

# Shopping, Demand Composition, and Equilibrium Prices

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**Abstract.** This paper develops an equilibrium theory of expenditure inequality and price dispersion to study how retail prices respond to households' shopping behavior. Heterogeneity in the effort to search for prices implies that the price elasticity faced by retailers depends on the composition of demand. For a search market with price posting, I show analytically that retailers optimally charge higher markups if goods are mainly consumed by low-search-effort households. Additional predictions on the shape of posted price distributions are consistent with evidence from US supermarket scanner micro-data. I embed search for prices into an incomplete markets model with non-homothetic preferences and equilibrium price dispersion for multiple varieties. Endogenous heterogeneity in search effort allows the model to match evidence on differences in prices paid for identical goods and reduces inequality in consumption relative to expenditure. I show that the equilibrium response of posted prices across products doubles this direct effect of search on inequality. In addition, the model reconciles conflicting evidence on the cyclical nature of retail markups, as aggregate shocks change the composition of demand. Finally, I find that the response of posted prices to a redistributive earnings tax compensates top earners for up to 14% of their losses.

*Keywords:* Household Heterogeneity, Expenditures, Price Search, Markups.

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# 1 Introduction

Understanding inequality in households' consumption is essential to infer the welfare consequences of income and wealth inequality. A growing literature emphasizes heterogeneity in prices across households and distinguishes consumption from expenditure inequality (e.g. Aguiar and Hurst 2005, 2007). This distinction is important because posted prices for identical products exhibit significant dispersion and poor households search for bargains to pay less for the same good. Previous work abstracts from any equilibrium effect of this shopping effort on posted prices. However, if buyers search more for cheap offers, retailers face higher competition and optimally reduce the prices they post. This response matters for distinguishing expenditure and consumption inequality because households do not buy the same basket of goods and retailers can discriminate prices across products. It also matters for understanding the impact of aggregate shocks and policies, as the adjustment of posted prices determines the full effect of changes in shopping effort on the average price of consumption across households.

This paper develops an equilibrium theory of expenditure inequality and price dispersion that accounts for the response of posted prices to the shopping behavior of heterogeneous households. First, I provide analytical results on how retailers post prices taking the level of shopping effort as given and test theoretical predictions against large US micro-data on grocery transactions. Second, I quantify the effect of retailers' price posting on the distinction between expenditure and consumption inequality in equilibrium. Finally, I highlight the implications of heterogeneous shopping effort for the cyclicalities of retail prices and markups, as well as for the response of prices to redistributive earnings taxes.

The framework developed in this paper incorporates frictional goods markets in the spirit of Burdett and Judd (1983) in an Aiyagari-Bewley-Huggett economy with multiple goods. Heterogeneous households decide on their spending, savings, and shopping effort. Shopping effort is subject to a utility cost. Households allocate their total expenditure across multiple varieties of a grocery good and an outside good. Consumption baskets vary systematically across households due to non-homothetic preferences over grocery varieties. The markets for grocery varieties are subject to search frictions. For every unit of consumption they purchase, households have to search for price quotes and draw either one or two offers simultaneously from the equilibrium distribution of posted prices. Higher shopping effort increases the probability that a household observes two prices and can select the cheaper offer. The price distribution for each variety is determined endogenously as the optimal solution to retailers' price posting problem, which trades off higher margins per sale against undercutting simultaneously observed alternative offers.

The first result of this paper is that with heterogeneity in shopping effort, posted prices depend on the composition of demand. To show this analytically, I focus on retailers' price posting problem for a single variety and take households' choices as given. I derive closed-form expressions for the moments of the posted price distribution and find that demand-weighted shopping effort is a sufficient statistic for retailers to take into account rich household heterogeneity. I show that the average posted price decreases in demand-weighted effort, driven by a reduction in profit margins. A higher demand-weighted shopping effort means that the average buyer is more likely to observe two prices and substitute towards a cheaper offer. As a result, retailers face a higher average price elasticity. Therefore, if a larger share of demand comes from households exerting more shopping effort, retailers' best response is to reduce their markups and post lower prices.

In addition, the skewness of posted price distributions strictly increases in demand-weighted search effort and is independent of all other model parameters. This result provides a testable prediction that is directly linked to the mechanism generating price dispersion. For price dispersion to exist in equilibrium, retailers have to be indifferent between posting low and high prices within a distribution. To keep retailers indifferent when shopping effort increases, the distribution has to become more dense at the bottom and less dense at the top, i.e. its skewness must increase.

Empirical evidence supports the relationship between the skewness and demand-weighted search effort in micro-data on households' grocery transactions from the Nielsen Consumer Panel. I first show that high-spending, high-income, and employed households exert lower shopping effort and pay higher prices for identical barcodes. To test the relationship between households' effort and skewness, I exploit variation in demand-weighted shopping effort across products due to differences in households' consumption baskets. In line with theory, the skewness of local, barcode-level price distributions increases in the share of total expenditure for a given barcode stemming from households with higher search effort.

In equilibrium of the full model, households generate demand-weighted shopping effort for each good endogenously in response to the distributions of posted prices. I solve for the equilibrium in households' choices and posted price distributions numerically. To quantify the equilibrium effect of shopping on posted prices, I calibrate the model to evidence from the Nielsen Consumer Panel. I match differences in prices paid within and across varieties and heterogeneity in consumption baskets along the expenditure distribution, as well as price dispersion across products. In addition, the model can account for untargeted moments such as the distribution of expenditures in the data.

The calibrated model shows that the equilibrium response of posted prices more than doubles the effect of shopping effort on the difference between consumption and expenditure inequality. The literature so far has measured the effect of shopping by focusing

on differences in prices paid for a given product (see e.g. Aguiar and Hurst 2007; Arslan et al. 2021; Pytka 2022). Under this definition, shopping reduces the cost of consumption for the bottom versus the top expenditure quintile by 2% in the model and in the data. However, because high- and low-spending households do not buy the same products, retailers target their prices to the buyers they face and post lower average margins for products in the basket of low-spending (high-search) households. In the model, I show that these differences in posted margins across varieties reduce the cost of consumption for the bottom quintile of expenditures by an additional 2.5% relative to the top quintile. Abstracting from the overall effect of shopping overstates consumption inequality between the top and bottom quintile by 5% given the same observed distribution of grocery expenditures. Half of this effect is accounted for by differences in posted margins across varieties. Focusing on welfare to account for the disutility of shopping effort, again the direct and the equilibrium effect of shopping are equally important for inequality.

In addition, accounting for heterogeneity in shopping effort has implications for the cyclicity of prices and markups in response to aggregate shocks. I implement an aggregate shock based on the decline in net worth and losses in labor earnings during the Great Recession. The model generates a 0.7% decline in average prices paid upon impact. 0.6 percentage points are accounted for by changes in posted prices as retailers respond with lower markups to an increase in demand-weighted shopping effort. Only 0.1 percentage points can be attributed to a decline in the average price paid relative to the average posted price. This finding shows how focusing on prices paid relative to prices posted understates the effect of shopping on the cost of consumption over the business cycle.

The change in posted prices reported above is almost entirely driven by the decline in wealth. Losses in earnings have little impact on retailers' price posting despite accounting for a similar loss in disposable resources. This result arises because wealth losses are relatively more concentrated at the top of the income distribution and earnings losses at the bottom. In response to a loss in her earnings or wealth, any household increases her search effort and reduces consumption. If low-income households reduce their consumption, the composition of demand shifts in favor of high-income households with low search effort, incentivizing retailers to raise prices. Therefore, in response to earnings losses at the bottom of the distribution, this shift in demand composition offsets the increase in individual search effort. In response to a decline in wealth at the top, the increase in individual effort and the composition effect go in the same direction and unambiguously reduce prices and markups. This result reconciles seemingly conflicting empirical evidence, suggesting procyclical price and markup responses to house price shocks (Stroebel and Vavra 2019) and acyclical responses to unemployment fluctuations (Anderson et al. 2020). Overall, composition effects reduce the on-impact response of posted prices to the combined shock by one third.

Finally, I show that the response of posted prices to shifts in demand composition partially compensates net contributors to redistributive policies for the decline in their income. To do so, I introduce a flat tax on labor earnings and rebate the proceeds lump-sum to all households. As this policy redistributes resources towards low-income (high-shopping-effort) households, it increases their share in aggregate demand and hence increases demand-weighted shopping effort. In an economy with a higher level of redistribution, retailers therefore optimally choose to reduce their markups and post lower prices. This channel compensates net contributors in the top quintile of expenditures for 5-14% of the decline in their after-tax earnings.

The paper is structured as follows: Section 1.1 discusses related literature. Section 2 presents analytical results on the response of posted prices to shopping effort. Section 3 provides empirical evidence on shopping effort and price distributions. Section 4 outlines the equilibrium model and its calibration. Section 5 studies the implications for inequality. Section 6 presents the results on cyclicity and policies. Section 7 concludes.

## 1.1 Related Literature

**Search Frictions.** Seminal contributions on price search in the goods market include Butters (1977), Varian (1980), and Burdett and Judd (1983). I build on the latter, which has been widely applied in macroeconomic research.<sup>1</sup> I extend the previous work by providing analytical results on how the moments of posted price distributions respond to the distribution of shopping effort in a Burdett-Judd market.

In shopping economies with rich heterogeneity in income and wealth, Arslan et al. (2021) take posted prices as given and Pytka (2022) endogenizes the price distribution for a single good. Both papers focus on the direct effect of shopping on prices paid for life-cycle inequality and the response to idiosyncratic income shocks in a stationary economy. The equilibrium search framework presented in this paper is the first with rich household heterogeneity and endogenous price distributions for multiple varieties. I employ it to study how the equilibrium response of posted prices to shopping affects inequality.

Equilibrium effects of shopping effort on posted prices allow Alessandria (2009) to explain movements of relative prices across countries and Kaplan and Menzio (2016) to generate self-fulfilling unemployment fluctuations. Both setups feature price dispersion for a single good and stylized heterogeneity with finite types of shoppers. I show how rich hetero-

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<sup>1</sup>See e.g. Albrecht et al. (2021), Burdett and Menzio (2018), and Menzio (2021). Additional work on the macroeconomics of goods market frictions and households' shopping behavior includes e.g. Angelini and Brès (2022), Bai et al. (2019), Coibion et al. (2015), Gaballo and Paciello (2021), Kryvtsov and Vincent (2021), Petrosky-Nadeau and Wasmer (2015), and Sara-Zaror (2022).

geneity can affect the cyclicalness of retail prices due to shifts in demand composition when accounting for the incidence of aggregate shocks.<sup>2</sup>

**Expenditure Inequality.** The paper also relates to the empirical literature on expenditure inequality (e.g. Aguiar and Bils 2015; Attanasio and Pistaferri 2016; Coibion et al. 2021). Most closely related are the seminal contributions on the direct effect of shopping effort on prices paid by Aguiar and Hurst (2005, 2007) and subsequent work (e.g. Aguiar et al. 2013; Broda et al. 2009; Griffith et al. 2009; Nevo and Wong 2019; Pisano et al. 2022; Pytka 2022). My findings suggest that the equilibrium response of posted prices more than doubles the direct effect of shopping on inequality studied previously.

**Non-Homotheticities.** The literature on non-homotheticities dates back to Engel’s Law in 1857. Most closely related is the recent work focusing on CES-preferences at the barcode level (Argente and Lee 2021; Auer et al. 2022; Faber and Fally 2022; Handbury 2021; Jaravel 2019). Non-homotheticities at this disaggregated level are often interpreted as substitution along a quality margin (Bils and Klenow 2001; Bisgaard Larsen and Weisert 2020; Ferraro and Valaitis 2022; Jaimovich et al. 2019). Mongey and Waugh (2022) generate non-homotheticities from logit-preferences in an incomplete-markets economy. None of the previous work considers interactions with shopping effort and price dispersion.

**Retail Prices and Markups.** The paper also extends the empirical literature on retail prices and markups. Seminal work by Kaplan and Menzio (2015) and Kaplan et al. (2019) provides evidence on the structure of price distributions but does not consider their comovement with demand composition across products. Stroebel and Vavra (2019) find retail prices and markups to respond procyclically to local variations in house prices and attribute this pattern to empirically observed changes in shopping behavior. Anderson et al. (2020) find markups paid to co-vary positively with proxies for local income, driven by differences in products bought. Their findings are in line with the theory of this paper.

Closely related is the complementary work of Sangani (2022), providing evidence on higher markups for goods bought by high-income households. He rationalizes his findings by combining the single-variety model of Burdett and Judd (1983) with stylized household heterogeneity and studies the implications of increasing income inequality for the rise in aggregate markups. In contrast, I provide direct empirical evidence on the mechanism, testing predictions on the relationship between shopping and the shape of price distributions. My focus is the feedback between equilibrium prices and inequality. Hence, I develop a model with rich household heterogeneity in the tradition of Bewley (1977) and Aiyagari (1994), featuring non-homothetic preferences and endogenous price distributions for multiple varieties.

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<sup>2</sup>Huo and Ríos-Rull (2015) develop a framework with heterogeneous households and directed search for quantities and show how shifts in demand composition can affect productivity.

## 2 The Mechanism: Price Posting with Search Frictions

To study how household heterogeneity can affect posted price distributions, I analyze retailers' price posting problem in a frictional product market. Throughout this section, I take the distribution of households, their shopping effort, and consumption choices as given and focus on the distribution of posted prices. I build on the price posting problem of a single-variety retailer in a market with consumer search as introduced by Burdett and Judd (1983) and Pytka (2022). Within this framework, I characterize analytically how moments of the posted price distribution respond to the distribution of households.

### 2.1 Retailers' Problem and Posted Price Distributions

Consider the market for a single variety  $j$ , which is produced at homogeneous marginal cost  $\kappa_j$ , and for which all consumers have identical maximum willingness to pay  $\bar{p}_j > \kappa_j$ . The variety is sold by a continuum of homogeneous retailers of measure one. The demand side of the market consists of a continuum of households indexed by their type  $i$ , with  $\lambda_i$  being the distribution over types. A type  $i$  household is characterized by her disposable resources  $x_i$  and consumes a quantity  $c_j(x_i) \geq 0$  of variety  $j$ , which she splits into a measure  $c_j(x_i)$  of infinitesimal purchases. The market for the variety is subject to incomplete information. For each purchase she makes, a household observes either one or two price postings, drawn at random from the equilibrium distribution of posted prices  $F_j(p)$ . The probability of observing two price draws for any given purchase is determined by the household's shopping effort  $s(x_i) \in [0, 1]$ , i.e. shopping effort is the intensity with which households search for a second price observation. For purchases with a single price observation the household buys the good if the observed price is below the maximum willingness to pay  $\bar{p}_j$ . Purchases with two simultaneous price observations are made at the lowest offer below  $\bar{p}_j$ .

**Retailers' Problem.** Retailers commit to a price for variety  $j$  before meeting any buyers. They post prices to maximize their profits, taking expectations over the type of household they will meet in the market and how likely any type is to see a second price offer simultaneously. The total profits of a retailer posting price  $p$  are given by

$$\pi_j(p) = \underbrace{C_j}_{\substack{\text{demand} \\ \text{per retailer} \\ \text{(market size)}}} \underbrace{\left[ \int \frac{\lambda^i c_j(x_i)}{C_j} [(1 - s(x_i)) + s(x_i)2(1 - F_j(p))] di \right]}_{\substack{\text{sales per demand} \\ \text{(market share)}}} \underbrace{(p - \kappa_j)}_{\substack{\text{profit} \\ \text{per sale} \\ \text{(margin)}},$$

where  $C_j = \int \lambda_i c_j(x_i) di$  is total demand for variety  $j$  and  $\frac{\lambda_i c_j(x_i)}{C_j}$  the fraction of demand accounted for by households of type  $i$ . In words, profits are given as the margin per sale  $(p - \kappa_j)$  times total demand per retailer ( $C_j$ ) times the market share. To determine her

market share, the retailer considers the likelihood with which any buyer she meets in the market observes a second price quote simultaneously: With probability  $\frac{\lambda_i c_j(x_i)}{C_j}$  she meets a type  $i$  household, and with probability  $s(x_i)$  this household has a simultaneous second price observation conditional on being type  $i$ . In this case the retailer only makes a sale if her price offer is lower than the second quote, which conditional on posting price  $p$  occurs with probability  $(1 - F_j(p))$ .<sup>3</sup> The problem can be simplified to

$$\pi_j(p) = C_j [(1 - \bar{s}_j) + \bar{s}_j 2(1 - F_j(p))] (p - \kappa_j), \quad (1)$$

where

$$\bar{s}_j = \int \frac{\lambda_i c_j(x_i)}{C_j} s(x_i) di \quad (2)$$

is the *demand-weighted average search effort* in the market. Deciding on the price to post in this market, retailers trade off between margins per sale and their market share. A higher price increases the margin earned per sale ( $p - k_j$ ) but increases the probability to be undercut by a competitor  $F_j(p)$  and hence decreases demand at the extensive margin. Taking into account demand-weighted search effort  $\bar{s}_j$  is key for the second effect as it determines the ex-ante likelihood that the average buyer observes a second price and therefore the ex-ante likelihood any retailer has to compete for a purchase. In this sense,  $\bar{s}_j$  determines the price elasticity of demand across retailers.

As retailers are homogeneous, a non-degenerate equilibrium price distribution requires them to be indifferent between posting a range of prices. For any price increase on the support of the posted distribution, the benefit of earning a higher margin on the current number of sales has to be exactly offset by the cost of a loss in market share. Formally, this requires  $\frac{\partial \pi(p)}{\partial p} = 0$  which yields

$$\underbrace{C_j [(1 - \bar{s}_j) + \bar{s}_j 2(1 - F_j(p))]}_{\text{current sales}} = \underbrace{C_j [\bar{s}_j 2 f_j(p)]}_{\text{loss in sales}} \underbrace{(p - \kappa_j)}_{\text{current margin}}. \quad (3)$$

The market size  $C_j$  cancels from the expression as retailers are infinitesimal and only compete over their share in a total number of sales they take as given. Demand-weighted average shopping effort  $\bar{s}_j$  summarizes all relevant information about the distribution of households and is a sufficient statistic for the retailer to post a price.

**Posted Price Distribution.** For given  $\kappa_j$ ,  $\bar{p}_j$ , and  $0 < \bar{s}_j < 1$ , Burdett and Judd (1983) and Pytka (2022) show that a unique and continuous equilibrium distribution of posted

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<sup>3</sup>The multiplication of the second term by 2 captures that the retailer can be either the first or second of two price observations.

prices  $F_j(p)$  exists with compact support  $[\underline{p}_j, \bar{p}_j]$ , where

$$F_j(p) = \begin{cases} 0 & \text{if } p < \underline{p}_j \\ 1 - \frac{1 - \bar{s}_j}{2\bar{s}_j} \frac{\bar{p}_j - p}{p - \kappa_j} & \text{if } p \in [\underline{p}_j, \bar{p}_j] \\ 1 & \text{if } p > \bar{p}_j \end{cases} \quad (4)$$

and

$$\underline{p}_j = \kappa_j + (\bar{p}_j - \kappa_j) \frac{1 - \bar{s}_j}{1 + \bar{s}_j}.$$

Retailers play a mixed strategy, randomizing prices over the interval  $[\underline{p}_j, \bar{p}_j]$  according to the density  $f_j(p)$  associated with  $F_j(p)$ . The distribution of posted prices depends on the marginal cost  $\kappa_j$  and households' maximum willingness to pay  $\bar{p}_j$ , as well as demand-weighted shopping effort  $\bar{s}_j$ , but is independent of total demand per retailer  $C_j$ . As marginal cost are constant across retailers,  $F_j(p)$  is a distribution of markups.

## 2.2 The Effect of Heterogeneous Shopping on Posted Prices

How does the distribution of households affect posted prices? As demand-weighted effort  $\bar{s}_j$  is a sufficient statistic for retailers' pricing decision, an answer to this question can be split into two steps: (i) How does  $\bar{s}_j$  change with the distribution of households? and (ii) How does the distribution of posted prices respond to changes in  $\bar{s}_j$ ?

**Demand-Weighted Shopping Effort.** Focus first on how the distribution of households determines  $\bar{s}_j$ . Equation (2) implies that a retailer takes into account type  $i$  households' shopping effort according to their share in total demand  $\frac{\lambda_i c_j(x_i)}{C_j}$ . From here on out I will refer to the vector of these shares as *demand composition*. Differences in demand composition shift the weights attached to each household's idiosyncratic search behavior. In this way, heterogeneity in individual effort  $s(x_i)$  creates a role for demand composition to affect  $\bar{s}_j$  and through it posted prices.  $\bar{s}_j$  is higher if a larger share of demand is accounted for by households with a higher shopping effort. Taking (shifts in) demand composition into account is important to fully capture how changes in the distribution of disposable income affect  $\bar{s}_j$ . Consider an increase in type  $i$ 's disposable resources  $x_i$  holding the resources of all other households constant. The derivative of  $\bar{s}_j$  w.r.t. type  $i$ 's disposable resources is given by

$$\frac{\partial \bar{s}_j}{\partial x_i} = \frac{\lambda_i c_j(x_i)}{C_j} \frac{\partial s(x_i)}{\partial x_i} + \frac{\lambda_i}{C_j} (s(x_i) - \bar{s}_j) \frac{\partial c_j(x_i)}{\partial x_i}. \quad (5)$$

The first term is the change in type  $i$ 's shopping effort, which is weighted by her share in demand. The second term captures shifts in demand composition. Whether a change in type  $i$ 's income increases or decreases  $\bar{s}_j$  through its effects on shopping behavior and on

demand composition depends on the properties of  $s(x_i)$  and  $c(x_i)$ . The sign of the direct effect on shopping is pinned down by the slope of the shopping policy function  $\frac{\partial s(x_i)}{\partial x_i}$ . The demand composition effect depends on a household's position in the distribution of shopping effort interacted with the change in her consumption policy. If  $j$  is a normal good  $\left(\frac{\partial c_j(x_i)}{\partial x_i} > 0\right)$  shifts in demand composition increase  $\bar{s}_j$  in response to increases in the disposable income of high shopping households with  $s(x_i) > \bar{s}_j$  and decrease  $\bar{s}_j$  in response to increases in  $x_i$  for low shopping households ( $s(x_i) < \bar{s}_j$ ). If  $j$  is an inferior good  $\left(\frac{\partial c_j(x_i)}{\partial x_i} < 0\right)$  the argument is reversed.

**Moments of the Posted Price Distribution.** Even without disciplining households' behavior we can assess how changes in  $\bar{s}_j$  affect posted prices. Given  $\bar{s}_j$ , equation (4) determines the ensuing posted price distribution. Taking the derivative of (4) with respect to  $\bar{s}_j$  yields  $\frac{\partial F_j(p)}{\partial \bar{s}_j} \geq 0$ , i.e. a distribution with lower demand-weighted shopping effort  $\bar{s}_j$  has first-order stochastic dominance over any distribution with higher  $\bar{s}_j$  and hence a greater probability to observe high posted prices. Figure 1 highlights this result graphically. It shows that for given  $\kappa_j$  and  $\bar{p}_j$  a lower level of  $\bar{s}_j$  shifts mass of the posted density towards the maximum willingness to pay, away from the marginal cost.

Given the analytical characterization of  $F_j(p)$ , the problem yields closed form solutions for the moments of the distribution and their relation with  $\bar{s}_j$ . Expressions for the first three central moments are presented in Proposition 1.

