Online Appendix
Rising Concentration of Household Shopping, Superstar Firms, and Implications for Retail Markups

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Contents

A Measuring Retail Concentration

We use the Herfindahl-Hirschman Index (HHI) as our primary measure of retail concentration at the household level and different geographical levels.

Household retail concentration is constructed in three steps. First, for each household i and retail firm f, we calculate the total expenditure R_{if}^t in period t. Second, the associated market share is

$$S_{if}^t = \frac{R_{if}^t}{\sum_f R_{if}^t}.$$

Finally, household concentration is the HHI of the above market share:

$$H_i^t = \sum_f (S_{if}^t)^2.$$

We further calculate the regional average household concentration, defined as the weighted average of household concentration in a given region. Let $r(i,t)$ denote the region where household i lives in period t. The set of households who lives in region r in period t is $I_{rt} = \{i : r(i,t) = r\}$. Regional average household concentration can then be calculated from

$$\bar{H}_r^t = \sum_{i \in I_{rt}} \alpha_{ir}^t H_i^t.$$

The household weight α_{ir}^t depends on all the households' sampling weight (projection factor) w_{ir}^t and total expenditure R_{if}^t:

$$\alpha_{ir}^t = \frac{\sum_f (w_{ir}^t R_{if}^t)}{\sum_{i:r(i,t)=r} \sum_f (w_{ir}^t R_{if}^t)}.$$

We use a similar measure for retail concentration at different geographical units, such as counties, Scantrack markets as defined by NielsenIQ, and nationally. Following the above definition, the market share for retail firm f at time t in region r is

$$S_{fr}^t = \frac{\sum_{i \in I_{rt}} (w_{ir}^t R_{if}^t)}{\sum_f \sum_{i \in I_{rt}} (w_{ir}^t R_{if}^t)}.$$

The HHI of region r in period t becomes

$$H_r^t = \sum_f (S_{fr}^t)^2.$$

We call it the aggregate retail concentration (or region HHI) of region r in period t, which is a measure of regional concentration.

A.1 RZ Decomposition

Moreover, we follow Radaelli and Zenga (2002) (RZ) to define the cross-household variance of retail concentration:

$$V_r^t = \sum_{i:r(i,t)=r} \alpha_{ir}^t \left(\sum_f (S_{if}^t - S_{fr}^t)^2 \right).$$

We can formally relate region average household concentration and region aggregate concentration with the decomposition:

$$H_r^t = \bar{H}_r^t - V_r^t.$$

This decomposition suggests that if all the households' consumption patterns in each retail chain are the same, then $\bar{V}_r^t = 0$ and the region average household concentration is a perfect reflection of the region aggregate concentration in the region.

Therefore, beginning at the national level, we can decompose changes in national aggregate HHI $\Delta H = H^t - H^{t-n}$ into changes in the national average region HHI minus the cross-region variance:

$$\Delta H = \Delta \sum_r \alpha_r H_r - \Delta \sum_r \alpha_r V_r$$

$$\Delta\text{National HHI} = \Delta\text{Average Region HHI} - \Delta\text{Cross-region variance.}$$

At the regional level, we can decompose changes in the region aggregate HHI into changes in the region average household HHI minus the cross-household variance:

$$\Delta H_r = \Delta \sum_r \sum_i \alpha_{ir} H_{ir} - \Delta \sum_r \sum_i \alpha_{ir} V_{ir}.$$

$$\Delta\text{Region HHI} = \Delta\text{Average Household HHI} - \Delta\text{Cross-household variance.}$$

At the household level, we can further classify expenditures at the household-product-category level S_{ic}. We then decompose changes in the household aggregate HHI into changes in the household average category HHI minus the cross-category variance:

$$\Delta H_{ir} = \Delta \sum_r \sum_i \sum_c \alpha_{irc} H_{irc} - \Delta \sum_r \sum_i \sum_c \alpha_{irc} V_{irc}$$

$$\Delta\text{Household HHI} = \Delta\text{Average Household-category HHI} - \Delta\text{Cross-category variance.}$$

Combining all four levels, changes in national aggregate HHI can be formally decomposed into changes in the following four terms: Household-category HHI H_{irc}, household cross-category variance V_{irc}, regional cross-household variance V_{ir}, and national cross-region variance V_r. We write out the entire decomposition as follows:

$$
\begin{aligned}
\Delta H &= \Delta \sum_r \sum_i \sum_c \alpha_{irc} H_{irc} - \Delta \sum_r \sum_i \sum_c \alpha_{irc} V_{irc} \\
&\quad - \Delta \sum_r \sum_i \alpha_{ir} V_{ir} - \Delta \sum_r \alpha_r V_r \\
\Delta\text{National HHI} &= \Delta\text{Household-category HHI} - \Delta\text{Cross-category variance} \\
&\quad - \Delta\text{Cross-household variance} - \Delta\text{Cross-region variance},
\end{aligned}
$$

where

$$
H_{irc} = \sum_f (S_{irfc})^2,\ V_{irc} = \sum_f (S_{irfc} - S_{irf})^2,\ \alpha_{irc} = \frac{w_{ir} R_{irc}}{\sum_i \sum_r \sum_c w_{ir} R_{irc}}.
$$

To investigate whether composition changes in our dataset, such as the entry and exit of regions or households, are driving our results, we also use a Dynamic Olley-Pakes decomposition (Melitz and Polanec 2015) on top of the RZ decomposition, as shown below:

$$
\begin{aligned}
&\Delta \sum_r \sum_i \sum_c \alpha_{irc} H_{irc} \\
&= (H_{S2} - H_{S1}) + \alpha_{E2}\left(H_{E2} - H_{S2}\right) + \alpha_{X1}\left(H_{S1} - H_{X1}\right) \\
&= \Delta \bar{H}_S + \Delta cov_S + \alpha_{E2}\left(H_{E2} - H_{S2}\right) + \alpha_{X1}\left(H_{S1} - H_{X1}\right) \\
&\alpha_{Gt} = \sum_{i \in G} \alpha_{it},\ H_{Gt} = \sum_{i \in G} \frac{\alpha_{it}}{\alpha_{Gt}} H_{it}
\end{aligned}
$$

Applying this decomposition to each of the four terms decomposing the national aggregate HHI in online Appendix Table I3, we find that within-survivor growth is driving most of the variation.

A.2 RZ Decomposition by Firm

Moreover, we can show that the aggregate HHI, average region HHI, and cross-region variance can be decomposed into contributions by various groups of firms (e.g. group $\mathcal{F}_1$ and $\mathcal{F}_2$) as follows:

$$
\begin{aligned}
H &= \sum_{f\in\mathcal{F}_1}(S_f)^2 + \sum_{f\in\mathcal{F}_2}(S_f)^2 \\
H &= \sum_r \alpha_r H_r - \sum_r \alpha_r V_r \\
&= \sum_r \alpha_r \sum_f (S_{fr})^2 - \sum_r \alpha_r \sum_f (S_{fr} - S_f)^2 \\
&= \sum_r \alpha_r \left(\sum_{f\in\mathcal{F}_1}(S_{fr})^2 + \sum_{f\in\mathcal{F}_2}(S_{fr})^2 \right) - \sum_r \alpha_r \left(\sum_{f\in\mathcal{F}_1}(S_{fr} - S_f)^2 + \sum_{f\in\mathcal{F}_2}(S_{fr} - S_f)^2 \right) \\
&= \sum_{f\in\mathcal{F}_1}\sum_r \alpha_r (S_{fr})^2 + \sum_{f\in\mathcal{F}_2}\sum_r \alpha_r (S_{fr})^2 - \sum_{f\in\mathcal{F}_1}\sum_r \alpha_r (S_{fr} - S_f)^2 - \sum_{f\in\mathcal{F}_2}\sum_r \alpha_r (S_{fr} - S_f)^2
\end{aligned}
$$

B National HHI, Regional HHI, and Superstar Firms

How are superstar firms linked to the rise in national HHI but a relatively moderate increase in regional HHI? First, we show how many superstar firms are expanding across the nation and opening stores in more markets using the NielsenIQ TDLinx data in online Appendix Table I1.[32] We separate retail chains into two groups: the top 40 retail chains by revenue rank over the sample period (superstar firms), and other chains outside the top 40. The median superstar chain has increased the number of stores by 11% from 2004-2019, while the median chain outside the top 40 has decreased by 7%. We show in online Appendix Figure J5 that using the number of stores in each retail chain and market to calculate the HHI gives a similar pattern to using revenue in the HMS, with region HHI and cross-region variance both increasing to contribute to an increasing aggregate HHI. These facts are consistent with findings in Hsieh and Rossi-Hansberg (2019) and Smith and Ocampo (2025).

Next, we show in online Appendix Section A.2 that the concentration trends can be decomposed into contributions by various groups of firms. We illustrate how the two groups of chains contribute to rising concentration in online Appendix Figure J6. Although superstar firms drive trends in both aggregate HHI and region HHI, changes in cross-region variance is driven by both groups of firms. One potential reason is that the expansion of chains into more geographic locations can either increase or decrease cross-region variance.[33] As shown in online Appendix Table I1 and I2, there is considerable dispersion in cross-region variance

[32] We acquired the NielsenIQ TDLinx data from 2004-2019 to obtain monthly-level store counts for each retail chain at the market level.

[33] For intuition, consider a chain with one store in one region. The cross-region variance will be very small as the regional market share is zero in almost every region except the one in which the chain has a store, and the national market share is also close to zero. As a chain expands into more geographic locations gradually, more and more locations will have non-zero market shares and the national market share will also increase. Hence, cross-region variance will increase. At a certain point, the number of regions without stores will diminish, and cross-region variance may decrease. Each region becomes more similar as the whole nation becomes more saturated with stores from this chain. Therefore, it is likely that as a chain expands across the nation region by region, cross-region variance will first increase and then decrease, unless stores are opened separately in each market in a relatively uniform fashion. We find that in our data, it is indeed the case that some superstar firms first experience a rise in cross-region variance and then a fall in cross-region variance.

across both superstars and other chains.

C Robustness of Household HHI Trends

In this section, we show that the rise of household HHI is robust to potential changes to the sample of households in the HMS. First, we show that our results are robust to adding various controls in online Appendix Figure J10. In online Appendix Figure J10a, we regress household HHI on various control variables and plot the year fixed effects for each specification. We control for the number of years the household has been in the sample, total expenditures, household fixed effects, as well as household and regional demographics. All of these specifications continue to show a rising trend for household HHI. In online Appendix Figure J10b, we show that our sample captures an average of real expenditures that is roughly constant over the sample period.

Second, we show that the flat trend in real expenditures is consistent with a flat trend for the same set of products in the Consumption Expenditure Survey (CEX). In online Appendix Figure J11, we show the average annual expenditure of food-at-home and matched non-durable goods captured by NielsenIQ, as classified by Coibion et al. (2021a), in the Consumption Expenditure Survey (CEX) Interview Survey (IS) from 2004-2015 using the latest available NBER CEX data. We show these trends with and without controls for various household demographics. Household expenditures in the non-magnet sample, with an annual average of roughly \$3200, covers over 60% of matched non-durable goods in the CEX, which has an annual average of roughly \$5000.

Third, our main results use only products with barcodes. NielsenIQ also captures products without standard barcodes using their own classification system. This data, known as magnet data, includes items such as fruits, vegetables, meats, and in-store baked goods. However, only a subset of households regularly report magnet product purchases starting from 2007. These magnet households have been increasing substantially over the sample period, with their proportion increasing from about 35% in 2007 to 87% in 2019. Using only magnet households, we show in online Appendix Figure J12 that the average household HHI has been decreasing for magnet products, although this trend is not very robust across specifications. This could be driven by large changes in the magnet sample, and we see large fluctuations in average real expenditures over the sample period. We show in online Appendix Figure J13 that average household HHI continues to show an upward trend using all products for magnet households, although the trend is slightly attenuated relative to the barcode-only sample. Since the trend in average real expenditures again shows a lot of fluctuation, we focus on using only the non-magnet sample for our main results.

D Additional Analyses on Online Shopping

One possible explanation for the statistically insignificant effect of online shopping on household HHI using e-commerce platforms in Section 4.3 is that the share of grocery products that households purchase on the major e-commerce platform is small in the majority of our sample period, whereas food accounts for 60-70% of the expenditure in the HMS. In more recent years, the major e-commerce platform has introduced same-day shipping and invested more in logistics networks. This may change offline shopping patterns, as shown by Edgel et al. (2023). We also investigate the impact of same-day shipping and last-mile facilities investments on household retail HHI after 2017, using a similar empirical strategy to Edgel et al. (2023). The results are shown in online Appendix Table I14. Using the reduced-form estimates, we find that for the period of 2017-2019, the availability of the same-day shipping in the zip code where the household lives can increase household retail HHI. The effect is stronger for areas with more last-mile facilities. The BOTE is 0.019 if we use the distance to the closest last-mile facility for each zip code, and 0.032 if we use the number of last-mile facilities.[34] Thus, our two empirical exercises suggest that online shopping can play a role in increasing household retail HHI. However, the effects we estimate remain quite small.

The analysis above may underestimate the the effect of online shopping as we only consider the impact of one major e-commerce platform. We complement this analysis with an additional exercise, using broadband availability as a proxy for online shopping accessibility. Our findings indicate that greater availability of high-speed Internet does not lead to an increase in household HHI. However, households in areas with more broadband providers tend to make fewer shopping trips. Results are shown in online Appendix Table I15.

E Other Hypotheses

What are some other hypotheses that can explain the rise in household concentration? In online Appendix Section E.1, we explore the effect of changes in the opportunity cost of time on households. We find that an increase in the opportunity cost of time can reduce the number of shopping trips and thus lead to a rise in household HHI. In online Appendix Section E.2, we further discuss changes in the cost of travel, improvements in leisure technology, diverging tastes between households, and increases in consumer loyalty could be contributing factors, whereas converging tastes within households due to positive assortative matching in household formation, income inequality, and income polarization are less likely to be key contributing factors. We leave an in-depth exploration of these other factors for future research.

E.1 Time Costs

We investigate the impact of changes in time costs among households with two exercises. We first show using an event study that an episode of non-employment, which should lower time costs, decreases household HHI and raises the number of shopping trips. Next, following the literature on opportunity costs of time, we use variation in household characteristics over time and proxies of labor demand shocks across demographic groups as IVs for the number of shopping trips. We estimate that a decrease in the number of shopping trips raises household HHI, cross-household variance, and varieties per trip. Our BOTEs imply that the decrease in shopping trips has the potential to explain the entire rise in household HHI.

First, we regress household HHI or the number of shopping trips on an indicator for whether the female or male household head is not working, focusing on prime-aged household

[34] The first stage F-stat is only about 1, suggesting that our IV estimates will not be reliable with this set of independent variables. We conjecture that this is because same-day shipping affects mostly food, for which the online share is very small in our data. In contrast, the sales tax affects all product categories.

heads from age 25-54. Household and period fixed effects are included. We use both OLS and methods robust to heterogeneous treatment effects following DCDH. We show the cumulative effect of non-employment on household HHI and the number of shopping trips for both female and male heads in online Appendix Figure J21 and J22 respectively, using both OLS and following DCDH. We find that pre-trends are parallel and non-employment for female heads leads to a decline in household HHI by about 1 percentage point and a rise in the number of shopping trips by about 5%, while results are statistically insignificant for male heads. This is consistent with D'Acunto et al. (2021), who document that females are predominantly the primary shopper in households with both genders as household heads. These figures suggest that shifts in the opportunity cost of time of primary shoppers of households can have a significant effect on household HHI and shopping time. Given that the female employment rate for prime-aged workers rose from 69% to 74% during the recovery in our sample period as shown in online Appendix Figure J23, we calculate a BOTE of close to 1% from the rise in prime-aged female employment rates.[35] Since these estimates are only relevant for the extensive margin, we further investigate the impact of changes in average real wages and unemployment rates using our proxies for labor demand shocks.

Next, we follow AH and use the number of shopping trips per household in each time period as a proxy for the amount of shopping time spent. Figure 5 in Coibion et al. (2021a) offers support for the use of this proxy, since it shows similar trends in shopping time using the American Time Use Survey (ATUS). We then evaluate how plausibly exogenous changes in shopping time affect household retail concentration. Specifically, our estimating equation is as follows:

$$Y_{it} = \beta \times N_{it} + X_{it}'\gamma + \alpha_i + \alpha_t + \varepsilon_{it}. \tag{17}$$

We regress our outcomes of interest such as household HHI on the number of shopping trips N_{it} for each household-period it along with a vector of control variables. We then instrument for the number of shopping trips with a series of IVs following AH and Aguiar et al. (2013).

First, we use household characteristics as IVs. By including household and time fixed effects, we can extend beyond using cross-sectional variation as in AH and leverage within-household variation in household characteristics, using household age, size, and employment status as IVs. A caveat is that these IVs themselves may reflect changes in unobservables and shopping needs. We address these threats to identification in several ways. First, we directly control for shopping needs X_{it} as in AH by including the log of the quantity index derived from the RPI as well as the log number of UPCs and product groups purchased per period. Second, we show that our results are robust to using a wide range of IVs, which assuages concerns that the IVs themselves may be reflecting changes in unobservables.

Second, we use proxies of labor demand shocks as IVs to further address threats to identification. We first document that based on the Current Population Survey Merged Outgoing Rotation Groups (CPS MORG), average hourly real wages have been rising over the

[35] About 50% of households have a prime-aged female head so a 5 percentage point increase in female employment rates can raise household HHI by 0.5*0.05*0.01 = 0.025 percentage points, which is about 0.8% of the 3 percentage point rise in household HHI during the recovery.

sample period and unemployment rate rose substantially during the recession but gradually dropped to levels below those before the recession. This is consistent with the fall in shopping trips shown in online Appendix Figure 4, which stagnated during the recession before falling further during the recovery. We show the trends for average wages and unemployment rate by gender and age group in online Appendix Figure J24, and by gender and education group in online Appendix Figure J25. As seen in these figures, trends do differ by gender, age, and education.

We follow Aguiar et al. (2013) and Aguiar et al. (2021) by using these differential changes as proxies of labor demand shocks that affect the opportunity cost of time, using national-level changes in both average wages and unemployment rates by household group as IVs. Our identifying assumption is that these changes reflect differential shifts in labor demand across various household demographic characteristics that are plausibly exogenous to unobservables affecting individual household shopping behavior. We construct these proxies at various levels of aggregation across household characteristics in the CPS MORG, such as age and education cells across the US. We match these proxies to households in the HMS using the mode of their characteristics over the sample period to avoid using variation induced by shifts in characteristics over time.

It is important to note that these labor demand shocks could be driven by cyclical factors such as unemployment as opposed to long-run trends. Therefore, if the rise in opportunity cost of time is driven by business-cycle variation, this rise in household concentration may be reversed during recessionary periods, similar to how we observe a dip in household concentration in Figure 1 during the Great Recession. However, if the rise in opportunity cost of time is driven by more long-run trends such as changes in real wages, a rise in leisure technology, or shopping trip costs as we will discuss in online Appendix Section E.2, the impact of time costs on household concentration may be more long-lasting. Our empirical strategy focuses more on providing a proof-of-concept that aims to leverage plausibly exogenous sources of variation to show how time costs can raise household HHI.

We show our results from estimating equation (17) using additional household characteristics as IVs in online Appendix Table I16. We first show OLS results with and without controls for shopping needs. We find that adding controls increases the effect of shopping trips on household HHI. A 1% decrease in the number of trips increases household HHI by about 0.2 percentage points. This is consistent with the fact that unobservables affecting household HHI, such as changes in shopping needs, may also affect the number of shopping trips. For the remaining specifications, we continue to control for shopping needs to isolate the effect of time costs on household HHI separate from the effect it also has on shopping quantities.

We find that using household age, size, and employment as IVs generate nearly identical coefficients in line with our event study estimates. These results are also robust to adding a county-time fixed effect to control for potential supply-side changes that vary over time within a county. The size of the first-stage F-stat implies the IV is relevant and the signs of the first-stage coefficients are consistent with a priori reasoning, i.e. increased household age, decreased household size, and unemployment all increase the amount of shopping trips. Using the average change in shopping trips over the sample period to calculate our BOTE, we find that shopping time has the potential to explain the entire rise in household HHI, with BOTEs ranging from 40%-100%. However, this BOTE can reflect both endogenous and exogenous factors affecting shopping time.

Therefore, we now focus on a potentially exogenous force decreasing shopping time by presenting results in online Appendix Table I17 using national changes in group-level averages of male and female real wages, unemployment rates, and both as IVs. These groups include (1) age, (2) education, and (3) age plus education combined. While the magnitudes of the estimated coefficients do vary by IV, nearly all coefficients are statistically and economically significant. In all of the specifications, the first-stage F-stat passes the usual thresholds and the signs of the first-stage coefficient are consistent with a priori reasoning, i.e. rises in wages and drops in unemployment decrease shopping time. The BOTE using changes in shopping trips range from about 80%-220%, while the BOTE using only changes in the IVs range from about 0-14%. This suggests that labor demand shocks by age and education group do increase the opportunity cost of time and can explain up to 14% of the rise in household HHI.

E.2 Additional Hypotheses

We also investigate changes in the cost of travel as a potential hypothesis. Following Gelman et al. (2016), who argue that gas prices during 2014-2015 were driven by unanticipated, permanent, and exogenous supply shocks, we estimate the effect of the number of shopping trips on household HHI using state- or city-level gas prices from the Energy Information Administration (EIA) and Bureau of Labor Statistics (BLS) as IVs. We focus on the period of 2010-2016 to avoid using recessionary shocks that may also be driven by the demand side. Our identifying assumption is that the elasticity of gas prices to supply shocks, i.e. demand elasticity for gas, is plausibly exogenous to unobservables affecting household HHI. Note that we have controlled for shopping needs to attempt to account for income effects. We show our results in online Appendix Table I18. We wish to interpret these results with caution, since the first-stage F-statistic is quite weak, ranging from 4-8. The BOTE implies that the rise in gas prices from 2004-2019 could explain up to 12% of the rise in household HHI, but since gas prices actually fell from 2010-2016 as shown in online Appendix Figure J26, changes in gas prices cannot explain the rise of household HHI during this period. Nonetheless, these results provide suggestive evidence that a rise in the cost of travel, in this case gas prices, does lower shopping time and raise household HHI.

In addition to the cost of travel, factors such as a rise in the preference for leisure and a rise in leisure technology can also increase the opportunity cost of shopping time. Our theoretical results in online Appendix Section F show that these factors can indeed raise both household concentration and cross-household variance. Using the ATUS sample from Aguiar et al. (2021), we find that the drop in weekly shopping time from 2004-2007 to 2014-2017 is smaller for men relative to women, which stands in contrast with the rise of recreational computing being the largest for young men. Shopping time fell by about 18% for women aged 21-30 from a base of 6.2 hours to 5.1 hours, and 15% for women aged 31-55 from a base of about 6.5 hours to 5.5 hours. Men aged 21-30 experienced a fall of about 10% from a base of 4 hours to 3.6 hours, while men aged 31-55 experienced the smallest drop of 5% from a base of 4.1 hours to 3.9 hours. Table 1 of Aguiar et al. (2021) shows that the rise in leisure was largest for young men (2.3 hours) but also significant for women (1.6 and 1.3 hours), and smallest for older men (0.6 hours). Therefore, the rise in recreational computing technology seems insufficient to explain the rise in household concentration for both younger and older women as shown in Figure 3d. Other forms of leisure technology that impact women in both of these age groups could be a contributing factor.[36]

We also consider the possibility of whether tastes are converging within households, which may be the case if there is increasing positive assortative matching on tastes in household formation. Online Appendix Figure J8 shows that the increase in household HHI holds across all household sizes and is slightly larger for households with more members. Given that single-member households experienced a substantial increase in household HHI, we believe that converging tastes within households is unlikely to be a key explanation for rising household concentration.

Our results on cross-household variance are also consistent with increasing divergence in tastes between households. However, our theoretical results in online Appendix Section F.4 imply that diverging tastes are not necessary to generate increases in cross-household variance. As long as there is heterogeneity in shopping costs across households, even if the degree of heterogeneity remains unchanged over time, a rise in the opportunity cost of shopping time can generate rising cross-household variance because households will polarize to their preferred retailers and the overlap in choice sets will decrease. We leave an in-depth exploration of diverging tastes for future research.

The rise in household concentration and cross-household variance can also be consistent with increasing consumer loyalty. For example, club stores require customers to become members in order to shop there, which may encourage households to only shop at retailers at which they are members. Our results show that a club store entry actually lowers household HHI, but this is insufficient to rule out loyalty as a contributing factor since club stores could lower household HHI for other reasons that we discussed previously such as lower product variety, potentially offsetting some of the loyalty effect. Therefore, we leave loyalty as an explanation for further exploration in future research.

We also investigate the differences across regions based on urban-rural classifications interacted with household income in online Appendix Figure J8. We find that household concentration trends across income groups remain similar even after conditioning on urban-rural classification. Given the magnitude of increases are similar between income groups, we believe that changes in income inequality and polarization are unlikely to be key drivers of rising household concentration through compositional shifts. However, income inequality and polarization could drive the divergence in tastes between households that we discussed above, and there could be resulting supply responses by retailers to cater to these tastes in the same way that producers of brands respond as shown in Faber and Fally (2022).

F Conceptual Framework

To illustrate the underlying mechanisms and rationalize these empirical results, we develop a conceptual framework that incorporates the explanations discussed in the previous section. For simplicity, we first focus on the demand side only and discuss supply-side equilibrium responses of firm markups in Section 5. We model a household's allocation

[36] While we do not have a simple empirical strategy to quantify the size of these effects, one possibility could be to estimate a leisure demand system following Aguiar et al. (2021).

decision for consumption and time, and derive comparative statics for each of the variables of interest. We show the conditions under which evolutions in both supply and demand can affect household concentration and consumer welfare. All details and derivations are shown in online Appendix Section G.

F.1 Households' Decision

Households value consumption goods and leisure, and are constrained by their income and time. Each household determines the consumption bundle, which consists of quantities of goods purchased in the stores that the household visits. We denote stores, retail chains, and firms interchangeably since our data provides us with a retail-chain identifier only. We assume households have CES preferences as a parsimonious way to incorporate gains from variety. Each household faces a set of stores with a firm-specific variety-adjusted price index and location features. The time cost of making a trip to each firm depends on the firm location. Each household then chooses to visit the subset of firms that generate a higher marginal benefit from purchasing products than the marginal trip costs. This extends upon standard CES preferences by introducing an extensive margin of firm choice such that not all firms are visited. Both labor and non-labor income are spent on consumption goods. Time is allocated to labor, leisure and visiting stores.

We adopt a Cobb-Douglas utility function for each household.[37] The optimization problem for a household can be expressed as follows:

$$\max_{\mathcal{V}\subset\mathcal{F},X,L,h} U = X(\mathcal{V})^{1-\rho}L^{\rho} \tag{18}$$

$$s.t.\ Y = wh + K = P(\mathcal{V})X(\mathcal{V}) \tag{19}$$

$$\tau(\mathcal{V}) + L + h = T,\ \text{where } \tau(\mathcal{V}) = \int_{f\in\mathcal{V}} t_f df \tag{20}$$

Let L denote leisure time, with a preference parameter ρ as shown in equation (27). Let $\mathcal{F}$ denote the set of firms that are available to the household and $\mathcal{V} \subset \mathcal{F}$ is the set of firms that the household chooses to visit. $X(\mathcal{V})$ is a composite consumption good that the household purchases from the firm set $\mathcal{V}$. To describe households' multi-store multi-product shopping behavior, we assume two CES nests for firms and product varieties for the composite good as shown in equation (21):

$$X(\mathcal{V}) = \left(\int_{f\in\mathcal{V}} (\varphi_f x_f)^{\frac{\sigma^F-1}{\sigma^F}} df\right)^{\frac{\sigma^F}{\sigma^F-1}},\ x_f = \left(\int_{u\in\mathcal{U}_f} (\varphi_u x_u)^{\frac{\sigma^U-1}{\sigma^U}} du\right)^{\frac{\sigma^U}{\sigma^U-1}} \tag{21}$$

We follow Hottman et al. (2016) for the CES nests of the consumption goods. The first nest is for firms. For each firm $f \in \mathcal{V}$, it has a taste parameter φ_f and quantity consumed x_f. The elasticity of substitution between firms is σ^F. The second nest is for product variety within firms, which enables the household to choose a set of products $\mathcal{U}_f$ from firm f. Each

[37] Results are nearly identical and give the same intuition using a separable consumption-leisure constant relative risk aversion (CRRA) utility function that is common in labor supply life-cycle models.

product has a taste parameter φ_u and quantity consumed x_u with an elasticity of substitution σ^U between products.[38]

The household has income Y from supplying labor hours h at wage w and non-labor income K, which is used to buy consumption goods. We use $P(\mathcal{V})$ to denote the price of the composite good $X(\mathcal{V})$ from all the chosen firms. The amount of time a household has is T, which is split among shopping time $\tau(\mathcal{V})$, leisure L, and labor supply h. Shopping time $\tau(\mathcal{V})$ is the integral of the shopping cost for each firm t_f over all the firms $\mathcal{V}$ that the household chooses to visit.

The household maximizes utility by choosing firms $\mathcal{V}$, quantity of consumption goods $X(\mathcal{V})$, leisure time L, and labor supply h, subject to the budget constraint in equation (19) and time constraint in equation (20).

