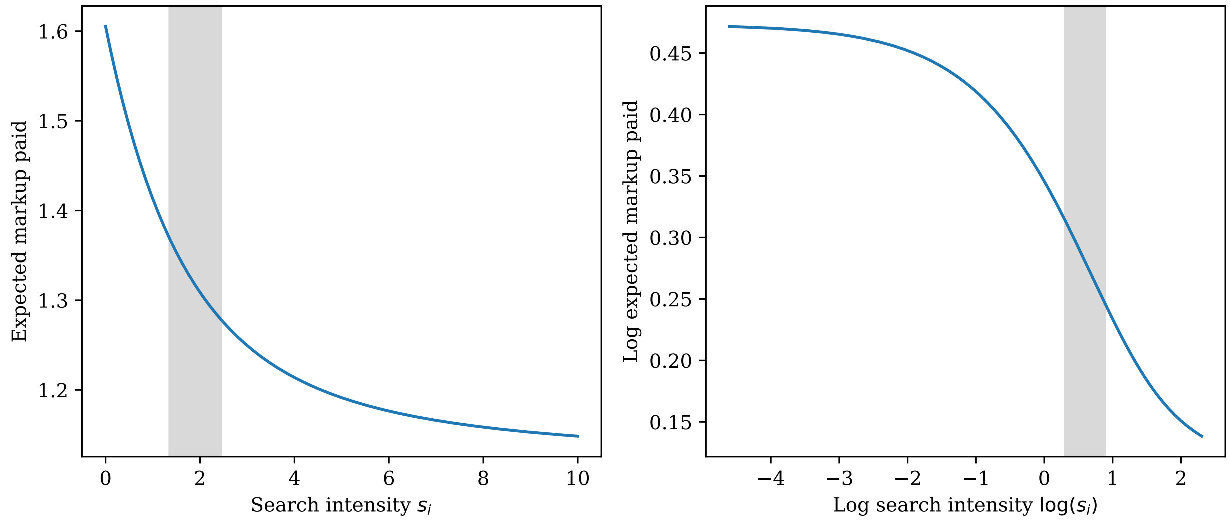
Figure D.1 plots the post-tax income-weighted density of households in post-tax 2009 USD from Saez and Zucman (2019). For the purposes of plotting only, I fit a Gaussian kernel with a bandwidth of 0.25 log income points to percentiles of the distribution documented by Saez and Zucman (2019).

Figure D.2 plots the expected price paid as a function of the a household's search intensity s_i in the baseline calibration. The shaded region indicates the range of search intensities s_i chosen by income groups in the baseline calibration. The elasticity of markups paid to search effort (which is equal to the elasticity of markups paid to shopping time for any household i) is 11.0–11.6 percent for households in the shaded region.

Appendix E Sequential Search Model

As an alternative search technology to the nonsequential search in the main text, in this appendix I describe a model where households search for products sequentially. The

Figure D.2: Returns to consumer search.



Notes: The shaded region indicates the range of search intensities s_i chosen by income groups in the baseline calibration. The elasticity of markups paid to income is 11.0-11.6% across income groups.

model parallels the labor market sequential search model by Burdett and Mortensen (1998). Again, the innovation in the model is that heterogeneous households endogenously choose search intensities.

E.1 Households

There is a unit measure of households indexed by type $i \in [0, \infty)$. Types are distributed in the population according to the density $dH(i)$, where $H(i)$ is the share of households with type less than or equal to i. Households search for an identical good sold by a measure of m firms. All households are risk-neutral and discount future utility at rate r. As in canonical models of search frictions, households know the distribution of prices offered by firms, $F(p)$, but do not know which retailer sells at which price. Denote $\underline{p}$ and $\bar{p}$ the infimum and supremum of the support of F.

