Homo Satiabilis: The Effect of Changing Income Inequality on Markups

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Abstract

A firm behaving optimally will set its markup – the ratio of price to marginal cost – based on the price elasticity for its product. One way that price elasticities might differ across time or across products is the ready availability, or not, of close substitutes – what we might think of as competition or market power. However, it might equally be that consumers differ in their individual price elasticities, at which point the composition of demand matters. In this spirit, this paper examines how the increase in income inequality since 1980 can help to explain the changing distribution of firm markups. Using a rich dataset on retail markups, I first show that income and markups are related: rich consumers tend to pay higher markups. In fact, as a consumer's income increases, they do not necessarily increase the physical quantity of products purchased, but rather trade up to more expensive products with higher markups. To match these facts, I create a novel model of satiable preferences. I show that these preferences can be aggregated and resemble a discrete choice model extended to a macroeconomic environment. I calibrate the model to match facts about income, consumption and markups in 2016 and then change the income distribution to that prevailing in 1983. The increase in income inequality leads to a change in the composition of demand across firms, leading high quality, high markup firms to increase their markups, while low-quality, low-markup firms leave their prices relatively unchanged. The model generates empirically consistent movements in the distribution of markups: the average and dispersion both increase. The model is able to explain approximately 25% of the change in the average markup.

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1 Introduction

As a man's riches increase, his food and drink become more various and costly, but his appetite is limited by nature.
-Alfred Marshall

Several recent papers have found that markups have changed significantly since the 1980s (De Loecker et al. 2020, Hall 2018, Barkai 2020, Autor et al. 2020). Not only has the average increased, but so has the variance: most of the increase is due an expansion of the top of the markup distribution, while the median markup has remained relatively unchanged (De Loecker et al., 2020). Most papers focus on the supply side causes of changing aggregate elasticities: the ready availability of, or threat of, close substitutes – what we might think of as competition or market power (e.g. Autor et al. 2020, Barkai 2020, De Loecker et al. 2021, Grullon et al. 2019).

The purpose of this paper is to argue that, although supply-side forces may play a part, some part of the change in the distribution of markups may be the result of changes in the demand side; in particular, changes in the distribution of income. I show that this is able to go some way to explaining not only the increase in the average markup, but also the increase in its variance.

In brief, this paper argues that, because of declining marginal utility of consumption, rich consumers are less price sensitive than poor consumers. Thus, goods whose customer base is mostly rich will tend to face lower price elasticities and charge higher markups. However, a changing distribution of income will change the relative importance of different income groups to a firm's customer base. When income inequality increases, a firm catering to the high-end of the market will see fewer median income consumers, for whom they may have been keeping their prices low, and more rich consumers, who are relatively price insensitive. Such a firm will find its aggregate price elasticity falls and will thus increase its markup further.

However, the effect of increasing income inequality on a firm's markup will depend on its relative share of poor and rich customers. Thus, more basic products, who I find cater relatively equally to rich and poor consumers, will see an increase in both relatively price insensitive and relatively price sensitive consumers, leading to little change in their markups. The overall result is that the high markup firms who cater to the rich see increasing markups, while lower markup, basic product firms see relatively little change; the average markup increases, and so does the variance. I construct, calibrate and simulate a model to investigate the importance of this channel, finding that the increase in income inequality between 1983 and 2016 can explain about a quarter of the change in the sales-weighted average markup. Moreoever, as in the data, this change is accomplished by an increase in markups at the top of the distribution, while those closer to the bottom stay relatively unchanged.

This argument relies heavily on the structure of demand. Indeed, a major claim of the paper – and the one which gives it its name – is that consumers have satiable preferences. It is this satiability which (A) gives consumers a decreasing marginal utility of income and (B) means that rich and poor consumers will purchase fundamentally different bundles of goods. These claims ensure that luxury products will carry higher markups, and that a change in the distribution of income will affect the markups of luxury and basic firms differently. Of course satiable preferences are not the only set of preferences with these two features. However, although the shapes of Engel curves matters for the structure of the argument, they will matter most for any numerical results we get out of a calibrated model. Establishing the correct structure of demand is thus important. Therefore, in Section 2, I explore the composition of demand and its relationship to markups. To understand this chapter's argument, note that a product's price elasticity is simply the weighted average price elasticity of its customers:

$$\eta_i = \int \eta_i(y) \frac{q_i(y)}{Q_i} \ dF(y)$$

where $q_i(y)$ and $\eta_i(y)$ are, respectively, the quantity and price elasticity for good i by consumers with income y, and Q_i is the total quantity of good i purchased by consumers of all incomes. Several authors have found empirically that poor consumers tend to have lower price elasticities than rich consumers (c.f. Stroebel and Vavra 2019, DellaVigna and

Gentzkow 2019, Auer et al. 2022). Given this, we should expect the customer base of a firm to be correlated with its markup, and that rich consumers should pay higher markups on average. Using a rich dataset of retail markups, I show in Section 2 that this is the case and that rich consumers tend to pay higher markups than poor consumers. Furthermore, this is the result of rich consumers purchasing different products which have higher markups; it is not the result of rich consumers purchasing identical products at higher prices.[1]

If the price elasticity faced by a firm depends on the weighted average of the elasticities of its customers, then changes in the distribution of these customers will have impacts on a firm's overall price elasticity, and therefore its markup. Taking the total differential of elasticity with respect to the distribution of income yields:

$$d\eta_i = \int \underbrace{(\eta_i(y) - \eta_i)}_{\text{Relative elasticity}} \quad \underbrace{\frac{q_i(y)}{Q_i}}_{\text{Engel curve}} \quad df(y)\ dy$$

To a first order, a firm's elasticity will change depending on how elasticities differ across income groups, and the likelihood of each income group purchasing the product. This latter depends on the shape of a product's Engel curves. It therefore becomes important to understand how consumption and elasticities vary across goods and across the income distribution. Therefore, in Section 3, I examine consumption patterns using the Nielsen Homescan Consumer Panel dataset. Here, I find two important facts that a model of consumption should be able to replicate. First, I find that inferiority is very common, with around 3/4 of Engel curves in the dataset having a significant downward sloping component. Not surprisingly, inferiority is correlated with relative prices. Looking within a given category of products – for example, milk – more expensive goods are more likely be normal, i.e. to have strictly increasing Engel curves. Second, I show that as incomes increase, average expenditures increase – not a particularly surprising fact! However, what is perhaps more surprising, the increase in expenditure is largely the result of increases in average prices paid, rather than

[1] Anderson et al. (2020) come to the same conclusion using variation in markups at the regional level. Using a very similar dataset, Sangani (2022) also shows that average markups paid increase in the income of customers, although, through the lens of his model, he attributes this to higher prices paid for identical products.

increases in total physical quantities consumed. It is not that rich consumers purchase *more* food or *more* clothing, but rather *more expensive* food and *more expensive* clothing. Taken with the first fact, this suggests a process for consumption in which, as income increases, consumers trade up to higher-priced, higher-utility goods, rather than consuming more goods of a given quality. This process seems to bear out both in the Nielsen sample and in the Consumer Expenditure Survey.

Section 3 suggests that these facts about consumption makes sense as the result of satiable preferences. By this, I mean that goods fulfil needs, and that once these needs are satisfied, consuming additional units of similar goods will yield no additional utility. To use the example given in the quote above from Alfred Marshall, food and drink fulfil a need – calories – which is satiable. Past some income level households no longer increase their consumption of calories. Despite this, the grocery bag of the rich household will differ from that of the poor: name brands will replace store brands, luxury wines will replace cheap beer, organic will replace non-organic, fresh will replace canned, etc. Because consumers cannot increase their utility by increasing the quantity of a given good, they increase utility by increasing the average quality consumed. Thus, consumers trade up to higher quality products as incomes increase.

Section 4 develops a novel model of satiable consumer preferences. Satiability means that at the individual level, consumers form a hierarchy of purchases: they first purchase those goods with the highest utility per dollar spent – necessities – and only at higher incomes do they trade up to lower priority goods – luxuries. When these preferences are aggregated, they resemble a discrete choice demand system, modified to account for the macroeconomic nature of the model.

This hierarchical model of consumption has important implications for the markup decisions of firms. In the model, the decision to trade up to more expensive products is a function of both income and price. A firm lowering its price a little bit is apt to attract consumers for whom that product is next in their hierarchy. To give an example, if the price of a luxury Lamborghini dropped by $5,000, the firm might expect to attract purchases from middle-to-high income consumers, but not low-income consumers. For poor consumers, a luxury car is not enough of a priority, and would mean giving up purchases of necessities, which yield a much higher utility per dollar spent. Conversely, dropping the price of a basic car may attract purchases from low-income consumers, who now find it preferable to other means of transportation, although this price decrease will do little to attract purchases from high-income consumers, who are already consuming cars of higher quality.[2]

Thus, firms with different customer bases will react react differently to the same change in the income distribution. Each considers the size of potential markets it can gain by lowering its price, and the size of these markets are shaped by the distribution of income and by the patterns of consumption across the income distribution.

This means that the pricing of basic and luxury products will respond differently to a hollowing-out of the income distribution. In the calibrated model, high-markup, luxury firms now see fewer median income consumers who, for a sufficiently low price, would purchase their products. They therefore raise their prices and their markups. The mass of poor consumers is inconsequential for the luxury firm: its higher cost means that it would have to lower its price to uneconomical levels to attract these consumers. Meanwhile, basic firms have a relatively equal share of rich and poor consumers, and thus the changing distribution of income has only a small (positive) effect on their markups. The overall effect of an increase in income inequality is an increase in the variance of markups, but also an increase in the average markup.

Section 5 investigates the numerical importance of this channel. I calibrate the model developed in Section 4 to the economy in 2016, and then shock the model by changing the distribution of income to that prevailing in 1983, keeping the median the same. The result is a fall in the average sales-weighted markup from 1.59 to 1.5 – about a quarter of the empirical change. Importantly, this is increase in the average is driven mostly by an increase

[2]Here also, Alfred Marshall beats us to the punch. In his *Principles*, he writes: "The current prices of wall-fruit, of the better kinds of fish and other moderately expensive luxuries are such as to make the consumption of them by the middle classes increase much with every fall in price... While the demand on part of the rich and on the part of the working class is less elastic, the former because it is already nearly satiated, the latter because the price is still too high."

in markups for already high-markup firms while the markups of low-markup basic goods barely change.

Section 6 shows that this model has important welfare implications concerning increasing income inequality. Not surprisingly, a concave utility function means that an increase in income inequality will tend to be welfare decreasing. However, I show that the endogenous effect on prices and markups play an important mitigating role. In the model, the increase in income inequality also increases average markups, which has a negative effect on welfare. However, this fall in welfare would be even worse if all markups had increased equally – the fact that markups increase most for the rich lowers real income inequality to some extent, mitigating the decrease in welfare. I quantify all of these effects.

Related Literature Authors have tended to concentrate on the increasing average markup rather than the overall change in the distribution. Explanations rely on the fact that rational firms will set markups based on price elasticities – the more sensitive one's customers are to price increases, the less one can get away with high prices. Consequently, seeking to explain rising markups could equally be phrased as seeking to explain falling aggregate price elasticities. Explanations have tended to rely on supply-side arguments, often about market power and competition (Autor et al. 2020, Barkai 2020, De Loecker et al. 2021, Hall 2018, Grullon et al. 2019, Cavenaile et al. 2019, Eggertsson et al. 2018, Gutiérrez and Philippon 2017); the fewer competitors firms face, the harder it is for consumers to switch away from the products of a price-increasing firm.

However, price elasticities may differ for reasons other than the competitive structure of an industry. Indeed, to the extent that price elasticities differ across customers, any force which alters the composition of consumers has the capability of altering aggregate price elasticities. Thus, a few recent papers examine how the changing distribution of consumers might impact aggregate elasticities, and therefore markups: Bornstein (2021) looks at the changing age profile of the economy, while Sangani (2022) looks at changes in the income distribution.

In a concurrent paper, Sangani (2022) argues that rich consumers have a low price elasticity which is the result of low search intensity. Consumers purchase goods at the lowest price available. However, rich consumers have a relatively high search cost, and therefore search less and are more likely to purchase high-price, high-markup goods.[3] As shown in Section 2, differences in prices paid for identical products explains only a very small fraction of the higher markups paid by rich consumers. Rather, markups are higher for rich consumers because they purchase distinct, higher-quality, products.[4] Thus, like Sangani (2022), this paper considers changes in the distribution of income. However, unlike Sangani, this paper expressly models the non-homotheticity of consumer choice: as incomes grow, rich consumers will purchase higher-quality, higher-markup goods. Because of this non-homotheticity, producers of luxury goods will behave differently in response to an increase in income inequality than will producers of inferior goods.

Several papers have shown empirically that income matters for price elasticities and pricing. Stroebel and Vavra (2019) find that markups vary positively with housing wealth. Using an instrument for price changes, DellaVigna and Gentzkow (2019) find that price elaticities are larger in poorer zip codes. Using data on the appreciation of the Swiss franc, Auer et al. (2022) show that the consumption of low-income consumers is more price-elastic.

In terms of preferences, this paper suggests that satiability may be an important feature of consumption behaviour. Satiability, as a concept, is not novel, although there have been few attempts to model it formally – a lacunae I try to address here. As already mentioned, Marshall (1920) is replete with references to satiability as well as its effect on price elasticities of demand (see Footnote 2). The view is present earlier, however, being found also among the early marginalists, who noted that falling marginal utility could eventually reach zero for at least some goods.[5]

[3]Note that one difference here is that differences in consumer behaviour are due to differences the marginal cost of search time rather than differences in marginal utility of consumption.

[4]Anderson et al. (2020) find that markups differ in richer zip codes because of variation in products purchased, rather than a variation in prices charged for identical products.

[5]Marshall (1920) uses the "law of satiable wants" and the "law of diminishing utility" interchangeably. In his chapter on the theory of value, Menger (1871) notes that abundant goods, like water in a stream, become non-economic (having no-value) once consumers reach a point of satiation. He makes a similar point later regarding satiation in terms of food. With regards to economic necessities, Jevons (1871) writes: "The necessaries of life are so few and simple that man is soon satisfied in regard to these, and desires to extend his range of enjoyment."

As I will show, satiability also gives rise to consumption which is hierarchical: a consumer's most important needs are satisfied first (say, food or shelter), while less important needs are satisfied last (say, luxuries). Again, this is very similar to the view of the early marginalists. This is particularly evident in Menger (1871).[6] The view that consumption proceeded in a hierarchical fashion was elaborated in greater detail by Roy (1943), whose goal was to answer questions regarding aggregate price elasticities[7] (for an English translation see Roy (2005)). It has also been popular with some in the Cambridge tradition (c.f. Pasinetti 1981 and Lavoie 2014). More recently, Foellmi and Zweimüller (2006), Foellmi et al. (2014) and Foellmi and Zweimüller (2017) adopt hierarchical preferences to examine the effects of inequality on economic growth.

A related section of the literature explores how income affects quality choice, with higher income individuals consuming higher quality products. Thus, using data from the Consumer Expenditure Survey, Bils and Klenow (2001) show that both quantity and quality increase with incomes. They model this with a utility function in which consumers have preferences over quantity and quality of consumption goods. Similar analysis and utility functions are found in Jaimovich et al. (2019), Jaimovich et al. (2020), and Ferraro and Valaitis (2022). As we will see below (Section 3), although Bils and Klenow (2001) employ preferences which are normal in both quantity and quality, a detailed examanation of the data suggests that only quality is everywhere normal. Contrarily, depending on how goods are defined, quantity either decrease after some income threshold, or at least levels off.

[6] Menger writes: "The maintenance of our lives depends on the satisfaction of our need for food, and also, in our climate, on clothing our bodies and having shelter at our disposal. But merely a higher degree of well-being depends on our having a coach, a chessboard, etc. Thus we observe that men fear the lack of food, clothing, and shelter much more than the lack of a coach, a chessboard, etc."

[7] It's interesting that, despite the close similarity to the views of Maslow (1943), Roy (1943) seems to have arrived at this idea independently, and possibly earlier. Due to delays brought on by World War II, Roy's paper was submitted several years before 1943. Furthermore, Roy suggests that he arrived at these ideas in the early 1930s in response to criticism from Marschak.

2 Markups and Income

I start by showing that the average markup paid by a consumer varies positively with income. To do so, I construct a dataset of retail markups by matching the Nielsen Homescan Consumer Panel and Price Trak Wholesale datasets. Nielsen Homescan Consumer Panel is a panel dataset of 40,000-60,000 U.S. households. It asks respondents to record purchases of all goods meant for personal, in-home use. Purchases are recorded with in-home scanners or mobile apps. For each purchase, we are able to observe the product's unique UPC barcode. Respondents also provide demographic information, including binned household income. Like Sangani (2022) and Handbury (2021), I exclude households with annual income below \$12,000. The Price Trak Wholesale database is collected through a weekly monitoring service of 12 grocery wholesalers. Wholesale costs are also recorded at the UPC level. Because the Homescan dataset contains details on prices paid by consumers, while Price Trak contains information on wholesale costs, matching the two datasets allows us to construct product-level retail markups. I do so using 2018 data, which yields a matched dataset of 414,256 UPCs. Different retailers may pay different wholesale prices for identical UPCs. However, unable to observe any such difference, I assume that each retailer pays the average wholesale cost for a given UPC in the data. Still, consumers may pay different markups on average either because (a) they purchase different UPCs with different wholesale costs and different prices, or (b) they purchase the same UPCs, but pay different prices.

Moreover, consumers may be buying effectively identical products with different UPCs. Although goods are registered at the UPC level, the dataset contains brand information. Products which are otherwise equivalent, but sold in different sizes will have different UPCs. For example, a 6-pack of Coca-Cola will have a different UPC than a 2-litre bottle. Note, however, that the same brand might exist across different product lines. For example, Tetley sells tea bags, but also bottled iced tea. Thus, I define a product as a pair {brand, product module}, where product module is Nielsen's most detailed description of product types. Examples of product module are peanut butter, frozen pizza, ready to eat cereals, and disposable razors. Finally, it should be noted that the description of brands is fairly granular. For example, Coca-Cola, Coca-Cola Vanilla and Coca-Cola Diet Vanilla all appear as separate products in our dataset. To account for potential measurement error, I trim the lowest and highest 1% of markups from the sample.

For each income group, y, and each product, i, I calculate the average sales-weighted markup paid as:

$$\mathbb{E}(\mu_i|y) = \sum_n \frac{p_{i,n}q_{i,n}}{\sum_m p_{i,m}q_{i,m}} \frac{p_{i,n}}{\phi_i} \quad \forall n, m \in y \tag{1}$$

where n and m index individuals. Meanwhile, the average markup across products for consumers in income group y is:

$$\begin{aligned}\mathbb{E}(\mu|y) &= \sum_i \frac{\sum_n p_{i,n}q_{i,n}}{\sum_n \sum_j p_{j,n}q_{j,n}} \mathbb{E}(\mu_i|y) \quad \forall n \in y \\ &= \sum_i S_i(y)\mathbb{E}(\mu_i|y)\end{aligned} \tag{2}$$

where $S_i(y)$ is the expenditure share by income group y on good i.