Next, we describe the solution of the model. We solve for the demand for consumption goods at the firm and product level, obtaining the following expressions for $x_f, f \in \mathcal{V}$ and $x_u, u \in \mathcal{U}_f$:

$$x_f = (\varphi_f)^{\sigma^F-1} Y P(\mathcal{V})^{\sigma^F-1} (p_f)^{-\sigma^F} \tag{22}$$

$$x_u = (\varphi_f)^{\sigma^F-1} (\varphi_u)^{\sigma^U-1} Y P(\mathcal{V})^{\sigma^F-1} (p_f)^{\sigma^U-\sigma^F} (p_u)^{-\sigma^U} \tag{23}$$

where $p_u, u \in \mathcal{U}_f$ is the price of each product in firm f. The price indices for total consumption $P(\mathcal{V})$ and consumption in each firm $p_f, f \in \mathcal{V}$ are

$$P(\mathcal{V}) = \left(\int_{f \in \mathcal{V}} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \right)^{\frac{1}{1-\sigma^F}}, \; p_f = \left(\int_{u \in \mathcal{U}_f} \left(\frac{p_u}{\varphi_u} \right)^{1-\sigma^U} du \right)^{\frac{1}{1-\sigma^U}}. \tag{24}$$

Based on equation (21), we get the demand for composite good $X(\mathcal{V})$ and solve for optimal leisure and labor hours for a given set $\mathcal{V}$. Substituting these expressions into the utility function, we can follow Bronnenberg (2015) and derive that the optimal cutoff firm f^* in the set of firms $\mathcal{F}$ satisfies the following condition:

$$\frac{Y P(\mathcal{V})^{\sigma^F-1} \left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F}}{\sigma^F - 1} = w t_{f^*} \tag{25}$$

Equation (25) equalizes the marginal benefit and cost of visiting an additional firm. The marginal benefit increases as the taste-adjusted price of a firm decreases relative to the price index $P(\mathcal{V})$ the household faces, decreases with elasticity of substitution σ^F, and increases with income Y. The marginal cost increases with wage w, which also represents the opportunity cost of time, and shopping cost t_f. A firm will be visited whenever the marginal benefit exceeds the marginal cost.

Without loss of generality, we can arrange firms in a weakly ascending order of the scalar

[38] We can also similarly allow for time costs to buy each product, e.g. it takes time to search and become aware of a product, which implies that not all products in each visited firm will be bought. Michelacci et al. (2021) highlight the implications of incorporating these product adoption expenditures in detail. We abstract from this in our main setup for tractability.

index $g_f \equiv t_f \left(\frac{p_f}{\varphi_f}\right)^{\sigma^F-1}$ on a continuum $[\underline{f}, \overline{f}] \subset \mathbb{R}_+$.[39] For any two firms $f, f' \in [\underline{f}, \overline{f}]$,

$$f < f' \Leftrightarrow t_f \left(\frac{p_f}{\varphi_f}\right)^{\sigma^F-1} \leq t_{f'} \left(\frac{p_{f'}}{\varphi_{f'}}\right)^{\sigma^F-1}. \tag{26}$$

Firm $\underline{f}$ and firm $\overline{f}$ represent the lower bound and and upper bound in the available set of firms $\mathcal{F}$.[40] Based on equation (25), the household visits all the firms that satisfies $t_f \left(\frac{p_f}{\varphi_f}\right)^{\sigma^F-1} \leq \frac{YP(\mathcal{V})^{\sigma^F-1}}{w(\sigma^F-1)}$. We can thus write the set of firms visited by the households as $\mathcal{V} = \{f, f \in \{\mathcal{F} \cap [\underline{f}, f^*]\}\}$, where $f^* \in \mathcal{F}$ is the cutoff firm such that the household does not visit any firm $f > f^*$. We can prove that there exists a unique f^* that maximizes utility. We proceed to comparative statics using this setup.

F.2 Comparative Statics

We can derive expressions for each firm's market share at the household level and household retail concentration from the above setup. We then show comparative statics of household retail HHI in response to changes in various parameters of interest in online Appendix Table I19.

First, we consider the entry of a new firm f^N. Based on our derivations, whether household HHI increases or decreases depends on the difference between the price index of the new firm, firms that the household stops visiting, and those that are still visited. If the difference is large enough with a relatively low price index for the new firm, household HHI increases. For the majority of entries, household HHI is likely to decrease. We show in online Appendix G the conditions under which household HHI increases and decreases with an entry. This is consistent with our empirical results that the opening of club stores, which tend to have a similar price index to other stores, decreases household HHI. The entry of firms like a supercenter is more likely to increase household HHI, as its price index is much smaller than most of the incumbent firms due to its much larger product variety and lower relative prices.

Alternatively, if the new firm has a scalar index that is smaller than the original lower bound, i.e. $g_{f^N} < g_{\underline{f}}$, then we model the event as a fall in the lower limit. The new continuum of firms is $[f^N, \overline{f}]$, with $f^N < \underline{f}$. We can also derive a condition under which a decrease in the lower bound raises household HHI. This can model the entry of supercenters to a market where such type of firms did not exist. When the household stops visiting many incumbent firms after the entry, household HHI increases.

Second, we consider changes that decrease a firm's price index p_f by lowering product prices or raising product variety. A rise in p_f can either increase or decrease household HHI,

[39] Assuming the firms lie on a continuum allows for higher analytical tractability and the use of integrals. We could also allow for discrete firms and use summations instead with similar intuitions for all of our derivations. For example, we find that assuming discrete firms allow us to understand the entry of new firms more richly.

[40] This does not mean $\mathcal{F} \equiv [\underline{f}, \overline{f}]$. The available firms belong to the continuum, but does not need to cover the continuum. If $f \in \mathcal{F}$, then $f \in [\underline{f}, \overline{f}]$, but not the other way round.

depending on whether the firm price index decreases favor firms with a larger or smaller initial firm price index. We derive a condition under which household HHI would increase as the price index decreases in online Appendix Section G.

Third, we analyze changes on the demand side. The key parameter is wage w as the opportunity cost of time. When wage increases, the marginal cost of the RHS of equation (25) rises, but the total income Y on the LHS also goes up. We derive that as wage w increases, household HHI also increases. Note that wage and income has opposite impacts on household HHI. When a rise in non-labor income K increases total income Y, the cutoff price increases and household HHI declines, which is consistent with the fact that higher income households have lower household HHI as shown in Figure 3a.

All of these results are intuitive and consistent with our empirical results that the entry of supercenters, an increase in product variety, and a rise in the opportunity cost of time raise household HHI. This model also allows for other mechanisms that may affect household HHI, such as an increase in trip costs due to gas price increases, changes in leisure technology etc. We provide discussions of these factors in online Appendix Section E and derive how they affect household HHI in online Appendix Section G. We also discuss how the increase in cross-household variance can be explained by our model when we allow for household heterogeneity in online Appendix Section F.4.

F.3 Welfare

We discuss the implications on consumer welfare from various changes on the supply side and demand side. Using the envelope theorem, we can derive comparative statics on welfare. We summarize these results in online Appendix Table I19.

First, consider changes on the supply side. The entry of a new firm f^N increases welfare as long as that firm is visited, since a firm is only visited if the marginal benefit exceeds the marginal cost.[41] Similarly, a fall in minimum firm price index $\underline{f}$ increases welfare. A fall in the price index p_f of any firm will increase welfare as long as that firm is visited. Therefore, all of these supply-side changes should increase welfare.

Second, consider changes on the demand side. A rise in wage w raises welfare as it increases income Y. Let the shopping cost be $t_f = t\delta_f$, where t is the time cost per distance traveled and δ_f is the distance of the consumer from each firm indexed by f. A rise in the time cost per distance traveled t lowers welfare, since more time is spent shopping, decreasing both income Y and leisure L. A rise in leisure technology θ unambiguously raises welfare by increasing the value of leisure. Therefore, the source of the rise in opportunity cost of time is crucial in determining whether welfare increases or decreases.

F.4 Heterogeneity

The analysis in online Appendix Section F is for a representative household. To explain the increase in cross-household variance during the same period as household HHI goes up, we need to allow for heterogeneity across households within the same region.

[41] If the consumer stops visiting certain firms in favor of the new firm, it must be the case that these firms are giving lower net benefits than the new firm by revealed preference.

We consider a simple case with only two groups of households to illustrate heterogeneity. To achieve this, we first assume that only trip costs t_{if} vary by household i. We assume that firms have identical taste parameters φ_f equal to one. This is simply done for expositional purposes and allows us to index each firm by their price index p_f rather their taste-adjusted price index $\frac{p_f}{\varphi_f}$. Next, we place some structure on the relationship between t_f and p_f, which is key in forming the scalar index g_f. We assume that the shopping cost at each firm t_{if} is a function of the price index p_f in each firm, with $t_i'(p_f) < 0$. This is consistent with the fact that firms with larger variety and lower prices, i.e. lower p_f, tend to be located farther away from consumers relative to firms with lower variety and higher prices, due to higher costs of land in areas with higher population density and the need for larger square footage stores in order to stock higher variety and lower prices through economies of scale. We can show that if $t_i'(p_f)$ is small enough in absolute value, there exists a unique cutoff firm $p_{\overline{f*}}$ that satisfies equation (25) such that consumers only buy from firms that have a price index within the set $[p_{\underline{f}}, p_{\overline{f^*}}]$. On the other hand, if $t_i'(p_f)$ is large enough in absolute value, we can also derive conditions under which there exists a unique $p_{\underline{f^*}}$ such that households visit retailers in the set $[p_{\underline{f^*}}, p_{\overline{f}}]$.

Therefore, if there is a group of consumers with a less negative $t_i'(\cdot)$ (Group 1) and another group with a more negative $t_i'(\cdot)$ (Group 2), Group 1 will consume only from low price index firms in the set $[p_{\underline{f}}, p_{\overline{f^*}}]$ and Group 2 will only consume from high price index firms in the set $[p_{\underline{f^*}}, p_{\overline{f}}]$. We can consider households in Group 2 as those who find it far more costly to visit firms with large variety and low prices that are generally located away from population centers, e.g. households that do not have cars.

Suppose there exists a set of firms from which both groups consume, i.e. $p_{\underline{f^*}} < p_{\overline{f^*}}$. As household HHI increases from both the supply and demand-side changes we discussed previously, the set of firms that each group visits will decrease, decreasing $p_{\overline{f^*}}$ for Group 1 and increasing $p_{\underline{f^*}}$ for Group 2. Cross-household variance will increase as each group polarizes into their respective set of firms. Group 1 will polarize towards low price index firms with larger variety, lower prices, and higher shopping costs, while Group 2 will polarize towards high price index firms with lower variety, higher prices, and lower shopping costs.

We can extend this intuition to cases with many household groups or even household-specific heterogeneity. As household HHI increases, households shrink the set of firms they consume from. If there is sufficient overlap between different households but also a sufficient level of heterogeneity across households, households will polarize towards their preferred firms and overlap will decrease, raising cross-household variance. Therefore, this is consistent with our empirical results that demand-side changes such as a rise in wage w will all increase household HHI and increase cross-household variance. For supply-side changes such as the entry of stores and variety change within stores, the impact on cross-household variance depends on the household groups that are affected. For example, if Group 2 consumers do not visit club stores, then the entry of club stores does not change their household HHI, and any change in cross-household variance will only result from changes in consumption of the first group. Hence, these changes may have a smaller effect on cross-household variance, consistent with our findings that the entry of supercenters and club stores do not have a statistically significant effect on cross-household variance.

G Derivations

G.1 Markup Formulas

Using equation (8), (9), and (10), we can rewrite the aggregate markup in (11) as follows:

$$\mathcal{M} = \sum_f \frac{1}{\frac{1}{S_f} - \frac{1}{S_f \varepsilon_f}} = \sum_f M\left(\sum_i \frac{Y_i}{Y} S_{if}, \sum_{i\in I_f} \frac{Y_i}{Y} S_{if}\varepsilon_{if}(S_{if}, Y_i)\right)$$

$$M(x_1, x_2) \equiv \frac{1}{\frac{1}{x_1} - \frac{1}{x_2}}, M_{x_1} > 0, M_{x_2} < 0$$

$$S_f\varepsilon_f = \sum_{i\in I_f} \frac{YS_f}{\sum_f YS_f}\frac{Y_iS_{if}}{YS_f}\varepsilon_{if}(S_{if}, Y_i) = \sum_{i\in I_f} \frac{Y_iS_{if}}{\sum_f YS_f}\varepsilon_{if}(S_{if}, Y_i) = \sum_{i\in I_f} \frac{Y_i}{Y} S_{if}\varepsilon_{if}(S_{if}, Y_i)$$

Under symmetric translog demand and monopolistic competition, we can show that the aggregate markup can be derived as follows:

$$\varepsilon_{if}(S_{if}, Y_i) = 1 + \frac{\bar{\sigma}}{S_{if}}$$

$$\varepsilon_f = \sum_{i\in I_f} \frac{Y_iS_{if}}{\sum_i Y_iS_{if}}\left(1 + \frac{\bar{\sigma}}{S_{if}}\right) = 1 + \frac{\bar{\sigma}}{\bar{S}_{if}}$$

$$\bar{S}_{if} \equiv \sum_{i\in I_f} \frac{Y_i}{\sum_{i\in I_f} Y_i} S_{if}$$

$$\mathcal{M} = \sum_f S_f \frac{\varepsilon_f}{\varepsilon_f - 1} = \sum_f S_f \frac{1 + \frac{\bar{\sigma}}{\bar{S}_{if}}}{\frac{\bar{\sigma}}{\bar{S}_{if}}} = 1 + \frac{1}{\bar{\sigma}}\sum_f\sum_i \frac{Y_i}{Y}\bar{S}_{if}S_{if}$$

G.2 Households' Problem

The optimization problem for a household can be expressed as follows:

$$\max_{\mathcal{V}\subset\mathcal{F},X,L,h} U = X(\mathcal{V})^{1-\rho}L^{\rho} \tag{27}$$

$$s.t.\ Y = wh + K = P(\mathcal{V})X(\mathcal{V}) \tag{28}$$

$$\tau(\mathcal{V}) + L + h = T, \text{ where } \tau(\mathcal{V}) = \int_{f\in\mathcal{V}} t_f df \tag{29}$$

We assume two CES nests for firms and product varieties for the composite good as shown in equation (30):

$$X(\mathcal{V}) = \left(\int_{f\in\mathcal{V}} (\varphi_f x_f)^{\frac{\sigma^F-1}{\sigma^F}} df\right)^{\frac{\sigma^F}{\sigma^F-1}},\ x_f = \left(\int_{u\in\mathcal{U}_f} (\varphi_u x_u)^{\frac{\sigma^U-1}{\sigma^U}} du\right)^{\frac{\sigma^U}{\sigma^U-1}} \tag{30}$$

Demand

We solve for the demand equation for firms with the Lagrangian $\mathcal{L}$ and apply standard CES algebra as shown in Bronnenberg (2015).

$$\mathcal{L} = U(X(\mathcal{V}), L(\mathcal{V})) + \lambda \left(wT + K - w\left(\tau(\mathcal{V}) + L\right) - \int_{f\in\mathcal{V}} p_f x_f df \right)$$

$$\frac{\partial \mathcal{L}}{\partial x_f} = (1-\rho)\left(\int_{f\in\mathcal{V}} (\varphi_f x_f)^{\frac{\sigma^F-1}{\sigma^F}} df\right)^{\frac{\sigma^F}{\sigma^F-1}(1-\rho)-1} L(\mathcal{V})^{\rho}(\varphi_f)^{\frac{\sigma^F-1}{\sigma^F}} x_f^{-\frac{1}{\sigma^F}} - \lambda p_f = 0$$

Integrate both sides after multiplying by $x_f \Rightarrow$

$$(1-\rho)X(\mathcal{V})^{-\rho+\frac{1}{\sigma^F}} L(\mathcal{V})^{\rho} \int_{f\in\mathcal{V}} (\varphi_f x_f)^{\frac{\sigma^F-1}{\sigma^F}} df = \lambda \int_{f\in\mathcal{V}} p_f x_f df$$

$$\frac{(1-\rho)X(\mathcal{V})^{-\rho}L(\mathcal{V})^{\rho}}{P(\mathcal{V})} = \lambda \quad \because Y = P(\mathcal{V})X(\mathcal{V})$$

Substitute λ back into the FOC following standard CES algebra $\Rightarrow$

$$x_f = A(\mathcal{V}) p_f^{-\sigma} \varphi_f^{\sigma^F-1}$$

$$A(\mathcal{V}) = Y P(\mathcal{V})^{\sigma^F-1}$$

$$P(\mathcal{V}) = \left(\int_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^{\frac{1}{1-\sigma^F}}$$

Solving for the demand at the firm and product level following Hottman et al. (2016), we have the following equations:

$$\begin{aligned}
x_f &= A(\mathcal{V}) p_f^{-\sigma^F} \varphi_f^{\sigma^F-1} \\
A(\mathcal{V}) &= Y P(\mathcal{V})^{\sigma^F-1},\ P = \left(\int_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^{\frac{1}{1-\sigma^F}} \\
x_u &= (\varphi_f)^{\sigma^F-1} (\varphi_u)^{\sigma^U-1} Y P(\mathcal{V})^{\sigma^F-1} (p_f)^{\sigma^U-\sigma^F} (p_u)^{-\sigma^U} \\
&= x_f (\varphi_u)^{\sigma^U-1} \left(\frac{p_f}{p_u}\right)^{\sigma^U} \\
p_f &= \left(\int_{u\in\mathcal{U}_f} \left(\frac{p_u}{\varphi_u}\right)^{1-\sigma^U}\right)^{\frac{1}{1-\sigma^U}} \\
&= \left(\underbrace{N_f}_{\text{Scope}} \quad \underbrace{\frac{1}{N_f}\int_{u\in\mathcal{U}_f} \left(\frac{p_u}{\varphi_u}\right)^{1-\sigma^U}}_{\text{Average product taste-adjusted prices}} \right)^{\frac{1}{1-\sigma^U}}
\end{aligned}$$

<u>Leisure</u>

Similarly, using the first-order condition (FOC) for leisure, we have

$$\frac{\partial \mathcal{L}}{\partial L} = \rho L(\mathcal{V})^{\rho-1} X(\mathcal{V})^{1-\rho} = \lambda w$$

$$L(\mathcal{V}) = \left(\frac{\lambda w}{\rho X(\mathcal{V})^{1-\rho}}\right)^{\frac{1}{\rho-1}} = \left(\frac{\lambda w}{\rho}\right)^{\frac{1}{\rho-1}} X(\mathcal{V}) \longrightarrow \frac{\rho L(\mathcal{V})^{\rho-1} X(\mathcal{V})^{1-\rho}}{w} = \lambda$$

Next, we also show the standard CES result that income equals the price index times quantity consumed.

$$\text{FOC: } \varphi_f x_f = YP(\mathcal{V})^{\sigma^F-1}\left(\frac{p_f}{\varphi_f}\right)^{-\sigma^F}$$

$$(\varphi_f x_f)^{\frac{\sigma^F-1}{\sigma^F}} = \left(YP(\mathcal{V})^{\sigma^F-1}\left(\frac{p_f}{\varphi_f}\right)^{-\sigma^F}\right)^{\frac{\sigma^F-1}{\sigma^F}}$$

$$\int_{f\in\mathcal{V}} (\varphi_f x_f)^{\frac{\sigma^F-1}{\sigma^F}} df = \left(YP(\mathcal{V})^{\sigma^F-1}\right)^{\frac{\sigma^F-1}{\sigma^F}} \int_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df$$

$$X(\mathcal{V}) = YP(\mathcal{V})^{\sigma^F-1} P(\mathcal{V})^{(1-\sigma^F)\frac{\sigma^F}{\sigma^F-1}} = YP(\mathcal{V})^{-1} \Rightarrow Y = P(\mathcal{V})X(\mathcal{V})$$

Given a Cobb-Douglas utility function for consumption and leisure, we combine these results with the CES utility to obtain the optimal leisure and consumption.

$$\max_{c,\ell} U(c,\ell) = c^{1-\rho}\ell^{\rho} \ s.t. \left.\begin{matrix} p_c c = wh + K \\ h + \ell + \tau = T \end{matrix}\right\} p_c c + w\ell + w\tau = wT + K$$

$$\mathcal{L} = c^{1-\rho}\ell^{\rho} + \lambda(wT + K - w\ell - w\tau - p_c c)$$

$$\left.\begin{matrix} \frac{\partial \mathcal{L}}{\partial c} = (1-\rho)c^{1-\rho-1}\ell^{\rho} - \lambda p_c = 0 \\ \frac{\partial \mathcal{L}}{\partial \ell} = \rho\ell^{\rho-1}c^{1-\rho} - \lambda w = 0 \end{matrix}\right\} \lambda = \frac{(1-\rho)c^{-\rho}\ell^{\rho}}{p_c} = \frac{\rho\ell^{\rho-1}c^{1-\rho}}{w} \Rightarrow c = \ell^{\rho-\rho+1}\cdot\frac{1-\rho}{\rho}\frac{w}{p_c}$$

$$c = \frac{1-\rho}{\rho}\frac{w\ell}{p_c} \Leftrightarrow \ell = \frac{\rho}{1-\rho}\frac{c}{w}p_c$$

$$\frac{1-\rho}{\rho}w\ell + w\ell + w\tau = wT + K$$

$$\frac{1}{\rho}w\ell = wT - w\tau$$

$$\ell = \frac{\rho\left(w(T-\tau) + K\right)}{w}$$

$$c = \frac{(1-\rho)\left(w(T-\tau) + K\right)}{p_c}$$

$$\begin{aligned} \lambda &= (1-\rho)\left((1-\rho)\frac{(w(T-\tau)+K)}{p_c}\right)^{-\rho}\left(\rho\left(w(T-\tau)+K\right)\right)^{\rho}\frac{1}{p_c} \\ &= (1-\rho)^{1-\rho}\left(\frac{w}{p_c}\right)^{-\rho}\rho^{\rho}\frac{1}{p_c} = \rho^{\rho}(1-\rho)^{1-\rho}\frac{1}{\rho p_c^{1-\rho}w^{\rho}} \end{aligned}$$

$$\begin{aligned} \therefore L(\mathcal{V}) &= \frac{\rho\left(w(T-\tau(\mathcal{V})) + K\right)}{w} \\ X(\mathcal{V}) &= \frac{(1-\rho)\left(w(T-\tau(\mathcal{V})) + K\right)}{P} = \frac{Y}{P} = \frac{w(T-\tau) - wL + K}{P} \\ Y &= (1-\rho)\left(w(T-\tau(\mathcal{V})) + K\right) \\ &= w(T - \tau(\mathcal{V}) - L(\mathcal{V})) + K \end{aligned}$$

Leisure technology

To incorporate the possibility of changes in leisure technology in a simple manner, assume leisure can be scaled by a technology factor of θ as follows, which gives the following equation for consumption and leisure:

$$\max_{c,\ell} u(c,\ell) = c^{1-\rho}(\ell^{\theta})^{\rho} \ s.t. \ p_c c + w\ell + w\tau = wT + K$$

$$\left.\begin{array}{l} \frac{\partial \mathcal{L}}{\partial c} = (1-\rho)c^{1-\rho-1}\left(\ell^{\theta}\right)^{\rho} - \lambda p_c = 0 \\ \frac{\partial \mathcal{L}}{\partial \ell} = \theta\rho\ell^{\theta\rho-1}c^{1-\rho} - \lambda w = 0 \end{array}\right\} \lambda = \frac{(1-\rho)c^{-\rho}\ell^{\theta\rho}}{p_c} = \frac{\theta\rho\ell^{\theta\rho-1}c^{1-\rho}}{w}$$

$$\Rightarrow c = \frac{1-\rho}{\theta\rho}\frac{w\ell}{p_c} \Rightarrow \frac{1-\rho}{\theta\rho}w\ell + w\ell + w\tau = wT + K$$

$$\ell = \frac{\theta\rho}{1-\rho+\theta\rho}\frac{w(T-\tau)+K}{w}$$

$$c = \frac{1-\rho}{1-\rho+\theta\rho}\frac{w(T-\tau)+K}{p_c}$$

Variety

Without loss of generality, assume $\mathcal{V} = [\underline{f}, f^*] \subset \mathbb{R}_+$. We can derive the optimal variety using the indirect utility function by substituting the optimal x_f into the utility function:

$$U = \left(\int_{f\in\mathcal{V}} (\varphi(f))^{\frac{\sigma^F-1}{\sigma^F}} \left(YP^{\sigma^F-1}p_f^{-\sigma^F}\varphi_f^{\sigma^F-1}\right)^{\frac{\sigma^F-1}{\sigma^F}} df\right)^{\frac{\sigma^F}{\sigma^F-1}(1-\rho)} L(\mathcal{V})^{\rho}$$

$$= \left(\frac{Y}{P(\mathcal{V})}\right)^{1-\rho} L(\mathcal{V})^{\rho}$$

$$= \left((1-\rho)w\left(T - \overbrace{\int_{\underline{f}}^{f^*} t_f df}^{\tau(\mathcal{V})}\right)\overbrace{\left(\int_{\underline{f}}^{f^*}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^{\frac{1}{\sigma^F-1}}}^{P(\mathcal{V})^{-1}}\right)^{1-\rho} \left(\rho\left(T - \int_{\underline{f}}^{f^*} t_f df\right)\right)^{\rho}$$

We can derive the optimal cutoff variety f^*. The FOC for variety is then:

$$\begin{aligned}
\frac{\partial U}{\partial f^*} &= L(\mathcal{V})^{\rho}(1-\rho)\left(\frac{Y}{P}\right)^{-\rho}\left(P^{-1}\frac{\partial Y}{\partial f^*}+Y\frac{\partial P^{-1}}{\partial f^*}\right)+\left(\frac{Y}{P}\right)^{1-\rho}\rho L(\mathcal{V})^{\rho-1}\frac{\partial L(\mathcal{V})}{\partial f^*}\\
&= L(\mathcal{V})^{\rho-1}\left(\frac{Y}{P}\right)^{1-\rho}\rho\left(\frac{1}{w}\frac{\partial Y}{\partial f^*}+\frac{1}{w}\frac{\partial P^{-1}}{\partial f^*}PY+\frac{\partial L(\mathcal{V})}{\partial f^*}\right)\\
&= \lambda\left[-(1-\rho)wt_{f^*}+\frac{YP(\mathcal{V})^{\sigma^F-1}}{\sigma^F-1}\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{1-\sigma^F}-\rho wt_{f^*}\right]\\
&= \lambda\left[-wt_{f^*}+\frac{A(\mathcal{V})\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{1-\sigma^F}}{\sigma^F-1}\right] \qquad (31)
\end{aligned}$$

Substituting these expressions into the utility function, we can follow Bronnenberg (2015) and derive that the optimal cutoff variety f^* in the set of varieties $\mathcal{V}$ satisfies the following condition:

$$\frac{A(\mathcal{V})\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{1-\sigma^F}}{\sigma^F-1} = wt_{f^*}$$

$$A(\mathcal{V}) = YP(\mathcal{V})^{\sigma^F-1} = (1-\rho)w\left(T-\tau(\mathcal{V})\right)\left(\int_{f\in\mathcal{V}}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}df\right)^{-1}$$

Without loss of generality, we can arrange firms in a weakly ascending order of the scalar index $wt_f\left(\frac{p_f}{\varphi_f}\right)^{\sigma^F-1}$ on a continuum $[\underline{f},\overline{f}]\subset\mathbb{R}_+$. For any two firms $f,f'\in[\underline{f},\overline{f}]$,

$$f<f' \Leftrightarrow t_f\left(\frac{p_f}{\varphi_f}\right)^{\sigma^F-1} \le t_{f'}\left(\frac{p_{f'}}{\varphi_{f'}}\right)^{\sigma^F-1}.$$

Firm $\underline{f}$ and firm $\overline{f}$ represent the lower bound and and upper bound in the available set of firms $\mathcal{F}$.[42] Based on equation (31), the household visits all the firms that satisfies $\frac{\partial U}{\partial f^*}\ge 0 \Rightarrow t_f\left(\frac{p_f}{\varphi_f}\right)^{\sigma^F-1}\le\frac{YP(\mathcal{V})^{\sigma^F-1}}{w(\sigma^F-1)}$. We can thus write the set of firms visited by the households as $\mathcal{V}=\{f,f\in\{\mathcal{F}\cap[\underline{f},f^*]\}\}$, where $f^*\in\mathcal{F}$ is the cutoff firm such that the household does not visit any firm $f>f^*$.