At any moment, a household is either "matched" to a retailer or unmatched. Matching can be thought of as a consumption habit—for instance, a household may be used to buying milk from a certain retail outlet. At an arrival rate λ_i, household i receives information about the price of the good sold by another retailer. (As we will see later, the arrival rate of new price quotes is a result of i's endogenous choice of search intensity.) Since households search randomly across retailers, this new price quote is assumed to be a random draw from $F(p)$. Households have no recall of previous price quotes and may only switch to buying from the new retailer at the time when the quote arrives. Matches between households and retailers are destroyed at an exogenous positive rate δ (which can be interpreted as discontinued products, price changes, or store closures).

At time t, household i's flow utility is

$$u_{i,t} = \begin{cases} z_i(T - t_i) + R - p_{i,t} & \text{if } i \text{ purchases good at price } p_{i,t} \text{ in period } t \\ z_i(T - t_i) & \text{otherwise} \end{cases}$$

where t_i is the time i spends shopping, $T - t_i$ is the time i spends working with wage equal to i's labor productivity z_i, and R is the value of the good (which I assume is identical across households).

Given this setup, the expected discounted lifetime utility of household i when unmatched, $V_{i,0}$, and when matched to a retailer offering the good at price p, $V_{i,1}(p)$, satisfy

$$rV_{i,0} = z_i\left(T - t_i\right) + \lambda_i\left[\int_{\underline{p}}^{\bar{p}} \max\left\{V_{i,1}\left(p\right) - V_{i,0}, 0\right\} dF(p)\right],$$

$$rV_{i,1}\left(p\right) = z_i\left(T - t_i\right) + R - p + \lambda_i\left[\int_{\underline{p}}^{\bar{p}} \max\left\{V_{i,1}\left(x\right) - V_{i,1}\left(p\right), 0\right\} dF(x)\right] + \delta\left[V_{i,0} - V_{i,1}\left(p\right)\right].$$

It is straightforward to show that $V_{i,1}(p) \geq V_{i,0}$ only if $p \leq R$. For this reason, R is the maximum price at which any household is willing to buy the good. As I will show below, no firm chooses to set a price above R in equilibrium, so we can simplify all subsequent expressions using $F(R) = 1$.

I will now proceed in two steps. First, I show that if there is some p in the support of F such that $\underline{p} < p < \bar{p}$ (the distribution of prices F has more than two unique points in its support), the steady-state distribution of prices paid by a household i first-order stochastically dominate the prices paid by another household j if and only if $\lambda_i < \lambda_j$. Second, I endogenize household's decision of search intensity and derive sufficient conditions under which search intensity is decreasing with i.

Denote the steady-state distribution of prices paid by household i by $G_i(p)$ and the fraction of households of type i that are unmatched to a retailer at any moment by ϕ_i. In steady state, the flows of households of type i to a retailer with price greater than or equal to p must equal the out-flows of households of type i matched to a retailer with price greater than or equal to p:

$$\lambda_i\left[F(R) - F(p)\right]\phi_i dH(i) = \left[\delta + \lambda_i F(p)\right]\left(1 - \phi_i\right)\left[1 - G_i(p)\right] dH(i).$$

Setting $p = \underline{p}$ allows us to solve for the unmatched fraction of households of type i, ϕ_i, and we then find that the distribution of prices paid by household i is

$$G_i(p) = \frac{(\delta + \lambda_i)\, F(p)}{\delta + \lambda_i F(p)}.$$

Suppose we have two households i and j where $\lambda_i < \lambda_j$. The distribution of prices paid by household i first order stochastically dominates that paid by household j if $G_i(p) \leq G_j(p)$ for all p and $G_i(p) < G_j(p)$ for some p. Since

$$G_j(p) = G_i(p) + \frac{\delta F(p)\,(1 - F(p))}{\left[\delta + \lambda_i F(p)\right]\left[\delta + \lambda_j F(p)\right]} \left(\lambda_j - \lambda_i\right), \tag{14}$$

it is clear that $G_j(p) \leq G_i(p)$ for all p and that the inequality will hold strictly for any p where $F(p)$ is not zero or one. Equation (14) conveys the main intuition for cross-sectional differences in prices paid across households due to differences in search intensity: by increasing search intensity λ_i, a household shifts the steady-state distribution of prices it pays to the left.

