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Inequality and Market Power: Evidence from the United States and China

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Inequality and Market Power: Evidence from the United States and China*

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Abstract

Using barcode-level data from the NielsenIQ Homescan Consumer Panel, we study how income inequality affects the prices of identical goods across US counties. We find that higher inequality reduces prices for products with low market shares but increases prices for products with high market shares. With higher inequality, larger firms, which sell more high-market-share goods, tend to raise prices, while smaller firms lower them. We find a similar pattern using Chinese export data across countries. To interpret these findings, we develop a model where a mean-preserving spread in income affects pricing through the convexity of demand and the convexity of the price derivative of demand with respect to income. We derive conditions under which inequality raises the price elasticity for low-market-share products and lowers it for high-market-share products, matching our empirical results.

Keywords: Consumer Heterogeneity, Income Inequality, Prices, Markups

JEL Codes: L11, D31, D43, F14

*Researchers own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. We thank Yucheng Yang for sharing the GS1 Global Data. We thank Costas Arkolakis, Robert C. Feenstra, and Alessandro Sforza for early suggestions. We are grateful for comments from Jan Bakker, Giuseppe Berlingieri, Anne-Célia Disdier, Jessie Handbury, Fadi Hassan, Thierry Mayer, Isabelle Mejean, Mathieu Parenti, Akira Sasahara, and seminar participants at Keio University, University of Geneva, PSE/Sciences Po, UEA Berlin, Bocconi University, University of Milan, and ETSG. Financial support from the Natural Science Foundation of China (Grant No. 72322007;72503230) is gratefully acknowledged by Mingzhi Xu. Financial support from the Carlsberg Foundation and from the Jorcks Fond is gratefully acknowledged by Luca Macedoni.

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1 Introduction

Over the past few decades, advanced economies have experienced a notable decline in the labor’s share of national income while profits have risen [Autor et al., 2020, Baqaee and Farhi, 2020, Kehrig and Vincent, 2021]. A prominent explanation for this trend is the growing dominance of “superstar firms”—large firms with high markups and low labor shares [Autor et al., 2020]. Consistent with this view, recent evidence shows a broad-based increase in market power and firm-level markups across industries [De Loecker et al., 2020]. In parallel, income inequality has widened significantly since the 1980s in many countries [Piketty and Saez, 2006, Piketty, 2014, Piketty et al., 2018].¹ A large body of work has documented that consumers with different incomes exhibit different shopping behaviors [Fajgelbaum and Khandelwal, 2016, Faber and Fally, 2021, Neiman and Vavra, 2023, Feenstra et al., 2025]. As a result, rising inequality may influence the demand faced by firms, with potential implications for their prices and markups. This paper asks: does rising income inequality affect firm pricing, and in particular, does it benefit larger firms?

We use barcode-level data from the NielsenIQ Homescan Consumer Panel (2004–2018) to study how firms price identical goods across US counties with different levels of income inequality, while holding average income constant. The data report prices and quantities at the barcode-level and shopping trip, which we aggregate to the firm–product–retail chain–county level, where a product is a barcode. We link this information to county-level Gini coefficients from the Current Population Survey. We control for production and distribution costs using product–time fixed effects and firm–retailer and firm–county fixed effects. To address variation in local competition, we include product group–county–year fixed effects, where product groups are barcode-level aggregates defined by NielsenIQ. Retailer–year fixed effects account for markup policies at the retailer level, and retailer–county fixed effects capture local demand or cost conditions specific to a retailer’s operations within a county. These controls collectively absorb a wide range of unobservable factors, arguably leaving us with variation in barcode-level markups.

Our main result is that the effect of income inequality on prices varies systematically across products, depending on their market size measured by their initial sales or the initial market shares. Higher inequality lowers prices for low-market-size

¹For the US, [Auten and Splinter \[2024\]](#) provide alternative estimates suggesting a more modest increase in inequality than those reported by [Piketty et al. \[2018\]](#).

products while raising them for high-market-size products. On average, this effect is about 40% as large as the effect of per capita income, which increases prices uniformly across the product distribution. Quantitatively, a one standard deviation increase in inequality raises prices by 1.6% for products in the top 1% of the market share distribution, while lowering prices for products below the 64th percentile. The net effect is a 0.39% increase in average prices—compared to a 1% increase associated with a one standard deviation increase in per capita income. The small magnitude of the results can be attributed to two factors. First, measurement error in inequality likely induces attenuation bias: using instrumental variables yields an average effect about seven times larger. Second, the small effects are consistent with the limited within-chain price dispersion documented by [DellaVigna and Gentzkow \[2019\]](#) and with our inclusion of retailer fixed effects, which compress price variation.

Because large firms disproportionately sell high-market share products but also maintain wide product scopes including products with low market shares, the net effect of inequality on firm-level prices is ambiguous. Empirically, we find that larger firms tend to raise their average prices in more unequal markets, while smaller firms reduce theirs. This pattern holds whether prices are averaged across products or weighted by sales. A similar pattern emerges across retailers: larger chains tend to raise prices as inequality rises, while smaller retailers lower them. Hence, our results suggest that the rising inequality documented in several countries can be a driver of the rising markups of large firms.

We investigate two potential mechanisms that could explain our results. The first is price discrimination driven by market segmentation: firms may tailor prices across retailers, charging higher markups in areas with more affluent consumers. However, we find that the majority of retailers are attended by consumers from a wide range of income groups, and most barcodes are purchased across income quartiles, in line with the findings of [Pytko \[2024\]](#). This lack of market segmentation suggests that price discrimination is not the primary driver of our results.

A second explanation is consumer sorting: rising inequality might shift demand toward wealthier consumers, who are less price sensitive and more likely to buy from larger firms. [Mongey and Waugh \[2025\]](#) argue that heterogeneity in consumer sorting across firms is a key mechanism behind cross-sectional variation in prices, a view supported by empirical evidence from several studies [[De Loecker and Warzynski, 2012](#), [Faber and Fally, 2021](#), [Sangani, 2022](#)]. We confirm this cross-sectional pattern

in our data: both products and firms with higher market shares tend to sell relatively more to richer households. However, we find limited evidence that rising inequality increases the share of high-income consumers purchasing from large firms. While some evidence of this channel appears at the product level, it does not explain our baseline results. In fact, controlling for these sorting patterns leaves the inequality–price relationship largely unchanged.

Given that neither price discrimination nor sorting can fully account for our findings, we propose a simple model in which mean-preserving changes in the income distribution affect aggregate demand and demand elasticities, even in the absence of price discrimination. We analyze the pricing decisions of a firm selling a product to consumer segments defined by income.² We compare the pricing decision of a firm facing a representative consumer (with average income) to that of a firm facing heterogeneous consumer segments with unequal incomes. The firm cannot price-discriminate across income segments.

The introduction of inequality creates segments with different demand elasticities: some consumers are less elastic, while others are more elastic. When the firm sets a uniform price, it balances extracting more surplus from less elastic customers against losing sales from more elastic ones. This tradeoff may vary across firms depending on their marginal costs. Crucially, our framework captures how inequality simultaneously alters segments’ demand elasticities and expenditure shares across firms, both of which shape pricing incentives.

Our model shows that the price effects of a mean-preserving spread in income hinge on two critical properties of demand: (i) the convexity of demand in income and (ii) the convexity of the price derivative of demand with respect to income. If demand is convex in income, higher inequality raises aggregate demand.³ If the price derivative of demand is convex in income, then inequality reduces price sensitivities. These properties jointly determine whether inequality pushes firms toward higher or lower markups.

Our empirical results are consistent with demand functions that are concave in

²In some markets, the term *segment* may refer to categories of products (e.g., SUVs vs. compact cars). In our analysis, however, consumer segments refer specifically to groups of consumers sharing the same income level.

³For example, if the good is normal, and demand is convex in income, an increase in inequality raises aggregate demand because the additional demand from richer consumers more than offsets the decline from poorer ones.

income but exhibit convex price sensitivity in income. Under these conditions, a rise in inequality lowers aggregate demand (hurting high-cost, low-scale firms) but reduces price sensitivity (benefiting low-cost, high-scale firms). As a result, small firms with low market share products reduce prices, while large firms increase them, which is consistent with our empirical findings.

To assess the external validity of our findings, we replicate our baseline regressions using international trade data on Chinese exports. Although the data are less granular (products are defined at the 8-digit Harmonized System level instead of the barcode level), we observe the same pattern: rising destination-country inequality lowers unit values for firm-products with low export values but raises them for high-value ones. This supports the generality of our mechanism beyond the US retail market.

Related Literature. The relationship between inequality and prices is a relatively understudied subject.⁴ Choi et al. [2009] pioneered the exploration of the link between prices and income inequality. More recent studies have aimed to identify the direction of this relationship, with mixed results. Two studies, Bekkers et al. [2012] and Ciani [2021], found that as the income inequality of a destination increases, the exported unit values decrease. In contrast, Flach and Janeba [2017] found that increased inequality correlates with higher prices.

A contribution of our study is the use of barcode-level product data, enabled by the NielsenIQ data. This approach allows us to compare the price of a barcode across different counties, ensuring no differences in quality could influence the results. This contrasts with studies based on customs data that use the Harmonized System classification, such as those conducted by Bekkers et al. [2012], Flach and Janeba [2017], and Ciani [2021], where price differences may be driven by variations in quality.⁵ Moreover, we uncover heterogeneous responses to income inequality depending on

⁴In contrast, the relationship between *average income* and prices has been the subject of extensive research. Refer for instance to works by Alessandria and Kaboski [2011], Handbury and Weinstein [2015], Simonovska [2015], DellaVigna and Gentzkow [2019], Stroebl and Vavra [2019], and Handbury [2021]. Relatedly, Latzer and Mayneris [2021] approach the issue from a different perspective and demonstrate a positive correlation between a country’s income inequality and its export unit prices. Hillrichs and Vannoorenberghe [2021] develop a new method to estimate within-country income inequality using import data and assuming non-homothetic preferences.

⁵In fact, both Bekkers et al. [2012] and Flach and Janeba [2017] propose theories suggesting that income inequality impacts the average price of exported goods due to its influence on the quality composition of exported product codes. Cross-country studies with barcode level data show that price differences across destinations are not entirely due to quality differences. For instance, see Simonovska [2015] and Macedoni and Mattana [2024].

the market share of products and, thus, the effects of inequality on average prices depends on the distribution of market shares.

Our theory speaks to two seemingly contrasting strands in the literature. Models of monopolistic competition with atomistic firms, such as [Foellmi and Zweimüller \[2004\]](#), [Bekkers et al. \[2012\]](#), and [Kichko and Picard \[2023\]](#), predict that greater inequality lowers prices, while the oligopoly model of [Feenstra et al. \[2025\]](#) implies the opposite, with inequality raising prices. These varied predictions motivate our focus on the heterogeneous consequences of inequality across products with different market sizes, and our model derives the conditions on the demand function under which either outcome can arise.

A related contribution is [Foellmi et al. \[2025\]](#), who develop an international trade model with income inequality in which some products are mass-market goods purchased broadly across the income distribution, while others are luxury goods consumed only by richer households. Their model predicts that a mean-preserving spread in income raises the prices of mass-market goods and lowers the prices of luxury goods. This prediction is consistent with our finding that products with higher sales become more expensive as inequality rises. The underlying mechanism, however, is less aligned with the Nielsen data: we show that high-sales products attain higher expenditure shares among richer households, and that most products are in fact consumed across the income distribution.

Our paper complements the recent work by [Mongey and Waugh \[2025\]](#), who develop a model in which market power and income inequality interact through the sorting of consumers across firms: richer households have a larger expenditure shares on goods produced by larger firms, and since richer households have a lower demand elasticity, larger firms can charge higher markups.⁶ Our model instead considers changes in the income distribution that can affect both the demand elasticities and the sorting of consumers simultaneously.⁷ Our empirical analysis shows that their mechanism helps explain cross-sectional variation in prices across products and firms: in particular, products and firms with higher sales tend to have larger market share

⁶Relatedly, [Nocco \[2009\]](#) studies how changes in the relative share of skilled versus unskilled workers with different preferences affect equilibrium prices. When the demand composition shifts toward skilled consumers and firms may respond by raising prices.

⁷Moreover, our theoretical exercise considers the effects of an increase in income inequality holding average income constant at the firm level. Changes in the sorting of consumers necessarily affect the average income of a firm's consumer base.

in richer consumer segments. However, we find limited evidence that *changes* in income inequality lead to meaningful shifts in the sorting of consumers across firms and products, and these dynamics do not fully account for our main empirical findings.

This paper contributes to the expanding field of research that employs scanner data to investigate differences in the cost of living across different income groups. Jaravel [2019] finds that increases in nominal income inequality are exacerbated by an increase in product varieties that cater to the taste of richer households, thereby lowering their relative cost of living. Chang et al. [2021], Sangani [2022], and Pytka [2024] provide evidence that suggests that richer households purchase goods with higher prices and markups.⁸ These results are consistent with the finding of Faber and Fally [2021], which show that larger firms, which typically charge higher markups, tend to cater to the preferences of richer consumers. Handbury [2021] shows that prices and product varieties offered in local markets are correlated with local tastes, so that richer households are better off in richer cities and poorer households are better off cities with lower average income. Our contribution to this literature is to uncover a mechanism by which the transmission of nominal income inequality into real income inequality is dampened, since inequality increases the prices of products with larger market share, which are disproportionately consumed by richer households.⁹

While we focus on the direction of causality running from consumer income inequality to firms' markups, we recognize that other mechanisms may also be at play. For instance, Leonardi [2015] shows that an increase in the relative supply of skilled labor can shift demand toward high-skill intensive products, thereby raising the college wage premium. Impullitti and Rendahl [2025] argue that higher entry costs increase the markups and valuations of incumbent firms, leading to greater returns on assets and, consequently, higher wealth inequality. Our findings do not contradict these perspectives and instead suggest a possible amplification mechanism: as inequality raises prices and profits for larger firms, the resulting increase in returns may further reinforce inequality.

The paper is organized as follows. Section 2 presents the data we use in the empirical analysis. Section 3 provides our main empirical findings. Section 4 builds a model to rationalize the evidence. Section 5 concludes.

⁸This outcome can be rationalized by the models of Pytka [2024] and Nord [2023] where households differ in their search intensity for lower prices.

⁹There is a parallel literature that leverages the scanner data to study the unequal effects of trade shocks across consumers [Bai and Stumpner, 2019, Borusyak and Jaravel, 2021, Ma et al., 2025].

2 Data Description

Our main dataset is the NielsenIQ Homescan Consumer Panel database collected by NielsenIQ (US) and provided by the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business and the Current Population Survey provided by the US Census Bureau. As additional evidence for the role of consumer heterogeneity on firm pricing strategy, we replicated our analysis with exporter-level data from China.

NielsenIQ Homescan Consumer Panel (NHCP). We draw on the NHCP to obtain detailed price and sales information at both the barcode and household level. Households participating in the panel are provided with optical scanners and instructed to record every purchase of consumer packaged goods—regardless of the retailer or outlet type—by scanning product barcodes at the time of purchase. Each shopping trip generates a rich set of data that includes the date of purchase, the Universal Product Code (UPC), the transaction price, quantity purchased, retail chain identifier, and total expenditure. The dataset covers approximately 119 million shopping trips made between 2004 and 2018, with an average annual sample size of around 50,000 households.¹⁰ In what follows, we clarify several key terms that are used frequently throughout the analysis. For each term, we describe its empirical counterpart in the data and explain how it maps to variables in the model.

I. Products. We define products at the most granular level available in the Nielsen data, where each item is uniquely identified by a combination of barcode and version codes. Specifically, we use the 12-digit Universal Product Code (*upc*), which identifies the barcode, together with the version code (*upc_ver_uc*), generated by the University of Chicago. For example, both a six-pack of a soda and a single can share the same UPC but differ in their version codes. For simplicity, we use the term “product” or “UPC” to refer to this combined identifier throughout the analysis. Nielsen assigns each product to a broader product group, with all groups classified into 125 mutually exclusive categories such as candy, gum, soup, cereal, and coffee. To ensure sufficient variation and comparability, our baseline regression analysis focuses on products sold in more than 100 retailers in a given year.

¹⁰For further documentation of the NHCP, see [Hottman et al. \[2016\]](#), [Feenstra et al. \[2020\]](#), and [Faber and Fally \[2021\]](#).

II. Firms. We use data from the GS1 Company Database to identify the company owning a given UPC. GS1 is a not-for-profit information standards organization that provides barcodes to manufacturers globally. The GS1 Company Database includes information that firms document when registering a barcode with GS1, such as company name, location, and the company GS1 prefix information. A GS1 company prefix is a unique identifier assigned to the beginning digits of every barcode registered by that company. The prefix allows us to assign individual product UPC codes to the owning company, which identifies the company that owns the brand [Hottman et al., 2016]. For instance, a firm in our data is Procter & Gamble, which owns several brands, such as Crest in the oral hygiene products, and Pantene and Head & Shoulders in the hair care products.¹¹

III. Retailers. The Nielsen data cover roughly 800 retailers and 50,000 individual stores, identified by masked retailer and store codes. The retailer and store identifiers are recorded as *retailer_code* and *store_code_uc*, respectively. Each store belongs to a retailer. To address the potential sparsity of observations at the individual store level, we aggregate prices to the retailer level. This approach is also consistent with evidence showing that within-retailer price variation for a given product is limited, indicating that pricing decisions are largely made at the retailer level rather than by individual stores [DellaVigna and Gentzkow, 2019].

IV. Prices. Our main dependent variable is the price p_{pfrdt} of a product p sold by firm f in retailer r and county d in year t is the ratio of annual revenue to units sold. To remove outliers, we first compute the average price of each product by year and then calculate the standard deviation of a local retailer chain’s price from the annual average. We exclude a local retailer chain’s product observation if its deviation exceeds three standard deviations from the nationwide average price.

Figures A.1 and A.2 in the supplemental appendix present county-level prices for two widely purchased products: a packaged butter and a soda. The butter map shows prices per pound ranging from about USD 2.50 to more than USD 5.50. Lower

¹¹We are unable to obtain a firm identifier for 12% of UPCs when we match GS1 data with the UPC lists. In these cases, we drop the UPCs without a firm identifier. When a retailer outsources production of a private-label product, the UPC is attributed to the retailer [Hottman et al., 2016]. The NHCP dataset includes 72,387 firms, with 334 firms remaining in our analysis sample after restricting to products sold in at least 100 retailers. This restriction is not applied in the extension with markup estimation of Supplemental Appendix A.6.

prices are concentrated along parts of the West Coast, while some of the highest prices appear in Arizona and scattered counties in the Southeast. For soda, the price of a 12-ounce can ranges from roughly USD 0.90 to USD 1.70. Counties in California, Texas, and Florida exhibit particularly wide spreads, with neighboring areas sometimes showing differences of 30–40 cents per can. These examples make clear that retail prices vary both across and within states, with patterns that are not confined to a few regions but observed nationally.

County-Level Variables. We measure county-level income inequality using data from the US Current Population Survey (CPS). The CPS provides individual income information for a large, nationally representative sample and includes geographic identifiers at the county level. Using Stata’s *ineqdeco* package, we compute both the Gini coefficient and the Theil index, with details of the calculations provided in Supplemental Appendix A.2. Because the CPS covers only a subset of counties, our inequality measures are available for a limited sample. For example, in 2018, we obtain measures for roughly 300 counties—out of 2,668 counties in the Nielsen dataset—yet these counties accounted for 42% of total sales.¹² To complement these measures, we incorporate annual county-level GDP data from the Bureau of Economic Analysis (BEA) and population data from the US Census Bureau (USCB).