Variety and Leisure Technology

The FOC for variety can be derived similarly when allowing for leisure technology θ as

[42]This does not mean $\mathcal{F}\equiv[\underline{f},\overline{f}]$. The available firms belong to the continuum, but does not need to cover the continuum. If $f\in\mathcal{F}$, then $f\in[\underline{f},\overline{f}]$, but not the other way round.

follows:

$$
\begin{aligned}
X(\mathcal{V}) &= \frac{1-\rho}{1-\rho+\theta\rho}\frac{w(T-\tau(\mathcal{V}))+K}{P} \\
U &= \left(\frac{Y}{P}\right)^{1-\rho} L(\mathcal{V})^{\theta\rho} \\
\frac{\partial U}{\partial f^*} &= L(\mathcal{V})^{\theta\rho}(1-\rho)\left(\frac{Y}{P}\right)^{-\rho}\left(P^{-1}\frac{\partial Y}{\partial f^*}+Y\frac{\partial P^{-1}}{\partial f^*}\right)+\left(\frac{Y}{P}\right)^{1-\rho}\theta\rho L(\mathcal{V})^{\theta\rho-1}\frac{\partial L(\mathcal{V})}{\partial f^*} \\
&= L(\mathcal{V})^{\theta\rho-1}\left(\frac{Y}{P}\right)^{1-\rho}\theta\rho\left(\frac{1}{w}\frac{\partial Y}{\partial f^*}+\frac{1}{w}\frac{\partial P^{-1}}{\partial f^*}PY+\frac{\partial L(\mathcal{V})}{\partial f^*}\right) \\
&= \lambda\left[-wt_{f^*}+\frac{A(\mathcal{V})\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{1-\sigma^F}}{\sigma^F-1}\right] \\
Y &= w(T-\tau(\mathcal{V})-L)+K = \frac{1-\rho}{1-\rho+\theta\rho}\left(w(T-\tau(\mathcal{V}))+K\right), A(\mathcal{V}) = YP(\mathcal{V})^{\sigma^F-1}
\end{aligned}
$$

Uniqueness + existence of f^*

To more rigorously show that existence and uniqueness of f^*, we can write out the FOC in equation (31) in detail as follows:

$$
\frac{1}{\int_{\underline{f}}^{f^*}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}df}\frac{(1-\rho)\left(w\left(T-\int_{\underline{f}}^{f^*}t_f df\right)+K\right)}{w(\sigma^F-1)} - t_{f^*}\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{\sigma^F-1} = 0 \tag{32}
$$

$$
G(f') = \underbrace{\frac{1}{\int_{\underline{f}}^{f'}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}df}}_{A^{-1}}\underbrace{\frac{(1-\rho)\left(w\left(T-\int_{\underline{f}}^{f'}t_f df\right)+K\right)}{w(\sigma^F-1)}}_{B} - \underbrace{t_f\left(\frac{p_{f'}}{\varphi_{f'}}\right)^{\sigma^F-1}}_{g_{f'}}
$$

We then show that the FOC is above zero at the lower bound $\underline{f}$, below zero at the upper bound $\overline{f}$, and that its derivative is negative. Therefore, f^* uniquely maximizes utility.

$$
\text{Assume } G(\underline{f}) = \frac{1}{\left(\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}\right)^{1-\sigma^F}}\frac{(1-\rho)\left(w\left(T-t_{\underline{f}}\right)+K\right)}{w(\sigma^F-1)} - t_{\underline{f}}\left(\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}\right)^{\sigma^F-1} > 0
$$

$$
\text{Assume } G(\overline{f}) = \frac{1}{\int_{\underline{f}}^{\overline{f}}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}df}\frac{(1-\rho)\left(w\left(T-\int_{\underline{f}}^{\overline{f}}t_f df\right)+K\right)}{w(\sigma^F-1)} - t_{\overline{f}}\left(\frac{p_{\overline{f}}}{\varphi_{\overline{f}}}\right)^{\sigma^F-1} < 0
$$

$$
\begin{aligned}
G'(f') = (B)\left(-A^{-2}\right)\left(\frac{p_{f'}}{\varphi_{f'}}\right)^{1-\sigma^F} \qquad & < 0 \\
+ (A^{-1})\frac{1-\rho}{\sigma^F - 1}\left(-t_{f'}\right) \qquad & < 0 \\
- \frac{dg_{f'}}{df'} \qquad & < 0 \because f' \text{ is sorted in ascending order of } g_{f'} \\
< 0 &
\end{aligned}
$$

G.3 Household Retail Concentration

For each household, the market share for each firm f can be written as follows:

$$
S_f = \frac{p_f x_f}{Y} = \begin{cases} \left(\frac{p_f}{P(\mathcal{V})\varphi_f}\right)^{1-\sigma^F} & \text{if } \frac{YP(\mathcal{V})^{\sigma^F-1}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}}{w(\sigma^F-1)} \geq t_f \\ 0 & \text{otherwise} \end{cases}
$$

Based on the definition of household HHI, we thus get the expression for household retail concentration (H) :

$$
H = \int_{f\in\mathcal{V}} (S_f)^2 \, df = \frac{\int_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{2(1-\sigma^F)} df}{\left(\int_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^2} = \frac{\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{2(1-\sigma^F)} df}{\left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^2} \tag{33}
$$

We can then show some comparative statics of household HHI in response to changes in various parameters. First, we consider the entry of a new firm f^N. Let f^{**} denote the new cutoff firm after the entry. If $f^N \in (\underline{f}, f^*)$, then the new cutoff must satisfy $f^{**} \in [f^N, f^*]$. This is because when a new firm enters, the aggregate price index declines and total income may also decline. The LHS of equation (25) for an incumbent firm declines, making it less likely to be visited. Thus, $f^{**} \in [f^N, f^*]$. Let $\mathcal{V} = \mathcal{F} \cap [\underline{f}, f^*]$ denote the incumbent firms that are visited by the household before entry. Let $\mathcal{X} = \mathcal{F} \cap (f^{**}, f^*]$ denote the incumbent firms that are dropped by the household after the entry. Note that if $f^{**} = f^*$, $\mathcal{X} = \emptyset$. The difference in household retail HHI before (H) and after the entry (H^N) is calculated as follows:

$$
H^N - H = \frac{\sum_{f\in\{\mathcal{V}-\mathcal{X}\}\cap\{f^N\}} \left(\frac{p_f}{\varphi_f}\right)^{2(1-\sigma^F)}}{\left(\sum_{f\in\{\mathcal{V}-\mathcal{X}\}\cap\{f^N\}} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^2} - \frac{\sum_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{2(1-\sigma^F)}}{\left(\sum_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^2} \tag{34}
$$

Let $B = \sum_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{2(1-\sigma^F)}$, $C = \sum_{f\in\mathcal{V}} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}$, $E = \left(\frac{p_{f^N}}{\varphi_{f^N}}\right)^{1-\sigma^F}$, $X =$

$\sum_{f\in\mathcal{X}}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}$, $Z=\sum_{f\in\mathcal{X}}\left(\frac{p_f}{\varphi_f}\right)^{2(1-\sigma^F)}$. We can write equation (34) as follows:

$$\begin{aligned}
H^N - H &= \frac{B+E^2-Z}{(C+E-X)^2} - \frac{B}{C^2} \\
&= \frac{C^2(E^2-Z) - B(E-X)^2 - 2BC(E-X)}{C^2(C+E-X)^2} \\
\text{(By definition,}\quad X^2 \geq Z) \quad &\geq \frac{C^2(E^2-X^2) - B(E-X)^2 - 2BC(E-X)}{C^2(C+E-X)^2} \\
&= \frac{(E-X)[C^2(E+X) - B(E-X) - 2BC]}{C^2(C+E-X)^2}
\end{aligned}$$

If the household changes the set of firms that they visit after an entry, then the new aggregate price index must be lower, otherwise the household can always choose the old set. Thus, we must have $E > X$. Then we will have $H^N - H > 0$ when

$$\begin{aligned}
&C^2(E+X) - B(E-X) - 2BC > 0 \\
&(1-\frac{B}{C^2})E > \frac{2B}{C} - \left(1+\frac{B}{C^2}\right)X \\
&E > C\frac{2H}{1-H} - X\frac{1+H}{1-H}
\end{aligned} \tag{35}$$

From the definition, we know that $C^{1/(1-\sigma^F)}$ is the original aggregate price index before entry and $X^{1/(1-\sigma^F)}$ is the price index for the firms to be dropped after entry. For most of cases, $C^{1/(1-\sigma^F)}$ should be much larger than $X^{1/(1-\sigma^F)}$, i.e. $X \ll C$. We need E to be large enough so that the household HHI increases. Since E declines as the adjusted price index for the new firm p_{f^N}/φ_{f^N} increases, equation (35) suggests the adjusted price index for the new firm needs to be sufficiently low. In the special case that the cutoff does not change after entry, the condition becomes $E > C\frac{2H}{1-H}$, which is a stricter condition. Thus, when a firm with sufficiently low price index enters, the household HHI may increase. Otherwise, household HHI declines.

Next, we show that any parameters, in this case denoted by γ, that decrease the cutoff firm index $g_{f'}$ will increase household HHI. Intuitively, the set of retailers that households consume from $[\underline{f}, f^*]$ will decrease as f^* decreases.

$$\frac{df^*}{d\gamma} < 0 \Rightarrow \frac{dH}{d\gamma} > 0 \tag{36}$$

$$
\begin{aligned}
\frac{dH}{d\gamma} = & \int_{\underline{f}}^{f^*} \left(\left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} \right)^2 df \\
& \cdot \left(-2 \left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \right)^{-3} \left(\left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F} \frac{df^*}{d\gamma} + \int_{\underline{f}}^{f^*} \frac{\partial \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F}}{\partial \gamma} df \right) \right) \\
& + \frac{1}{\left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \right)^2} \left(\left(\left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F} \right)^2 \frac{df^*}{d\gamma} + \int_{\underline{f}}^{f^*} \frac{\partial \left(\left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} \right)^2}{\partial \gamma} df \right) \\
& = \frac{\left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F}}{\left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \right)^2} \left(\frac{2 \int_{\underline{f}}^{f^*} \left(\left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} \right)^2 df}{\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df} - \left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F} \right) \left(-\frac{df^*}{d\gamma} \right)
\end{aligned}
$$

$$
\frac{df^*}{d\gamma} < 0 \Rightarrow \frac{dH_i}{d\gamma} > 0 \text{ if } \frac{2 \int_{\underline{f}}^{f^*} \left(\left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} \right)^2 df}{\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df} > \left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F}
$$

$$
\text{Jensen's inequality} \Rightarrow \int \left(\left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} \right)^2 df \geqslant \left(\int \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \right)^2
$$

$$
\text{WTS } 2 \int_{\underline{f}}^{f^*} \left(\left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} \right)^2 df > \left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F} \int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df
$$

$$
\begin{aligned}
& 2 \int_{\underline{f}}^{f^*} \left(\left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} \right)^2 df \geqslant 2 \left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \right)^2 \\
& > \left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \right)^2 \geq \left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F} \int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \\
& \quad \because \int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f} \right)^{1-\sigma^F} df \geq \left(\frac{p_{f^*}}{\varphi_{f^*}} \right)^{1-\sigma^F}
\end{aligned}
$$

Given this fact, we can use equation (32) to derive comparative statics of the cutoff firm f^* in response to changes in various parameters to see how these parameters change household HHI. These comparative statics can then be compared against our empirical findings.

First, consider changes on the demand side. Let the shopping cost be $t_f = t\delta_f$, where t is the time cost per distance traveled and δ_f is the distance of the consumer from each firm indexed by f.

Extensive margin (f^*, Comparative Statics)

$$G(f^*) = \underbrace{\frac{1}{\int_{\underline{f}}^{f^*}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df}}_{A^{-1}} \underbrace{\frac{(1-\rho)\left(w\left(T-\int_{\underline{f}}^{f^*} t\delta_f df\right)+K\right)}{w(\sigma^F-1)}}_{B} - \underbrace{t\delta_f\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{\sigma^F-1}}_{g_{f^*}}$$

$$\begin{aligned}\frac{df^*}{dt} &= -\frac{\frac{\partial G(f^*,t)}{\partial t}}{\frac{\partial G(f^*,t)}{\partial f^*}} \\ &= \frac{\delta_f^*\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{\sigma^F-1} + (A^{-1})\,\frac{1-\rho}{\sigma^F-1}\left(\int_{\underline{f}}^{f^*}\delta_f df\right)}{\frac{\partial G(f^*,t)}{\partial f^*}} \\ &-\frac{\partial G(f^*,t)}{\partial t} > 0, \frac{\partial G(f^*,t)}{\partial f^*} < 0 \Rightarrow \frac{df^*}{dt} < 0\end{aligned}$$

$$\begin{aligned}\frac{df^*}{dw} &= -\frac{\frac{\partial G(f^*,w)}{\partial w}}{\frac{\partial G(f^*,w)}{\partial f^*}} \\ &= \frac{(A^{-1})\,\frac{1-\rho}{\sigma^F-1}Kw^{-2}}{\frac{\partial G(f^*,w)}{\partial f^*}} \\ &-\frac{\partial G(f^*,w)}{\partial w} > 0, \frac{\partial G(f^*,\rho)}{\partial f^*} < 0 \Rightarrow \frac{df^*}{dw} < 0\end{aligned}$$

$$\begin{aligned}\frac{df^*}{d\rho} &= -\frac{\frac{\partial G(f^*,\rho)}{\partial \rho}}{\frac{\partial G(f^*,\rho)}{\partial f^*}} \\ &= \frac{(A^{-1})\,\frac{1}{w(\sigma^F-1)}\left(w\left(T-\int_{\underline{f}}^{f^*} t\delta_f df\right)+K\right)}{\frac{\partial G(f^*,\rho)}{\partial f^*}} \\ &-\frac{\partial G(f^*,\rho)}{\partial \rho} > 0, \frac{\partial G(f^*,\rho)}{\partial f^*} < 0 \Rightarrow \frac{df^*}{d\rho} < 0\end{aligned}$$

Let $t_f = t(f, \beta)$ and $\dfrac{\partial t_f}{\partial \beta} < 0$

$$\frac{df^*}{d\beta} = -\frac{\frac{G(f^*,\beta)}{\partial \beta}}{\frac{\partial G(f^*,\beta)}{\partial f^*}}$$

$$= \frac{\frac{\partial t_f}{\partial \beta}\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{\sigma^F-1} + A^{-1}\frac{1-\rho}{\sigma^F-1}\int_{\underline{f}}^{f^*}\frac{\partial t_f}{\partial \beta}df}{\frac{\partial G(f^*,\beta)}{\partial f^*}}$$

$$-\frac{\partial G(f^*,\beta)}{\partial \beta} < 0, \frac{\partial G(f^*,\beta)}{\partial f^*} < 0 \Rightarrow \frac{df^*}{d\beta} > 0$$

$$\frac{df^*}{d\underline{f}} = -\frac{\frac{\partial G(f^*,\underline{f})}{\partial \underline{f}}}{\frac{\partial G(f^*,\underline{f})}{\partial f^*}}$$

$$= \frac{-A^{-1}\frac{1-\rho}{\sigma^F-1}t_{\underline{f}} - (A^{-2}B)\left(\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}\right)^{1-\sigma^F}}{\frac{\partial G(f^*,\beta)}{\partial f}}$$

$$-\frac{\partial G(f^*,\underline{f})}{\partial \underline{f}} < 0, \frac{\partial G(f^*,\underline{f})}{\partial f} < 0 \Rightarrow \frac{df^*}{d\underline{f}} > 0$$

$$H = \int_f (S_f)^2 \, df = \frac{\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{2\left(1-\sigma^F\right)} df}{\left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^2}$$

$$\frac{dH}{d\underline{f}} = \int_{\underline{f}}^{f^*} \left(\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^2 df$$

$$\cdot \left(-2\left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^{-3} \left(\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{1-\sigma^F} \frac{df^*}{d\underline{f}} - \left(\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}\right)^{1-\sigma^F} + \int_{\underline{f}}^{f^*} \frac{\partial \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}}{\partial \underline{f}} df\right)\right)$$

$$+ \frac{1}{\left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^2} \left(\left(\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{1-\sigma^F}\right)^2 \frac{df^*}{d\underline{f}} - \left(\left(\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}\right)^{1-\sigma^F}\right)^2 + \int_{\underline{f}}^{f^*} \frac{\partial \left(\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^2}{\partial \underline{f}} df\right)$$

$$= -\frac{\left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{1-\sigma^F}}{\left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^2} \underbrace{\left(\frac{2\int_{\underline{f}}^{f^*} \left(\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^2 df}{\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df} - \left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{1-\sigma^F}\right)}_{A_1} \frac{df^*}{d\underline{f}}$$

$$+ \frac{\left(\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}\right)^{1-\sigma^F}}{\left(\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^2} \underbrace{\left(\frac{2\int_{\underline{f}}^{f^*} \left(\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^2 df}{\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df} - \left(\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}\right)^{1-\sigma^F}\right)}_{A_2}$$

$$A_1 \geq A_2 > 0,\ \frac{df^*}{d\underline{f}} > \left(\frac{\frac{p_{f^*}}{\varphi_{f^*}}}{\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}}\right)^{\sigma^F - 1} \frac{A_2}{A_1} \Rightarrow \frac{dH}{d\underline{f}} < 0$$

$$
\begin{aligned}
\text{Let } h(f,\alpha) &= \left(\frac{p_f(\alpha)}{\varphi_f(\alpha)}\right)^{1-\sigma^F}, \ \frac{dh}{d\alpha} > 0 \\
H &= \frac{\int (h(f,\alpha))^2 df}{\left(\int h(f,\alpha) df\right)^2} \\
\frac{dH}{d\alpha} &= \frac{1}{\left(\int h\right)^2} \int 2h \frac{dh}{d\alpha} + \int h^2 \left(-2\left(\int h\right)^{-3} \int \frac{dh}{d\alpha}\right) \\
&= \frac{2}{\left(\int h\right)^2} \left(\int h \frac{dh}{d\alpha} - \int h^2 \left(\int h\right)^{-1} \int \frac{dh}{d\alpha}\right) > 0 \text{ if} \\
& \int h \int h \frac{dh}{d\alpha} - \int h^2 \int \frac{dh}{d\alpha} > 0 \\
& \int h \frac{dh}{d\alpha} > \frac{\int h^2 \int \frac{dh}{d\alpha}}{\int h} \geq \frac{(\int h)^2 \int \frac{dh}{d\alpha}}{\int h} = \int h \int \frac{dh}{d\alpha} \\
& \text{where we use Jensen's inequality for the} \geq \text{condition}
\end{aligned}
$$

$$
\begin{aligned}
G(f^*) &= \underbrace{\frac{1}{\int_{\underline{f}}^{f^*} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df}}_{A^{-1}} \underbrace{\frac{(1-\rho)\left(w\left(T - \int_{\underline{f}}^{f^*} t\delta_f df\right) + K\right)}{w(\sigma^F - 1)}}_{B} \underbrace{\frac{1}{1-\rho+\theta\rho}}_{C^{-1}} - t\delta(f^*) \left(\frac{p_{f^*}}{\varphi_{f^*}}\right)^{\sigma^F - 1} \\
&= 0
\end{aligned}
$$

$$
\begin{aligned}
\frac{df^*}{d\theta} &= -\frac{\frac{\partial G(f^*,\theta)}{\partial \theta}}{\frac{\partial G(f^*,\theta)}{\partial f^*}} \\
&= \frac{\left(A^{-1}B\right)\left(C^{-2}\right)\rho}{\frac{\partial G(f^*,t)}{\partial f^*}} \\
&- \frac{\partial G(f^*,\theta)}{\partial \theta} > 0, \frac{\partial G(f^*,\theta)}{\partial f^*} < 0 \Rightarrow \frac{df^*}{d\theta} < 0
\end{aligned}
$$

G.4 Welfare

$$
\begin{aligned}
U(X(\mathcal{V}),L(\mathcal{V})) &= X(\mathcal{V})^{1-\rho}L(\mathcal{V})^{\rho} \\
X(\mathcal{V}) &= \left(\int_{f\in\mathcal{V}} (\varphi_f x_f)^{\frac{\sigma-1}{\sigma}}\, dv\right)^{\frac{\sigma}{\sigma-1}} \\
\tau(\mathcal{V}) &= t\int_{f\in\mathcal{V}} \delta_f df \\
t_f &= t\delta_f \\
U &= \left(\frac{Y}{P}\right)^{1-\rho} L\left(\mathcal{V}\right)^{\rho} \\
\frac{Y}{P} &= (1-\rho)\left(w\left(T-\overbrace{\int_{f\in\mathcal{V}} t_f df}^{\tau(\mathcal{V})\equiv}\right)+K\right)\overbrace{\left(\int_{f\in\mathcal{V}}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F} df\right)^{\frac{1}{\sigma^F-1}}}^{P^{-1}} \\
L(\mathcal{V}) &= \frac{\rho\left(w\left(T-\int_{f\in\mathcal{V}} t_f df\right)+K\right)}{w}
\end{aligned}
$$

Applying the envelope theorem, we have

$$
\begin{aligned}
\left.\frac{dU}{dt}\right|_{f\in\mathcal{V}} &= (1-\rho)X(\mathcal{V})^{-\rho}\left[-(1-\rho)w\int_{f\in\mathcal{V}}\delta_f df P^{-1}\right]L(\mathcal{V})^{\rho} \\
&\quad + X(\mathcal{V})^{1-\rho}\rho L(\mathcal{V})^{\rho-1}\left[-\rho\int_{f\in\mathcal{V}}\delta_f df\right] \\
&= -X(\mathcal{V})^{-\rho}L(\mathcal{V})^{\rho-1}\int_{f\in\mathcal{V}}\delta_f df\left[(1-\rho)^2 wP^{-1}\underbrace{L(\mathcal{V})}_{\rho(T-\tau(\mathcal{V}))}+\rho^2\underbrace{X(\mathcal{V})}_{(1-\rho)w(T-\tau(\mathcal{V}))P^{-1}}\right] \\
&= -X(\mathcal{V})^{-\rho}L(\mathcal{V})^{\rho-1}\rho\int_{f\in\mathcal{V}}\delta_f df < 0
\end{aligned}
$$

$$
\begin{aligned}
U &= P^{\rho-1}(1-\rho)^{1-\rho}\rho^{\rho}\left[w^{1-\rho}(T-\tau(\mathcal{V}))+Kw^{-\rho}\right] \\
\left.\frac{dU}{dw}\right|_{f\in\mathcal{V}} &= P^{\rho-1}(1-\rho)^{1-\rho}\rho^{\rho}\left[(1-\rho)w^{-\rho}(T-\tau(\mathcal{V}))-K\rho w^{-\rho-1}\right] \\
&= P^{\rho-1}(1-\rho)^{1-\rho}\rho^{\rho}w^{-\rho-1}\left[(1-\rho)w(T-\tau(\mathcal{V})+K-K)-\rho K\right] \\
&= P^{\rho-1}(1-\rho)^{1-\rho}\rho^{\rho}w^{-\rho-1}\left(Y-K\right)>0 \\
&= P^{\rho-1}(1-\rho)^{1-\rho}\rho^{\rho}w^{-\rho}\left(T-\tau(\mathcal{V})-L(\mathcal{V})\right)>0
\end{aligned}
$$

$$
\begin{aligned}
lnU &= (1-\rho)ln\left(\frac{Y}{P}\right) + \rho lnL(\mathcal{V}) \\
\left.\frac{dlnU}{d\rho}\right|_{f\in\mathcal{V}} &= -ln\left(\frac{Y}{P}\right) + (1-\rho)\frac{1}{\frac{Y}{P}}\left(-w\left(T-\tau(\mathcal{V})\right)^{\rho-1}\right) + lnL(\mathcal{V}) + \rho\frac{1}{L(\mathcal{V})}(T-\tau(\mathcal{V})) \\
&= -ln(\frac{Y}{P}) - 1 + lnL(\mathcal{V}) + 1 = -ln\left(\frac{Y}{P}\right) + lnL(\mathcal{V}) > 0 \text{ if } L(\mathcal{V}) > \frac{Y}{P}
\end{aligned}
$$

$$
\begin{aligned}
\text{If } U\left(X(\mathcal{V}), L(\mathcal{V})\right) &= X(\mathcal{V})^{1-\rho}L(\mathcal{V})^{\theta\rho} \\
lnU &= (1-\rho)ln\left(\frac{Y}{P}\right) + \theta\rho lnL(\mathcal{V}) \\
\left.\frac{dlnU}{d\theta}\right|_{f\in\mathcal{V}} &= \rho lnL(\mathcal{V}) > 0
\end{aligned}
$$

$$
\begin{aligned}
&\text{Let } t_f = t(f,\beta) \text{ and } \frac{dt_f}{d\beta} < 0 \\
&\left.\frac{dU}{d\beta}\right|_{f\in\mathcal{V}} = -(1-\rho)X(\mathcal{V})^{-\rho}(1-\rho)wP^{-1}L(\mathcal{V})^{\rho}\frac{dt_f}{d\beta} - X(\mathcal{V})^{1-\rho}\rho L(\mathcal{V})^{\rho-1}\rho\frac{dt_f}{d\beta} > 0
\end{aligned}
$$

Using the FOC for variety and the conditions required for the existence of a unique cutoff firm, we have

$$
\left.\frac{dU}{d\underline{f}}\right|_{f\in\mathcal{V}} = -\lambda\left[-wt_{\underline{f}} + \frac{A(\mathcal{V})\left(\frac{p_{\underline{f}}}{\varphi_{\underline{f}}}\right)^{1-\sigma}}{\sigma-1}\right] < 0
$$

Similarly, when a new firm enters, welfare increases as long as the new firm is visited, i.e.

$$
\lambda\left[-wt_{f^N} + \frac{A(\mathcal{V})\left(\frac{p_{f^N}}{\varphi_{f^N}}\right)^{1-\sigma}}{\sigma-1}\right] > 0
$$

Let $h(f,\alpha) = \left(\frac{p_f(\alpha)}{\varphi_f(\alpha)}\right)^{1-\sigma^F}$, $\frac{dh}{d\alpha} > 0$

$$\left.\frac{dU}{d\alpha}\right|_{f\in\mathcal{V}} = \left(\overbrace{(1-\rho)\left(w(T-\tau(\mathcal{V}))+K\right)}^{Y(\mathcal{V})}\right)^{1-\rho}\left(\overbrace{\frac{\rho\left(w\left(T-\tau(\mathcal{V})\right)+K\right)}{w}}^{L(\mathcal{V})}\right)^{\rho}\frac{dP^{\rho-1}}{d\alpha}$$

$$\frac{dP^{\rho-1}}{d\alpha} = (\rho-1)P^{\rho-2}\frac{dP}{d\alpha} = \underbrace{(\rho-1)}_{<0}P^{\rho-2}\underbrace{\frac{1}{1-\sigma^F}}_{<0}\left(\int_{\underline{f}}^{f^*}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^{\frac{\sigma^F}{1-\sigma^F}}\underbrace{\frac{d\int_{\underline{f}}^{f^*}h(f,\alpha)df}{d\alpha}}_{>0} > 0$$

$$P = \left(\int_{f\in\mathcal{V}}\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}df\right)^{\frac{1}{1-\sigma^F}}$$

G.5 Heterogeneity

The analysis above is for a representative household. To explain the increase in cross-household variance during the same period as household HHI goes up, we need to allow for heterogeneity across households within the same region.

We consider a simple case with only two groups of households to illustrate heterogeneity. To achieve this, we first assume that only trip costs t_{if} vary by household i. We assume that firms have identical taste parameters φ_f equal to one. This is simply done for expositional purposes and allows us to index each firm by their price index p_f rather their taste-adjusted price index $\frac{p_f}{\varphi_f}$. Next, we place some structure on the relationship between t_f and p_f, which is key in forming the scalar index g_f. We assume that the shopping cost at each firm t_{if} is a function of the price index p_f in each firm, with $t_i'(p_f) < 0$. This is consistent with the fact that firms with larger variety and lower prices, i.e. lower p_f, tend to be located farther away from consumers relative to firms with lower variety and higher prices, due to higher costs of land in areas with higher population density and the need for larger square footage stores in order to stock higher variety and lower prices through economies of scale. We can show that if $t_i'(p_f)$ is small enough in absolute value, there exists a unique cutoff firm $p_{\overline{f^*}}$ that satisfies the following condition using equation (25), such that consumers only buy from firms that have a price index within the set $[p_{\underline{f}}, p_{\overline{f^*}}]$:

$$\frac{1}{\int_{p_{\underline{f}}}^{p_{\overline{f^*}}}(p_f)^{1-\sigma^F}df}\frac{(1-\rho)\left(w\left(T-\int_{p_{\underline{f}}}^{p_{\overline{f^*}}}t_f df\right)+K\right)}{w(\sigma^F-1)} - t_{f^*}\left(p_{\overline{f^*}}\right)^{\sigma^F-1} = 0 \tag{37}$$

Similar to the previous subsection, assume firms lie on a continuum $[p_{\underline{f}}, p_{\overline{f}}]$. We can derive the conditions under which there exists a unique $p_{\overline{f^*}}$ such that households visit retailers in the set $[p_{\underline{f}}, p_{\overline{f^*}}]$ that maximizes utility using the first-order condition:

$$G(p) = \underbrace{\frac{1}{\int_{p_{\underline{f}}}^{p} (p_f)^{1-\sigma^F} df}}_{A^{-1}} \underbrace{\frac{(1-\rho)\left(w\left(T - \int_{p_{\underline{f}}}^{p} t_f df\right) + K\right)}{w(\sigma^F - 1)}}_{B} - t(p)\,(p)^{\sigma^F - 1} = 0$$

$$\begin{aligned}
&\text{Assume } G(p_{\underline{f}}) > 0 \\
&\text{Assume } G(p_{\overline{f}}) < 0 \\
G'(p) &= -B(A^{-2})p^{1-\sigma^F} \qquad < 0 \\
&+ A^{-1}\frac{1-\rho}{\sigma^F - 1}(-t(p)) \qquad < 0 \\
&- (t'p^{\sigma^F-1} + tp^{\sigma^F}(\sigma^F - 1)) \\
&t'p^{\sigma^F-1} > tp^{\sigma^F}(1-\sigma^F) \Rightarrow G'(p) < 0
\end{aligned}$$

We can also derive the conditions under which there exists a unique $p_{\underline{f^*}}$ such that households visit retailers in the set $[p_{\underline{f^*}}, p_{\overline{f}}]$ that maximizes utility using the first-order condition:

$$G(p) = \underbrace{\frac{1}{\int_{p}^{p_{\overline{f}}} (p_f)^{1-\sigma^F} df}}_{A^{-1}} \underbrace{\frac{(1-\rho)\left(w\left(T - \int_{p}^{p_{\overline{f}}} t_f df\right) + K\right)}{w(\sigma^F - 1)}}_{B} - t(p)\,(p)^{\sigma^F - 1} = 0$$

$$\begin{aligned}
&\text{Assume } G(p_{\underline{f}}) < 0 \\
&\text{Assume } G(p_{\overline{f}}) > 0 \\
G'(p) &= B(A^{-2})p^{1-\sigma^F} \qquad > 0 \\
&+ A^{-1}\frac{1-\rho}{\sigma^F - 1}(t(p)) \qquad > 0 \\
&- (t'p^{\sigma^F-1} + tp^{\sigma^F}(\sigma^F - 1)) \\
&t'p^{\sigma^F-1} < tp^{\sigma^F}(1-\sigma^F) \Rightarrow G'(p) > 0
\end{aligned}$$

Therefore, if there is a group of consumers with a less negative t' (Group 1) and another group with a more negative t' (Group 2), Group 1 will consume only from low price index firms in the set $[p_{\underline{f}}, p_{\overline{f^*}}]$ and Group 2 will only consume from high price index firms in the set $[p_{\underline{f^*}}, p_{\overline{f}}]$. We can consider households in Group 2 as those who find it far more costly to visit firms with large variety and low prices that are generally located away from population centers, e.g. households that do not have cars.