Households choose to exert search effort to maximize expected discounted lifetime utility.

$$\lambda_i = \arg\max_{\lambda} \mathbb{E}\left[\int_0^{\infty} \exp(-rt)\; u_{i,t}\; dt\right].$$

I assume that the time required to achieve search intensity λ_i is given by the concave function

$$\lambda_i = 1 - \exp(-a_i t_i),$$

where a_i is shopping productivity that can vary across households. The first-order condition for λ_i equates the opportunity cost of i's time to the expected benefit from increasing search intensity:

$$\frac{z_i}{a_i} = \delta\,(1 - \lambda_i)\left[\frac{1}{(\delta + \lambda_i)^2} R - \int_{\underline{p}}^{R} \frac{\delta - \lambda_i F(p)}{\left[\delta + \lambda_i F(p)\right]^3} p dF(p)\right]. \tag{15}$$

Taking the comparative static with respect to i yields Proposition 3.

Proposition 3. *Search intensity λ_i is (weakly) decreasing in i if z_i/a_i is increasing in i (labor productivity increases faster than shopping productivity in i).*

Now that we know how the prices paid by a household depend on its search intensity, and how that search intensity is determined by a household's labor and shopping productivity, we can move on to the firm problem.

E.2 Firms

A measure M of ex ante identical firms with marginal cost mc set prices to maximize profits. The demand that a firm faces depends on its price and on the distribution of prices charged by other firms. In particular, the demand from household type i at a price $p \leq R$ is

$$\begin{aligned} D_i(p) &= \frac{1}{M} \frac{G_i(p^+) - G_i(p)}{F(p^+) - F(p)} \left(1 - \phi_i\right) dH(i) \\ &= \frac{\delta}{M} \frac{\lambda_i}{\left[\delta + \lambda_i F(p^+)\right]\left[\delta + \lambda_i F(p)\right]} dH(i), \end{aligned}$$

where p^+ is a price marginally greater than p. Demand at a price $p > R$ is zero since R is the reservation price for all households.

Aggregating across households, we find that a firm charging price $p \leq R$ has profits

$$\pi(p) = (p - mc) \frac{\delta}{M} \int_0^\infty \frac{\lambda_i}{\left[\delta + \lambda_i F(p^+)\right]\left[\delta + \lambda_i F(p)\right]} dH(i).$$

The price distribution F is an equilibrium price distribution if firms charging p in the support of F make identical profits π, but any firm charging $p \notin \text{supp}(F)$ makes profits strictly less than π. As long as $R > mc$, $\pi(R) > 0$ and so the maximum price in the support of F must be less than or equal to R. As such, we can limit our focus to distributions F where $\bar{p} \leq R$.

We can also rule out non-continuous distributions for F. The intuition is the same as in the Burdett and Mortensen (1998) model with identical workers: if F has a mass point at some $\hat{p}$, then a firm offering a price slightly lower than $\hat{p}$ will have significantly higher demand and only a marginal loss in profits per item sold.

Consider the profits of a firm charging that maximum price $\bar{p}$:

$$\pi(\bar{p}) = (\bar{p} - mc) \frac{\delta}{M} \int_0^\infty \frac{\lambda_i}{(\delta + \lambda_i)^2} dH(i). \tag{16}$$

Clearly, $\pi(\bar{p})$ is strictly increasing in $\bar{p}$, so the maximum price will exactly equal the households' reservation price R. Since $\pi(p) = \pi(R)$ for all $p \in \text{supp}(F)$, we can pin down the minimum price in F and the overall shape of F:

$$\underline{p} = mc + \delta^2 (R - mc) \frac{\int_0^\infty \frac{\lambda_i}{(\delta+\lambda_i)^2} dH(i)}{\int_0^\infty \lambda_i dH(i)} \quad \text{and} \quad \frac{\int_0^\infty \frac{\lambda_i}{(\delta+\lambda_i)^2} dH(i)}{\int_0^\infty \frac{\lambda_i}{[\delta+\lambda_i F(p)]^2} dH(i)} = \frac{p - mc}{R - mc}. \tag{17}$$

E.3 Equilibrium

Given R, mc, and household distribution $H(i)$, an equilibrium is a tuple $\left(\{\lambda_i\}_{i=0}^{\infty}, F, \pi, M\right)$ where household type i's search intensity λ_i maximizes its expected discounted lifetime utility given F, all firms choosing a price $p \in \text{supp}(F)$ have profit π given the prices charged by other firms F, any price $p \notin \text{supp}(F)$ results in profits that are strictly less than π, and M is such that the zero profit condition holds.