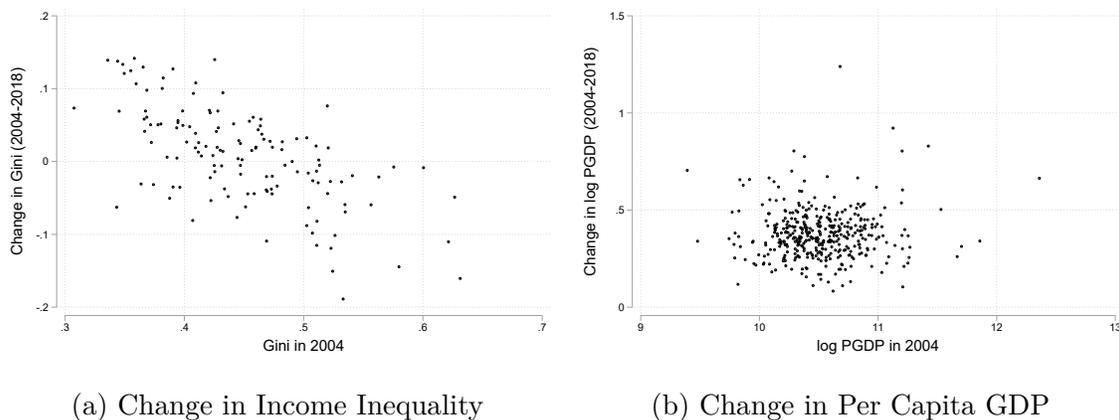
Figure 1 shows how income inequality (Panel (a)) and per capita GDP (Panel (b)) evolved across US counties between 2004 and 2018. In 2004, Gini coefficients ranged from 0.30 in Scott County, Iowa, to 0.63 in Cameron County, Texas. For comparison, the World Bank reports a Gini coefficient of 0.40 for the United States as a whole, 0.30 for France, and 0.65 for South Africa. Moreover, between 2004 and 2018, counties with higher initial inequality tended to experience smaller subsequent increases in inequality or even decreases. In 2004, per capita income (in logs) ranged from 9.4 in Livingston Parish, Louisiana (about USD 13,400), to 12.4 in New York County, New York (about USD 268,000). Average per capita income growth over the 14-year period was roughly 45%, with no clear relationship to initial income.

Using the CPS, we can probe more deeply into the sources of variation in county-

¹²Figure A.3 compares our CPS-based national Gini series with estimates from the World Income Inequality Database (WIID) and the World Development Indicators (WDI). Despite differences in sources and methodology, all three display similar trends over 2004–2018, supporting the validity of our measure. Additional validation of our county-level inequality measures is provided in Supplemental Appendix A.3.

level income inequality. Supplemental Appendix A.3 shows that changes in inequality within a county are only weakly correlated with migration flows, suggesting that population movements play a limited role. Instead, most of the observed variation reflects widening disparities *between* richer and poorer individuals, rather than shifts *within* these groups. This pattern is consistent with broader national trends documented in the literature, which attributes rising inequality in the United States to long-run forces such as differences in educational attainment [Goldin and Katz, 2007, Hoffmann et al., 2020], skill-biased technological change [Acemoglu and Autor, 2011], and institutional factors like declining unionization and changes in minimum wages [Fortin et al., 2021]. The evidence suggests that county-level changes in inequality are shaped mainly by broad structural forces rather than by local shocks tied to firm behavior, making them a useful source of exogenous variation for our analysis.

Figure 1: Income Inequality and Average Income Changes Across Counties, 2004–2018



Note: Each point represents a county observed in both 2004 and 2018. Panel (a) plots the absolute change in the Gini coefficient against its initial level in 2004. Panel (b) plots the log change in per capita GDP against its initial level in 2004.

Chinese Customs Dataset. To place our findings in a broader international context, we draw on confidential Chinese customs transaction-level data covering the period 2007–2015. These records report every export and import transaction at the firm level, with products classified using the eight-digit Harmonized System (HS) codes, which serve as our operational definition of a product. Importantly, the customs data link each transaction to the exporting firm and the destination country, enabling us to observe how different firms price and distribute similar goods across

markets. The dataset spans more than 7,000 distinct products and records the precise destination country for each shipment, making it one of the most detailed trade databases available worldwide. For our analysis, we classify products according to the Broad Economic Categories (BEC) framework—distinguishing consumption, intermediate, and capital goods—and focus on HS codes corresponding to consumption goods. This yields a sample of roughly 2,000 distinct products exported across a wide range of destination markets. To complement the trade data, we obtain measures of inequality (the Gini coefficient and Theil index), GDP, and population at the national level from the World Income Inequality Database.

Table 1: Descriptive Statistics

Variable	Description	Num. Obs.	Mean	Std	Min	Max
<i>Panel (a): Evidence from the United States, 2004-2018</i>						
$\ln p_{fprdt}$	Price (USD)	29,516,802	0.72	0.67	-4.61	4.96
$\ln Sales_{fprdt}$	Sales (USD)	29,583,426	1.62	1.12	-4.61	11.72
$Gini_{dt}$	Gini Index in destination county	4,071	0.44	0.07	0.20	0.76
$Theil_{dt}$	Theil Index in destination county	4,071	0.36	0.13	0.07	1.47
$\ln PGDP_{dt}$	Per Capita GDP in destination county (USD)	4,071	10.70	0.39	9.72	13.02
$\ln POP_{dt}$	Population in destination county	4,071	12.74	0.83	10.38	16.13
<i>Panel (b): Evidence from Chinese Exporters, 2007-2015</i>						
$\ln p_{pfdt}$	Price (CNY)	22,452,956	1.60	1.66	-9.84	19.59
$\ln Sales_{pfdt}$	Sales (CNY)	22,452,956	9.35	2.25	0.00	21.36
$Gini_{dt}$	Gini Index in destination market	750	0.37	0.08	0.24	0.71
$Theil_{dt}$	Theil Index in destination market	346	0.33	0.17	0.12	1.42
$\ln PGDP_{dt}$	Per Capita GDP in destination market (USD)	750	9.77	0.98	6.79	11.70
$\ln POP_{dt}$	Population in destination market	750	16.22	1.62	9.23	20.96

Note: Panel (a) reports summary statistics for the United States over 2004–2018. Retail prices and sales are drawn from the NielsenIQ Homescan Consumer Panel (NHCP), while county-level inequality measures are calculated from the Current Population Survey (CPS). County GDP and population data come from the Bureau of Economic Analysis (BEA) and the U.S. Census Bureau (USCB). Panel (b) reports statistics for Chinese exporters over 2007–2015. Export prices and sales are taken from the Chinese Customs Database, and destination-market covariates, including inequality, GDP, and population, are obtained from the World Income Inequality Database (WIID).

Table 1 reports the descriptive statistics for all used variables. As shown, the distribution of inequality across destination countries mirrors that observed across US counties: the standard deviation of the Gini coefficient is 0.07 across counties and 0.08 across countries, with similar distributions for the Theil index (see Supplemental Appendix Figure A.5). This close correspondence underscores the comparability of the two settings and highlights the value of the customs data for studying how firms respond to heterogeneous inequality shocks in global markets.

3 Empirical Analysis

3.1 Baseline Empirical Specification

We exploit variation in changes in local income inequality across US counties to examine its impact on firms’ pricing decisions and estimate the following regression model:

$$\begin{aligned} \ln p_{prdt} = & \beta_1 Ineq_{dt} + \beta_2 (Ineq_{dt} \times MarketSize_{prdt0}) + \beta_3 MarketSize_{prdt0} \\ & + X'_{dt} \Gamma_1 + X'_{prdt} \Gamma_2 + \delta_{pt} + \delta_{rt} + \delta_{fd} + \delta_{fr} + \delta_{rd} + \delta_{g(p)dt} + \epsilon_{prdt}, \end{aligned} \quad (1)$$

Our primary outcome variable, $\ln p_{prdt}$, is the logarithm of the average unit price of UPC product p sold in retailer r in county d and year t . Because each UPC uniquely identifies a firm, we omit the firm subscript for simplicity. The main explanatory variable, $Ineq_{dt}$, measures the degree of income inequality in county d at time t . We also include county-year controls X_{dt} and a rich set of fixed effects to absorb unobserved heterogeneity. To address the computational burden of high-dimensional fixed effects, we restrict the sample to products sold in at least 100 retailers. This restriction not only makes estimation feasible but also improves comparability across products. Combined with retailer-year fixed effects, it ensures that our results are not driven by differences in product assortments across chains—an important consideration, since inequality could otherwise affect prices indirectly if households with different income levels shop at different retailers. Standard errors are clustered at the firm level to allow for arbitrary correlation within firms.

Inequality and Market Size of Products. In our baseline specification, inequality is measured using the Gini coefficient, with robustness checks reported in the supplemental appendix employing the Theil index. All specifications yield consistent results. A key component of the model is the inclusion of $MarketSize_{prdt0}$, which denotes the baseline market size of product p sold by retailer r in county d , measured in the first year the product appears in that market (t_0).¹³

¹³Using the initial value avoids simultaneity: if we relied on contemporaneous sales, the measure of market size would itself be an outcome of current prices—higher prices could depress sales, while stronger demand could raise both sales and firms’ incentives to adjust prices. By fixing market size at its baseline, we ensure it reflects pre-determined market conditions rather than being jointly

We consider two complementary measures of market size. In our baseline specification, market size is defined as the log of sales at the product–retailer–county level in the initial sample year, $\ln Sales_{prdt0}$. As an alternative, we construct a relative measure of market size based on market shares. Specifically, we first aggregate total sales across all products at the retailer–county level in the initial year ($Sales_{rdt0}$) and then compute the share of sales for each product relative to this total, i.e., $Sales_{prdt0}/Sales_{rdt0}$. This alternative provides a scale-invariant measure of product importance within each retailer–county market.

The key coefficients of interest are β_1 and β_2 . The coefficient β_1 captures the direct effect of local income inequality on product-level prices, holding market size constant. By contrast, β_2 is the coefficient on the interaction term $Ineq_{dt} \times MarketSize_{prdt0}$, and it measures whether inequality affects pricing differently depending on the market size of the product, providing a direct test of heterogeneous responses.

Other Control Variables. The regression also includes a vector of county-year controls, X_{dt} , consisting of the log of per capita income and the log of population in each county and year. These variables are standard determinants of local prices in the Nielsen data [Handbury and Weinstein, 2015, Handbury, 2021]. Importantly, conditioning on per capita income allows us to separate the effect of inequality from changes in average income, ensuring that our results are not simply driven by shifts in the overall income distribution due to variation in the relative shares of high- and low-income households. In addition, we interact baseline market size $MarketSize_{prdt0}$ with the county-level controls to form X_{prdt} , which accounts for the possibility that the relationship between inequality and pricing depends jointly on market size and county-level economic conditions.

Fixed Effects. To isolate the effects of inequality on markups, we control for marginal production and delivery costs and for unobserved local market conditions by including several fixed effects. Product-year fixed effects (δ_{pt}) capture changes in marginal costs of a UPC that are common across counties and retailers. Firm-retailer (δ_{fr}) and firm-county (δ_{fd}) fixed effects account for distribution costs shared across all products sold by a given firm within a retailer or county. In addition, firm-retailer fixed effects absorb systematic differences in bargaining power between

determined with pricing decisions in the estimation period.

firms and retailers that could influence pricing outcomes. To control for retailer-level shocks, we introduce retailer-year fixed effects (δ_{rt}), which capture differences in average markups across retailers and over time. Retailer-county fixed effects (δ_{rd}) are included to absorb local demand or cost conditions that are specific to a retailer’s operations in a given county. Finally, product group–county–year fixed effects ($\delta_{g(p)dt}$) capture local variation in competitive intensity across related products, which may be correlated with inequality. The inclusion of these last fixed effects effectively absorbs all county-year level variation, which implies that we cannot separately identify the coefficient on inequality (β_1).

3.2 Baseline Results

We estimate the effect of income inequality on product prices by progressively adding richer sets of fixed effects, measuring county–year inequality with the Gini coefficient. Column (1) of Table 2 reports simple OLS results with only non–fixed-effects controls. Column (2) adds product–year fixed effects to absorb common marginal-cost shocks. Column (3) then incorporates firm–retailer and firm–county fixed effects to capture distribution costs. Column (4) adds retailer–year fixed effects, and column (5) adds retailer–county fixed effects, yielding the full model in specification (1).

In summary, across all specifications the estimated effect of income inequality on prices points in the same direction: the coefficient on $Ineq_{dt}$ is negative, while the coefficient on the interaction term $Ineq_{dt} \times \ln MarketSize_{prdt0}$ is positive. These findings imply that higher inequality is associated with lower prices for products with low sales. However, as product sales increase, the effect becomes progressively less negative, and eventually turns positive. Quantitatively, the turning point occurs at roughly the 64th percentile of product sales: for products above this threshold, inequality raises prices rather than lowering them. The magnitude of the estimates stabilizes once marginal-cost and distribution-cost factors are controlled for, as in column (3).

Table 3 shows that our results remain robust when product group–county–year fixed effects are included (column (2)) and when market size is measured by market share rather than sales (columns (3) and (4)).¹⁴ Columns (5) and (6) of Table 3

¹⁴Although the coefficient on initial market share is negative, the marginal effect of market share on prices is positive once all interactions are taken into account. At national means ($Gini_{dt} = 0.44$, $\ln PGDP_{dt} = 10.7$, $\ln POP_{dt} = 12.74$), the marginal effect is 0.34; even at the lowest observed values (0.20, 9.72, 10.38), the effect remains positive at 0.20.

Table 2: Effect of Income Inequality on Product Prices

Dep var: $\ln p_{prdt}$	(1)	(2)	(3)	(4)	(5)
$Ineq_{dt} \times \ln Sales_{prdt0}$	0.068*** (0.015)	0.026** (0.011)	0.025** (0.013)	0.026** (0.012)	0.026** (0.012)
$\ln Sales_{prdt0}$	0.910*** (0.068)	0.094*** (0.009)	0.085*** (0.009)	0.078*** (0.008)	0.067*** (0.014)
$Ineq_{dt}$	-0.036** (0.018)	-0.025 (0.025)	-0.041* (0.021)	-0.040* (0.021)	-0.040** (0.020)
Observation	29,583,426	29,583,155	29,549,523	29,549,127	29,535,724
R-squared	0.233	0.871	0.897	0.898	0.900
Other Controls	Y	Y	Y	Y	Y
<i>Fixed Effect:</i>					
UPC \times Year	-	Y	Y	Y	Y
Firm \times Retailer	-	-	Y	Y	Y
Firm \times County	-	-	Y	Y	Y
Retailer \times Year	-	-	-	Y	Y
Retailer \times County	-	-	-	-	Y

Note: The dependent variable is the logarithm of the average unit price of product p in retailer r , county d , and year t . $Ineq_{dt}$ denotes the county-level Gini coefficient of income inequality. Market size is measured as the log of baseline sales at the product–retailer–county level. Baseline values are defined in the first year of the sample. All regressions include county-year controls (log per capita GDP and log population, and their interactions with market size). Robust standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

show that the results remain robust under a stricter set of fixed effects, where firm–retailer and firm–county fixed effects are replaced with product–retailer and product–county fixed effects. This alternative specification directly controls for time-invariant transportation and distribution costs at the product level. The continued robustness of the estimates suggests that our baseline specification already provides an adequate control for these factors.

Table A.1 in the supplemental appendix reports the coefficients on the control variables. Consistent with Handbury and Weinstein [2015], we find that prices are higher in counties with larger populations and higher per capita income. Although the interaction between population size and product market size is negative, the overall effect of population on prices remains positive, even for the largest products. By contrast, the interaction between per capita income and product market size is statistically insignificant in nearly all specifications. This contrast underscores an important distinction between per capita income and income inequality: higher per capita income uniformly raises prices across the product-size distribution, whereas income inequality raises prices only for products with sufficiently large market size.

Table 3: Effect of Income Inequality on Product Prices

Dep var: $\ln p_{prdt}$	(1)	(2)	(3)	(4)	(5)	(6)
	Sale Size	Sale Size	Share Size	Share Size	Sale Size	Sale Size
$Ineq_{dt} \times MarketSize_{prdt0}$	0.026** (0.012)	0.029** (0.013)	0.118*** (0.035)	0.121*** (0.036)	0.018** (0.009)	0.022* (0.012)
$MarketSize_{prdt0}$	0.067*** (0.014)	0.064*** (0.015)	-0.800*** (0.146)	-0.788*** (0.138)	0.099*** (0.009)	0.097*** (0.009)
$Ineq_{dt}$	-0.040** (0.020)		-0.004* (0.002)		-0.029* (0.015)	
Observation	29,535,724	29,528,409	29,535,724	29,528,409	28,905,531	28,897,635
R-squared	0.900	0.902	0.899	0.901	0.921	0.922
Other Controls	Y	Y	Y	Y	Y	Y
<i>Fixed Effect:</i>						
UPC \times Year	Y	Y	Y	Y	Y	Y
Firm \times Retailer	Y	Y	Y	Y	Y	Y
Firm \times County	Y	Y	Y	Y	Y	Y
Retailer \times Year	Y	Y	Y	Y	Y	Y
Retailer \times County	Y	Y	Y	Y	Y	Y
Product Group \times County \times Year	-	Y	-	Y	-	Y
UPC \times Retailer	-	-	-	-	Y	Y
UPC \times County	-	-	-	-	Y	Y

Note: The dependent variable is the logarithm of the average unit price of product p in retailer r , county d , and year t . $Ineq_{dt}$ denotes the county-level Gini coefficient of income inequality. Market size is measured either as the log of baseline sales at the product-retailer-county level (columns 1, 2, 5, and 6) or as the product's baseline sales share within a retailer-county pair (columns 3 and 4). Baseline values are defined in the first year of the sample. All regressions include county-year controls (log per capita GDP and log population, and their interactions with market size) and the fixed effects listed in the table. Robust standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Magnitude Interpretation. Table 4 reports the sales-weighted price effects across selected percentiles of the product sales distribution, resulting from a one-standard-deviation increase in the Gini index (0.07). Column (1) shows that products in the lower half of the sales distribution (at or below the 50th percentile) experience price declines as inequality rises. In contrast, products at or above the 75th percentile display the opposite pattern, with larger products charging higher prices in response to greater inequality. Because sales are highly skewed, price changes among top-selling products dominate the overall sales-weighted average effect.

Quantitatively, a one-standard-deviation increase in inequality raises the sales-weighted average price by about 0.39 percent. When market size is measured by market share rather than sales, the corresponding effect is slightly smaller at 0.34 percent. To provide further perspective, column (2) normalizes the price change by the standard deviation of price residuals.¹⁵ This exercise indicates that a one-standard-

¹⁵Specifically, we calculate the standard deviation of price residuals from the fixed-effects regression: $\ln p_{pfrdt} = \delta_{pt} + \delta_{rt} + \delta_{fr} + \delta_{fd} + \delta_{rd} + \epsilon_{pfrdt}$, and use it to normalize the price changes.