The blue solid line in Figure 1 plots average markups as defined by eq. (2). It shows that average markups paid are increasing in income, from about 1.16 for those making between \$12,000-\$15,000 to about 1.21 for those making \$100,000+. This is relatively low compared to the average of about 1.6 found by De Loecker et al. (2020). However, it is very similar to the average they find for the retail sector, with estimates ranging from about 1.1 to 1.3. The average in this case is less important than the trend, i.e. that markups paid tend to increase with income.[8]

Sangani (2022) shows a figure similar to Figure 1. He attributes the difference in markups to differences in search behaviour across incomes: the rich have a higher cost of shopping time, and therefore spend less time searching for low prices. The result is that, *for identical*

[8] Sangani (2022) shows a similar figure but using data from 2007. Because Nielsen data in 2007 is top-coded at \$200,000 rather than \$100,000, he is able to observe this pattern over a larger domain. The general trend continues past \$100,000, increasing approximately linearly.

products, the rich will pay higher prices and therefore higher markups. This seems empirically plausible, given that Broda et al. (2009) find that, in the Nielsen Homescan Dataset, the average price paid for identical products increases by about 0.1% for every 10% increase in income.

To test this hypothesis, I consider the counterfactual average markup where expenditure shares are held constant at the level of individuals making between \$12,000-\$15,000, but allow markups paid to vary with income. In other words, I keep the composition of goods purchased the same as the poorest income group, while multiplying by the markups paid by richer consumers. More formally:

$$\mathbb{E}(\mu|y)_{cf} = \sum_i S_i(y = 12000)\mathbb{E}(\mu_i|y) \tag{3}$$

If the rich are paying higher markups because they are paying higher prices for identical products, then we would expect this counterfactual to explain a large share of the increase seen in the average markup. I plot this counterfactual in Figure 1. Keeping expenditure shares fixed, the average markup rises very little.

This suggests that positive relationship between household income and average markups is explained not by higher markups for identical products, but rather by consumers switching their consumption bundles to products with higher markups.

Discussion One explanation for the higher markups paid by rich consumers is that rich consumers have lower price elasticities, as found by DellaVigna and Gentzkow (2019) and Auer et al. (2022). We can represent this mathematically, by noting that a product's overall price elasticity is given by:

$$\eta_i = \int \eta_i(y) \frac{q_i(y)}{Q_i} dF(y) \tag{4}$$

where $\eta_i(y)$ is the price elasticity of consumers of income group y for good i, $q_i(y)$ is the average quantity of good i consumed by consumers of income group y, and Q_i is total quantity

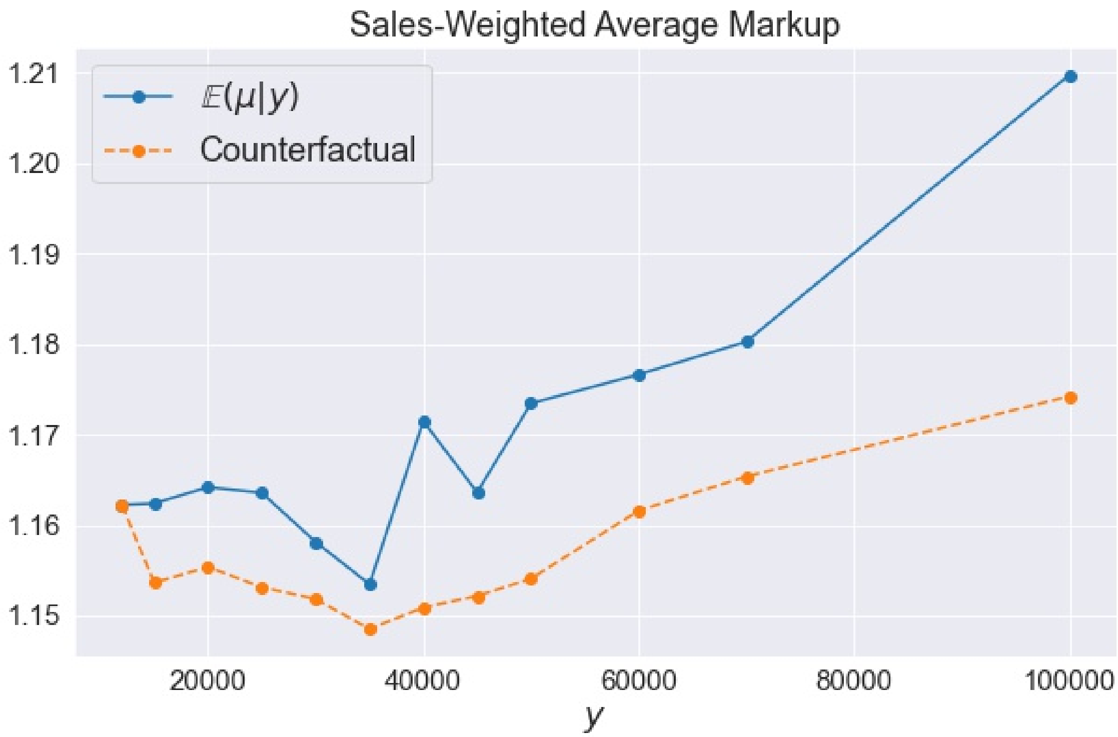


Figure 1: Average markup paid by different income groups, and counterfactual keeping expenditure shares fixed at the lowest income level

of good i, i.e.

$$Q_i = \int q_i(y)dF(y)$$

A product's overall price elasticity is simply the weighted-average of the price elasticities of all of its customers. If, on average, price elasticities are falling in income, we would expect products whose customer base is dominated by the rich to charge higher markups. Equally importantly, changes in the composition of income will change the weights on different income groups, and therefore change the aggregate elasticity. To be precise, taking the total differential of eq. (4) with respect to changes in the distribution of income:

$$d\eta_i = \int (\eta_i(y) - \eta_i)\frac{q_i(y)}{Q_i} \;\; df(y) \;\; dy \tag{5}$$

To a first order, changes in price elasticities, and therefore markups, are determined by the relative elasticities of different income groups, and their share of a product's total sales. Importantly, note that an increase in the number of rich consumers will have a different impact on the elasticity of a luxury product and a basic product. Because the luxury product sells mainly to rich consumers, the luxury firm will put a higher weight on changes in the number of rich consumers. Intuitively, this makes sense: an increase in the number of poor consumers will matter very little to the pricing decision of Ferrari, since poor consumers make up such a small share of Ferrari's total customer base.

Equation (5) also suggests what will be important to determine the effects of a change in the distribution of income on the distribution of markups. This equation is made up of two parts: (1) relative elasticities, $\eta_i(y) - \eta_i$, and (2) Engel curves, $q_i(y)/Q_i$. The second feature means that to find the effects of a change in the distribution of income on markups, it will be important to get the facts about the consumption process correct. In the next section, then, I examine what we can say about empirical Engel curves. I will suggest that these are well rationalized by a model of consumption in which preferences are satiable.

3 Consumption and Income

The previous section showed that markups paid vary positively with income, and suggested that this was due to differences in price elasticities across the income distribution. Once we allow for this, changes in the distribution of income can play an important part in determining changes in the distribution of markups. It also showed that one determinant of this effect will be the shape of Engel curves and, more broadly, the process of consumption across income groups. In this section, I observe these features empirically. I then argue that product-level consumption data can be well understood as the result of satiable preferences. There are two features of the data that satiable preferences allow us to match. First, I show that inferior products are ubiquitous in the data. Perhaps not surprisingly, low-price products tend to be inferior while high-price products tend to be normal. Taken together, this suggests that consumers are trading-up from low-price, low-quality goods to high-price, high-quality goods as their incomes increase.

Second, I give evidence that as incomes increase, expenditure increases, but this increase is almost entirely due to an increase in the average price paid for goods, rather than an increase in the number of physical units purchased. I suggest that both of these facts can be rationalized by the assumption that consumption is satiable: goods fulfil needs, and once these needs are met, additional units of similar goods will yield no additional utility. Instead, as incomes increase, consumers trade up to higher-priced, higher-quality goods.

To show these facts, I rely again on the Nielsen Homescan Database, although here I use the years 2006-2009. In these years, household income is top-coded at \$200,000 rather than at \$100,000.

I first show that inferior products are common in this dataset. To do so, I once again aggregate the data to the brand level. I am interested in quantity Engel curves, rather than expenditure Engel curves, since the latter confounds the effects of prices and quantities. Instead, I calculate Engel curves based on physical quantities (e.g. ml, oz...) and therefore some care must be taken as not all products of a given brand have common units of measurement. For example, tea is sold both in bags (measured with unit "count") and in liquid form (measured with unit "ml"). A given brand, like Lipton, may have UPCs which correspond to goods measured in both ways. Adding up these two quantities would produce nonsense. Therefore, I treat goods measured in different units as separate goods. Thus, Lipton tea bags are a different good than Lipton liquid tea. To this end, I modify my definition of a product in this section to be the triple {brand, product module, measurement units}.

Before constructing Engel curves, I keep only products that have sales in at least 8 out of 17 income groups. I construct Engel curves as the average amount of a product that is purchased by consumers within a given income category. To control for differences in household size, I only consider 3 or 4 person households. I then classify each Engel curve into either inferior, hump-shaped or normal. The classification is achieved by fitting each Engel curve with a quadratic function. The categorization rule is given in Table 1. Categorization is based on the slope of the Engel curve at $y = 0$ and the location of the turning point.

Intuitively, if the fitted function is mostly increasing over the domain, it is classified as normal. Conversely, if it decreases for a large part of the domain, it is classified as either hump-shaped or inferior.

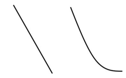
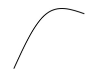
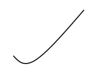
Classification	Slope at $y = 0$	Turning Point ($ thousands)	Shape
Inferior	-	> 100	
Inferior	-	< 0	
Inferior	+	$[0, 25]$	
Normal	+	< 0	
Normal	+	> 150	
Normal	-	$[0, 100]$	
Hump-Shaped	+	$[25, 150]$	

Table 1: Categorization rules for Engel curves

The results of the categorization are given in Table 2. Only a minority of products are classified as normal. That is, the average quantity purchased of a product is monotonically increasing in income in only a minority of cases. Instead, over 70% of products have Engel curves which slope downwards after some income threshold.

Classification	**Share**
Inferior	33.6%
Hump	40.8%
Normal	25.5 %

Table 2: Categorization of Engel curves in Nielsen Homescan

Perhaps not surprisingly, inferior goods also tend to have the cheapest prices. To demonstrate, I first calculate each brand's price as the sales-weighted price of all UPCs which make

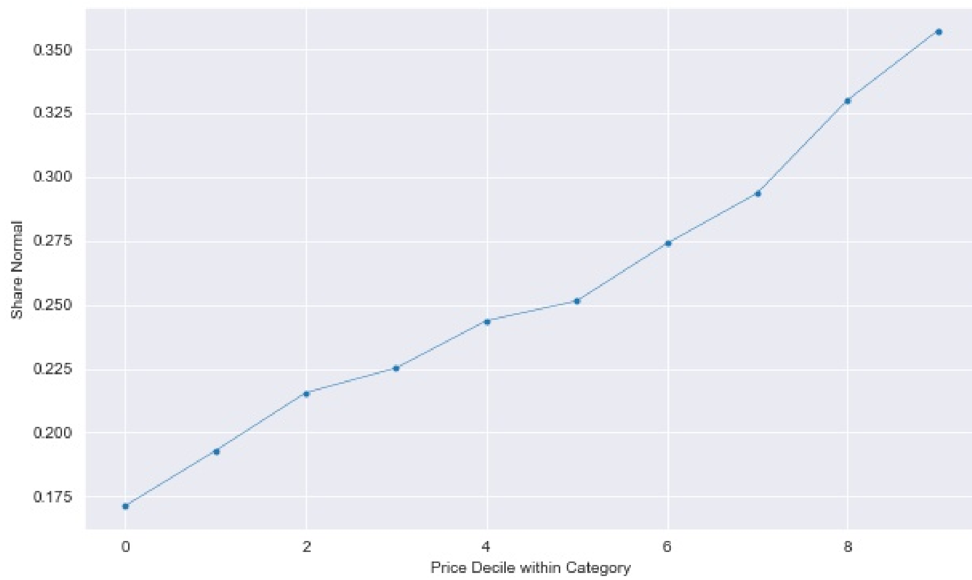


Figure 2: Share of Engel curves which are normal by price decile

up a product. I calculate the price decile to which each product belongs within its category, where category is defined as the pair {product module, units of measurement}. Figure 2 shows that the probability that a given product has a normal Engel curve is increasing in its price.

Finally, I examine aggregate expenditures. One minor puzzle here is that, despite the apparent ubiquity of inferior products, inferiority appears absent when considering expenditures on broad categories of goods. For example, calculating Engel curves using expenditures in the Consumer Expenditure Survey will suggest that consumption is generally normal. Although this is usually treated as evidence that physical purchases are increasing, it could equally be the result of consumers shifting to more expensive goods, with quantity the same. Thus, I next decompose aggregate expenditures in the Nielsen database into changes in physical quantities and average prices. To do so, notice that average expenditure by income group y is the sum of expenditures on each good, i, in each category, c:

$$X(y) = \sum_c \sum_{i \in c} p_{ic} q_{ic}(y)$$

Defining $Q_c(y) = \sum_{i \in c} q_{ic}(y)$:

$$X(y) = \sum_c Q_c(y) \frac{\sum_i p_{ic} q_{ic}(y)}{Q_c(y)}$$

$$X(y) = \sum_c Q_c(y) \mathbb{E}_c(p_{ic}|y)$$

In other words, total expenditure in a given category is total physical units purchased in that category multiplied by the average price paid. Then, the percentage difference in expenditures between any income group y and y' is given by:

$$\%\Delta X^{y,y'} = \sum_c \left(\%\Delta Q_c^{y,y'} + \%\Delta \mathbb{E}(p_{ic})^{y,y'} \right) \frac{X_c(y)}{X(y)} \tag{6}$$

where X_c is the expenditure on category c. This can then be divided into two parts:

$$\%\Delta X^{y,y'} = \underbrace{\sum_c \left(\%\Delta Q_c^{y,y'} \right) \frac{X_c(y)}{X(y)}}_{\text{Changes in quantity}} + \underbrace{\sum_c \left(\%\Delta \mathbb{E}(p_{ic})^{y,y'} \right) \frac{X_c(y)}{X(y)}}_{\text{Changes in average price}} \tag{7}$$

I perform this decomposition in Figure 3 for all expenditures in the Nielsen Homescan Database. Categories simply serve as weights, and so here I use Nielsen's more coarse category definition of a "product group". Examples of product groups are "Beer" and "Cereal", which are made up of several product modules, like "Stout and Porter" and "Ready to Eat Cereals", respsectively. Thus, the definition of a product category employed is the pair {product group, units of measurement}. Note that Q_c still makes sense as a physical aggregation since we are adding up like goods with common measurements. The result is that approximately all of the change in expenditure between the highest and lowest income groups is coming from changes in average price, rather than in physical units consumed. Some care should be taken: the Nielsen database does not contain the universe of products purchased by consumers. Consequently, it is possible (and likely) that the change in quantity is biased downwards, as rich consumers are switching to products not contained in the Nielsen database. For example, rich consumers are more likely to eat at restaurants and less likely to purchase food to be made at home. Given that the former is not captured in Nielsen, this would lead to an apparent decline in the total quantity consumed. Thus, for further evidence, I examine the same decomposition in the Consumer Expenditure Survey.

Figure 3: Decomposition of percent changes in expenditure relative to lowest income group

3.1 Consumer Durables in the Consumer Expenditure Survey

As mentioned above, it's difficult to infer physical quantity Engel curves in the Consumer Expenditure Survey (CEX). In general, the CEX asks respondents to report their *expenditures* on a given type of good, rather than the physical number of units. Thus, it can be hard to disentangle changes in quantities from changes in prices. However, as pointed out by Bils and Klenow (2001), we can reasonably infer prices and quantities from expenditure on consumer durables.

For example, if a household lists spending \$X on a washing machine in some quarter, we can reasonably assume that this was a single washing machine, the price of which was \$X. The explicit assumption is that purchases of these consumer durables is lumpy, and that households purchase no more than one in a given quarter.

For what follows, I use the public use microdata files from CEX for the years 2005-2008 for ease of comparison with the above section employing Nielsen data. To construct Engel curves, I bin households into income deciles, and assign incomes based on the mean income of this group.

I first employ the decomposition from Equation (7) on purchases of small appliances contained in the APB files of the CEX. Purchases in this file are coded by type of "appliance" and include such items as bicycles, telephones and accessories, radios, and televisions. For the sake of Equation (7), I define categories as types of appliance, while each purchase is treated as an individual product, with a price given by the recorded expenditure. The results are displayed in Figure 5.

Unlike the data in Nielsen, increases in quantity are a significant feature of increasing expenditures for small appliances in the CEX. However, despite this, physical quantity consumed still levels off after some income threshold. Households in the 9th and 10th decile seem to consume the same quantity of small appliances. In fact, for higher incomes – those in the 7th decile and above – increases in expenditure are largely explained by increases in average price, rather than increases in physical quantities. This is shown in Figure 7.

A similar pattern can also be seen for vehicles. The CEX asks respondents how many vehicles they own, and the price they paid for each.[9] Note that this measure is a stock, rather than a flow; we are comparing the (undepreciated) value of vehicle wealth of different income groups to the lowest income group. Still, as shown in Figure 6, although quantity is an important determinant of average expenditure for poorer households, this levels off for higher income households. Similar to small appliances, households in the 9th and 10th deciles seem to own the same number of vehicles.

Finally, for clothing purchases, the CEX asks respondents for the number of items pur-

[9] Here, I treat price as the sum of the net purchase price and any value of traded-in vehicles.