Suppose there exists a set of firms from which both groups consume, i.e. $p_{\underline{f^*}} < p_{\overline{f^*}}$. As household HHI increases from both the supply and demand-side changes we discussed previously, the set of firms that each group visits will decrease, decreasing $p_{\overline{f^*}}$ for Group 1 and increasing $p_{\underline{f^*}}$ for Group 2. Cross-household variance will increase as each group polarizes into their respective set of firms. Group 1 will polarize towards low price index firms with larger variety, lower prices, and higher shopping costs, while Group 2 will polarize towards high price index firms with low variety, higher prices, and lower shopping costs.

We can extend this intuition to cases with many household groups or even household-specific heterogeneity. As household HHI increases, households shrink the set of firms they consume from. If there is sufficient overlap between different households but also a sufficient level of heterogeneity across households, households will polarize towards their preferred firms and overlap will decrease, raising cross-household variance. Therefore, this is consistent with our empirical results that demand-side changes such as a rise in wage w will all increase household HHI and increase cross-household variance. For supply-side changes such as the entry of stores and variety change within stores, the impact on cross-household variance depend on the household groups that are affected. For example, if Group 2 consumers do not visit club stores, then the entry of club stores do not change their household HHI, and any change in cross-household variance will only result from changes in consumption of the first group. Hence, these changes may have a smaller effect on cross-household variance, consistent with our findings that the entry of supercenters and club stores do not have a statistically significant effect on cross-household variance.

G.6 Markups

What are the implications of our empirical results for market power? First, consider a general profit maximization problem for each firm f:

$$\max_{p_f} \Pi_f = S_f \int_i Y_i di - C_f$$

Under Bertrand competition, firm f chooses its firm price index p_f given its cost function C_f and its revenue is driven by demand equations that determine its market share S_f. The first-order condition (FOC) is then given by:

$$\frac{\partial \Pi_f}{\partial p_f} = \int_i Y_i di \frac{\partial S_f}{\partial p_f} - \frac{\partial C_f}{\partial p_f} = 0$$

Next, we have the following identity which relates the elasticity of the firm's residual demand elasticity of demand ε_f to the market share elasticity with respect to price:

$$\varepsilon_f = 1 - \frac{\partial S_f}{\partial p_f} \frac{p_f}{S_f} \tag{38}$$

The FOC then gives us the following equation for the firm-level markup $\mathcal{M}_f$ for firm f, which is defined as the price index p_f divided by the marginal cost MC_f, as a function of ε_f, which is the same across all products. This is true even without imposing product symmetry and is a property of nested demand systems, as mentioned in Hottman et al. (2016). Nocke and Schutz (2018) gives a more general version of this result.

$$\begin{aligned}
\frac{\partial \Pi_f}{\partial p_f} &= \int_i Y_i di \frac{\partial S_f}{\partial p_f} - \frac{\partial C_f}{\partial p_f} = 0 \\
\frac{S_f \int_i Y_i di}{p_f}(1-\varepsilon_f) + \frac{\partial C_f}{\partial x_f}\frac{\partial x_f}{\partial p_f}\frac{p_f}{x_f}\frac{x_f}{p_f} &= 0 \\
x_f(1-\varepsilon_f) + MC_f \varepsilon_f \frac{x_f}{p_f} &= 0 \\
\mathcal{M}_f \equiv \frac{p_f}{mc_f} &= \frac{\varepsilon_f}{\varepsilon_f - 1}
\end{aligned}$$

Note that x_f is the firm quantity index that equates revenue $S_f \int_i Y_i di$ to the product of the price index p_f and quantity index x_f.

How does a firm choose its price index? We show a more detailed supply-side setup following Hottman et al. (2016) with product variety choice as well as entry and exit of firms and products.

Each firm f chooses its set of UPCs $u \in \{\underline{u_f}, \ldots, \overline{u_f}\}$ and their prices $\{p_u^U\}$ to maximize its profits, taking into account these effects on the aggregate price index. We can then formulate the profit-maximization problem as follows:

$$\max_{\{\underline{u_f},\ldots,\overline{u_f}\},\{p_u^U\}} \Pi_f = \sum_{k=\underline{u_f}}^{\overline{u_f}} p_k^U Y_k^U - A_k(Y_k^U) - N_f^U H_f^U - H_f^F$$

We index the UPCs sold by the firm from the largest $(\underline{u_f})$ to the smallest $(\overline{u_f})$ in sales; and the total number of goods sold by the firm is denoted by N_f^U, where $\overline{u_f} = \underline{u_f} + N_f^U$. $A_k(Y_u^U)$ is the variable cost function with respect to the quantities of each product Y_u^U. H_f^U is the fixed market entry cost for each UPC and H_f^F is the fixed cost of market entry for each firm.

We then have the following FOC with respect to p_u^U:

$$\frac{\partial \Pi_f}{\partial p_u^U} = Y_u^U + \sum_{k=\underline{u_f}}^{\underline{u_f}+N_f^U} \left(p_k^U \frac{dY_k^U}{dp_u^U} - \frac{dA_k(Y_k^U)}{dY_k^U}\frac{dY_k^U}{dp_u^U} \right) = 0 \tag{39}$$

Setting UPC supply equal to demand, we have:

$$\begin{aligned}
Y_k^U &= \sum_i Y_i S_f^F S_k^U \frac{1}{p_k^U} \\
\frac{\partial Y_k^U}{\partial p_u^U} &= \frac{\sum_i Y_i}{p_k^U}\left(S_k^U \frac{\partial S_f^F}{\partial p_f^F}\frac{\partial p_f^F}{\partial p_u^U} + S_f^F \frac{\partial S_k^U}{\partial p_u^U}\right) \text{ if } u \neq k \\
\frac{\partial Y_u^U}{\partial p_u^U} &= \frac{\sum_i Y_i}{p_u^U}\left(S_u^U \frac{\partial S_f^F}{\partial p_f^F}\frac{\partial p_f^F}{\partial p_u^U} + S_f^F \frac{\partial S_u^U}{\partial p_u^U}\right) - \sum_i Y_i S_f^F S_u^U (p_u^U)^{-2}
\end{aligned} \tag{40}$$

Using the properties of CES demand, the expenditure share of product u within firm f equals the elasticity of the firm price index with respect to the price of product u:

$$S_u^U = \frac{\left(\frac{p_u^U}{\varphi_u^U}\right)^{\sigma^U-1}}{\sum_{k\in\mathcal{U}_f}\left(\frac{p_k^U}{\varphi_k^U}\right)^{\sigma^U-1}} \tag{41}$$

This implies the standard cross- and own-market share elasticity:

$$\frac{\partial S_k^U}{\partial p_u^U}\frac{p_u^U}{S_k^U} = (\sigma^U-1)S_k^U \text{ if } u \neq k \tag{42}$$
$$\frac{\partial S_u^U}{\partial p_u^U}\frac{p_u^U}{S_u^U} = (\sigma^U-1)S_u^U + 1 - \sigma^U \tag{43}$$

Plugging these elasticities back into equation (40) and using equation (38), we have:

$$\frac{\partial Y_k^U}{\partial p_u^U}\frac{p_u^U}{Y_k^U} = (1-\varepsilon_f^F)S_u^U + (\sigma^U-1)S_u^U = (\sigma^U-\varepsilon_f^F)S_u^U \text{ if } u \neq k$$
$$\frac{\partial Y_u^U}{\partial p_u^U}\frac{p_u^U}{Y_u^U} = (1-\varepsilon_f^F)S_u^U + 1 - \sigma^U + (\sigma^U-1)S_u^U - 1 = (\sigma^U-\varepsilon_f^F)S_u^U - \sigma^U \tag{44}$$

We define the markup as $\mathcal{M}_k \equiv \frac{p_k^U}{\frac{\partial A_k(Y_k^U)}{\partial Y_k^U}}$ and marginal cost for product k as $\frac{\partial A_k(Y_k^U)}{\partial Y_k^U} \equiv MC_k^U$. Plugging these output elasticities back into the FOC in equation (39):

$$Y_u^U + \sum_k \left(p_k^U - MC_k\right)(\sigma^U-\varepsilon_f^F)S_u^U\frac{Y_u^U}{p_u^U} + (p_u^U - MC_u^U)(-\sigma^U)\frac{Y_u^U}{p_u^U} = 0 \tag{45}$$

From this equation, we see that markups only vary at the firm level as discussed previously. Therefore, we can now solve for the firm-level markup M_f^F as follows:

$$0 = Y_u^U + \left(1-\frac{1}{M_f^F}\right)(\sigma^U-\varepsilon_f^F)\frac{S_u^U}{p_u^U}\sum_k p_k^U Y_k^U + \left(1-\frac{1}{M_f^F}\right)(-\sigma^U)Y_u^U = 0 \tag{46}$$
$$\mathcal{M}_f = \frac{\varepsilon_f}{\varepsilon_f - 1} \tag{47}$$

Therefore, we obtain the product-level markup for all products as the firm-level markup as a function of each firm's residual demand elasticity ε_f^F.

Next, we link this general markup formula to the demand setup we derived in online Appendix Section G.2 in order to facilitate quantitative analysis with our data. Recall that the market share S_{if} of firm f for household i can be written as follows:

$$S_{if} = S_f(\mathcal{V}_i) = \begin{cases} \left(P_i \frac{\varphi_f}{p_f}\right)^{\sigma^F - 1} & \text{if } \frac{Y S_{if}}{w(\sigma^F-1)} \geq t_{if} \\ 0 & \text{otherwise} \end{cases} \tag{48}$$

$$P_i = P(\mathcal{V}_i) = \left(\sum_{f \in \mathcal{V}_i} \left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^{\frac{1}{1-\sigma^F}} \tag{49}$$

The market share, household price index, and income are all dependent on the specific set of firms $\mathcal{V}_i$ that household i consumes from, and $\mathcal{V}_i$ is a function of t_{if} by equation (48). We now allow for consumer heterogeneity more generally, allowing each household i to have a different shopping costs t_{if} and income Y_i.[43] Therefore, consumer heterogeneity can be fully characterized by the joint density function $g(t_1, \ldots, t_F, y)$, where F is the total number of firms and y is income. Since equation (48) is monotonic in t_{if}, for each firm f there exists a set of households $i*$ such that equation (48) holds. Households $i*$ then represents the marginal consumers for firm f. We can then write the market share S_f as follows:

$$\forall f,\ \exists i^* \text{ s.t. } \frac{Y(\mathcal{V}_{i*}) S_{if}(\mathcal{V}_{i*})}{w(\sigma^F - 1)} = t_{fi*} \equiv a_f \tag{50}$$

$$S_f = \frac{\int_i Y_i S_{if} di}{\int_i Y_i di} \tag{51}$$

$$= \frac{\int_{\underline{y}}^{\overline{y}} \int_{\boldsymbol{a}_f} y \left(P\left(\boldsymbol{t}, \boldsymbol{p}, \boldsymbol{\varphi}, y\right) \left(\frac{\varphi_f}{p_f}\right)\right)^{\sigma^F - 1} g(\boldsymbol{t}, y) dy d^F \boldsymbol{t}}{\int_i Y_i di} \tag{52}$$

The aggregate price index for each household i is a function of household-specific shopping costs for each firm with a total number of F firms, denoted as an F-tuple $\boldsymbol{t} = (t_1, \ldots, t_F)$, the price indices of each firm $\boldsymbol{p}$, and the firm-specific tastes $\boldsymbol{\varphi}$ as a result of equation (48) and equation (49). Each firm f is only visited by households with $t_f \in [0, a_f]$ by equation (50) so $\boldsymbol{a}_f = [0, \infty] \times \ldots \times [0, a_f] \times \ldots \times [0, \infty]$, and $\int_{\boldsymbol{a}_f} d^F \boldsymbol{t} \equiv \int_0^\infty \ldots \int_0^{a_f} \ldots \int_0^\infty dt_F \ldots dt_1$.

We can then differentiate the expression for firm market shares in equation (52) to obtain the market share elasticities. The firm market share elasticity can then be derived as follows

[43] Since we do not observe their wages in our data, we assume their wages are the same at the average level. Note that we also simplify the setup by ignoring how shopping costs affect total income through its effect on labor hours.

using Leibniz's integral rule:

$$\begin{aligned}
\frac{\partial S_f}{\partial p_f}\frac{p_f}{S_f} &= \frac{p_f}{S_f\int Y_i di}\frac{\partial}{\partial p_f}\left[\int_{\underline{y}}^{\overline{y}}\int_0^{\infty}\dots\int_0^{a_f}\dots\int_0^{\infty} h\left(\boldsymbol{t},\boldsymbol{p},\boldsymbol{\varphi},y\right)dyd^F\boldsymbol{t}\right] \\
&= \frac{p_f}{S_f\int Y_i di}\Bigg(\int_{\underline{y}}^{\overline{y}}\int_0^{\infty}\dots\int_0^{a_f}\dots\int_0^{\infty}\frac{\partial h}{\partial p_f}dyd^F\boldsymbol{t} \\
&+\int_{\underline{y}}^{\overline{y}}\int_0^{\infty}\dots\int_0^{\infty}\frac{\partial a_f}{\partial p_f}h\left(t_1,\dots,a_f,\dots,t_F,y\right)dydt_F\dots dt_1\Bigg) \\
&= IMS + EMS
\end{aligned}$$

For ease of exposition, assume that income Y_i is independent of p_f, since shopping costs are a small portion of time spent relative to work hours. Relaxing this assumption would allow the Y_i to shift as weights in response to changes in prices, which complicates the analysis without affecting the main intuition. Given the household market share S_{if}, we can derive the following household market share elasticities under monopolistic competition and Bertrand competition:

$$\begin{aligned}
S_{if} &= \left(P_i\frac{\varphi_f}{p_f}\right)^{\sigma^F-1} \\
\frac{\partial S_{if}}{\partial p_f} &= (P\varphi_f)^{\sigma^F-1}\frac{\partial\left(\frac{1}{p_f}\right)^{\sigma^F-1}}{\partial p_f}+\left(\frac{\varphi_f}{p_f}\right)^{\sigma^F-1}\frac{\partial P^{\sigma^F-1}}{\partial p_f} \\
&= (P\varphi_f)^{\sigma^F-1}(1-\sigma^F)(p_f)^{-\sigma^F}+\left(\frac{\varphi_f}{p_f}\right)^{\sigma^F-1}\frac{\partial P^{\sigma^F-1}}{\partial p_f} \\
P &= \left(\int_f\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^{\frac{1}{1-\sigma^F}} \text{ if monopolistic competition} \\
P &= \left(\sum_f\left(\frac{p_f}{\varphi_f}\right)^{1-\sigma^F}\right)^{\frac{1}{1-\sigma^F}} \text{ if Bertrand competition} \\
\frac{\partial P^{\sigma^F-1}}{\partial p_f} &= \begin{cases}0 & \text{if monopolistic competition}\\ (\sigma^F-1)P^{\sigma^F-2}\varphi^{\sigma^F-1}\left(\frac{P}{p_f}\right)^{\sigma^F} & \text{if Bertrand competition}\end{cases} \\
\frac{\partial S_{if}}{\partial p_f}\frac{p_f}{S_{if}} &= \begin{cases}1-\sigma^F & \text{if monopolistic competition}\\ (1-S_{if})(1-\sigma^F) & \text{if Bertrand competition}\end{cases}
\end{aligned}$$

We can then rewrite the intensive margin IMS of the market share elasticity more simply as follows:

$$
\begin{aligned}
IMS &= \int_{\underline{y}}^{\overline{y}} \int_0^\infty \dots \int_0^{a_f} \dots \int_0^\infty \frac{\partial h}{\partial p_f} dyd^F \boldsymbol{t} \\
&= \frac{(1-\sigma^F)}{YS_f} \int_{\underline{y}}^{\overline{y}} \int_0^\infty \dots \int_0^{a_f} \dots \int_0^\infty \left(S_{fi} - S_{fi}^2\right) yg(\boldsymbol{t}, y) dyd^F \boldsymbol{t} \\
&= \frac{1-\sigma^F}{YS_f} \left[YS_f - \int_{\underline{y}}^{\overline{y}} \int_0^\infty \dots \int_0^{a_f} \dots \int_0^\infty S_{fi}^2 yg(\boldsymbol{t}, y) dyd^F \boldsymbol{t} \right] \\
&= 1 - \sigma^F + (\sigma^F - 1) \int_{\underline{y}}^{\overline{y}} \int_0^\infty \dots \int_0^{a_f} \dots \int_0^\infty S_{fi} \cdot \frac{S_{fi} yg(\boldsymbol{t}, y)}{S_f \int_i Y_i di} dyd^F \boldsymbol{t}
\end{aligned}
$$

We can also rewrite the extensive margin EMS of the market share elasticity more simply as follows:

$$
\begin{aligned}
\frac{\partial a_f}{\partial p_f} p_f &= \frac{y}{w(\sigma^F - 1)} \left(\frac{\partial P_i^{\sigma^F - 1}}{\partial p_f} p_f \left(\frac{\varphi_f}{p_f}\right)^{\sigma^F - 1} + P_i^{\sigma^F - 1} \varphi_f^{\sigma^F - 1} \frac{\partial p_f^{1-\sigma^F}}{\partial p_f} p_f \right) \\
&= \frac{y}{w(\sigma^F - 1)} \left[(\sigma^F - 1) \left(S_{fi}^*\right)^2 + (1 - \sigma^F) S_{fi}^* \right] \\
&= \frac{y}{w} \left[S_{fi}^* \left(S_{fi}^* - 1\right) \right] \\
&= -\frac{y}{w} S_{fi}^* \left(1 - S_{fi}^*\right) = -(\sigma^F - 1) t_{fi}^* \left(1 - S_{fi}^*\right)
\end{aligned}
$$

$$
\begin{aligned}
EMS &= \frac{p_f}{S_f \int Y_i di} \left(\int_{\underline{y}}^{\overline{y}} \int_0^\infty \dots \int_0^\infty \frac{\partial a_f}{\partial p_f} h\left(t_1, \dots, a_f, \dots, t_F, y\right) dydt_F \dots dt_1 \right) \\
&= \int_{\underline{y}}^{\overline{y}} \int_0^\infty \dots \int_0^\infty \frac{-Y_i^*}{w} S_{fi}^* \left(1 - S_{fi}^*\right) g\left(t_1, \dots, t_{fi}^*, \dots, t_F, y\right) \frac{Y_i^* S_{fi}^*}{S_f \int Y_i di} dydt_F \dots dt_1
\end{aligned}
$$

Under monopolistic competition, the market share elasticity is only dependent on the elasticity of substitution σ^F. Under Bertrand competition, a change in the price index of firm f affects the aggregate price index P. The market share elasticity depends on both σ^F and the market share S_{if}. A larger market share lowers the absolute value of the market share elasticity, lowering the elasticity of demand and raising the markup. Substituting the household market share elasticities into the market share elasticity and hence the demand elasticity, we can derive the markup under monopolistic competition and

Bertrand competition:

$$\begin{aligned}
\mathcal{M}_f &= \frac{\varepsilon_f}{\varepsilon_f - 1} \\
&= \frac{1 - \frac{\partial S_f}{\partial p_f}\frac{p_f}{S_f}}{1 - \frac{\partial S_f}{\partial p_f}\frac{p_f}{S_f} - 1} \\
&= \frac{1 - IMS - EMS}{1 - IMS - EMS - 1} \\
&= \frac{IM + EM}{IM + EM - 1} \text{ where } IM \equiv 1 - IMS, EM \equiv -EMS \\
&= \frac{\sigma^F - IMH + EM}{\sigma^F - 1 + IMH + EM}
\end{aligned}$$

The markups under monopolistic competition and Bertrand competition can be written out as follows in equations (53) and (54) respectively:[44]

$$\begin{aligned}
\mathcal{M}_f &= \frac{\sigma^F + EM}{\sigma^F - 1 + EM} && (53) \\
EM &= \int_{\underline{y}}^{\overline{y}} \int_{\boldsymbol{a}_{-f}} \frac{Y_i^*}{w} S_{if}^* g\left(a_f | \boldsymbol{t}_{-f}, y\right) k\left(\boldsymbol{t}_{-f}, y\right) \frac{Y_i^* S_{fi}^*}{S_f \int Y_i di} dy d^{F-1} \boldsymbol{t}_{-f} \\
&= \sum_i \frac{Y_i^*}{w} S_{if}^* g\left(t_{fi}^*\right) \frac{Y_i^* S_{fi}^*}{S_f \sum_i Y_i}
\end{aligned}$$

$$\begin{aligned}
\mathcal{M}_f &= \frac{\sigma^F + EM - IMH}{\sigma^F - 1 + EM - IMH} && (54) \\
EM &= \int_{\underline{y}}^{\overline{y}} \int_{\boldsymbol{a}_{-f}} \frac{Y_i^*}{w} S_{if}^* \left(1 - S_{fi}^*\right) g\left(a_f | \boldsymbol{t}_{-f}, y\right) k\left(\boldsymbol{t}_{-f}, y\right) \frac{Y_i^* S_{fi}^*}{S_f \int Y_i di} dy d^{F-1} \boldsymbol{t}_{-f} \\
&= \sum_i \frac{Y_i^*}{w} S_{if}^* \left(1 - S_{fi}^*\right) g\left(t_{fi}^*\right) \frac{Y_i^* S_{fi}^*}{S_f \sum_i Y_i} && (55) \\
IMH &= \left(\sigma^F - 1\right) \int_{\underline{y}}^{\overline{y}} \int_{\boldsymbol{a}_f} S_{fi} \cdot \frac{S_{fi} y g(\boldsymbol{t}, y)}{S_f \int_i Y_i di} dy d^F \boldsymbol{t} \\
&= \left(\sigma^F - 1\right) \sum_i S_{if} \frac{S_{if} Y_i}{S_f \sum_i Y_i} && (56)
\end{aligned}$$

We discretely approximate the integral and move from integrating over density functions to sums across individuals. In short, we assume that each individual represents a unique point in the domain of the vector of shopping costs and income, and hence the density function equals one for every individual, i.e. $\int_{\underline{y}}^{\overline{y}} \int_0^{\infty} \ldots \int_0^{a_f} \ldots \int_0^{\infty} g(\boldsymbol{t}, y) dy d^F \boldsymbol{t}$ equals the

[44]Note that $\boldsymbol{t}_{-f}$ represents the $F-1$-tuple $(t_1, \ldots, t_{f-1}, t_{f+1}, \ldots, t_F)$ and $\boldsymbol{a}_{-f} = [0, a_1] \times \ldots \times [0, a_{f-1}] \times [0, a_{f+1}] \times \ldots \times [0, a_F]$, where $a_1 = a_{f-1} = a_{f+1} = a_F = \infty$.

total number of households that shop at firm f $\sum_{i \in I_f}$, where I_f is the set of households that shop at firm f, and $g(t_{1i}, \ldots, t_{iF}, Y_i)dyd^F\boldsymbol{t} = 1$.

Therefore, the markup differs from the standard CES markup $\frac{\sigma^F}{\sigma^F-1}$ in two ways. First, there is an additional extensive margin term EM that lowers the markup, since the existence of such marginal consumers increases the demand elasticity. This term is a function of several terms which include the share of firm sales from marginal consumers and the shopping cost at the margin. This extensive margin term is analogous to the additional extensive margin term in Neiman and Vavra (2021). In contrast to their paper which focuses on taste heterogeneity across products, we allow for consumer heterogeneity to work through the shopping cost t. Under Bertrand competition, the extensive margin term is further scaled by $1 - S_f(\mathcal{V}_{i*})$ to account for the effect on the aggregate price index.

Second, there is an intensive margin term IMH that increases markups due to Bertrand competition in addition to consumer heterogeneity. This term closely resembles the household HHI but aggregates to the firm level rather than the household level. This term has also been highlighted in Feenstra et al. (2022), who again focus on taste heterogeneity across products. Intuitively, firms do not weight demand elasticities across consumers equally, but optimally use a greater weight on low-elasticity consumers, such that when consumer heterogeneity is present, they can charge higher markups and obtain higher profits, since the gains from charging higher markups to the lower elasticity consumers offsets the loss in demand on higher elasticity consumers. Crucially, this term increases as the variance of market shares across households increases, since firms can charge higher markups when there is a larger share of lower elasticity consumers.

The aggregate markup $\mathcal{M}$ is then the share-weighted average of all firm markups:

$$\mathcal{M} = \int_f S_f \mathcal{M}_f df$$

H Calibration Details

Calibrating the EM term We calibrate the EM term in equation (15). We first calculate an upper bound for shopping costs t_{if} by using equation (48) for each household. We estimate the density of shopping costs for consumers at the margin $g(t_{fi*})$ by fitting a parametric distribution. This upper bound of shopping costs equals the actual shopping costs for marginal consumers. We adopt two approaches to infer who the marginal consumers are. In our preferred approach, we assume that consumers at the entry and exit margins are marginal consumers.[45] Therefore, firms with more consumers on the margin and higher expenditures for marginal consumers relative to other firms will have a larger EM term.[46] In our second approach, we sum up the upper bounds for shopping costs for all consumers

[45]We classify a consumer as an entrant if they go from zero to non-zero expenditures from one period to the next, and as an exiter if they go from non-zero to zero expenditures from one period to the next. We do this only for households after they have entered the sample for at least one year or are at least one year from exiting the sample to avoid censoring. Hence, we cannot calculate the markups in the first year or last year of our sample period.

[46]This is true up to the point where the household market share is very large, since $1 - S^*_{if}$ scales the EM term.

and multiply this sum with various percentages of people on the margin from 0% to 100%. Therefore, this approach assumes that marginal consumers are randomly distributed along the shopping cost distribution.

The model allows households to make one trip to one firm, but visit multiple firms in each period. Therefore, we can approximate the number of periods by either using the total number of shopping trips, which serves as an upper bound, or the number of trips to their top firm. This serves as a lower bound as the household may not visit the top firm every period. Our results indicate that using either of these methods gives almost identical results. We then aggregate equation (48) to each household-firm-year by summing over the number of shopping trips. Therefore, the inferred upper bound for t_{if} is higher for a household i with high expenditures YS_{if} in firm f but a low number of trips.

We use the average hourly wage w from the CPS by year, assume a constant 25% tax rate to obtain a post-tax hourly wage, then scale it by 0.75 following Goldszmidt et al. (2020) to obtain an estimate of the opportunity cost of time.

The upper bound for the shopping costs closely follows a log-normal distribution, which we use to approximate the distribution for each firm.

Further explorations and robustness checks How do these changes in markups affect different households? We calculate markups for each household by multiplying their expenditure share in each firm with that firm's markup. We do this both by allowing expenditure shares to vary over time or fixing them with shares calculated across the entire sample period. We show in online Appendix Figure J29 and online Appendix Figure J30 the household markups by percentile for both varying and fixed weights, in levels and changes since 2004. We find that similar to online Appendix Figure J3c, households with higher levels of markups are experiencing larger increases. This implies that inequality in markups across households has increased over time.

We show in online Appendix Figure J31 that our results are qualitatively robust to using different elasticities of substitution. The markup levels decrease with the elasticity of substitution, which also decreases the magnitude of changes over time. The changes range from roughly 4 to 6 percentage points as we move the elasticity of substitution from 5.5 to 3.5.

We show in online Appendix Figure J32 that our results are robust to different assumptions about how to calibrate the extensive margin term. We show that the extensive margin contributes a negligible proportion to changes in markups, even as it lowers the level of markups. The first approximation method allows for different proportions of marginal consumers for each firm and aligns closely with the second approximation method in levels when the percentage of marginal consumers is set at 25%.

We also show that our results are robust to assuming Cournot rather than Bertrand competition in online Appendix Figure J33, although the aggregate markup is much higher than those from the previous literature, which suggests that Bertrand competition may be a more reasonable assumption.

We can also calibrate local markups region-by-region, which allows firms to make entry and exit decisions for each region. To allow firms to set markups locally, we can first calculate markups at the firm-region level and then aggregate to the national level.[47] Our results are

[47]More precisely, we have $\mathcal{M} = \int_f S_f \left(\int_r \mathcal{M}_{rf} dr\right) df$, where M_{rf} is calculated using equation (14) but

nearly identical with this approach.