Table 4: Counterfactual Price Effects by Sales Percentile

Sales Distribution		(1)	(2)	(3)
Percentile	$\ln Sales_{prdt0}$	% Change	% Change (Normalized)	% Change (Relative to Income Effects)
1th	-0.62	-0.39%	-4.92%	-141.52%
5th	-0.01	-0.28%	-2.73%	-74.39%
25th	0.69	-0.15%	-1.64%	-31.07%
50th	1.18	-0.06%	-0.74%	-10.88%
75th	1.82	0.05%	0.62%	7.83%
95th	3.06	0.28%	3.38%	31.42%
99th	4.14	0.48%	6.14%	44.57%
Whole Aggregation		0.39%	5.60%	39.62%

Note: This table reports counterfactual changes in product prices across percentiles of the sales distribution, simulated from a one-standard-deviation increase in county-level income inequality (0.07 in the Gini index). Column (1) presents the sales-weighted percentage change in prices at each sales percentile. Column (2) normalizes these effects by the standard deviation of price residuals from the fixed-effects regression $\ln p_{pfrdt} = \delta_{pt} + \delta_{rt} + \delta_{fr} + \delta_{fd} + \delta_{rd} + \epsilon_{pfrdt}$, providing a scale-free measure of magnitude. Column (3) expresses the price effects in column (1) relative to those generated by a one-standard-deviation increase in log per capita income (0.39), allowing a direct comparison between the role of inequality and average income. All values are sales-weighted within each product percentile group. The final row reports aggregate effects for the entire sample.

deviation increase in inequality corresponds to a 5.6 percent increase relative to the standard deviation of price residuals. For additional context, column (3) compares the effects of inequality with those of per capita income. A one-standard-deviation increase in the Gini index has roughly 40 percent of the price impact associated with a one-standard-deviation increase in log per capita income (0.39). Overall, the price impact associated with a one-standard-deviation increase in the Gini index is approximately 40% of the effect resulting from a one-standard-deviation increase in per capita income.

3.3 Instrumental Variable Approach

A potential concern in regressing prices on measures of income inequality is reverse causality: changes in product prices may influence the returns to different factors of production, thereby feeding back into income inequality. We believe this concern is limited in our context, since price changes at the level of individual UPCs are unlikely to be large enough to shift factor incomes at the county level. Nevertheless, to further mitigate potential endogeneity bias, we implement an instrumental variable (IV) strategy.

Our instrument follows the logic of Doerr et al. [2024] by interacting each county’s initial level of inequality with the subsequent national evolution of inequality. Specif-

ically, we use the county’s Gini coefficient in 1996—eight years prior to the start of our sample—and interact it with the leave-one-out national trend in the Gini index, computed by excluding the county itself from the national average:

$$\widehat{Gini}_{dt} = Gini_{d,1996} \times \frac{1}{N-1} \sum_{j \neq d}^N \frac{Gini_{jt}}{Gini_{j,1996}}. \quad (2)$$

The resulting measure, \widehat{Gini}_{dt} , captures how inequality would have evolved in county d if it had followed the national trend, scaled by its initial level of inequality. We then use this predicted series as an instrument for the observed county-level Gini between 2004 and 2018. The validity of our instrument rests on its ability to capture national shifts in inequality while remaining orthogonal to local price shocks. The leave-one-out national trend reflects broad forces such as technological change, globalization, and macroeconomic shifts that drive inequality across the country but are unlikely to be influenced by prices in any single county.

IV Results. Table 5 reports the instrumental variable estimates. Columns (1) and (2) present results without and with product group–county–year fixed effects, respectively. The IV specification reduces the sample size from 29.5 million observations in the baseline OLS to 19.8 million, owing to missing county-level Gini data in 1996. For comparability, column (3) replicates the baseline OLS estimate from column (1) of Table 3 using the restricted IV sample. The results confirm the robustness of our baseline findings: the coefficients on inequality and its interaction with product market size remains statistically significant across specifications.

The IV estimates are larger in magnitude than the OLS results, consistent with attenuation bias arising from noise in county–year Gini coefficients.¹⁶ To further demonstrate the presence of attenuation bias, we re-estimate the baseline OLS using smoothed measures of inequality. Column (4) reports results based on a three-year moving average, $Ineq_{dt}^{3yrs} = \frac{1}{3} \sum_{\tau \in \{-1,0,1\}} Ineq_{d,t+\tau}$, which yields a larger coefficient than the baseline estimate. Column (5) shows similar results when using a five-year moving average. In both cases, smoothing reduces transitory noise in the Gini coefficient and produces estimates that are closer in magnitude to the IV results.

¹⁶Formally, the probability limit of the OLS estimator under measurement error is $\beta^{OLS} = \beta \times \text{Var}(\text{Inequality}) / [\text{Var}(\text{Inequality}) + \text{Var}(\text{Noise})]$. When the variance of the measurement error is large, the OLS coefficient is attenuated toward zero.

Table 5: Effect of Income Inequality on Product Prices (IV Results)

Dep var: $\ln p_{prdt}$	(1)	(2)	(3)	(4)	(5)
	IV	IV	OLS (IV sample)	OLS (3 yrs Ineq)	OLS (5 yrs Ineq)
$Ineq_{dt} \times \ln Sales_{prdt0}$	0.162*** (0.062)	0.166*** (0.055)	0.022** (0.011)	0.044** (0.019)	0.055** (0.023)
$\ln Sales_{prdt0}$	0.072*** (0.011)	0.069*** (0.013)	0.061*** (0.014)	0.069*** (0.014)	0.069*** (0.014)
$Ineq_{dt}$	-0.218** (0.099)		-0.034* (0.019)	-0.071** (0.034)	-0.089** (0.039)
Observation	19,795,401	19,791,362	19,795,401	29,535,724	29,535,724
Other Controls	Y	Y	Y	Y	Y
<i>Fixed Effect:</i>					
UPC \times Year	Y	Y	Y	Y	Y
Firm \times Retailer	Y	Y	Y	Y	Y
Firm \times County	Y	Y	Y	Y	Y
Retailer \times Year	Y	Y	Y	Y	Y
Retailer \times County	Y	Y	Y	Y	Y
Product Group \times County \times Year	-	Y	-	-	-

Note: The dependent variable is the logarithm of the average unit price of product p in retailer r , county d , and year t . $Ineq_{dt}$ denotes the county-level Gini coefficient of income inequality. Market size is measured as the log of baseline sales at the product–retailer–county level. Baseline values are defined in the first year of the sample. Columns (1) and (2) present IV estimates, with column (2) including product group–county–year fixed effects. Column (3) reports OLS estimates restricted to the IV sample for comparability. Columns (4) and (5) present OLS estimates using inequality smoothed over three and five years. Robust standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Quantitatively, the IV estimates imply that a one–standard–deviation increase in inequality raises the sales–weighted average price by 2.7 percent, approximately seven times the baseline effect reported in column (1) of Table 4. By contrast, when we smooth the Gini coefficients, the corresponding price effects are 0.65 and 0.81 percent under the three–year and five–year moving averages, respectively.

3.4 Prices and Inequality across Firms and Retailers

Effects across Firms. Whether large firms raise prices in response to higher inequality is not obvious a priori. Their size reflects, in part, the dominance of high–market–share products, which tend to become more expensive as inequality rises. At the same time, large firms typically operate a broad portfolio that also includes many low–market–share products, whose prices would fall with higher inequality. Thus, the overall effect on firm-level prices depends on the balance of these product types within a firm’s mix. For example, a firm with a substantial number of low–market–share goods may still experience an overall price decline, even if its best-selling products see price increases.

Panels (a) and (b) of Figure 2 illustrates this mechanism by plotting firm-level

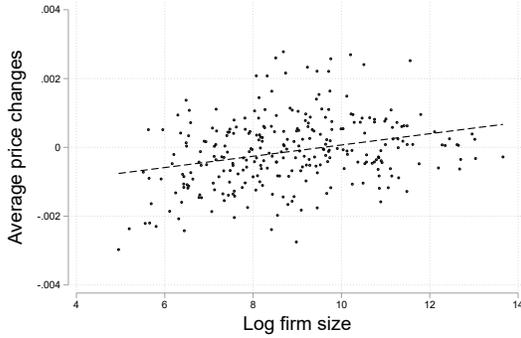
price changes in 2004, following a one-standard-deviation increase in inequality, against total firm sales. We report both a simple average across products and a sales-weighted average using local retailer sales. The results reveal a generally positive relationship between the average price change and firm sales, suggesting that higher inequality tends to benefit large firms. However, the relationship is not perfect; there is considerable variation, particularly among medium-sized firms. For instance, when examining the simple average price change, some medium-sized firms appear to lower prices in response to higher inequality, likely because their product mix includes a larger number of low-sales items. This effect is notably diminished when using the sales-weighted average, where the incidence of declining prices is largely confined to the smallest firms.

Effects across Retailers. We conduct a parallel analysis at the retailer level, examining how the average price response to inequality varies with a retail chain’s market size, as displayed in Panels (c) and (d) of Figure 2. The pattern is strikingly consistent with the firm-level evidence: larger retailers tend to raise prices when inequality rises, while smaller ones are more likely to lower them. These results suggest that rising income inequality since the 1980s could be a potential factor that explains the increase in the market power of the largest, or superstar, firms.

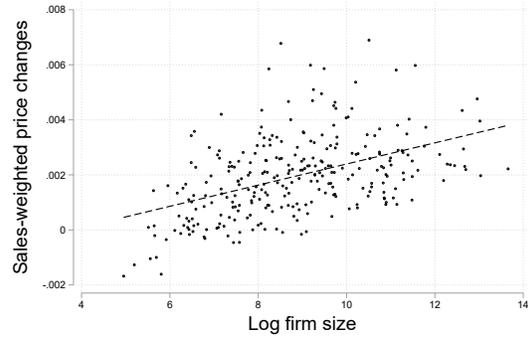
3.5 Robustness

Alternative Measures of Inequality. We replace the Gini coefficient with two widely used alternatives: the Theil index and the coefficient of variation of income. These results are reported in columns (1) and (2) of Table A.2 in the Supplemental Appendix. Both measures are constructed from the Current Population Survey at the county-year level, with the coefficient of variation defined as the standard deviation of income relative to its mean. Across both specifications, the results remain consistent in terms of both statistical and economic significance. Quantitatively, a one-standard-deviation increase in the Theil index (0.13) is associated with a 0.32 percent increase in the sales-weighted average price, while a one-standard-deviation increase in the coefficient of variation (0.30) yields an effect of 0.25 percent. These magnitudes are closely aligned with our baseline estimates, reinforcing the conclusion that the inequality-price relationship is not sensitive to the particular measure of inequality employed.

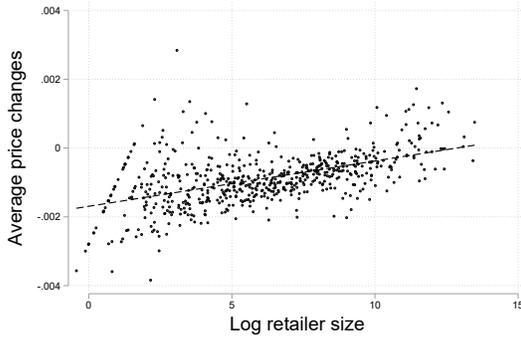
Figure 2: Price Change from 1 S.D. Rise in Inequality, 2004



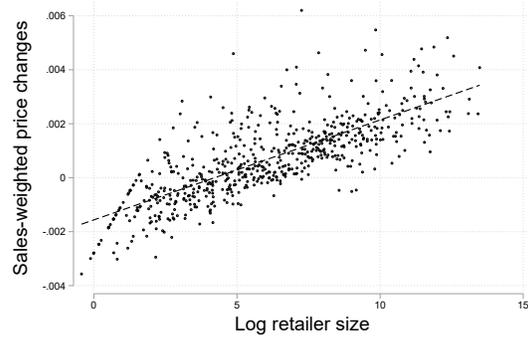
(a) Firm size, simple average



(b) Firm size, sales-weighted average



(c) Retailer size, simple average



(d) Retailer size, sales-weighted average

Note: This figure shows the average price change associated with a one-standard-deviation increase in income inequality in 2004, disaggregated by firm size (top panels) and retailer size (bottom panels). Panels (a) and (c) report simple averages across all products sold by a firm or retailer, while Panels (b) and (d) report sales-weighted averages using local retailer sales to reflect the relative importance of different products. The figure illustrates that larger firms and retailers are more likely to raise prices in response to rising inequality, while smaller ones are more likely to lower them.

Alternative Sample Restrictions and Aggregation. Columns (3) and (4) of Table A.2 assess the robustness of our results to alternative sample restrictions and aggregation choices. Instead of limiting attention to products sold by at least 100 retailers, we apply a more stringent criterion, restricting the sample to products available in at least 500 counties in the NielsenIQ data. The estimated coefficients remain very similar to the baseline results, suggesting that the findings are not driven by products with narrow geographic coverage.¹⁷ We also test robustness to data aggregation. Specifically, we re-estimate the regressions using product–county level data, redefining the dependent variable as $\ln p_{pdt}$ and measuring sales as $\ln \text{Size}_{pdt0}$. The results once again corroborate our baseline findings. Under this specification, a one-standard-deviation increase in the Gini coefficient (0.07) is associated with a 0.1 percent rise in the sales-weighted average price.

Robustness across Product Categories and Retailers. To assess the robustness of our results, we examine how the inequality–price relationship varies across product categories and retailer types (Supplemental Appendix A.5). Nielsen assigns each UPC to one of 125 mutually exclusive categories, ranging from candy and gum to soup, cereal, coffee, and fresh produce. Disaggregating by category, as shown in Figure A.6, we find that most categories replicate our baseline pattern: products with larger market size tend to command higher prices in counties with greater income inequality. The effect is strongest for fresh produce—which represents about 10 percent of sales in our sample—where a one-standard-deviation increase in the Gini coefficient raises the average price by 0.83 percent. The pattern is not uniform, however. In a few categories—such as flour, frozen prepared foods, ice cream, and pet care—the inequality–price gradient is reversed. In these markets, larger products become relatively cheaper in more unequal counties, while smaller products exhibit price increases. Detailed point estimates by product group are reported in Table A.3.

We next explore retailer heterogeneity. Figure A.7 displays the distribution of point estimates, with full results in Table A.4. The overall effect is concentrated among grocery chains, which account for 64 percent of sales in our sample. Within these outlets, a one-standard-deviation increase in the Gini coefficient raises the average price by 0.36 percent. The inequality effect is even more pronounced in specialized

¹⁷Because the analysis requires matching with county-level variables such as inequality, GDP, and population, the effective estimation sample is about 300 counties, even for products appearing in more than 500 counties in the raw data.

retail formats—including Coop/Farm/Feed stores, service stations, gas mini-marts, and fruit stands—where prices respond more strongly to local income dispersion.

Evidence from Estimated Markups. Our baseline analysis examines how inequality shapes market power through prices. To reinforce these findings, we provide complementary evidence using estimated firm-level markups. We adopt a production function estimation approach, widely used in the industrial organization literature [De Loecker and Warzynski, 2012, De Loecker et al., 2020, De Loecker, 2021]. This method assumes firms minimize costs with respect to flexible inputs, and defines the markup as the wedge between the revenue share of materials and their output elasticity.

By merging the NielsenIQ data with the Compustat database through GS1 firm-identifiers, we estimate sector-specific production functions and compute markups at the firm level. To evaluate the impact of income inequality on markups, we construct a Bartik-style exposure measure to income inequality, so that firms with larger sales in more unequal counties are more exposed to income inequality. Details are provided in Supplemental Appendix A.6. The regression results, reported in Supplemental Appendix Table A.5, reveal a consistent pattern of heterogeneity across firms, with larger firms increasing their markups with higher income inequality.

3.6 Mechanisms

To understand how inequality shapes firm pricing, in this section we examine whether our results are driven by price discrimination (e.g., firms are able to sell the same good at different prices to different consumers) or by consumer sorting (e.g., richer households buying relatively more of high-market-share products).

Feasibility of Price Discrimination. First, we consider price discrimination. For instance, suppose that in counties with greater income inequality, consumers from different income brackets may shop at distinct stores. This segmentation allows firms to price discriminate by either charging different prices for the same barcode or offering differentiated barcodes, to cater to the taste of different segments. To account for these possibilities, our regressions focus on barcodes available across a broad set of retail chains and counties, incorporating retail fixed effects to exploit within-chain variation. In this section, we present additional evidence suggesting that, for most

firms and barcodes, price discrimination is not feasible. This is because consumers across different income levels tend to shop at the same stores, reside in the same counties, and purchase identical barcodes. Furthermore, the majority of barcodes are purchased across multiple counties and retail chains.

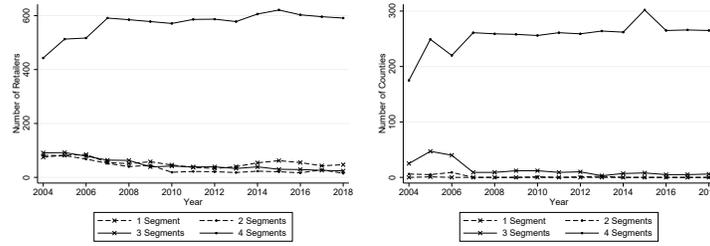
Using Nielsen Household Panel data, we categorize households into four income brackets: (i) below \$30,000, (ii) \$30,000–\$60,000, (iii) \$60,000–\$100,000, and (iv) above \$100,000. We then count the number of retailers that serve only one income group, as well as those that serve two, three, or all four groups. Panel (a) of Figure 3 shows that the vast majority of retailers, roughly 600 out of 700, record positive sales to households from all four income brackets. Similarly, Panel (b) reveals that nearly all counties in our sample include Nielsen households from each income group.

In the bottom panels of Figure 3, we examine how products (UPCs) are distributed across income segments. Panel (c) shows that while a substantial share of products is purchased by households in all four income groups, a non-negligible number appear to be purchased exclusively within a single segment. This pattern, however, is largely mechanical: given the high dimensionality of the product space relative to the number of households, many products are purchased by only one household in a given year, and thus are, by construction, linked to a single income group.¹⁸ To address this issue, Panels (d) and (e) restrict the sample to products purchased by at least two and five households, respectively. Under these thresholds, the share of products confined to a single income segment drops sharply and becomes the smallest among the four groupings. This shift suggests that once we condition on products with broader consumer reach, overlap across income groups is the norm rather than the exception. Moreover, Supplemental Appendix A.7 documents that most products in our dataset are sold across multiple counties and retailers, further limiting the scope for firms to segment markets by income. These patterns suggest that price discrimination through income-specific product targeting is likely to be limited in practice.

Inequality and Consumer Sorting. We next examine whether our results reflect shifts in market share across income segments. Mongey and Waugh [2025] propose a mechanism whereby rising inequality leads wealthier households to concentrate their purchases among large firms, while poorer households shift toward smaller ones.