**Proposition 1** *The mean  $\mu_j^F$ , standard deviation  $\sigma_j^F$ , and skewness  $\gamma_j^F$  of the posted price distribution  $F_j(p)$  for given  $\kappa_j$ ,  $\bar{p}_j$ , and  $0 < \bar{s}_j < 1$  can be derived as*

(i)

$$\mu_j^F = \kappa_j + \underbrace{(\bar{p}_j - \kappa_j) \frac{1 - \bar{s}_j}{2\bar{s}_j} \log\left(\frac{1 + \bar{s}_j}{1 - \bar{s}_j}\right)}_{\text{average posted margin}},$$

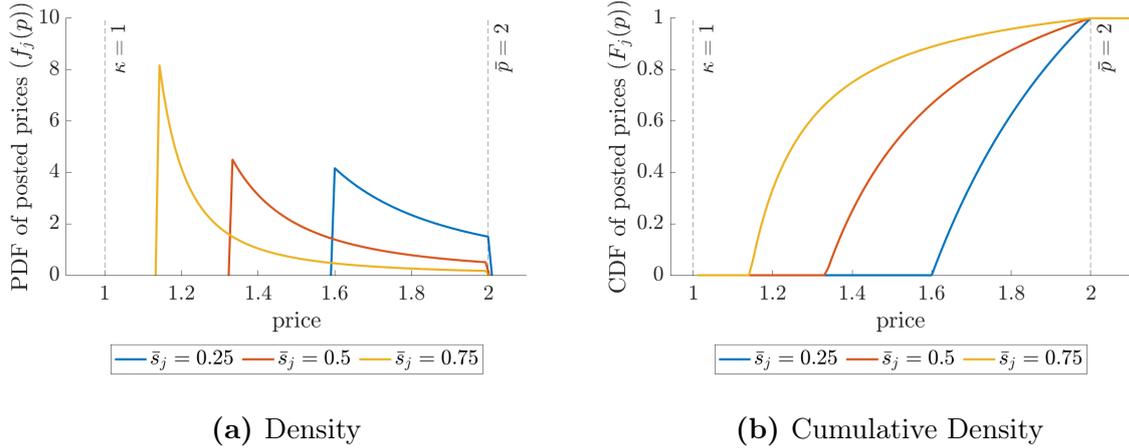
(ii)

$$\sigma_j^F = \sqrt{(\bar{p}_j - \kappa_j)^2 \left( \frac{1 - \bar{s}_j}{1 + \bar{s}_j} - \left( \frac{1 - \bar{s}_j}{2\bar{s}_j} \right)^2 \log\left(\frac{1 + \bar{s}_j}{1 - \bar{s}_j}\right)^2 \right)},$$

(iii)

$$\gamma_j^F = \frac{\frac{1 - \bar{s}_j}{4\bar{s}_j} \left( 1 - \left( \frac{1 - \bar{s}_j}{1 + \bar{s}_j} \right)^2 \right) - 3 \frac{(1 - \bar{s}_j)^2}{2\bar{s}_j + 2\bar{s}_j^2} \log\left(\frac{1 + \bar{s}_j}{1 - \bar{s}_j}\right) + 2 \left( \frac{1 - \bar{s}_j}{2\bar{s}_j} \right)^3 \log\left(\frac{1 + \bar{s}_j}{1 - \bar{s}_j}\right)^3}{\left( \frac{1 - \bar{s}_j}{1 + \bar{s}_j} - \left( \frac{1 - \bar{s}_j}{2\bar{s}_j} \right)^2 \log\left(\frac{1 + \bar{s}_j}{1 - \bar{s}_j}\right)^2 \right)^{\frac{3}{2}}}.$$

**Proof.** *Follows from equation (4) and the standard formulas for the first three central moments of any continuous distribution. ■*



**Figure 1:** Posted Price Distributions

**Note:** Price distributions derived from retailers' optimal price posting problem for marginal cost  $\kappa_j = 1$ , maximum willingness to pay  $\bar{p}_j = 2$ , and three levels of demand-weighted shopping effort  $\bar{s}_j$ .

Proposition 2 implies that the average price posted is increasing in marginal cost  $\kappa_j$  and maximum willingness to pay  $\bar{p}_j$ , but decreasing in demand-weighted shopping effort  $\bar{s}_j$ . Figure 2a illustrates this result graphically.

**Proposition 2** *The mean of the posted price distribution  $\mu_j^F$  is strictly increasing in marginal cost  $\kappa_j$  and maximum willingness to pay  $\bar{p}_j$ , but strictly decreasing in demand-weighted search effort  $\bar{s}_j$  for  $0 < \bar{s}_j < 1$ , i.e.*

$$(i) \frac{\partial \mu_j^F}{\partial \kappa_j} > 0, \quad (ii) \frac{\partial \mu_j^F}{\partial \bar{p}_j} > 0, \quad (iii) \frac{\partial \mu_j^F}{\partial \bar{s}_j} < 0.$$

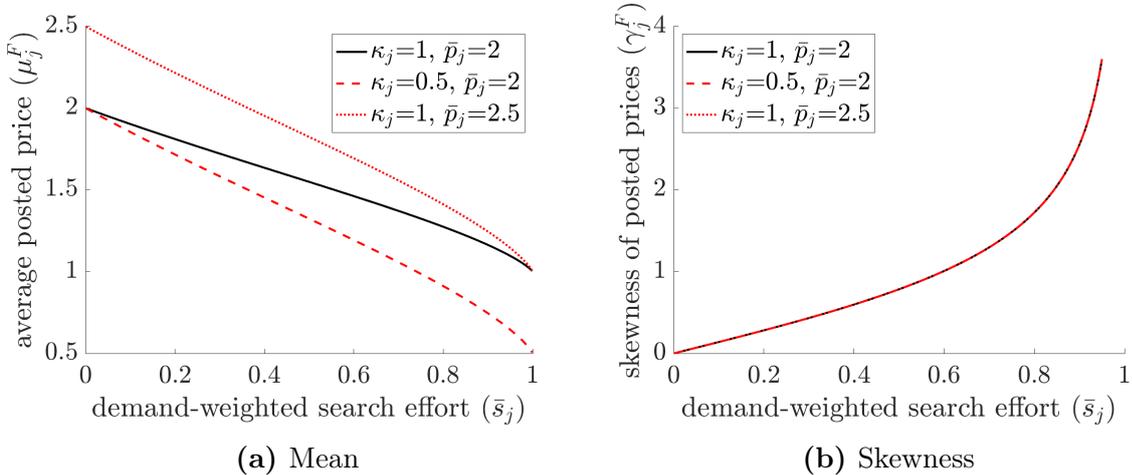
**Proof.** *Follows from taking first derivatives of  $\mu_j^F$ .* ■

The effect of shopping on the average price posted operates through changes in profit margins over marginal cost  $\kappa_j$ , which are strictly decreasing in equilibrium shopping effort  $\left(\frac{\partial(\mu_j^F - \kappa_j)}{\partial \bar{s}_j} < 0\right)$ . Higher demand-weighted shopping effort increases the price elasticity a seller faces. An increase in  $\bar{s}_j$  makes it more likely that the average buyer observes a second price, and hence tilts sellers' tradeoff between higher margins and retaining market share in favor of the latter.

In the limit, the setup approaches two well known special cases: If all buyers observe two prices simultaneously ( $\bar{s}_j = 1$ ), retailers solve a Bertrand competition problem and post marginal cost ( $\mu_j^F = \kappa_j$ ). If no buyer observes two prices simultaneously ( $\bar{s}_j = 0$ ), all retailers have a monopoly for any buyer they meet and extract buyers maximum willingness to pay ( $\mu_j^F = \bar{p}_j$ ). Households' shopping effort determines a market's position between these two extremes by regulating the price elasticity retailers face.

Together with the effect of (changes in) demand composition on  $\bar{s}_j$  described above, the relationship between the average price posted  $\mu_j^F$  and demand-weighted effort captures

the mechanism at the heart of this paper: If a larger share of demand is accounted for by low-search households, retailers face a lower average price elasticity (lower  $\bar{s}_j$ ) and optimally post higher prices (markups). This is how taking into account retailers' optimal response to changes in demand composition yields equilibrium effects of heterogeneity in shopping effort on posted prices.



**Figure 2:** Moments of the Posted Price Distribution

**Note:** Theoretical moments of the posted price distribution  $F_j(p)$  as a function of demand-weighted shopping effort  $\bar{s}_j$ , for different values of marginal cost  $\kappa_j$  and maximum willingness to pay  $\bar{p}_j$ .

The theoretical relation between demand-weighted shopping effort  $\bar{s}_j$  and the skewness of the price distribution provides a sharp, empirically testable prediction of the response of posted prices to households' shopping effort. As shown in Proposition 3 below and highlighted graphically in Figure 2b, the skewness of the posted price distribution is a function only of demand-weighted shopping effort  $\bar{s}_j$  and independent of parameters. Furthermore, it is strictly increasing in  $\bar{s}_j$ .

**Proposition 3** *The skewness of the posted price distribution  $\gamma_j^F$  is strictly increasing in demand-weighted search effort  $\bar{s}_j$  for  $0 < \bar{s}_j < 1$ , but independent of marginal cost  $\kappa_j$  and maximum willingness to pay  $\bar{p}_j$ , i.e.*

$$(i) \frac{\partial \gamma_j^F}{\partial \kappa_j} = 0, \quad (ii) \frac{\partial \gamma_j^F}{\partial \bar{p}_j} = 0, \quad (iii) \frac{\partial \gamma_j^F}{\partial \bar{s}_j} > 0.$$

**Proof.** Follows from taking first derivatives of  $\gamma_j^F$ . ■

The intuition for this finding goes back to retailers' indifference condition in equation (3). Given a distribution of posted prices, an increase in demand-weighted search effort increases sales of retailers with low prices and decreases them for retailers with high prices, as households on average buy more at cheaper offers. This increases the benefit of raising prices at the bottom and decreases the benefit at the top. To offset this effect and keep retailers indifferent between posting low and high prices, the loss in market share

when raising prices has to increase at the bottom and decrease at the top. This requires the distribution of posted prices to be more dense at the bottom and less dense at the top. A more (less) dense distribution increases (decreases) the number of competitors that additionally undercut a retailer when raising prices marginally. A distribution that is more dense at the bottom and less dense at the top exhibits higher skewness.

**Robustness.** Appendix A shows that the distribution of posted prices remains unchanged when introducing free entry and fixed cost of operating and that under reasonable calibrations heterogeneity in marginal cost leaves average prices decreasing and the skewness increasing in shopping effort.<sup>4</sup>

### 3 Evidence on Shopping Effort and Price Distributions

This section provides empirical evidence on shopping effort across households and price distributions across goods. First, I focus on how shopping effort changes with households' expenditure to provide motivation for the quantitative model below. Second, I test Proposition 3 empirically. I exploit differences in demand composition across goods and evidence on households' shopping effort to show that the skewness of price distributions indeed increases in demand-weighted shopping effort.

**Data.** For all empirical results I rely on data from the Nielsen Consumer Panel for 2007-2019. The dataset provides detailed information on the grocery purchases of approximately 60,000 US households per year, recording both quantities purchased and prices paid for every store visit at the barcode level. In addition, the data contains annual information on households' demographic characteristics such as income, household composition, employment, and the place of residence.<sup>5</sup>

#### 3.1 Shopping Effort across Households

Studying how shopping behavior changes across households requires a measure of search effort. The Nielsen dataset does not provide direct information on the time spent searching for prices. I therefore rely on two proxies for households' shopping effort. First, I focus on the outcome of the search process – heterogeneity in the prices paid for identical barcodes – and construct household level price indices in the spirit of Aguiar and Hurst (2007). Second, I consider the number of stores households visit. Kaplan and Menzio (2015) show that an effective way to reduce prices paid is to visit more stores or the same store more often, controlling for the number of purchases.

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<sup>4</sup>I focus on homogeneous marginal cost as they should be interpreted as wholesale cost and wholesale price differentiation among retailers within a geographic area is prohibited in the US under the federal Robinson-Patman Act and more commonly applied state legislations (e.g. Nakamura (2008)).

<sup>5</sup>Further information on the dataset is provided in Appendix B.1.

**Price Index.** The total cost of household  $i$ 's consumption bundle in year  $t$  across all barcodes  $j$  is

$$X_{it} = \sum_j p_{jit} c_{jit},$$

where  $p_{jit}$  is the quantity-weighted average price paid by household  $i$  in year  $t$  for barcode  $j$  and  $c_{jit}$  is the respective quantity consumed. I further compute counterfactual cost  $\tilde{X}_{it}$  assuming the household pays the national, quantity-weighted average price across all households  $\tilde{p}_{jt}$  for each transaction of barcode  $j$  such that<sup>6</sup>

$$\tilde{X}_{it} = \sum_j \tilde{p}_{jt} c_{jit}.$$

A household's price index is defined as the ratio between true and counterfactual cost

$$P_{it} = \left( \frac{X_{it}}{\tilde{X}_{it}} - 1 \right) * 100.$$

It can be interpreted as the percentage difference in the cost of household  $i$ 's consumption bundle in year  $t$  relative to paying average prices for each of the barcodes purchased. A high index value indicates relatively high prices paid within barcodes and therefore low shopping effort. The relationship between this price index and households' overall expenditure levels is not trivially positive: While higher prices on a given basket of goods necessarily increase expenditure, high-spending households could in principle be buying a larger basket but be paying less for each individual product. The size of the basket is controlled for by normalizing the actual cost of consumption  $X_{it}$  by counterfactual spending  $\tilde{X}_{it}$ . I regress annual individual price indices on household ( $\eta_i$ ) as well as year-state ( $\alpha_{st}$ ) fixed effects and controls ( $Z_{it}$ )

$$P_{it} = \eta_i + \alpha_{st} + \gamma Z_{it} + \epsilon_{it}. \tag{6}$$

The fixed effects control for all constant unobserved characteristics and for local economic conditions at the year-state level. The vector  $Z_{it}$  contains a set of time-varying observed characteristics: Most importantly, I include the logarithm of annual grocery spending to measure how shopping effort changes along the expenditure distribution. To control for other variables commonly associated with shopping effort, I include dummies for households' taxable income between \$30k-60k, \$60k-100k, or above \$100k (omitting the category below \$30k as baseline), the number of non-employed household heads (baseline is no non-employed head), whether the (male) household head is of working age (25-

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<sup>6</sup>I define  $\tilde{p}_{jt}$  annually at the national level. An alternative, more restrictive definition that has been commonly used in the literature defines average prices at the local and quarterly level. I show in Appendix B.2 that this definition is subject to a small sample bias attenuating results. Nevertheless, findings based on local average prices are qualitatively similar.

65), and the square root of household size.<sup>7</sup> Nielsen-provided household-level sampling weights are applied throughout. Standard errors are clustered at the household level.

**Table 1:** Shopping Effort across Households

	price index	trips per purchase
	(1)	(2)
log(expenditure)	0.706*** (0.078)	-0.042*** (0.001)
income 30k-60k	0.080* (0.046)	-0.001* (0.001)
income 60k-100k	0.178*** (0.057)	-0.002** (0.001)
income >100k	0.326*** (0.070)	-0.002** (0.001)
1 non-employed household head	-0.236*** (0.037)	0.002*** (0.000)
2 non-employed household heads	-0.422*** (0.068)	0.004*** (0.001)
mean		0.15
FE year-state	X	X
FE household	X	X
Observations	801,398	801,398

**Note:** Regression of shopping effort on household characteristics. Column (1) index of individual prices paid vs. national annual average price. Column (2) annual number of shopping trips divided by number of purchases. Data from Nielsen Consumer Panel waves 2007-2019. Observations weighted with Nielsen provided sample weights. Standard errors clustered at the household level. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table 1 reports selected results of estimating equation (6).<sup>8</sup> It shows that a higher level of household expenditures is associated with paying higher prices for identical goods. In addition, prices paid increase in income and decrease in the number of non-employed household heads. The findings suggest that households with higher spending or income

<sup>7</sup>Grocery expenditures are equivalence scale adjusted by dividing by the square root of household size and deflated to 2019 USD with the urban CPI. Income is reported in the Nielsen dataset as a binned variable and refers to the tax base of the previous year, i.e. household income two years prior to the survey wave. To the extent that household income is persistent at a two-year horizon, it can be seen as an approximation of households' current income but is a noisy measure of the true value.

<sup>8</sup>Full results are reported in column (1) of Table 9 in Appendix B.2.

and fewer non-employed household heads exert lower shopping effort. The results for income and employment status are in line with the findings reported in the literature.<sup>9</sup> The result on expenditure is novel.

The relation between expenditure levels and prices paid is sizeable, especially relative to the relation between prices and income. A move from the lowest to the highest income bin increases prices paid by 0.326 percent. Each income bin accounts for roughly 25% of households, so a move from the lowest to the highest bin is approximately equivalent to moving from the lowest to the highest income quartile. In comparison, doubling a household's grocery expenditures is associated with a 0.706 percent increase in prices for the same barcode. The top expenditure quintile spends roughly five times as much as the bottom quintile, translating the coefficient into a 2.8% difference in prices paid between the bottom and top of the expenditure distribution.

**Trips per Purchase.** I define a shopping trip as a visit to a unique store at a unique day. To control for the size of the consumption basket, I divide the number of annual trips a household undertakes by the number of her purchases, where a purchase is defined as a transaction involving a unique barcode in a given store on a given day. Column (2) of Table 1 shows that the results obtained via the price index also hold when measuring shopping effort as the number of trips per purchase: Households with higher expenditure or income make fewer trips per purchase while households with more non-employed members make more trips. Again the coefficient on households' expenditure is sizeable: The average number of trips per purchase is 0.15 (a household makes on average 6.67 purchases per shopping trip). Doubling a household's expenditures reduces it by 0.042.

The strong relation between households' shopping effort and expenditure levels is well in line with a mechanism introduced in Pytka (2022). As households with higher expenditure make more purchases, they have to search more often to achieve the same average reduction in prices. Hence, reducing the average price paid becomes more costly as the size of a household's basket increases. I take the strong relation between spending levels and households' shopping behavior as motivation for developing a quantitative model centered around households' expenditure below.

### 3.2 Demand Composition and Price Distributions

Having identified dimensions of heterogeneity in shopping effort, I move on to an empirical test of the relationship between shopping and posted price distributions. Testing for a reduction in retailers margins in response to higher shopping effort would require data on markups at the seller-good level. However, for a test of the relationship between the skewness of price distributions and effort outlined in Proposition 3, it is sufficient to

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<sup>9</sup>See e.g. Aguiar and Hurst (2007), Kaplan and Menzio (2016) and Pytka (2022).

observe price distributions and demand-weighted shopping effort. Both are available in the Nielsen dataset.

**Demand-Weighted Shopping Effort.** According to the theory outline in Section 2, retailers should consider the shopping effort of households weighted by their share in overall demand for the variety they sell. I exploit variation in demand composition across products and compute for each barcode the national, annual expenditure shares stemming from different groups of households, sorted by their shopping effort.<sup>10</sup> Building on the results above, I consider separately the five quintiles of the expenditure distribution, four bins of household income, as well as the number of non-employed household heads. To be in line with the predictions from Section 2 and the results on households' shopping behavior above, the skewness of price distributions should be decreasing in the expenditure share coming from high-spending or high-income households, but increasing in the share of demand from households with more non-employed heads.

**Price Distributions.** A price distribution consists of all transactions observed for a barcode  $j$ , within a region  $r$  and time period  $t$ . In line with Kaplan and Menzio (2015), I define a region as a Scantrack Market Area (SMA) and the time period to be a quarter.<sup>11</sup> The price associated with a transaction is defined as the total amount paid less of coupon values, divided by the quantity purchased. To control for outliers, I drop all transactions for which the reported amount paid less of coupons is zero or negative. For the baseline analysis, I consider all price distributions containing at least 25 transactions and compute the skewness of each distribution weighting individual price observations with household weights and quantities purchased.

**Estimation.** To test for the relationship between skewness and shopping derived from theory, I regress the skewness of a price distribution  $(j, r, t)$  on the national expenditure shares of each household group  $g$ , for variety  $j$  in the respective year  $y(t)$ . I run separate regressions defining groups based on expenditure quintiles, income bins, and the number of non-employed household heads, excluding the lowest expenditure quintile, the lowest income bin and households with no non-employed head respectively as a baseline. The

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<sup>10</sup>I use annual and national shares as Nielsen is representative at this level. Using aggregate rather than local shares is justified by the evidence on uniform price setting of large retail chains across locations (see e.g. DellaVigna and Gentzkow 2019), making national rather than local demand composition the relevant statistic for their price setting.

<sup>11</sup>The choice for what definition of a region and which time period to consider trades off between two forces: A narrow definition ensures that any variation in prices can be confidently allocated to (and exploited by) search frictions, while it also reduces the number of price observations per distribution and hence makes the analysis more noisy. For the ensuing analysis to be valid it is not necessary that households have access to every price within a region, but only that the distribution of prices is identical for any subregion. As Scantrack Markets are defined by industry professionals as target regions for marketing purposes, retailers pricing can be assumed to be sufficiently similar within such regions to ensure identical price distributions throughout.

specification is given in equation (7).

$$skew_{j,r,t} = \theta_m + \mu_{r,t} + \sum_{g=2}^G \beta_g share_{j,g,y(t)} + \varepsilon_{j,r,t} \quad (7)$$

To control for local economic conditions and product characteristics, I include time-region fixed effects ( $\mu_{r,t}$ ) as well as fixed effects for Nielsen-defined product modules ( $\theta_m$ ). I do not control for barcode fixed effects to exploit variation in expenditure shares across different barcodes.<sup>12</sup> The included fixed effects demean the skewness by product category and by region at a given point in time. Therefore, the coefficients of interest  $\beta_g$  are identified by the covariation of demand composition and differences in the skewness of distributions among closely substitutable barcodes within a given region and period. All regressions are weighted by the total amount of expenditures contained in the respective price distributions. Standard errors are clustered at the barcode-year level.

**Table 2:** Demand Composition and the Skewness of Price Distributions

	by expenditures			by income		by employment
	all	working age		working age		all
	(1)	(2)		(3)		(4)
expenditure quintile 2	-1.638*** (0.242)	-1.467*** (0.206)	income 30k-60k	-0.136 (0.133)	1 non-employed household head	0.864*** (0.115)
expenditure quintile 3	-2.309*** (0.256)	-2.076*** (0.221)	income 60k-100k	-0.824*** (0.155)	2 non-employed household heads	1.011*** (0.210)
expenditure quintile 4	-3.067*** (0.258)	-2.582*** (0.219)	income >100k	-0.820*** (0.139)		
expenditure quintile 5	-3.412*** (0.253)	-3.007*** (0.224)				
FE product module	X	X		X		X
FE quarter-SMA	X	X		X		X
Observations	3,026,551	3,026,404		3,026,404		3,026,551

**Note:** Regression of the skewness of price distributions on demand shares by household groups. Price distributions defined as all transactions of a barcode within a Scantrack Market Region and quarter. Demand shares defined as the share of national annual spending on a barcode by each group of households. Data from Nielsen Consumer Panel waves 2007-2019. Observations weighted by total sales in given price distribution. Standard errors clustered at the barcode-year level. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table 2 reports the results. The skewness of price distributions is monotonically decreasing in the share of expenditure stemming from higher spending households (column (1)). The coefficients should be interpreted as the relative skewness compared to the omitted baseline group. For column (1): If a barcode is bought entirely by households in the fifth

<sup>12</sup>Nielsen-defined product modules are the first level of aggregation above barcodes and capture product characteristics at a granular level. Examples of product modules in Nielsen are e.g. “fresh apples” or “fresh oranges” for different categories of fresh fruits.

quintile of the expenditure distribution, the skewness of its price distribution decreases by 3.4 relative to a barcode bought entirely by the first quintile. All differences w.r.t. the baseline group are statistically significant at the 1%-level. The finding is robust to measuring expenditure shares conditional on the (male) household head being between age 25-65 to account for spending patterns of student and retiree households (column (2)). Similar findings pertain by income group, again conditioning on working age households (column (3)). In addition, the skewness is monotonically increasing in the number of non-employed household heads (column (4)). All specifications suggest one conclusion: The skewness of price distributions decreases in the share of expenditure stemming from low-effort households. This is well in line with Proposition 3 and provides strong evidence in favor of the theoretical relationship between search effort and posted prices.

**Robustness.** In Appendix B.3, I report further robustness with respect to how the skewness of price distributions is measured for the specification of column (1) of Table 2. Table 10 in Appendix B.3 reports results without using weights in the regression, computing the skewness based on unweighted price observations, or based on household weights only. All findings are robust to using alternative weighting schemes. The decrease of skewness in expenditure is also robust when using Kelly’s measure of skewness, which is less sensitive to outliers.<sup>13</sup> As Table 11 in Appendix B.3 shows, results become quantitatively stronger if considering only price distributions with at least 50 or 100 transactions. The robustness tests alleviate potential concerns that price distributions are constructed based on transaction data sampled from households. As the findings are robust to not weighting by quantities purchased and focusing on distributions with many transactions (where each posted price has a better chance of entering the sample) it is unlikely that households’ purchase behavior is driving the results.<sup>14</sup>

## 4 A Theory of Inequality and Price Dispersion

In Section 2 I have taken households’ choices as given to derive analytical results on how posted prices respond to the choices of households. In equilibrium, households’ shopping effort and consumption choices are themselves a function of the distributions of posted prices. To account for this feedback between households’ choices and retailers’ price posting, this section develops an equilibrium theory of expenditure inequality and price dispersion and disciplines it against evidence from the Nielsen Consumer Panel.

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<sup>13</sup>The units of the coefficients are not comparable for Kelly’s measure of skewness, so no statements can be made about the relative magnitude of the results in column (2) of Table 10 in Appendix B.3.