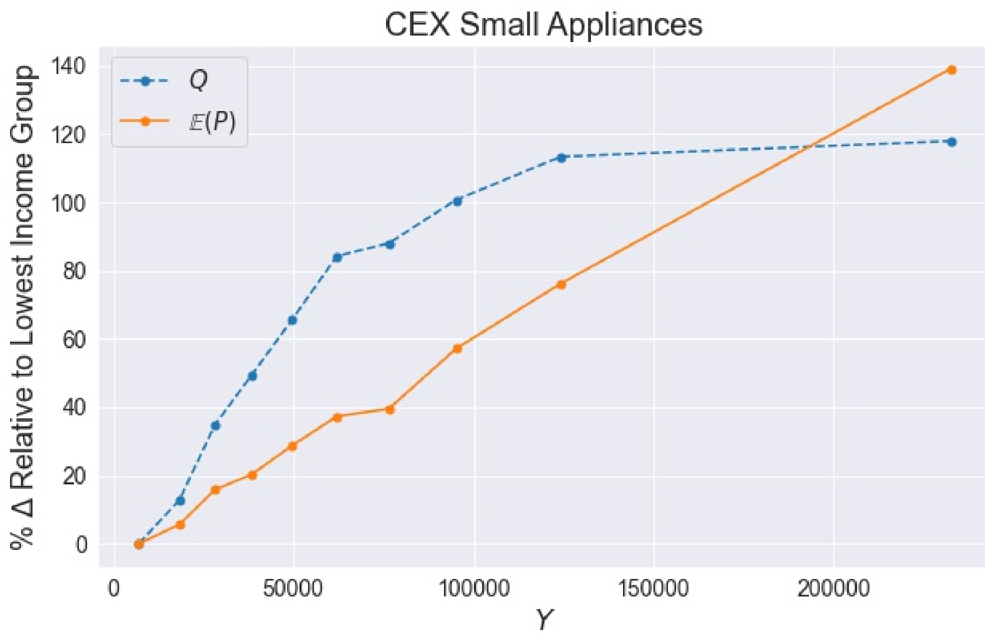


Figure 4: Decomposition of percent changes in expenditure relative to lowest income group for small appliances in the CEX

chased, as well as the price. Not all respondents provide quantities, and I drop all such observations. Items are coded by type of clothing, for example pants, suits, footwear, and skirts. Thus, I once again perform the decomposition of Equation (7) using types of clothing as categories. The results are shown in Figure 8. Clothing seems more like expenditures in Nielsen: most income groups consume the same physical quantity of clothing on average; what differs is the price paid.

3.2 Satiability as an Explanation

Taken together, the above facts suggest that past some income threshold, as incomes increase consumers don't necessarily purchase more goods, but rather purchase more expensive products. In particular, they trade up from low-price to high-price products. I suggest that both facts are well explained by consumption being satiable. By this, I mean that goods fulfil some needs, and once these needs are met, additional consumption of similar goods yields

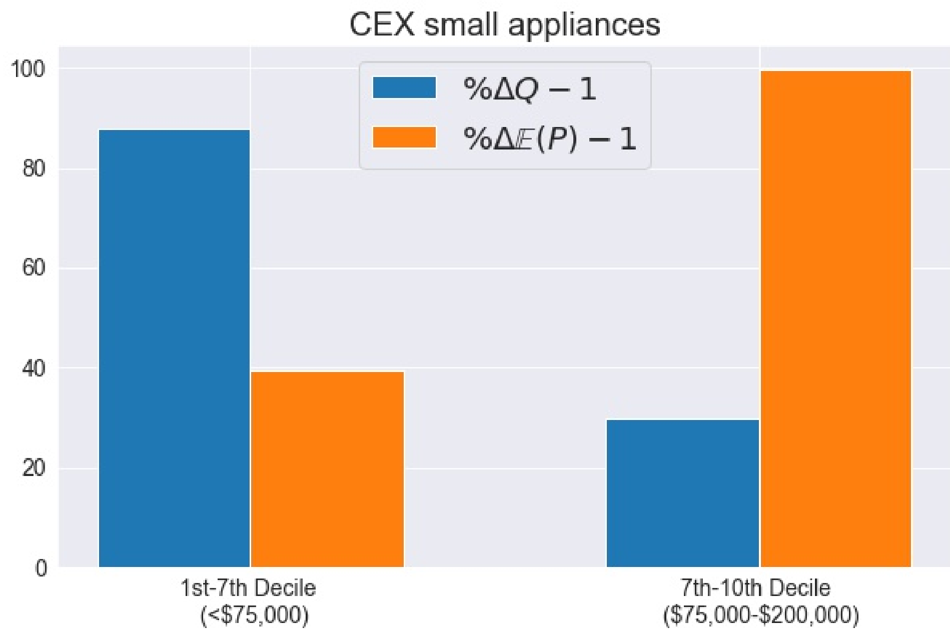


Figure 5: Decomposition of percent changes in expenditure relative to lowest income group for small appliances in the CEX

no additional utility.

Of course, the fact that physical quantities consumed are not increasing in income is well explained by satiability: consumers need only so many units of a good, say food, to fulfil their needs regardless of their income.

The presence of inferior goods as evidence for satiability is perhaps more complex. Inferior goods are difficult to generate with standard preferences. Past attempts at generating them have often relied on abandoning concavity in the utility function (c.f. Liebhafsky 1969).[10] To see the difficulty, consider a simple Cobb-Douglas utility function:

$$U(x, y) = x^{\alpha} y^{1-\alpha}$$

[10] Liebhafsky (1969) uses the utility function $U(x, y) = \alpha \ln x + \frac{y^2}{2}$. The implication is that the marginal utility of consuming good y is increasing in its consumption. It seems difficult to identify such goods. Moffatt (2002) makes the similar point that past attempts at generating Giffen goods – a family of inferior products – tend to rely on abandoning quasi-concavity. Moffatt (2002) proves that a quasi-concave utility funtion can generate Giffen behaviour, although he doesn't give an example of such a utility function.

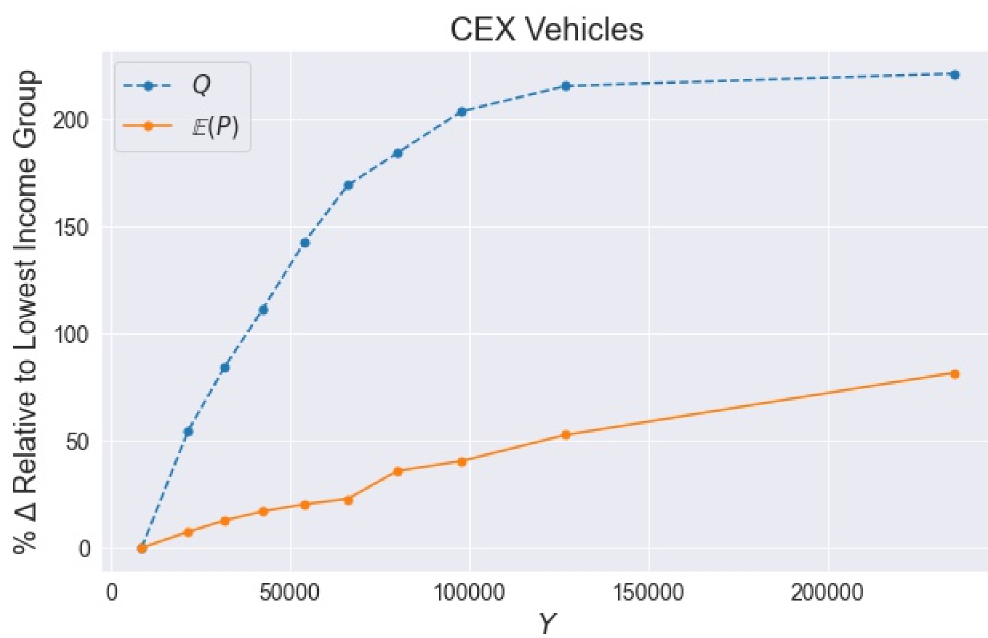


Figure 6: Decomposition of percent changes in expenditure relative to lowest income group for vehicles in the CEX

The reason this utility function cannot generate inferior goods is because of the assumptions we like to make about the derivatives of utility functions: $dU/dx > 0$, $dU^2/dx^2 < 0$ and $dU^2/dxdy \geq 0$. The last two features mean that as I consume more of good x, the relative benefit of consuming y increases, and therefore I also want to consume more y. Given that both goods yield positive utilities, as income increases I will consume more of both. As mentioned above, one solution is to do away with quasi-concavity. The result would be that at least one good becomes increasingly desirable the more I consume it. However, it's difficult to think of common examples of such goods.

Another solution might be to allow $dU^2/dxdy < 0$.[11] Note that this means that, as consumption of one good increases, the marginal utility of the other falls, leading the consumer to potentially want to switch from consuming one good to the other. Note also that $dU^2/dxdy < 0$ describes well two products which fulfil the same satiable need. Although the

[11] This is the case in the model of Onuma (2020), who generates inferior goods by assuming that consumers make both quality and quantity choices across goods. This will be similar to the model presented in Section 4.

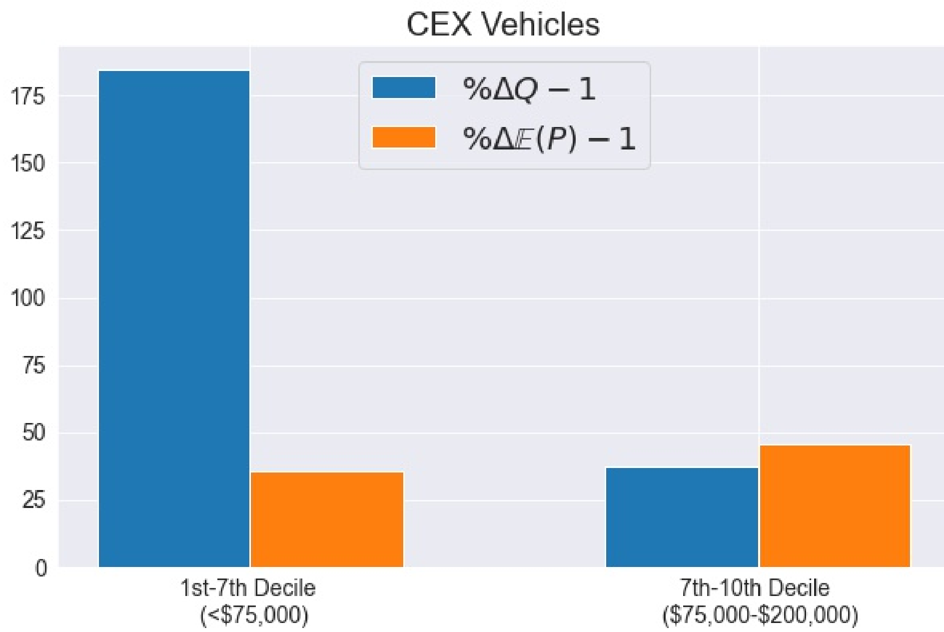


Figure 7: Decomposition of percent changes in expenditure relative to lowest income group for vehicles in the CEX

marginal utility of consuming only a hamburger is positive, it falls to 0 (or perhaps negative) if I first consume a lasagna.

4 A model of satiable preferences and inferior goods

This section develops a model of consumer preferences that are satiable and are capable of generating the consumption patterns seen in Section 3. In this section I write down a very general version of the model, although in Section 5 I simplify it for the sake of calibration.

4.1 Hierarchical Consumption

Each good, i, is part of a category, c. Categories are defined by the needs which they fulfil. For example, Arm & Hammer toothpaste might be a good in the category "oral hygiene". Because preferences are satiable, consumers can consume at most 1 unit of a good in a given

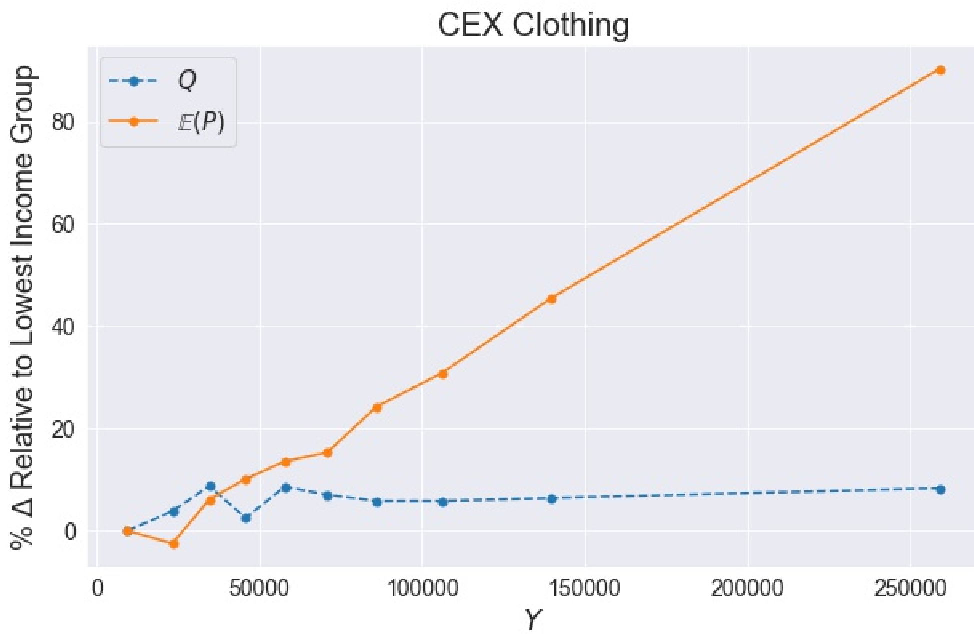


Figure 8: Decomposition of percent changes in expenditure relative to lowest income group for clothing in the CEX

category.[12] Each good is defined by a utility parameter u_{ic} and a price p_{ic}. An individual who consumes good i in category c receives the common utility component u_{ic} as well as an individual good-specific utility shock, ε_{icn}, which is i.i.d. across consumers and goods. Thus, utility for consumer n of consuming good i in category c is:

$$U_{icn} = u_{ic} + \varepsilon_{icn}$$

Consumer n, with income y_n solves the problem:

$$\max_{\{q_{icn}\}} \sum_c \sum_{i \in c} q_{icn} U_{icn}$$
$$\text{s.t.} \quad \sum_c \sum_{i \in c} p_{icn} q_{icn} \leq y_n$$

[12]Implicit in this formulation is that any amount of the good consumed above 1 unit yields no additional utility as the need has been satiated.

$$\sum_{i \in c} q_{icn} \in [0, 1] \quad \forall c$$

where the first constraint is the budget constraint, and the second constraint is the satiability constraint. For simplicity, the satiability constraint allows fractional values, i.e. consumers can consume a fraction of a given good, but not more than 1 unit.

There is no closed-form solution, however the problem may be solved by an intuitive algorithm. Consider a consumer's choice of where to spend their first dollar of income. Obviously, the choice is the good which will yield the highest utility per dollar spent, U_{icn}/p_{ic}. Call this first good i^* in category c'. Because utility is linear in the consumption of this good, the consumer will devote each additional unit of income to purchasing this good until income reaches $p_{i^*c'}$, at which point they will have consumed the maximum amount possible, i.e. 1 unit. When income exceeds this level, what will their next choice be? The consumer may consume a good in another category, or they may switch the good they are consuming in category c' by trading up to a higher-price, higher-utility product. In particular, they must now consider the additional utility per additional dollar spent from trading up, or

$$\frac{U_{ic'n} - U_{i^*c'n}}{p_{ic'n} - p_{i*c'n}}$$

Note that this value must be positive, and therefore the new good must have higher utility and higher price.[13]

Why does the consumer choose a low-utility (inferior) product initially and then switch to a higher-utility (luxury) product when income is sufficiently high? Note that the inferior product is a more *efficient* means to gain utility, i.e. it has the highest U/p ratio. Meanwhile, although the luxury product has a lower U/p ratio, it yields greater utility overall. This behaviour is the result of satiability. If preferences weren't satiable, the consumer would simply consume more of whichever good has the highest U/p ratio. However, because of satiability, after the consumer has consumed their maximum of 1 unit, the only way to increase utility is to trade up to higher-utility, higher-priced goods. Thus, a low-income

[13]Note that the consumer will never switch to a good with a lower utility and higher price; such a good is strictly worse.

consumer might find that the basic car is the most efficient way to receive utility in the transportation category. However, a high-income consumer will find that the car with heated seats and sunroof yields greater utility overall, and therefore is preferable once their basic transportation needs have already been met.[14]

Importantly, this model leads to solution which is hierarchical. By this, I mean that consumers rank their purchases from most important to least important and then allocate their limited incomes accordingly. Hierarchical consumption models are usually derived from the premise that consumers have needs which vary in importance.[15] In these models, there exists some income threshold after which a consumer will purchase a given good, after first having satisfied "higher" needs. Because of trading up, the model presented here has the added feature that there may exist an even higher income threshold past which the consumer no longer purchases this good. In other words, there may be an income threshold at which consumption of a given good is "turned on", and another higher threshold at which point is "turned off".[16]

Lastly, note that because the consumer prioritizes those purchases with the greatest ratio of additional utility per dollar spent and there is no complementarity in preferences, consumers will have a falling marginal utility of income.

Example As a brief example, consider a consumer faced with the following utilities and prices:

[14] Another way to think about this is that consumers are purchasing features which are bundled together as goods (Lancaster, 1971). Basic products, like the base model car, contain the most important features – the ability to drive between two points – while luxury products contain this feature as well as additional features – the comfort of heated seats, for example. To the extent that the primary features outweigh the secondary features in terms of utility per dollar spent, the consumer first purchases the basic model, and only at higher income levels do they purchase the luxury model.

[15] See the discussion of this type of model in the related literature section.

[16] For example, at a low income threshold a consumer may own a basic sedan, but at a higher income threshold, they will instead own a luxury car, but *not own* the basic sedan.

	Transportation			Smart Phone	
	Bus Pass	Hatchback	Lamborghini	Motorolla	iPhone
U	1	1.5	1.75	0.6	0.9
p	1	2	3	1	2

Table 3: Utilities and prices in two categories

Using the solution algorithm described above, it's evident that the consumer's first purchase will be of the bus pass, as this yields the highest U/p ratio of 1. Looking at the consumer's next consumption choice, the utility per dollar spent of trading up to the hatchback, $(1.5-1)/(2-1) = 0.5$, the Lamborghini, $(1.75-1)/(3-1) = 0.375$, or of consuming the iPhone, $(0.9/2 = 0.45)$, are strictly worse than the utility of consuming the Motorolla $0.6/1 = 0.6$. Consequently, this latter will be next in the consumer's hierarchy. We can continue in this way, which yields the following ranking of bundles:

	Bundle	**y**	**U**
1.	(∅,∅)	0	0.0
2.	(Bus, ∅)	1	1.0
3.	(Bus, Motorolla)	2	1.6
4.	(Hatchback, Motorolla)	3	2.1
5.	(Hatchback, iPhone)	4	2.4
6.	(Lamborghini, iPhone)	5	2.65

Table 4: Ranking of bundles

Note that the hierarchy allows us to draw Engel curves for individual goods. For example, at $y = 2$ the consumer purchases the bundle (Bus Pass, Motorolla). If the consumer's income is incrementally higher, however, they begin to trade up from the bus pass to the Hatchback. At $y = 3$, this process is complete. Then for income incrementally greater than $y = 4$, the consumer begins to trade up to the Lamborghini. Consequently, we can draw the resulting Engel curve for the Hatchback, shown in Figure 9.