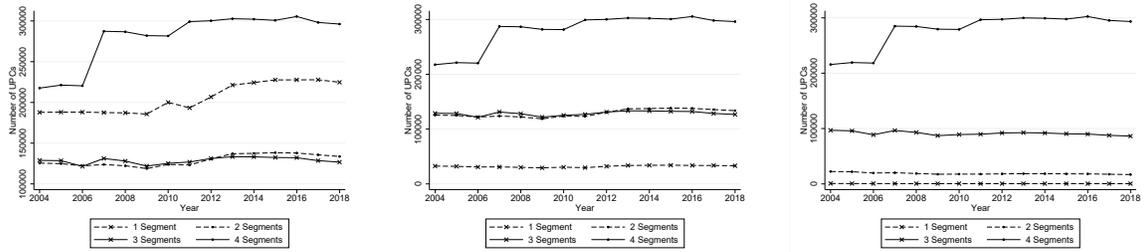
¹⁸Contrary to our regressions, we are not restricting the sample to products sold in at least 100 retailers in this analysis.

Figure 3: Segment Reach of Retailers, Counties, and Products (UPCs)



(a) Retailers

(b) Counties



(c) All UPCs

(d) ≥ 2 Households

(e) ≥ 5 Households

Note: This figure documents the extent of overlap across income groups in both retailer/county coverage and product (UPC) purchases. The top figures illustrate the number of retailers (Panel a) and counties (Panel b) that serve different numbers of income segments each year, based on Nielsen Household Panel data from 2004 to 2018. Households are classified into four income groups: (i) below \$30,000, (ii) \$30,000–\$60,000, (iii) \$60,000–\$100,000, and (iv) above \$100,000. A retailer (or county) is said to reach a given number of segments if it records nonzero purchases from households in that many income groups. The top line in each panel represents retailers or counties reaching all four income groups. The bottom figures plot the number of unique UPCs (products) that are purchased by one, two, three, or four distinct income segments in each year from 2004 to 2018, based on Nielsen Household Panel data. A UPC is defined as reaching a segment if it is purchased by at least one household within that income group. Panel (c) includes all UPCs in the data. Panels (d) and (e) restrict the sample to UPCs purchased by at least two and five households, respectively, within a given year. The y-axis reports the number of UPCs in each segment-reach category (1 to 4), while the x-axis shows calendar years.

This reallocation of demand would, in turn, exert upward pricing pressure on larger firms and downward pressure on smaller ones. To test this channel, we assess how a firm’s sales distribution across income segments varies with local income inequality. Specifically, we estimate the following regression model:

$$ShareQ_{i_{f_{dt}}} = \beta_1 Ineq_{dt} + \beta_2 \ln Sales_{f_{dt}} + Z'_{dt} \Gamma + \delta_{fd} + \delta_{ft} + \epsilon_{f_{dt}} \quad (3)$$

where $ShareQ_{i_{fdt}}$ denotes the share of a firm’s total sales attributed to income segment $i = 1, \dots, 4$. Specifically, we first decompose a firm’s county-level sales ($Sales_{fdt}$) into four components based on the income segments of the purchasing households, denoted as $Sales_{fdt}^{Q_i}$. Then, $ShareQ_{i_{fdt}}$ is calculated as the ratio $Sales_{fdt}^{Q_i}/Sales_{fdt}$. The specification controls for firm size (via $\ln Sales_{fdt}$) and county-level characteristics, including $\ln PGDP_{dt}$ and $\ln POP_{dt}$. We include firm-county and firm-year fixed effects, and cluster standard errors at the firm level.

Table 6 shows that larger firms have disproportionately higher market shares among wealthier consumers, consistent with Faber and Fally [2021]. Given this finding, we argue that our identified mechanism may partially dampen the transmission from nominal to real income inequality. In fact, we have previously documented that larger firms tend to charge higher average prices in areas with greater income inequality. Crucially, because these firms sell disproportionately to higher-income households, the resulting price increases are primarily borne by those at the top of the income distribution. Table 6 also shows that the direct impact of inequality on consumer sorting across income segments appears limited. Although we observe a positive correlation between inequality and market shares in the lowest income segment, this relationship becomes small and statistically insignificant once we interact inequality with firm size, as shown in columns (5)–(8) of Panel (a). Therefore, rising inequality does not meaningfully reshape how consumers sort across firms.

While our baseline analysis is conducted at the product level, it does not directly reflect firm-level sorting. To ensure consistency, we replicate regression (3) at the product–retailer–county level, calculating the annual share of consumers reached in each income segment. Panel (b) of Table 6 presents the results from this more granular specification, which reveals a modest pattern of consumer reallocation that varies with product size. For the second income quartile, higher inequality is associated with a gain in market share for products with low sales. However, this effect declines as product size increases and eventually becomes negative once sales exceed the 97th percentile. In contrast, within the third income quartile, inequality initially leads to a reduction in market share for smaller products. This effect diminishes with size and ultimately turns positive for products above the 95th percentile. These patterns point to subtle, product-size-dependent shifts in consumer composition, though the aggregate impact remains limited.

To evaluate whether consumer sorting explains our baseline pricing results, we

Table 6: Income Inequality and Market Reach Across Income Segments

<i>Panel (a): Market reach at $f - d - t$ level</i>								
Dep var: $\ln \text{Share}Q_{i_{fat}}$	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q1	(6) Q2	(7) Q3	(8) Q4
$\ln \text{Sales}_{fat}$	-0.016*** (0.001)	-0.007*** (0.001)	-0.000 (0.001)	0.023*** (0.001)				
Ineq_{dt}	-0.006 (0.004)	0.009** (0.004)	-0.008* (0.004)	0.004 (0.004)	0.002 (0.012)	0.019 (0.014)	-0.016 (0.013)	-0.005 (0.014)
$\text{Ineq}_{dt} \times \ln \text{Sales}_{fat0}$					-0.002 (0.002)	-0.002 (0.002)	0.002 (0.002)	0.002 (0.003)
Observation	969,731	969,731	969,731	969,731	969,731	969,731	969,731	969,731
R-squared	0.272	0.214	0.208	0.305	0.269	0.214	0.208	0.302
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y
<i>Fixed Effect:</i>								
Firm \times County	Y	Y	Y	Y	Y	Y	Y	Y
Firm \times Year	Y	Y	Y	Y	Y	Y	Y	Y
<i>Panel (b): Market reach at $p - r - d - t$ level</i>								
Dep var: $\text{Share}Q_{i_{prdt}}$	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q1&Q2	(6) Q3&Q4		
$\text{Ineq}_{dt} \times \ln \text{Sales}_{prdt0}$	-0.002 (0.002)	-0.009*** (0.002)	0.008*** (0.002)	0.003 (0.003)	-0.011*** (0.003)	0.011*** (0.003)		
$\ln \text{Sales}_{prdt0}$	-0.020*** (0.003)	-0.007** (0.003)	0.023*** (0.003)	0.005 (0.005)	-0.027*** (0.004)	0.027*** (0.004)		
Ineq_{dt}	-0.004 (0.004)	0.031*** (0.004)	-0.025*** (0.004)	-0.001 (0.005)	0.027*** (0.003)	-0.027*** (0.003)		
Observation	29,535,724	29,535,724	29,535,724	29,535,724	29,535,724	29,535,724		
R-squared	0.084	0.063	0.063	0.103	0.101	0.101		
Other Controls	Y	Y	Y	Y	Y	Y		
<i>Fixed Effect:</i>								
UPC \times Year	Y	Y	Y	Y	Y	Y		
Firm \times Retailer	Y	Y	Y	Y	Y	Y		
Firm \times County	Y	Y	Y	Y	Y	Y		
Retailer \times Year	Y	Y	Y	Y	Y	Y		
Retailer \times County	Y	Y	Y	Y	Y	Y		

Note: This table examines how a firm's or product's market reach varies across income segments in response to local income inequality. Panel (a) reports regressions at the firm-county-year level, where the dependent variable is the log share of sales to income segment i out of the firm's total county-level sales. Panel (b) presents results at the product-retailer-county-year level, using the share of consumers from segment i among all buyers of a given product. Ineq_{dt} measures county-level income inequality, and sales are interacted with inequality to test for heterogeneous effects by size. All regressions include controls for county-level log per capita GDP and log population. Fixed effects vary by panel and are indicated in the table. Robust standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

augment the main regression by controlling for the share of consumers in the third and fourth income quartiles—that is, the top half of the income distribution—as well as their interaction with product size. Table A.6 in the Supplemental Appendix reports the results. The estimated coefficients on income inequality remain virtually unchanged, regardless of whether product size is measured by total sales or by market share. This stability suggests that the pricing response to inequality does not stem from changes in the composition of the consumer base, but rather reflects firms' direct adjustment to income dispersion in the market.

3.7 Extended Evidence from Chinese Exporters

As complementary evidence, we extend our analysis using firm–product–destination transaction data from the Chinese Customs Trade Statistics. This dataset provides detailed information on export quantities and values at the HS eight-digit–firm–destination level for the universe of Chinese merchandise trade. We focus on the period from 2007 to 2015. In this setting, we examine how income inequality in destination countries influences the unit values charged by Chinese exporters. A product p is defined as an HS eight-digit code, a firm f is identified as a Chinese exporter, and a destination d refers to the importing country. We then apply the same regression specification as in our baseline analysis (1).

We control for destination-country characteristics by including log per capita GDP and log population, along with their interactions with baseline sales $\ln Sales_{pfdt0}$. Standard errors are clustered at the firm level, and descriptive statistics for all variables are reported in Table 1. Because products are defined at the HS eight-digit level, unit values may also reflect differences in product quality or product composition across destinations. As a result, these extended results should be interpreted with caution: they may capture not only how inequality affects markups, but also its effects on quality and product composition.

Table 7 presents the main results using the Gini coefficient as our measure of inequality, while Supplemental Appendix Table A.7 reports the coefficients on the control variables. Consistent with our baseline findings, higher income inequality is associated with lower prices for products with small sales. The effect attenuates as product market size increases and eventually turns positive: beginning at roughly the 80th percentile of product sales, inequality raises rather than lowers prices. This pattern is robust to alternative measures of inequality, including the Theil index, and to a variety of fixed-effects specifications. Quantitatively, a one–standard deviation increase in the destination-country Gini index (0.08) raises the sales-weighted average export price by about 1.0%, while an equivalent increase in the Theil index (0.17) produces a slightly larger effect of 1.3%.

Table 7: Export Prices and Income Inequality: HS 8-digit Products by Chinese Firms

Dep var: $\ln p_{pfdt}$	(1)	(2)	(3)	(4)
	Gini	Gini	Theil	Theil
$Ineq_{dt} \times \ln Sales_{pfdt0}$	0.034*** (0.003)	0.048*** (0.011)	0.006*** (0.002)	0.039*** (0.005)
$\ln Sales_{pfdt0}$	0.104*** (0.006)		0.103*** (0.007)	
$Ineq_{dt}$	-0.369*** (0.037)		-0.009 (0.018)	
Observation	22,418,272	11,106,107	15,311,989	7,626,146
R-squared	0.718	0.917	0.706	0.909
Other Controls	Y	Y	Y	Y
<u>Fixed Effect:</u>				
Year	Y	Y	Y	Y
Product	Y	Y	Y	Y
Country	Y	Y	Y	Y
Firm	Y	Y	Y	Y
Product \times Year	-	Y	-	Y
County \times Year	-	Y	-	Y
Firm \times Year	-	Y	-	Y
Product \times County \times Firm	-	Y	-	Y

Note: The dependent variable is the log of export prices at the HS 8-digit product–firm–destination–year level. The main explanatory variable is the interaction between destination-country inequality ($Ineq_{dt}$, measured by either the Gini or Theil index) and baseline product–firm–destination sales ($\ln Sales_{pfdt0}$). This interaction captures how the effect of inequality on prices depends on a firm’s initial market size in each destination. Columns (1)–(2) use the Gini index and columns (3)–(4) use the Theil index. All regressions include country-year controls (log per capita GDP and log population of destination country, and their interactions with baseline sales) and the fixed effects listed in the table. Robust standard errors are clustered at the firm level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4 Theoretical Analysis

This section develops a model that links consumer inequality in income to firms’ pricing rules and markups. We consider a differentiated-goods sector with a discrete number I of income groups, or segments, indexed by i . Consumers in segment i share the same income z_i and identical preferences, and there are L_i consumers in that segment. Income levels differ across segments.¹⁹

¹⁹At the most disaggregated level, segments may be interpreted as individual households, with L_i denoting the size of household i . The analysis is robust to allowing a continuous distribution of incomes. The assumption of a discrete number of segments mirrors our empirical analysis of consumer reach.

On the production side, we focus on the problem of a firm supplying a single product. Restricting attention to single-product firms allows us to abstract from product-mix decisions and potential cannibalization effects.²⁰ To isolate the impact of consumer heterogeneity on firm-level markups, we also abstract from firm entry and from the general equilibrium of the model. We assume that firms cannot price discriminate across consumers. This reflects the empirical evidence that households with different incomes largely purchase the same products from the same stores within a given geographic area. Our framework therefore captures retail markets in which all consumers face a uniform price. Personalized discounts or targeted promotions are excluded from consideration. If price discrimination were feasible, firms would set segment-specific prices based on the income and demand of each group. In its absence, however, firms must set a single uniform price while accounting for the underlying heterogeneity of their customers. The central question of the theory is whether this uniform price, holding marginal cost fixed, is higher or lower than the price a firm would charge if it faced a representative “average” consumer.

4.1 Firm’s Problem

Consider a firm that produces a single variety at constant unit cost c and sets a uniform price p across all consumer segments. The demand from segment i is given by the direct demand function:

$$q_i = q(p, z_i) \tag{4}$$

where q_i depends on the firm’s price p and the income z_i of segment i .²¹ Firm profits are therefore:

$$\pi = \sum_{i=1}^I L_i q(p, z_i) (p - c) \tag{5}$$

where L_i denotes the size of segment i . The firm maximizes profits by choosing p . The first-order condition is:

$$\text{FOC: } (p - c) \sum_{i=1}^I L_i \frac{\partial q(p, z_i)}{\partial p} + \sum_{i=1}^I L_i q(p, z_i) = 0 \tag{6}$$

²⁰For a numerical analysis of multi-product firms and cannibalization effects in the presence of consumer heterogeneity and oligopoly, see [Feenstra et al. \[2025\]](#).

²¹Although we refer to z_i as income, to remain consistent with the empirical analysis, it may also be interpreted more generally as a preference parameter specific to segment i .

Define the price elasticity of demand for segment i as $\epsilon(p, z_i) = -\frac{\partial q(p, z_i)}{\partial p} \frac{p}{q(p, z_i)}$ and let $s_i(p, z_i) = \frac{pL_i q(p, z_i)}{\sum_{i=1}^I pL_i q(p, z_i)}$ denote the share of segment i in the firm's total sales. Using these definitions, the first-order condition can be expressed compactly as:

$$-\frac{p-c}{p} \sum_{i=1}^I s_i(p, z_i) \epsilon(p, z_i) + 1 = 0 \quad (7)$$

This expression shows that the firm's optimal markup, $\frac{p-c}{p}$, is the inverse of a sales-weighted average elasticity of demand across all consumer segments. In other words, pricing depends not only on how sensitive each group is to price but also on the share of total revenue that each segment contributes. As a special case, if all consumers belong to a single segment, then $s_i = 1$ and the condition reduces to the familiar Lerner rule, $\frac{p-c}{p} = 1/\epsilon(p, z_i)$.²²

Optimal Price and Demand Elasticity. The firm's optimal price equals:

$$p = \frac{\bar{\epsilon}(p, \mathbf{z})}{\bar{\epsilon}(p, \mathbf{z}) - 1} c \quad (8)$$

where

$$\bar{\epsilon}(p, \mathbf{z}) = \sum_{i=1}^I s_i(p, z_i) \epsilon(p, z_i) \quad (9)$$

is the average demand elasticity across segments, and \mathbf{z} is the vector of segment incomes. Thus, the firm charges a price that equals a markup over marginal costs, where the markup depends on the average demand elasticity in the market, given the price p and the vector of incomes \mathbf{z} . If a firm's share on less elastic consumers increases, the firm will be able to charge a higher price.²³

Our objective is to examine the conditions under which a mean-preserving spread in consumer income, \mathbf{z} , leads to higher or lower prices. Specifically, we investigate

²²Supplemental Appendix B.1 shows how the problem can alternatively be solved under the assumption that the firm chooses quantities rather than price.

²³Similarly to the mechanism proposed by Mongey and Waugh [2025], equation (9) can link three facts that have been documented in the literature: (i) that large firms sell more to richer households [Faber and Fally, 2021]; (ii) that large firms have higher markups [De Loecker and Warzynski, 2012]; and (iii) that richer households pay higher prices [Sangani, 2022]. If richer households have lower demand elasticity $\epsilon(p, z_i)$ than poorer households, conditional on the same price, and larger firms have larger demand shares from richer households, larger firms will charge a higher markup, according to (8) and (9).

whether an increase in income dispersion, while holding per capita income constant, results in higher or lower prices. Equations (8) and (9) imply that changes in the income distribution affect prices by influencing the average demand elasticity faced by the firm at its optimal price. If changes in the income distribution increase the average demand elasticity, the firm will reduce its price; conversely, if these changes decrease the average demand elasticity, the firm will raise its price. While [Mongey and Waugh \[2025\]](#) show that higher firms charge higher prices in the presence of inequality because consumers with low-demand elasticities spend more on products from large firms, in our case, we study the effects of inequality without making any assumptions on how inequality affects the sorting of consumers.

The intuition is as follows. Moving from a representative consumer to multiple income segments inevitably introduces at least one group with relatively low demand elasticity. Charging a higher price allows the firm to capture more surplus from that group, but at the cost of lower sales to more price-sensitive consumers. The firm’s pricing decision therefore reflects a tradeoff between exploiting low-elasticity demand and maintaining sales to high-elasticity segments. In the next section, we show that which effect dominates depends on the curvature of the demand function, and we derive the conditions under which greater income dispersion leads to higher or lower equilibrium prices.

4.2 The Effects of Inequality on Prices

Equations (8) and (9) are well-suited for comparing prices across firms: given consumer demand elasticities, firms vary in the share of sales to each segment, leading to differences in pricing. However, our objective is to examine how changes in the income distribution affect prices. Such changes influence both demand elasticities and the composition of a firm’s demand share across segments. To better capture the mechanisms through which inequality impacts prices, it is more convenient to reformulate the FOC. In particular, we define the function $G(p, z)$ as:

$$G(p, z) = (p - c) \frac{\partial q(p, z)}{\partial p} + q(p, z) \quad (10)$$

where we assume that $G(p, z)$ is decreasing in p . This guarantees that the first-order condition is well defined for any single segment, ensuring concavity of the profit function even when the firm serves only one segment. Under this formulation, the

first-order condition in (6) can be expressed as:

$$\text{FOC: } \sum_{i=1}^I \alpha_i G(p, z_i) = 0 \quad (11)$$

where $\alpha_i = \frac{L_i}{\sum_{i=1}^I L_i}$ denotes the population share of segment i . Following the notation of Feenstra et al. [2025], let p_{HetC} denote the optimal price for a firm facing heterogeneous consumers, defined as:

$$p_{HetC} : \sum_{i=1}^I \alpha_i G(p_{HetC}, z_i) = 0 \quad (12)$$

Conversely, let p_{RepC} be the optimal price for a firm facing a representative consumer with average income $\bar{z} = \sum_{i=1}^I \alpha_i z_i$:

$$p_{RepC} : G\left(p_{RepC}, \sum_{i=1}^I \alpha_i z_i\right) = 0 \quad (13)$$

To assess which price is higher, we compare the FOC in (12) with that in (13). A sufficient condition is given by the curvature of $G(p, z)$ in income z : if $G(p, z)$ is convex in z , greater income inequality raises prices, whereas if it is concave, greater inequality lowers prices.