H.1 Markups with Wholesale Cost Data

We compare our calibrated markups against markups that we calculate using HMS prices matched with wholesale costs from PromoData. The PromoData Price-Trak service provides weekly wholesale costs at the market level obtained from 12 grocery wholesaler organizations for about 100,000 UPCs each year from 2006-2012. As discussed in Sangani (2024), wholesale prices from the PromoData are similar across markets so we calculate both market and national wholesale costs in order to achieve broader data coverage. The matched samples cover about 3% and 22% of HMS expenditures when matched to market and national wholesale costs respectively. As discussed in Allcott et al. (2019), although the Robinson-Patman Act prohibits wholesale price discrimination, the act is increasingly unenforced and manufacturers often offer more subtle contractual incentives that generate variation in effective marginal cost across retailers. Given the PromoData wholesale costs are obtained from just 12 grocery wholesale organizations, we may be able to capture aggregate trends in wholesale costs but not variation across retailers.

We calculate markups for the matched sample of products in several ways. First, we construct retailer-level chained Tornqvist indices for both prices and wholesale costs using the matched sample of products. Therefore, the same basket of products is used across each pair of years but the basket is allowed to vary over time. We then construct a markup index by taking the log difference between the price and wholesale cost index. Second, we directly calculate a weighted markup for each retailer by taking a revenue-weighted average of the markups across all products in each retailer. To control for changes in product composition, we also calculate weighted markups using a balanced set of products that appear in each year throughout the sample period.

We first investigate trends in these markups in online Appendix Figure J34. We find that markup indices using either national or market wholesale costs both show a rise in markups from 2006-2012 by about 25% and 7% respectively. These trends replicate our finding that the rise in markups slows down during the recession and picks up during the recovery. The national wholesale cost index has decreased slightly while the price index has risen, consistent with Döpper et al. (2024). The market wholesale cost index has increased slightly but less than the price index. On the other hand, the weighted markups are increasing every year but experiences a big drop in levels in 2008, suggesting that it is important to compare the same set of products rather than allow the product composition to change over the years. The weighted markups using a balanced set of products show a more stable trend in markups but lower levels.

Next, we regress our theory-calibrated markups estimated in Section 4.5 on these calculated markups at the retailer-year level. First, we focus on levels in markups by adding only year fixed effects to our regressions in online Appendix Table I20. The coefficients are negative for markups calculated using national wholesale costs but statistically insignificant for markups calculated using market wholesale costs. Since our data does not contain any retailer-level variation in wholesale costs, this implies that retailers with higher calibrated

aggregates across households for firm f in region r rather than across all regions.

markups have lower price levels, consistent with our theoretical predictions. Next, we focus on changes in log markups by adding retailer fixed effects to the year fixed effects. We find that the relationships between the calibrated markup changes and the price or markup index changes are weak in online Appendix Table I21. There is a positive and statistically significant estimate for the markup index using market PromoData but the point estimate is very small. We again find very weak relationships between the calibrated markup changes and the weighted markup changes in online Appendix Table I22. We do find some suggestive evidence that the calibrated markup changes are negatively related to price index changes when using the full HMS sample to construct retailer-level price indices rather than just products that can be matched to the PromoData. However, the results are again quite small in magnitude.

Overall, these results suggest that markups calculated using the PromoData do exhibit increasing aggregate trends but they do not capture the retailer-level variation that our model captures, since the PromoData does not contain any retailer-level variation in wholesale costs.

I Tables

Table I1: Change in cross-region variance, relative number of stores and markets, 2004-2019

	mean	sd	min	p25	p50	p75	max	count
Other chains								
Cross-region variance	5.26e-06	.0000535	-.000119	-1.23e-07	2.32e-08	3.65e-07	.00122	715
Number of stores	1.29	1.98	0	.5	.934	1.34	28	270
Number of markets	1.21	.97	.167	1	1	1	11	269
Top chains								
Cross-region variance	.0000849	.000604	-.0036	-5.82e-07	1.62e-06	.0000623	.00251	74
Number of stores	1.47	1.29	.157	.839	1.11	1.78	8.5	51
Number of markets	1.11	.636	.25	.727	1	1.22	4	51

Notes: This table summarizes the change in cross-region variance (in the number of stores), the relative number of stores and markets for each retail chain from 2004-2019, separating the distribution into two groups: the top 40 retail chains by revenue rank over the sample period, and other chains outside the top 40. The relative number of stores and markets is normalized to 1 in 2004q1.

Table I2: Change in cross-region variance, 2004-2019

	mean	sd	min	p25	p50	p75	max	count
Other chains	9.49e-06	.0000766	-.000728	-2.49e-08	1.58e-09	5.22e-07	.000948	664
Top chains	.000111	.000792	-.00416	-.0000224	.0000288	.000428	.00143	51

Notes: This table summarizes the change in cross-region variance for each retail chain from 2004-2019, separating the distribution into two groups: the top 40 retail chains by revenue rank over the sample period, and other chains outside the top 40.

Table I3: RZ-DOPD: Change in aggregate HHI, 2004-2015

	Category HHI	Category Variance	Household Variance	Region Variance
Survivor	0.05446	0.00363	-0.05547	0.02463
Within Survivor	0.02969	0.04744	-0.04799	0.03182
Between Survivor	0.02477	-0.04381	-0.00748	-0.00719
Entrants	0.00185	0.01687	-0.00378	-0.00218
Exiters	-0.02241	0.00302	0.01210	0.00089

Notes: This table decomposes the change in aggregate HHI following online Appendix Section A.1. We also use a Dynamic Olley-Pakes decomposition (Melitz and Polanec 2015) on top of the RZ decomposition and apply it to each of the four terms that the aggregate HHI is composed of: Household-category HHI, household cross-category variance, regional cross-household variance, and national cross-region variance.

Table I4: Effect of Entry: Number of Stores Within Own 5-digit Zip Code and Distance Bands

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Store Type	Supercenters				Clubs			
VARIABLES	Household HHI							
Num	0.00857***	0.00898***			-0.0125***	-0.0108***		
	(0.00231)	(0.00233)			(0.00266)	(0.00275)		
Num < 1 mile			0.00819***	0.00701***			-0.0124***	-0.0107***
			(0.00229)	(0.00233)			(0.00262)	(0.00265)
1 mile ≤ Num < 3 miles			0.000433	0.000262			-0.00454*	-0.00420*
			(0.00219)	(0.00223)			(0.00243)	(0.00247)
3 miles ≤ Num < 5 miles			-0.000199	-0.000514			-0.00513***	-0.00474***
			(0.00136)	(0.00140)			(0.00145)	(0.00150)
5 miles ≤ Num < 7 miles			-0.000943	-0.000495			-0.00136	-0.000821
			(0.00116)	(0.00120)			(0.00125)	(0.00130)
7 miles ≤ Num < 9 miles			0.000461	0.000262			-0.00255**	-0.00162
			(0.00106)	(0.00110)			(0.00115)	(0.00120)
9 miles ≤ Num < 11 miles			-0.0000257	0.000209			-0.000314	0.000484
			(0.00103)	(0.00108)			(0.00111)	(0.00115)
Observations	1630281	1452065	1627536	1627531	2181023	1775106	2177501	2177489
R-squared	0.696	0.692	0.697	0.699	0.684	0.682	0.684	0.687
Prob > F	0.000	0.000	0.033	0.142	0.000	0.000	0.000	0.000
Number of units	120376	107583	120154	120154	146262	122242	146014	146014
Number of clusters	120376	107583	120154	120154	146262	122242	146014	146014
Baseline	X				X			
Controls		X				X		
Distance bands			X				X	
Distance bands + market-specific trends				X				X

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Controls refer to control variables such as log housing price, log unemployment rate, log population, and log average wages. Distance bands refers to the number of supercenters or club stores within 1 mile of each household's 5-digit zip code population-weighted centroid, 1 to 3 miles, 3 to 5 miles etc. Markets refer to the Nielsen Scantrack market level, since NielsenIQ classifies regions into around 50 market areas. These market dummies are interacted with a time trend for market-specific trends.

Table I5: Effects of Entry on Other Measures of Concentration

VARIABLES	(1) Num Retailers	(2) Within dept HHI	(3) Cross dept variance	(4) Cross HH variance	(5) Num Retailers	(6) Within dept HHI	(7) Cross dept variance	(8) Cross HH variance
NumSup	-0.229***	0.00281	-0.00542***	-0.000173				
	(0.0447)	(0.00244)	(0.00109)	(0.00263)				
NumClub3					0.246***	-0.0154***	-0.00134	-0.00264
					(0.0562)	(0.00302)	(0.00129)	(0.00325)
Observations	121723	134482	134482	134482	98588	99805	99805	99805
R-squared	0.695	0.667	0.506	0.627	0.703	0.667	0.510	0.632
Prob > F	0.000	0.249	0.000	0.947	0.000	0.000	0.299	0.416
Household-Quarter FE	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X
Number of units	9062	9371	9371	9371	6560	6323	6323	6323
Number of clusters	9062	9371	9371	9371	6560	6323	6323	6323
BOTE	0.167	0.112	0.297	-0.004	-0.180	-0.752	0.074	-0.050

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Includes only households living in zip5 with store entry during the period. BOTE refers to a back-of-the-envelope estimate of how much each independent variable explains the rise in household retail concentration. This is calculated by multiplying the estimated coefficient by the total change in the independent variable over the sample period, then dividing this number by the total change in household retail concentration in the sample period.

Table I6: Effects of Entry on Number of Trips and Varieties per Trip

VARIABLES	(1) TripNum	(2) UPC per trip	(3) ProductGroup per trip	(4) Dept per trip	(5) TripNum	(6) UPC per trip	(7) ProductGroup per trip	(8) Dept per trip
NumSup	-0.203	0.0893	0.0659*	0.0317***				
	(0.211)	(0.0602)	(0.0349)	(0.00943)				
NumClubs					0.960***	-0.281***	-0.159***	-0.0364***
					(0.283)	(0.0664)	(0.0387)	(0.0112)
Observations	134495	134495	134495	134495	109651	109651	109651	109651
R-squared	0.755	0.778	0.790	0.766	0.766	0.789	0.799	0.771
Prob > F	0.336	0.138	0.059	0.001	0.001	0.000	0.000	0.001
Household-Quarter FE	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X
Number of units	9371	9371	9371	9371	6814	6814	6814	6814
Number of clusters	9371	9371	9371	9371	6814	6814	6814	6814
BOTE	0.040	0.131	0.143	0.163	-0.126	-0.314	-0.279	-0.150

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Includes only households living in zip5 with store entry during the period. BOTE refers to a back-of-the-envelope estimate of how much each independent variable explains the rise in household retail concentration. This is calculated by multiplying the estimated coefficient by the total change in the independent variable over the sample period, then dividing this number by the total change in household retail concentration in the sample period.

Table I7: Difference between the most affected households and the least affected households for supercenter entry

	Mean Diff	sd	p-value
hh_hhi_yq	0.053	0.023	0.546
tripnum_yq	-1.931	2.204	1.000
numsup	0.038	0.040	1.000
numclubs	-0.082	0.050	0.887
ind.hhincomeQ1	**0.362**	0.177	0.680
ind.hhincomeQ2	**0.344**	0.169	0.682
ind.hhincomeQ3	-0.213	0.160	0.972
ind.hhincomeQ4	-0.494	0.162	0.152
ind.hhsize1	**0.283**	0.162	0.843
ind.hhsize2	-0.673	0.169	0.014**
ind.hhsize3plus	**0.390**	0.187	0.661
ind.ageAbove55	**-0.686**	0.210	0.101
ind.CentralMetro	-0.751	0.324	0.528
ind.LFringeMetro	0.126	0.270	1.000
ind.MediumMetro	-0.362	0.252	0.949
ind.SmallMetro	**0.719**	0.209	0.058*
ind.Micropolitan	0.105	0.115	1.000
ind.Noncore	0.164	0.082	0.710

Notes: The most affected group has top 10% sorted effect. The least affected group has bottom 10% sorted effect. The difference is average value for the most affected minus the least affected.

Table I8: Difference between the most affected households and the least affected households for clubs entry

	Mean Diff	sd	p-value
hh_hhi_yq	0.052	0.030	0.952
tripnum_yq	-7.433	2.746	0.495
num_sup	-0.176	0.116	0.983
numclubsoc	0.071	0.047	0.983
ind.hhincomeQ1	0.044	0.141	1.000
ind.hhincomeQ2	0.134	0.141	1.000
ind.hhincomeQ3	-0.552	0.175	0.319
ind.hhincomeQ4	0.374	0.228	0.962
ind.hhsize1	0.191	0.189	1.000
ind.hhsize2	-0.704	0.195	0.157
ind.hhsize3plus	0.514	0.222	0.732
ind.ageAbove55	-0.927	0.222	0.057*
ind.CentralMetro	-0.782	0.233	0.235
ind.LFringeMetro	0.849	0.306	0.480
ind.MediumMetro	-0.429	0.250	0.956
ind.SmallMetro	0.321	0.232	0.996
ind.Micropolitan	0.040	0.152	1.000
ind.Noncore	0.000	0.000	

Notes: The most affected group has top 10% sorted effect. The least affected group has bottom 10% sorted effect. The difference is average value for the most affected minus the least affected.

Table I9: Effect of Variety and Prices on Household Retail Concentration

	(1)	(2)	(3)	(4)	(5)	(6)
Data	HMS				RMS	
VARIABLES	Household HHI					
Variety: UPCs	0.0210***		0.0206***		0.0913***	
	(0.00485)		(0.00438)		(0.0177)	
Variety: Modules		0.0992***		0.0897***		0.0619
		(0.0219)		(0.0188)		(0.0625)
RPI (County)	-0.136***	-0.108***				
	(0.0292)	(0.0306)				
RPI (US)			-0.227***	-0.215***		
			(0.0302)	(0.0308)		
Price Index					0.0184	-0.0205
					(0.0330)	(0.0347)
Observations	3491193	3491193	3605864	3605864	974443	974443
R-squared	0.663	0.661	0.662	0.660	0.696	0.696
Prob > F	0.000	0.000	0.000	0.000	0.000	0.296
Number of units	185449	185449	190795	190795	82135	82135
Number of clusters	185449	185449	190795	190795	82135	82135
First stage F-stat	400.448	72.449	428.909	72.872	1624.059	409.923
BOTE: All	0.027	0.034	0.025	0.030	0.160	0.002
BOTE: Variety	0.038	0.043	0.040	0.044	0.159	0.004
BOTE: Prices	-0.012	-0.009	-0.015	-0.014	0.001	-0.002

Notes: Robust standard errors are in parentheses, clustered by household. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Household and period fixed effects are included. Variety: UPCs refers to the number of UPCs per store, Variety: Modules refers to the number of product modules per store, RPI (county) refers to the RPI using county-level reference prices as constructed in Section 4.1, RPI (US) uses national-level reference prices, and Price Index is a store price index constructed following Leung (2021b). To calculate the BOTEs resulting from changes in the IV only, we multiply the change in the IVs by their respective first-stage coefficients for each independent variable, and then further multiply the changes in each variable by their second-stage coefficients respectively. For the store price index BOTE, we use the change in the RPI IV over the sample period, which reflects the degree to which larger chains changed prices relative to its competitors.

Table I10: Effect of Variety and Prices on Other Measures of Concentration, HMS

VARIABLES	(1) Num Retailers	(2)	(3) Within-dept HHI	(4)	(5) Cross-dept variance	(6)	(7) Cross-HH variance	(8)
Variety: UPCs	-0.204***		0.0159***		-0.00470***		-0.00131	
	(0.0789)		(0.00408)		(0.00174)		(0.00482)	
Variety: Modules		-0.939***		0.0551***		-0.0346***		-0.0106
		(0.322)		(0.0168)		(0.00733)		(0.0202)
RPI (US)	3.129***	3.005***	-0.194***	-0.189***	0.0323***	0.0265**	0.0217	0.0199
	(0.543)	(0.548)	(0.0284)	(0.0286)	(0.0125)	(0.0127)	(0.0324)	(0.0323)
Observations	3605864	3605864	3605864	3605864	3605864	3605864	3605864	3605864
R-squared	0.684	0.683	0.638	0.638	0.492	0.490	0.579	0.579
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000
Number of units	190795	190795	190795	190795	190795	190795	190795	190795
Number of clusters	190795	190795	190795	190795	190795	190795	190795	190795
First stage F-stat	428.909	72.872	428.909	72.872	428.909	72.872	428.909	72.872
BOTE: All	0.006	0.008	0.029	0.023	0.019	0.041	-0.001	-0.005
BOTE: Variety	0.013	0.015	0.049	0.043	0.025	0.046	-0.003	-0.006
BOTE: Prices	-0.006	-0.006	-0.020	-0.020	-0.006	-0.005	0.002	0.002

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Household and period fixed effects are included. Variety: UPCs refers to the number of UPCs per store, Variety: Modules refers to the number of product modules per store, RPI (county) refers to the RPI using county-level reference prices as constructed in Section 4.1, RPI (US) uses national-level reference prices, and Price Index is a store price index constructed following Leung (2021b). To calculate the BOTEs resulting from changes in the IV only, we multiply the change in the IVs by their respective first-stage coefficients for each independent variable, and then further multiply the changes in each variable by their second-stage coefficients respectively. For the store price index BOTE, we use the change in the RPI IV over the sample period, which reflects the degree to which larger chains changed prices relative to its competitors.

Table I11: Effect of Variety and Prices on Other Measures of Concentration, RMS

VARIABLES	(1) Num Retailers	(2)	(3) Within-dept HHI	(4)	(5) Cross-dept variance	(6)	(7) Cross-HH variance	(8)
Variety: UPCs	-1.058***		0.0864***		-0.00487		-0.0177	
	(0.312)		(0.0167)		(0.00713)		(0.0190)	
Variety: Modules		-3.083***		0.0143		-0.0476*		-0.201***
		(1.102)		(0.0584)		(0.0281)		(0.0742)
Price Index	0.675	0.596	0.00385	-0.0430	-0.0146	-0.0224	0.00145	-0.0334
	(0.607)	(0.636)	(0.0313)	(0.0328)	(0.0150)	(0.0160)	(0.0350)	(0.0377)
Observations	974443	974443	974443	974443	974443	974443	974443	974443
R-squared	0.718	0.718	0.681	0.681	0.522	0.522	0.631	0.631
Prob > F	0.000	0.000	0.000	0.146	0.990	0.004	0.998	0.000
Number of units	82135	82135	82135	82135	82135	82135	82135	82135
Number of clusters	82135	82135	82135	82135	82135	82135	82135	82135
First stage F-stat	1624.059	409.923	1624.059	409.923	1624.059	409.923	1624.059	409.923
BOTE: All	0.065	0.005	0.349	-0.006	0.023	0.012	-0.045	-0.023
BOTE: Variety	0.066	0.007	0.349	0.002	0.021	0.008	-0.046	-0.019
BOTE: Prices	-0.001	-0.002	0.000	-0.008	0.002	0.005	0.000	-0.004

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Household and period fixed effects are included. Variety: UPCs refers to the number of UPCs per store, Variety: Modules refers to the number of product modules per store, RPI (county) refers to the RPI using county-level reference prices as constructed in Section 4.1, RPI (US) uses national-level reference prices, and Price Index is a store price index constructed following Leung (2021b). To calculate the BOTEs resulting from changes in the IV only, we multiply the change in the IVs by their respective first-stage coefficients for each independent variable, and then further multiply the changes in each variable by their second-stage coefficients respectively. For the store price index BOTE, we use the change in the RPI IV over the sample period, which reflects the degree to which larger chains changed prices relative to its competitors.

Table I12: Effect of Variety and Prices on Trip Measures, HMS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	TripNum		UPC per trip		Groups per trip		Dept per trip	
Variety: UPCs	-0.476		0.750***		0.407***		0.0571***	
	(0.404)		(0.0984)		(0.0586)		(0.00724)	
Variety: Modules		-1.664		3.171***		1.754***		0.271***
		(1.614)		(0.461)		(0.269)		(0.0357)
RPI (US)	-2.831	-3.002	-2.688***	-2.294***	-1.590***	-1.369***	-0.239***	-0.202***
	(2.819)	(2.816)	(0.691)	(0.726)	(0.408)	(0.425)	(0.0496)	(0.0533)
Observations	3605864	3605864	3605864	3605864	3605856	3605856	3605856	3605856
R-squared	0.726	0.726	0.767	0.762	0.779	0.776	0.695	0.687
Prob > F	0.102	0.321	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	190795	190795	190795	190795	190795	190795	190795	190795
Number of clusters	190795	190795	190795	190795	190795	190795	190795	190795
First stage F-stat	428.909	72.872	428.909	72.872	428.907	72.871	428.907	72.871
BOTE: All	0.009	0.008	0.077	0.084	0.067	0.075	0.326	0.406
BOTE: Variety	0.007	0.006	0.087	0.093	0.077	0.084	0.379	0.451
BOTE: Prices	0.001	0.002	-0.011	-0.009	-0.010	-0.009	-0.053	-0.045

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Household and period fixed effects are included. Variety: UPCs refers to the number of UPCs per store, Variety: Modules refers to the number of product modules per store, RPI (county) refers to the RPI using county-level reference prices as constructed in Section 4.1, RPI (US) uses national-level reference prices, and Price Index is a store price index constructed following Leung (2021b). To calculate the BOTEs resulting from changes in the IV only, we multiply the change in the IVs by their respective first-stage coefficients for each independent variable, and then further multiply the changes in each variable by their second-stage coefficients respectively. For the store price index BOTE, we use the change in the RPI IV over the sample period, which reflects the degree to which larger chains changed prices relative to its competitors.

Table I13: Effect of Variety and Prices on Trip Measures, RMS

VARIABLES	(1) TripNum	(2)	(3) UPC per trip	(4)	(5) Groups per trip	(6)	(7) Dept per trip	(8)
Variety: UPCs	-3.900***		1.702***		0.912***		0.150***	
	(1.472)		(0.430)		(0.237)		(0.0265)	
Variety: Modules		-0.782		2.062		0.738		0.264***
		(4.965)		(1.414)		(0.816)		(0.0980)
Price Index	-9.486***	-7.402**	1.674**	1.151	0.856**	0.493	0.0474	0.0197
	(3.083)	(3.183)	(0.743)	(0.793)	(0.433)	(0.460)	(0.0528)	(0.0558)
Observations	974443	974443	974443	974443	974443	974443	974443	974443
R-squared	0.768	0.768	0.795	0.795	0.807	0.807	0.722	0.722
Prob > F	0.000	0.000	0.000	0.034	0.000	0.941	0.000	0.000
Number of units	82135	82135	82135	82135	82135	82135	82135	82135
Number of clusters	82135	82135	82135	82135	82135	82135	82135	82135
First stage F-stat	1624.059	409.923	1624.059	409.923	1624.059	409.923	1624.059	409.923
BOTE: All	0.058	0.005	0.147	0.011	0.128	0.007	0.338	0.024
BOTE: Variety	0.055	0.000	0.144	0.006	0.125	0.004	0.335	0.022
BOTE: Prices	0.003	0.005	0.004	0.005	0.003	0.003	0.003	0.002

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Household and period fixed effects are included. Variety: UPCs refers to the number of UPCs per store, Variety: Modules refers to the number of product modules per store, RPI (county) refers to the RPI using county-level reference prices as constructed in Section 4.1, RPI (US) uses national-level reference prices, and Price Index is a store price index constructed following Leung (2021b). To calculate the BOTEs resulting from changes in the IV only, we multiply the change in the IVs by their respective first-stage coefficients for each independent variable, and then further multiply the changes in each variable by their second-stage coefficients respectively. For the store price index BOTE, we use the change in the RPI IV over the sample period, which reflects the degree to which larger chains changed prices relative to its competitors.

Table I14: Effect of online shopping on household HHI, using e-commerce same-day shipping

VARIABLES	(1) Online share	(2) HH HHI	(3) Log trips	(4) Online share	(5) HH HHI	(6) Log trips
Same-day (zip)	0.000749	-0.00290	0.00194	0.0000931	0.00459**	0.00226
	(0.000901)	(0.00230)	(0.00662)	(0.000970)	(0.00231)	(0.00680)
Same-day (zip) × LM(1-2)	-0.000493	0.00347	-0.00593			
	(0.000859)	(0.00226)	(0.00646)			
Same-day (zip) × LM(3-6)	-0.00341**	0.00325	-0.00159			
	(0.00156)	(0.00336)	(0.00981)			
Same-day (zip) × LM(7+)	-0.0125	0.0358*	-0.0759			
	(0.0103)	(0.0205)	(0.0686)			
LM(1-2)	0.000295	-0.00120	0.000193			
	(0.000483)	(0.00109)	(0.00315)			
LM(3-6)	0.00269**	-0.00154	0.000172			
	(0.00135)	(0.00270)	(0.00805)			
LM(7+)	0.0128	-0.0370*	0.0743			
	(0.0101)	(0.0201)	(0.0679)			
Same-day (zip) × log(LM dist)				0.0000302	-0.00193**	-0.00146
				(0.000337)	(0.000833)	(0.00242)
log(LM dist)				0.000146	-0.000105	0.00380***
				(0.000188)	(0.000434)	(0.00124)
Observations	738890	738890	738890	738358	738358	738358
R-squared	0.658	0.765	0.774	0.658	0.765	0.774
Prob > F	0.450	0.456	0.794	0.834	0.075	0.016
Number of units	81264	81264	81264	81212	81212	81212
Number of clusters	81264	81264	81264	81212	81212	81212
BOTE		0.032	0.018		0.019	0.00065

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Household and year-quarter fixed effects are included. Same-day (zip) refers to the availability of same-day shipping by the major e-commerce platform, which is 1 when the service is available and 0 when it is not. LM dist refers to the distance of each household's population-weighted zip code centroid to its closest last-mile facility of the major e-commerce platform. LM (1-2) is a dummy variable that is 1 if there are 1 or 2 last-mile facilities within a 25-mile radius of the population-weighted centroid of a household's zip code in the given year-quarter. Likewise, LM (3-6) and LM(7+) are equal to 1 when there are 3 to 6 or more than 7 last-mile facilities respectively. BOTE refers to a back-of-the-envelope estimate of how much same-day shipping explains the rise in the household retail concentration. This is calculated by multiplying the estimated coefficient by the total change in the ratio of same-day shipping zip-codes over the sample period, 2017-2019, then dividing this number by the total change in the household retail concentration during this period.

Table I15: Effect of online shopping on household HHI, using broadband accessibility

VARIABLES	Online share	HH HHI	Log trips	Online share	HH HHI	Log trips
Speed 200Kbps=1	-0.000530**	0.000120	-0.00173			
	(0.000246)	(0.000611)	(0.00178)			
Speed 10Mbps=1				0.00108***	0.000447	-0.000576
				(0.000279)	(0.000657)	(0.00193)
Log Provider Num	0.000592	0.000685	-0.00714**	0.000511	0.000678	-0.00725**
	(0.000518)	(0.00121)	(0.00355)	(0.000517)	(0.00121)	(0.00355)
Observations	2691290	2691294	2691294	2691290	2691294	2691294
R-squared	0.507	0.681	0.697	0.507	0.681	0.697
Prob > F	0.057	0.833	0.077	0.000	0.677	0.119
Number of units	158690	158690	158690	158690	158690	158690
Number of clusters	158690	158690	158690	158690	158690	158690

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Household and year-quarter fixed effects are included. Speed 200Kbps (10M) is a dummy that equals to 1 when the share of households with a broadband downstream speed above 200Kbps (10M) within a given county is greater than 60%. Both speed group data are from FCC and are available after year 2008. Log Provider num is the logrithm of the average number of broadband providers per census tract within the zip code where a household lives. The data is available online from 2008-2018 at `https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0250732`.

Table I16: Effect of shopping trips on household HHI, IV with household characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IV	None	None: Controls	Age	Size		Employment	
VARIABLES	Household HHI						
Log Trips	-0.129***	-0.201***	-0.204***	-0.203***	-0.198***	-0.218***	-0.222***
	(0.000364)	(0.000613)	(0.00291)	(0.0141)	(0.0145)	(0.0134)	(0.0137)
Observations	3668938	3622992	2312242	3622992	3622926	3622992	3622926
R-squared	0.712	0.724	0.384	0.724	0.739	0.724	0.739
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	194524	193527	2650	193527	193526	193527	193526
Number of clusters	194524	193527	136238	193527	193526	193527	193526
First stage F-stat			6225.057	102.427	98.491	116.170	109.195
BOTE: Trips	0.613	0.957	0.941	0.963	0.939	1.036	1.055
County-time FE			X		X		X

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Household and period fixed effects are included. Controls are control variables for shopping needs as in AH, which include the log of the quantity index derived from the RPI as well as the log number of UPCs and product groups purchased per period. BOTE refers to a back-of-the-envelope estimate of how much each independent variable (log trips) explains the rise in household retail concentration. This is calculated by multiplying the estimated coefficient by the total change in the independent variable over the sample period, then dividing this number by the total change in household retail concentration in the sample period.