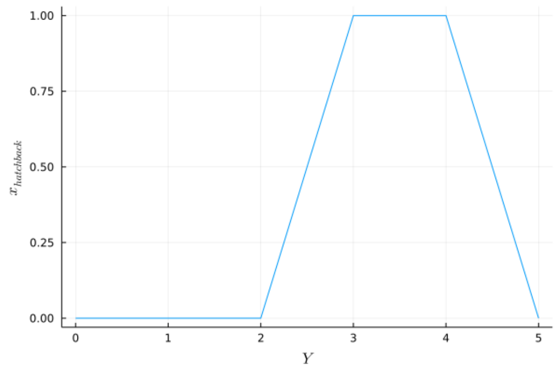


Figure 9: Individual's Engel curve for Hatchback

4.2 Effect of price changes on individual demand

Changes in price can change the location of a good in a consumer's hierarchy. Recall that the benefit of trading up from good 1 to good 2 is given by $(U_2 - U_1)/(p_2 - p_1)$. A decrease in the price of good 2 makes the benefit of trading up higher. Similarly, the benefit of trading up from good 2 to another good falls. The consequence is an expansion of the consumer's Engel curve for this good. Assuming a sufficiently large change in the price, the additional benefit increases the priority of consuming this good at lower levels of income and decreases the priority of trading up to higher utility goods at higher income levels.

Note, however, that the effect on a consumer's actual consumption choice depends on their level of income. For example, imagine that prior to a price decrease, a consumer will consume $q_A > 0$ in the income range (Y_l, Y_h) and consume $q_A = 1$ in the range (Y_l^*, Y_h^*). A price decrease makes the consumer more likely to trade up to good q_A at an earlier level of income, and to trade away from it at a higher level of income. Consequently, without loss of generality, following a price decrease, the income range over which the individual chooses $q_A > 0$ will become

$$(Y_l - \epsilon_l, Y_h + \epsilon_h) \qquad \epsilon_h, \epsilon_l \geq 0$$

Therefore, effective consumption of the good will only change if the consumer has income in the range $(Y_l - \epsilon_l, Y_l^*)$ or in the range $(Y_h^*, Y_h + \epsilon_h)$. This is illustrated in Figure 10.

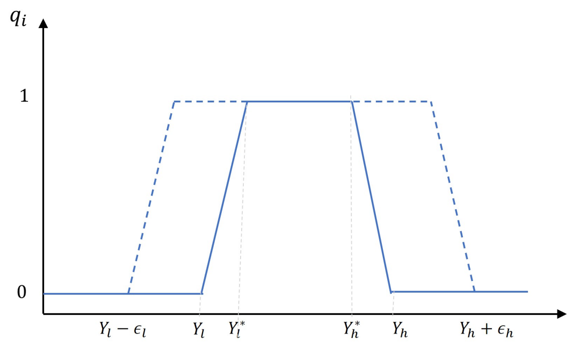


Figure 10: Effect of a price decrease

Consider the intuition for this result. There will be some luxury products which, even after a price decrease, low-income consumers will not want to purchase. For example, dropping the price of a Mercedes by $2,000 likely won't change the buying decision of many low-income households. These low-income consumers have higher consumption priorities, like purchasing basic necessities, and even at lower prices, luxuries still are not worthwhile. Similarly, there are some low-quality products which, even given a drop in price, rich consumers will not buy. Even given a low price for a bus pass, many rich consumers will still choose the comfort and convenience of driving, which yields greater utility.

To anticipate the results that follow, note that this means that the price elasticity of demand for a given product will depend on the mass of individuals within the "switching range" of income. Lowering the price of a Lamborghini will attract as many customers as there are for whom Lamborghini is nearby in their hierarchy. Thus, price elasticity will depend on the size of this mass, but not on the size of the mass of poor consumers.

4.3 The number and size of categories

To make it easier to aggregate the demands of many consumers, it is useful to first develop the idea of categories.

Categories are defined by a given need. However, the same set of goods may be available to meet many different needs. Indeed, this is obviously the case when we realize that needs are temporally specific. For example, the need for calories arises multiple times in a day, and each day of the week. Consequently, we can think of the need "calories for breakfast today", which is a distinct need from "calories for lunch tomorrow".[17] Note that although the same set of goods is available to fulfil these needs, a consumer may choose different products: pancakes for breakfast today, egg salad for lunch tomorrow, etc.

To account for this, I introduce the concept of "subcategories". Subcategories are defined by a temporally specific need – for example "breakfast today". We say that two subcategories belong to the same category if the subcategories contain the same set of goods. Therefore two subcategories, "breakfast today" and "lunch tomorrow" define two needs which are satisfied by the same sets of goods: food. As a result, we say that both of these subcategories belong to the same category: "food".

With this in mind, I assume that there exists a countably infinite number of subcategories on the interval $(0, C]$. Define subcategories within the subinterval $(C_{j-1}, C_j]$ as being part of category j. Any two subcategories within a category contain the same set of goods, with the same u and p values. For simplicity, although goods may belong to multiple subcategories (by definition), I assume that goods belong to only one category. Importantly, however, the consumer's utility shock, ε_{icn} is allowed to differ between subcategories. Thus, it is possible that a consumer will choose a different product in two subcategories of the same category – keeping with our example of food, I may prefer egg salad for lunch today, but soup for lunch tomorrow.

However, since there is a countably infinite number of subcategories on $(C_{j-1}, C_j]$, by the law of large numbers all consumers will have the same distribution of ε shocks across subcategories within a given category. Because of this, all consumers will face the same hierarchy in terms of goods – although these goods may exist in different subcategories. To give an example, consumer A's and consumer B's hierarchies will both have the consumer trade up to "eggs" at an income level of $\bar{y}$, although for consumer A this will be for breakfast today, while for consumer B it will be for breakfast on Thursday. Therefore, consumers with the same income will consume the same set of goods within a given category. Consequently,

[17] This is similar to the definition of goods given by Arrow and Debreu (1954), albeit we will assume that needs and not goods are temporally specific.

consumers with the same income will have the same demand for a given good, albeit this demand will occur in different subcategories.

4.4 Aggregate demand for a good

Define $V_n(y)$ as the maximized utility of consumer n given their income and define

$$\lambda_n(y) = dV_n/dy$$

which is the marginal utility of income. Note that, given the the hierarchical nature of consumption described in Section 4.1, $\lambda_n(Y_n)$ is simply the additional utility per dollar spent for the consumer at the current level of income in their hierarchy. Furthermore, recall that, because consumers prioritize those purchases with the greatest ratio of additional utility per dollar spent, we have that $\lambda_n'(y) < 0$.

Importantly, because of the restrictions we made on categories in Section 4.3, we have that

$$\lambda_n(y) = \lambda_m(y) = \lambda(y)$$

The countably infinite number of identical subcategories and the law of large numbers ensures that the marginal utility of money is not individually specific, but depends only on income.

We can now redefine the consumers problem within a category as:

$$\max_{i \in c}\{u_{ic} + \varepsilon_{icn} - \lambda(y_n)p_{ic}\} \tag{8}$$

The consumer chooses the good within a category which maximizes indirect utility. Note that, higher income consumers have a lower marginal utility of money, and therefore put lower weight on prices in their decision. For this reason, as incomes increase, consumers will tend to choose higher-utility, higher-price products.

Finally, assume that the ε shocks are i.i.d. with cumulative distribution function and probability distribution function G and g respectively. A consumer will purchase good i in category c if and only if

$$u_{ic} - \lambda(y_n)p_{ic} + \varepsilon_{icn} \geq u_{jc} - \lambda(y_n)p_{jc} + \varepsilon_{jcn} \qquad \forall j \in c$$

or

$$\varepsilon_{jnc} \leq u_{ic} - u_{jc} - \lambda(y_n)(p_{ic} - p_{jc}) + \varepsilon_{icn} \quad \forall j \in c$$

Then, keeping in mind that there are a countably infinite number of subcategories which include good i, demand for good i by a consumer with income y is given by:

$$q_i(y) = M_c \int \prod_{j \neq i} G\big(u_i - u_j - \lambda(y)(p_i - p_j) + \varepsilon\big) g\big(\varepsilon\big) d\varepsilon \ ; \quad i, j \in kc \tag{9}$$

where $M_k = C_c - C_{c-1}$ is the size of category k, which contains good i. Finally, aggregate demand for good i is given by:

$$Q_i = N \int q_i(y) dF(y) \tag{10}$$

where N is the number of consumers, and F is the cdf of the income distribution.

Of course (8) and (9) will be recognizable for those familar with the literature in discrete choice models (c.f. Train 2009). For example, adopting the assumption that ε takes an extreme value type I (Gumbel) distribution would change (9) into a logit demand equation of the form:

$$q_i(y) = M_c \frac{e^{u_i - \lambda(y) p_i}}{\sum_{j \in c} e^{u_j - \lambda(y) p_j}}$$

4.5 Marginal utility of money and relation to the single-category discrete choice model

Up until now we have defined $\lambda(y)$, the marginal utility of money, implicitly: it is the derivative of maximized utility with respect to income. In the language of our hierarchical model, it is the additional utility per dollar spent on the next good in the consumer's hierarchy.

Note that, $\lambda(y)$ can be backed out of (9) given the consumer's budget constraint. In particular, define total expenditure as $\chi(\lambda; u, p)$. Then, from the budget constraint we have

$$\chi = \sum_i q_i(\lambda; u, p) p_i$$

since expenditure must be equal to income,

$$y = \chi(\lambda; u, p)$$

Which we can invert to get an expression for $\lambda(y)$:

$$\lambda(y) = \chi^{-1}(y; u, p) \tag{11}$$

In other words, λ is simply the value of the marginal utility of money which equates the budget constraint.

In some sense, the model presented here is a macroeconomic extension of a discrete-choice model. It extends the reasoning from consumption in a single market to consumption of all goods, and (11) is the necessary modification for this extension. Consider how this model differs from the usual single-industry discrete choice model (e.g. Nevo 2001 or Berry et al. 1995). In the latter, λ either does not depend on y or else depends in a simple way, (e.g. price enters as $\alpha \log(y - p_i)$). Importantly, however, it does not depend, or depends in a limited way, on the u and p parameters of the modeled products.

Partly, this is due to the fact that λ represents the value of the outside option – the additional utility per dollar spent on goods *outside* of the modeled industry. Evidently, since here we are modeling all industries, the "outside good" of any one category is a good in another category which we are also choosing to model and therefore depends on the chosen u and p values.

In fact, in our model, $\lambda(y)$ depends not only on the u, p values in other categories, but also on the u and p values *within* a given category – note that (11) depends on the entire vector of u and p. The reason is that $\lambda(y)$ is a function of the consumer's hierarchy, which in turn depends on all u and p values. Imagine, for example, that the prices of all cars fall by 50%. One effect will be that cars will be given higher priority in the consumer's hierarchy – consumers will purchase cars at a lower income. However, this change in the consumer's hierarchy will also have direct effects on $\lambda(y)$. For one, consumers with lower incomes are now receiving a larger utility per dollar spent.[18] Meanwhile, any consumer already consuming a car receives a pure income effect: it now costs them less to buy the same bundle of goods, and thus for a given level of income, they are able to move further up their hierarchy to lower priority goods. Since λ declines the further a consumer moves up their hierarchy, this will tend to depress $\lambda(y)$ at higher levels of income. See A.1 and A.2 in the appendix for simple numerical examples.

Note that a similar argument can be employed for a change in the average utility of cars. Here too, the consumer's entire hierarchy is changed, and thus so too is $\lambda(y)$.

Of course, the extent to which the feedback of u and p values on $\lambda(y)$ is important depends on the size of our modeled industry (or industries) relative to consumers' total purchases. Although for a single small industry it may be valid to treat λ as exogenous, this is not the case when dealing with the macroeconomy.

In fact, this will be important in conducting an experiment in which prices are changing throughout the economy due to changes in firm markups. Forcing $\lambda(y)$ to remain unchanged may bias numerical estimates. To anticipate a little, Section 5.8 will show the size of this bias in the case of our modeled experiment.

4.6 Firms

Firms are single-good firms, although their good may be purchased in multiple subcategories. As shown in Section 2, price discrimination is not a significant factor explaining differences in average markups paid across income groups. Therefore I assume that firms cannot price discriminate and must set a single price for their product. Each firm's product has a utility

[18] This is evident from a revealed preference argument: households will only switch consumption following a price decrease if the change leads to higher utility per dollar spent.

parameter u_i and a constant cost parameter ϕ_i.

Firms choose a price to maximize their profits, subject to demand, given by (9) and (10). In other words, firm i solves:

$$\max_{p_i} Q_i(p_i - \phi_i)$$

$$\text{s.t. } Q_i = M_k \int \int \prod_{j \neq i \in k} G\big(u_i - u_j - \lambda(y)(p_i - p_j) + \varepsilon\big) g\big(\varepsilon\big) d\varepsilon \quad dF(y)$$

$$\lambda(y) = \zeta^{-1}(y; u, p)$$

The firm's choice depends explicitly on the prices of other firms in the same category. Not surprisingly, goods which fulfil the same need are in direct competition for a consumer's purchase. Thus demand for good i depends on the price of good j, where i and j are in the same category.

However, note that demand for product i also depends implicitly on the prices of goods in *different* categories through their effect on $\lambda(y)$. Thinking about the consumer's hierarchy, this is not surprising. A decrease in the price of a good in category c can lead a consumer to delay trading up to the next good in their hierarchy in category k. For example, a drop in the price of a Mercedes may increase the probability that certain consumers purchase this car, but this will mean switching consumption away from other goods – whether they are cars or not! Some consumers may choose to trade up to a Mercedes at lower levels of income, and forego trading up to a larger house, for example. In this sense, all goods are in competition one with the other; competition is not limited to goods of the same category.

Firms set prices optimally, which results in equilibrium markups given by eq. (12):

$$\mu_i = \frac{p_i}{\phi_i} = \frac{\eta_i}{\eta_i - 1} \tag{12}$$

where $\eta_i = \int \eta_i(y) \frac{q_i(y)}{Q_i} f(y) \quad dy$. I solve for the Nash Equilibrium where all firms' prices are the best response to the prices set by all other firms, including those in different categories.

5 Experiment

This section calibrates the model from Section 4 to match facts about consumption in 2006-2009, and markups in 2016. The model is calibrated using the empirical distribution of income in 2016. Then, the calibrated model is shocked by changing the distribution of income to that prevailing in 1983, keeping the median fixed. In this way, I use the model to examine the impact of a change in income inequality on the level and distribution of markups.

I abstract from changes in the median income between these two periods. To include this income growth would require a richer model by, for example, including assumptions about the source of growth. Note that growth is not simply a movement up a fixed hierarchy. Put another way, the consumption of the poor today is not simply the consumption of the rich a century ago. Rather, consumers' hierarchies are changing. This is true not simply because of decreases in costs for a fixed set of goods, but more importantly because of the introduction of new goods. Income growth does not mean that all individuals can now afford a Model T, but more importantly that the line of cars available to consumers have increased in quality.

Thus, the experiment here is to assume that the utility and cost relationships between goods of differing relative qualities are unchanged between these periods. The only exogenous change, then, is the increase in income inequality.

To measure the change in income inequality, I empirically estimate the distribution of income using the total income statistic from the 1983 and 2016 editions of the Survey of Consumer Finances.

5.1 Assumptions about Demand

First, some simplifications. Subcategories were simply a device introduced to arrive at a eq. (9). For simplicity, I drop references to subcategories in what follows. All that matters for demand is the set of goods in each category, their average utilities and prices.

In the introduction, I noted that price elasticities – and therefore markups – may vary for several reasons. The reason emphasized in this paper is that consumers with different incomes may have different price sensitivities for different products – a demand-side relation. However, clearly there are important supply-side determinants as well: the level of competition as proxied by the number of directly competing firms, as well as the ability of these firms to differentiate their products.

Part of the calibration which follows will be focused on disentangling these different sources of markup variation. Thus, we require a model which is flexible enough to have these multiple determinants of price elasticity: income-specific price sensitivites, number of competitors, and degree of similarity between competitors.

To this end, I assume that some goods within a category are more similar than others, and that this similarity depends on quality. For example, consumers may see Mercedes and Lamborghini as more substitutable than Mercedes and Toyota. To model this, I assume that within a category, goods can be classified into nests based on quality. That is, there are N_l firms classified into quality nest l. To be precise, the vector of individual-good-specific shocks within a category, ε_c, has cumulative distribution given by:

$$exp\Big\{\Big(-\sum_{l=1}^{L}(\sum_{j\in B_l} e^{-\frac{\varepsilon_j}{\theta_c\sigma_l}})^{\sigma_l}\Big)\Big\} \tag{13}$$

Those familiar with discrete choice models will recognize this distribution as giving rise to a nested logit model. Each good is classified into a nest – in our case based on quality – with utility shocks correlated within nests, but not correlated outside of nests. In other words, if Lamborghini and Mercedes are two high quality cars, they will be classified into the same nest. The result is that a consumer who has a preference for Lamborghini will likely also prefer Mercedes. To be clear, there are two reasons which might lead a consumer to purchase a high-quality, high-price car: either they have high income and therefore a low marginal utility of money, $\lambda(y)$, or else they have a preference for luxury cars.

The parameter $\sigma_l \in (0,1)$ controls the degree of correlation between shocks, with a higher value of σ_l meaning a *lower* degree of correlation. Put another way, we can think of σ_l as a measure of product differentiation. Goods within a nest are more differentiated the higher is σ_l. Finally, the parameter θ_c controls the overall variance of shocks in good category c.

Note that we might expect the variance of shocks to scale with the average utility and price in a category. In other words, we would expect larger shocks in a category like "housing", where a single unit has a high utility and price, than in a category like "chocolate bars", where each unit has a lower utility and price.

Thus, from eq. (9), demand for good i of quality nest l in category c by an individual with income y is:

$$q_{ilc}(y) = M_c \frac{e^{\frac{u_i - \lambda(y)p_i}{\theta_c \sigma_l}} \left(\sum_{j \in B_{lc}} e^{\frac{u_j - \lambda(y)p_j}{\theta_c \sigma_l}} \right)^{\sigma_l - 1}}{\sum_{k=1}^{L_c} \left(\sum_{j \in B_{kc}} e^{\frac{u_j - \lambda(y)p_j}{\theta_c \sigma_k}} \right)^{\sigma_k}} \tag{14}$$

where B_{cl} is the set of goods in nest l in good category c. For simplicity, I assume that all goods within a quality nest have the same utility and cost parameters. In other words:

$$u_i = u_j := u_l \quad \text{if } i, j \in B_{lc}$$

$$\phi_i = \phi_j := \phi_l \quad \text{if } i, j \in B_{lc}$$

Given that firms within a nest are *ex-ante* identical, they will also charge the same price in equilibrium.

$$p_i = p_j := p_l \quad \text{if } i, j \in B_{lc}$$

Thus, the equilibrium quantity of a given good in nest l is given by:

$$q_{lc}(y) = M_c \frac{N_l^{\sigma_l - 1} e^{\frac{u_l - \lambda(y)p_l}{\theta_c}}}{\sum_{k=1}^{L} N_k^{\sigma_k} e^{\frac{u_k - \lambda(y)p_k}{\theta_c}}} \tag{15}$$

and the elasticity of demand for a good in nest l is given by:

$$\eta_{lc}(y) = \frac{\lambda(y)p_l}{\theta_c} \left(\frac{N_l - 1}{N_l} \frac{1}{\sigma_l} + \frac{1}{N_l} (1 - \frac{N_l q_{lc}(y)}{M_c}) \right) \tag{16}$$

Although goods within a nest have the same u and ϕ, they are still differentiated goods in the sense that consumers may have preferences for one over the other. As mentioned above, this degree of differentiation is governed by $\sigma_l \in (0, 1)$. Note, in particular, that

$$\frac{d\eta_{lc}(y)}{d\sigma_l} < 0$$

i.e., the more differentiated the products, the lower is the price elasticity of demand. Intuitively, the less a consumer sees products as substitutes, the less changes in price will matter for their consumption decision.