Formally, by Jensen's inequality,

$$\sum_{i=1}^I \alpha_i G(p, z_i) \geq G\left(p, \sum_{i=1}^I \alpha_i z_i\right) \quad \text{if} \quad \frac{\partial^2 G(p, z)}{\partial z^2} > 0 \quad (14)$$

with strict inequality whenever z_i differs across at least two segments. Because $G(p, z)$ is decreasing in p , inequality (14) implies $p_{HetC} \geq p_{RepC}$. Thus, when $G(p, z)$ is convex in income, a firm sets a higher price for heterogeneous consumers than for a representative consumer with average income. Intuitively, greater income dispersion lowers the average demand elasticity, which translates into higher equilibrium prices. Conversely,

$$\sum_{i=1}^I \alpha_i G(p, z_i) \leq G\left(p, \sum_{i=1}^I \alpha_i z_i\right) \quad \text{if} \quad \frac{\partial^2 G(p, z)}{\partial z^2} < 0, \quad (15)$$

with strict inequality again if incomes differ across segments. In this case, since $G(p, z)$ decreases with p , it follows that $p_{HetC} \leq p_{RepC}$. Hence, if $G(p, z)$ is concave in income, greater inequality induces the firm to charge lower prices. In short, the curvature of $G(p, z)$ in income determines the sign of the inequality effect on prices.

To make this precise, consider the second derivative:

$$\frac{\partial^2 G(p, z)}{\partial z^2} = \frac{\partial^2 q(p, z)}{\partial z^2} + (p - c) \frac{\partial^3 q(p, z)}{\partial p \partial z^2} \quad (16)$$

This expression consists of two distinct components. First, the term $\frac{\partial^2 q(p, z)}{\partial z^2}$ captures the *curvature of demand with respect to income*, indicating whether demand is convex or concave in z . If demand is convex in income z , then greater income dispersion increases the aggregate demand faced by a firm. To provide intuition, consider a normal good. With higher income dispersion, relative to a representative consumer, the income increase among wealthier households leads to a disproportionately large rise in demand, which more than compensates for the reduction in demand from the lower incomes of poorer households.

The second term, $\frac{\partial^3 q(p, z)}{\partial p \partial z^2}$, captures the *curvature of the price derivative of demand with respect to income*, indicating whether the price derivative of demand for the product is concave or convex in income. If the price derivative of demand is convex in income, higher income inequality causes a smaller change in quantity demanded given the same absolute change in price.²⁴

Depending on the signs of $\frac{\partial^3 q(p, z)}{\partial p \partial z^2}$ and $\frac{\partial^2 q(p, z)}{\partial z^2}$, we can identify four distinct cases, each corresponding to a different impact of income dispersion on prices. The outcomes are summarized in Table 8.

Case 1: Inequality Raises Prices for All Firms. This case arises when both derivatives are positive. If $\frac{\partial^3 q(p, z)}{\partial p \partial z^2} > 0$ and $\frac{\partial^2 q(p, z)}{\partial z^2} > 0$, then it follows that $\frac{\partial^2 G(p, z)}{\partial z^2} > 0$. In this environment, greater inequality increases aggregate demand because demand is convex in income, while at the same time it reduces price sensitivity since the price derivative of demand is also convex in income. The combination of stronger demand

²⁴To illustrate this, suppose that demand is linear in price, with a slope that depends on income: $\frac{\partial q(p, z)}{\partial p} = -b(z)$. The condition for convexity of the price derivative of demand, $\frac{\partial^3 q(p, z)}{\partial p \partial z^2} = -b''(z) > 0$, implies that $b''(z) < 0$. In other words, the absolute value of the slope of the direct demand curve is concave in income. This implies that an increase in income inequality reduces the value of $b(z)$, making the quantity demanded less sensitive to absolute changes in prices.

and weaker price sensitivity leads all firms to raise their prices.

Case 2: Inequality Raises Prices for Efficient Firms. This case, which is consistent with the empirical evidence, arises when $\frac{\partial^3 q(p,z)}{\partial p \partial z^2} > 0$ and $\frac{\partial^2 q(p,z)}{\partial z^2} < 0$. In this setting, convexity of $G(p, z)$ requires the following condition:

$$p + \frac{\partial^2 q(p, z)}{\partial z^2} \Big/ \frac{\partial^3 q(p, z)}{\partial p \partial z^2} > c \quad (17)$$

Hence, if c is sufficiently small (i.e., the firm is efficient enough), $G(p, z)$ becomes convex in income, and the firm will charge a higher price as inequality increases. Conversely, less efficient firms will reduce their prices.²⁵ The conditions governing the convexity of demand and the slope of demand with respect to income imply that higher income inequality leads to a downward shift in the aggregate demand and a flattening of the quantity-price relationship (or a steepening of the inverse demand function): consumers become less price-sensitive, but aggregate demand decreases. The results indicate that only the most efficient firms, which sell larger quantities, benefit from the reduced price sensitivity, while for smaller firms, the drop in aggregate demand outweighs the effects of reduced price sensitivity.

Case 3: Inequality Raises Prices for Inefficient Firms. This case is the mirror image of Case 2. It arises when $\frac{\partial^3 q(p,z)}{\partial p \partial z^2} < 0$ and $\frac{\partial^2 q(p,z)}{\partial z^2} > 0$. In this scenario, convexity of $G(p, z)$ requires the following condition:

$$p + \frac{\partial^2 q(p, z)}{\partial z^2} \Big/ \frac{\partial^3 q(p, z)}{\partial p \partial z^2} < c \quad (18)$$

Thus, if c is sufficiently high (that is, the firm is relatively inefficient), then $G(p, z)$ becomes convex in income, and the firm raises its price as inequality increases. By contrast, more efficient firms do not satisfy this condition and respond to higher inequality by lowering their prices. The mechanism works in the opposite direction from Case 2. Higher inequality expands aggregate demand, since demand is convex in income, but it also makes consumers more price-sensitive, since the price derivative

²⁵Importantly, for a given firm, the inequality in (17) may only hold for certain segments. Specifically, if $\frac{\partial^2 q(p,z)}{\partial z^2} \Big/ \frac{\partial^3 q(p,z)}{\partial p \partial z^2}$ varies with z , it could be that the convexity of $G(p, z)$ depends on the income level z . In such cases, the inequality may not hold uniformly, and no clear prediction can be made.

of demand is concave in income. Less efficient firms, which produce at smaller scale, benefit from the stronger demand and are able to increase prices. For more efficient firms, however, the heightened price sensitivity dominates, leading them to cut prices as inequality rises.

Case 4: Inequality Lowers Prices for All Firms. Finally, this case is the exact opposite of Case 1. It arises when both derivatives are negative. If $\frac{\partial^3 q(p,z)}{\partial p \partial z^2} < 0$ and $\frac{\partial^2 q(p,z)}{\partial z^2} < 0$ then it follows that $\frac{\partial^2 G(p,z)}{\partial z^2} < 0$. In this environment, greater inequality lowers aggregate demand, since demand is concave in income, while at the same time it raises price sensitivity, since the price derivative of demand is also concave in income. The joint effect of weaker demand and stronger price sensitivity drives all firms to reduce their prices.

Table 8: Implications of Income Inequality for Equilibrium Prices

	$\frac{\partial^2 q(p,z)}{\partial z^2} < 0$ <i>(demand concave in income)</i>	$\frac{\partial^2 q(p,z)}{\partial z^2} > 0$ <i>(demand convex in income)</i>
$\frac{\partial^3 q(p,z)}{\partial p \partial z^2} < 0$ <i>(price derivative concave in income)</i>	(1) $p \downarrow$ for all firms	(3) $p \uparrow$ for high-cost firms
$\frac{\partial^3 q(p,z)}{\partial p \partial z^2} > 0$ <i>(price derivative convex in income)</i>	(2) $p \uparrow$ for low-cost firms	(4) $p \uparrow$ for all firms

Note: The classification is based on the curvature of demand with respect to income, $\partial^2 q(p,z)/\partial z^2$, and the curvature of the price derivative of demand with respect to income, $\partial^3 q(p,z)/\partial p \partial z^2$. Combining these two properties of demand yields four cases for the effects of an increase in income inequality holding constant average income: (1) uniformly lower prices, (2) higher prices for low-cost firms, (3) higher prices for high-cost firms, and (4) uniformly higher prices across all firms.

4.3 An Example with Specific Preferences

Identifying preferences that meet the conditions above is challenging for two main reasons. First, the preferences most commonly used in the literature, such as homothetic or Stone-Geary—satisfy the Gorman form, $q_i(p) = a_i(p) + b(p)z_i$, which implies the existence of a representative consumer. In this case, aggregate demand is linear

in income, so changes in the income distribution have no effect on aggregate demand or prices. Second, some preferences (including Stone-Geary) satisfy the Gorman form only if all consumers purchase the same set of varieties. If consumers instead purchase different sets of varieties, the term $b(p)$ may vary across individuals, breaking the Gorman structure. The difficulty is that in this case the relationship between z_i and q_i must be determined in general equilibrium, since the set of consumed and produced varieties can itself depend on the distribution of z_i . Addressing this requires additional assumptions about technology, the nature of competition among firms, and the sources of income inequality (e.g., whether it is driven by differences in labor skills). These extensions go beyond the scope of our analysis.²⁶

The approach we adopt is to allow other parameters of the utility function to vary with income, without specifying the exact mapping. To illustrate, we assume consumers have heterogeneous preferences captured by the following demand function:

$$q(p, z) = (ap)^{-\sigma(z)} \quad (19)$$

where p is the price, a is a demand shifter, and z denotes income. The function $\sigma(z)$ governs the price elasticity of consumers and is assumed to be smooth with:

$$\sigma'(z) < 0 \quad \text{and} \quad \sigma''(z) > 0.$$

The assumption that the demand elasticity is declining in income is in line with the predictions of most non-homothetic preferences used in the literature. The assumption that the demand elasticity is convex in income allows this demand function to generate the four cases shown above. Depending on the values of the parameters and on the function $\sigma(z)$, these preferences allow for each of the four cases mentioned above. Since the empirical evidence is most consistent with Case 2, our focus in this section is on the sufficient conditions under which that case arises.

In Supplemental Appendix B.2, we show that this demand system can be derived from the implicit non-homothetic CES utility of Matsuyama [2023], once income z is

²⁶One alternative is to focus on variables correlated with income that can be treated as the source of consumer heterogeneity. For example, Feenstra et al. [2025] compare the price set by a firm when serving consumers with different demand shares to the price it would set for a representative consumer with the average demand share. The authors do not model how income inequality maps into those shares.

replaced by household utility U . This implicit utility is given by:

$$\left[\sum_{j=1}^n \beta_j(U)^{1/\sigma(U)} q_j^{1-\frac{1}{\sigma(U)}} \right]^{\frac{\sigma(U)}{\sigma(U)-1}} = 1.$$

To our knowledge, existing applications of this utility have assumed that $\sigma(U) = \sigma$ is constant and let the taste shifters $\beta_j(U)$ vary with U —see, for instance, [Comin et al. \[2021\]](#). As we demonstrate in Supplemental Appendix [B.2](#), when σ is constant the distribution of incomes (or utilities) has no effect on prices. Allowing σ to vary with income (or utility) is therefore essential to obtain the heterogeneous demand responses that drive our results. Leaving the detailed derivations to Supplemental Appendix [B.3](#), a set of sufficient conditions for Case 2 is given by:²⁷

$$\ln(ap) < \frac{\sigma''(z)}{(\sigma'(z))^2}, \quad (20)$$

$$2 \ln(ap) - \sigma(z)(\ln(ap))^2 > \frac{\sigma''(z)}{(\sigma'(z))^2} [1 - \sigma(z) \ln(ap)]. \quad (21)$$

If the price lies within the range defined by the inequalities (which can be ensured by choosing an appropriate range for marginal costs), then more efficient firms with lower marginal costs will respond to higher inequality by raising prices, while less efficient firms with higher marginal costs will respond by cutting them.²⁸

5 Conclusions

This paper investigates how income inequality affects firms' markups, providing evidence from both the United States and China. Leveraging detailed barcode-level data from the NielsenIQ Homescan Consumer Panel and international trade data from Chinese Customs, we demonstrate that the relationship between inequality and prices varies according to products market size. Specifically, we find that higher income inequality reduces prices for products with low sales or low market shares but raises prices for high-selling products. As a result, larger firms, which typically sell

²⁷Without loss of generality, we assume that $\ln(ap) > 0$.

²⁸For example, suppose the relationship between demand elasticity and income is given by $\sigma(z) = (1+z)^{-\rho}$ with $\rho > 0$. Then the sufficient condition for Case 2 reduces to $\frac{(3\rho+1)-\sqrt{5\rho^2+2\rho+1}}{2\rho} (1+z)^\rho < \log(ap) < \frac{\rho+1}{\rho} (1+z)^\rho$.

more high-sales products, tend to increase their average prices when inequality rises, while smaller firms are more likely to reduce their prices.

To explain these findings, we develop a theoretical model in which a firm sells a single product to heterogeneous consumer segments with different incomes and demand elasticities. The firm cannot price discriminate across segments and must set a single price for all consumers. The model predicts that the effect of inequality on prices depends on both the convexity of the demand function and the curvature of the price derivative of demand with respect to income, and it can rationalize the observed empirical pattern.

The results of this paper indicate that the rise in income inequality over the last few decades may be a contributing factor to the increase in both the profit share and market power of firms. Our empirical findings suggest that rising inequality amplifies market power by enabling larger firms to raise prices, thereby pushing up average markups in the economy. Therefore, policies aimed at reducing income inequality—such as progressive taxation, targeted transfers, or stronger collective bargaining—may have broader macroeconomic implications beyond equity. By reshaping the distribution of purchasing power, such policies can influence firm pricing behavior and, in turn, affect aggregate price indexes. In this sense, inequality is not merely a distributional concern; it is a structural variable that interacts with firm behavior and demand elasticity, making it relevant to both competition and monetary policy.

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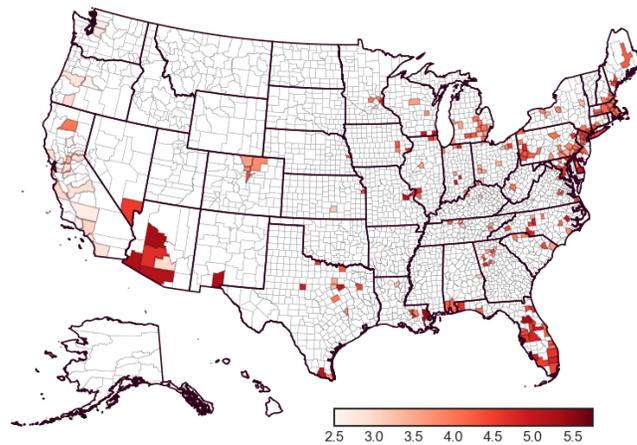
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Supplemental Appendix

A Data Appendix

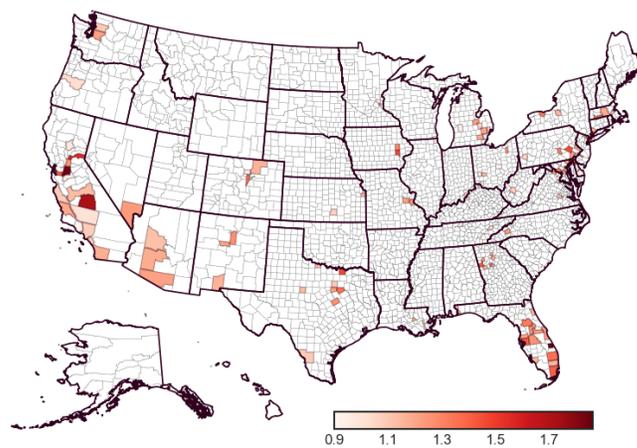
A.1 Descriptive Analysis

Figure A.1: Distribution of Prices for a Top-Selling Butter, 2018



Note: The analysis is limited to about 300 counties for which information on income inequality, GDP, and population is available. The map is based on this restricted sample.

Figure A.2: Distribution of Prices for a Top-Selling Soda, 2018



Note: The analysis is limited to about 300 counties for which information on income inequality, GDP, and population is available. The map is based on this restricted sample.

A.2 Measures of Income Inequality

Following [Boyce et al. \[2016\]](#), we construct two standard measures of income inequality at the county-year level: the Gini coefficient and the Theil index. These measures are calculated using individual household income data from the Current Population Survey (CPS).

Gini Coefficient. The Gini coefficient captures the dispersion of income across households and is computed using the following formula:

$$Gini = 1 + \left(\frac{1}{n}\right) - \left[\frac{2}{MeanY * n^2}\right] \sum_{i=1}^n [(n - i + 1) * Y_i] \quad (A.1)$$

where Y_i is the total family income of household i , n is the total number of households, and $MeanY$ is the average income across all households in the sample. The formula ranks households from lowest to highest income before applying weights, so that households at the bottom of the distribution are assigned higher weights. The Gini coefficient ranges between 0 (perfect equality) and 1 (perfect inequality), with higher values indicating more unequal income distributions.

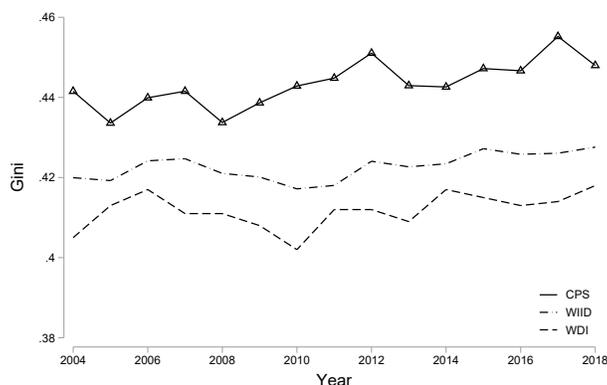
Theil Index. As a complementary measure, we compute the Theil index, also known as the Generalized Entropy measure $GE(1)$, which is particularly sensitive to changes at the upper end of the income distribution. The formula is given by:

$$Theil = \sum_{i=1}^n \left(\frac{w_i}{N}\right) \left(\frac{Y_i}{MeanY}\right) \log\left(\frac{Y_i}{MeanY}\right) \quad (A.2)$$

where Y_i is the income of household i , w_i is the population weight associated with that household, and $N = \sum_{i=1}^n w_i$ is the total weighted population. Like the Gini, the Theil index takes a value of zero under perfect equality, and increases with greater income dispersion. However, unlike the Gini, it is unbounded above and can capture more extreme inequality in the tails of the distribution.

Validation. Figure [A.3](#) benchmarks our constructed Gini series against two widely cited external sources—the WIID and the WDI. To ensure consistency, we aggregate our county-level Gini estimates to the national level for each year in the sample.

Figure A.3: National Trend of US Inequality, 2004–2018



Note: This figure compares the national trend in income inequality based on our CPS-derived Gini estimates to those reported by the World Income Inequality Database (WIID) and the World Development Indicators (WDI). Our Gini series is constructed by averaging county-level Gini coefficients across the US for each year between 2004 and 2018.