<sup>14</sup>In future work, I plan to extend the analysis to the Nielsen Retail Scanner dataset providing information on posted prices sampled directly from stores.

## 4.1 Households with Non-Homothetic Preferences and Shopping

Households are infinitely lived and heterogeneous in their labor earnings  $zw$ .  $w$  is the common wage rate per unit of labor and  $z$  households' idiosyncratic labor productivity, evolving exogenously according to a first order Markov process. Households supply  $z$  efficiency units of labor inelastically. In addition, they earn a return  $r$  per unit of beginning of period assets  $a$ . Households decide jointly on their future asset holdings  $a'$ , quantities consumed of each variety  $j \in J$  of a grocery good  $\{c_j\}_{j=1}^J$  and an outside (non-grocery) good  $c_O$ , and shopping effort  $s$ .

Households' decision problem can be split into two stages. In a first stage a household divides her resources between savings  $a'$  and total expenditure  $e$  to solve

$$\begin{aligned} V(z, a) &= \max_{e, a' \geq 0} U(e) + \beta \mathbb{E}_{z'|z} V(z', a') \\ \text{s.t. } & e + a' \leq (1 + r)a + zw. \end{aligned} \tag{8}$$

The utility of expenditure  $U(e)$  summarizes the second stage in which households decide on their allocation of consumption across grocery varieties and the outside good as well as their choice for shopping effort, conditional on expenditure. They solve

$$\begin{aligned} U(e) &= \max_{s \in [0,1], \{c_j\}_{j=1}^J, c_O} u(\mathcal{C}) - v(s, \mathcal{C}) \\ \text{s.t. } & \mathcal{C} = (c_G)^\alpha (c_O)^{1-\alpha} \\ & c_G = \left[ \sum_{j=1}^J (\mathcal{C})^{\frac{q_j}{\sigma}} (c_j)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \\ & c_O + \sum_{j=1}^J p_j(s) c_j \leq e. \end{aligned} \tag{9}$$

The outside good is taken to be the numeraire and its price is normalized to 1.  $u(\cdot)$  are households' preferences over the consumption aggregator  $\mathcal{C}$  and  $v(s, \mathcal{C})$  is the disutility of exerting shopping effort. I assume that the disutility of effort depends on the level of consumption  $\mathcal{C}$  to capture in reduced form that households have to search more often for prices if they have a larger consumption basket.<sup>15</sup>

Due to the two stage setup, the distribution of expenditures fully determines the distribution of shopping effort and consumption baskets across households. The structure allows me to focus on data moments of the expenditure distribution when disciplining households' shopping and consumption policies below.

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<sup>15</sup>This mechanism is micro-founded in Pytka (2022) who also provides evidence that conditional on employment high-income households spend more time making purchases and rules out that this is due to shopping as a leisure activity.

**Consumption Allocation.** The aggregator  $\mathcal{C}$  is a Cobb-Douglas function defined over grocery and non-grocery consumption. Grocery consumption  $c_G$  is itself a non-homothetic CES aggregator over varieties  $j \in J$  in the spirit of Comin et al. (2021) and Handbury (2021). For given total consumption  $\mathcal{C}$  and shopping effort  $s$ , it defines a demand system across varieties that can be characterized in terms of expenditure shares  $\omega_j$ , where the optimal allocation satisfies

$$\frac{\omega_j}{\omega_k} = \mathcal{C}^{q_j - q_k} \left( \frac{p_j(s)}{p_k(s)} \right)^{1-\sigma}.$$

Varieties should be considered close substitutes and can be thought of as different barcodes within a Nielsen defined product module. I focus on this low level of product differentiation as a significant degree of non-homotheticities occurs at this granular definition of a variety.<sup>16</sup> The parameters  $\{q_j\}_{j=1}^J$  govern the expenditure elasticity of demand: With  $\mathcal{C}$  increasing in expenditures, the relative expenditure share of variety  $j$  vs. variety  $k$   $\left(\frac{\omega_j}{\omega_k}\right)$  is increasing in total spending  $e$  iff  $q_j > q_k$ . In line with the literature's interpretation of more expensive varieties among close substitutes as higher quality products, I will refer to varieties with a high  $q_j$  as *high-quality*.<sup>17</sup> Under this interpretation, the non-homotheticities considered arise because high-spending households have a stronger taste for quality.

The price of the optimal grocery consumption bundle (of one unit  $c_G$ ) is given as

$$p_G(\mathcal{C}, s) = \left( \sum_{j=1}^J \mathcal{C}^{q_j} (p_j(s))^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

The Cobb-Douglas aggregator  $\mathcal{C}$  implies optimal shares of expenditures on groceries  $e_G$  and the outside good  $e_O$  given by

$$\omega_G = \frac{e_G}{e} = \frac{p_G(\mathcal{C}, s)c_G}{e} = \alpha \quad \text{and} \quad \omega_O = \frac{e_O}{e} = \frac{c_O}{e} = 1 - \alpha.$$

For given shopping effort  $s$  and expenditure level  $e$  the consumption aggregator is a solution to the non-linear equation

$$\mathcal{C} = \frac{e}{P(\mathcal{C}, s)}, \tag{10}$$

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<sup>16</sup>In Appendix B.4 I compared consumption baskets along the expenditure distribution in the Nielsen data and show that significant non-homotheticities arise when defining a product as a barcode as compared to aggregating goods at the product module level. This is in line with e.g. Jaravel (2019).

<sup>17</sup>See e.g. Bils and Klenow (2001), Bisgaard Larsen and Weissert (2020), or Argente and Lee (2021).

where the price index associated with  $\mathcal{C}$  is given as

$$P(\mathcal{C}, s) = \left( \frac{p_G(\mathcal{C}, s)}{\alpha} \right)^\alpha \left( \frac{1}{1 - \alpha} \right)^{1 - \alpha}.$$

**Shopping Effort.** The price a household pays for any variety  $j$  of the grocery good is a function of her shopping effort. Households' optimal choice of shopping effort equates the marginal benefits of shopping with the marginal disutility of exerting effort such that

$$\underbrace{-v_s(s, \mathcal{C})}_{\text{marginal disutility of shopping}} = \underbrace{\frac{\partial p_G(\mathcal{C}, s)}{\partial s} c_G}_{\text{change in BC}} \underbrace{(1 - \alpha) \frac{\mathcal{C}}{c_O} [u'(\mathcal{C}) - v_C(s, \mathcal{C})]}_{\text{marginal benefit of relaxing BC}}. \quad (11)$$

The benefit of shopping is the change in the budget constraint times the marginal utility of additional available resources, here expressed as the marginal utility of consuming one more unit of  $c_O$ .<sup>18</sup> Increasing shopping effort reduces the cost of consumption and relaxes the budget by  $\frac{\partial p_G(\mathcal{C}, s)}{\partial s} c_G$ , where the change in the price index depends on households' consumption basket and the return to shopping for each variety. It is given by

$$\frac{\partial p_G(\mathcal{C}, s)}{\partial s} = p_G(\mathcal{C}, s)^\sigma \sum_{j=1}^J c^{q_j} (p_j(s))^{-\sigma} \underbrace{\frac{\partial p_j(s)}{\partial s}}_{\text{return to shopping}}.$$

The relationship between prices and shopping effort, i.e. the return to shopping effort  $\frac{\partial p_j(s)}{\partial s}$ , is an equilibrium object and depends on the distribution of posted prices.

## 4.2 Equilibrium in the Goods Market and Return to Shopping

**Production.** All grocery varieties and the outside good are produced and sold to retailers at marginal cost by fully competitive production firms. Producers operate linear technologies with labor  $N$  as the single input factor. I assume production functions  $y_O = N_O$  and  $y_j = \frac{1}{\kappa_j} N_j$ , so that with the outside good as the numeraire the equilibrium wage is determined as  $w = 1$  and the marginal cost of producing a unit of variety  $j$  is given by  $\kappa_j$ . In line with Kaplan and Menzio (2016), I assume that households can transform the outside good into groceries of variety  $j$  at a rate  $\frac{1}{\bar{p}_j}$  implying a maximum willingness to pay  $\bar{p}_j$  to purchase variety  $j$  from a retailer. Households' assets are invested in a risk-free bond at exogenous interest rate  $r$ . Under these assumptions, the model outcomes can be interpreted as the equilibrium of a small open economy or as the equilibrium in a subregion (state) of a large economy like the US.

<sup>18</sup>At the optimal solution, marginal utility could also be expressed in terms of spending the additional unit of available resources on any of the grocery varieties or the composite grocery good  $c_G$ .

**Market Structure.** The outside good is traded in a perfectly competitive market and its price is independent of shopping effort, whereas all varieties of grocery consumption are sold in markets that are subject to search frictions. There is a separate search market for each grocery variety  $j$ . The distribution of posted prices for each variety  $F_j(p)$  is determined by the optimal price posting of a mass of single-variety retailers. As before, retailers post prices for variety  $j$  given equilibrium search effort  $\bar{s}_j$ , marginal cost  $\kappa_j$  and maximum willingness to pay  $\bar{p}_j$ . I deviate from the setup laid out in Section 2 and assume that a retailer selling variety  $j$  is subject to a per period fixed cost of operation  $K_j$  and the mass  $M_j$  of active retailers selling variety  $j$  is determined by free entry. Profits of posting price  $p$  in the market for variety  $j$  are given by

$$\tilde{\pi}_j(p) = \frac{C_j}{M_j} [(1 - \bar{s}_j) + \bar{s}_j 2(1 - F_j(p))] (p - \kappa_j) - K_j = \frac{\pi_j(p)}{M_j} - K_j,$$

where  $\pi_j(p)$  is retailers' profits of posting  $p$  in the version of the model without fixed cost of operating and a given mass one of retailers as outlined in Section 2. Appendix A.1 proves that this setup yields a distribution of posted prices equivalent to the one derived in Section 2, while the mass of entrants  $M_j$  ensures that  $\tilde{\pi}_j(p) = 0$ , i.e. retailers make zero profits in equilibrium. Beyond ensuring zero profits,  $M_j$  and  $K_j$  do not influence equilibrium allocations and only their product is uniquely determined by  $\pi_j(p) = M_j K_j$  for any  $p$  on the support of  $F_j(p)$ .

**Return to Search.** To determine the relationship  $p_j(s)$  between prices paid for variety  $j$  and households' shopping effort, I follow Pytka (2022). The distribution of effective prices for a single purchase of variety  $j$  when exerting shopping effort  $s$  is given as

$$G_j(p|s) = (1 - s)F_j(p) + s(1 - (1 - F_j(p))^2).$$

The assumptions that households split their total demand for each variety into a continuum of purchases and that every price observation is an i.i.d. random draw from  $F_j(p)$  ensure that there is no uncertainty about the total cost of purchasing a quantity  $c_j$ . Pytka (2022) shows that the average price paid per purchase of variety  $j$  is

$$p_j(s^i) = \mathbb{E}_j^G[p|s^i] = \mu_j^F - s^i (\mu_j^F - \mathbb{E}_j^F[\min\{p', p''\}]), \quad (12)$$

such that

$$\frac{\partial p_j(s^i)}{\partial s^i} = - (\mu_j^F - \mathbb{E}_j^F[\min\{p', p''\}]) = \text{const.} < 0.$$

The two constants  $\mu_j^F$  and  $\frac{\partial p_j(s^i)}{\partial s^i} < 0$  are sufficient statistics to capture the impact of the price distribution of variety  $j$  on households' behavior, i.e. all that households need to know to decide on their demand for each variety and their shopping effort. This feature

simplifies the computational solution of the model significantly as households do not need to keep track of the entire price distribution. It also suggests that matching the average price and a measure of price dispersion across varieties is sufficient to discipline  $p_j(s^i)$ , as the dispersion of prices is closely related to the equilibrium object  $\frac{\partial p_j(s^i)}{\partial s^i}$ .

**Equilibrium.** A stationary equilibrium in the economy consists of households' value function  $V(z, a)$ , consumption policy functions  $\{c_O(z, a), \{c_j(z, a)\}_{j=1}^J\}$ , shopping policy  $s(z, a)$ , expenditure policy  $e(z, a)$  and savings policy  $a'(z, a)$ , the induced distribution of households across states  $\lambda(z, a)$ , aggregated demand  $\{C_j\}_{j=1}^J$  and demand-weighted shopping effort  $\{\bar{s}_j\}_{j=1}^J$  for each variety, posted price distributions  $\{F_j(p)\}_{j=1}^J$  and implied pricing functions  $\{p_j(s)\}_{j=1}^J$ , where

(i) Given  $\{p_j(s)\}_{j=1}^J$ , households' value and policy functions solve (8) and (9).

(ii) The distribution of households is a stationary solution to the law of motion

$$\lambda(z', a') = \int \int \lambda(z, a) Pr(z'|z) \mathbf{1}_{a'=a(z,a)} dz da.$$

(iii) Aggregated demand for variety  $j$  is given by

$$C_j = \int \int \lambda(z, a) c_j(z, a) dz da.$$

(iv) Demand weighted shopping effort for variety  $j$  is given by

$$\bar{s}_j = \int \int \frac{\lambda(z, a) c_j(z, a)}{C_j} s(z, a) dz da.$$

(v) Given  $\{\bar{s}_j\}_{j=1}^J$ , the posted price distributions  $\{F_j(p)\}_{j=1}^J$  solve (4).

(vi) Given  $\{F_j(p)\}_{j=1}^J$ , the pricing functions  $\{p_j(s)\}_{j=1}^J$  satisfy (12).

### 4.3 Calibration

I calibrate the model at annual frequency. The calibration proceeds in three steps: I first calibrate the income process outside of the model, describe functional forms and set some parameters exogenously, and finally calibrate all remaining parameters to match targets on expenditure composition, price dispersion, and macro aggregates.

**Income Process.** The process for idiosyncratic productivity is the same as in Ferriere et al. (2022) and Mendicino et al. (2022). I assume an AR(1) with innovations from a Gaussian mixture, to capture higher moments of income risk as reported e.g. in Guvenen

et al. (2021). I target the cross-sectional variance of income, as well as moments of the distribution of income changes. Data targets are obtained from De Nardi et al. (2020). Details on the calibration of the income process are delegated to Appendix C.1.

**Functional Forms and External Parameters.** I assume CRRA preferences for  $u(\cdot)$  and a disutility of shopping effort as a function of the consumption aggregator  $\mathcal{C}$  such that

$$u(\mathcal{C}) = \frac{\mathcal{C}^{1-\phi} - 1}{1-\phi} \quad \text{and} \quad v(s, \mathcal{C}) = \psi_1 \mathcal{C}^{\psi_2} \frac{s^2}{1-s}.$$

The term  $\frac{s^2}{1-s}$  ensures that households will prefer an interior solution for  $s$ .<sup>19</sup> I restrict  $\psi_1 > 0$  and  $\psi_2 > 0$  to obtain a disutility of effort increasing in  $\mathcal{C}$  and capture the need to search more often for prices when making more purchases. In this spirit,  $\psi_2$  determines the economies of scale in shopping effort.

The calibrated version of the model features three varieties (levels of quality), i.e.  $J = 3$ .<sup>20</sup> In line with the evidence on low-level elasticities of substitution sampled in Jaravel and Olivi (2021), I set  $\sigma = 2$ . Furthermore, I normalize the medium quality to  $q_2 = 0$  and marginal cost of the lowest quality to the outside good, i.e.  $\kappa_1 = 1$ . The CRRA parameter is set to  $\phi = 2$  and the annual real interest rate to  $r = 0.02$ .

Based on Broda and Parker (2014), I set  $\alpha = 0.35$  to the share of non-durable and services consumption covered by the Nielsen dataset. This is a conservative choice, as search frictions and price dispersion can be expected to matter beyond the products covered by Nielsen. Without data for additional product categories, I restrict the search friction to the share of goods covered in Nielsen. Under this assumption, I interpret all results on overall consumption  $\mathcal{C}$  and welfare as a lower bound on the consequences of shopping frictions for inequality and report results based on grocery consumption  $c_G$  separately as an approximation for an economy with  $\alpha = 1$ .

**Internal Parameters.** The remaining parameters to be calibrated are  $(\psi_1, \psi_2, \kappa_2, \kappa_3, \bar{p}_1, \bar{p}_2, \bar{p}_3, \beta, q_1, q_3)$ . As they do not influence allocations, I do not need to account for the fixed cost  $K_j$  in the calibration. I impose  $q_1 = -q_3$  and  $\bar{p}_j = a + b(\kappa_j - \kappa_1)$ . This leaves eight parameters for which I target eight moments, divided into three groups.

At the aggregate level, I target a wealth-to-income ratio of 3. While all parameters can influence all moments, the one most closely linked to the wealth to income ratio is  $\beta$ . Furthermore, I target an average retail markup of 1.39, computed based on the US

<sup>19</sup>It yields  $v(0, \mathcal{C}) = 0$ ,  $v(1, \mathcal{C}) = \infty$ ,  $v_s(0, \mathcal{C}) = 0$ ,  $v_s(1, \mathcal{C}) = \infty$ . Under these assumptions households optimally choose  $0 < s < 1$  iff  $\frac{\partial p_j(s^i)}{\partial s^i} < 0$ . An interior solution for  $s$  facilitates the computational solution of the model.

<sup>20</sup>Considering versions of the model with 4 or 5 varieties does not alter the conclusions drawn below.

Census’ Annual Retail Trade Survey.<sup>21</sup> This value lies within the set of results reported for retail markups in the literature, ranging from 1.31 (Sangani 2022) to 1.45 (Hall 2018). The aggregate markup is closely related to  $\psi_1$ , which governs average shopping effort and hence the average price elasticity of demand across retailers.

**Table 3:** Calibration Targets and Model Fit

Target	Data	Model	Source
basket overlap (Q1 vs. Q5)	63.28%	63.76%	Nielsen (2007-2019)
$\Delta p$ across varieties (Q1 vs. Q5)	7.2%	7.2%	Nielsen (2007-2019)
$\Delta p$ within varieties (Q1 vs. Q5)	2%	2%	Nielsen (2007-2019)
mean( $CoV_j$ )	0.1920	0.1915	Nielsen (2007-2019)
$CoV_2 - CoV_1$	-0.0120	-0.0078	Nielsen (2007-2019)
$CoV_3 - CoV_1$	-0.0203	-0.0211	Nielsen (2007-2019)
average markup	1.39	1.39	ARTS (2007-2019)
wealth/income	3	3	

**Note:** Results of the internal calibration of  $(\psi_1, \psi_2, \kappa_2, \kappa_3, \bar{p}_1, \bar{p}_2, \bar{p}_3, \beta, q_1, q_3)$ .

A second set of moments targets price dispersion across varieties. These moments are closely related to the return to search. Capturing the right returns to search across varieties (and therefore across consumption baskets) is important for the correct identification of the elasticity of shopping to expenditures. Targets for price dispersion are computed from the Nielsen Consumer Panel based on the same definition of a price distribution as in Section 3.2, i.e. pooling transactions for a given barcode within a Scantrack region and a quarter. To account for differences in the average price across barcodes in the data, I focus on the coefficient of variation (CoV).<sup>22</sup> I target the expenditure-weighted average CoV across all price distributions. In addition, I run a regression of the CoV on demand composition by barcode as specified in equation (7) for the skewness, including on the right-hand side the quintiles of the expenditure distribution. I target the implied differences in the CoV across varieties based on the endogenous demand composition (spending shares across quintiles) in the model. Targets for price dispersion interact most closely with the values for  $\bar{p}_j$  relative to  $\kappa_j$ .

The final set of moments contains targets on expenditure composition across households, again measured from the Nielsen data. This set of targets is particularly important as it identifies the elasticities of consumption baskets and shopping effort to households’ expenditure and with them the main mechanism of this paper. To discipline how consumption baskets change across households, I target the (dis)similarity in expenditure

<sup>21</sup>I use data for 2007-2019 and take sales divided by purchases net of the change in inventories for *food and beverage stores, health and personal care stores, and general merchandise stores* as the categories most closely reflecting the retailers covered in Nielsen. I weight markups across categories by total sales.

<sup>22</sup>Targeting the coefficient of variation is equivalent to normalizing all prices by the mean and computing the standard deviation of normalized prices as e.g. in Kaplan and Menzio (2015).

**Table 4:** Calibrated Parameter Values

Parameter	Value	Notes
$J$	3	
$\sigma$	2.0	Jaravel and Olivi (2021)
$\alpha$	0.35	Broda and Parker (2014)
$\phi$	2.0	
$r$	0.02	
$q_j$	$[-0.67 \ 0 \ 0.67]$	
$\psi_1$	0.0023	
$\psi_2$	0.21	
$\kappa_j$	$[1 \ 1.06 \ 1.219]$	
$\bar{p}_j$	$[2.55 \ 2.65 \ 2.90]$	$2.55 + 1.6(\kappa_j - \kappa_1)$
$\beta$	0.9232	

**Note:** Summary of calibrated parameter values.  $(J, \alpha, \sigma, \phi, r)$  are set externally.  $(\psi_1, \psi_2, \kappa_2, \kappa_3, \bar{p}_1, \bar{p}_2, \bar{p}_3, \beta, q_1, q_3)$  are calibrated internally.

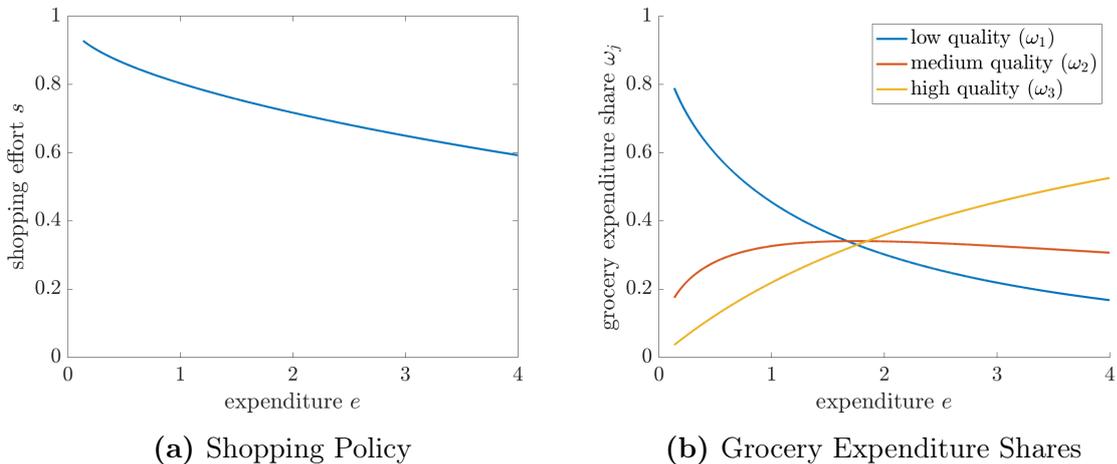
shares  $\omega_j$  at the barcode level between the first and the fifth quintile of the expenditure distribution. For this purpose, I interpret the vector of expenditure shares for a group of households as a discrete distribution over the universe of available varieties (barcodes) and measure the similarity between two such distributions as the histogram overlap. Full details on the construction of this target are provided in Appendix B.4. The barcode-level overlap between consumption baskets at the bottom and top of the expenditure distribution is about 63%. In addition, I target the annual savings as a share of respective grocery expenditure of households at the bottom quintile of expenditures relative to the top quintile, due to (i) buying similar varieties that are cheaper on average and (ii) paying less for identical varieties. I measure (i) as the difference between the per-unit average prices of a barcode and the per-unit average price of all barcodes within a Nielsen product module. (ii) is measured as the difference in the price a household pays for a barcode to the average price for this barcode across all households. More details on the construction of these targets are provided in Section 5.1. Price differences across varieties reduce expenditures of the bottom relative to the top quintile by 7.2% and price differences within varieties by 2.0% of annual spending. Given the returns to search across varieties (and consumption baskets) identified by the moments on price dispersion, the difference in prices paid for identical varieties identifies  $\psi_2$ , which governs the shape of households' shopping policy along the expenditure distribution. The overlap in consumption baskets and price differences across varieties interact closely with relative expenditure elasticities  $q_j$  as well as  $\kappa_j$  and  $\bar{p}_j$  across varieties.

A description of the algorithm applied to solve the model is delegated to Appendix C.2. Table 3 summarizes all targets and shows that the model is able to match the moments considered. Table 4 reports the calibrated parameter values. Noteworthy is the fact that

the calibration yields  $\psi_2 < 1$ . This value implies increasing returns to scale in shopping effort as the utility cost of exerting a given effort  $s$  increases less than one-for-one with the consumption aggregator  $\mathcal{C}$ .