Moreover, as expected we have:

$$\frac{d\eta_{lc}(y)}{dN_l} > 0$$

and

$$\frac{d\eta_{lc}(y)}{d\lambda(y)} > 0$$

In other words, the more direct competitors there are, or the more consumers are price sensitive, the higher will be a firm's elasticity.

5.1.1 Outside Goods

In each category, I assume there are N_0 outside goods with $u_0 = p_0 = 0$ and $\sigma_0 = 1$.

5.2 Estimation of $\lambda(y)$

As mentioned above, one goal of the calibration is to disentangle the multiple determinants of elasticities and markups. Where possible, I draw the relevant parameters directly from the data. Start with $\lambda(y)$. Intuitively, $\lambda(y)$ determines the degree to which different income groups care about price when making their consumption decision. Consequently, observing market shares for high and low price products across income groups will allow us to estimate $\lambda(y)$. Taking the natural log of eq. (15), we have:

$$\log(q_{lc}(y)) = \log(M_c) + \log(N_l^{\sigma_l - 1}) + \frac{u_l - \lambda(y)p_l}{\theta_c} - \log(D_c)$$

where D_c is simply the denominator of eq. (15). Subtract $\overline{\log(q_c(y)}$, the average within the category:

$$\begin{aligned} \zeta(y)_{lc} &= \log\left(q_{lc}(y)\right) - \overline{\log\left(q_c(y)\right)} \\ &= \log(N_l^{\sigma_l - 1}) - \overline{\log(N_c^{\sigma - 1})} + \frac{u_l - \bar{u_c} - \lambda(y)(p_l - \bar{p_c})}{\theta_c} \end{aligned} \tag{17}$$

where bars represent averages within the category. Finally, subtract $\zeta(y')_{lc}$:

$$\zeta(y)_{lc} - \zeta(y')_{lc} = -\frac{\lambda(y) - \lambda(y')}{\theta_c}\left(p_l - \bar{p_c}\right) \tag{18}$$

The left-hand side of eq. (18) is a double difference: the change in relative market shares across income groups. In effect, eq. (18) says that relative market shares will vary across income groups based on the change in λ, and relative prices. Intuitively, as a consumer's income increases, they tend to switch from low- to high-price products, and the rate at which they switch is governed by the rate at which λ changes.

I estimate eq. (18) using the Nielsen data from Section 3. Data in the Nielsen panel is submitted by participants, and is subject to error. Recall that I calculate prices by dividing the variable "total amount spent" by the variable "quantity purchased". To ensure homogeneity in measurement, I then divided this price by the quantity contained in one unit – for example by the ml or oz size of the product. In other words, what I am interested in is the price per ml, or price per oz. A cursory examination reveals several instances of participant error. For example, when buying a 6-pack of a product, some users recorded that they purchased a single unit (correct from our standpoint, where a unit is a UPC), while others recorded that they purchased 6 units. Note that failing to address this would result in a miscalculated price which is 6 times smaller in the latter case. To minimize measurement error, I express each price as its ratio to the mean price in its category, and then trim the top and bottom 5% of all such prices.[19]

Next, in eq. (18), I set $y' = y_{200,000}$, the incomes of those in the highest income bin. Since $\lambda(y)$ is falling in income, denote $\lambda(y_{200,000}) := \lambda_0$. Define the following variables:

$$\tilde{\lambda}(y) = \lambda(y) - \lambda_0$$

$$\tilde{p}_{lc} = p_{lc} - \bar{p}_c$$

$$\tilde{\zeta}_{lc}(y) = \zeta_{lc}(y) - \zeta_{lc}(y_{200,000})$$

Thus, eq. (18) becomes

$$\tilde{\zeta}_{lc}(y) = \frac{\tilde{\lambda}(y)}{\theta_c}\tilde{p}_{lc}$$

which is a simple linear equation in with two sets of unknown parameters: θ_c and $\tilde{\lambda}(y)$. These parameters are separately estimable given that λ_c varies across categories, but not income groups, while the reverse is true for $\tilde{\lambda}(y)$.

For a given vector of category-level variances, $\{\theta_c\}$, the OLS estimate of each $\tilde{\lambda}(y)$ is given by:

$$\hat{\lambda}(y) = \frac{\sum_c \theta_c^{-1} \sum_l \tilde{\zeta}_{lc}(y)\tilde{p}_{lc}}{\sum_c \theta_c^{-2} \sum_l \tilde{p}_{lc}^2} \tag{19}$$

While for a given vector of deviations of $\lambda(y)$ from the highest income group, $\{\tilde{\lambda}(y)\}$, the OLS estimate of a given category-level variances is given by:

$$\hat{\theta}_c^{-1} = \frac{\sum_y \tilde{\lambda}(y) \sum_l \tilde{\zeta}_{lc}(y)\tilde{p}_{lc}}{\sum_y \tilde{\lambda}(y)^2 \sum_l \tilde{p}_{lc}^2} \tag{20}$$

I simply iterate over eq. (19) and eq. (20) until convergence. Figure 11 shows the resulting estimates. As predicted by the theory, $\lambda(y)$ seems to be a decreasing function.

[19] This still allows for significant price variation, eliminating products with price to mean ratios less than 0.01 and greater than 3.25.

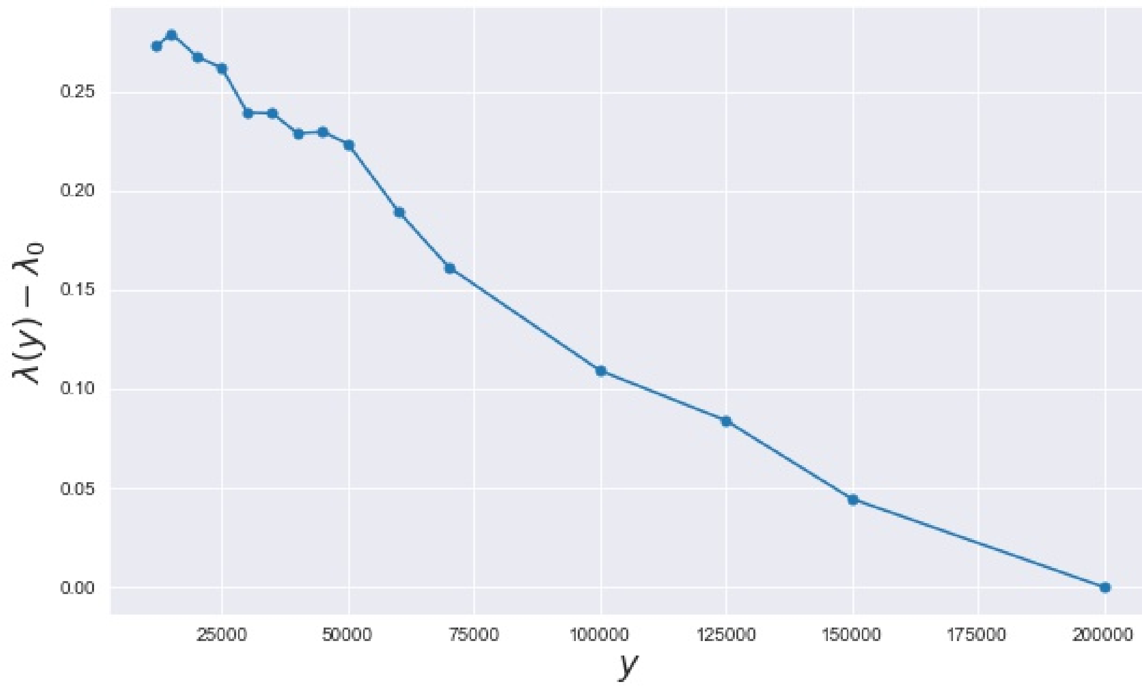


Figure 11: Estimates of the marginal utility of money relative to those making ≥$200,000

5.3 The number of competitors in each nest

Recall that nests are defined as groups of firms with identical marginal costs, average utilities, and prices in equilibrium. I opt for a fairly fine-grained definition of nests. In particular, in each category, I divide prices by the mean price, and then bin goods into bins with width 0.05. I then calculate the average number of competitors, conditional on at least one firm operating in that price bin. Figure 12 displays the result. The cheapest products within a category have the highest number of competitors, while the most expensive tend to have the lowest number of competitors. The distribution resembles an exponential distribution.

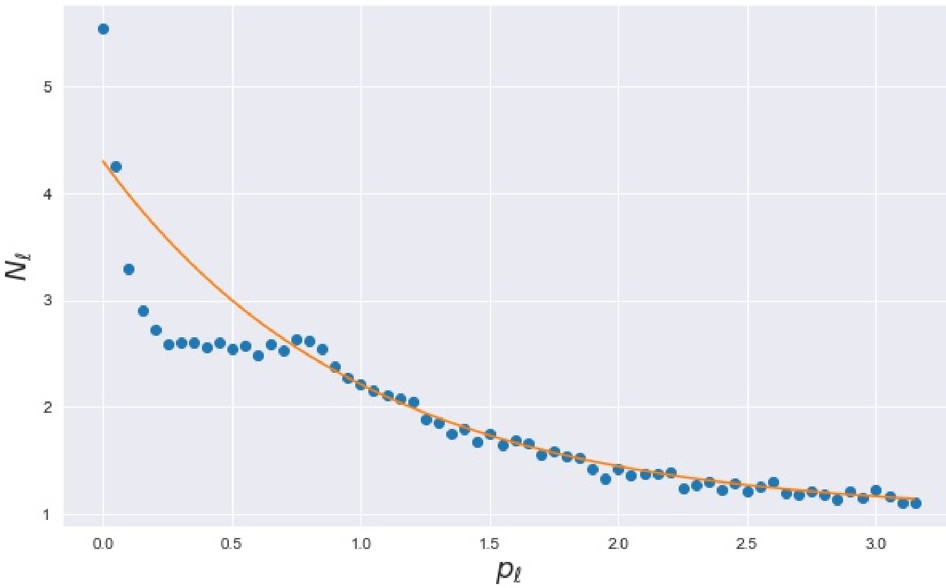


Figure 12: The average number of competitors within a nest

5.4 The relationship between u and p

I assume that there is some relationship between $u_l - \bar{u}_c$ and $p_l - \bar{p}_c$ which does not differ across categories. Therefore, for each category and each income group, we can rearrange eq. (17) to solve for $(u_l - \bar{u}_c)/\theta_c$. Taking the weighted average of each such value gives us our estimate of this value. In particular, our estimate is given by:

$$\frac{u_\ell - \bar{u_c}}{\theta_c} = \sum_i \frac{\alpha_i}{G_Y} \sum_y \left[\zeta_{i\ell c}(y) + \lambda(y) \frac{(p_{i\ell} - \bar{p}_c)}{\theta_c} - \left((\sigma_\ell - 1) n_\ell - \overline{(\sigma - 1) n_c} \right) \right] \tag{21}$$

where n is the natural log of N, G_Y is the number of income bins, and α_i is the expenditure share on good i within nest ℓ. For smoothness in the calibration, I approximate the relationship between u and p across nests using a linear spline fit to the decile averages.

Importantly, note that this estimate depends on parameters which have already been estimated, $\tilde{\lambda}, \theta_c, N_\ell$, and the unestimated parameters, σ_ℓ and λ_0.[20] I therefore leave λ_0 and σ_ℓ to be free parameters to be chosen in the calibration.

For reference, fig. 13 shows the resulting relationship between u and p for a few values of σ and λ_0.

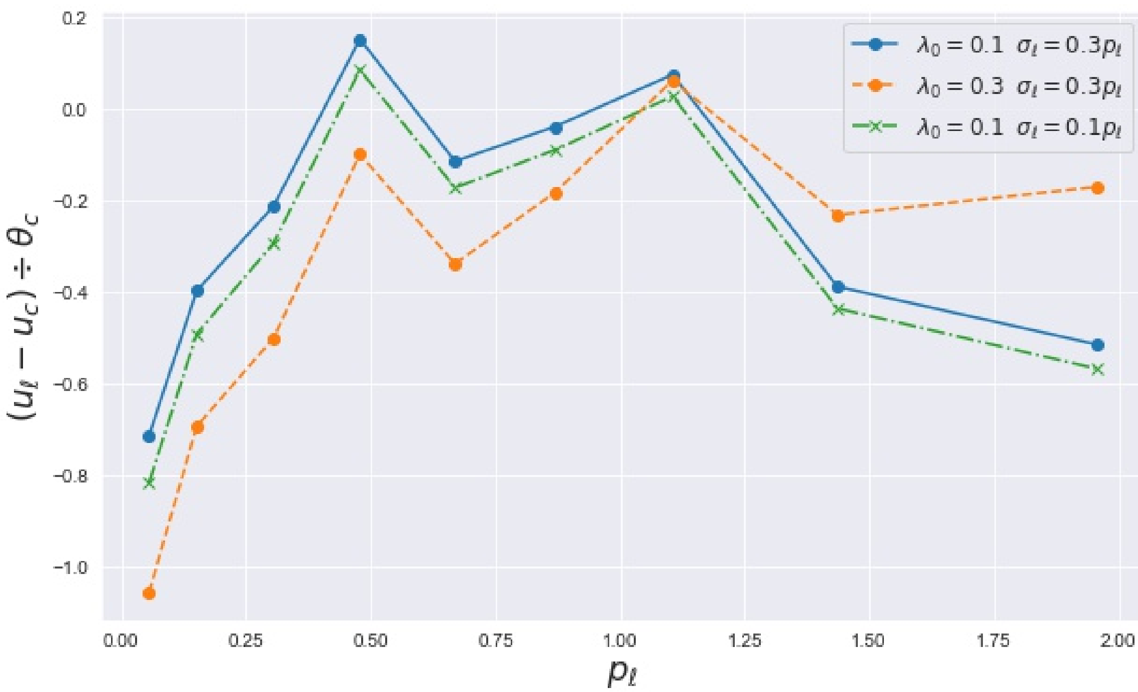


Figure 13: The relationship between u and p for some values of λ_0 and σ.

Changing λ_0 – i.e. shifting all values of $\lambda(y)$ by a constant – has the effect of making the relationship between u and p steeper. As discussed in the next section, I will model σ_l as a simple linear function across nests. Figure 13 shows that changes in the slope of this function have only a small effect of the shape of the u, p relationship, effectively shifting it up and down.

[20]Note that I could also use the empirical number of competitors within a category and nest, rather than the average across categories which was calculated in section 5.3. I opt for the latter, however, as it's possible that we do not observe all competitors in a given category in our data. Therefore, the estimates from section 5.3 may represent a better measurement of overall competition.

5.5 Remaining parameters and calibration targets

For simplicity, I assume there is only one category. Thus, the remaining parameters to be estimated and their associated calibration targets are listed in Table 5.

Target	Value	Main Parameter
$\mathbb{E}(\mu)$	1.6	λ_0
$\lambda(y)$	Figure 11	θ, M, N_0
$\frac{d \ln \mathbb{E}(\mu \vert y)}{dy}$	0.0004327	σ
p_ℓ	0.05ℓ	ϕ_ℓ

Table 5: Calibration targets and parameters to be estimated

Given that λ_0 controls the average value of $\lambda(y)$, and therefore the average price sensitivity of consumers, it has a strong effect on the average markup in the economy, $\mathbb{E}(\mu)$.

Recall that, as stated in eq. (11), $\lambda(y)$ is determined in equilibrium as the value of λ which equates a consumer's budget constraint. Recalling that we have simplified to consider only one representative category, we rewrite the budget constraint:

$$y = M \sum_{l} N_\ell q_\ell(\lambda; u, p, \theta, N_0) p_\ell \tag{22}$$

Thus, the value of $\lambda(y)$ will depend on u and p, both of which are externally calibrated, as well as M, θ and N_0, the last of which is the number of "outside goods", with $u_0 = p_0 = 0$. Figure 14 shows the effects of these variables on $\lambda(y)$ for a very simple simulation.[21]

To understand the effects these variables have, it can be useful to think of fig. 14 as showing expenditure (y) a a function of λ – we've simply switched the axes. It is more intuitive to think of how the changes in parameters affect expenditure for a given λ. For example, increasing M has the effect of rotating $\lambda(y)$ out since $y = M \sum_\ell q_\ell p_\ell$ and therefore the increase in expenditure is proportional to expenditure.

Increasing N_0 has the effect of decreasing $\lambda(y)$ most for lower income groups. This is because, the larger are the number of outside good, the more likely consumers are to consume

[21] The simulation uses $u = c = \{1, 2, 3\}, \mu = N = \sigma = \{1, 1, 1\}$

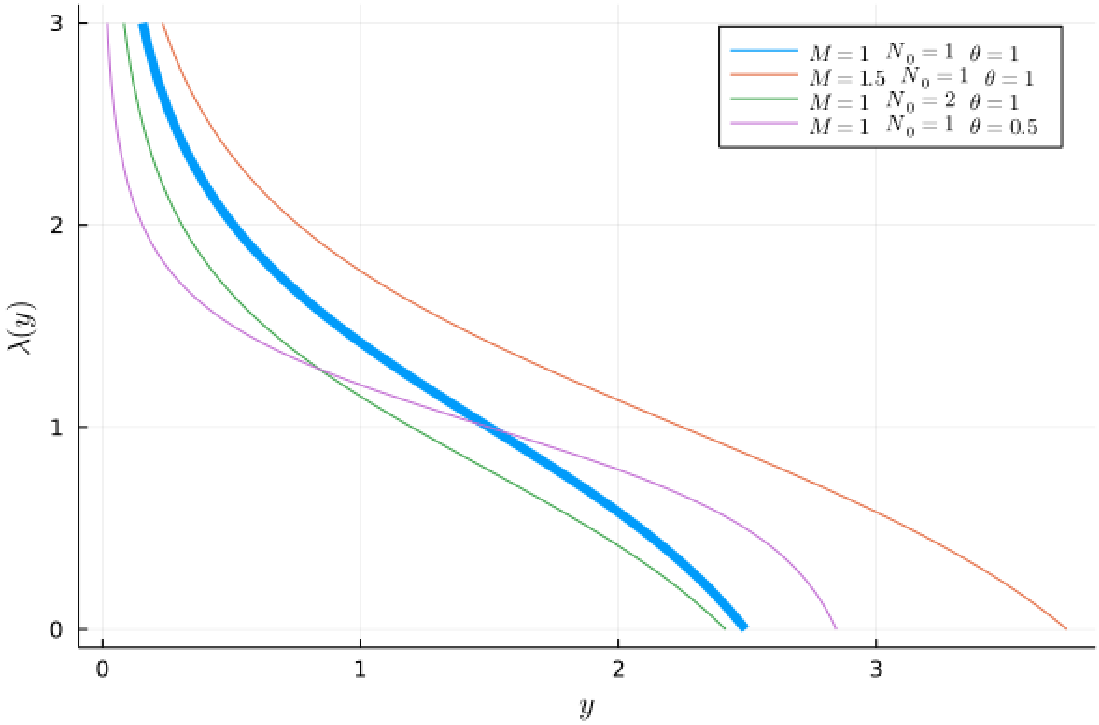


Figure 14: Effects of M, N_0, and θ on $\lambda(y)$

them, and therefore spend $p = 0$. These goods are closest substitutes for other low price goods, which tend to be consumed by low-income consumers. Therefore, the effects are largest at the bottom of the income distribution.