Despite differences in data sources, aggregation methods, and underlying definitions of income, the three series exhibit broadly similar trends over the 2004–2018 period. This close correspondence provides reassurance regarding the validity and robustness of our inequality measures.

A.3 Sources of Variation in Income Inequality

To better understand what drives the county-level income inequality measures used in our regression analysis, we examine the sources of variation using microdata from the CPS. The CPS records each individual’s migration status in the prior year, which allows us to classify residents as either *movers* (new entrants to the county) or *stayers* (incumbents). Using this distinction, we decompose income inequality within each county-year using the Theil index:

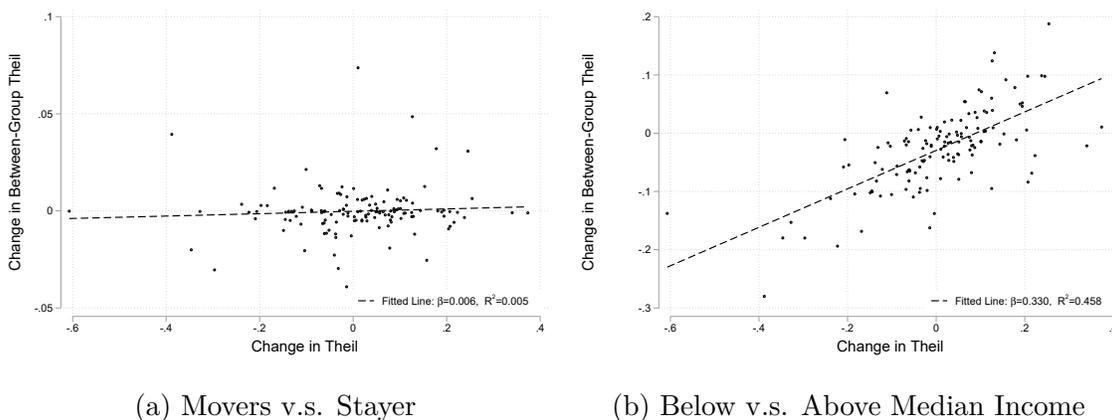
$$T_{dt} = T_{dt}^{\text{Between}} + T_{dt}^{\text{Within}},$$

where T_{dt}^{Between} captures inequality attributable to average income differences between movers and stayers in county d and year t , and T_{dt}^{Within} captures residual inequality within these groups. While this decomposition allows us to separate inequality across groups, it does not isolate the contribution of changes in group composition (e.g., a rising share of movers). To quantify how much of the rise in inequality can be traced

to changes in group disparities, we examine the change in each component over time. Specifically, for each county d , we compute the change in the overall Theil index and its between-group component from 2004 to 2018:

$$\Delta T_d \equiv T_{d,2018} - T_{d,2004}, \quad \Delta T_d^{\text{Between}} \equiv T_{d,2018}^{\text{Between}} - T_{d,2004}^{\text{Between}}.$$

Figure A.4: Decomposition of Income Inequality Change, 2004–2018



Note: Each point represents a US county. Panel (a) plots the change in the Theil index between 2004 and 2018 against the between-group component attributable to income differences between movers and stayers. Panel (b) shows the same comparison using income groups (below vs. above \$15,000 in 2004) instead of migration status. The slope of the fitted line and R^2 indicate the explanatory power of each grouping.

Part (a) of Figure A.4 plots ΔT_d against $\Delta T_d^{\text{Between}}$ where each dot represents a county. We estimate the linear relationship:

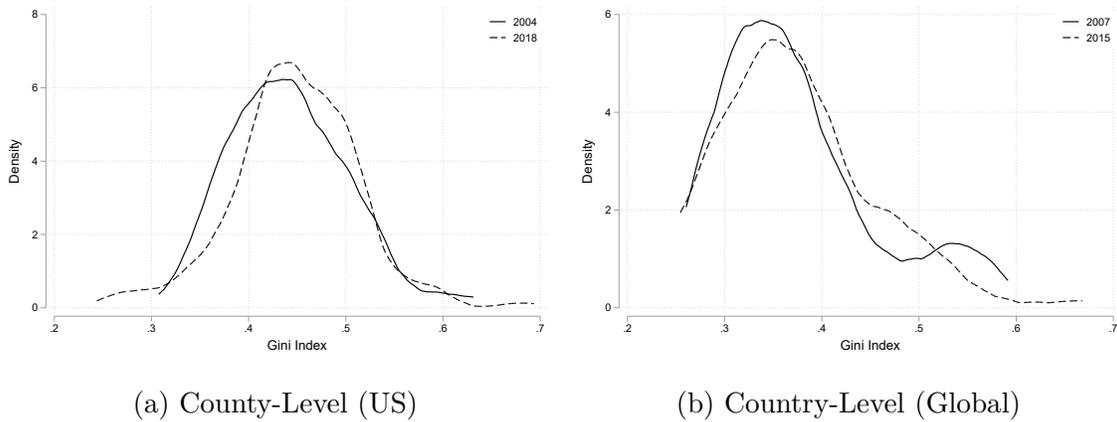
$$\Delta T_d = \alpha_0 + \alpha_1 \Delta T_d^{\text{Between}}.$$

and find that the resulting $R^2 = 0.005$, suggesting that changes in inequality between movers and stayers account for virtually none of the cross-county variation in overall inequality growth. In other words, compositional shifts due to migration are not a major driver of inequality trends at the county level. In contrast, panel (b) adopts a different grouping. We divide individuals based on their income in 2004, those earning below versus above \$15,000, and perform an analogous decomposition. In this case, the between-group component explains a substantially larger share of the variation: the fitted regression yields an $R^2 = 0.46$, indicating that differences across income

groups account for roughly 46% of the variation in inequality changes across counties. These results suggest that income polarization, rather than demographic shifts such as migration, is the dominant source of variation in local inequality trends over our sample period.

To further validate the representativeness of our county-level inequality variation, Figure A.5 compares the distribution of Gini indices across US counties with the cross-country distribution from the World Income Inequality Database. Panel (a) shows the kernel density of the Gini index at the county level in 2004 and 2018, while panel (b) plots the corresponding distribution across countries for 2007 and 2015. The difference in years is due to the different coverages of our samples. The comparison illustrates that US counties exhibit substantial dispersion in inequality levels, comparable to that observed across countries.

Figure A.5: Gini Index Variation: County-Level vs. Country-Level



Note: Panel (a) shows the kernel density of the county-level Gini index in the United States for 2004 and 2018, computed from the CPS. Panel (b) presents the kernel density of country-level Gini indices in 2007 and 2015 from the World Income Inequality Database (WIID). The comparison illustrates the substantial within-country variation across US counties.

A.4 Robustness Analyses

Table A.1: Effect of Income Inequality on Product Prices

Dep var: $\ln p_{prdt}$	(1)	(2)	(3)	(4)	(5)	(6)
	Sale Size	Sale Size	Share Size	Share Size	Sale Size	Sale Size
$Ineq_{dt} \times MarketSize_{prdt0}$	0.026** (0.012)	0.029** (0.013)	0.118*** (0.035)	0.121*** (0.036)	0.018** (0.009)	0.022* (0.012)
$\ln PGDP_{dt} \times MarketSize_{prdt0}$	0.004 (0.004)	0.005 (0.005)	0.084*** (0.014)	0.090*** (0.018)	0.003 (0.004)	0.003 (0.004)
$\ln POP_{dt} \times MarketSize_{prdt0}$	-0.007*** (0.002)	-0.007*** (0.002)	0.015 (0.010)	0.009 (0.006)	-0.008*** (0.003)	-0.008*** (0.003)
$MarketSize_{prdt0}$	0.067*** (0.014)	0.064*** (0.015)	-0.800*** (0.146)	-0.788*** (0.138)	0.099*** (0.009)	0.097*** (0.009)
$Ineq_{dt}$	-0.040** (0.020)		-0.004* (0.002)		-0.029* (0.015)	
$\ln PGDP_{dt}$	0.010** (0.005)		0.014*** (0.002)		0.011*** (0.004)	
$\ln POP_{dt}$	0.038*** (0.006)		0.028*** (0.004)		0.039*** (0.007)	
Observation	29,535,724	29,528,409	29,535,724	29,528,409	28,905,531	28,897,635
R-squared	0.900	0.902	0.899	0.901	0.921	0.922
<i>Fixed Effect:</i>						
UPC \times Year	Y	Y	Y	Y	Y	Y
Firm \times Retailer	Y	Y	Y	Y	Y	Y
Firm \times County	Y	Y	Y	Y	Y	Y
Retailer \times Year	Y	Y	Y	Y	Y	Y
Retailer \times County	Y	Y	Y	Y	Y	Y
Product Group \times County \times Year	-	Y	-	Y	-	Y
UPC \times Retailer	-	-	-	-	Y	Y
UPC \times County	-	-	-	-	Y	Y

Note: The dependent variable is the logarithm of the average unit price of product p in retailer r , county d , and year t . $Ineq_{dt}$ denotes the county-level Gini coefficient of income inequality. Market size is measured either as the log of baseline sales at the product–retailer–county level (columns 1, 2, 5, and 6) or as the product’s baseline sales share within a retailer–county pair (columns 3 and 4). Baseline values are defined in the first year of the sample. All regressions include county-year controls (log per capita GDP and log population, and their interactions with market size) and the fixed effects listed in the table. Robust standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

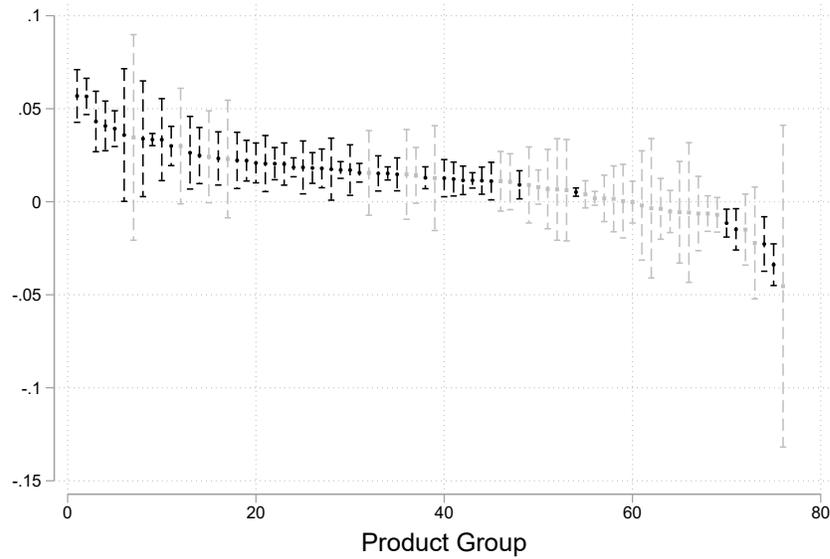
Table A.2: Robustness of Inequality Effects on Prices

Dep var: $\ln p_{prdt}(\ln p_{prdt})$	(1)	(2)	(3)	(4)
	Alternative Inequality Measure		Alternative	Sample
	Theil Index	Coefficient of Variation	Sample	Aggregation
$Ineq_{dt} \times \ln Sales_{prdt0}(\ln Sales_{prdt0})$	0.012** (0.006)	0.004* (0.002)	0.025** (0.011)	0.007*** (0.001)
$\ln Sales_{prdt0}(\ln Sales_{prdt0})$	0.071*** (0.012)	0.069*** (0.013)	0.046*** (0.017)	0.063*** (0.009)
$Ineq_{dt}$	-0.018* (0.010)	-0.006 (0.004)	-0.040** (0.019)	-0.020*** (0.003)
Observation	29,535,724	29,535,724	26,760,333	10,912,039
R-squared	0.900	0.900	0.905	0.937
Other Controls	Y	Y	Y	Y
<u>Fixed Effect:</u>				
UPC \times Year	Y	Y	Y	Y
Firm \times Retailer	Y	Y	Y	-
Firm \times County	Y	Y	Y	Y
Retailer \times Year	Y	Y	Y	-
Retailer \times County	Y	Y	Y	-

Note: This table reports robustness checks of the baseline regressions, which examine how local income inequality interacts with product sales size to affect log prices. Columns (1) and (2) replace the Gini coefficient with alternative measures of inequality: the Theil index and the coefficient of variation of income. Column (3) restricts the sample to products sold in at least 500 counties, compared with the baseline criterion of at least 100 retailers in the Nielsen data. Column (4) aggregates the data from the product–retailer–county level to the product–county level, redefining the dependent variable as $\ln p_{prdt}$ and the size measure as $\ln Sales_{prdt0}$. All specifications include the same set of controls and fixed effects as in the baseline. Robust standard errors are clustered at the firm level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.5 Heterogeneity by Product Group and Retailer

Figure A.6: Estimated Effect of Income Inequality on Product Prices by Product Group



Note: The figure illustrates the heterogeneity in the inequality–price relationship across categories. Each point represents the estimated coefficient of income inequality interacted with product market size ($Inequality_{dt} \times \ln MarketSize_{prd0}$), reported separately by product group. Nielsen assigns each UPC to one of 125 mutually exclusive product categories, though groups with insufficient observations to support fixed-effects estimation are excluded. Vertical bars indicate 95 percent confidence intervals. Detailed regression estimates by product group are reported in Appendix Table [A.3](#).

Table A.3: Effect of Income Inequality on Product Prices by Product Group

(1) Product Group	(2) $Inequality_{dt} \times \ln Size_{prdt0}$	(3)	(4) $Inequality_{dt}$	(5)
CANDY	0.018***	(0.004)	-0.021***	(0.005)
FRUIT - CANNED	0.021**	(0.008)	-0.034**	(0.012)
GUM	0.022*	(0.008)	-0.025**	(0.007)
JAMS, JELLIES, SPREADS	0.016***	(0.003)	-0.015**	(0.006)
JUICE, DRINKS - CANNED, BOTTLED	0.015***	(0.002)	-0.026***	(0.005)
PET FOOD	0.005***	(0.001)	-0.010**	(0.003)
PREPARED FOOD-READY-TO-SERVE	0.011	(0.008)	-0.011	(0.011)
PREPARED FOOD-DRY MIXES	0.012**	(0.005)	-0.010	(0.007)
SEAFOOD - CANNED	0.007	(0.011)	-0.014	(0.014)
SOUP	0.011*	(0.005)	-0.016**	(0.007)
VEGETABLES - CANNED	-0.000	(0.006)	0.007	(0.013)
BAKING MIXES	0.017**	(0.007)	-0.027**	(0.010)
BAKING SUPPLIES	0.026**	(0.010)	-0.027*	(0.013)
BREAKFAST FOOD	0.030	(0.016)	-0.043	(0.026)
CEREAL	0.020***	(0.004)	-0.030**	(0.009)
COFFEE	-0.006	(0.014)	0.033	(0.042)
CONDIMENTS, GRAVIES, AND SAUCES	0.030***	(0.005)	-0.034***	(0.008)
DESSERTS, GELATINS, SYRUP	0.004	(0.004)	0.001	(0.007)
FLOUR	-0.034***	(0.006)	0.048***	(0.010)
FRUIT - DRIED	0.009	(0.010)	-0.034	(0.021)
NUTS	-0.005	(0.006)	0.004	(0.017)
PACKAGED MILK AND MODIFIERS	-0.004	(0.008)	0.017	(0.014)
PASTA	0.000	(0.010)	0.003	(0.011)
PICKLES, OLIVES, AND RELISH	0.023**	(0.007)	-0.049***	(0.009)
SALAD DRESSINGS, MAYO, TOPPINGS	0.021***	(0.005)	-0.014	(0.011)
SHORTENING, OIL	-0.006	(0.010)	0.017	(0.017)
SPICES, SEASONING, EXTRACTS	0.039***	(0.005)	-0.036***	(0.004)
SUGAR, SWEETENERS	0.018*	(0.007)	-0.026*	(0.011)
TABLE SYRUPS, MOLASSES	0.025**	(0.008)	-0.050	(0.037)
TEA	0.015**	(0.005)	-0.016	(0.009)
VEGETABLES AND GRAINS - DRIED	0.041***	(0.007)	-0.056	(0.029)
BREAD AND BAKED GOODS	0.036*	(0.018)	-0.081*	(0.043)
CARBONATED BEVERAGES	0.013***	(0.003)	-0.023***	(0.007)
COOKIES	0.019***	(0.003)	-0.025**	(0.008)
CRACKERS	0.018**	(0.005)	-0.027***	(0.007)
SNACKS	0.002	(0.002)	-0.000	(0.003)
SOFT DRINKS-NON-CARBONATED	0.008	(0.005)	-0.019	(0.011)
BAKED GOODS-FROZEN	0.011	(0.008)	0.003	(0.012)
BREAKFAST FOODS-FROZEN	0.015	(0.012)	-0.023	(0.032)
DESSERTS/FRUITS/TOPPINGS-FROZEN	-0.006	(0.019)	0.021	(0.020)
ICE CREAM, NOVELTIES	-0.015**	(0.006)	0.037***	(0.011)
PIZZA/SNACKS/HORS D'OEUVRES-FRZN	-0.006	(0.005)	0.001	(0.010)
PREPARED FOODS-FROZEN	-0.023***	(0.007)	0.035**	(0.015)
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	0.033***	(0.002)	-0.110***	(0.012)
VEGETABLES-FROZEN	0.012**	(0.004)	-0.019*	(0.010)
BUTTER AND MARGARINE	0.002	(0.009)	-0.007	(0.016)
CHEESE	0.035	(0.028)	-0.073	(0.058)
COT CHEESE, SOUR CREAM, TOPPINGS	-0.015	(0.010)	0.025*	(0.006)
DOUGH PRODUCTS	0.017*	(0.002)	-0.044**	(0.001)
EGGS	0.006	(0.014)	-0.009	(0.028)
MILK	-0.007	(0.005)	0.018	(0.010)

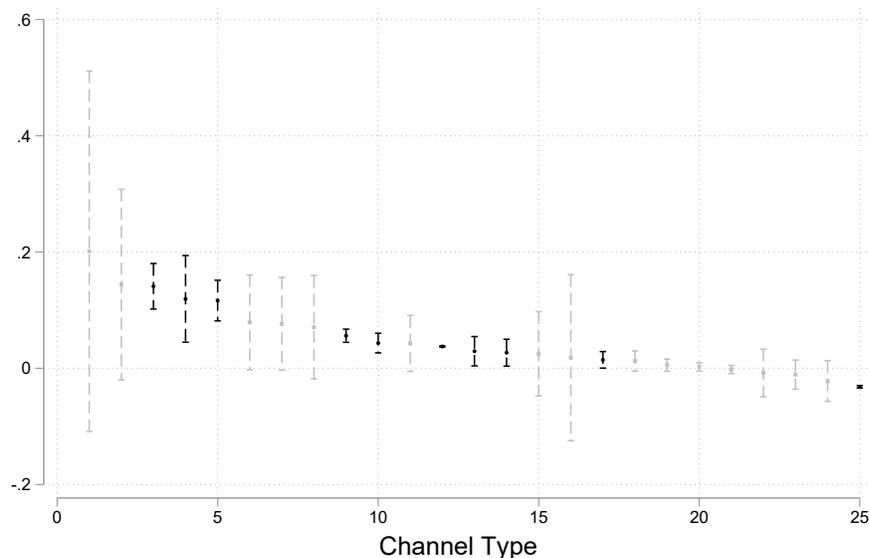
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Table (Continued): Effect of Income Inequality on Product Prices by Product Group