Equivalently, λ_i satisfies (15) for all i; π satisfies (16) with $\bar{p} = R$; M is such that $\pi = f_e$; and $F(p)$ is given by (17) for all $p \in [\underline{p}, R]$, is zero for $p < \underline{p}$ given in (17), and is one for $p > R$.

In equilibrium, the aggregate markup is

$$\bar{\mu} = 1 + \delta \left(\frac{R}{mc} - 1 \right) \frac{\int_0^\infty \frac{\lambda_i}{(\delta+\lambda_i)^2} dH(i)}{\int_0^\infty \frac{\lambda_i}{\delta+\lambda_i} dH(i)}.$$

E.4 Calibration

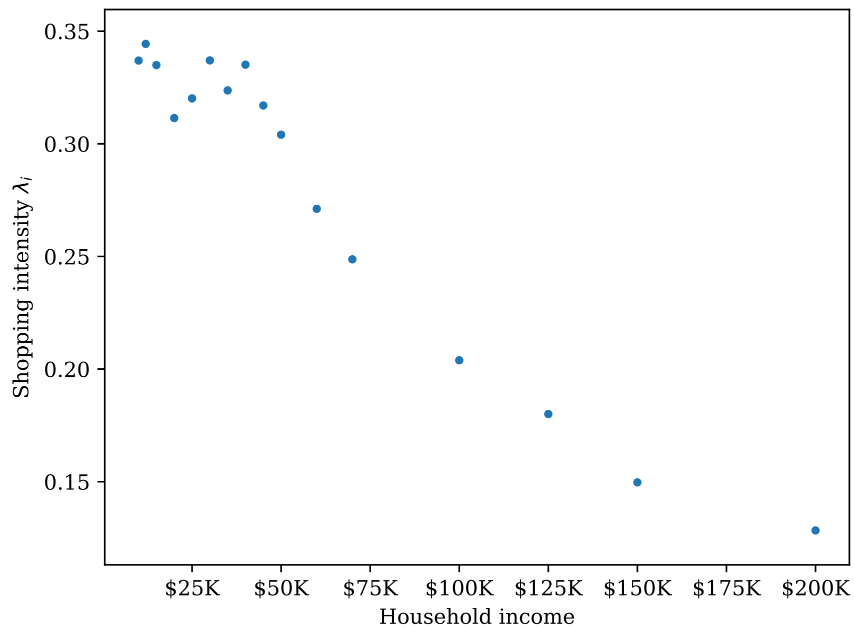
I calibrate the model using an analogous two-step procedure to the one described in the main text. Importantly, I find that the results in the sequential search model are more sensitive to the valuation R. So, I choose R by minimizing the distance between the 50th and 75th percentiles of the markup distribution for each household type and their empirical counterparts. I find $R = 2.03$, which is lower than the value used in the nonsequential search calibration. I choose $\delta = 0.10$; the results are not sensitive to the choice of δ.[30]

I reproduce figures from the main text in this calibration of the sequential search model: Figure E.1 shows the calibrated search intensities (λ_i) and shopping productivities (a_i); Figure E.2 shows the model's prediction of the change in markups over time, holding all factors other than the income distribution constant; and Figure E.3 reproduces additional facts about the decomposition of the rise in markups into within-firm changes and cross-