Table I17: Effect of shopping trips on household HHI, IVs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVs	Real wage			Unemployment Rate			Both		
IV group	Age	Education	Both	Age	Education	Both	Age	Education	Both
VARIABLES	Household HHI								
Log Trips	-0.434***	-0.181***	-0.331***	-0.170***	-0.336***	-0.243***	-0.298***	-0.282***	-0.291***
	(0.0773)	(0.0659)	(0.0498)	(0.0420)	(0.0699)	(0.0373)	(0.0361)	(0.0563)	(0.0306)
Observations	2285235	2305700	2278148	2285235	2305700	2278148	2285235	2305700	2278148
R-squared	0.675	0.737	0.720	0.737	0.717	0.737	0.728	0.730	0.730
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	128280	128764	128038	128280	128764	128038	128280	128764	128038
Number of clusters	128280	128764	128038	128280	128764	128038	128280	128764	128038
First stage F-stat	22.761	22.522	23.011	54.345	18.622	38.693	42.073	15.757	30.737
BOTE: Trips	2.182	0.839	1.674	0.814	1.607	1.191	1.541	1.341	1.535
BOTE: IVs	0.097	0.008	0.083	0.023	0.035	0.061	0.111	0.037	0.143

Notes: Robust standard errors are in parentheses, clustered by household. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Household and period fixed effects are included. We construct proxies for labor demand shocks at various levels of aggregation across household characteristics in the CPS MORG, such as age and education cells or both across the US, which we denote as an IV group. These IV's include real wages, unemployment rates, or both, which we denote as IVs. We allow these variables to differ by gender. We match these proxies to households in the HMS using the mode of their characteristics over the sample period to avoid using variation induced by shifts in characteristics over time. BOTE: Trips refers to a back-of-the-envelope estimate of how much each independent variable (log trips) explains the rise in household retail concentration. This is calculated by multiplying the estimated coefficient by the total change in the independent variable over the sample period, then dividing this number by the total change in household retail concentration in the sample period. To calculate the BOTEs resulting from changes in the IV only (BOTE: IVs), we multiply the change in the IVs by their respective first-stage coefficients for each independent variable, and then further multiply the changes in each variable by their second-stage coefficients respectively.

Table I18: Effect of shopping trips on household HHI, IV with state and city gas prices

	(1)	(2)	(3)
	EIA: State	EIA: City	BLS: City
VARIABLES	Household HHI		
Log Trips	-0.414**	-0.485*	-0.457**
	(0.164)	(0.252)	(0.195)
Observations	719840	426514	584339
R-squared	0.703	0.658	0.678
Prob > F	0.000	0.000	0.000
Number of units	49720	29902	41775
Number of clusters	49720	29902	41775
First stage F-stat	8.128	3.993	6.089
BOTE: Trips, 2004-2019	1.969	2.303	2.169
BOTE: IVs, 2004-2019	0.108	0.116	0.129
BOTE: Trips, 2010-2016	0.595	0.696	0.656
BOTE: IVs, 2010-2016	-0.068	-0.062	-0.079

Notes: Robust standard errors are in parentheses, clustered by household. *** p<0.01, ** p<0.05, * p<0.1. Household and period fixed effects are included. BOTE: Trips refers to a back-of-the-envelope estimate of how much each independent variable (log trips) explains the rise in household retail concentration. This is calculated by multiplying the estimated coefficient by the total change in the independent variable over the sample period, then dividing this number by the total change in household retail concentration in the sample period. To calculate the BOTEs resulting from changes in the IV only (BOTE: IVs), we multiply the change in the IVs by their respective first-stage coefficients for each independent variable, and then further multiply the changes in each variable by their second-stage coefficients respectively. We split these BOTEs into those for changes from 2004-2019 and 2010-2016 respectively.

Table I19: Comparative Statics: Household HHI and Welfare

Event	Model Parameter	HHI	Consumer Welfare
Demand			
Wage rises	$w\uparrow$	$\uparrow$	$\uparrow$
Leisure technology rises	$\theta\uparrow$	$\uparrow$	$\uparrow$
Trip cost rises	$t\uparrow$	$\uparrow$	$\downarrow$
Supply			
Entry of new firm	f^N	$\downarrow^*$	$\uparrow$
Entry of a supercenter	$\underline{f}\downarrow$	$\uparrow^{**}$	$\uparrow$
Prices $\downarrow$ or variety $\uparrow$	$p_f\downarrow$	$\uparrow^{***}$	$\uparrow$

Notes: This table summarizes some comparative statics from our model, both on the supply and demand side, and their implications for household HHI and welfare. * denotes that HHI drops unless the new firm has a sufficiently low price index, as derived in online Appendix Section G. ** denotes the fact that HHI increases when there is a sufficient decrease in f^*. *** denotes the fact that HHI increases when the price index decrease favors firms with lower initial price indices as derived in online Appendix Section G.

Table I20: Relationship between calibrated markups and PromoData markups, levels

	(1)	(2)	(3)	(4)
VARIABLES		Calibrated markup		
Markup, national PromoData	-0.0144*			
	(0.00873)			
Markup, balanced national PromoData		-0.152**		
		(0.0766)		
Markup, market PromoData			-0.0205	
			(0.0147)	
Markup, balanced market PromoData				0.0120
				(0.0533)
Observations	5448	2653	4062	742
R-squared	0.017	0.041	0.010	0.002
Prob > F	0.099	0.048	0.162	0.822
Number of units	1028	379	860	106
Number of clusters	1028	379	860	106

Notes: Robust standard errors are in parentheses, clustered by retailer. *** p<0.01, ** p<0.05, * p<0.1. Year fixed effects are included and observations are weighted by revenue. National PromoData refers to using wholesale costs across the entire nation whenever available, aggregating across markets. Market PromoData refers to using wholesale costs when matched to the same market only. Balanced refers to using only products that are available in all years of the sample period.

Table I21: Relationship between calibrated markups and PromoData markup indices, log changes

	(1)	(2)	(3)	(4)
VARIABLES		Calibrated markup		
Price index, national PromoData	0.00357			
	(0.00953)			
Markup index, national PromoData		-0.00106		
		(0.000973)		
Price index, market PromoData			0.00749	
			(0.00649)	
Markup index, market PromoData				0.00202***
				(0.000649)
Observations	4100	2454	2211	926
R-squared	0.981	0.981	0.986	0.992
Prob > F	0.708	0.278	0.249	0.002
Number of units	676	512	418	247
Number of clusters	676	512	418	247

Notes: Robust standard errors are in parentheses, clustered by retailer. *** p<0.01, ** p<0.05, * p<0.1. Retailer and year fixed effects are included and observations are weighted by revenue. National PromoData refers to using wholesale costs across the entire nation whenever available, aggregating across markets. Market PromoData refers to using wholesale costs when matched to the same market only. Indices are chained as Tornqvist indices.

Table I22: Relationship between calibrated markups and PromoData markups, log changes

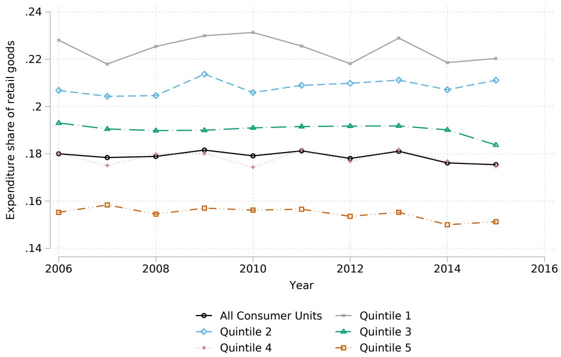
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			Calibrated markup			
Markup, national PromoData	0.00120					
	(0.00198)					
Markup, balanced national PromoData		-0.0134				
		(0.0110)				
Markup, market PromoData			-0.00486**			
			(0.00210)			
Markup, balanced market PromoData				-0.0118		
				(0.00720)		
RPI, full HMS					-0.0178	
					(0.0229)	
Price index, full HMS						-0.0286**
						(0.0137)
Observations	5357	2653	3962	742	12681	8420
R-squared	0.980	0.982	0.984	0.990	0.969	0.970
Prob > F	0.544	0.225	0.021	0.104	0.438	0.037
Number of units	937	379	760	106	1208	724
Number of clusters	937	379	760	106	1208	724

Notes: Robust standard errors are in parentheses, clustered by retailer. *** p<0.01, ** p<0.05, * p<0.1. Retailer and year fixed effects are included and observations are weighted by revenue. National PromoData refers to using wholesale costs across the entire nation whenever available, aggregating across markets. Market PromoData refers to using wholesale costs when matched to the same market only. Balanced refers to using only products that are available in all years of the sample period. Full HMS refers to using all products in the HMS rather than just products that can be matched to the PromoData. Indices are chained as Tornqvist indices.

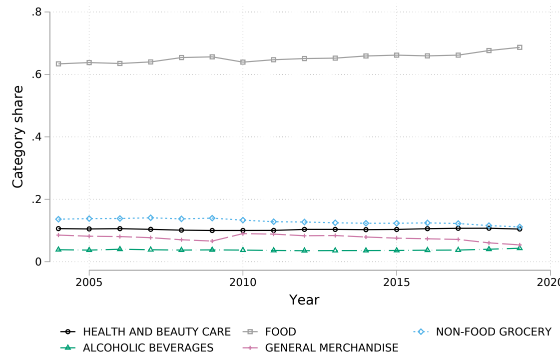
J Figures

Figure J1: Expenditure shares on NielsenIQ retail goods, CEX and HMS

(a) Expenditure shares on NielsenIQ retail goods by income quintile, CEX

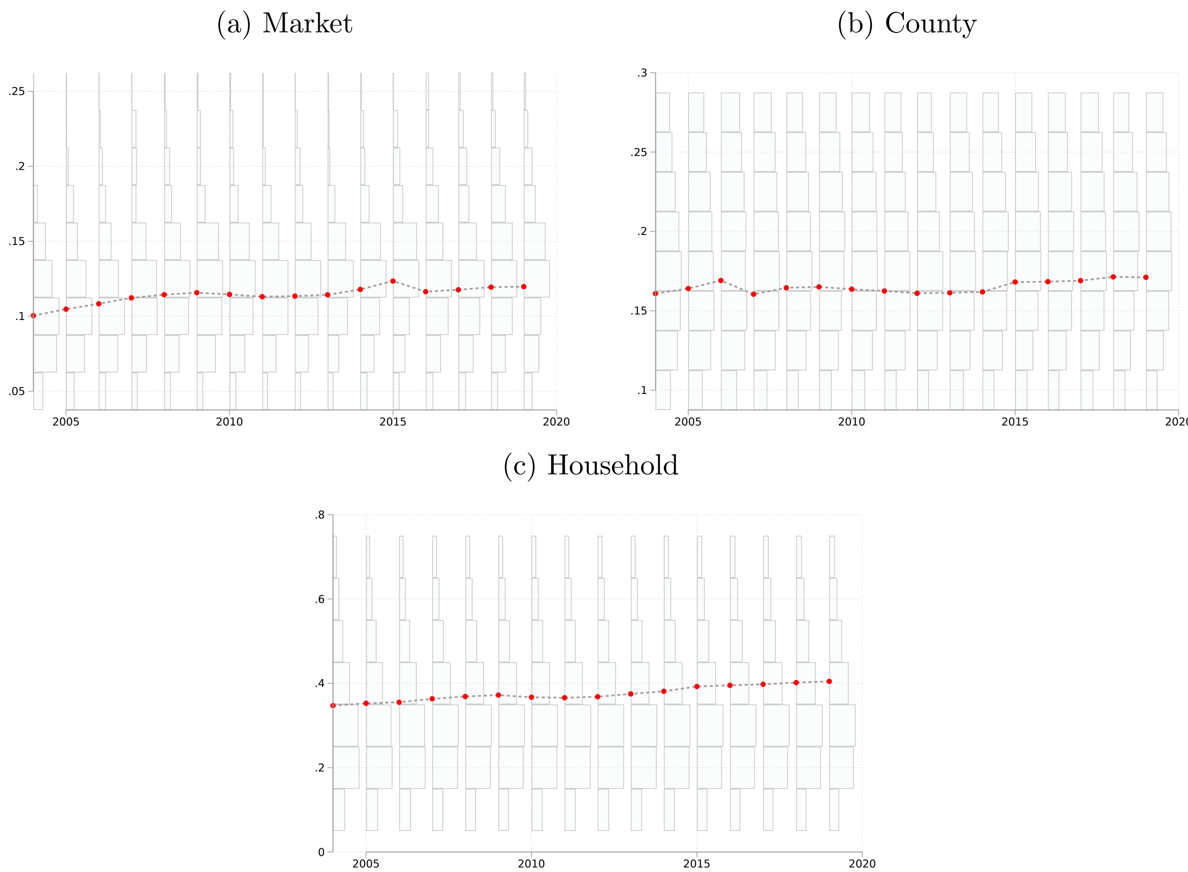


(b) Expenditure shares by product category, HMS



Notes: Panel (a) plots expenditure shares on retail goods by income quintile from 2006-2015, which range from an average of 15.48% for top quintile consumer units to 22.44% for bottom quintile consumer units. Data from the CEX are used and selected categories are all recorded by the NielsenIQ Consumer Panel, which include alcoholic beverages, drugs, food at home, toys, audio and visual equipment, medical supplies, household furnishings and equipment, housekeeping supplies, personal care products and services, and tobacco. Panel (b) plots expenditure shares by product category in the NielsenIQ Consumer Panel (HMS) from 2004-2019.

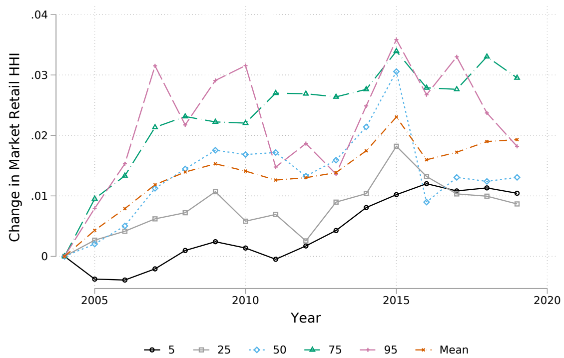
Figure J2: Retail Concentration Over Time



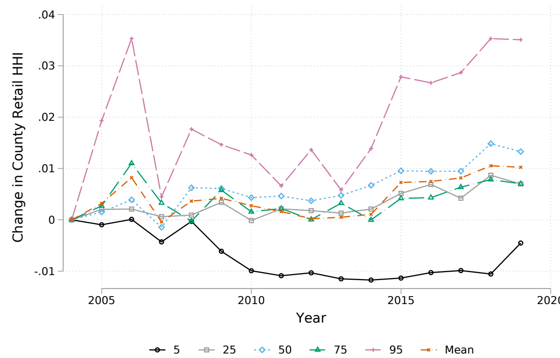
Notes: This figure plots the revenue-weighted average and distribution of retail concentration at the market, county, and household level respectively.

Figure J3: Retail Concentration Over Time By Percentile

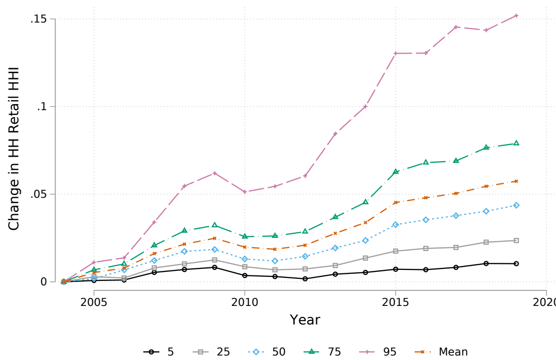
(a) Market



(b) County



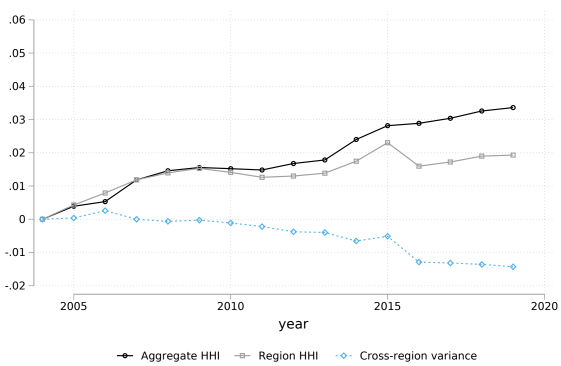
(c) Household



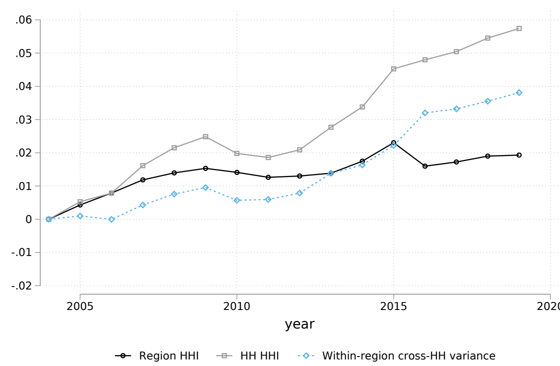
Notes: This figure plots the revenue-weighted changes of of retail concentration at the market, county, and household level respectively by percentile.

Figure J4: Decomposing Changes in Retail Concentration

(a) National and Market



(b) Market and Household

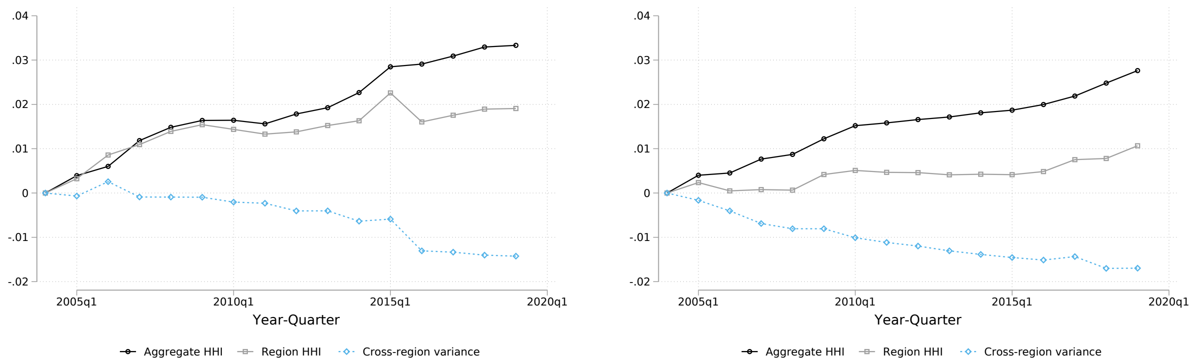


Notes: This figure shows that HHI can be decomposed at each level following Radaelli and Zenga (2002). For each term, we plot the yearly change over the sample period.

Figure J5: National and Market Concentration

(a) Revenue

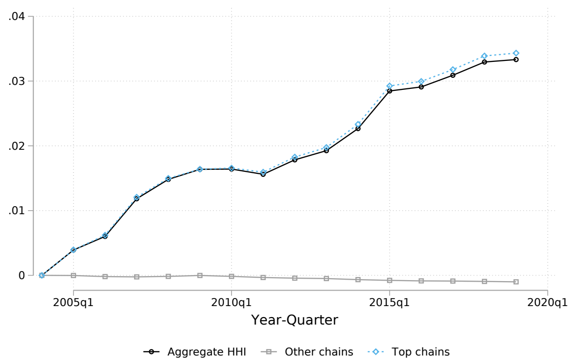
(b) Number of Stores



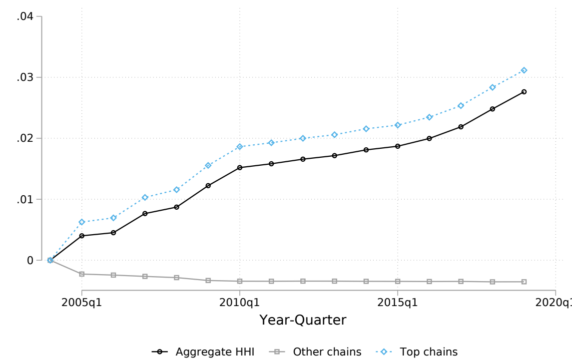
Notes: This figure shows that HHI can be decomposed at each level following Radaelli and Zenga (2002). For each term, we plot the yearly change over the sample period. We show this decomposition using two outcomes: revenue and the number of stores respectively.

Figure J6: Decomposing Changes in Retail Concentration by Groups of Chains

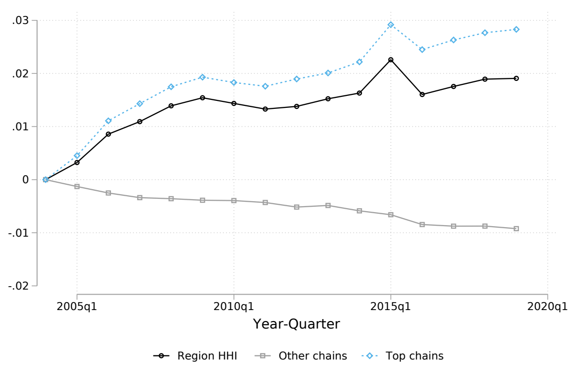
(a) Aggregate HHI, revenue



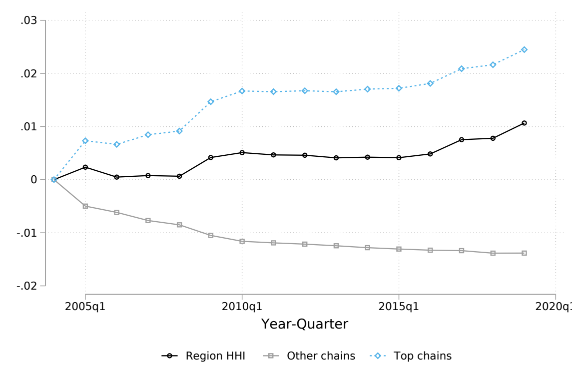
(b) Aggregate HHI, number of stores



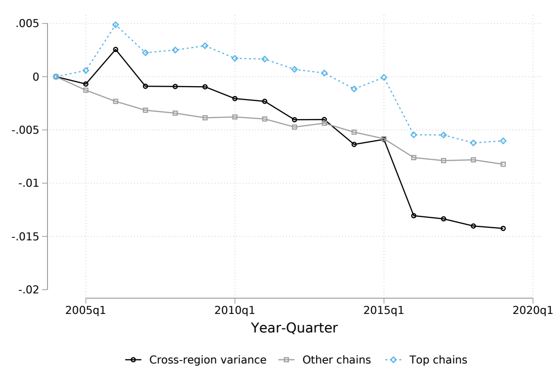
(c) Market HHI, revenue



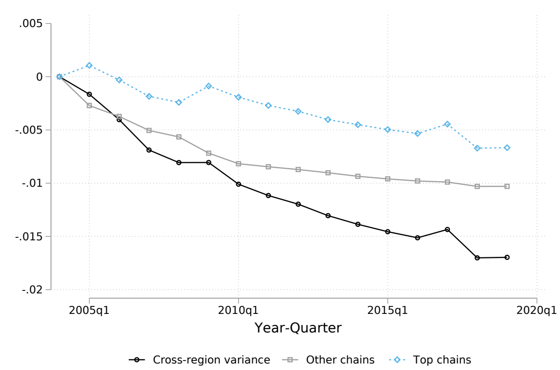
(d) Market HHI, number of stores



(e) Cross-market variance, revenue



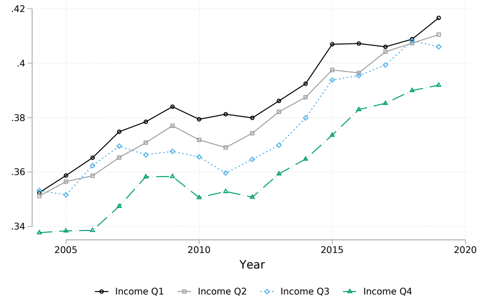
(f) Cross-market variance, number of stores



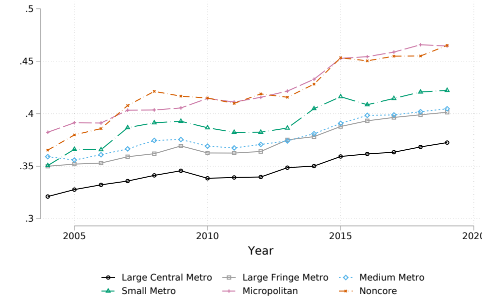
Notes: This figure shows that HHI can be decomposed at the market level following Radaelli and Zenga (2002) and further decomposed into the contributions by different groups of retail chains. For each term, we plot the yearly change over the sample period. We show this decomposition using two outcomes: revenue and the number of stores respectively. We group retail chains into two groups: the top 40 retail chains by revenue rank over the sample period, and other chains outside the top 40.

Figure J7: Household Retail Concentration by Demographic Group

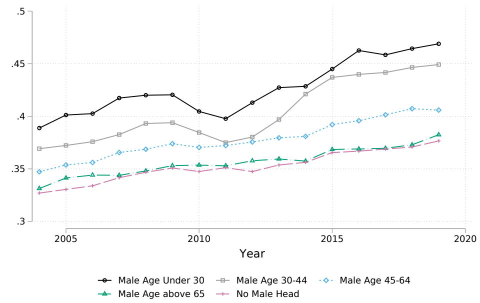
(a) Household Income



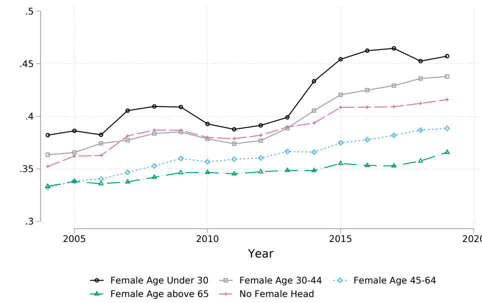
(b) Urban/Rural Counties



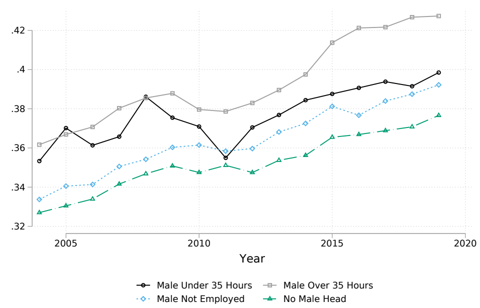
(c) Male Head Age



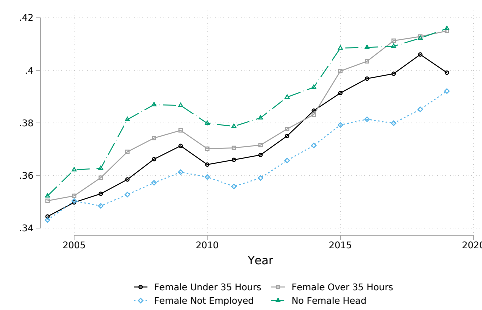
(d) Female Head Age



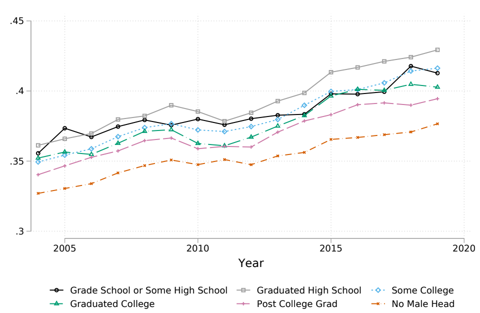
(e) Male Head Employment



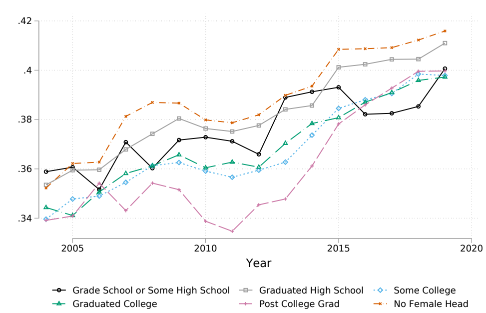
(f) Female Head Employment



(g) Male Head Education



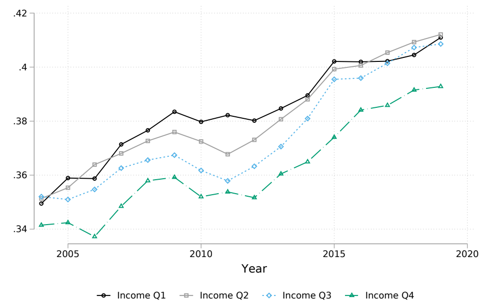
(h) Female Head Education



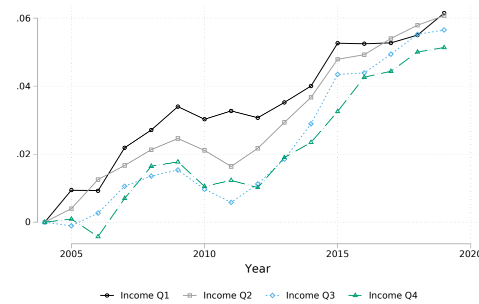
Notes: This figure plots the revenue-weighted average of retail concentration at the household level for different demographic groups. Panel (a) classifies households into four household income quartiles after adjusting for household size, with Q1 being the lowest income quartile and Q4 the highest income quartile. Panel (b) classifies households by the county they reside in and groups them based on the urban/rural classification of the National Center for Health Statistics (NCHS). Panel (c) and (d) classifies households by their male and female head's age. Panel (e) and (f) classifies households by their male and female head's hours of work. Panel (g) and (h) classifies households by their male and female head's level of education.