(1) Product Group	(2)	(3)	(4)	(5)
	$Inequality_{dt} \times \ln Size_{prdt0}$		$Inequality_{dt}$	
PUDDING, DESSERTS-DAIRY	0.033	(0.011)	-0.040	(0.011)
SNACKS, SPREADS, DIPS-DAIRY	0.034*	(0.016)	-0.050	(0.038)
YOGURT	0.011***	(0.002)	-0.015***	(0.004)
DRESSINGS/SALADS/PREP FOODS-DELI	0.057***	(0.005)	-0.111***	(0.024)
PACKAGED MEATS-DELI	0.024*	(0.013)	-0.051*	(0.026)
FRESH PRODUCE	0.057***	(0.007)	-0.110***	(0.018)
DETERGENTS	0.014	(0.008)	-0.026*	(0.013)
FRESHENERS AND DEODORIZERS	0.009	(0.004)	-0.027**	(0.005)
HOUSEHOLD CLEANERS	0.023	(0.016)	-0.034	(0.031)
HOUSEHOLD SUPPLIES	0.015	(0.012)	-0.029	(0.023)
LAUNDRY SUPPLIES	0.011**	(0.004)	-0.021***	(0.005)
PAPER PRODUCTS	0.002	(0.006)	0.006	(0.019)
PERSONAL SOAP AND BATH ADDITIVES	-0.004	(0.019)	-0.017	(0.032)
PET CARE	-0.011*	(0.004)	0.051**	(0.009)
TOBACCO & ACCESSORIES	0.013	(0.014)	-0.022	(0.060)
WRAPPING MATERIALS AND BAGS	0.013*	(0.005)	-0.020**	(0.005)
BEER	0.015**	(0.005)	-0.034*	(0.015)
WINE	0.043***	(0.008)	-0.079*	(0.037)
BATTERIES AND FLASHLIGHTS	0.007	(0.014)	-0.022	(0.030)
STATIONERY, SCHOOL SUPPLIES	-0.045	(0.044)	0.057*	(0.025)
COUGH AND COLD REMEDIES	0.020**	(0.006)	-0.062**	(0.020)
FIRST AID	-0.022	(0.015)	0.023	(0.034)
HAIR CARE	-0.002	(0.015)	-0.011*	(0.001)
MEDICATIONS/REMEDIES/HEALTH AIDS	0.022***	(0.006)	-0.049*	(0.024)
ORAL HYGIENE	0.018*	(0.009)	-0.009	(0.011)

Note: This table reports coefficient estimates from regressions of product prices on county-level income inequality, separately by product group. The key interaction term, $Inequality_{dt} \times \ln MarketSize_{prdt0}$, captures how inequality differentially affects products with larger versus smaller market size. All specifications include a rich set of fixed effects: product-year (δ_{pt}), firm-retailer (δ_{fr}), firm-county (δ_{fd}), retailer-year (δ_{rt}), and retailer-county (δ_{rd}). Control variables include log county per capita GDP and log county population, along with their interactions with product size. Standard errors are clustered at the firm level. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Figure A.7: Estimated Effect of Income Inequality on Product Prices by Retailer Channel



Note: The figure highlights systematic heterogeneity across retailer types. Each point represents the estimated coefficient of income inequality interacted with product market size ($Inequality_{dt} \times \ln MarketSize_{prdt0}$), reported separately by retailer channel. Nielsen classifies retailers into 66 mutually exclusive channels, though those with insufficient observations to support fixed-effects estimation are excluded. Vertical bars denote 95 percent confidence intervals. Detailed regression estimates by channel are provided in Appendix Table A.4.

A.6 Evidence from Estimated Markups

In this section, we examine whether income inequality is associated with changes in firms’ markups, defined as the wedge between prices and marginal costs.

Estimated Markups. One approach would be to estimate markups by inverting the demand system, combining our model’s structure with observed market shares—following the method used in Hottman et al. [2016] and Feenstra et al. [2025]. However, this strategy risks introducing circularity, since our structural model already embeds firm responses to inequality. Instead, we adopt a widely used production-function-based approach to markup estimation that does not rely on assumptions about the demand system or competitive conduct [De Loecker and Warzynski, 2012, De Loecker et al., 2020, De Loecker, 2021].

This “cost-based” approach builds on the idea that under cost minimization, the ratio of a variable input’s output elasticity to its revenue share reflects the firm’s

Table A.4: Effect of Income Inequality on Product Prices by Channel Type

(1) Channel type	(2) $Inequality_{dt} \times \ln Size_{prd0}$	(3)	(4) $Inequality_{dt}$	(5)
Bakery	0.071	(0.045)	-0.169	(0.151)
Butcher	0.056***	(0.006)	-0.143***	(0.027)
Close Out Store	-0.008	(0.021)	0.027	(0.023)
Convenience Store	0.077*	(0.041)	-0.128*	(0.067)
Coop/Farm/Feed	0.141***	(0.020)	-0.094**	(0.042)
Delicatessen	-0.011	(0.013)	0.039	(0.044)
Department Store	0.018	(0.073)	-0.022	(0.150)
Discount Store	0.002	(0.004)	0.002	(0.005)
Dollar Store	0.015**	(0.007)	-0.028***	(0.008)
Drug Store	0.005	(0.005)	-0.007	(0.010)
Free Sample/Gift	0.079*	(0.042)	-0.114*	(0.065)
Fruit Stand	0.117***	(0.018)	-0.108**	(0.050)
Gas Mini Mart	0.119***	(0.038)	-0.123**	(0.058)
Grocery	0.027**	(0.012)	-0.045**	(0.021)
Hardware/Home Improvement	0.201	(0.158)	-0.212	(0.179)
Liquor Store	0.025	(0.037)	0.034	(0.105)
Military Store	0.012	(0.009)	-0.045**	(0.018)
Online Shopping	-0.022	(0.018)	0.027	(0.035)
Pet Store	-0.002	(0.004)	-0.009	(0.012)
Quick Serve Restaurants	0.038***	(0.000)	-0.068***	(0.002)
Restaurant	-0.032***	(0.001)	0.191***	(0.005)
Service Station	0.144*	(0.084)	-0.165	(0.118)
Vending Machine	0.043	(0.025)	-0.085	(0.055)
Warehouse Club	0.043***	(0.009)	-0.093***	(0.034)
All Other Stores	0.029**	(0.013)	-0.096	(0.062)

Note: This table reports coefficient estimates of the effect of county-level income inequality on product prices, disaggregated by retailer channel. The interaction term, $Inequality_{dt} \times \ln MarketSize_{prd0}$, measures whether inequality raises the relative price of larger-market products compared with smaller ones. The main effect of $Inequality_{dt}$ captures the overall association between inequality and average prices in that channel. The specification includes an extensive set of fixed effects: product-year (δ_{pt}), firm-retailer (δ_{fr}), firm-county (δ_{fd}), retailer-year (δ_{rt}), and retailer-county (δ_{rd}). Control variables include log county per capita GDP, log county population, and their interactions with product size. Robust standard errors are clustered at the firm level. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

markup. Specifically, we estimate firm-level markups as:

$$\mu_{ft} = \frac{\theta_{ft}^M}{s_{ft}^M},$$

where θ_{ft}^M denotes the output elasticity of a flexible input (e.g., materials), estimated from a sector-specific production function, and s_{ft}^M is the observed share of that input in total revenue. We use Compustat data to obtain firm-level revenue and material expenditures, and follow [Akerberg et al. \[2015\]](#) to estimate the production function and recover input elasticities. This approach allows us to measure markups without

imposing assumptions on demand or market structure.

Limitations of Firm-Level Markup Estimation. One limitation of this approach is that we estimate the markups at the firm level, not the barcode level. The state-of-the-art method for estimating markups for multi-product firms necessitates data on single-product firms [De Loecker et al., 2016] and requires some products to be produced by multiple firms. Such data is critical since one lacks knowledge on the allocation of production factors and inputs for each product in a multi-product firm. To address this challenge, the literature has relied on the assumption that the technology for producing a product is common across firms, allowing the researcher to estimate a production function for single-product firms and use it for multi-product firms.

To estimate production functions and compute firm-level markups, we draw on firm-level balance sheet data from the Compustat database. We exclude financial firms (SIC codes 60–69), utilities (SIC 49), and any firms with incomplete financial records during the 2004–2018 period. The remaining firms are then matched to manufacturers in the NHCP dataset based on firm names. Compustat provides detailed information from publicly traded firms’ financial statements, including revenue, capital stock, employment, R&D expenditures, and cost of goods sold, along with industry classifications. These variables allow us to implement the production-function-based methodology of De Loecker and Warzynski [2012] and Akerberg et al. [2015] to estimate both markups and total factor productivity (TFP). We match firms in the NHCP database with those in the Compustat database, obtaining 1,058 publicly traded firms over our sample period. Our matched sample represents 21% of the total sales recorded in Compustat, which is comparable to the 22% reported by Argente et al. [2017].²⁹

Two important limitations apply to this exercise. First, due to the nature of the available data, we are unable to estimate markups at the product (UPC) level.³⁰ As noted in Section 2, each barcode in the NHCP is uniquely produced by a single firm, and detailed product-level cost data are not available. Second, our estimated markups do not vary across counties. Since Compustat provides firm-level financials but lacks geographic disaggregation of production costs or sales, we are restricted

²⁹There are 72,387 firms in the NHCP data and 12,481 in the Compustat data.

³⁰To the best of our knowledge, combining the production function approach to barcode level data has only been done for the brewery industry by De Loecker and Scott [2022].

to firm-level markup estimates that are uniform across the firm’s entire footprint. Despite these limitations, our analysis remains informative. By linking Compustat firms to the counties in which their products are sold (via NHCP), we examine whether firms that disproportionately sell to high-inequality counties exhibit systematically different markup behavior than those serving more equal regions. In this way, the markup analysis complements our price-based regressions by providing a firm-side perspective on how inequality shapes market outcomes.

Empirical Specification. We construct a firm-level measure of exposure to local income inequality, defined as:

$$IneqExpo_{ft} = \sum_d \lambda_{fdt} \times Ineq_{dt}, \quad \lambda_{fdt} = \frac{Sales_{fdt}}{\sum_d Sales_{fdt}} \quad (\text{A.3})$$

where λ_{fdt} denotes the share of firm f ’s sales in county d relative to its total sales across all counties in year t , and $Ineq_{dt}$ is the local inequality measure (e.g., Gini coefficient) in that county-year. A higher value of $IneqExpo_{ft}$ reflects greater exposure to markets characterized by higher income inequality. Summary statistics for this measure are reported in Panel (a) of Table 1. To ensure that our results are not confounded by differences in market size or income levels, we construct analogous exposure measures for per capita GDP and population:

$$PGDPExpo_{ft} = \sum_d \lambda_{fdt} \times \ln PGDP_{dt}, \quad POPExpo_{ft} = \sum_d \lambda_{fdt} \times \ln POP_{dt}, \quad (\text{A.4})$$

where $PGDP_{dt}$ and POP_{dt} represent the per capita GDP and total population of county d in year t , respectively. We then estimate the following regression to test how inequality exposure interacts with firm size to shape markups:

$$\ln \mu_{ft} = \beta_1 IneqExpo_{ft} + \beta_2 (IneqExpo_{ft} \times \ln y_{ft0}) + Z'_{ft} \Gamma + \delta_f + \delta_t + \delta_{s(f)t} + \epsilon_{ft}, \quad (\text{A.5})$$

where μ_{ft} is the markup of firm f in year t , and y_{ft0} is the baseline firm size in the first year, which we measure with total assets since sales are already included in the exposure measure. The vector Z_{ft} includes additional firm-level controls such as exposure to income levels ($PGDPExpo_{ft}$) and market size ($POPExpo_{ft}$), their

interactions with baseline firm size, the capital-labor ratio, and total employment. We include firm fixed effects (δ_f), year fixed effects (δ_t), and sector-year fixed effects ($\delta_{s(f)t}$). Standard errors are clustered at the firm level.

Table A.5: Income Inequality and Firm Markups: Regression Results for US Firms

Dep var: $\ln \mu_{ft}$	Gini Index			Theil Index		
	(1)	(2)	(3)	(4)	(5)	(6)
$IneqExpo_{ft} \times \ln y_{ft0}$	0.156* (0.089)	0.162* (0.095)	0.198* (0.118)	0.075* (0.045)	0.081* (0.049)	0.096 (0.061)
$PGDPExpo_{ft} \times \ln y_{ft0}$	-0.009 (0.009)	-0.012 (0.010)	-0.016 (0.012)	-0.008 (0.009)	-0.011 (0.009)	-0.015 (0.011)
$POPExpo_{ft} \times \ln y_{ft0}$	0.001 (0.005)	0.004 (0.005)	0.008 (0.006)	0.002 (0.005)	0.005 (0.005)	0.009 (0.006)
$IneqExpo_{ft}$	-0.891 (0.572)	-0.794 (0.621)	-1.023 (0.755)	-0.531* (0.297)	-0.508 (0.328)	-0.630 (0.393)
$PGDPExpo_{ft}$	0.059 (0.041)	0.077* (0.043)	0.096* (0.054)	0.051 (0.041)	0.072* (0.043)	0.088* (0.053)
$POPExpo_{ft}$	-0.007 (0.034)	-0.033 (0.035)	-0.047 (0.044)	-0.009 (0.032)	-0.035 (0.034)	-0.050 (0.041)
Observations	3,269	3,108	2,972	3,269	3,108	2,972
R-squared	0.922	0.927	0.931	0.922	0.927	0.931
Firm Controls	-	-	Y	-	-	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Sector \times Year FE	-	Y	Y	-	-	Y

Note: This table reports regressions of the natural logarithm of firm-level markups ($\ln \mu_{ft}$) on exposure to local income inequality, interacted with firm size. Inequality exposure ($IneqExpo_{ft}$) is calculated using a Bartik-style measure that weights county-level inequality by the firm's geographic sales shares across markets. Firm size is measured as the log of baseline assets in the first year. Columns (1)–(3) use the Gini coefficient, while Columns (4)–(6) use the Theil index to measure inequality. Firm-level controls include the capital-labor ratio, and total employment. Robust standard errors are reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Results. Table A.5 presents the regression results. Consistent with the price-based analysis in the main text, we find heterogeneous effects of income inequality on firm markups that depend on firm size. As in the baseline specification, the interaction between inequality and firm size is positive and statistically significant. These findings are robust to alternative measures of inequality, including both the Gini coefficient and the Theil index. However, the coefficient on inequality exposure ($IneqExpo_{ft}$) is not statistically significant in most specifications, even though the sign of the coefficient is broadly consistent with expectations. This lack of statistical precision is likely driven by attenuation bias resulting from measurement error in both the independent and

dependent variables.

Table A.6: Robustness Check: Controlling for Consumer Sorting Effects

Dep var: $\ln p_{prdt}$	(1) Sale Size	(2) Sale Size	(3) Share Size	(4) Share Size
$Ineq_{dt} \times MarketSize_{prdt0}$	0.024** (0.011)	0.028** (0.012)	0.098*** (0.030)	0.100*** (0.031)
$\ln PGDP_{dt} \times MarketSize_{prdt0}$	0.004 (0.004)	0.005 (0.005)	0.083*** (0.015)	0.089*** (0.018)
$\ln POP_{dt} \times MarketSize_{prdt0}$	-0.006*** (0.002)	-0.007*** (0.002)	0.019* (0.010)	0.013* (0.007)
$ShareQ3\&4_{prdt} \times MarketSize_{prdt0}$	0.005 (0.005)	0.005 (0.005)	0.062*** (0.022)	0.061*** (0.022)
$MarketSize_{prdt0}$	0.061*** (0.019)	0.058*** (0.020)	-0.874*** (0.169)	-0.859*** (0.157)
$Ineq_{dt}$	-0.038** (0.018)		-0.004* (0.002)	
$\ln PGDP_{dt}$	0.010** (0.004)		0.014*** (0.002)	
$\ln POP_{dt}$	0.037*** (0.005)		0.028*** (0.004)	
$ShareQ3\&4_{prdt}$	0.004 (0.007)	0.004 (0.007)	0.011*** (0.001)	0.011*** (0.001)
Observation	29,469,303	29,461,994	29,469,303	29,461,994
R-squared	0.901	0.903	0.899	0.901
<i>Fixed Effect:</i>				
UPC \times Year	Y	Y	Y	Y
Firm \times Retailer	Y	Y	Y	Y
Firm \times County	Y	Y	Y	Y
Retailer \times Year	Y	Y	Y	Y
Retailer \times County	Y	Y	Y	Y
Product Group \times County \times Year	-	Y	-	Y

Note: This table reports regressions of product-level prices ($\ln p_{prdt}$) on income inequality and other market characteristics, controlling for potential consumer sorting effects. The key regressor is the interaction between local income inequality ($Ineq_{dt}$) and baseline market size ($MarketSize_{prdt0}$), which tests whether inequality affects pricing differently in larger versus smaller markets. Columns (1)–(2) use sales-based measures of market size, while Columns (3)–(4) use market-share-based measures. Additional controls include interactions of $MarketSize_{prdt0}$ with log per capita GDP, log population, and the share of consumption accounted for by the top two quartiles of households ($ShareQ3\&4_{prdt}$). Main effects of inequality, income, population, and household share are also included where indicated. All regressions include a rich set of fixed effects: UPC-by-year, retailer-by-year, firm-by-retailer, firm-by-county, and retailer-by-county. Columns (2) and (4) further control for product-group-by-county-by-year fixed effects, which absorb time-varying shocks to consumer demand and local sorting within product groups. Robust standard errors are clustered at the firm level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

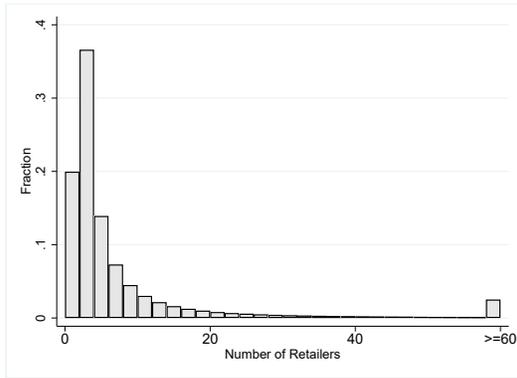
Table A.7: Export Prices and Income Inequality: HS 8-digit Products by Chinese Firms

Dep var: $\ln p_{pfdt}$	(1) Gini	(2) Gini	(3) Theil	(4) Theil
$Ineq_{dt} \times \ln Sales_{pfdt0}$	0.034*** (0.003)	0.048*** (0.011)	0.006*** (0.002)	0.039*** (0.005)
$\ln PGDP_{dt} \times \ln Sales_{pfdt0}$	-0.005*** (0.000)	0.018*** (0.005)	-0.005*** (0.001)	0.038*** (0.007)
$\ln POP_{dt} \times \ln Sales_{pfdt0}$	-0.000** (0.000)	-0.147*** (0.018)	0.000** (0.000)	-0.109*** (0.018)
$\ln Sales_{pfdt0}$	0.104*** (0.006)		0.103*** (0.007)	
$Ineq_{dt}$	-0.369*** (0.037)		-0.009 (0.018)	
$\ln PGDP_{dt}$	-0.018* (0.010)		-0.021 (0.014)	
$\ln POP_{dt}$	0.129*** (0.024)		0.070** (0.029)	
Observation	22,418,272	11,106,107	15,311,989	7,626,146
R-squared	0.718	0.917	0.706	0.909
<u>Fixed Effect:</u>				
Year	Y	Y	Y	Y
Product	Y	Y	Y	Y
Country	Y	Y	Y	Y
Firm	Y	Y	Y	Y
Product \times Year	-	Y	-	Y
County \times Year	-	Y	-	Y
Firm \times Year	-	Y	-	Y
Product \times County \times Firm	-	Y	-	Y