#### 4.4 Model Properties and Validation

**Policy Functions.** The policy functions implied by the first stage spending-savings problem are standard, expenditures and future asset holdings are increasing in disposable resources ( $zw + (1+r)a$ ) and the expenditure policy is concave. Figure 3 displays selected policy functions for the second stage problem of choosing shopping effort and allocating spending across goods. It shows that shopping effort is decreasing and mildly convex in households' total expenditure  $e$  and that households with higher expenditures allocate a larger share of their consumption basket to varieties with higher quality (higher elasticity  $q_j$ ) due to their non-homothetic preferences.<sup>23</sup>



**Figure 3:** Shopping Effort and Consumption Baskets

**Note:** Model implied shopping effort  $s$  and expenditure shares  $\omega_j$  across grocery varieties  $j$  as a function of total household expenditure  $e$ . Expenditure shares are computed as total spending of a household on variety  $j$  divided by her total grocery expenditures  $e^G = \alpha e$ .

**Demand Composition.** Table 5 shows that the non-homotheticity in households' preferences leads to significant differences in demand composition across grocery varieties. While households in the bottom quintile of the expenditure distribution account for 11.38% of the spending on the low quality variety, they account for only 2.49% of spending on the high quality variety. On the other hand, households in the top quintile of the expenditure distribution account for 51.45% of spending on the highest quality variety but only 26.42% on the lowest quality variety. Intuitively, each household is more important for the demand of varieties in her own consumption basket.<sup>24</sup>

<sup>23</sup>The policy function for non-grocery consumption follows trivially from  $c_O = (1 - \alpha)e$ .

<sup>24</sup>Table 15 in Appendix C.5 shows this both for the model and the data. For a more formal discussion of how to measure this in the data refer to Appendix B.4.

**Table 5:** Demand Composition of Grocery Varieties

	quintile of expenditures				
	Q1	Q2	Q3	Q4	Q5
low quality ( $q_1$ )	0.1138	0.1752	0.2107	0.2360	0.2642
medium quality ( $q_2$ )	0.0555	0.1228	0.1838	0.2521	0.3859
high quality ( $q_3$ )	0.0249	0.0770	0.1432	0.2405	0.5145

**Note:** Model implied demand shares by varieties of the grocery good and expenditure quintile. Demand shares are computed as total sales of variety  $j$  to quintile  $g$  divided by total sales of variety  $j$ .

**Price Distributions.** Table 6 provides summary statistics for the model generated price distributions. In line with households' shopping policy and the demand composition across varieties, demand-weighted shopping effort  $\bar{s}_j$  is decreasing in quality  $q_j$ . The average price paid  $\mu_j^G$  is lower than the average price posted  $\mu_j^F$  for each variety due to households' search for cheaper offers. The standard deviation of posted prices  $\sigma_j^F$  increases with  $q_j$  and so does the return to search (i.e.  $\frac{\partial p_j(s^i)}{\partial s^i}$  is more negative). This implies that high-spending households exert lower search effort despite a higher return to search for their consumption basket.

**Table 6:** Price Distributions of Grocery Varieties

		quality of grocery variety		
		low ( $q_1$ )	medium ( $q_2$ )	high ( $q_3$ )
demand-weighted shopping effort	$\bar{s}_j$	0.76	0.73	0.71
average price posted	$\mu_j^F$	1.49	1.60	1.83
average price paid	$\mu_j^G$	1.38	1.48	1.71
standard deviation of posted prices	$\sigma_j^F$	0.30	0.31	0.33
return to search	$\frac{\partial p_j(s^i)}{\partial s^i}$	-0.15	-0.16	-0.17
skewness of posted prices	$\gamma_j^F$	1.51	1.42	1.33

**Note:** Summary statistics of model implied price distributions for each grocery variety  $j$ .

The skewness of price distributions decreases in the demand share of high spending households, qualitatively in line with the empirical results in Section 3.2. The differences in skewness generated by the model can account for one third of the differences predicted by the empirical results based on the model implied demand composition. The lower magnitude is of little concern for the results below, as by construction of the pricing function  $p_j(s)$  households' choices are determined by the first two moments of a distribution.

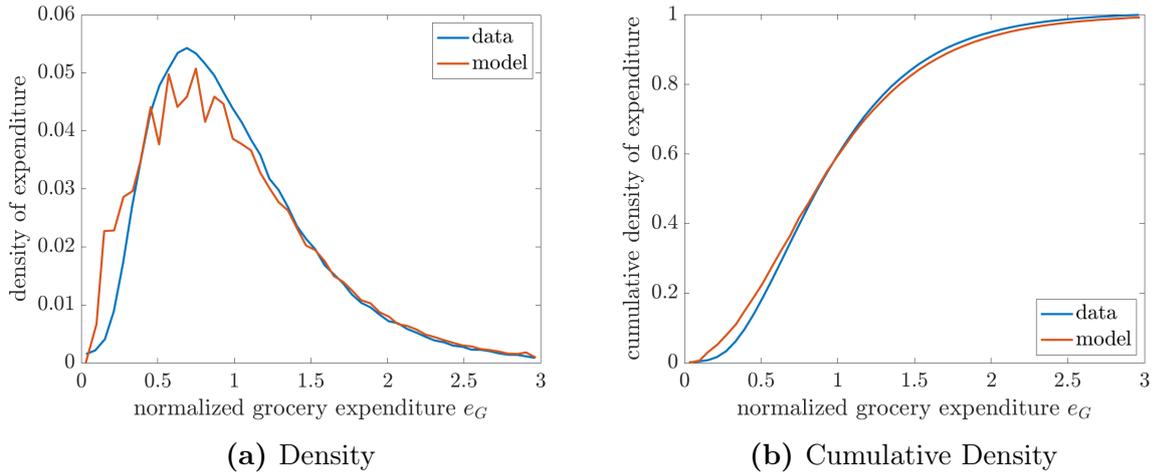
**Inequality.** Table 7 reports the distribution of total disposable income in the model ( $zw + ra$ ) as well as data on total household income after taxes and transfers from the Congressional Budget Office (CBO). The model generates realistic inequality in income.

**Table 7:** Income Distribution – Model vs. Data

	quintile of post-tax income				
	Q1	Q2	Q3	Q4	Q5
<b>Model</b>	5.02%	10.50%	15.78%	23.89%	44.79%
<b>Data</b>	6.44%	10.91%	14.70%	20.31%	47.65%

**Note:** Fit of the model implied income distribution. In the model, income is measured as labor and financial income ( $zw + ra$ ). Data moments for household income after taxes and transfers from Congressional Budget Office (CBO) for 2007-2018.

Due to the two-stage setup of the household problem, shopping effort and the allocation of consumption across varieties are determined conditional on expenditure  $e$ . Matching the distribution of expenditures therefore ensures a realistic distribution of shopping and consumption policies in the model. Figure 4 plots the model implied distribution of grocery expenditures along with its equivalent from the Nielsen dataset. While the

**Figure 4:** Distribution of Grocery Expenditures – Model vs. Data

**Note:** Fit of the model implied distribution of grocery expenditures  $e_G = \alpha e$ . Model and data distributions normalized to mean 1 and sorted into 50 equally spaced bins between 0 and the maximum expenditure level. Data from Nielsen Consumer Panel 2007-2019. Household-level grocery expenditures are equivalence scale adjusted and deflated with the Urban CPI to 2019. I winsorize the top 1% of data.

calibration targets include moments of the labor earnings process and match the empirical overlap in consumption baskets, as well as price differences within and across varieties, the dispersion in households' expenditure is not included in the calibration. Nevertheless, the model does remarkably well in capturing the empirically observed distribution of grocery expenditures. This finding provides confirmation that the model is a suitable framework for studying the relationship between expenditure inequality and posted prices.

## 5 Implications for Expenditure Inequality

### 5.1 Price Differences across Households

Before studying the consequences of shopping effort for inequality, I quantify price differences across and within varieties along the expenditure distribution. To make the model and data comparable along this dimension, I focus on the contribution of price differences relative to expenditure and provide a novel decomposition of households' grocery spending.

The first step of a price-based decomposition of expenditure inequality in the data is to make per-unit prices comparable across products. Therefore, I sort all barcodes into groups of similar products, defining a group as all items within a Nielsen product module measured in the same unit, and normalize prices and quantities by the size of a product.<sup>25</sup> Total annual grocery expenditure  $e_i^G$  for a given household  $i$  is the sum of spending  $e_{ijk}^G$  over all barcodes  $j$  in all groups  $k$ . Spending per barcode is the quantity-weighted average per-unit price paid by the household for barcode  $j$  in group  $k$   $p_{ijk}$  times the units consumed  $c_{ijk}$ . Further, define  $\hat{p}_{jk}$  as the quantity-weighted average price paid for variety  $j$  across all households and  $\tilde{p}_k$  as the average of  $\hat{p}_{jk}$  within group  $k$ . For example, for the module “fresh apples” measured in pieces  $\tilde{p}_k$  is the average price per apple across all households and all barcodes of apples,  $\hat{p}_{jk}$  the average price for one specific type of apple across households, and  $p_{ijk}$  the average price one specific household pays for one specific type of apple. In the model, I consider a single (representative) group  $k$  and all three varieties  $j$  as close substitutes of identical size within that group. Decompose  $e_i^G$  as

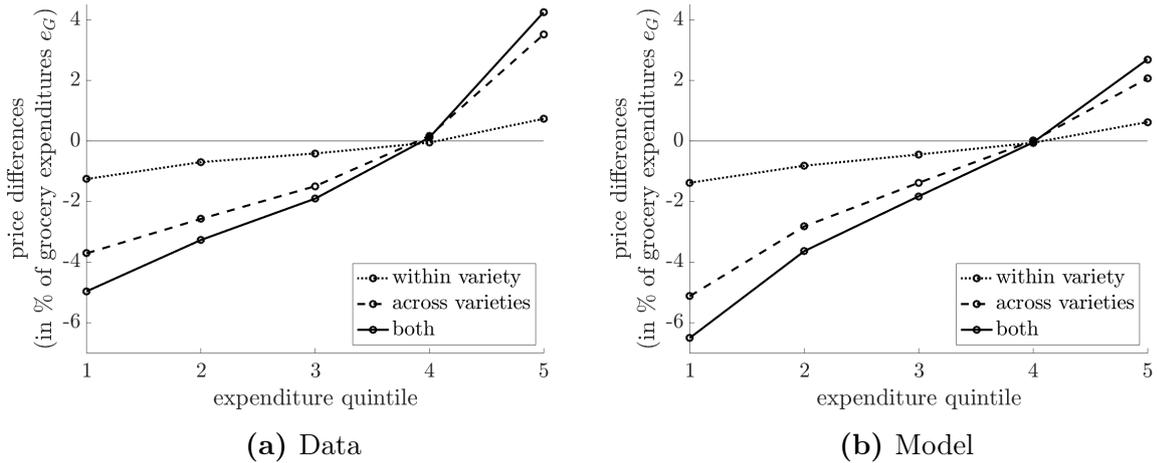
$$\begin{aligned}
 e_i^G &= \sum_k \sum_{j \in J_k} e_{ijk}^G = \sum_k \sum_{j \in J_k} p_{ijk} c_{ijk} \\
 &= \underbrace{\sum_k \sum_{j \in J_k} (p_{ijk} - \hat{p}_{jk}) c_{ijk}}_{\substack{\text{within varieties} \\ \text{(direct effect of shopping)}}} + \underbrace{\sum_k \sum_{j \in J_k} (\hat{p}_{jk} - \tilde{p}_k) c_{ijk}}_{\text{across varieties}} + \underbrace{\sum_k \sum_{j \in J_k} \tilde{p}_k c_{ijk}}_{\text{quantities}}.
 \end{aligned}$$

The first term captures price differences within identical products between what an individual household pays relative to other households. In the model, this is driven by differences in the direct effect of shopping on reducing the average price per unit given the posted price distribution. The second term captures differences across products, due to heterogeneity in consumption baskets. In line with the interpretation of demand elasticities  $q_j$ , the literature has referred to these differences in the average price across close

<sup>25</sup>E.g. I group together all barcodes in the module “fresh apples” that are measured in pieces and divide the price of each barcode by the number of individual apples included to get a price per apple. Most product modules have one dominant unit of measurement and there is no systematic difference in purchases across households in the unit dimension as Appendix B.4 shows.

substitutes as quality (e.g. Argente and Lee 2021; Bisgaard Larsen and Weissert 2020; Jaimovich et al. 2019). The last term summarizes households’ counterfactual expenditure absent any price differences within or across products, where all variation of expenditures within a group  $k$  is due to differences in the quantity consumed.

Figure 5a shows the results of the empirical decomposition by quintile of the expenditure distribution, expressed as a fraction of grocery expenditure. Households at the bottom of the distribution have about 5.5% lower expenditure due to deviations from the average price  $\tilde{p}_k$  within module-unit bins. 1.5pp. are due to lower prices within products, i.e. driven by the direct effect of shopping effort. 4pp. are due to lower prices across the products bought. At the top of the distribution, price differences increase total spending by 4%, 3.5pp. of which due to differences across products. In between, the contribution of price differences within and across products is monotonically increasing in expenditure. The reported magnitudes are well in line with the findings of e.g. Aguiar and Hurst (2007) and Bisgaard Larsen and Weissert (2020) under alternative approaches.



**Figure 5:** Price Differences along the Expenditure Distribution

**Note:** Price differences by expenditure quintile in the model and data, as a share of households’ grocery spending. “Within variety” refers to differences between the price paid by a given household and the average price for a given product (direct effect of shopping), while “across varieties” is the difference in average prices across different products. Data from the Nielsen Consumer Panel 2007-2019. In the data, the price within products is computed by barcode and the price across products is computed across barcodes within a product module (by unit of measurement).

We can interpret these findings in terms of their contribution to expenditure inequality. Inequality is often measured as a ratio between the top and the bottom of the distribution (e.g. Aguiar and Bilal 2015). Define  $\tilde{e}_i^G = \sum_k \sum_{j \in J_k} \tilde{p}_k c_{ijk}$  as a household’s counterfactual grocery spending absent price differences within and across products. The results of Figure 5a imply that price differences within and across varieties can account for 10% of expenditure inequality between the top and bottom quintile. I.e. expenditure inequality

measured as the ratio of counterfactual expenditure  $\tilde{e}^G$  between the top to bottom quintile of the expenditure distribution is about 10% lower compared to true expenditure  $e^G$ .<sup>26</sup>

Figure 5b shows that the model is able to reproduce the empirical patterns. It is important to note that only the differences within and across varieties between the lowest and highest quintile are included in the set of targeted moments. The model does well at reproducing the levels and slope of both margins along the entire expenditure distribution.

**Robustness.** Table 12 in Appendix B.5 provides estimates from a regression of the contribution of price differences within and across barcodes on households' expenditure and controls to show that their relationship is robust to other household characteristics.<sup>27</sup>

## 5.2 Equilibrium Effects of Shopping on Inequality

While the previous section provides descriptive evidence on how prices contribute to expenditure inequality, interpreting their contribution to real inequality requires one further step. Price differences across households can be either due to differences in marginal costs for the products bought or due to differences in the margins paid. It is important to distinguish between the two. While a higher marginal cost cannot be avoided to purchase a preferred good, a higher margin implies that it would be feasible to achieve the same consumption allocation with lower expenditures. Higher margins reflect the cost imperfect competition in the product market imposes on households. While I cannot distinguish between marginal cost and margins in the data, the model allows me to disentangle them.

**Direct and Equilibrium Effect of Shopping.** In the previous decomposition, differences in prices within varieties are entirely due to margin differences. They capture the direct effect of differences in households' shopping effort, paying less for an identical product given the posted price distribution. However, differences in average (posted) prices across varieties can be due to either marginal costs or average margins posted. As Proposition 1 has shown, differences in average posted margins across varieties can be attributed to the equilibrium effect of search frictions and shopping behavior on posted prices. This effect operates through retailers' response to demand-weighted shopping effort  $\bar{s}_j$ , which changes across varieties due to the differences in demand composition induced by non-homotheticities in households' preferences. I therefore attribute differences in average margins across varieties ( $\hat{p}_{jk} - \kappa_{jk}$ ) to the equilibrium effect of shopping. This leaves differences in marginal cost of variety  $j$  relative to the average marginal cost in

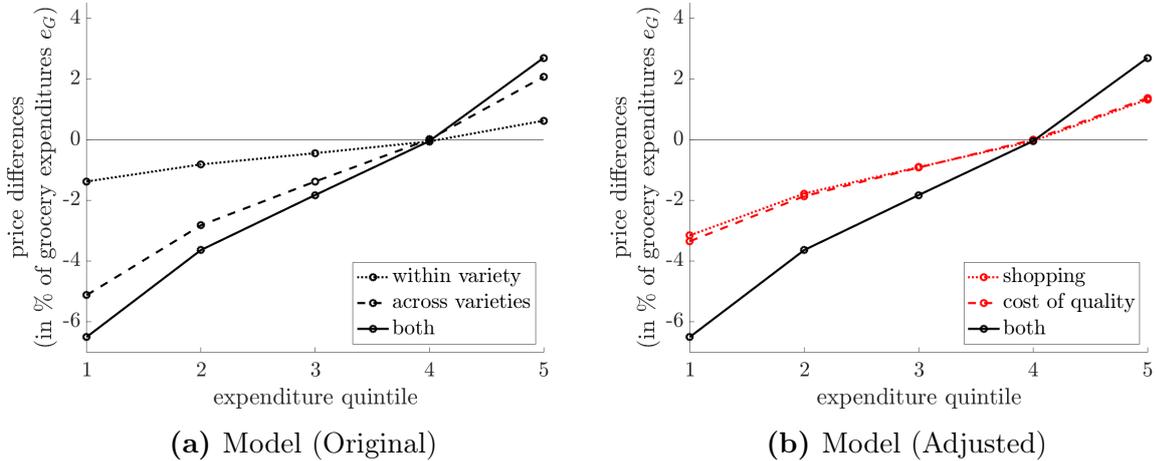
<sup>26</sup>Figure 17 in Appendix B.5 shows that this number increases to 12% when considering deciles.

<sup>27</sup>I include income, employment status, age, household size, household and year-state fixed effects. To relate price differences within products to households' shopping effort, I report again the evidence on trips-per-purchase from Section 3.1. Running a regression of the price differences within and across varieties on log-expenditure in the model slightly underpredicts the estimates from the data (0.68 vs. 0.95 for differences within and 2.5 vs. 3.4 across) but is consistent with the relative magnitudes.

group  $k$  ( $\kappa_{jk} - \tilde{\kappa}_k$ ) to explain the remaining price gap across products. In line with the interpretation of higher  $q_j$  as quality, I will refer to this term as *cost of quality*. I adjust the decomposition accordingly.

$$\begin{aligned}
e_i^G &= \underbrace{\sum_k \sum_{j \in J_k} (p_{ijk} - \hat{p}_{jk}) c_{ijk}}_{\substack{\text{within varieties} \\ \text{(direct effect of shopping)}}} + \underbrace{\sum_k \sum_{j \in J_k} (\hat{p}_{jk} - \tilde{p}_k) c_{ijk}}_{\text{across varieties}} + \sum_k \sum_{j \in J_k} \tilde{p}_k c_{ijk} \\
&= \underbrace{\sum_k \sum_{j \in J_k} (p_{ijk} - \hat{p}_{jk}) c_{ijk} + ((\hat{p}_{jk} - \kappa_{jk}) - (\tilde{p}_k - \tilde{\kappa}_k)) c_{ijk}}_{\text{shopping (direct+equilibrium)}} + \underbrace{\sum_k \sum_{j \in J_k} (\kappa_{jk} - \tilde{\kappa}_k) c_{ijk}}_{\text{cost of quality}} + \sum_k \sum_{j \in J_k} \tilde{p}_k c_{ijk}
\end{aligned}$$

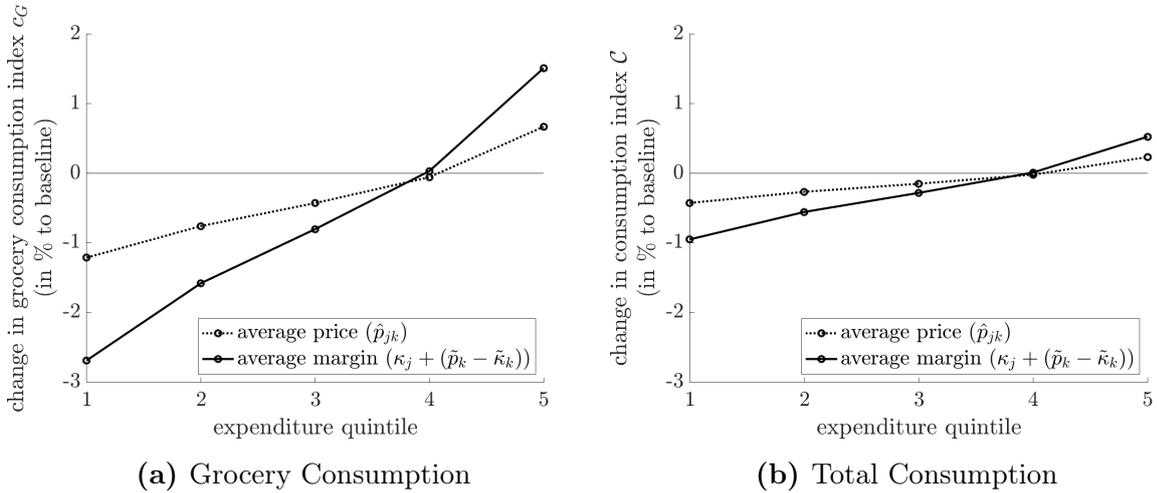
Figure 6 presents the results for the adjusted decomposition alongside the original results from Figure 5b. It shows that accounting for the equilibrium effect of search frictions and differences in  $\bar{s}_j$  on margins across varieties more than doubles the contribution of shopping to expenditure inequality, relative to the direct effect on price differences within products. This makes the overall effect of shopping equally important as differences in marginal costs across varieties. According to this decomposition, shopping alone through its direct and equilibrium effects can account for 5% of inequality in household expenditures between the bottom and top quintile of expenditures. This contribution is entirely due to the consequences of imperfect competition and should therefore be seen as a reduction in real consumption inequality relative to expenditure inequality.



**Figure 6:** Price Differences along the Expenditure Distribution - The Effect of Shopping  
**Note:** Price differences by expenditure quintile in the model, as a share of households’ grocery spending. In the *original* decomposition, “within variety” refers to differences between the price paid by a given household and the average price for a given product (direct effect of shopping), while “across varieties” is the difference in average prices across different products. In the *adjusted* decomposition, “shopping” refers to price differences within and margin differences across products (direct and equilibrium effect of shopping) and “cost of quality” to differences in marginal costs across products.

**Consumption Inequality.** The effect of heterogeneous shopping behavior on the relationship between expenditure and consumption inequality can be best understood by the following thought experiment: Fix the distribution of expenditures and allow households to optimally choose their consumption bundles assuming (i) all households pay the average price  $\hat{p}_{jk}$  for each variety or (ii) all households pay the marginal cost plus the average margin  $\kappa_j + (\tilde{p}_k - \tilde{\kappa}_j)$  for each variety. The former eliminates the direct effect of shopping on inequality. The latter additionally shuts down its equilibrium effect and is the sum of the quantity term and the cost of quality above.

Figure 7a shows by how much grocery consumption would change on average within each expenditure quintile under the alternative prices. Without the direct and indirect effect of shopping, grocery consumption  $c_G$  for the bottom quintile would be approximately 3% lower at identical expenditures and 2% higher for the top quintile. About half of the difference can be attributed to the direct and equilibrium effect respectively. We can again measure inequality as the ratio of top to bottom quintiles' consumption. The findings confirm that with identical inequality in grocery expenditures, inequality in consumption would be approximately 5% higher without the direct and equilibrium effect of shopping. The effect is muted when focusing on total consumption  $\mathcal{C}$  in Figure 7b, as the outside good is not subject to any search frictions. The result on  $\mathcal{C}$  sets the lower bound for shopping's overall effect on consumption inequality to 1.5%. With similar search frictions for all consumption, the overall effect would be close to the results reported for  $c_G$ .