Figure J8: Household Retail Concentration by Demographic Group

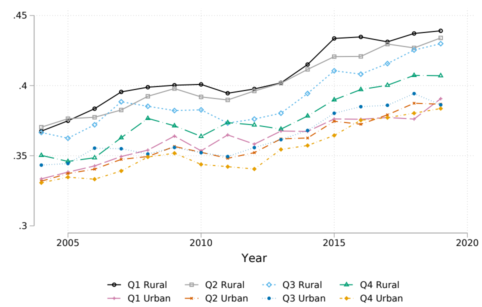
(a) Household Income, No Size Adjustment, Levels



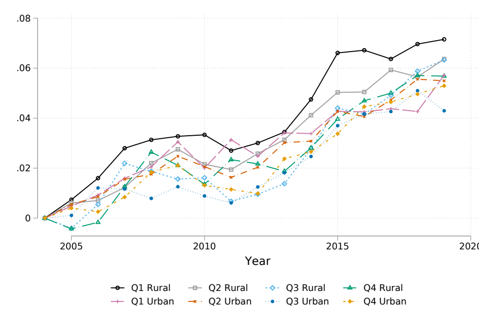
(b) Household Income, No Size Adjustment, Changes



(c) Household Income and Urban/Rural, Levels



(d) Household Income and Urban/Rural, Changes



(e) Household Size, Levels

(f) Household Size, Changes

Notes: This figure plots the levels and changes (since 2004) of revenue-weighted average of retail concentration at the household level for different demographic groups. Panel (a) and (b) classify households into four household income quartiles, with Q1 being the lowest income quartile and Q4 the highest income quartile. Panel (c) and (d) classify households by the county they reside in and groups them based on the urban/rural classification of the National Center for Health Statistics (NCHS) and interact with household income after adjusting for household size. Panel (e) and (f) classify households by their household size.

Figure J9: Household Concentration by Product Department

(a) Levels (b) Changes

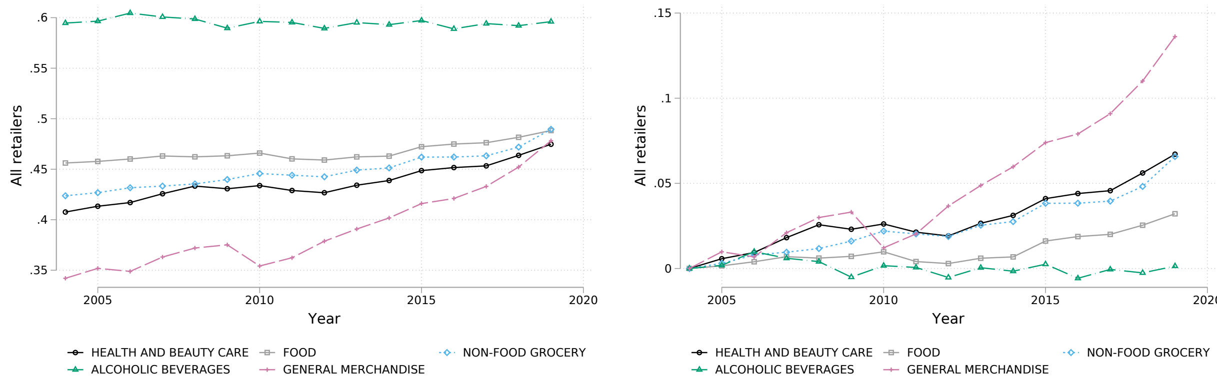
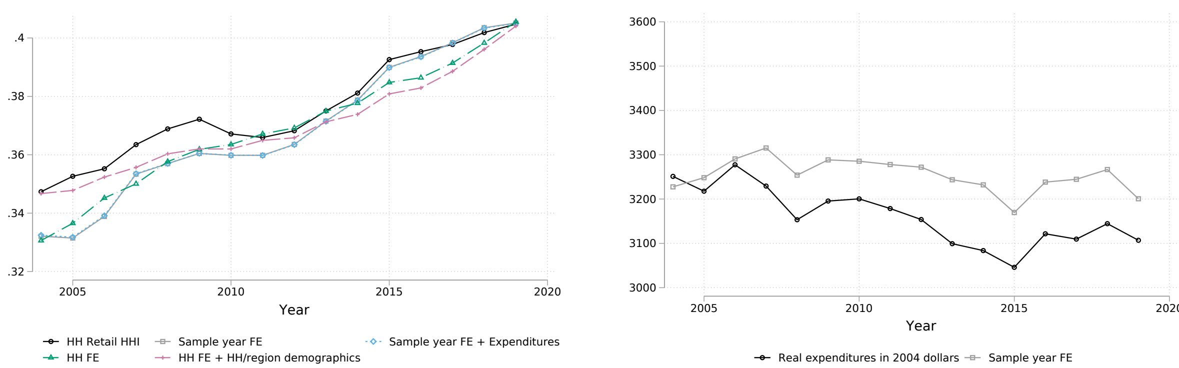


Figure J10: Non-Magnet Products Only

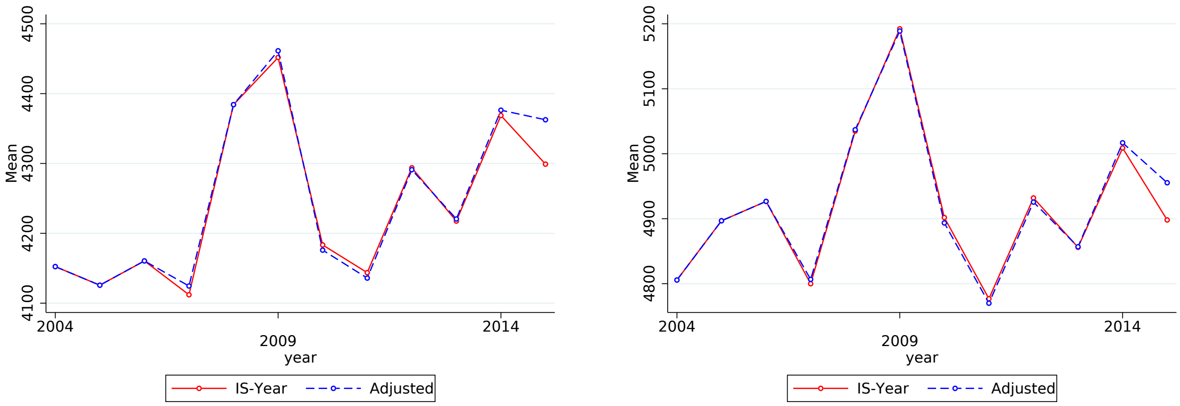
(a) Household HHI (b) Real Expenditures



Notes: This figure shows trends for average household HHI and annual real expenditures from 2004-2019 for non-magnet products only. Non-magnet products are products with standard barcodes. NielsenIQ also captures products without standard barcodes using their own classification system. This data, known as magnet data, includes items such as fruits, vegetables, meats, and in-store baked goods. In Panel (a), we regress household HHI on various control variables and plot the year fixed effects for each specification. We control for the number of years the household has been in the sample (sample year FE), total expenditures, household fixed effects (HH FE), as well as household and regional demographics.

Figure J11: Real expenditures, CEX

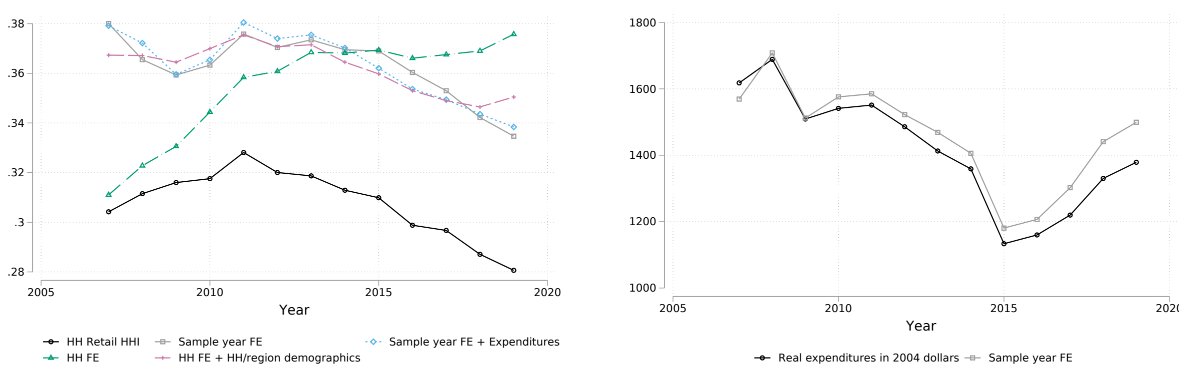
(a) Food at home (b) NielsenIQ non-durable goods



Notes: This figure shows the average annual expenditure of food-at-home and matched non-durable goods captured by NielsenIQ, as classified by Coibion et al. (2021a), in the Consumption Expenditure Survey (CEX) Interview Survey (IS). The adjusted series follows Coibion et al. (2021a) in controlling for various household demographics.

Figure J12: Magnet Products Only

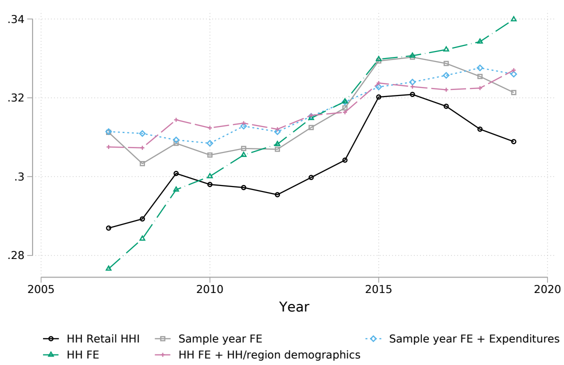
(a) Household HHI (b) Real Expenditures



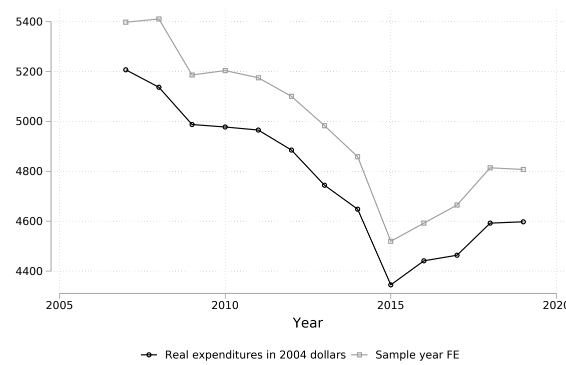
Notes: This figure shows trends for average household HHI and annual real expenditures from 2007-2019 for magnet products only. NielsenIQ also captures products without standard barcodes using their own classification system. This data, known as magnet data, includes items such as fruits, vegetables, meats, and in-store baked goods. In Panel (a), we regress household HHI on various control variables and plot the year fixed effects for each specification. We control for the number of years the household has been in the sample (sample year FE), total expenditures, household fixed effects (HH FE), as well as household and regional demographics.

Figure J13: All products, both magnet and non-magnet

(a) Household HHI



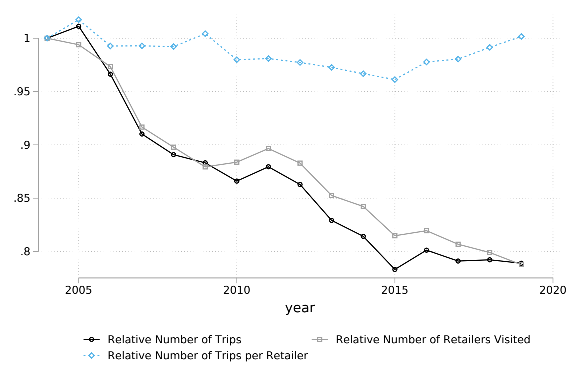
(b) Real Expenditures



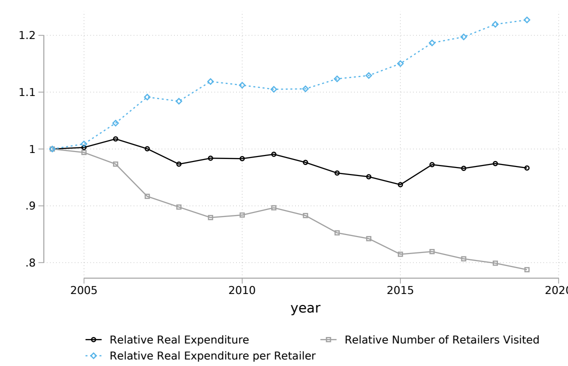
Notes: This figure shows trends for average household HHI and annual real expenditures from 2007-2019. Non-magnet products are products with standard barcodes. NielsenIQ also captures products without standard barcodes using their own classification system. This data, known as magnet data, includes items such as fruits, vegetables, meats, and in-store baked goods. In Panel (a), we regress household HHI on various control variables and plot the year fixed effects for each specification. We control for the number of years the household has been in the sample (sample year FE), total expenditures, household fixed effects (HH FE), as well as household and regional demographics.

Figure J14: Decomposing trips, expenditures, and number of retailers per household

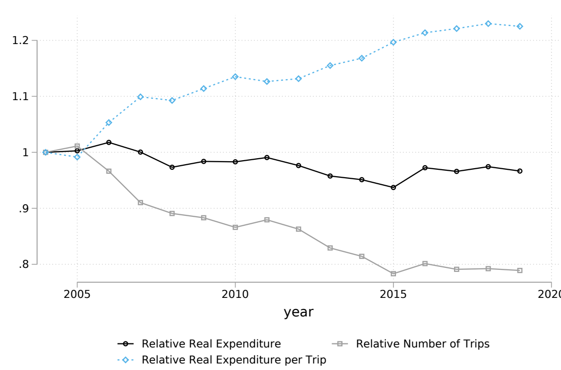
(a) Number of trips, number of retailers, and trips per retailer



(b) Real expenditure, number of retailers, and expenditures per retailer



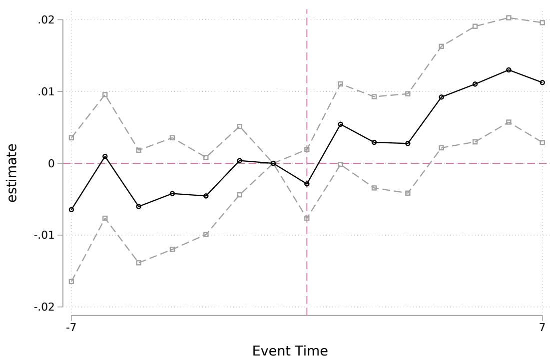
(c) Real expenditure, number of trips, and expenditures per trip

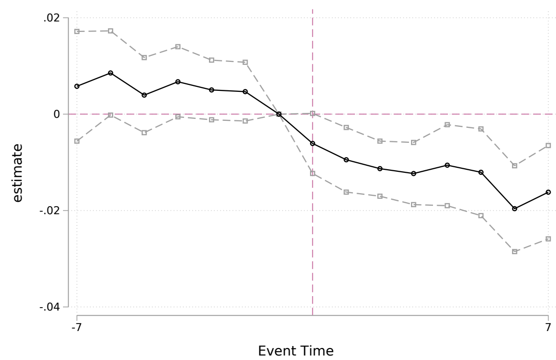


Notes: In Panel (a), this figure plots the annual sampling-weighted average of households' number of shopping trips per quarter, number of retailers visited per year, and trips per retailer, divided by their level in 2004. In Panel (b), this figure plots the annual sampling-weighted average of households' real expenditure, number of retailers visited per year, and expenditures per retailer, divided by their level in 2004. In Panel (c), this figure plots the annual sampling-weighted average of households' real expenditure, number of trips, and expenditures per trip, divided by their level in 2004.

Figure J15: Event Study Graph for Store Entry

(a) Supercenter Entry (b) Club Entry

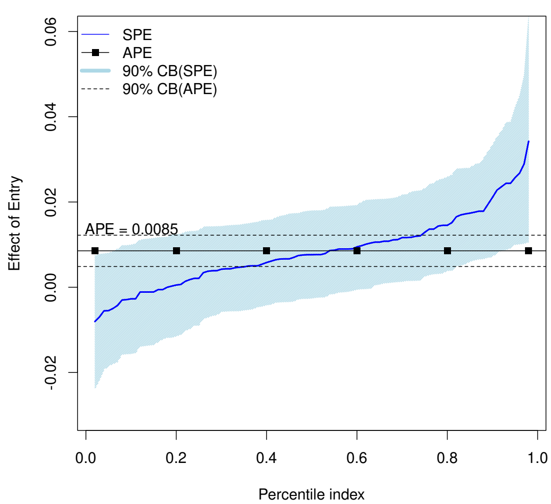




Notes: This figure plots the sum of estimated coefficients for each period, along with the 95% confidence intervals, from regressions using a distributed lag model following de Chaisemartin and D'Haultfœuille (2020), where household retail HHI is regressed on the number of supercenters and club stores respectively. Household and period fixed effects are included.

Figure J16: Sorted Effects across Households

(a) Supercenter Entry (b) Club Entry



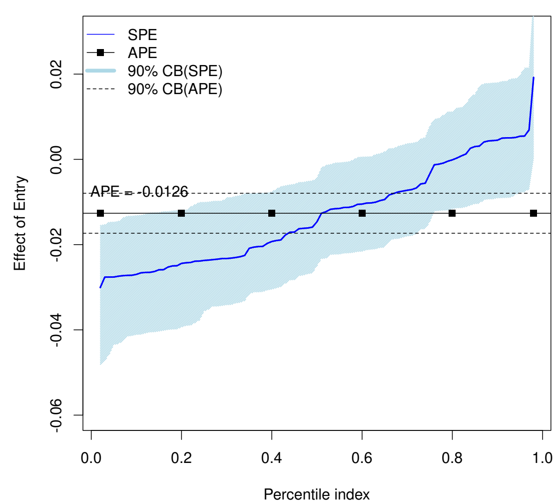
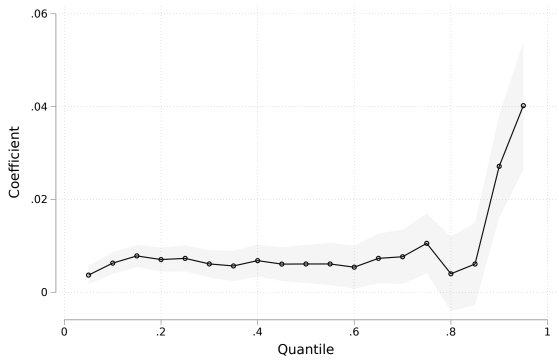


Figure J17: Quantile Treatment Effects

(a) Supercenter Entry

(b) Club Entry



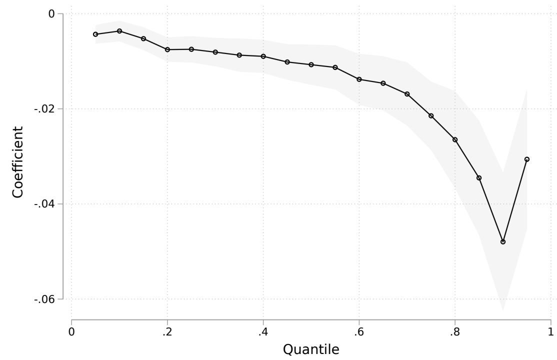
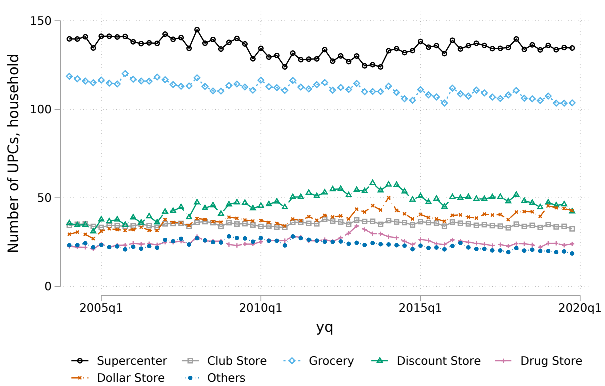
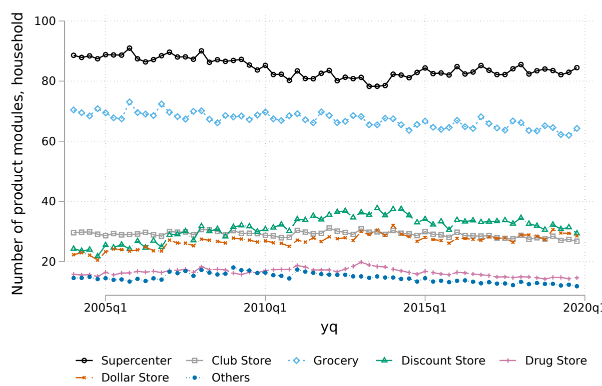


Figure J18: Product Assortment in Big-box Stores

(a) UPCs

(b) Product Modules

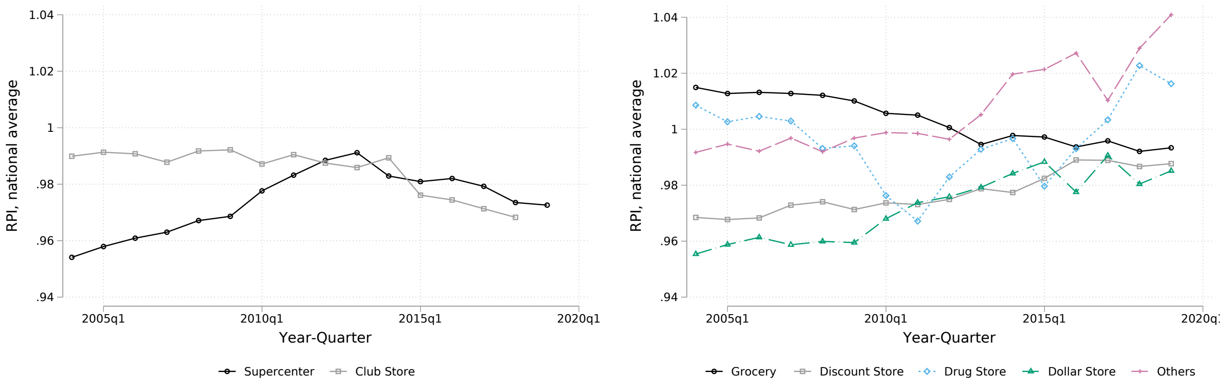




Notes: This figure plots the sample-weighted average number of UPCs and product modules households buy in each type of store per quarter.

Figure J19: RPI in Big-box Stores and Other Channel Types

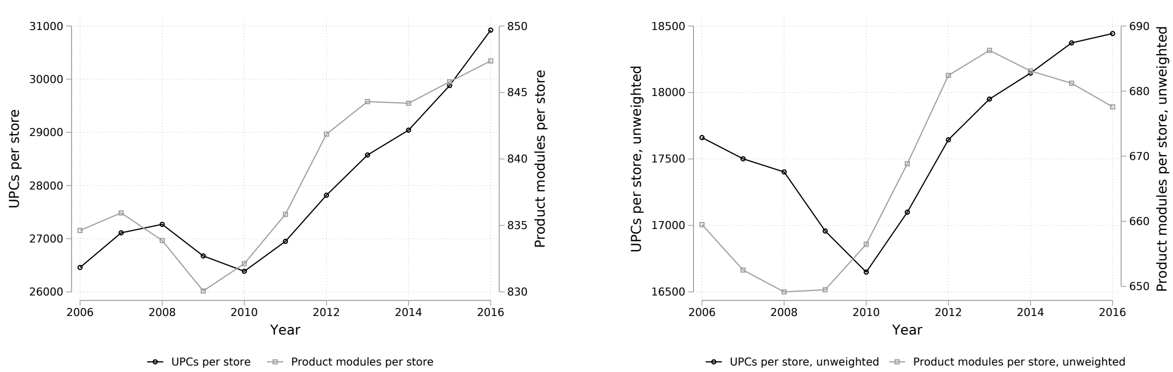
(a) Big-box Stores (b) Other Channel Types



Notes: This figure plots the relative price index (RPI) of each retailer or channel type following AH. To construct a retailer RPI, we calculate the ratio between total expenditure for each good and the counterfactual expenditure of each good at its average price in the reference region. We then take the weighted average across goods and counties to calculate a national RPI for each retailer that uses national averages as reference prices.

Figure J20: UPCs and product modules per store, RMS

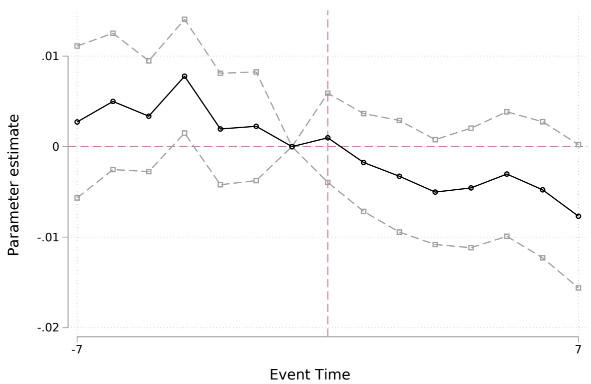
(a) Store revenue-weighted (b) Unweighted



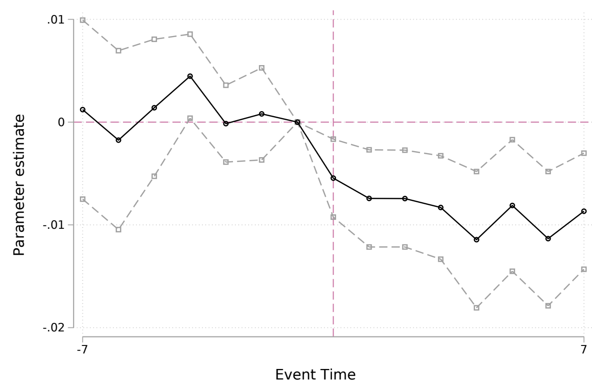
Notes: This figure shows the number of UPCs and product modules per store in the RMS. The average is either calculated as the weighted average across all stores using store revenue as weights or is unweighted.

Figure J21: Effects of non-employment, female heads

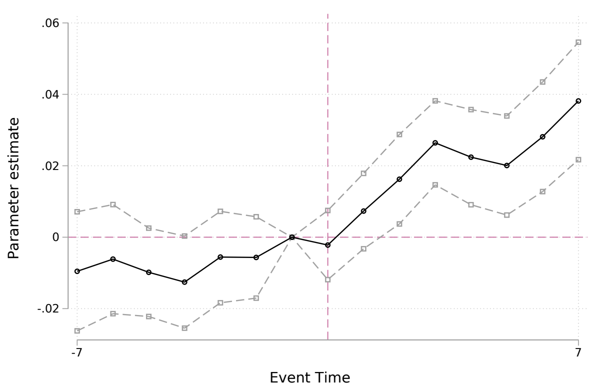
(a) Household HHI, OLS



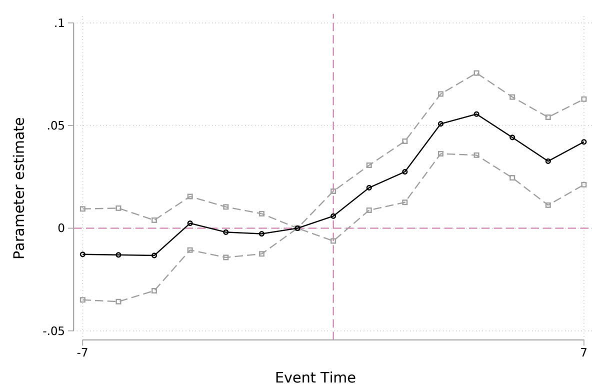
(b) Household HHI, DCDH



(c) Log trips, OLS



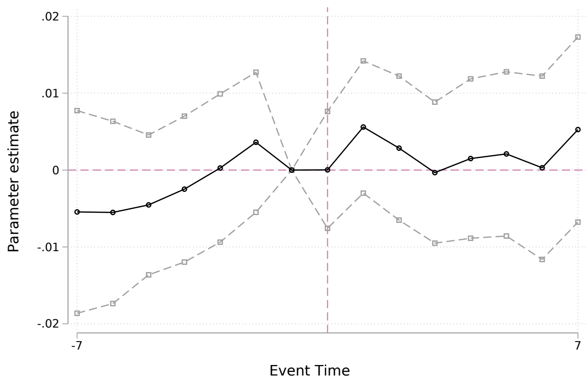
(d) Log trips, DCDH



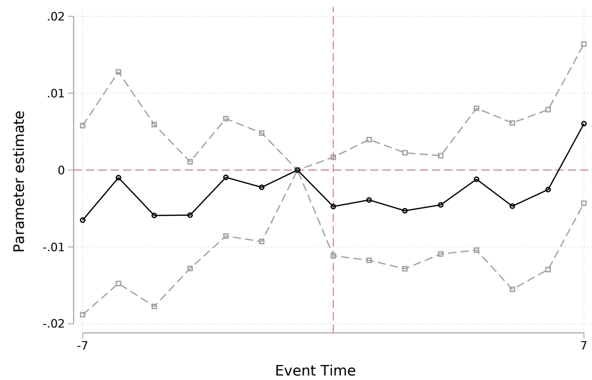
Notes: This figure plots the sum of estimated coefficients for each period, along with the 95% confidence intervals, from regressions using a distributed lag model, where household retail HHI is regressed on an indicator for whether the household is not working. The sample focuses on prime-aged household heads from age 25-54. Household and period fixed effects are included. We use both OLS and methods robust to heterogeneous treatment effects following de Chaisemartin and D'Haultfœuille (2020).