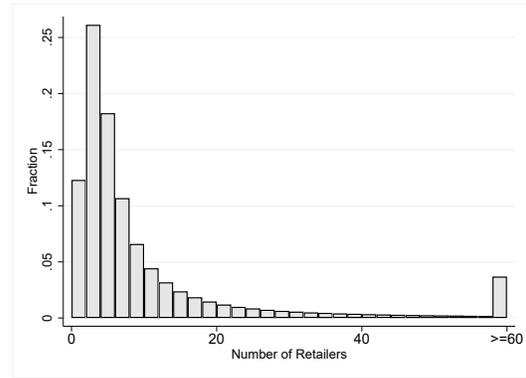
Note: The dependent variable is the log of export prices at the HS 8-digit product–firm–destination–year level. The main explanatory variable is the interaction between destination-country inequality ($Ineq_{dt}$, measured by either the Gini or Theil index) and baseline product–firm–destination sales ($\ln Sales_{pfdt0}$). This interaction captures how the effect of inequality on prices depends on a firm’s initial market size in each destination. Columns (1)–(2) use the Gini index and columns (3)–(4) use the Theil index. All regressions include country-year controls (log per capita GDP and log population of destination country, and their interactions with baseline sales) and the fixed effects listed in the table. Robust standard errors are clustered at the firm level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.7 Reach of UPCs across Retailers and Counties

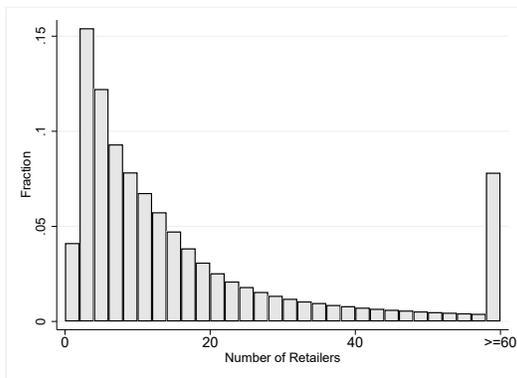
Figure A.8: Number of Retailers per UPC: Refined UPC Samples



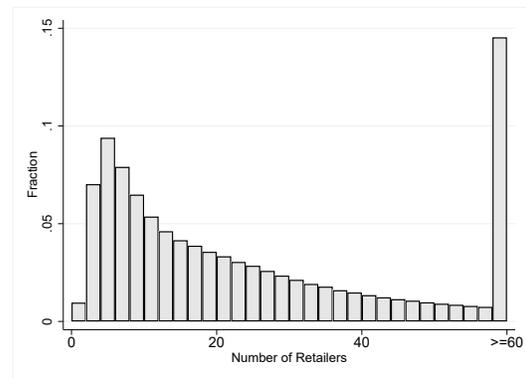
(a) At least 2 households



(b) At least 5 households



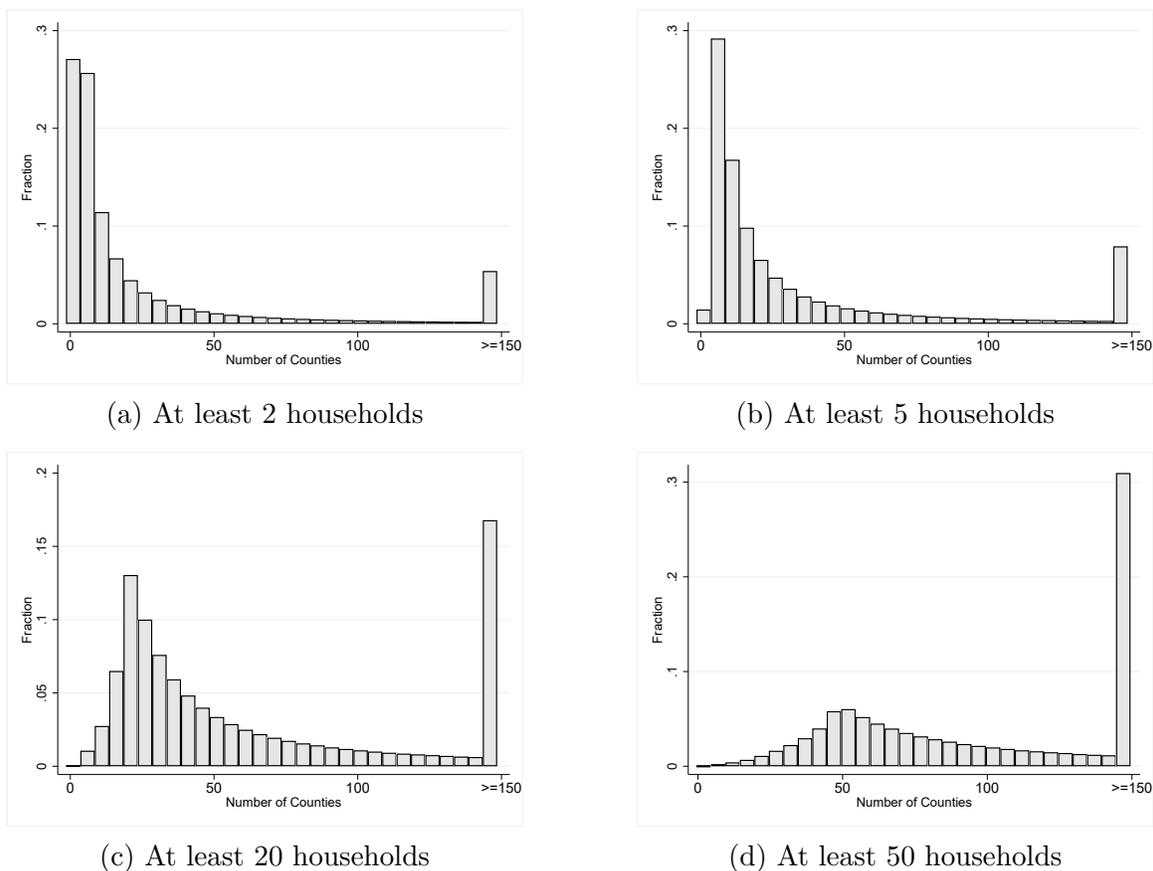
(c) At least 20 households



(d) At least 50 households

Note: Each panel shows the distribution of the number of retailers carrying a given UPC after sample refinement. Panels differ by the minimum number of distinct households purchasing the UPC. Raising the household threshold filters out rarely purchased products, yielding UPCs that are more representative of broad consumer demand but with a smaller sample size.

Figure A.9: Number of Counties per UPC: Refined UPC Samples



Note: Each panel shows the distribution of the number of counties in which a given UPC is observed after sample refinement. Panels differ by the minimum number of households purchasing each UPC. Raising the household threshold filters out rarely purchased products, yielding UPCs that are more representative of broad consumer demand but with a smaller sample size.

B Theory Appendix

B.1 Firm Quantity Optimization Problem

In this section, we analyze the firm's optimization problem when it chooses output quantities rather than setting prices directly. The key distinction is that the price is determined in equilibrium and must be common across consumer segments, while the firm retains the ability to allocate quantities across segments. This requires imposing the condition that the demand system delivers a single market-clearing price consistent across all segments. Formally, let the inverse demand for the firm's

product in segment i be given by:

$$p = p(q_i, z_i) \quad (\text{B.6})$$

where p denotes the equilibrium price, q_i is the quantity allocated to segment i , and z_i captures the income of segment i . The firm's profits are given by:

$$\pi = \sum_{i=1}^I L_i q_i (p(q_i, z_i) - c) \quad (\text{B.7})$$

where L_i denotes the size of consumer segment i and c is the constant marginal cost of production. A key feature of the problem is that the price of the firm's product must be identical across all consumer segments. This consistency condition requires:

$$p(q_i, z_i) = p(q_j, z_j) \quad \forall i, j = 1, \dots, I \quad (\text{B.8})$$

Using (B.8), the quantity for any segment i can be expressed as an implicit function of the quantity in a reference segment j , i.e. $q_i = q_i(q_j)$. Totally differentiating (B.8) yields the relationship between segment-level quantities:

$$\frac{dq_i}{dq_j} = \frac{\frac{\partial p(q_j, z_j)}{\partial q_j}}{\frac{\partial p(q_i, z_i)}{\partial q_i}} \quad (\text{B.9})$$

Substituting this relationship, the firm's profit function can be rewritten in terms of the reference segment's quantity q_j :

$$\pi = \sum_{i=1}^I L_i q_i(q_j) (p(q_i(q_j), z_i) - c) \quad (\text{B.10})$$

The first-order condition (FOC) for profit maximization is obtained by differentiating with respect to q_j :

$$\sum_{i=1}^I L_i \frac{dq_i}{dq_j} (p(q_i(q_j), z_i) - c) + \sum_{i=1}^I L_i q_i(q_j) \frac{\partial p(q_i, z_i)}{\partial q_i} \frac{dq_i}{dq_j} = 0 \quad (\text{B.11})$$

$$(p - c) \sum_{i=1}^I L_i \frac{dq_i}{dq_j} + \sum_{i=1}^I L_i q_i(q_j) \frac{\partial p(q_i, z_i)}{\partial q_i} \frac{dq_i}{dq_j} = 0 \quad (\text{B.12})$$

$$(p - c) \frac{\partial p(q_j, z_j)}{\partial q_j} \sum_{i=1}^I L_i \left(\frac{\partial p(q_i, z_i)}{\partial q_i} \right)^{-1} + \frac{\partial p(q_j, z_j)}{\partial q_j} \sum_{i=1}^I L_i q_i(q_j) = 0 \quad (\text{B.13})$$

$$(p - c) \sum_{i=1}^I L_i \left(\frac{\partial p(q_i, z_i)}{\partial q_i} \right)^{-1} + \sum_{i=1}^I L_i q_i(q_j) = 0 \quad (\text{B.14})$$

This condition is structurally equivalent to the expression derived in the main text (see equation (6)). The two formulations coincide when $\left(\frac{\partial p(q_i, z_i)}{\partial q_i} \right)^{-1} = \frac{\partial q(p, z_i)}{\partial p}$ which holds under monopolistic competition.

B.2 Implicit Non-Homothetic CES Utility Function

[Matsuyama \[2023\]](#) defines the implicit non-homothetic CES utility U as:

$$F(U, \mathbf{q}) = \left[\sum_{j=1}^n \beta_j(U)^{1/\sigma(U)} q_j^{1 - \frac{1}{\sigma(U)}} \right]^{\frac{\sigma(U)}{\sigma(U)-1}} - 1 = 0,$$

with $\sigma(U) > 1$ and $\sigma'(U) < 0$. Most applications in the literature (e.g., [Comin et al. \[2021\]](#)) assume that $\sigma(U) = \sigma$ is constant. In that case, solving the consumer's problem leads to a demand function of the form:

$$q_j(p, U) = A_j(U) p_j^{-\sigma}, \quad (\text{B.15})$$

where the attribute z (income in our baseline model) is replaced by the utility U of the household. Given this demand structure, assuming monopolistic competition (so that firms take the demand shifter $A_j(U)$ as given), dropping product subscripts, and recalling that subscript i denotes a consumer segment, the first-order condition simplifies to:

$$(p - c) \sum_{i=1}^I L_i q(p, U_i) (-\sigma p^{-1}) + \sum_{i=1}^I L_i q(p, U_i) = \left(-\sigma p^{-1} (p - c) + 1 \right) \sum_{i=1}^I L_i q(p, U_i) = 0.$$

Since the term $\sum_{i=1}^I L_i q(p, U_i)$ cancels out, the optimal price is simply a constant markup over marginal cost. Hence, the dispersion in utilities does not affect prices in the constant- σ case.

To obtain the demand function used in the main text, we instead allow $\sigma(U)$ to vary with U . For simplicity, we set $\beta_j(U) = 1$ without loss of generality, since this

term does not affect pricing. To characterize the demand system, we first compute the marginal utility with respect to good j , which equals:

$$\frac{dU}{dq_j} = - \frac{(\sigma(U) - 1)^2}{\sigma'(U)} \frac{q_j^{-1/\sigma(U)}}{S(U, \mathbf{q}) \left(-\frac{\sigma(U)}{\sigma(U)-1} \ln S(U, \mathbf{q}) + \frac{1}{S(U, \mathbf{q})} \sum_{j=1}^n q_j^{1-\frac{1}{\sigma(U)}} \ln q_j \right)}.$$

where

$$S(U, \mathbf{q}) \equiv \sum_{j=1}^n q_j^{1-\frac{1}{\sigma(U)}}, \quad m(U) = \frac{\sigma(U)}{\sigma(U) - 1},$$

Because we assume $\sigma'(U) < 0$, the prefactor $-(\sigma(U) - 1)^2/\sigma'(U)$ is strictly positive for $\sigma(U) > 1$. Hence, the demand function can be written as:

$$q_j = A(U, \mathbf{q}) p_j^{-\sigma(U)}. \quad (\text{B.16})$$

Since the demand shifter $A(U, \mathbf{q})$ does not affect optimal markups, we treat it as constant and obtain the demand function reported in the main text (with utility U replaced by the household attribute z): $q = a p^{-\sigma(z)}$.

B.3 Derivations

We begin with the demand function:

$$q(p, z) = (ap)^{-\sigma(z)}$$

where p is the price, z denotes a characteristic of the consumer (such as income or demographic type), a is a scaling parameter, and $\sigma(z)$ is the demand elasticity, which may vary with z . From this functional form, several useful derivatives follow directly. First, differentiating with respect to price:

$$\frac{\partial q(p, z)}{\partial p} = -\frac{\sigma(z)}{p} q(p, z). \quad (\text{B.17})$$

Second, differentiating with respect to z yields:

$$\frac{\partial q(p, z)}{\partial z} = -\sigma'(z) \ln(ap) q(p, z). \quad (\text{B.18})$$

Finally, the second derivative with respect to z equals:

$$\frac{\partial^2 q(p, z)}{\partial z^2} = q(p, z) \left[(\sigma'(z))^2 (\ln(ap))^2 - \sigma''(z) \ln(ap) \right]. \quad (\text{B.19})$$

For convenience, we define the function so that $\partial^2 q(p, z)/\partial z^2 = q(p, z) A(z, p)$:

$$A(z, p) \equiv (\sigma'(z))^2 (\ln(ap))^2 - \sigma''(z) \ln(ap).$$

Differentiating once more with respect to p , we obtain:

$$\frac{\partial^3 q(p, z)}{\partial p \partial z^2} = \frac{q(p, z)}{p} B(z, p),$$

where

$$B(z, p) \equiv (\sigma'(z))^2 \left[2 \ln(ap) - \sigma(z) (\ln(ap))^2 \right] + \sigma''(z) \left[\sigma(z) \ln(ap) - 1 \right].$$

Combining these results, we obtain:

$$\frac{\partial^2 G(p, z)}{\partial z^2} = q(p, z) \left[A(z, p) + \frac{p - c}{p} B(z, p) \right] \quad (\text{B.20})$$

where $A(z, p)$ captures the curvature of demand with respect to z and $B(z, p)$ reflects the interaction between price changes and heterogeneity in $\sigma(z)$. The implications for firm pricing hinge on the signs of $A(z, p)$ and $B(z, p)$. Four distinct cases arise:

- **Case 1:** $A(z, p) > 0$ and $B(z, p) > 0$. In this case $G(p, z)$ is convex in z . A mean-preserving spread in the income distribution increases demand convexity, which raises the optimal price for all firms.
- **Case 2:** $A(z, p) < 0$ and $B(z, p) > 0$. Here the effect of greater income dispersion depends on the firm's productivity (through its marginal cost c). The threshold condition is given by

$$p + \frac{p A(z, p)}{B(z, p)} \geq c. \quad (\text{B.21})$$

Firms with low marginal costs (high productivity) may raise their prices, while higher-cost firms lower them.

- **Case 3:** $A(z, p) > 0$ and $B(z, p) < 0$. A similar threshold condition applies, but the direction of the inequality is reversed:

$$p + \frac{pA(z, p)}{B(z, p)} \leq c.$$

In this case, the response to a mean-preserving spread again depends on cost differences across firms, but in the opposite way.

- **Case 4:** $A(z, p) < 0$ and $B(z, p) < 0$. In this case $G(p, z)$ is concave in z . A mean-preserving spread in income reduces the optimal price for all firms.

B.3.1 Derivation of Case 2

Case 2 corresponds to the situation where $A(z, p) < 0$ and $B(z, p) > 0$. A convenient set of sufficient conditions for $A(z, p) < 0$ and $B(z, p) > 0$ is³¹:

$$\ln(ap) < \frac{\sigma''(z)}{(\sigma'(z))^2}, \quad (\text{B.22})$$

$$2\ln(ap) - \sigma(z)(\ln(ap))^2 > \frac{\sigma''(z)}{(\sigma'(z))^2} [1 - \sigma(z)\ln(ap)]. \quad (\text{B.23})$$

Example: functional form for $\sigma(z)$. Suppose the elasticity of substitution depends on income as:

$$\sigma(z) = (1+z)^{-\rho}, \quad \rho > 0.$$

Differentiating yields:

$$\sigma'(z) = -\rho(1+z)^{-\rho-1} \quad \text{and} \quad \sigma''(z) = \rho(\rho+1)(1+z)^{-\rho-2}.$$

It follows that:

$$\frac{\sigma''(z)}{(\sigma'(z))^2} = \frac{\rho+1}{\rho}(1+z)^\rho.$$

Hence, a sufficient condition for $A(z, p) < 0$ is:

$$\ln(ap) < \frac{\rho+1}{\rho}(1+z)^\rho. \quad (\text{B.24})$$

Moreover, one can show that a sufficient condition for $B(z, p) > 0$ is that $\ln(ap)$ lies

³¹Throughout, we assume $\ln(ap) > 0$.

in the interval:

$$\frac{(3\rho + 1) - \sqrt{5\rho^2 + 2\rho + 1}}{2\rho} (1 + z)^\rho < \log(ap) < \frac{(3\rho + 1) + \sqrt{5\rho^2 + 2\rho + 1}}{2\rho} (1 + z)^\rho. \quad (\text{B.25})$$

Comparing these two sets of bounds, note that the upper bound implied by the condition $A(z, p) < 0$ is more restrictive than the upper bound implied by $B(z, p) > 0$. Therefore, the sufficient condition for *Case 2*, namely $A(z, p) < 0$ and $B(z, p) > 0$, can be summarized as:

$$\frac{(3\rho + 1) - \sqrt{5\rho^2 + 2\rho + 1}}{2\rho} (1 + z)^\rho < \log(ap) < \frac{\rho + 1}{\rho} (1 + z)^\rho. \quad (\text{B.26})$$

Analogous steps yield the conditions for the other cases.