Finally, decreasing θ decreases the variance of ϵ. The effect is that consumers increase the homogeneity of goods they purchase – more than before, low-income consumers purchase low-price goods and high-income consumers purchase high-price goods. This increases expenditures of high-income consumers and decreases expenditures for low-income consumers. The result is that $\lambda(y)$ tends to flatten out.

I also target the semi-elasticity of $\mathbb{E}(\mu|y)$ with respect to y, as estimated and shown in Figure 1. I express y in thousands. This semi-elasticity is 0.0004327 – in other words, a \$1,000 increase in income tends to increase a consumer's average markup paid by .043 percent.

To meet this target, I allow σ_ℓ to vary linearly with the price of a product nest. In particular, I assume:

$$\sigma_\ell = \sigma p_\ell \tag{23}$$

Recall that a higher value of σ_ℓ means that goods are more differentiated, and therefore will have lower price elasticities and higher markups in equilibrium. Thus, the higher is σ, the greater will be the relative markups of the highest price products, and the higher will the slope of $\mathbb{E}(\mu|y)$.

One bit of caution is necessary however. Values of σ_ℓ must lie between 0 and 1 to ensure that preferences are consistent with utility maximization (McFadden 1979, Daly and Zachary 1978). Thus, we put restrictions on σ such that

$$\sigma \in \left[0, \frac{1}{\max\{p_\ell\}}\right]$$

Finally, the marginal costs ϕ_ℓ are chosen such that equilibrium prices are evenly dispersed, with a maximum price of 3.25.

5.6 Calibration results

Table 6 shows the parameter estimates resulting from the calibration, while Table 7 shows the resulting values of $\mathbb{E}(\mu)$ and $d\ln\mathbb{E}(\mu|y)/dy$. Figure 15 shows the fit of $\lambda(y)$ relative to the data.

	Calibration value
λ_0	0.099986
N_0	358.77
M	2402.14
σ	0.299762
θ	0.127436

Table 6: Parameter estimates

Figure 16 shows that, as is the case empirically, in the calibrated model richer consumers

	Target	Model Outcome
$\mathbb{E}(\mu)$	1.6	1.5872
$\frac{d \ln \mathbb{E}(\mu \vert y)}{dy}$	0.0004327	0.0004254

Table 7: Results of calibration

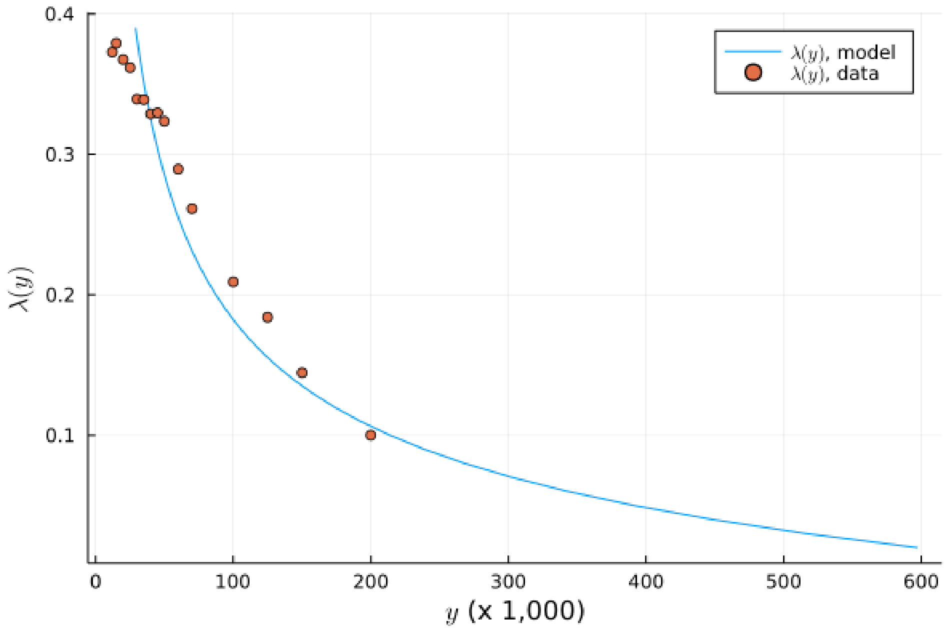


Figure 15: Model fit of $\lambda(y)$

pay higher markups on average than do poor consumers. The reason that richer consumers pay higher markups is that they tend to buy more expensive products, and these firms charge higher markups. Figure 17 shows the relationship between firms' costs and their markups.

Recall that in the model, a firm's markup may be large for any of three reasons: it faces few direct competitors (a low N_ℓ), its direct competitors sell goods which are very differentiated (a high σ_ℓ), or its customers tend to have low price sensitivity (a low $\mathbb{E}\big(\lambda(y)\big)$). In fact, starting from eq. (16), and noting that products tend to have fairly low market shares (i.e. $1 - q/M \approx 0$), we can rewrite the equation for price elasticities as:

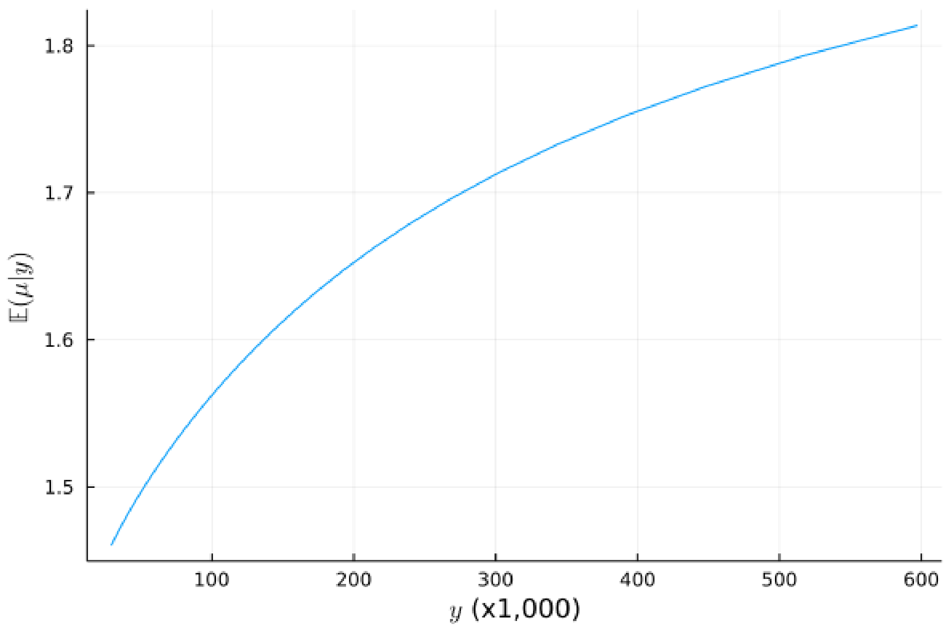


Figure 16: Average markups paid as a function of income in the calibrated model

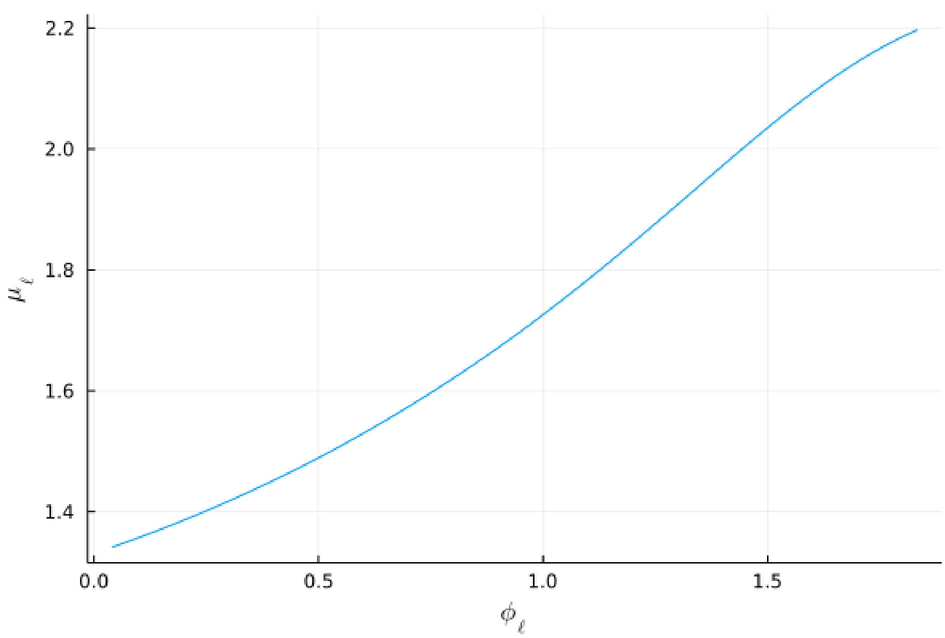


Figure 17: The relationship between firm costs and markups

$$\eta_\ell \approx \frac{p_\ell}{\theta} \underbrace{\left[\frac{N_\ell - 1}{N_\ell}\frac{1}{\sigma_\ell} + \frac{1}{N_\ell}\right]}_{\text{Competition}} \underbrace{\left[\sum_y \omega_\ell(y)\lambda(y)\right]}_{\text{Price-Sensitivty}} \tag{24}$$

where

$$\omega_\ell = \frac{q_\ell(y)f(y)}{\sum_y q_\ell(y)f(y)}$$

$f(y)$ is the mass of consumers in income group y, and thus $\omega_\ell(y)$ is the quantity weight of income group y in a firm in nest ℓ's sales.

Therefore, the price elasticity of a firm in nest ℓ is the product of three terms: its price; the level of competition, which combines the number of direct competitors and how similar their products are; and how price sensitive are its consumers.

Taking logs of eq. (24), we can decompose the changes in elasticity across firms as:

$$\ln \eta_\ell = \ln p_\ell + \ln \text{Competition}_\ell + \ln \text{Price-Sensitivity}_\ell \tag{25}$$

Figure 18 shows each element of eq. (25) relative to that of the lowest cost firm. Most of decline in elasticities between the lowest and highest cost firm is due to changes in competition. However, the competition effect dominates only for low cost firms. To demonstrate, Figure 19 shows the same decomposition only for high cost firms. For these high cost firms, differences in price sensitivity across their customer bases are the most important factor in explaining declining elasticities and higher markups.

5.7 Results of Experiment

Given the calibrated model, I ask how the distribution of markups would change if the dispersion of income around the median changed to that prevailing in 1983. Figure 20 shows the distribution of income in 2016, and the median-adjusted distribution of income in 1983. Both distributions are smoothed empirical distributions of total income derived from the Survey of Consumer Finances.

First, note that the distribution ends at \$600,000. This is the result of our estimated

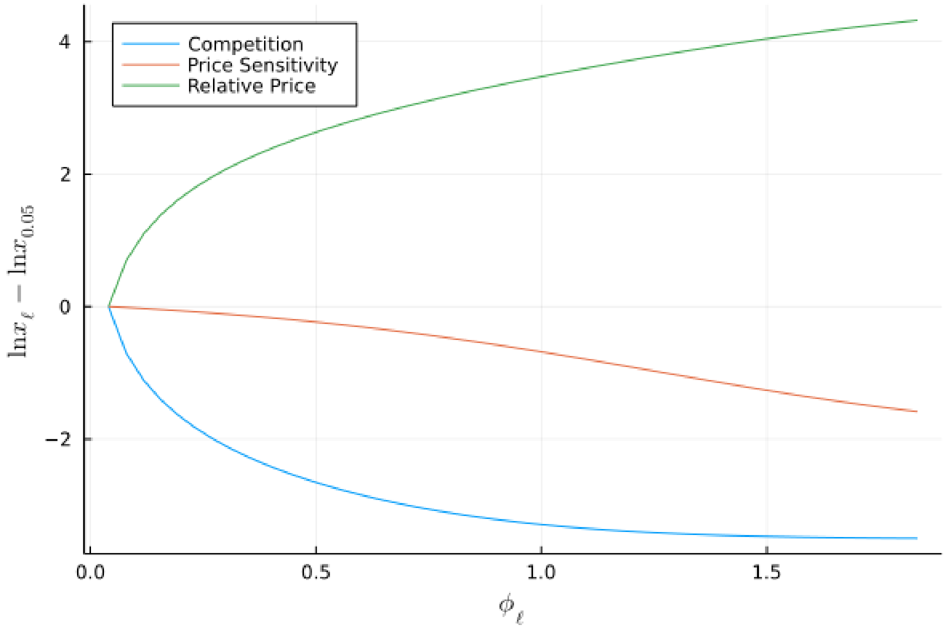


Figure 18: Decomposition of elasticity relative to the lowest-cost firm

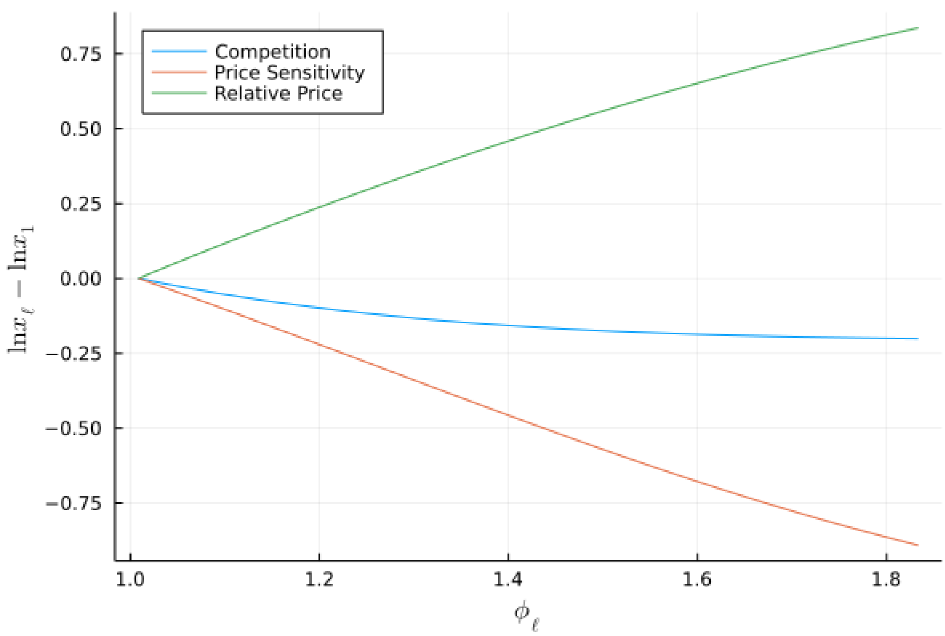


Figure 19: Decomposition of relative elasticity for high cost firms

$\lambda(y)$ being equal to 0 at this level of income.[22] Since $\lambda(y)$ cannot become negative, I assume that all households above this threshold have the same near-zero value of λ. Since households' aggregate consumption behaviour differs only because of $\lambda(y)$, this means that the consumption of all households above this threshold is identical. Thus, for the sake of the experiment, we may treat them as one income group with mass given by $1 - F(600)$.[23]

Second, note that the change in the distribution of income between 1983 and 2016 is well-described by the hollowing-out metaphor. In 2016, there is a greater mass of households with incomes in the bottom and the top of the distribution, but a smaller mass in the middle.

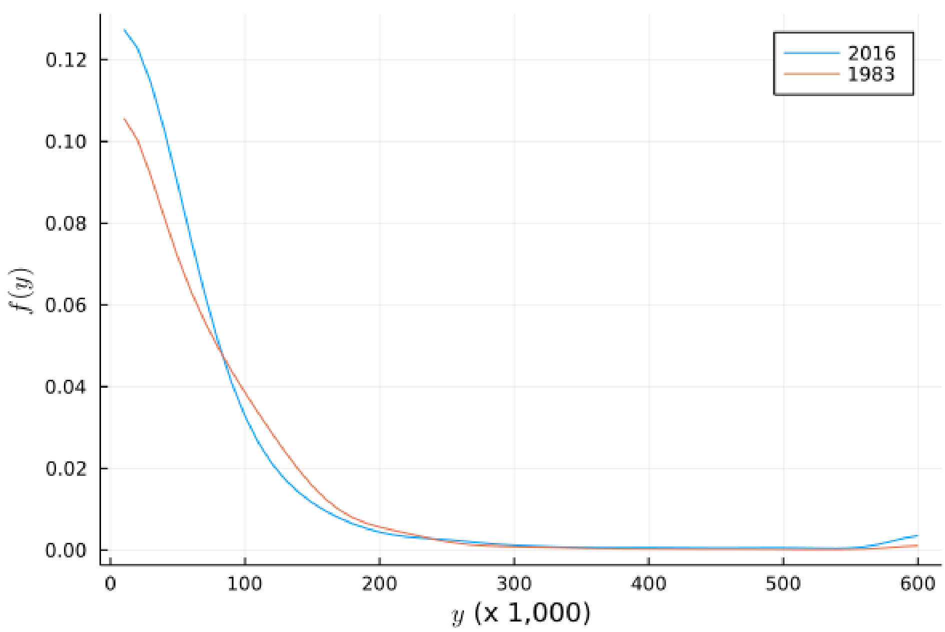


Figure 20: The change in income distribution around the median between 1983 and 2016

Table 8 shows the results of the experiment on the distribution of markups. Two things are clear: first, the average markup has decreased and second, this is accompanied by a fall in the elasticity of average markup paid with respect to income. In particular, the average markup given the 1983 distribution of income is 1.50 compared to the calibrated 2016 markup of 1.59. According to De Loecker et al. (2021), the average sales-weighted markup in 1983

[22]In fact, for the sake of calibration I keep the minimum value of $\lambda(y)$ to be slightly above 0 to avoid infinite price elasticities.

[23]We can assume that the excess of income over expenditure is used to purchase some financial assets.