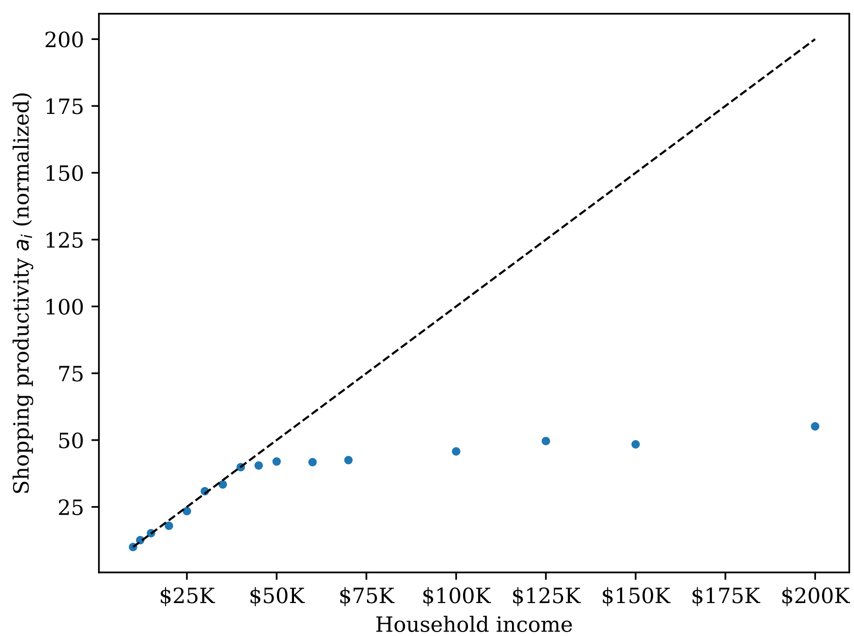
[30] As can be seen from the equations driving the model, λ_i/δ drives the behavior of the price distribution and the aggregate markup. So, the calibration chooses values of λ_i/δ that fit the data, and the choice of δ simply normalizes the results.

firm reallocations. The results are strikingly similar to the results of the nonsequential search calibration presented in the main text.

Figure E.1: Calibrated shopping intensity λ_i and shopping productivity a_i.



(a) Search intensity λ_i.



(b) Shopping productivity a_i.

Figure E.2: Predicted aggregate retail markup under income distributions from 1950–2018.

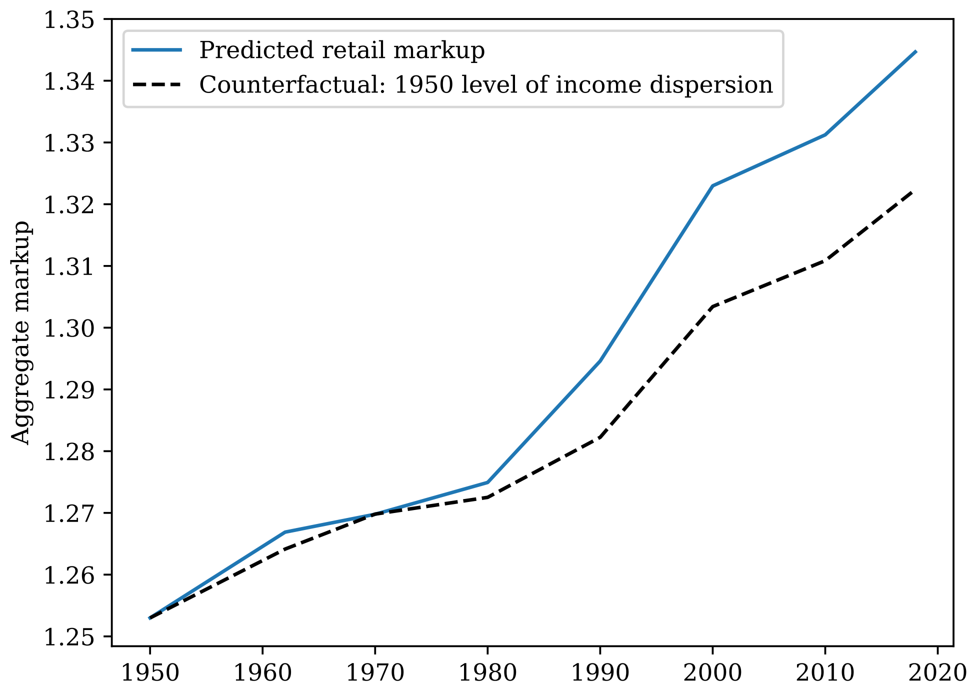
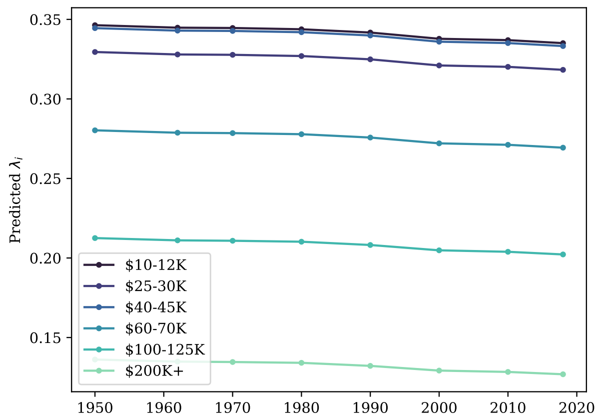
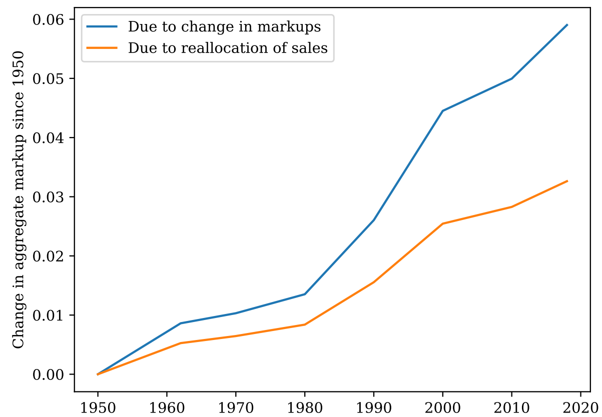