**Figure 7:** Shopping Effort and Consumption Inequality

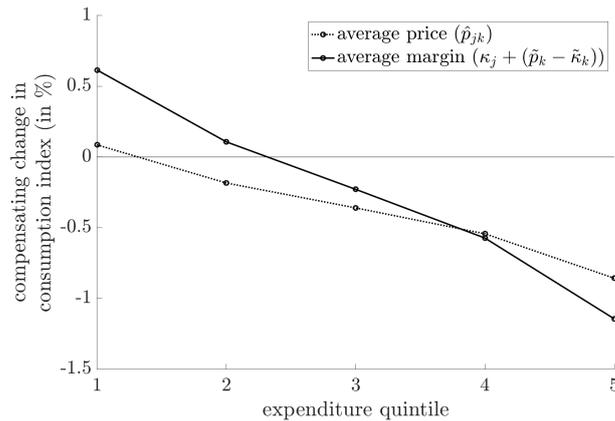
**Note:** Change in households' grocery ( $c_G$ ) and total consumption ( $\mathcal{C}$ ) absent shopping effort. Counterfactuals fix the expenditure distribution and let households choose a basket assuming they have to pay (i) the average price within each grocery variety (shutting down the direct effect of shopping) or (ii) marginal cost plus the average margin across varieties (shutting down the direct and equilibrium effect).

**Welfare.** The findings on consumption inequality do not take into consideration the full consequence for households' welfare, as they abstract from the disutility of shopping

effort. To interpret the equilibrium effect of shopping in terms of welfare, I again fix the expenditure distribution and compute the one-period utility for each household under the assumption that no household exerts any search effort and all households (i) pay the average prices  $\hat{p}_{jk}$  or (ii) pay the marginal cost plus average profit margins  $\kappa_{jk} + (\tilde{p}_k - \tilde{\kappa}_k)$  for each variety. I then ask by how much consumption  $\mathcal{C}$  in the alternative economy would need to change to make a household with expenditure  $e$  indifferent between living there for one period or living one period in the steady state economy.<sup>28</sup> Formally, the necessary change in consumption is defined as

$$\Delta \mathcal{C}^{CF}(e) = \left( \frac{U(e) + \frac{1}{1-\phi}}{u(\mathcal{C}^{CF}(e)) + \frac{1}{1-\phi}} \right)^{\frac{1}{1-\phi}} - 1,$$

where  $U(e)$  is the steady state one-period utility of spending  $e$ ,  $u(\cdot)$  the CRRA utility function, and  $\mathcal{C}^{CF}(e)$  the consumption level associated with spending  $e$  in one of the counterfactual economies.



**Figure 8:** Welfare Effects of Shopping Effort

**Note:** Change in total consumption index ( $\mathcal{C}$ ) under alternative prices and zero shopping effort to make a household indifferent between living one period in an alternative economy and one period in the steady state economy. Counterfactuals fix the expenditure distribution and let households choose a basket assuming they have to pay (i) the average price within each grocery variety (shutting down the direct effect of shopping) or (ii) marginal cost plus the average margin across varieties (shutting down the direct and equilibrium effect).

Figure 8 reports the results, averaging the consumption change within each expenditure quintile. It shows that the bottom quintile of expenditures is almost equally well off when paying average prices but not exerting shopping effort (shutting off the direct effect of shopping). The cost of higher prices is offset by reducing the disutility of effort to zero. The top quintile would forego 0.85% of consumption to face the average price paid for a variety without exerting shopping effort. If households instead were to pay the

<sup>28</sup>Results for infinite horizon welfare measures are reported in Appendix C.3.

average margin (shutting off direct and equilibrium effects), the bottom quintile would need to receive an increase of 0.6% in their consumption to be indifferent to the steady state, while the top quintile would forego up to 1.15% of consumption. These findings imply that the direct and equilibrium effect of shopping jointly reduce inequality in (one-period) welfare by 1.75%. 0.9pp. of the effect are attributable to the equilibrium response of posted prices. Again, this is a lower bound as I restrict search frictions to groceries.

**Externalities.** As retailers' price posting targets the average buyer in the market, each agents' search effort imposes an externality on the prices faced by all other households. Non-homotheticities and the partial separation of demand into different varieties reduce this externality. The model economy allows for a quantification of this reduction in externalities and of the remaining externality due to the non-zero overlap in households' consumption baskets. To do so, I construct counterfactual price distributions based on alternative values of demand-weighted shopping effort  $\bar{s}_j$  across varieties.<sup>29</sup>

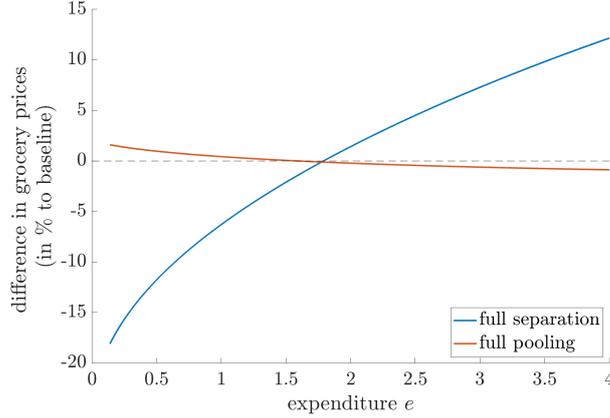
For a *full pooling* counterfactual, I assume demand-weighted effort  $\bar{s}_j$  is the same across all varieties and let retailers post prices based on the average composition of demand. To equalize  $\bar{s}_j$  across varieties, I compute the average shopping effort weighting individuals' shopping policies with their share in total demand across all varieties such that  $\bar{s}_j = \int \int \frac{\lambda(z,a) \sum_{j=1}^J c_j(z,a)}{\sum_{j=1}^J C_j} s(z,a) dz da$ . I fix households' consumption baskets and shopping policies at their equilibrium values and compute the percentage change in their cost of consumption if they were drawing from the distributions retailers post when facing the counterfactual  $\bar{s}_j$  for all varieties.<sup>30</sup> The *full pooling* line in Figure 9 plots the results over the range of the model implied expenditure distribution. If  $\bar{s}_j$  would be identical across all varieties, households at the bottom of the expenditure distribution would spend around 2% more on their consumption bundle while households at the top could save around 1% while buying the same basket, in line with the equilibrium effect of shopping.

Next, I allow households to draw from price distributions targeted to their individual shopping effort. In this counterfactual a household in state  $(z, a)$  draws for each variety from a price distribution that retailers' would post if all other households were exerting the same shopping effort, i.e.  $\bar{s}_j = s(z, a)$ . In this counterfactual, I obtain *full separation*. Figure 9 shows that the remaining externality is sizeable. Fixing shopping effort and consumption baskets, households at the bottom of the expenditure distribution could save an additional 18% if they were to face targeted price distributions, i.e. if retailers

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<sup>29</sup>Sangani (2022) conducts a similar exercise in a model economy with a single good and, despite a different calibration approach, finds similar magnitudes for the difference between the pooling and full separation scenario. In addition, I provide a quantification of how much the externality is reduced due to partial separation in the goods market, which is not possible in a single-good economy.

<sup>30</sup>The exercise can be interpreted as the change in a Laspeyres price index.



**Figure 9:** Shopping Externality

**Note:** Change in households' prices paid under alternative posted price distributions. Baseline is the calibrated steady-state. Counterfactuals fix the expenditure distribution, consumption baskets and shopping effort. *Full pooling* assumes price distributions for each variety determined as the best response to average search effort  $\bar{s}_j = \int \int \frac{\lambda(z,a) \sum_{j=1}^J c_j(z,a)}{\sum_{j=1}^J C_j} s(z,a) dz da$ . *Full separation* assumes individually targeted price distributions for each variety determined as the best response to individual search effort  $\bar{s}_j = s(z,a)$ .

could perfectly discriminate between household types. The high-spending households on the other hand would pay up to 12% more in a world with perfect discrimination.<sup>31</sup>

The large size of the remaining externality can be accounted for by the generally higher spending levels at the top of the expenditure distribution. While high-spending households consume relatively less of the goods that are important in low-spending households' baskets, they still account for a sizeable share of expenditures across all varieties due to their higher level of expenditures.<sup>32</sup>

Overall, the findings show that differences in demand composition across goods and the ensuing equilibrium effects of heterogeneity in shopping effort on posted prices have substantial implications for how we should interpret inequality in expenditures in terms of consumption and welfare. The previous literature, such as Aguiar and Hurst (2007), Arslan et al. (2021), and Pytka (2022), has focussed on how households can reduce the price they pay for a given variety. The findings outlined above suggest that shopping provides additional insurance of similar magnitude through the effect of low-income households' collective search effort on the prices posted for the products they purchase.

<sup>31</sup>Retailers do not leave money on the table due to a lack of price discrimination. Holding households' policy functions constant, the difference in total sales is less than 0.01% across scenarios. Lower profits on low-search households are almost perfectly offset by higher profits on high-search households.

<sup>32</sup>Appendix B.4 shows that this is in line with the data.

## 6 Implications for Average Prices and Markups

The relationship between demand-weighted shopping effort and posted prices makes the average price and markup in the economy a function of the distribution of expenditure across households. The distribution of households can change, e.g. when the economy is hit by aggregate shocks or when policies change the economic environment. In this section, I consider first how the response of posted prices to shopping effort has contributed to price dynamics during the Great Recession and how shifts in demand composition can affect the cyclical nature of average retail prices and markups in general. In addition, I provide evidence on how the response of posted prices to demand composition can affect the cost of redistributive taxation for high-earning households.

### 6.1 Shopping and Prices over the Business Cycle

A growing empirical literature studies the cyclical properties of retail prices and markups in response to aggregate demand shocks, but so far remains inconclusive. E.g. Anderson et al. (2020) find acyclical prices and markups in response to local unemployment shocks while Stroebel and Vavra (2019) find strongly procyclical responses to changes in local house prices. I revisit these findings in the model economy by focussing on the Great Recession period around 2008.

The Great Recession saw both substantial earnings losses due to an increase in unemployment and losses in wealth in response to the decline in house prices. I construct a similar shock and hit the model economy with an unexpected one-time loss in households' net worth and persistent earnings losses differentiated by households' labor productivity state  $z$ . I choose an equal loss in wealth of 15% for all households, to match the decline in households' net worth between the last quarter of 2007 and first quarter of 2009 as reported in the US Financial Accounts (Table Z.1).<sup>33</sup> For losses in labor earnings along the income distribution, I build on the findings of Heathcote et al. (2020). I take their estimates for earnings changes at different points of the income distribution in 2008-2010 for the first three periods after the shock hits and let earnings return to their steady state level by  $t = 6$ . A mapping of the findings in Heathcote et al. (2020) into the labor productivity states of the model is provided in Table 14 in Appendix C.5. It shows that losses are heavily concentrated at the bottom of the earnings distribution. Overall, the two components of the shock are comparable in magnitude. The decline in wealth amounts to roughly 32% of aggregate annual income in the model economy and the cumulated earnings loss to 24%.

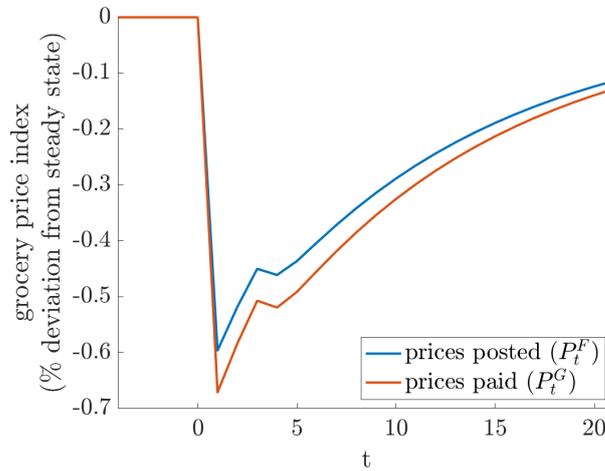
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<sup>33</sup>This choice is in line with the decline in wealth growth for the top two quintiles of the wealth distribution (those households holding significant wealth) reported in Krueger et al. (2016).

To measure the cyclical properties of retail prices, I focus on a Laspeyres index of average prices across grocery varieties, given by

$$P_t^l = \frac{\sum_{j=1}^J C_j^{SS} \mu_{jt}^l}{\sum_{j=1}^J C_j^{SS}}.$$

The Laspeyres index abstracts from changes in households' baskets when aggregating prices and is therefore ideally suited to isolate price changes. I will consider separately changes in the Laspeyres index for two definitions of average prices per variety: average posted prices  $P_t^F$  and average prices paid  $P_t^G$ . Throughout the exercises conducted in this section I keep all parameters at their steady-state values. Any response of posted and paid prices is therefore by construction driven by changes in households' (demand-weighted) shopping effort and its effect on posted and paid prices.

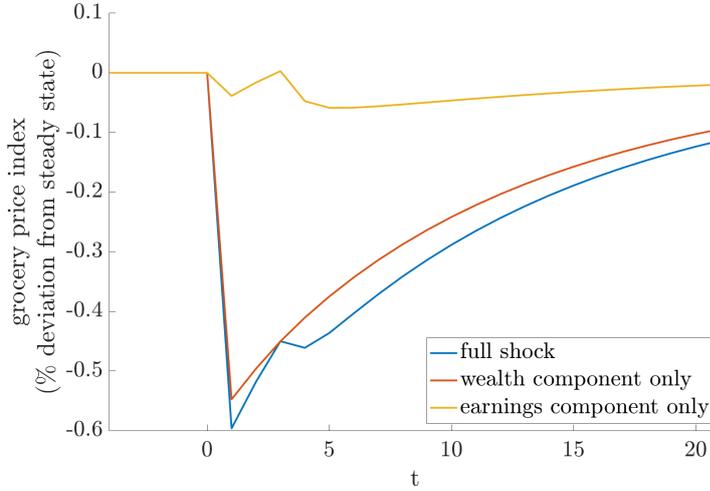


**Figure 10:** Prices Posted and Prices Paid during the Great Recession

**Note:** Model implied response of an aggregate Laspeyres index  $P_t^l = \frac{\sum_{j=1}^J C_j^{SS} \mu_{jt}^l}{\sum_{j=1}^J C_j^{SS}}$  of prices posted ( $P_t^F$ ) and prices paid ( $P_t^G$ ) to the Great Recession shock (15% loss in wealth and earnings losses from Heathcote et al. (2020)).

Figure 10 plots the response of the aggregate Laspeyres index of grocery prices, separately for prices posted  $P_t^F$  and prices paid  $P_t^G$ . It shows that changes in households' shopping behavior reduced prices paid by about 0.7% during the Great Recession. This effect is predominantly driven by a reduction in posted prices as retailers' respond to households' choices in equilibrium. Posted prices declined by 0.6 percentage points while changes in paid prices relative to posted prices account for only 0.1 percentage points of the overall decline in prices paid. Hence, taking into account the equilibrium effect on posted prices

in response to changes in demand-weighted shopping effort is quantitatively important for fluctuations in retail prices during the Great Recession.<sup>34</sup>



**Figure 11:** Response of Posted Prices to Losses in Earnings and Wealth

**Note:** Model implied response of an aggregate Laspeyres index  $P_t^F = \frac{\sum_{j=1}^J C_j^{SS} \mu_{jt}^F}{\sum_{j=1}^J C_j^{SS}}$  of prices posted to the Great Recession shock (15% loss in wealth and earnings losses from Heathcote et al. (2020)). Full shock decomposed into response to loss in earnings and loss in wealth.

Next, I study whether the change in the index of posted prices is driven by the decline in wealth or losses in labor earnings. To isolate their respective effects on posted prices, I hit the economy only with a loss in wealth or only with a loss in labor earnings. Figure 11 plots the response of the posted price index  $P_t^F$  for each of the two components separately and for the combined response. It shows that the response of posted prices is almost entirely driven by the reduction in wealth, while retailers barely react to the decline in earnings. With all parameters, including marginal cost  $\kappa_j$ , fixed at steady-state levels, these price responses are driven entirely by changes in posted markups. Hence, the model yields procyclical responses of retail prices and markups to the decline in wealth, but acyclical responses to the change in labor earnings during the Great Recession. This finding shows that the model can reconcile the conflicting empirical evidence presented in Stroebel and Vavra (2019) and Anderson et al. (2020).<sup>35</sup>

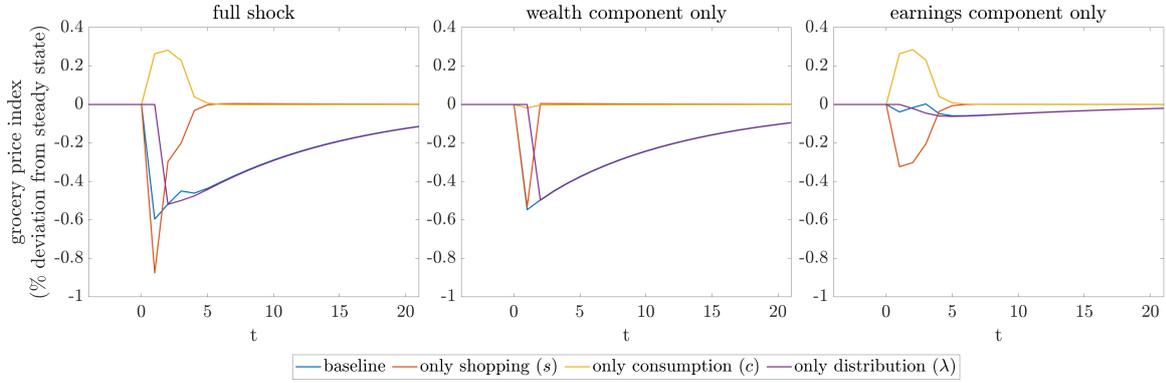
<sup>34</sup>Despite the absence of any adjustment cost, the dynamics of the model are not inconsistent with significant price stickiness. The price distribution for each variety on impact of the shock overlaps to about 96% with its steady-state counterpart. Therefore, the model can be consistent with up to 96% of retailers not adjusting their prices, as they are indifferent between any price on the support of the posted distribution. This is in line with the findings of Burdett and Menzio (2018).

<sup>35</sup>The model also resonates with the literature quantitatively. Figure 23 in Appendix C.5 shows that the decline in aggregate grocery prices (markups) paid in response to a 1% decline in households' wealth is about 0.04%. This elasticity is at the lower end but of similar magnitude as the range of estimates for the elasticity of retail prices to house prices reported in Stroebel and Vavra (2019), who find values of 0.02-0.2. Assuming that most household wealth is held in real estate and that households' have a levered position in housing due to mortgages implies that a 1% wealth shock is a conservative choice to capture the consequences of a 1% decline in house values.

To understand the mechanism behind this result, I decompose the price response into the forces shaping it in equilibrium. In the model, posted prices (markups) respond only to changes in demand-weighted shopping effort

$$\bar{s}_{jt} = \int \int \frac{\lambda_t(z, a) c_{jt}(z, a)}{C_{jt}} s_t(z, a) dz da.$$

Demand weighted effort either changes because of adjustments in individual search effort, or because changes in demand composition alter how retailers take the effort of different households into account. The effect of individual search behavior is captured by the response of  $\bar{s}_{jt}$  to changes in shopping policies  $s_t(z, a)$ . Shifts in demand composition arise due to changes in households' consumption policies  $c_{jt}(z, a)$  or the distribution of households across the state space  $\lambda_t(z, a)$ . I consider the contribution of each of the three separately, fixing the others at steady state level.



**Figure 12:** Decomposition of Posted Price Responses

**Note:** Response of an aggregate Laspeyres index of posted prices  $P_t^F = \frac{\sum_{j=1}^J C_j^{SS} \mu_{jt}^F}{\sum_{j=1}^J C_j^{SS}}$  to the Great Recession shock (15% loss in wealth and earnings losses from Heathcote et al. (2020)). Panels report responses to the full shock, only the wealth, and only the earnings component. Complete response as a baseline, for each panel decomposed into the response to changes in consumption policies, shopping policies, and the distribution of households, holding the respective others constant at steady state levels.

Figure 12 plots the decomposition of price responses separately for the full shock and only the wealth and earnings component respectively. Changes in households' shopping policies alone reduce prices in response to both the wealth and earnings component, as each affected household increases her search effort to insure against an income loss. What accounts for the differences in cyclicity are differential responses of demand composition, driven by changes in households' consumption policies and the distribution of agents across the state space. This is due to the incidence of the shocks, earnings losses being concentrated among low income households and high-income households facing a larger absolute decline in wealth.

The stronger low-income households are affected the more they have to reduce consumption and the lower becomes their share in overall demand. Retailers now face relatively more high-income buyers and respond to this shift in demand composition by attaching more weight to their (lower) shopping effort. In response, they increase prices. For the earnings component, this demand composition effect is strong enough to offset the direct increase in shopping effort. As high-income households are disproportionately affected by the wealth component, the effect of changes in households' consumption policies goes in the opposite direction and reallocates relative demand towards low-income (high-effort) households. In addition, high-income households significantly reduce their savings which increases their future shopping effort as they have become relatively poorer. This effect is captured by changes in the distribution of agents across the state space and drives the response of prices to the wealth component from the second period onwards. In combination of both components the change in households' consumption policies dampens the response of retail prices to the increase in individual shopping effort by about one third, emphasising the quantitative importance of shifts in demand composition during the Great Recession.<sup>36</sup>

The implications for inequality are in sharp contrast to the results of the previous section. While heterogeneity in demand composition across varieties provides additional insurance by reducing the prices charged on goods bought by low-income households, shifts in demand composition over the business cycle amplify inequalities. High-earning households are partially compensated through a decline in posted prices when they are hit by an aggregate income loss. Low-earning households might see prices rise if they lose income as retailers adjust posted prices to their declining share in aggregate demand.

The findings presented in this section extend the work of Kaplan and Menzio (2016) who introduce demand composition effects in a model with two types of agents: Employed and unemployed. In order to sustain multiple equilibria and self fulfilling unemployment fluctuations, their framework requires a decline in aggregate income to be associated with an increasing role for (high-search-effort) unemployed households and a resulting decline in prices and profit margins for firms. The results derived in this paper from a framework with rich household heterogeneity suggest that shifts in demand composition can dampen or amplify the responses of retail prices to households' shopping effort, depending on the incidence of aggregate income shocks.

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<sup>36</sup>Appendix C.4 provides additional evidence on the effect of demand composition on the cyclicity of retail prices by simulating the same decline in aggregate income but distributing it differentially along the earnings distribution. It shows that if losses are sufficiently concentrated among the bottom of the distribution, retail prices can increase in response to a decline in aggregate earnings.

## 6.2 Demand Composition Across Policy Regimes

When posted prices become a function of the distribution of income and wealth in the economy, policies (re-)shaping these distributions affect households' cost of consumption. This section shows how posted prices respond to redistributive taxation. For that purpose, I introduce a flat tax on earnings and redistribute the proceeds equally as a lump sum payment to all households. Introducing the policy alters the budget constraint to

$$e + a' \leq (1 + r)a + (1 - \tau)zw + T,$$

where the government-budget-clearing transfer satisfies  $T = \int \int \lambda(z, a)zw \, dzda$ .<sup>37</sup>

I solve for the steady state of the model for given  $\tau$  and compute the ensuing changes in households' earnings post taxes and transfers

$$\Delta \text{earn}(z, a) = \frac{(1 - \tau)zw + T - zw}{zw} = \frac{T - \tau zw}{zw}$$

as well as changes in an individual Laspeyres index for total consumption  $P^{lasp}(z, a)$

$$\Delta P^{lasp}(z, a) = \frac{\tilde{e}^\tau(z, a)}{e^0(z, a)} - 1 = \frac{c_O^0 + \sum_{j=1}^J p_j^\tau(s^0(z, a))c_j^0(z, a)}{c_O^0 + \sum_{j=1}^J p_j^0(s^0(z, a))c_j^0(z, a)} - 1$$

and grocery consumption  $p_G^{lasp}(z, a)$

$$\Delta p_G^{lasp}(z, a) = \frac{\tilde{e}_G^\tau(z, a)}{e_G^0(z, a)} - 1 = \frac{\sum_{j=1}^J p_j^\tau(s^0(z, a))c_j^0(z, a)}{\sum_{j=1}^J p_j^0(s^0(z, a))c_j^0(z, a)} - 1.$$

where  $p_j^\tau(s)$  is the price paid for grocery variety  $j$  by a household exerting effort  $s$  in an economy with redistributive tax  $\tau$ . The index should be interpreted as the counterfactual expenditure level  $\tilde{e}^\tau(z, a)$  a household in state  $(z, a)$  needs to buy the same basket as in the original steady state with the same shopping effort. Again, I focus on changes in a Laspeyres index and keep all policy functions at the original steady state with  $\tau = 0$  to isolate changes in posted prices. For a fall in prices, the Laspeyres index provides a lower bound on the welfare impact as households can gain further by adjusting their choices.

The change in households' real income without reoptimizing policy functions is approximated by  $\Delta \text{earn}(z, a) - \Delta P^{lasp}(z, a)$ . I aggregate changes in earnings and prices by expenditure quintile using the distribution of households in the original steady state. Table 8 presents results for a 5% earnings tax ( $\tau = 0.05$ ). Overall, prices decline in response to the policy change as with more redistribution a larger share of demand is

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<sup>37</sup>As the process for  $z$  is calibrated to households' earnings post taxes and transfers, the introduction of  $\tau$  should be interpreted as additional redistribution relative to the current US system.

accounted for by relatively low-income (high-shopping-effort) households. This drives up demand-weighted search effort and hence drives down the prices of grocery goods. The effect is even stronger for varieties with higher quality  $q_j$ , yielding larger declines in the price index of high-spending households.

While the transfer dominates changes in real income at the bottom of the expenditure distribution, price changes are relatively more important at the top of the distribution and can compensate net contributors for a significant share of their earnings loss. Due to the assumption of a perfectly competitive outside good market, the reported changes in the aggregate price index  $P$  provides a lower bound while the results for  $p_G$  provide an upper bound if all consumption was subject to the same frictions. Table 8 shows that households at the top of the expenditure distribution are compensated for 5-14% of the loss in their post-tax earnings due to the response of posted price distributions.

**Table 8:** Earnings and Price Changes under Redistributive Policies ( $\tau = 0.05$ )

		quintile of expenditures				
		Q1	Q2	Q3	Q4	Q5
income	$\Delta\text{earn}$	16.66%	5.21%	1.91%	-0.15%	-2.06%
prices	$\Delta P$	-0.08%	-0.09%	-0.09%	-0.09%	-0.10%
	$\Delta p_G$	-0.23%	-0.25%	-0.26%	-0.27%	-0.28%
share $\Delta P$	$\frac{-\Delta P}{ \Delta\text{earn} }$	0.5%	1.6%	4.7%	62.3%	4.8%
share $\Delta p_G$	$\frac{-\Delta p_G}{ \Delta\text{earn} }$	1.4%	4.7%	13.4%	178%	13.7%

**Note:** Average change in post-tax earnings ( $\Delta\text{earn}$ ), grocery ( $\Delta p_G$ ), and aggregate Laspeyres price index ( $\Delta P$ ) within each expenditure quintile in response to a 5% earnings tax and budget neutral transfer.

Table 16 in Appendix C.5 reports price and income changes for alternative values of  $\tau$ . While both the income and price effects increase in the degree of redistribution (with higher values of  $\tau$ ), their relative contributions to the overall change in real income remains similar across all policy regimes considered.

The findings show that the effect of redistribution on demand composition reduces estimates of the loss from taxation at the top. Net contributors to redistribution schemes can benefit from lower price levels as retailers' place more weight on the purchase behavior of low-income households, reducing the real burden of redistributive policies.

## 7 Conclusion

This paper develops an equilibrium theory of expenditure inequality and price dispersion, featuring search for prices, heterogeneous households' with non-homothetic preferences, and endogenous price distributions for multiple varieties. I provide analytical results on retailers' best response to households' shopping effort and show that average posted prices

decline in the share of demand stemming from high-search-effort households. Theoretical predictions on the skewness of posted price distributions are in line with empirical evidence from the Nielsen Consumer Panel. The calibrated model replicates salient features of expenditure inequality and price dispersion. It shows that the response of posted prices across varieties doubles the contribution of shopping effort to the difference between inequality in expenditure and consumption. After a shock similar to the Great Recession, posted prices respond to losses in wealth but not to losses in earnings. By showing the importance of accounting for the incidence of aggregate shocks, the model reconciles conflicting evidence on the cyclical nature of retail markups. Finally, I show that endogenous price changes in response to redistributive policies reduce the loss from redistribution at the top by up to 14%. All of these results highlight the importance of accounting for equilibrium effects of heterogeneity in households' shopping effort and demand composition when thinking about retail prices.

The focus of this paper is on households' shopping effort and heterogeneity in price elasticities across retailers for a given product. Recent evidence by Auer et al. (2022) suggests additional heterogeneity in price elasticities across products, generating an additional role of demand composition for posted prices. In the interest of tractability and introducing rich household heterogeneity, retailers' price posting problem has been deliberately kept simple. An alternative approach would be to take the results of this paper as motivation and introduce stylized heterogeneity in price elasticities and demand composition into a more evolved price setting problem. Possible extensions include e.g. multiproduct price posting as in Kaplan et al. (2019) or state dependent price adjustments as in Golosov and Lucas (2007), Midrigan (2011), and Burdett and Menzies (2018). I leave all these extensions for future work.

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## A Extensions to the Retailer Problem

### A.1 Entry and Fixed Cost of Operating

Consider a version of the price posting problem outlined in Section 2.1 where retailers selling variety  $j$  are subject to a per-period fixed cost of operating  $K_j$  and the total mass of retailers  $M_j$  is determined endogenously by free entry. With all other notation as before, the total profits of a retailer posting price  $p$  in the adjusted model are given by

$$\tilde{\pi}_j(p) = \frac{C_j}{M_j} [(1 - \bar{s}_j) + \bar{s}_j 2(1 - F_j(p))] (p - \kappa_j) - K_j = \frac{\pi_j(p)}{M_j} - K_j,$$

where  $\pi_j(p)$  is retailers' profits of posting  $p$  in the version of the model without fixed cost of operating and a fixed mass one of retailers. To sustain an equilibrium distribution of posted prices retailers have to be again indifferent between all prices on the support of the posted distribution. Take two posted prices  $p_1$  and  $p_2$ , indifference requires

$$\begin{aligned} \tilde{\pi}_j(p_1) &= \tilde{\pi}_j(p_2) \\ \Rightarrow \frac{\pi_j(p_1)}{M_j} - K_j &= \frac{\pi_j(p_2)}{M_j} - K_j \\ \Rightarrow \pi_j(p_1) &= \pi_j(p_2). \end{aligned}$$

The indifference condition between prices is independent of  $M_j$  and  $K_j$ , i.e. independent of entry and fixed cost of operating, and identical to the condition in the original model. This implies the distribution of posted prices  $F_j(p)$  is identical to the model without entry and fixed cost. To solve the model with fixed cost and entry, one can therefore first recover the posted price distribution as well as the constant profits at any price on the support of  $F_j(p)$ , denoted  $\bar{\pi}_j$ , in the original model and solve for  $M_j$  given this solution. Free entry requires zero total profits of operating, i.e.  $\tilde{\pi}_j(p) = 0$ . The equilibrium mass of retailers is therefore given by  $M_j = \frac{\bar{\pi}_j}{K_j}$ .

### A.2 Heterogeneous Marginal Cost

Take the setup from Section 2.1 but consider a continuous distribution of retailers over marginal cost, with CDF  $\Gamma_j(\kappa)$  and support  $[\underline{\kappa}_j, \bar{\kappa}_j]$  and assume  $\bar{\kappa}_j = \bar{p}_j$ . I.e. consider a distribution of active retailers for which the support has to end at the maximum willingness to pay. This assumption imposes no restriction on the solution as no retailer with marginal cost above  $\bar{p}_j$  could ever make a sale with positive profits. Profits of a retailer with marginal cost  $\kappa$  of posting price  $p$  for variety  $j$  are given by

$$\pi_j(p, \kappa) = (p - \kappa) ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p))) C_j$$

Define  $p(\kappa)$  as the set of prices maximizing  $\pi_j(p, \kappa)$  for given  $F_j(p)$ , i.e. the indifference set of posted prices for a retailer with marginal cost  $\kappa$ .

### A.2.1 Solving for the Distribution of Posted Prices

To solve for the equilibrium distribution of posted prices I follow closely the steps of Burdett and Mortensen (1998) or Mortensen (2003) for a similar model of wage posting.

#### 1. Properties of the Distribution

By similar argument as in Burdett and Judd (1983), the posted distribution  $F_j(p)$  has no mass points, has a connected support, and the upper bound of the support of  $F_j(p)$  is  $\bar{p}_j$ . Intuitively, all three can be shown by providing a profitable deviation in price posting if an posted price distribution is violating one of the three conditions.

#### 2. Prices Posted Are Weakly Increasing in Marginal Cost

For any  $\kappa'' > \kappa'$ ,  $p' \in p(\kappa')$ , and  $p'' \in p(\kappa'')$  it has to hold that  $\pi_j(p', \kappa') > \pi_j(p'', \kappa'')$  and  $p'' \geq p'$ , i.e. profits are strictly decreasing and prices are weakly increasing in marginal costs. To do so, note the following

$$\pi'_j(p', \kappa') = (p' - \kappa') ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p'))) C_j \quad (\star 1)$$

$$\geq (p'' - \kappa') ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p''))) C_j \quad (\star 2)$$

$$> (p'' - \kappa'') ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p''))) C_j = \pi_j(p'', \kappa'') \quad (\star 3)$$

$$\geq (p' - \kappa'') ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p'))) C_j \quad (\star 4)$$

Where the steps from  $(\star 1)$  to  $(\star 2)$  and  $(\star 3)$  to  $(\star 4)$  follow from the optimality of  $p' \in p(\kappa')$  and  $p'' \in p(\kappa'')$  respectively and the step from  $(\star 2)$  to  $(\star 3)$  from  $\kappa'' > \kappa'$ . From above, it is immediately clear that  $\pi_j(p', \kappa') > \pi_j(p'', \kappa'')$ , i.e. profits are strictly decreasing in  $\kappa$ . To see that  $p'' \geq p'$  note that  $(\star 1) - (\star 4) \geq (\star 2) - (\star 3) > 0$  and hence

$$(\kappa'' - \kappa') ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p'))) \geq (\kappa'' - \kappa') ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p'')))$$

which yields  $F_j(p'') \geq F_j(p')$  and therefore, as any cumulative distribution cannot be decreasing,  $p'' \geq p'$ . So any price optimal at  $\kappa'$  cannot be higher than any price optimal at  $\kappa''$ . Hence,  $p(\kappa')$  and  $p(\kappa'')$  can intersect in at most one boundary point. With a continuous distribution of marginal cost, the latter also implies that  $p(\kappa)$  has to be single valued.

### 3. The Price Distribution is a Shifted Distribution of Marginal Cost

By the single value property of  $p(\kappa)$

$$F_j(p) = F_j(p(\kappa)) = \Gamma_j(\kappa)$$

and hence

$$F'_j(p(\kappa)) = f_j(p(\kappa)) = \frac{\Gamma'_j(\kappa)}{p'(\kappa)}$$

### 4. The Price Function $p(\kappa)$ Solves Retailers Profit Maximization

Analogue to before, the profits of a retailer with marginal cost  $\kappa$  posting price  $p$  are given by

$$\pi_j(p, \kappa) = (p - \kappa) ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p))) C_j$$

and the profit maximizing price satisfies

$$\frac{\partial \pi}{\partial p} = ((1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p)) - (p - \kappa)2\bar{s}_j F'_j(p)) C_j = 0$$

which yields

$$1 = \frac{(p - \kappa)2\bar{s}_j F'_j(p)}{(1 - \bar{s}_j) + 2\bar{s}_j(1 - F_j(p))}$$

and by the result of 3.)

$$p'(\kappa) = \frac{(p(\kappa) - \kappa)2\bar{s}_j \Gamma'_j(\kappa)}{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(\kappa))}$$

This differential equation together with the boundary condition  $p(\bar{\kappa}) = \bar{\kappa} = \bar{p}$  pins down the unique solution to  $p(\kappa)$  and hence to  $F'_j(p)$ . The boundary condition holds because the upper bound of any price distribution has to be at  $\bar{p}$  (else there are profitable deviations) and a firm with marginal cost  $\kappa = \bar{\kappa} = \bar{p}$  will only be willing to post this price.

### 5. Obtaining a Solution

Define

$$T(k) = \log((1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(\kappa)))$$

such that

$$T'(k) = \frac{-2\bar{s}_j \Gamma'_j(\kappa)}{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(\kappa))}$$

We can rewrite the first difference equation pinning down the pricing function as

$$p'(\kappa) = -(p(\kappa) - \kappa)T'(\kappa) \Rightarrow p'(\kappa) + T'(\kappa)p(\kappa) = \kappa T'(\kappa)$$

Therefore, any solution has to satisfy (multiply both sides by  $e^{T(\kappa)}$  before integrating)

$$p(\kappa)e^{T(\kappa)} = \int_{\underline{\kappa}}^{\kappa} xT'(x)e^{T(x)}dx + A = \kappa e^{T(\kappa)} - \underline{\kappa}e^{T(\underline{\kappa})} - \int_{\underline{\kappa}}^{\kappa} e^{T(x)}dx + A$$

where the second equality follows from integration by parts. Hence

$$p(\kappa) = \kappa + e^{-T(\kappa)} \left[ A - \underline{\kappa}e^{T(\underline{\kappa})} - \int_{\underline{\kappa}}^{\kappa} e^{T(x)}dx \right]$$

Using the boundary condition  $p(\bar{\kappa}) = \bar{\kappa}$  it follows that

$$A = \underline{\kappa}e^{T(\underline{\kappa})} + \int_{\underline{\kappa}}^{\bar{\kappa}} e^{T(x)}dx$$

The solution to the pricing function and the distribution of posted prices is hence given as

$$p(\kappa) = \kappa + e^{-T(\kappa)} \int_{\kappa}^{\bar{\kappa}} e^{T(x)}dx = \kappa + \int_{\kappa}^{\bar{\kappa}} \frac{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(x))}{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(\kappa))} dx$$

with derivative

$$p'(\kappa) = 1 - 1 - (-2\bar{s}_j\Gamma'_j(\kappa)) \int_{\kappa}^{\bar{\kappa}} \frac{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(x))}{[(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(\kappa))]^2} dx > 0$$

and therefore

$$F'(p) = \frac{\Gamma'_j(\kappa)}{p'(\kappa)} = \frac{1}{2\bar{s}_j \int_{\kappa}^{\bar{\kappa}} \frac{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(x))}{[(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(\kappa))]^2} dx} = \frac{[(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(\kappa))]^2}{2\bar{s}_j(\bar{\kappa} - \kappa)(1 + \bar{s}_j) - 4\bar{s}_j^2 \int_{\kappa}^{\bar{\kappa}} \Gamma_j(x)dx}$$

We cannot conclude anything on how the profit margins (markups) per sale are changing with marginal cost  $\kappa$ . To see this note that

$$p(\kappa) - \kappa = \int_{\kappa}^{\bar{\kappa}} \frac{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(x))}{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(\kappa))} dx$$

and hence

$$\frac{\partial(p(\kappa) - \kappa)}{\partial\kappa} = p'(\kappa) - 1 = -1 + 2\bar{s}_j\Gamma'_j(\kappa) \int_{\kappa}^{\bar{\kappa}} \frac{(1 - \bar{s}_j) + 2\bar{s}_j(1 - \Gamma_j(x))}{[(1 - \bar{s}_j) + 2\bar{s}(1 - \Gamma_j(\kappa))]^2} dx$$

So whether markups are increasing or decreasing in marginal costs depends on the shape of the distribution  $\Gamma_j(\kappa)$ . Intuitively, retailers' optimization trades off higher margins (markups) against a decrease in demand, where the latter depends on the distribution of prices which in turn depends on the distribution of marginal costs.

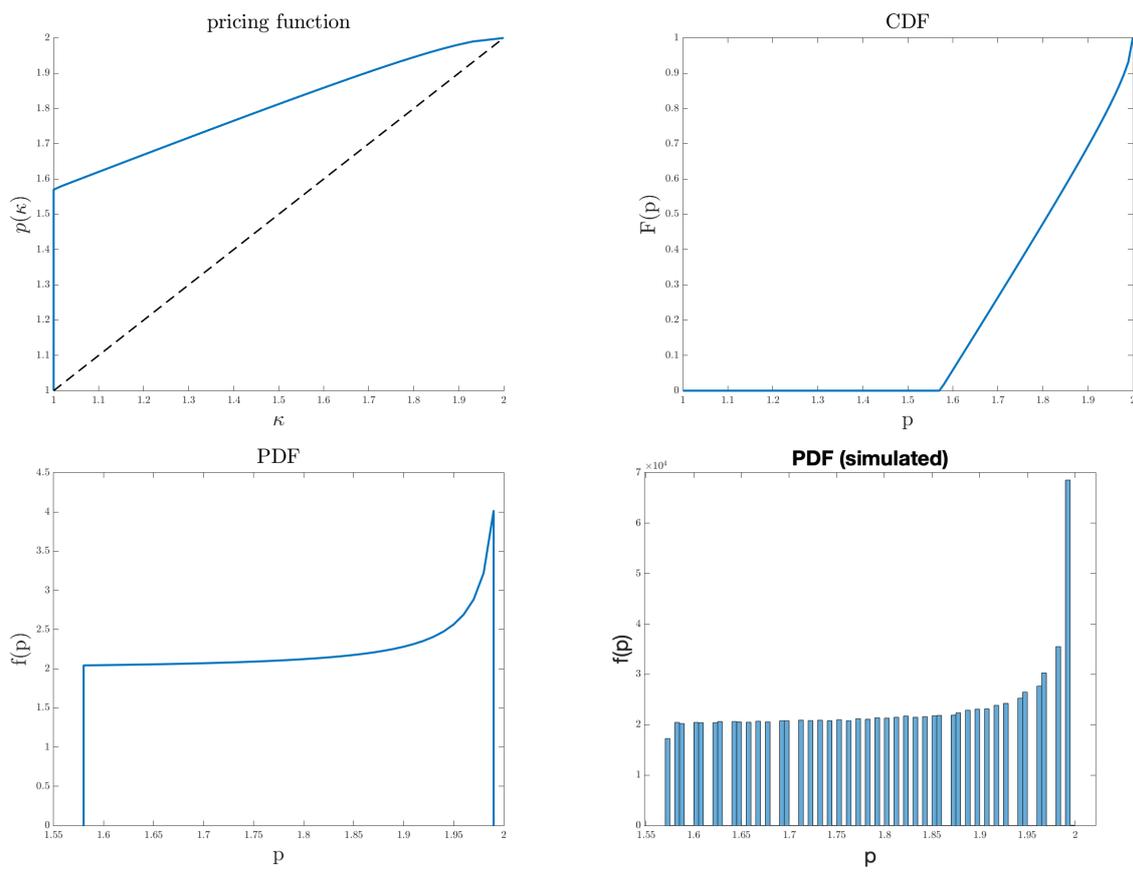
### A.2.2 Quantitative Results under Uniform Marginal Costs

While an analytical characterization of how the moments of the price distribution respond to changes in demand-weighted shopping effort  $\bar{s}_j$  under heterogeneous marginal cost is beyond the scope of this paper, I show robustness of the analytical results for the baseline model by reporting numerical simulations. I assume a uniform distribution of marginal cost over  $[\underline{\kappa}_j, \bar{\kappa}_j]$  and consider parameterizations with  $\bar{p}_j \in \{1, 2, 3, 4, 5\}$ ,  $\kappa_{min} \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7\}$  such that  $\underline{\kappa}_j = \kappa_{min}\bar{p}_j$  and  $\bar{\kappa}_j = \bar{p}_j$ . I take  $\bar{p}_j = 3$  and  $\kappa_{min} = 0$  as the baseline and change one parameter at a time, simulating 1,000,000 price draws for each combination of parameters and computing the mean and skewness of the posted price distribution.

To highlight the properties of a solution to the model with heterogeneous  $\kappa$ , Figure 13 plots the pricing function  $p(k)$  and CDF  $F_j(p)$  as well as the analytical and simulated PDF of a single calibrated version with  $\bar{\kappa} = \bar{p} = 2$ ,  $\underline{\kappa} = 1$ ,  $\bar{s} = 0.75$ .

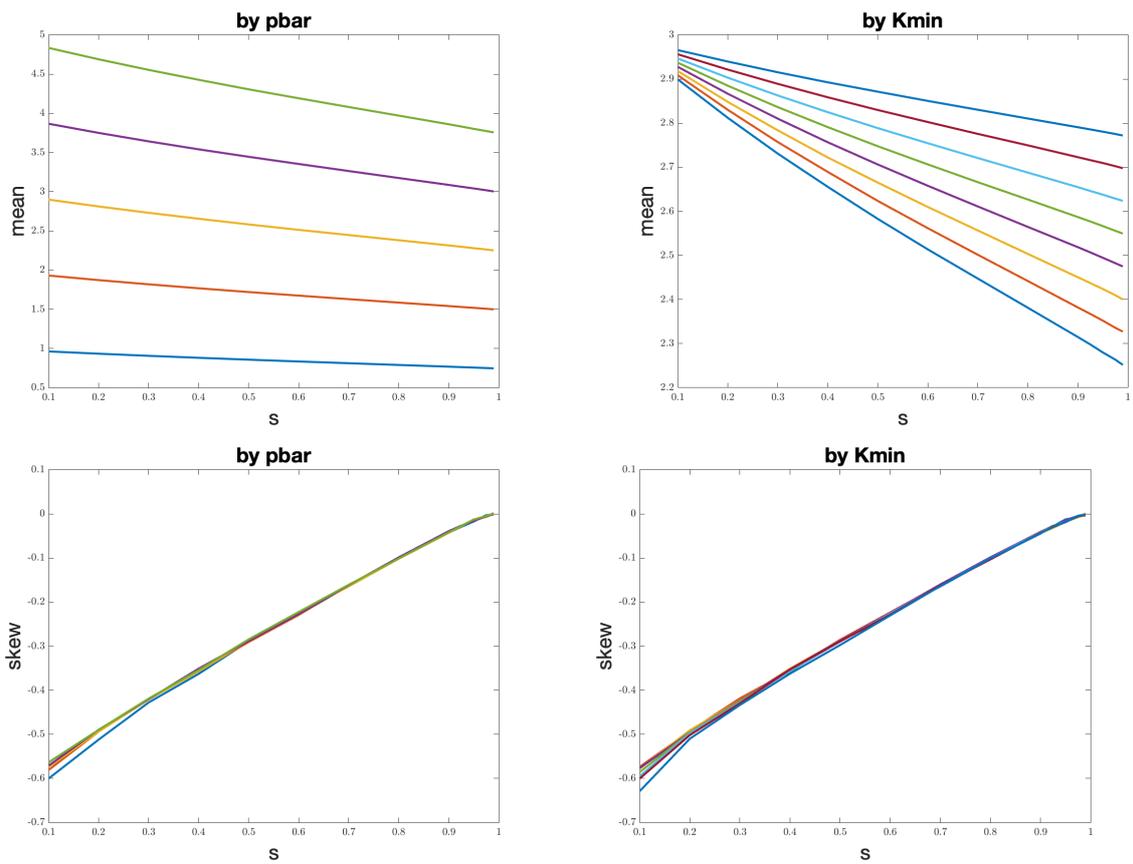
Figure 14 recovers the result of skewness being a strictly increasing function of average search effort  $\bar{s}$ . Other parameters do not have considerable influence on the skewness of the price distribution. For the mean of posted prices the main mechanism pertains: For any combination of parameters considered the average posted price is decreasing in shopping effort. This is because the pricing function gets more and more concentrated at the maximum willingness to pay when  $\bar{s}$  goes to zero.

Results for other types of distributions (exponential, logistic) as well as a version with a discrete set of marginal-cost types yield similar conclusions: While under some calibrations small regions of skewness decreasing in shopping effort are possible, these usually exist only for  $\bar{s}_j \approx 1$  and are associated with counterfactually low levels of price dispersion. Exploiting the skewness of price distributions for an empirical test of the mechanism is therefore a reasonable approximation even in a world with potentially heterogeneous marginal cost.



**Figure 13:** Uniform Distribution - Example

**Note:** Model solution for a calibration with uniform distribution of marginal costs,  $\bar{p} = 2$ ,  $\underline{\kappa} = 1$ ,  $\bar{s} = 0.75$ .



**Figure 14:** Uniform Distribution - Simulations

**Note:** Moments of simulated price distributions over  $\bar{s} \in [0, 1]$  for a calibration with uniform distribution and different values of  $\bar{p}$  and  $\underline{\kappa}$ .

## B Empirical Appendix

### B.1 The Nielsen Dataset

All empirical results presented in this paper are based on the Nielsen Consumer Panel, provided via the Kilts Center for Marketing at Chicago Booth. The dataset is a nationally representative, annual panel of around 60,000 US households who report on their grocery expenditures at daily as well as demographic information at annual frequency. Demographic variables include e.g. information on household composition, age, education, occupation, employment status, income, and location of residence. The dataset is constructed as a panel and the median household remains in the sample for about 3 consecutive waves. Nielsen applies several quality checks such as minimum reporting requirements to the sample before making data available. Households in the sample are provided with a device to record the prices and quantities of all purchases made in stores by scanning the barcodes of the items they bought (or record prices manually if the store is not participating in Nielsen's sample). The focus of the dataset is on grocery and drug stores, supermarkets and superstores, covering approximately 35% of spending excluding durable goods.<sup>38</sup>

Prices and quantities are reported at the barcode level. Nielsen organizes all barcodes into 10 departments (e.g. dry groceries or fresh foods), which are then divided into 125 product groups (e.g. snacks vs. pasta within dry groceries), and further split into about 1,100 product modules (e.g. potato chips vs. tortilla chips within snacks). Within product modules each variety is uniquely identified by its Universal Product Code (UPC), examples of a UPC are e.g. a box of Pringles Sour Cream and Onion or a bag of Lay's BBQ within the module potato chips. For each purchase of a barcode at a store at a given day, Nielsen records the quantity bought, the total price of the transaction, the value of all coupons used as well as the unique store identifier of the location where the purchase was made. Households' purchases can further be grouped into shopping trips, where a trip consists of all purchases of any barcode made by a household in a given store on a given day.

Data is provided in annual waves and I use the waves of 2007-2019. Data is also available for the period 2004-2006, but I focus on the later period due to a sample break between 2006 and 2007. All empirical results remain qualitatively unchanged if earlier waves are included. Across all households the dataset contains a total of about 7.5 million shopping trips and around 50 million purchases from a universe of 500,000 UPCs per wave.

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<sup>38</sup>For further details on the dataset and its application in Macroeconomic research see e.g. Argente and Lee (2021), Kaplan and Menzio (2015), Pisano et al. (2022), Broda and Parker (2014) or Michelacci et al. (2022).

No data on wealth is available in the Nielsen panel and income data is only available as categorical variable and reported as the tax base for the previous calendar year, i.e. refer to households taxable income two years prior to the sample. On the other hand, expenditures on the consumption categories covered in Nielsen are well measured. This is why for all baseline results on heterogeneity across households, I sort by their position in the expenditure distribution. Whenever I refer to expenditure, I adjust households' total annual expenditure measured in the Nielsen dataset by the square root of household size and (where applicable) sort them into quintiles/deciles based on their position in the expenditure distribution in the year of observation. Wherever dollar values are reported, these are adjusted to 2019 USD using the CPI for all Urban Consumers.

## B.2 Local vs. National Average Prices

For the baseline analysis of households' shopping effort I measure the prices households pay relative to the national, annual average price across all households. The literature often defines price distributions and the relative price a household pays more narrowly, i.e. over Scantrack Market regions and by quarter (see e.g. Kaplan and Menzio 2015). As also pointed out by Pytka (2022), this way of measuring households' shopping effort can be subject to a small sample bias. The bias can be alleviated by increasing the number of observations considered in computing average prices. In this appendix, I define the bias formally and show robustness of my main empirical findings to alternative definitions of average prices.

To measure shopping effort in the data, the literature generally compares relative prices paid and benchmarks household  $i$ 's average price  $p_{ij}$  for barcode  $j$  against the average price paid  $\bar{p}_j$  for the barcode across all households. This leads to a potential downward bias in the measured effect of shopping effort if household  $i$  accounts for a large share of transactions of barcode  $j$ . More formally, the price  $p_{ij}$  is defined as the quantity-weighted average over all transactions  $T_i$  of household  $i$

$$p_{ij} = \frac{\sum_{\tau=1}^{T_i} p_{\tau ij} q_{\tau ij}}{\sum_{\tau=1}^{T_i} q_{\tau ij}},$$

where  $p_{\tau ij}$  and  $q_{\tau ij}$  are respectively the price paid and quantity purchased of barcode  $j$  by household  $i$  in transaction  $\tau$ . The average price  $\bar{p}_j$  is defined accordingly as

$$\bar{p}_j = \frac{\sum_i \sum_{\tau=1}^{T_i} p_{\tau ij} q_{\tau ij}}{\sum_i \sum_{\tau=1}^{T_i} q_{\tau ij}}.$$

One can rewrite the average price paid as

$$\bar{p}_j = \nu_{ij} p_{ij} + (1 - \nu_{ij}) p_{-ij},$$

where  $\nu_{ij} = \frac{\sum_{\tau=1}^{T_i} q_{\tau ij}}{\sum_i \sum_{\tau=1}^{T_i} q_{\tau ij}}$  is household  $i$ 's share in demand for variety  $j$  and

$$p_{-ij} = \frac{\sum_h \sum_{\tau=1}^{T_h} p_{\tau hj} q_{\tau hj} - \sum_{\tau=1}^{T_i} p_{\tau ij} q_{\tau ij}}{\sum_h \sum_{\tau=1}^{T_h} q_{\tau hj} - \sum_{\tau=1}^{T_i} q_{\tau ij}}$$

is the average price paid by all households except household  $i$ . The difference of household  $i$ 's price relative to the average yields

$$\Delta p_{ij} = p_{ij} - \bar{p}_j = (1 - \nu_{ij})(p_{ij} - p_{-ij}).$$

While  $p_{-ij}$  is an unbiased measure of the true average price paid, the price difference will be biased towards zero by a factor  $(1 - \nu_{ij})$ , i.e. will be biased more the larger the demand share of household  $i$  for good  $j$ . A similar mechanism pertains for the household level price index described in Section 3.1.

A way to alleviate the bias is to increase the number of transactions considered to compute  $\bar{p}_j$ , thereby decreasing  $\nu_{ij}$ . This can be done by either computing the average price for barcode  $j$  at the national, annual level or defining it at the local, quarterly level but only considering transactions for barcodes with a minimum number of transactions in the region and quarter. Alternatively, one could also drop a household's own transactions when computing the average price. However, as for many goods there are only few households consuming it in a narrow region this increases the noise in average prices and often effectively implies dropping the good if a household accounts for a significant share of local purchases of this barcode.

Table 9 repeats the estimation in equation (6) for local average prices and barcodes with a minimum of 1, 25, 50 and 100 transactions respectively. The larger the minimum number of transactions, the closer the estimates (especially the coefficient on log-expenditures) get to the one obtained using national, annual average prices (column (1)). I take this as justification for focusing on the results based on national and annual average prices.

**Table 9:** Shopping Effort across Households (by Number of Transactions)

	price index (national) ( $N^{min} = 1$ ) (1)	price index (local) ( $N^{min} = 1$ ) (2)	price index (local) ( $N^{min} = 25$ ) (3)	price index (local) ( $N^{min} = 50$ ) (4)	price index (local) ( $N^{min} = 100$ ) (5)
log(expenditure)	0.706*** (0.078)	0.358*** (0.022)	0.456*** (0.066)	0.575*** (0.079)	0.678*** (0.102)
income 30k-60k	0.080* (0.046)	0.026 (0.024)	0.071 (0.060)	0.093 (0.081)	0.071 (0.109)
income 60k-100k	0.178*** (0.057)	0.076** (0.030)	0.208** (0.081)	0.294*** (0.108)	0.251* (0.141)
income >100k	0.326*** (0.070)	0.113*** (0.037)	0.254** (0.106)	0.354** (0.140)	0.156 (0.173)
1 non-employed household head	-0.236*** (0.037)	-0.104*** (0.019)	-0.163*** (0.051)	-0.214*** (0.066)	-0.287*** (0.092)
2 non-employed household heads	-0.422*** (0.068)	-0.200*** (0.036)	-0.319*** (0.087)	-0.348*** (0.111)	-0.618*** (0.156)
head's age 25-65	-0.013 (0.050)	0.021 (0.027)	0.095 (0.071)	0.093 (0.090)	0.211* (0.127)
sqrt(HH size)	0.399*** (0.066)	0.195*** (0.033)	0.222** (0.090)	0.277** (0.118)	0.403*** (0.152)
FE year-state	X	X	X	X	X
FE household	X	X	X	X	X
Observations	801,398	801,398	800,320	797,812	780,476

**Note:** Regression of household-level price index on characteristics. Column (1) price index (prices paid vs. average price) defined based on national annual average price. Column (2) price index (prices paid vs. average price) defined based on local quarterly average price. Column (3) price index (prices paid vs. average price) defined based on local quarterly average price, restricted to products with at least  $N = 25$  local quarterly observations. Column (4) price index (prices paid vs. average price) defined based on local quarterly average price, restricted to products with at least  $N = 50$  local quarterly observations.. Column (5) price index (prices paid vs. average price) defined based on local quarterly average price, restricted to products with at least  $N = 100$  local quarterly observations. Data obtained from Nielsen Consumer Panel waves 2007-2019. Observation weighted with Nielsen provided sample weights. Standard errors clustered at the household level. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

### B.3 Evidence on Demand Composition and Price Distributions

**Table 10:** Demand Composition and the Skewness of Price Distributions (Robustness)

	baseline	Kelly	unweighted regression	unweighted skewness	only HH weights skewness
	(1)	(2)	(3)	(4)	(5)
expenditure quintile 2	−1.638*** (0.242)	−0.135*** (0.043)	−1.802*** (0.143)	−1.450*** (0.215)	−1.627*** (0.239)
expenditure quintile 3	−2.309*** (0.256)	−0.226*** (0.043)	−2.583*** (0.163)	−2.100*** (0.230)	−2.354*** (0.251)
expenditure quintile 4	−3.067*** (0.258)	−0.282*** (0.042)	−3.374*** (0.178)	−2.793*** (0.244)	−3.062*** (0.260)
expenditure quintile 5	−3.412*** (0.253)	−0.382*** (0.040)	−4.066*** (0.188)	−3.151*** (0.244)	−3.425*** (0.255)
FE module	X	X	X	X	X
FE quarter-SMC	X	X	X	X	X
Observations	3,026,551	2,832,442	3,026,551	3,026,551	3,026,551

**Note:** Regression of the skewness of price distributions on demand shares by expenditure quintile. Price distributions defined as all transactions of a barcode within a Scantrack Market Region and quarter. Demand shares defined as the share of national annual spending on a barcode by quintile. Column (1): Baseline result, observations weighted with distribution by household weights and quantities purchased and across distributions by total expenditures included on given price distribution. Column (2): Baseline weights, Kelly’s measure of skewness. Column (3): No weighting of price distributions in regressions. Column (4): No weighting of price observations within distributions. Column (4): Price observations within distributions weighted by household weights but not quantities. Data obtained from Nielsen Consumer Panel waves 2007-2019. Standard errors clustered at the barcode-year level. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

**Table 11:** Demand Composition and Price Distributions (Number of Transactions)

	Nmin = 25	Nmin = 50	Nmin = 100
	(1)	(2)	(3)
expenditure quintile 2	-1.638*** (0.242)	-2.289*** (0.528)	-3.162*** (1.174)
expenditure quintile 3	-2.309*** (0.256)	-2.929*** (0.570)	-4.268*** (1.212)
expenditure quintile 4	-3.067*** (0.258)	-3.797*** (0.569)	-5.186*** (1.225)
expenditure quintile 5	-3.412*** (0.253)	-4.654*** (0.556)	-6.436*** (1.219)
FE module	X	X	X
FE quarter-SMC	X	X	X
Observations	3,026,551	803,604	202,067

**Note:** Regression of the skewness of price distributions on demand shares by expenditure quintile. Price distributions defined as all transactions of a barcode within a Scantrack Market Region and quarter. Demand shares defined as the share of national annual spending on a barcode by quintile. Column (1): Only price distributions with at least  $N = 25$  transactions. Column (2): Only price distributions with at least  $N = 50$  transactions. Column (3): Only price distributions with at least  $N = 100$  transactions. Data obtained from Nielsen Consumer Panel waves 2007-2019. Observations weighted by total expenditures included on given price distribution. Standard errors clustered at the barcode-year level. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

## B.4 Consumption Baskets and Separation in the Goods Market

Quantifying non-homotheticities in the data requires a measure for the similarity of consumption baskets. Define the consumption basket of any group  $g$  of households  $i$  via the share of their annual total expenditures allocated to each good  $\omega_j^g$ . The expenditure share of good  $j$  for group  $g$  in a given year is given as

$$\omega_j^g = \frac{\sum_{i \in g} e_j^i}{\sum_{j \in J} \sum_{i \in g} e_j^i}.$$

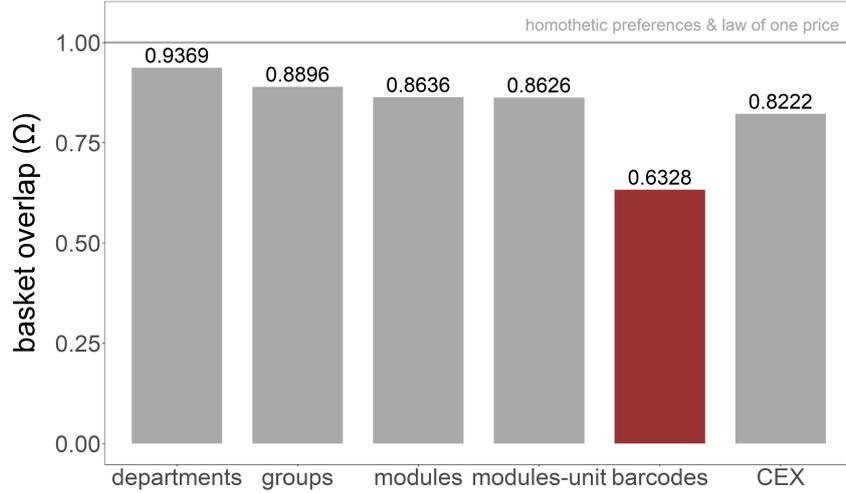
The vector of expenditure shares for any given group can be seen as a distribution over a discrete set of alternatives – the universe of available products. The similarity of two such vectors, i.e. the consumption baskets of two groups of households  $g$  and  $h$ , can be measured by computing the histogram overlap  $\Omega^{g,h}$  in expenditure shares, given as

$$\Omega^{g,h} = \sum_{j \in J} \min \{ \omega_j^g, \omega_j^h \}.$$

Note that under homothetic preferences and the law of one price  $\omega_j^g = \omega_j^h \forall j, g, h$  and hence  $\Omega^{gh} = 1$ , so any deviation of the overlap from one can be interpreted as a deviation from these assumptions. Conducting the analysis by groups of households accounts for variation in taste within groups and computing statistics at the annual frequency averages out seasonal fluctuations.

Figure 15 reports the histogram overlap between the first and fifth quintile of the distribution of annual expenditures, defining a good at different levels of aggregation. If products are broadly defined, e.g. at the Nielsen department level, the overlap in consumption baskets is as high as 94% and even when considering product modules it is still as high as 86%. Only at the lowest level of aggregation where products are unique UPCs (the barcode level) the overlap decreases substantially to 63%. I.e. consumption baskets of high and low expenditure households exhibit a significant mismatch driven by variation in purchases of closely substitutable goods within Nielsen-defined product modules. For the empirical decomposition in Section 5.1 it is also important to note that conditioning on units of measurement within product modules does not alter the overlap substantially compared to considering the entire module, i.e. there are no notable non-homotheticities by unit of measurement. The overlap between any other two quintiles of the expenditure distribution exhibits similar patterns. Overlap at any level of aggregation decreases monotonically in the distance (difference in total expenditures) between two groups.

To complement the analysis based on Nielsen data for even broader categories of consumption goods, the final bar in Figure 15 produces the overlap between the bottom



**Figure 15:** Consumption Basket Overlap - Top vs. Bottom Expenditure Quintile

**Note:** Histogram overlap in the vector of expenditure shares for the bottom and top quintile of expenditures, by different definitions of a product. First five columns derived from Nielsen Consumer Panel, final column from Consumer Expenditure Survey (CEX). CEX column considers 14 spending categories.

and top quintile of the income distribution in the Consumer Expenditure Survey (CEX) defining goods at the 14 most aggregated categories.<sup>39</sup> The non-homotheticity in CEX categories is roughly at the level of Nielsen defined product modules, while the barcode level overlap measured in Nielsen is approximately 25% lower.

Complementary evidence to the missing overlap in consumption baskets is a measure of how important the demand of other households is for the goods that any group of households buys. First, to determine how important demand from any group of households  $g$  is for a given good  $j$ , we define the *demand share* ( $DS$ ) of group  $h$  for good  $j$  as

$$DS_j^h = \frac{\sum_{i \in h} e_j^i}{\sum_{g \in G} \sum_{i \in g} e_j^i}.$$

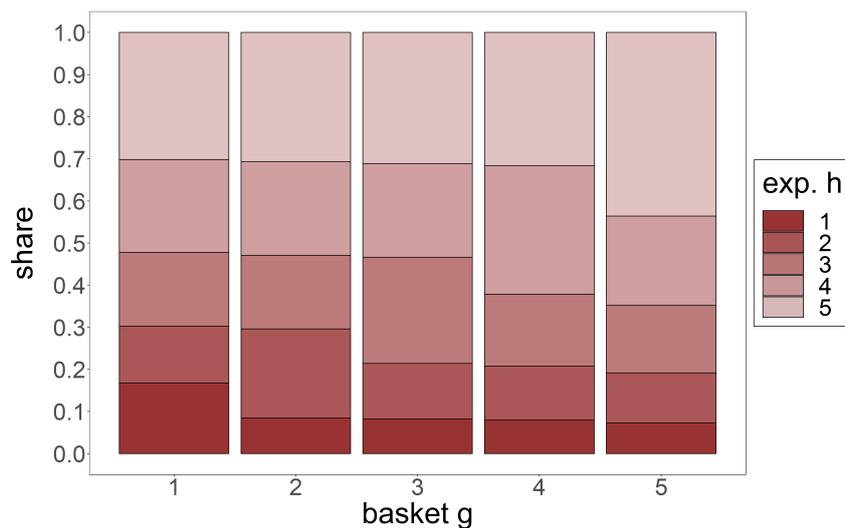
We can then weight the demand shares of group  $h$  with the basket of group  $g$  to compute the *cross market share* ( $CMS$ ) of group  $h$  for the basket of group  $g$ , defined as

$$CMS^{gh} = \sum_{j \in J} \omega_{jt}^g DS_j^h.$$

<sup>39</sup>I use aggregated series for consumption by category and income quintile reported by the Bureau of Labor Statistics (BLS). The 14 expenditure categories considered include: *food at home, food away from home, alcoholic beverages, housing, apparel and services, transportation, healthcare, entertainment personal care products and services, reading, education, tobacco products and smoking supplies, miscellaneous expenditures, cash contributions, personal insurance and pensions.*

This statistic can be interpreted as the average demand share of  $h$  in the basket of  $g$  and measures how important group  $h$  is for the demand of goods that group  $g$  buys.

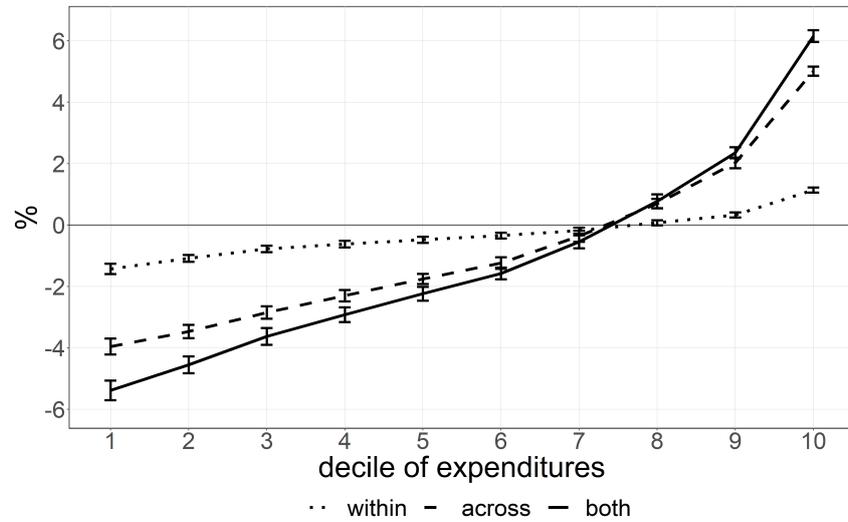
Figure 16 plots the cross market shares by quintile of the expenditure distribution at the barcode level. It shows that each group of households is substantially overrepresented in their own consumption baskets. E.g. the lowest expenditure quintile is twice as important for their own consumption basket as for the basket of the highest expenditure quintile.



**Figure 16:** Cross Market Shares

**Note:** Barcode-level cross market shares of expenditure quintile  $h$  for the basket of quintile  $g$ . Cross market shares are constructed weighting the share of demand for a product  $j$  coming from quintile  $h$  by the expenditure share  $\omega_j^g$  of product  $j$  in the basket of quintile  $g$ . Data from Nielsen Consumer Panel.

## B.5 Price Differences



**Figure 17:** Price Differences along the Expenditure Distribution – Deciles

**Note:** Price differences by expenditure quintile in the data, as a share of households' grocery spending. "Within" refers to differences between the price paid by a given household and the average price for a given product (direct effect of shopping), while "across" is the difference in average prices across different products. Data from the Nielsen Consumer Panel 2007-2019. The price within products is computed by barcode and the price across products is computed across barcodes within a product module (by unit of measurement). Confidence intervals bootstrapped with 100 draws at the household-year level.

**Table 12:** Price Differences - Regressions

	within products	across products	trips per purchase
	(1)	(2)	(3)
log(expenditure)	0.961*** (0.069)	3.426*** (0.147)	-0.042*** (0.001)
income 30k-60k	0.059 (0.050)	0.544*** (0.100)	-0.001* (0.001)
income 60k-100k	0.186*** (0.063)	1.048*** (0.127)	-0.002** (0.001)
income >100k	0.363*** (0.080)	1.451*** (0.160)	-0.002** (0.001)
1 non-employed household head	-0.284*** (0.041)	-0.665*** (0.083)	0.002*** (0.000)
2 non-employed household heads	-0.456*** (0.072)	-1.471*** (0.160)	0.004*** (0.001)
head's age 25-65	0.023 (0.054)	0.155 (0.113)	-0.001 (0.001)
sqrt(HH size)	0.544*** (0.073)	0.645*** (0.148)	-0.032*** (0.001)
mean			0.15
FE year-state	X	X	X
FE household	X	X	X
Observations	801,398	801,398	801,398

**Note:** Regression of the contribution of differences between prices paid and the average price (1) within product or (2) across products to expenditure inequality on household characteristics. Contributions defined as a share of households' grocery expenditures. The price within products is computed by barcode and the price across products is computed across barcodes within a product module by unit of measurement. Column (3) number of annual shopping trips (stores visited) divided by number of annual purchases (transactions for a barcode-store-day pair). Data from the Nielsen Consumer Panel waves 2007-2019. Standard errors clustered at the household level. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

## C Model Appendix

### C.1 Income Process

For households' idiosyncratic labor productivity  $z$ , I assume an AR(1) process with innovations from a Gaussian mixture, formally defined as

$$\log(z') = \rho \log(z) + \varepsilon$$

$$\varepsilon \sim \begin{cases} \mathcal{N}(\mu_{\varepsilon,1}, \sigma_{\varepsilon,1}^2) & \text{with probability } \chi \\ \mathcal{N}(\mu_{\varepsilon,2}, \sigma_{\varepsilon,2}^2) & \text{with probability } 1 - \chi \end{cases}$$

I discretize the process with 16 states for  $z$  following the method of Farmer and Toda (2017). The income process requires calibrating 6 parameters  $(\rho, p, \mu_{\varepsilon,1}, \sigma_{\varepsilon,1}^2, \mu_{\varepsilon,2}, \sigma_{\varepsilon,2}^2)$ . I impose  $\mu_{\varepsilon,2} = -\frac{\chi}{1-\chi}\mu_{\varepsilon,1}$  to obtain mean zero innovations and calibrate the remaining parameters to match five moments of annual, equivalence scale adjusted, post-tax household labor earnings: The cross-sectional variance of earnings, the standard deviation, skewness, kurtosis of annual earnings growth as well as the difference between the 90th and 10th percentile of annual earnings changes. Target values based on PSID data are obtained from De Nardi et al. (2020). For more information on how the target values are constructed see their Appendix A.3. All targets are reported in Table 13 along with the model counterparts. The associated parameter values are  $\rho = 0.91$ ,  $\sigma_1 = 0.59$ ,  $\sigma_2 = 0.23$ ,  $\chi = 0.082$ , and  $\mu_1 = -0.57$ .

**Table 13:** Calibration Targets – Income Process

Targets (Annual)	Model	Data
Cross Sectional Variance (Levels)	0.61	0.57
Standard Deviation of Changes	0.33	0.33
Skewness of Changes	-0.99	-0.98
Kurtosis of Changes	10.6	10.3
P90-P10 of Changes	0.53	0.64

**Note:** Results of the calibration of an AR(1) income process with Gaussian-mixture shocks. The process is discretized with 16 states following Farmer and Toda (2017). Data moments for the PSID obtained from De Nardi et al. (2020).

### C.2 Solution Method

The model is solved computationally. The solution to households' spending-savings problem is obtained by a version of the endogenous grid method (EGM) in the spirit of Carroll (2006). First, I solve for the consumption allocation and choice of shopping effort given expenditures, applying Broyden's method to the equations for households' consumption

aggregator (10) and optimality condition for effort (11). The optimal choices for consumption allocation and shopping effort provide a solution for  $U(e)$ . I approximate the derivative  $U'(e)$  numerically. With a numerical approximation of  $U'(e)$  at hand, I can apply the standard EGM to solve for households' spending-savings decision.

To solve for a steady state, I iterate on a the vector of demand-weighted search effort for all varieties  $\{\bar{s}_j\}_{j=1}^J$  jointly until a fixed point is reached. I make a guess for  $\{\bar{s}_j\}_{j=1}^J$ , solve for the implied price distributions and households' decisions, and finally aggregate households consumption and shopping policies to obtain an implied vector of demand-weighted shopping effort. I apply Broyden's method to update the guess for  $\{\bar{s}_j\}_{j=1}^J$ . Solving for aggregate dynamics requires finding a path for all demand-weighted shopping efforts  $\{\{\bar{s}_{jt}\}_{j=1}^J\}_{t=1}^T$ . I solve for these paths by applying the sequence-space Jacobian method of Auclert et al. (2021).

### C.3 Welfare Implications

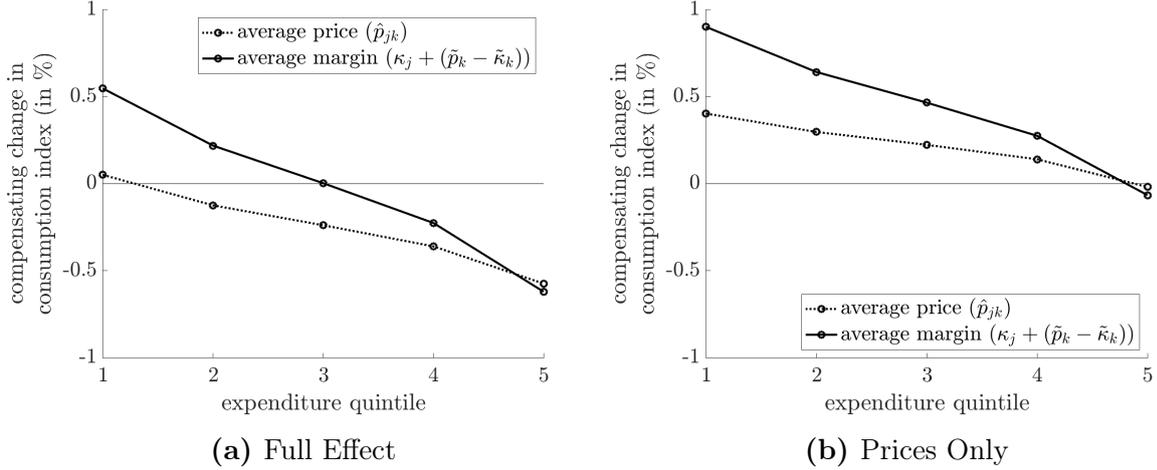
In addition to the one period results on welfare reported in Section 5, this appendix computes the long term effects of living in a counterfactual economy without search effort and alternative prices. As in the main text, I consider two counterfactuals, (i) all households paying the average price paid within each variety  $\hat{p}_{jk}$  or (ii) paying the marginal cost plus average profit margin across varieties  $\kappa_{jk} + (\tilde{p}_k - \tilde{\kappa}_k)$  for each variety. In both cases, there is no price dispersion for identical varieties, search effort is set to zero, and hence there is no disutility of effort.

I first compute welfare in terms of consumption-equivalent variation and ask by what percentage I would need to change consumption of a household with current idiosyncratic earnings  $z$  and assets  $a$  permanently to make her indifferent to the steady state in the counterfactual economy. Formally, this measure is defined as

$$\Delta \mathcal{C}^{CF}(z, a) = \left( \frac{V(z, a) + \frac{1}{(1-\phi)(1-\beta)}}{V^{CF}(z, a) + \frac{1}{(1-\phi)(1-\beta)}} \right)^{\frac{1}{1-\phi}} - 1,$$

where  $V(z, a)$  is a households' value function in steady state and  $V^{CF}(z, a)$  the value of living in the counterfactual economy.

Figure 18a reports the results for both counterfactuals. Its results are similar to the one-period findings presented in section 5.2. The consequences for the welfare of high spending households are attenuated, as taking into account the infinite horizon lets them internalize the probability of becoming a low spending household in the future. This forward looking effect reduces the impact of shopping on welfare inequality to about 1%.



**Figure 18:** Permanent Welfare Effects of Shopping Effort

**Note:** Permanent change in total consumption index ( $\mathcal{C}$ ) under alternative prices and zero shopping effort to make a household indifferent between living in the alternative economy and in the steady state economy. Counterfactuals allow households to optimally choose their savings and consumption baskets assuming they have to pay (i) the average price within each grocery variety or (ii) marginal cost plus the average margin across varieties. Panel (a) displays the full effect on welfare. Panel (b) uses a counterfactual measure of steady state welfare, abstracting from the disutility of effort, such that all differences are due to the alternative prices.

Figure 18b presents results using a counterfactual steady state value function without any disutility from shopping effort, computed as

$$V^{noshop}(z, a) = u(\mathcal{C}^{SS}(z, a)) + \beta \mathbb{E}_{z'|z} V^{noshop}(z', a'),$$

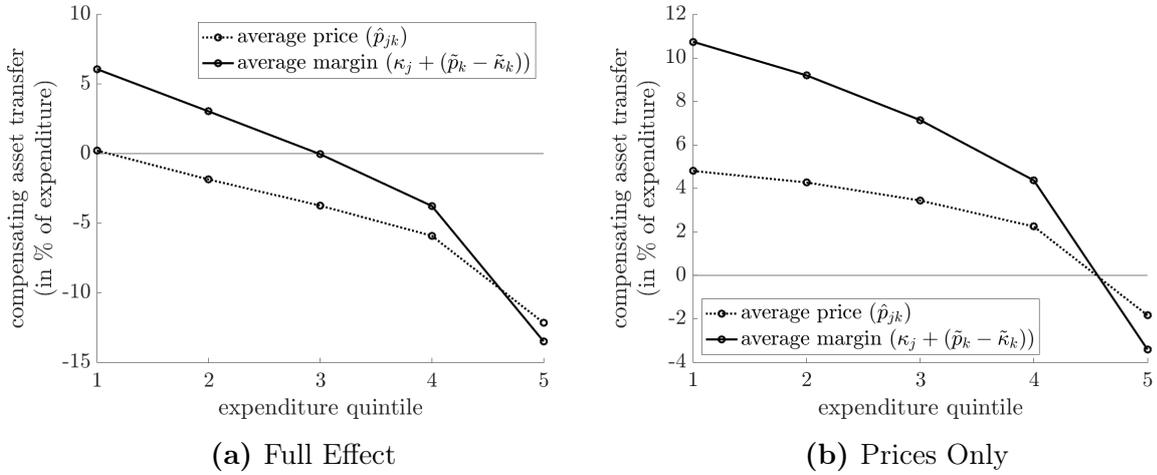
where  $\mathcal{C}^{SS}(z, a)$  is the steady state consumption level of a household in state  $(z, a)$ . This counterfactual isolates the welfare effect of price differences as it eliminates any welfare gains from setting the disutility of shopping effort to zero under the alternative price regimes. Abstracting from the reduction in disutility makes the counterfactual economies more costly in welfare terms for all households, but more so for the top quintile (0.56% in consumption terms) as opposed to the bottom quintile (0.35%).

As the welfare results based on the non-homothetic aggregate consumption index  $\mathcal{C}$  are not easily interpretable in terms of the quantities consumed, I compute an alternative measure by compensating households with a one-off change in their asset holdings  $\Delta(z, a)$  for moving them between the counterfactual economies and the steady state, such that

$$V^{CF}(z, a + \Delta(z, a)) = V(z, a).$$

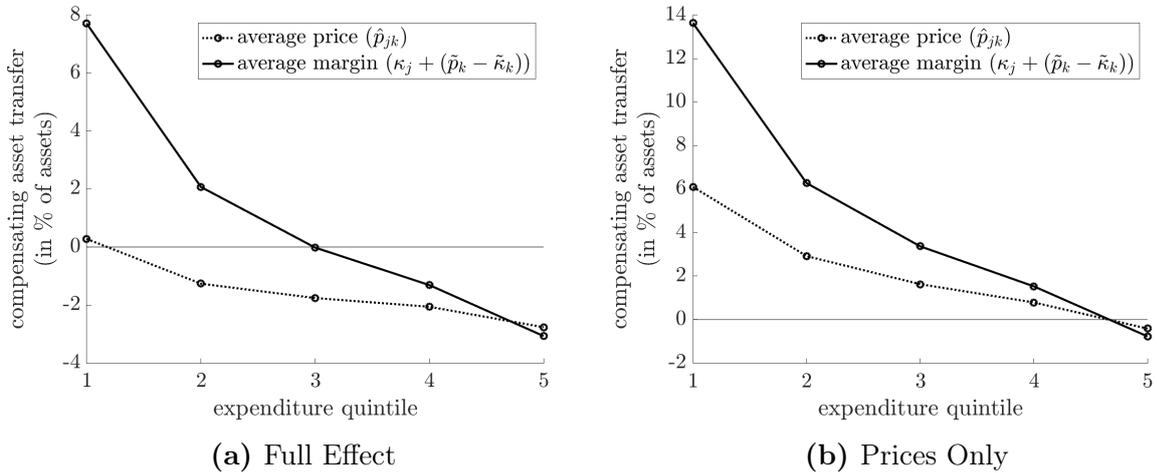
Figure 19 reports the transfer as a share of households' expenditures and Figure 20 as a share of households' assets. The conclusions from both figures with respect to the relative

contributions of direct and equilibrium effects are similar to the computations based on compensating changes in households consumption index  $\mathcal{C}$ .



**Figure 19:** Asset Transfer as a Share of Expenditures

**Note:** Change in initial asset holdings as a fraction of total expenditure under alternative prices and zero shopping effort to make a household indifferent between living in the alternative economy and in the steady state economy. Counterfactuals allow households to optimally choose their savings and consumption baskets assuming they have to pay (i) the average price within each grocery variety or (ii) marginal cost plus the average margin across varieties. Panel (a) displays the full effect on welfare. Panel (b) uses a counterfactual measure of steady state welfare, abstracting from the disutility of effort, such that all differences are due to the alternative prices.

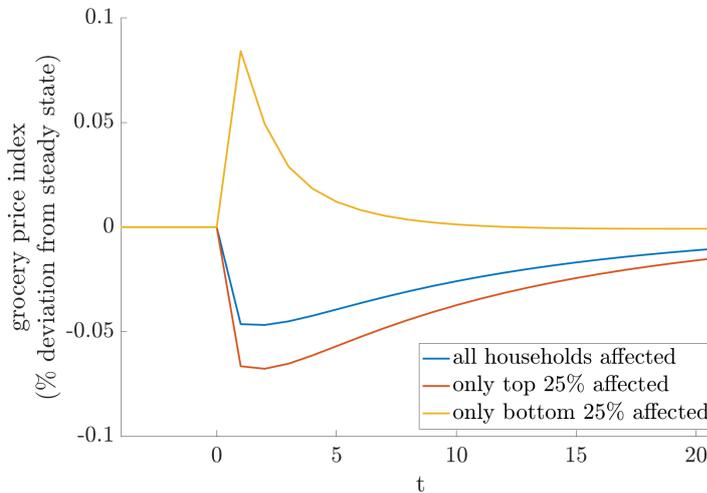


**Figure 20:** Asset Transfer as a Share of Assets

**Note:** Change in initial asset holdings as a fraction of assets under alternative prices and zero shopping effort to make a household indifferent between living in the alternative economy and in the steady state economy. Counterfactuals allow households to optimally choose their savings and consumption baskets assuming they have to pay (i) the average price within each grocery variety or (ii) marginal cost plus the average margin across varieties. Panel (a) displays the full effect on welfare. Panel (b) uses a counterfactual measure of steady state welfare, abstracting from the disutility of effort, such that all differences are due to the alternative prices.

## C.4 Cyclicalities of Retail Prices and Markups

To illustrate how the incidence of aggregate shocks can result in different responses of retail prices and markups even when the shock has identical size on aggregate, I simulate an unanticipated decline in aggregate earnings of 3% holding all parameters fixed at steady state values. Earnings revert back to their steady state level at a rate of 0.5 along a perfect foresight transition path. Consider three different scenarios: In a first scenario *all* households are affected, i.e. each household sees a 3% decline in her earnings. In a second scenario, aggregate income again falls by 3% but the losses are concentrated only on the *top* 25% households in the labor earnings distribution – each of them affected proportionately to their labor productivity. In a third scenario, the same aggregate loss affects only the *bottom* 25% of the labor earnings distribution.



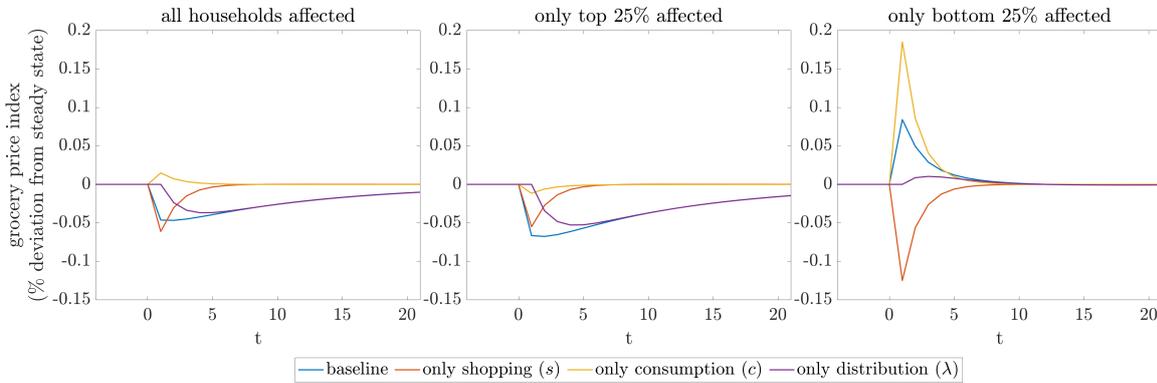
**Figure 21:** Aggregate Prices under Varying Incidence

**Note:** Response of an aggregate Laspeyres index of posted prices  $P_t^F = \frac{\sum_{j=1}^J C_j^{SS} \mu_{jt}^F}{\sum_{j=1}^J C_j^{SS}}$  to a 3% loss in aggregate labor earnings relative to the steady state, affecting (i) all households proportionately to their labor earnings, (ii) only the bottom quartile of labor earnings (proportionately to their earnings), or (iii) only the top quartile (proportionately to their earnings).

Figure 21 plots the response of a Laspeyres index of average prices posted for all three scenarios. Focusing first on the case with all households affected, prices decline in response to a loss in aggregate earnings. If losses are concentrated at the top of the distribution, prices become more procyclical. In response to the same loss in aggregate earnings concentrated among the bottom of the earnings distribution, prices in the model economy become countercyclical. As all parameters including marginal cost  $\kappa_j$  are fixed at steady-state levels, these price responses are driven entirely by changes in markups.

Again, I decompose the response for each scenario into the contribution of changes in shopping policies, consumption policies, and the distribution of households. Figure 22 plots the equilibrium response as a baseline together with the three counterfactuals for

each of the scenarios considered. As in the Great Recession exercise presented in Section 6 an increase in the shopping effort of affected households reduces posted prices under all three scenarios. Shopping policies change by more when losses are concentrated among low-income households, as for them the same aggregate shock is comparably larger relative to their earnings. What accounts for the differences in cyclicity are differential responses of demand composition, driven by changes in households' consumption policies and the distribution of agents across the state space. In line with the findings for earnings and wealth losses during the Great Recession, the more low-income households are affected the more they have to reduce consumption and the lower becomes their share in overall demand. Retailers attach more weight to the lower effort of high-income buyers and increase prices in response. For the scenario affecting only the bottom of the income distribution, this demand composition effect is strong enough to outweigh the direct increase in shopping effort, yielding an overall countercyclical price response.

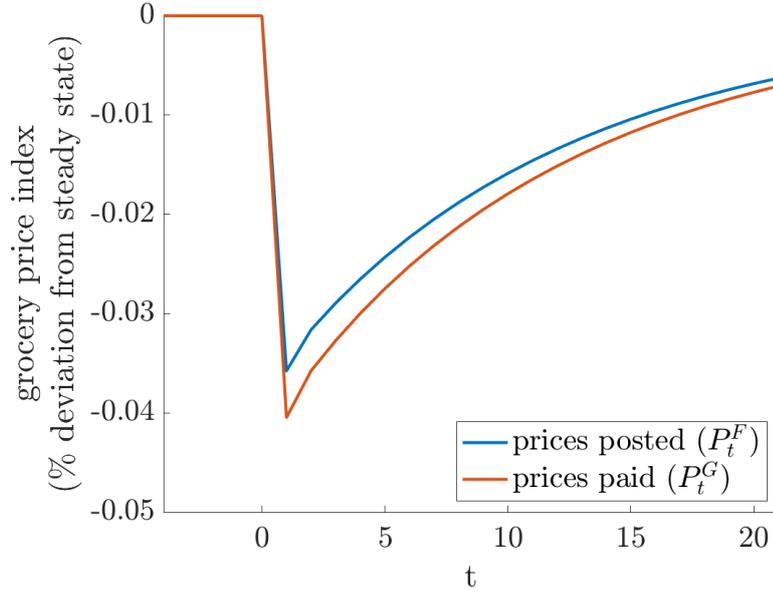


**Figure 22:** Average Prices and Aggregate Income Losses

**Note:** Response of an aggregate Laspeyres index of posted prices  $P_t^F = \frac{\sum_{j=1}^J C_j^{SS} \mu_{jt}^F}{\sum_{j=1}^J C_j^{SS}}$  to a 3% loss in aggregate labor earnings relative to the steady state, affecting (i) all households proportionately to their labor earnings, (ii) only the bottom quartile of labor earnings (proportionately to their earnings), or (iii) only the top quartile (proportionately to their earnings). Full response as baseline. Decomposed into response to changes in consumption policies (only  $c$ ), shopping policies (only  $s$ ), and the distribution of households (only  $\text{dist}$ ), holding the respective others constant at steady state levels.

This additional exercise shows that even with an identical decline in aggregate earnings the incidence of the shock along the distribution of households matters for the cyclicity of retail prices and markups.

## C.5 Additional Model Results



**Figure 23:** Prices Posted and Prices Paid in Response to a 1% Loss in Wealth

**Note:** Model implied response of an aggregate Laspeyres index  $P_t^l = \frac{\sum_{j=1}^J C_j^{SS} \mu_{jt}^l}{\sum_{j=1}^J C_j^{SS}}$  of prices posted ( $P_t^F$ ) and prices paid ( $P_t^G$ ) to a proportionate 1% decrease in beginning of period assets  $a$  for each household.

**Table 14:** Earnings Losses for Great Recession Shock

	$z_1 - z_6$	$z_7$	$z_8$	$z_9$	$z_{10}$	$z_{11}$	$z_{12} - z_{16}$
cumulative share of households	24%	34%	47%	60%	74%	84%	100%
linked percentile in Heathcote et al. (2020)	$P_{20}$	$P_{30}$	$P_{40}$	$\frac{P_{50}+P_{60}}{2}$	$P_{70}$	$P_{80}$	$P_{90}$
$\frac{z_t}{z^{SS}} - 1$							
$t = 1$ (2008)	-17.3%	-7.4%	-3.0%	-4.3%	-3%	-3%	-0.9%
$t = 2$ (2009)	-43.4%	-16.8%	-13.3%	-6.8%	-6.6%	-2.9%	-2.9%
$t = 3$ (2010)	-55.6%	-23.7%	-15.1%	-8.5%	-6.4%	-4.6%	-2.5%

**Note:** Calibration of earnings losses by productivity state in the Great Recession. Data moments obtained from Heathcote et al. (2020).

**Table 15:** Cross Market Shares – Model vs. Data

		model					data				
		market share of exp. quintile					market share of exp. quintile				
		Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
by basket of expenditure quintile	Q1	0.09	0.15	0.19	0.24	0.33	0.17	0.14	0.18	0.22	0.30
	Q2	0.08	0.14	0.19	0.24	0.35	0.08	0.21	0.18	0.22	0.31
	Q3	0.07	0.13	0.18	0.24	0.37	0.08	0.13	0.25	0.22	0.31
	Q4	0.07	0.13	0.18	0.24	0.39	0.08	0.13	0.17	0.30	0.32
	Q5	0.06	0.12	0.17	0.24	0.41	0.07	0.12	0.16	0.21	0.44

**Note:** Cross market shares are computed as the market share of a quintile for each variety averaged by the expenditure shares in the consumption basket of another quintile. Data obtained from Nielsen Consumer Panel waves 2007-2019, consumption baskets in the data defined at the barcode level.

**Table 16:** Earnings and Price Changes after Redistributive Policies (alternative  $\tau$ s)

		$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.15$	$\tau = 0.20$	$\tau = 0.25$
expenditure quintile 1	$\Delta\text{earn}$	16.66%	33.31%	49.97%	66.63%	83.29%
	$\Delta P$	-0.08%	-0.16%	-0.23%	-0.30%	-0.37%
	$\Delta p_G$	-0.23%	-0.44%	-0.65%	-0.86%	-1.05%
	$\frac{-\Delta P}{ \Delta\text{earn} }$	0.5%	0.5%	0.5%	0.5%	0.4%
	$\frac{-\Delta p_G}{ \Delta\text{earn} }$	1.4%	1.3%	1.3%	1.3%	1.3%
expenditure quintile 2	$\Delta\text{earn}$	5.22%	10.43%	15.65%	20.86%	26.08%
	$\Delta P$	-0.09%	-0.17%	-0.25%	-0.33%	-0.41%
	$\Delta p_G$	-0.25%	-0.49%	-0.72%	-0.95%	-1.17%
	$\frac{-\Delta P}{ \Delta\text{earn} }$	1.6%	1.6%	1.6%	1.6%	1.6%
	$\frac{-\Delta p_G}{ \Delta\text{earn} }$	4.7%	4.7%	4.6%	4.6%	4.5%
expenditure quintile 3	$\Delta\text{earn}$	1.91%	3.83%	5.74%	7.65%	9.57%
	$\Delta P$	-0.09%	-0.18%	-0.27%	-0.35%	-0.43%
	$\Delta p_G$	-0.26%	-0.51%	-0.76%	-1.00%	-1.24%
	$\frac{-\Delta P}{ \Delta\text{earn} }$	4.7%	4.7%	4.6%	4.6%	4.5%
	$\frac{-\Delta p_G}{ \Delta\text{earn} }$	13.4%	13.3%	13.2%	13.1%	13.0%
expenditure quintile 4	$\Delta\text{earn}$	-0.15%	-0.30%	-0.45%	-0.60%	-0.75%
	$\Delta P$	-0.09%	-0.19%	-0.28%	-0.37%	-0.46%
	$\Delta p_G$	-0.27%	-0.53%	-0.80%	-1.06%	-1.31%
	$\frac{-\Delta P}{ \Delta\text{earn} }$	62.3%	62.0%	61.8%	61.4%	60.9%
	$\frac{-\Delta p_G}{ \Delta\text{earn} }$	178.0%	177.3%	176.5%	175.4%	174.0%
expenditure quintile 5	$\Delta\text{earn}$	-2.06%	-4.12%	-6.18%	-8.24%	-10.30%
	$\Delta P$	-0.10%	-0.20%	-0.30%	-0.39%	-0.49%
	$\Delta p_G$	-0.28%	-0.55%	-0.85%	-1.13%	-1.40%
	$\frac{-\Delta P}{ \Delta\text{earn} }$	4.8%	4.8%	4.8%	4.8%	4.8%
	$\frac{-\Delta p_G}{ \Delta\text{earn} }$	13.7%	13.7%	13.7%	13.7%	13.6%

**Note:** Average change in post-tax earnings ( $\Delta\text{earn}$ ), grocery ( $\Delta p_G$ ), and aggregate Laspeyres price index ( $\Delta P$ ) within each expenditure quintile in response to an earnings tax  $\tau$  and budget neutral transfer.