	Model 2016	Model 1983
$\mathbb{E}(\mu)$	1.5872	1.5027
$\frac{d \ln \mathbb{E}(\mu\|y)}{dy}$	0.0005254	0.0001843

Table 8: Results of experiment

was approximately 1.25. Thus, the model is able to explain approximately 25% of the overall change.

Equally importantly is the means by which this fall in the average markup is generated. De Loecker et al. (2021) show that the change in markups over this period is mainly due to changes in markups at the top of the distribution: between the 1980s and present, the markups of high-markup firms expanded while those around the median stayed relatively the same.

Figure 21 shows how markups change for firms with different costs. In 1983, the markups charged by the high-cost, high-markup firms decline substantially Meanwhile, firms charging markups close to the average see little change. Note also that the changes among low-markup firms in Figure 21 also mirror the changes in the markup distribution found by De Loecker et al. (2021); over this time period the distribution of markups flattens out: there are a greater number of firms with very high markups, while the distribution around the median is relatively unchanged.

What accounts for the differential changes in markups across the markup distribution? Firms react differently to a change in the distribution of income depending on who their likely customers are. When income inequality increases, there is an increasing mass of poor consumers and an increasing mass of rich consumers. The former has the effect of increasing the incentive for firms to lower their price to attract this large mass of poor consumers. Conversely, the latter has the effect of increasing the number of low price sensitivity consumers, leading firms to want to increase markups. Which of these forces wins out depends on a firm's customers base. Luxury firms tend to care less about poor consumers, who are unlikely to buy their products even at reduced prices. Meanwhile, as we will see, basic firms tend to have similar amounts of rich and poor customers, and therefore will change their

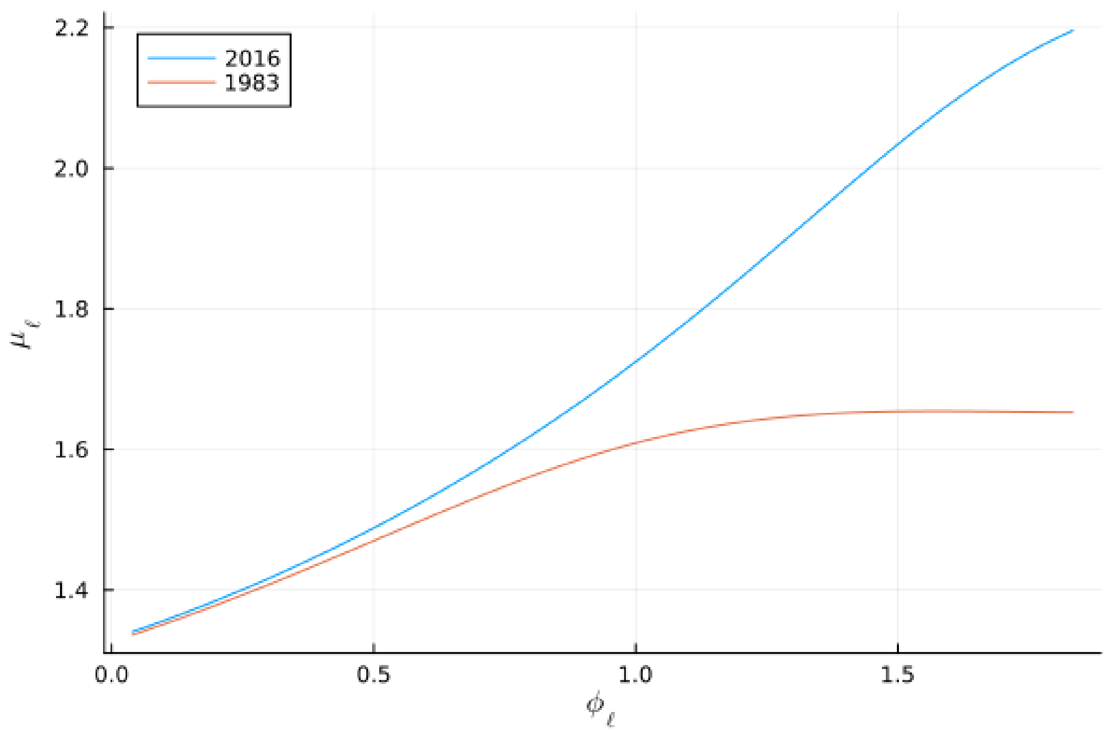


Figure 21: The change in markups across firms

markup very little.

To illustrate, recall that the first-order effect of a change in the income distribution on a firm's price elasticity is:

$$d\eta_i = \sum_y (\eta_i(y) - \eta_i) \frac{q_i(y)}{Q_i}\, df(y) \tag{26}$$

where

$$Q_i = \sum_y q_i(y) f(y)$$

Thus, increasing the mass of consumers in income group y effects the elasticity of firm i to the extent that consumers with income y have price elasticities which differ from the average, and to the extent that these consumers purchase a relatively large share of the output of firm i.

Consider then two firms from the calibrated model: one firm with relatively low cost, low markup, and a high fraction of consumers from the low-end of the income distribution, and the other with opposite characteristics. Call the first firm bas, for “basic”, and the second firm lux, for “luxury”. Figure 22 shows the Engel curves for each of these products. The basic firm’s product tends to appeal most to consumers near the middle of the income distribution, but less to those at the two tails. Meanwhile, the luxury firm’s product appeals most to high-income consumers.

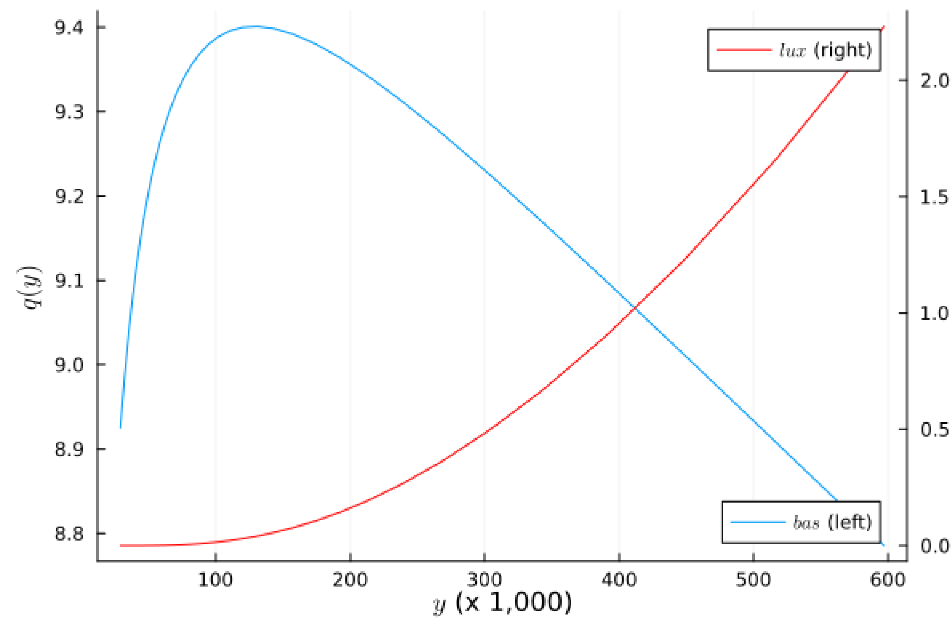


Figure 22: Engel curves from a luxury and a basic product in the experiment

For both firms, the price elasticity of their customers declines with income. Figure 23 shows the elasticity for each income group relative to the firm’s overall elasticity. Although both curves slope downwards, the curves cross zero at different points. Because the luxury firm’s customer base is largely high income consumers, its overall elasticity resembles the elasticity of its rich customers. Conversely, for the basic firm, its price elasticity more resembles the elasticity of its low-income customers.

Start with the luxury firm. The change in the distribution of income adds mass at the bottom where consumers have a relatively greater price elasticity. However, these consumers are unlikely to purchase any of the luxury product, as evidenced by the low value of q_{lux}

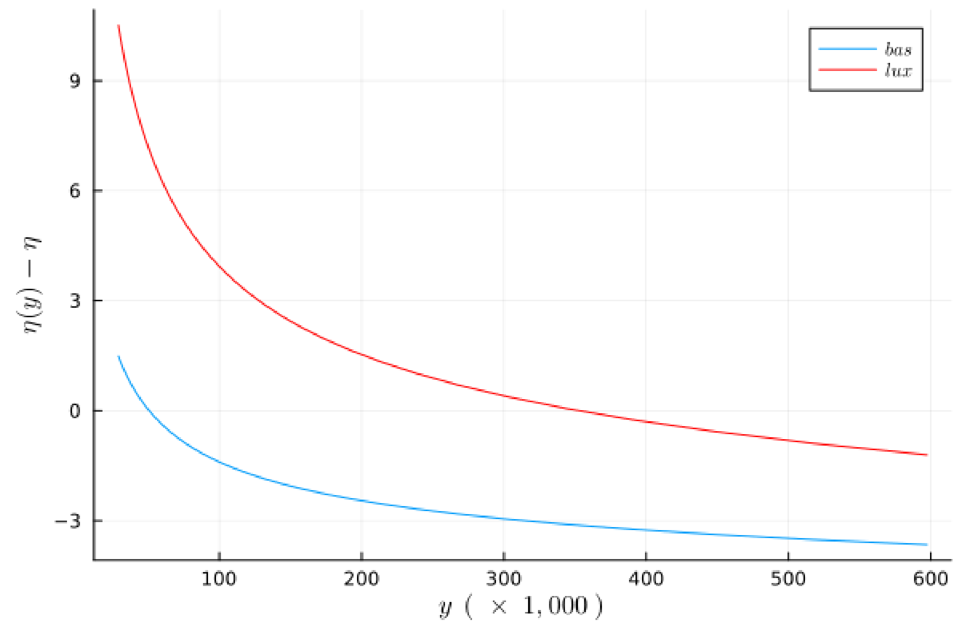


Figure 23: Relative elasticities for a luxury and a basic product in the experiment

for these groups. Thus, this change has little effect on the price decision of the luxury firm. However, there is also a declining mass of consumers around the middle – consumers who have a relatively high price elasticity – and an increasing mass of consumers at the top – consumers who have a relatively low price elasticity. The overall effect is that the price elasticity of the luxury firm falls, and it increases its markup.

The case of the basic firm is a little bit less clear given its hump-shaped Engel curve. The change in the distribution of income increases the mass of consumers at the bottom and the top, both of which are equally likely to purchase goods from the basic firm. Moreover, the low-income consumers have relatively high elasticities, and the high-income consumers have relatively low elasticities. Thus, it is not surprising that the overall effect on the basic firm's price elasticity is small. In the experiment, we find that it is small but positive.

5.8 The effect of an endogenous $\lambda(y)$

Section 4 stressed that an important difference between the model presented here and the traditional discrete choice model is that I allow $\lambda(y)$ to be endogenous. In the model presented here, $\lambda(y)$ captures the effects of changes in p and u in other categories. Consequently, when markups and prices have changed at an economy-wide level it may be an important channel to consider.

Thus, this section examines the effects of an endogenous $\lambda(y)$ in the above experiment. In particular, it asks: how different are the results if we force $\lambda(y)$ to maintain its calibrated values for 2016?

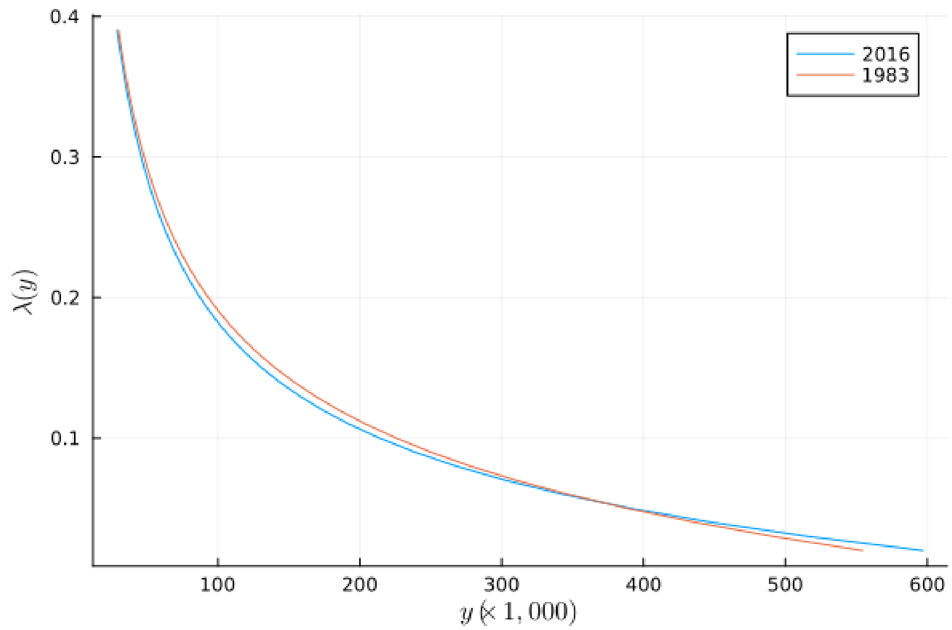


Figure 24: The endogenous change in $\lambda(y)$ between 1983 and 2016

Figure 24 shows the endogenous change in $\lambda(y)$ generated by the experiment. Overall, the changes are small. However, we can see that, moving from 2016 to 1983, there is an increase in $\lambda(y)$ for low income levels, but a decrease for high income levels. Recall that the graph $\lambda(y)$ is simply the graph of expenditure as a function of λ with its axes flipped. Thus, what Figure 24 says is that for high levels of λ, expenditures are higher in 1983, while for low levels of λ, expenditures are lower. Define $s_i(y) = q_i(y)/M$, the market share of good i among consumers of income y. Then consider the first-order change in expenditures with respect to changes in prices.

$$\begin{aligned} dy(\lambda) &= \sum_i \Big(q_i(\lambda) + p_i \frac{dq_i(\lambda)}{dp_i}\Big) dp_i \\ &= M\Bigg[\underbrace{\sum_i s_i(\lambda) dp_i}_{\text{Market Share}} - \underbrace{\lambda(y) \sum_i p_i s_i(\lambda)\Big(1 - s_i(\lambda)\Big) dp_i}_{\text{Price Sensitivity}}\Bigg] \end{aligned} \tag{27}$$

Changes in expenditure are the result of two effects. The first effect, denoted the "market share" effect above, says that consumers whose consumption basket is heavily weighted towards goods whose prices change the most will see the largest change in their expenditure. The "price sensitivity" effect on the other hand takes into account the equilibrium changes in quantities given changes in relative prices.

Consider the increase in prices between 1983 and 2016. In our case the prices of all goods increase, however, the increase in prices is highest for those goods most purchased by high-income consumers. Thus, the market share effect is stronger for the rich than for the poor, leading to generally higher levels of expenditure for a given λ. The price sensitivity effect goes in the opposite direction: because low-income consumers are are very price sensitive – i.e. have a high λ – they will adjust their consumption basket more than the rich. In particular, low-income consumers will see a larger shift of their consumption basket towards those goods whose price has increased relatively little, which are the lowest price goods. Thus, for low-income consumers, the price-sensitivity effect dominates and they see a decrease in λ, while for very high-income consumers, the market share effect dominates and they see an increase in λ.

Now, consider then the counterfactual in which we solve for the new equilibrium with the 1983 distribution of income, but $\lambda(y)$ is forced to remain at its 2016 values. One can consider the counterfactual as a partial equilibrium, intermediate step. Figure 25 shows the

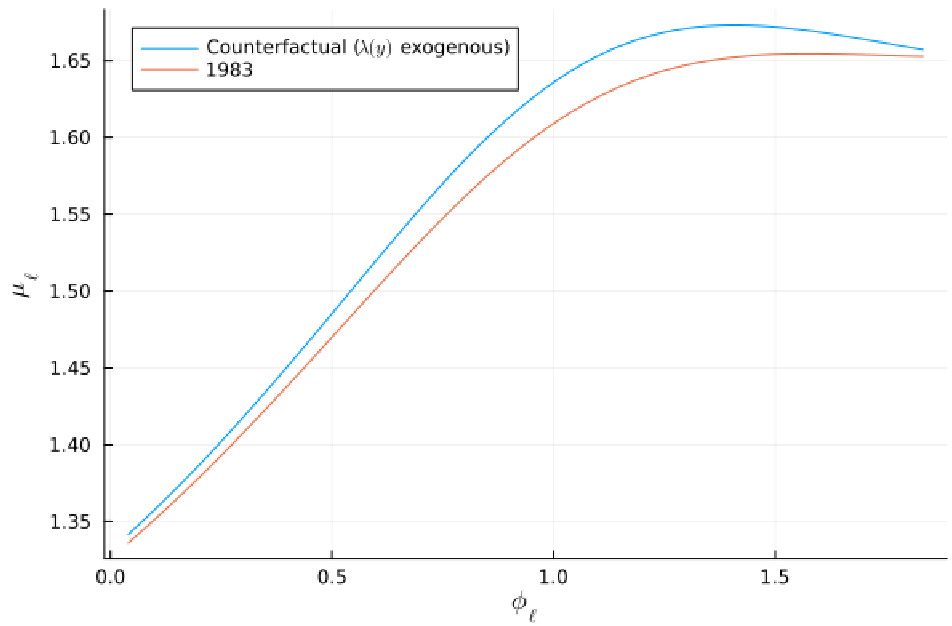


Figure 25: The relationship between markups and marginal cost if $\lambda(y)$ is exogenous

counterfactual values of μ. If $\lambda(y)$ is forced to remain at its 2016 values, all firms charge higher markups than they do in the unconstrained equilibrium, with the absolute difference in markups following a hump shape.

The reason that all firms have a higher markup in the counterfatual is that the majority of consumers are concentrated in the lower part of the income distribution. When $\lambda(y)$ is allowed to be endogenous, these consumers see an increase in their value of $\lambda(y)$ when we move from the 2016 to the 1983 distribution of income; this tends to push up elasticities, and decrease markups. Even though high-cost firms have a larger share of high-income consumers – some of whom have a fall in their $\lambda(y)$ – low-income consumers still make up a significant enough fraction of the customer base that the endogenous change in $\lambda(y)$ increases the aggregate elasticity.

If we kept $\lambda(y)$ fixed at it's value for 2016, the predicted sales-weighted aggregate markup for 1983 would be 1.5187 in the counterfactual equilibrium. This compares to 1.5027 for the full equilibrium in which $\lambda(y)$ changes endogenously. In other words, the change in $\lambda(y)$ explains about 20% of the change in the average markup.