Figure J22: Effects of non-employment, male heads

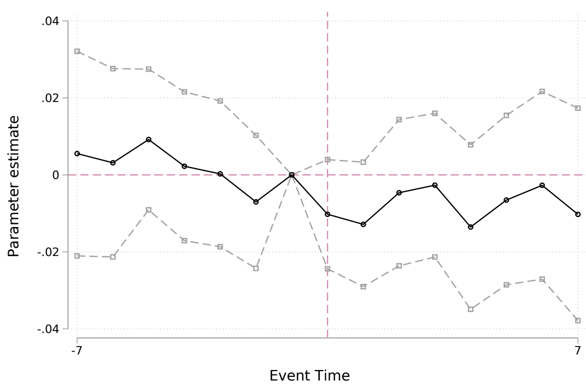
(a) Household HHI, OLS



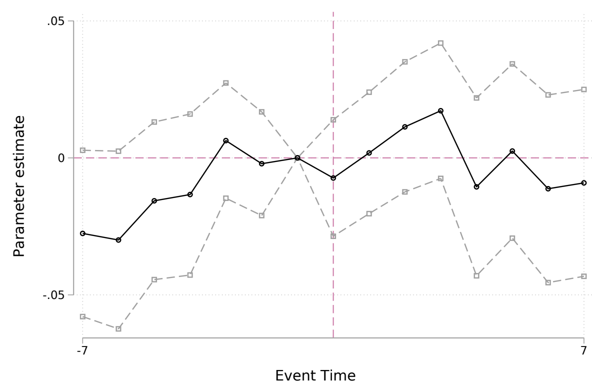
(b) Household HHI, DCDH



(c) Log trips, OLS



(d) Log trips, DCDH



Notes: This figure plots the sum of estimated coefficients for each period, along with the 95% confidence intervals, from regressions using a distributed lag model, where is regressed on an indicator for whether the household is not working. The sample focuses on prime-aged household heads from age 25-54. Household and period fixed effects are included. We use both OLS and methods robust to heterogeneous treatment effects following de Chaisemartin and D'Haultfœuille (2020).

Figure J23: Employment Rates for Females Aged 25-54, 2004-2019

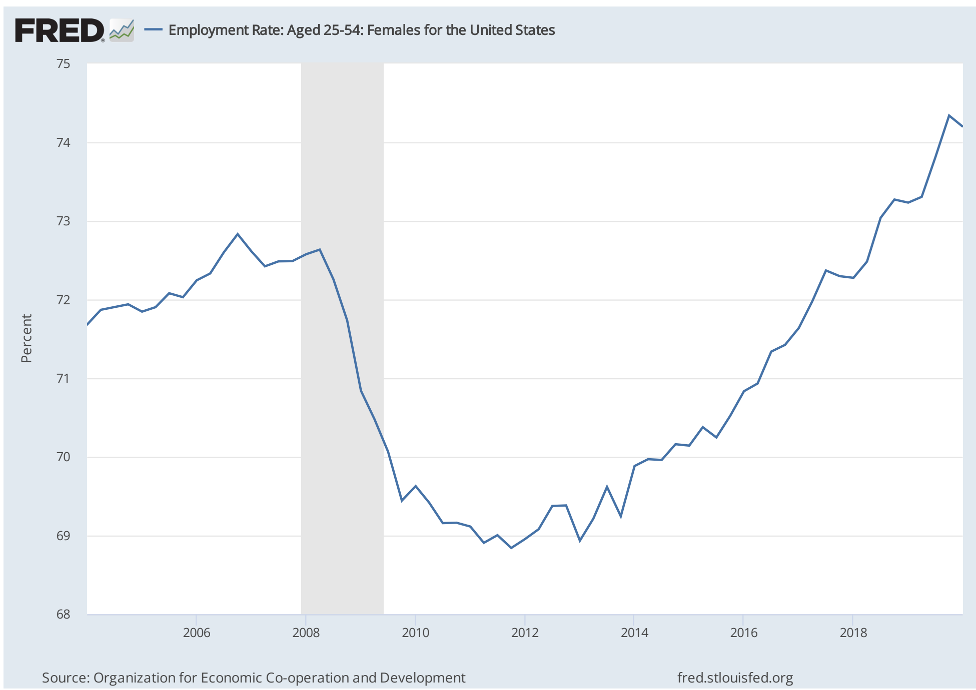
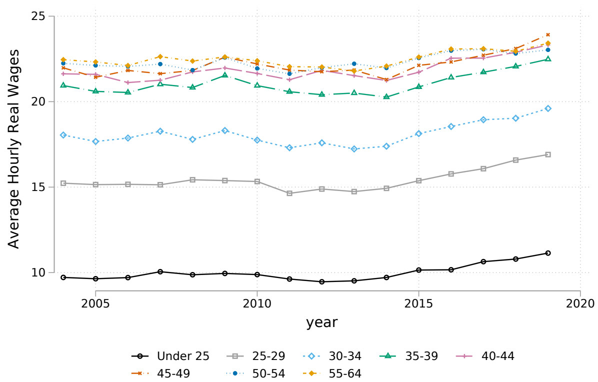
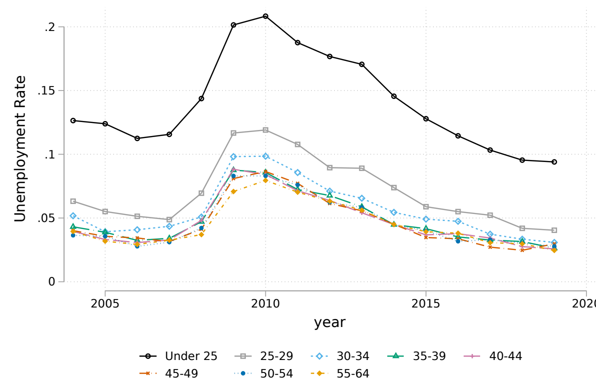


Figure J24: Time Costs by Age Group

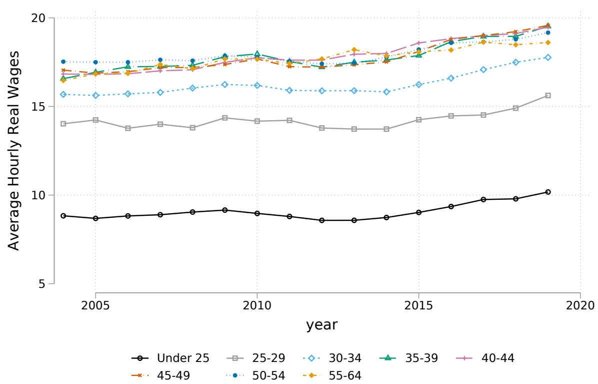
(a) Average Real Wages, Men



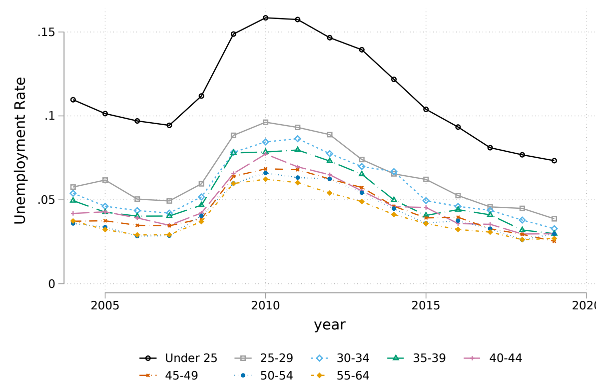
(b) Unemployment Rate, Men



(c) Average Real Wages, Women



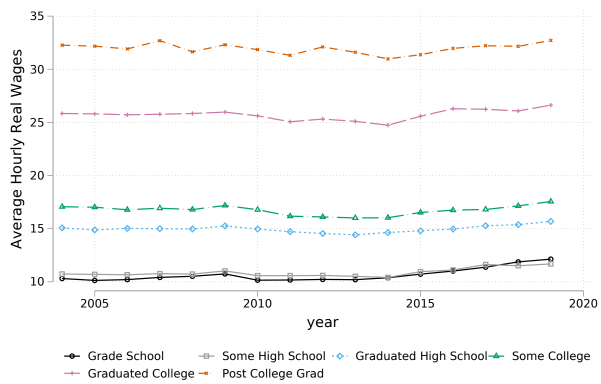
(d) Unemployment Rate, Women



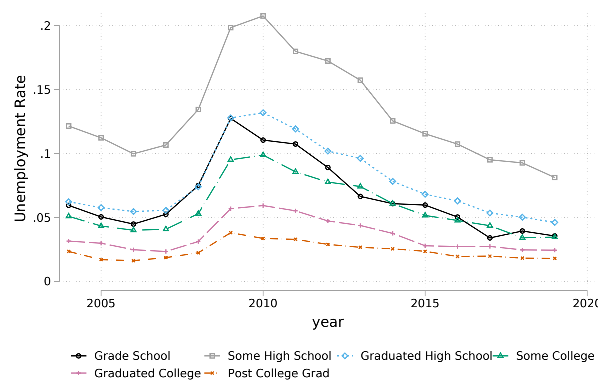
Notes: This figure plots average hourly real wages and unemployment rate by gender and age group based on the Current Population Survey Merged Outgoing Rotation Groups (CPS MORG).

Figure J25: Time Costs by Education

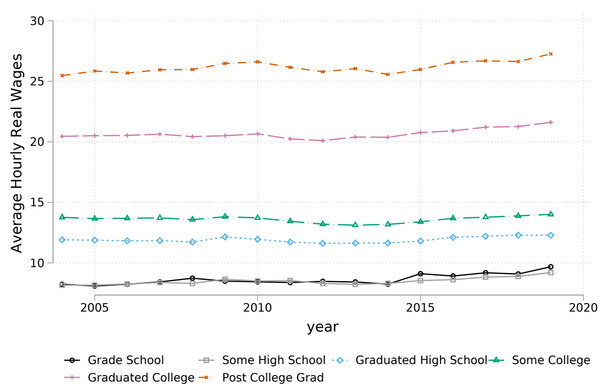
(a) Average Real Wages, Men



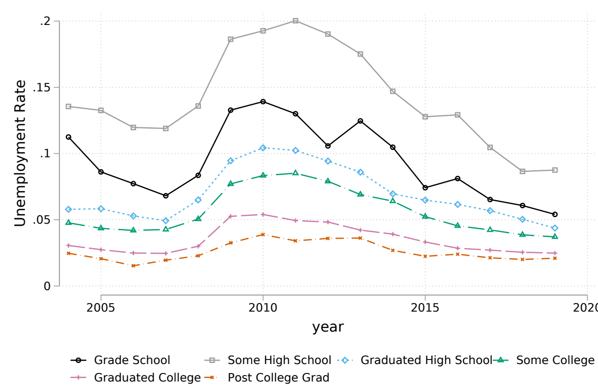
(b) Unemployment Rate, Men



(c) Average Real Wages, Women



(d) Unemployment Rate, Women



Notes: This figure plots average real hourly wages and unemployment rate by gender and education group based on the Current Population Survey Merged Outgoing Rotation Groups (CPS MORG).

Figure J26: US Regular All Formulations Gas Price, 2004-2019

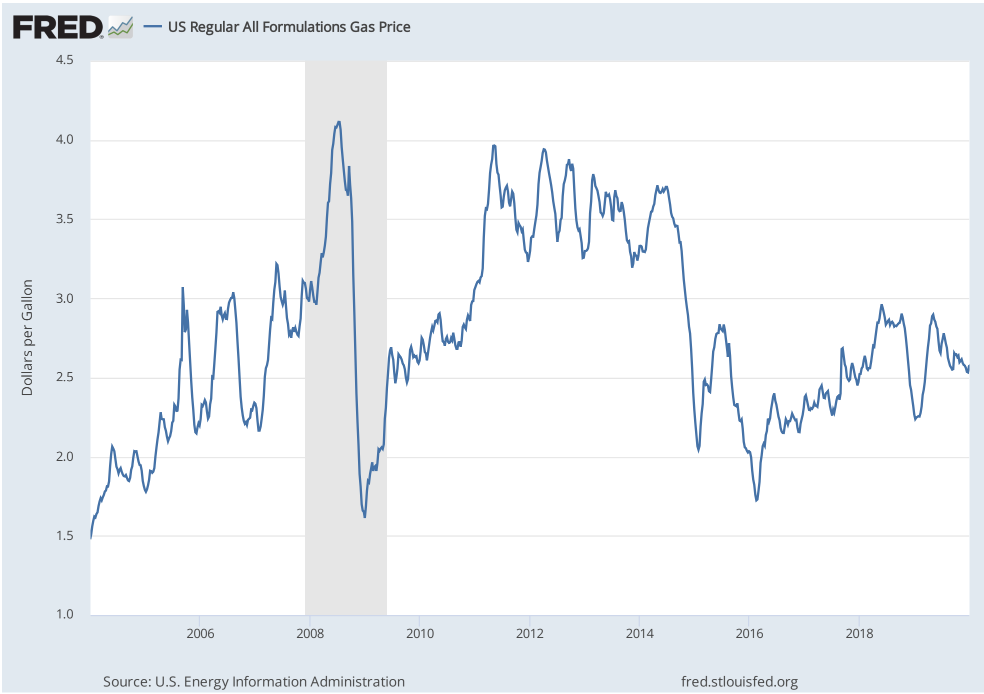
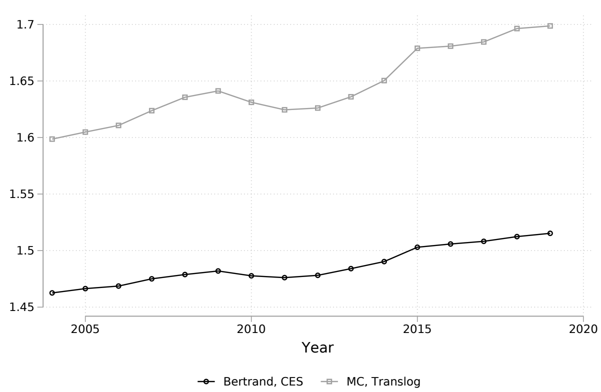
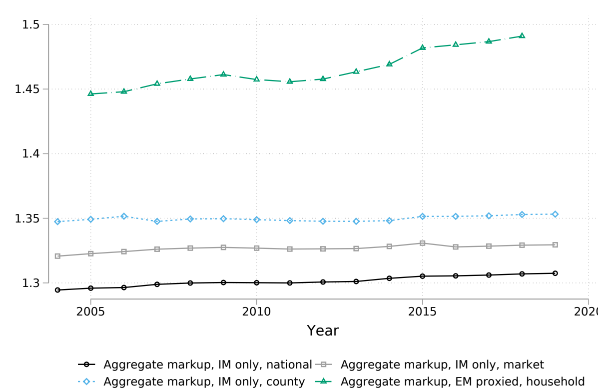


Figure J27: Aggregate markups, 2004-2019

(a) Levels



(b) Levels

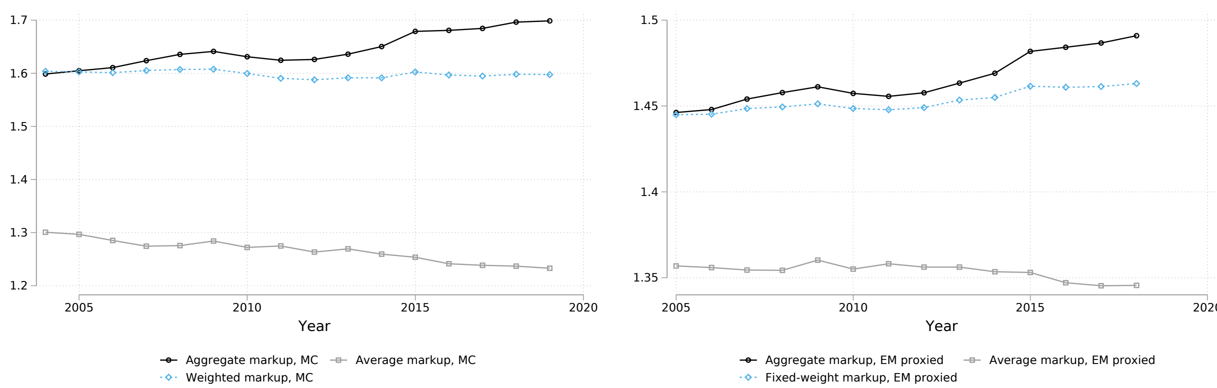


Panel (a) plots the trends in aggregate markup from 2004-2019 calculated under the assumption of Bertrand competition and CES demand versus monopolistic competition (MC) and symmetric translog demand. Panel (b) plots the trends in aggregate markup from 2004-2019 when calculated using different levels of aggregation, namely national, market, county, and household respectively. For the first three levels, we only calculate using the intensive margin heterogeneity (IMH) term in equation (14). For the household level, we can calculate using both intensive and extensive margin (EM) terms, using the upper bound for the EM, following equation (14). For the EM-proxied aggregate markup, we proxy consumers at the entry and exit margins as marginal consumers. We classify a consumer as an entrant if they go from zero to non-zero expenditures from one period to the next, and as an exiter if they go from non-zero to zero expenditures from one period to the next. We do this only for households after they have entered the sample for at least one year or are at least one year from exiting the sample to avoid censoring. Hence, we cannot calculate the markups in the first year or last year of our sample period.

Figure J28: Aggregate, average, and weighted markups, 2004-2019

(a) Levels, MC + Translog

(b) Levels, Bertrand + CES

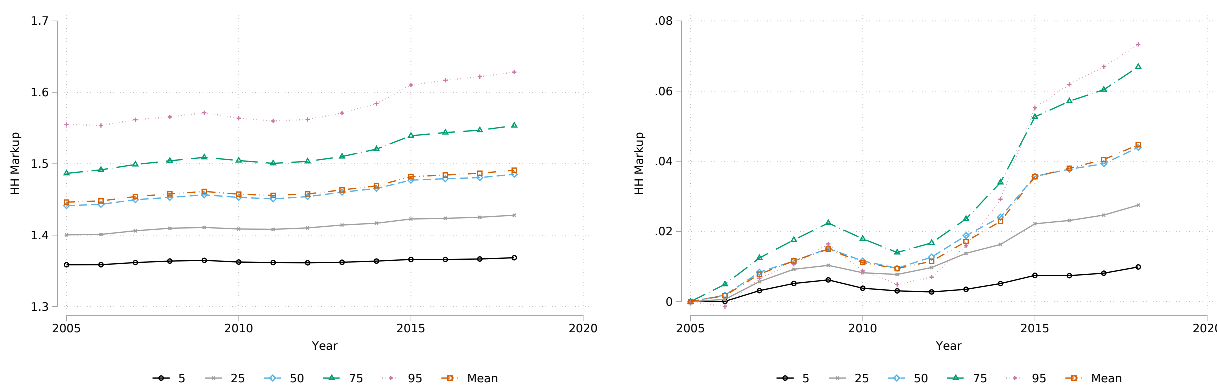


Notes: This figure plots the levels in firm markups from 2004-2019 when aggregated using different weights, assuming monopolistic competition (MC) and symmetric translog demand as well as Bertrand competition and CES demand. The default aggregate markup uses firm market shares over time as weights. Average markup uses a simple average for firms that were present in the entire sample period. Fixed-weight markup uses a weighted average, where weights are fixed to the aggregate market share in 2004, for firms that were present in the entire sample period.

Figure J29: Household markups by percentile, 2004-2019

(a) Levels

(b) Changes since 2004

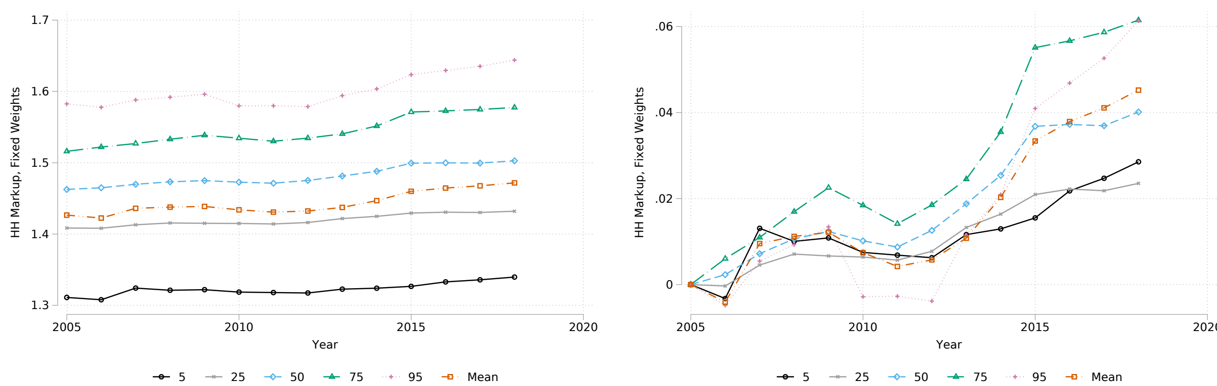


Notes: This figure plots the trends in household markups from 2004-2019 by percentile, both in levels and the magnitude of changes since 2004, assuming Bertrand competition. We calculate markups for each household by multiplying their expenditure share in each firm with that firm's markup, allowing expenditure shares to vary over time.

Figure J30: Household markups by percentile, fixed weights, 2004-2019

(a) Levels

(b) Changes since 2004

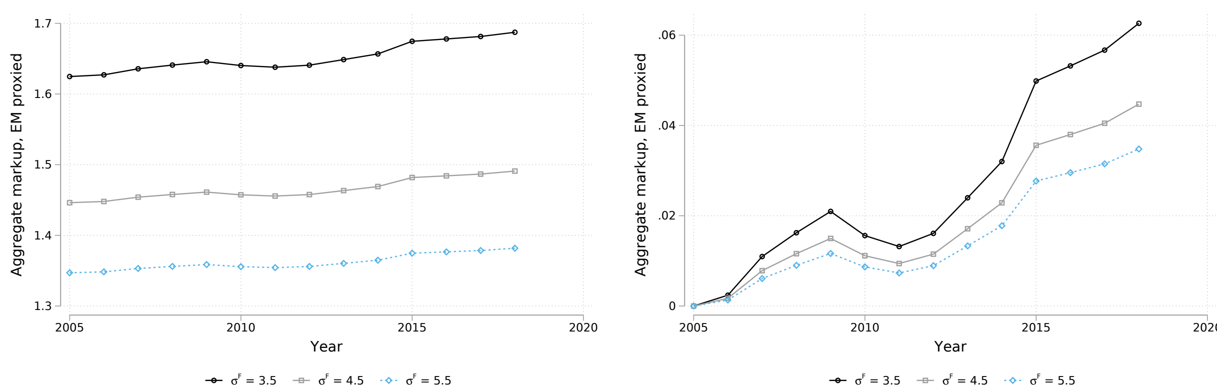


Notes: This figure plots the trends in household markups from 2004-2019 by percentile, both in levels and the magnitude of changes since 2004, assuming Bertrand competition. We calculate markups for each household by multiplying their expenditure share in each firm with that firm's markup. We do this both by fixing expenditures at their level calculated across the entire sample period.

Figure J31: Aggregate markups using different elasticities of substitution, 2004-2019

(a) Levels

(b) Changes since 2004

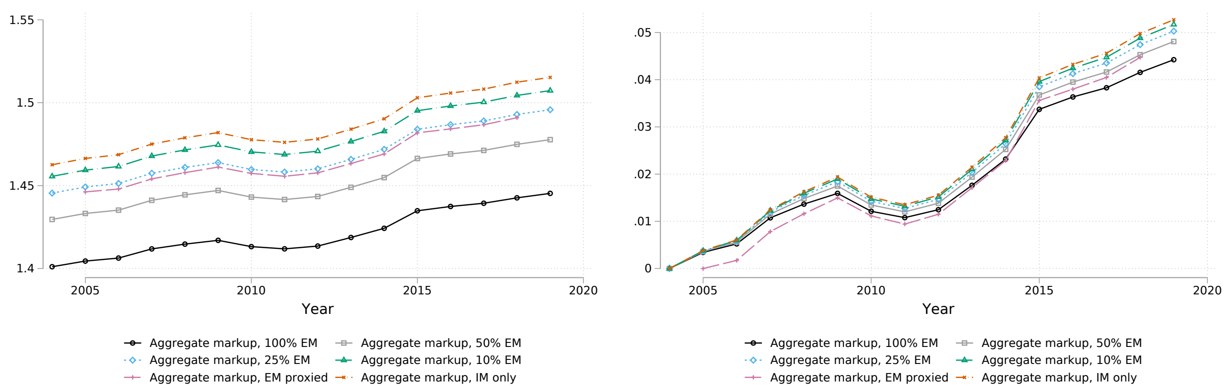


Notes: This figure plots the trends in firm markups from 2004-2019 when using different elasticities of substitution, assuming Bertrand competition, both in levels and the magnitude of changes since 2004.

Figure J32: Aggregate markups using different extensive margin bounds, 2004-2019

(a) Levels

(b) Changes since 2004

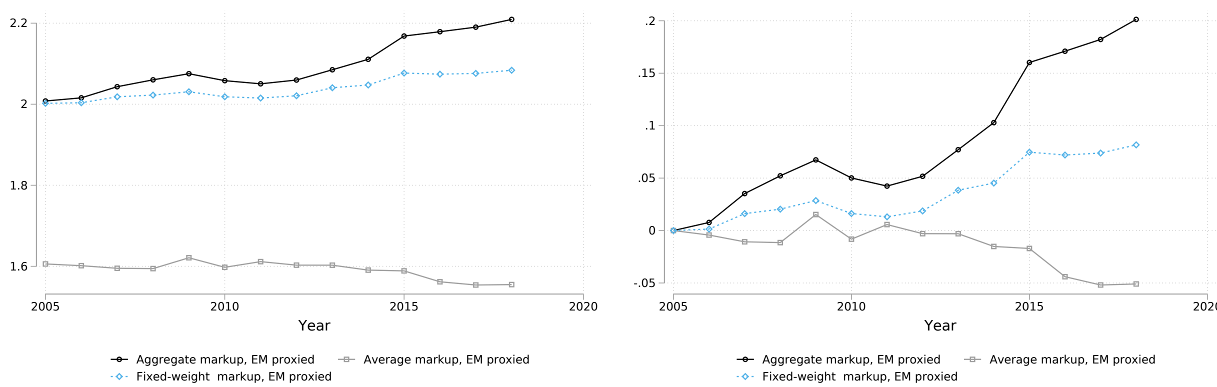


Notes: This figure plots the trends in firm markups from 2004-2019 when calibrated using different percentages of consumers on the margin, assuming Bertrand competition, both in levels and the magnitude of changes since 2004. For the EM-proxied aggregate markup, we proxy consumers at the entry and exit margins as marginal consumers. We classify a consumer as an entrant if they go from zero to non-zero expenditures from one period to the next, and as an exiter if they go from non-zero to zero expenditures from one period to the next. We do this only for households after they have entered the sample for at least one year or are at least one year from exiting the sample to avoid censoring. Hence, we cannot calculate the markups in the first year or last year of our sample period. In our second approach, we sum up the upper bounds for shopping costs for all consumers and multiply this sum with various percentages of people on the margin from 0% to 100%. Therefore, this approach assumes that marginal consumers are randomly distributed along the shopping cost distribution.

Figure J33: Aggregate, average, and weighted Cournot markups, 2004-2019

(a) Levels

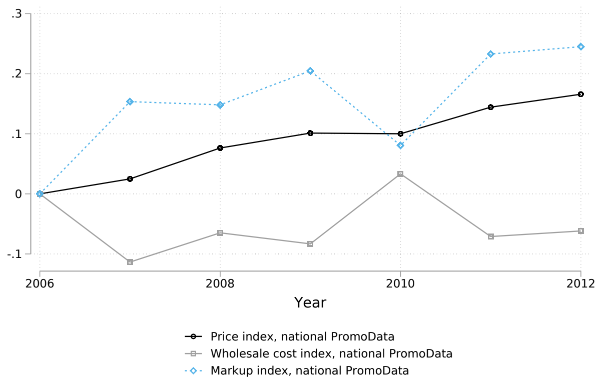
(b) Changes since 2004



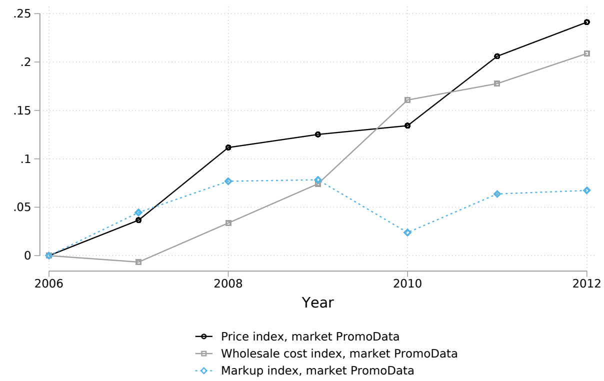
Notes: This figure plots the trends in firm markups from 2004-2019 when aggregated using different weights, assuming Cournot competition, both in levels and the magnitude of changes since 2004. The default aggregate markup uses firm market shares over time. Average markup uses a simple average for firms that were present in the entire sample period. Fixed-weight markup uses a weighted average, where weights are fixed to the aggregate market share in 2004, for firms that were present in the entire sample period.

Figure J34: Markup trends, PromoData

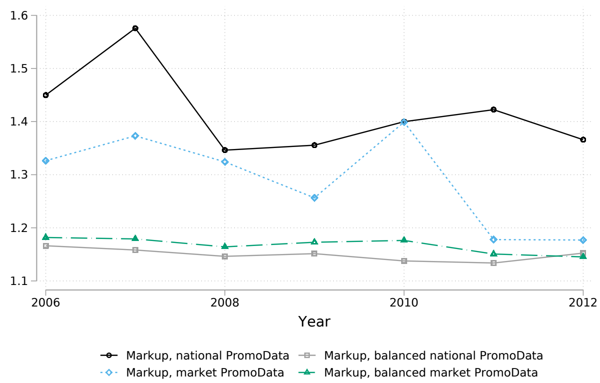
(a) Markup index, national wholesale costs



(b) Markup index, market wholesale costs



(c) Weighted markups, national and market wholesale costs



Notes: This figure plots markup indices and weighted markups using national and market wholesale costs from PromoData matched with HMS prices. National PromoData refers to using wholesale costs across the entire nation whenever available, aggregating across markets. Market PromoData refers to using wholesale costs when matched to the same market only. Balanced refers to using only products that are available in all years of the sample period. Indices are chained as Tornqvist indices.