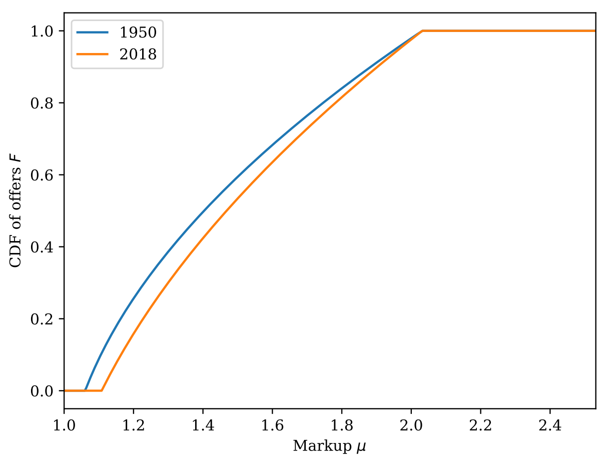
Figure E.3: Predictions of search model under counterfactual income distributions.



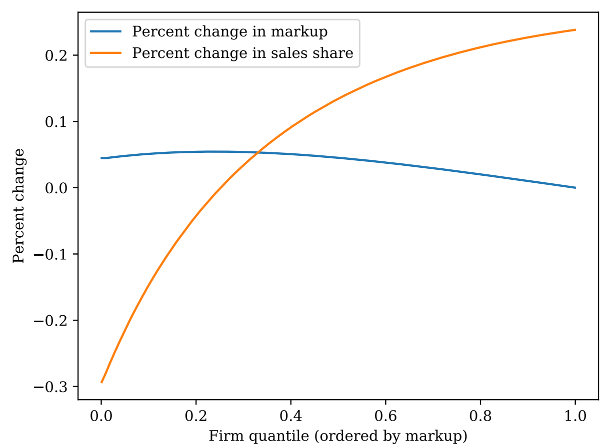
(a) Predicted search intensities λ_i.



(b) Decomposition of change in agg. markup.



(c) Offer distribution F in 1950 and 2018.



(d) Percent change in markups and sales shares by quantile from 1950 and 2018.