6 Welfare Analysis

What is the effect of the change in markups on welfare, and how does this effect depend on income? There is a relatively simple expression for a consumer's total utility:

$$V(y) = M\theta\Big(\gamma + \ln A\Big) + \lambda(y)y \tag{28}$$

where $V(y)$ is the maximized utility of a consumer with income y, γ is the Euler-Mascheroni constant and

$$A = \sum_{\ell} N_\ell^{\sigma_\ell} e^{\frac{u_\ell - \lambda(y)p_\ell}{\theta}} \tag{29}$$

Proof. The utility a consumer gets across all subcategories for a given good is given by:

$$\begin{aligned} V_i(y) &= \int_{-\infty}^{\infty} (u_i + \varepsilon_i) F_i\Big(\frac{u_i - u_1 - \lambda(y)(p_i - p_1) + \varepsilon_i}{\theta}, ..., \frac{u_i - u_w - \lambda(y)(p_i - p_w) + \varepsilon_i}{\theta}\Big) d\varepsilon_i \\ &= s_{i,\ell} u_i + \int_{-\infty}^{\infty} \varepsilon_i F_i\Big(\frac{u_i - u_1 - \lambda(y)(p_i - p_1) + \varepsilon_i}{\theta}, ..., \frac{u_i - u_w - \lambda(y)(p_i - p_w) + \varepsilon_i}{\theta}\Big) d\varepsilon_i \end{aligned}$$

Where F is the cumulative density of the vector of utility shocks, ε. The second line follows from the fact that $\int F_i(...)d\varepsilon_i$ is the equation for the market share of good i. Given that these shocks are nested extreme value, and that in equilibrium we have that $u_i = u_j = u_\ell$ and $p_i = p_j = p_\ell$ for all $i, j \in \ell$:

$$\begin{aligned} V_i(y) &= s_{i,\ell} u_\ell + \int_{-\infty}^{\infty} \frac{\varepsilon_i}{\theta} N_\ell^{\sigma_\ell - 1} e^{\frac{-\varepsilon_i}{\theta}} \quad \exp\Big\{ - \sum_k N_k^{\sigma_k} e^{-\frac{u_\ell - u_k - \lambda(y)(p_\ell - p_k) + \varepsilon_i}{\theta}} \Big\} d\varepsilon_i \\ &= s_{i,\ell} u_\ell + \int_{-\infty}^{\infty} \frac{\varepsilon_i}{\theta} N_\ell^{\sigma_\ell - 1} e^{\frac{-\varepsilon_i}{\theta}} \quad \exp\Big\{ - ABe^{\frac{-\varepsilon_i}{\theta}} \Big\} d\varepsilon_i \end{aligned}$$

where $B = e^{-(u_\ell - \lambda(y)p_\ell)/\theta}$. Using the change of variables $z = ABe^{\frac{-\varepsilon_i}{\theta}}$

$$
\begin{aligned}
V_i(y) &= s_{i,\ell}u_\ell - \theta\frac{N_\ell^{\sigma_\ell-1}}{AB}\left(\int_0^\infty (\ln z - \ln(AB))e^{-z}dz\right)\\
&= s_{i,\ell}u_\ell - \theta\frac{N_\ell^{\sigma_\ell-1}}{AB}\left(\int_0^\infty \ln z e^{-z}dz - \ln(AB)\int_0^\infty e^{-z}dz\right)\\
&= s_{i,\ell}u_\ell + \theta\frac{N_\ell^{\sigma_\ell-1}}{AB}\left(\gamma + \ln(AB)\right)
\end{aligned}
$$

Note that $s_{i,\ell} = N_\ell^{\sigma_\ell-1}/AB$. Therefore

$$
\begin{aligned}
V_i(y) &= s_{i,\ell}(u_\ell + \theta\gamma + \theta\ln(A) - u_\ell + \lambda(y)p_\ell)\\
&= s_{i,\ell}(\theta\gamma + \theta\ln(A) + \lambda(y)p_\ell)
\end{aligned}
$$

Finally, since $V(y) = M\sum_i V_i(y)$, $\sum_i s_i = 1$ and $\sum_i p_i s_i = y/M$, the result follows. □

There are two things that are noteworthy about Equation (28). First, note that the definition of $\lambda(y)$ follows from the equation:

$$
\begin{aligned}
\frac{dV(y)}{dy} &= M\theta\frac{d\ln A}{d\lambda}\lambda'(y) + \lambda'(y)y + \lambda(y)\\
&= -\lambda'(y)M\theta\sum_\ell \frac{N_\ell^{\sigma_\ell}e^{\frac{u_\ell-\lambda(y)p_\ell}{\theta}}}{A}\frac{p_\ell}{\theta} + \lambda'(y)y + \lambda(y)\\
&= -\lambda'(y)M\sum_\ell s_\ell p_\ell + \lambda'(y)y + \lambda(y)\\
&= -\lambda'(y)y + \lambda'(y)y + \lambda(y)\\
&= \lambda(y)
\end{aligned}
$$

Second is the similarity with the equation for expected utility in the case of the G.E.V. family of distributions derived by McFadden (1978). The difference arises from the fact that McFadden (1978) derives expected *indirect* utility, rather than total utility. Not surprisingly then, Equation (28) has an additional term to add back in $\lambda(y)y$, which is subtracted from indirect utility.

Thus, we can easily plot Equation (28) for 1983 and 2016, as shown in Figure 26. Moving from 1983 to 2016, utility decreases for all individuals, but decreases the most for those at the top of the income distribution.

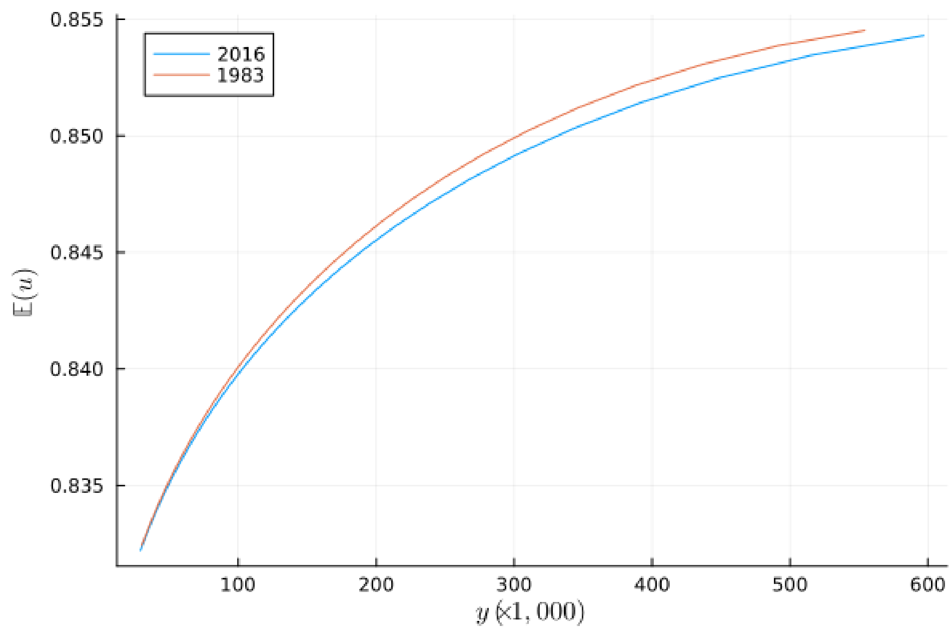


Figure 26: The change in expected utility for different levels of income

The result is not surprising given that markups increase most for the high cost, high markup firms which cater largely to high-income consumers. In fact, taking the total derivative of Equation (28) with respect to changes in equilibrium prices:

$$\begin{aligned} dU(y) &= \sum_i \Big(M\theta \frac{d \ln A}{dp_i} + M\theta \frac{d \ln A}{d\lambda(y)} \frac{d\lambda(y)}{dp_i} + y \frac{d\lambda(y)}{dp_i} \Big) dp_i \\ &= -M\theta\lambda(y) \sum_i s_i(y) dpi \end{aligned} \tag{30}$$

we can see that the first-order change in utility brought about by changes in price is proportional to the price change multiplied by the share of that good in a consumer's basket. Since the costs of high-price goods increase the most between 1983 and 2016, utility decreases the most for rich consumers, for whom these goods make up a larger share of their consumption basket.

To be more concrete about changes in welfare, we put the utility differences in equivalent variation terms. Figure 27 plots the percentage change in income necessary to make consumers of different income groups indifferent following the increase in markups from 1983 to 2016.

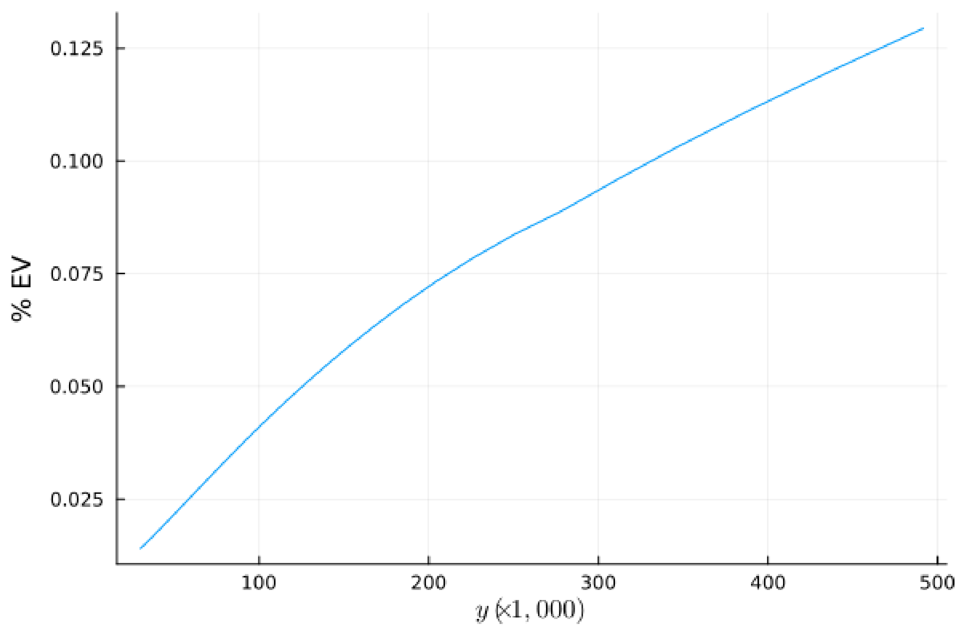


Figure 27: The percentage change in income necessary to make consumers as well off following the change in markups

Again, it's clear that rich consumers are hurt the most by the change in markups. Median income consumers need only about a 2.5% increase in their income to be just as well off after the change in markups. Contrarily, high income consumers with incomes of $500,000 would need an increase in their incomes of about 12.5%.

Some caution is necessary in interpreting these results. It does not say that an increase in income inequality will be worse for the rich than for the poor. Rather it says what the effect on an individual's welfare will *if their income stays the same*.

6.1 Change in total welfare

We can also calculate the total utility across all consumers in both cases. This change in utility will be the result of several effects. These are enumerated in Table 9, which shows the equivalent lump sum payment made to all consumers to produce the same change in utility between any two rows.

	Description	**Parameters**	**Δ EV** $(\times 1,000)$
1.	Baseline (1983)		0
2.	Average incomes adjustment	$y = y_{1983} + 2.690$	+2.690
3.	Effect of income dispersion	$F(y) = F_{2016}(y)$	-2.646
4.	Average markup effect	$\mu = \mu_{1983} + 0.078$	-3.394
5.	Markup dispersion effect	$\mu = \mu_{2016}$	+1.215
Total			-2.135

Table 9: Breakdown of changes in total utility

The table starts with all parameters equal to their 1983 values. When we changed the income distribution between 2016 and 1983, the median was kept fixed. However, there was still a change in the mean income. Thus, the second row of Table 9 adjusts the mean income to equal that of 2016. The result is equivalent to a lump-sum transfer of about \$2,700 to each consumer – an obviously positive welfare effect.

The third row allows income inequality to increase to its 2016 value. Because utility is a concave function in income, the increased income inequality produces a negative welfare effect, equivalent to lowering each consumer's income by \$2,6500.

The fourth row shows the result of increasing all markups by a fixed amount such that the resulting sales-weighted average markup is the same as in 2016. The resulting increase in prices results in a negative welfare effect, equivalent to removing almost \$4,000 from each consumer.

Finally, the fifth row shows the result of allowing the distribution of markups to be equal to their 2016 values. In this instance, not only is the sales-weighted average markup the same as in 2016, but so is the dispersion. Thus, between row 4 and row 5, markups *fall* on the low-cost products purchased most by poor consumers, but rise for the high-cost products purchased most by rich consumers. This last change acts as a redistribution of real income from the rich to the poor. Again, since utility is concave, the overall result is an increase in welfare, equivalent to a lump-sum transfer of $1,200.

6.2 Discussion

There has always been a utilitarian argument against increasing income inequality: so long as utility is a concave function, an increase in inequality will tend to decrease total welfare. The analysis above suggests that there may be an additional cost. In particular, in the model, the increase in income inequality between 1983 and 2016 leads to an increase in aggregate markups, which is even further welfare decreasing. The one extenuative is that the increase in markups is highest for the richest consumers, and lowest for the poorest consumers, which dulls the real increase in income inequality. However, in the model, the total effect of changing markups – both the change in the mean and the dispersion – is still negative, equivalent to a lump-sum tax of about $2,180 dollars.

In some sense, the changing dispersion in markups should not be surprising to economists. An increase in nominal income inequality leads to changing willingness to pay among consumers of different income groups, and prices adjust accordingly. Thus, prices for the poorest increase the least, given their now-lower ability to pay, while they increase the most for the rich. In this way, the utilitarian argument is dampened – albeit not fully – by endogenous changes in prices.

7 Conclusion

Previous studies on changing markups have focused on the increase in the average, and have relied on changes in competition and market power as explanations. This paper shows that changes in the distribution of income may also play a role in changing markups, and particularly may offer some explanation for changes in their variance.

I find that as consumers grow richer, they do not necessarily increase the quantity of physical units consumed, but rather change their consumption bundle to different higher-priced, higher-markup products. I show that this consumption process is well explained by preferences which are satiable.

Fitting this model to the data, I find that in response to an increase in income inequality, basic, high-markup firms will increase their markups while low-markup firms keep their markups unchanged. The calibrated model is able to explain 25% of the change in the average markup since 1983.

This model has implications for the analysis of rising income inequality. First it suggests that increasing inequality may beget further increases in income inequality. As income inequality increases, it leads to higher average markups, and higher average markups tend to flow towards high-income earners. Changes in income inequality due to other factors therefore may have a multiplier effect.

Conversely, the model also suggests that changes in markups may serve to dampen the *real* effects of rising income inequality. If rising inequality leads to falling relative prices for basic products, and rising relative prices for luxury products, then in real terms, inequality has increased by less.

Of course, the framework so far abstracts from changes on the supply-side. Certainly there has been increasing concentration, and this has been an important channel for changes in the distribution of markups. Future work should seek to disentangle these two forces. This is especially the case since changes on the demand side will have impacts on the supply side. Changes in relative demands for luxury and basic products may encourage entry or exit, as well as changing the potential innovation decisions for existing firms.

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A Examples

A.1 Effect of a price decrease on $\lambda(y)$ with two categories

Imagine a single individual consuming goods in two categories, each with two goods, and the following prices and utilities:

	Cars		Food	
	Hatchback	Lamborghini	Lentils	Steak
U	1	2	1	2
p	1	3	1.5	4.5

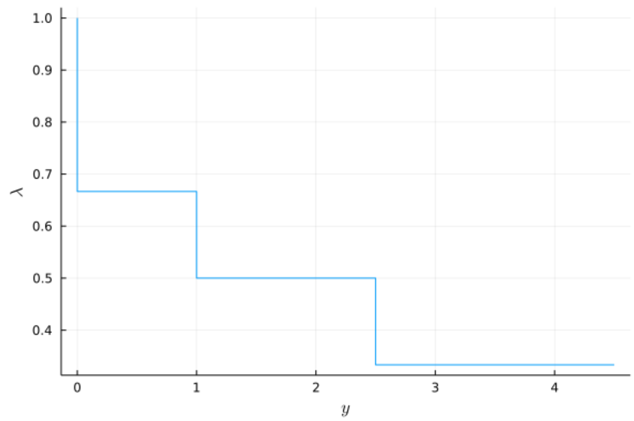
Table 10: Two categories, two goods

The consumer has the following hierarchy over purchases:

	Good	λ	y
1.	Hatchback	1	1
2.	Lentils	2/3	2.5
3.	Lamborghini (trade-up)	1/2	4.5
4.	Steak (trade-up)	1/3	7.5

Table 11: Ranking of bundles

Which yields the following for $\lambda(y)$



If the price of both cars are halved, we instead get the following hierarchy:

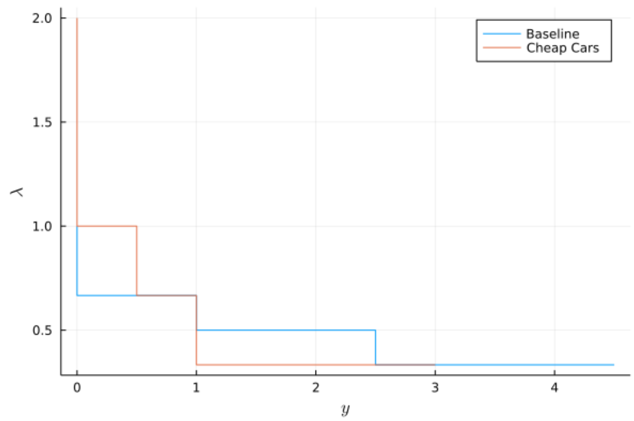
	Good	λ	y
1.	Hatchback	2	0.5
2.	Lamborghini (trade-up)	1	1
3.	Lentils	2/3	3
4.	Steak (trade-up)	1/3	6

Table 12: Ranking of bundles

The consumer receives a higher utility per dollar spent on cars, and therefore at lower levels of income, $\lambda(y)$ is higher. Conversely, due to the income effect, the consumer can now consume both food items at lower levels of income. Given that the utility per dollar spent on these goods hasn't changed, this means that $\lambda(y)$ is lower at higher levels of income. Comparing the new and old $\lambda(y)$ graphically:

A.2 Effect of a price decrease on $\lambda(y)$ with a continuum of categories and an infinite number of consumers

Imagine the same goods in Table 10, but now imagine they exist over a continuum of categories. That is there are a countably infinite number of identical categories of type "Cars" on the interval $[0, 1]$ and a countably infinite number of identical categories of type "Food"



on the interval $[1, 2]$.

Imagine that utility for consumer n of consuming good i in category c is given by $U_{icn} = u_{ic} + \varepsilon_{icn}$ where ε is i.i.d. extreme value type I.

Then, from (9) we have that the demand for good i of type k by a consumer with income y is:

$$q_i(y) = \frac{e^{u_i - \lambda(y)p_i}}{\sum_{j \in k} e^{u_j - \lambda(y)p_j}}$$

where $k \in \{\text{Cars}\ ,\ \text{Food}\}$ and each type also contains an outside good with $u_0 = p_0 = 0$.

Then using (11), we can solve for $\lambda(y)$ in the baseline case, and for the case where the price of cars drops by 50%. This yields the following: