Income Fluctuations and Firm Choice

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Abstract

How households shift spending across firms in response to income fluctuations is an important source of risk to individual firms. Using transaction-level data, we study how households interact with the universe of retailers following changes in income. We find that increases in income, both within and across households, result in substitution towards retailers that are higher quality, smaller, more profitable, have higher labor intensity, have higher R&D intensity, and have higher betas. Since these shifts do not average out across retailers, retailer choice has important implications for key financial and macroeconomic outcomes such as profitability and labor demand.

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1 Introduction

Household consumption decisions exhibit substantial heterogeneity, both in the cross-section of households and within households over time. Previous research has documented demand heterogeneity as a function of income and of household or product characteristics (e.g. Engle curves, choice of product variety). Moreover, heterogeneity in *how much* households respond to income changes (e.g., MPCs), *when* they respond (e.g. anticipation effects, intertemporal substitution), and the *type of products* that are most responsive (e.g. durability, cross-product substitution) has also been shown to matter for any number of fields, including finance and macroeconomics.

One largely unexplored source of demand heterogeneity is the selection of firms by households, a key driver of heterogeneity in firm performance both cross-sectionally and over the business cycle. While fluctuations in aggregate income are an important source of risk for firms, the shifting of household spending *across* firms in response to income changes is an important additional source of risk for individual firms.

In this paper we focus on the type of firm that households directly interact with most frequently: retailers. Specifically, we analyze how income fluctuations influence retailer choice. The paucity of research on retailer choice reflects the lack of retailer-specific data. Previous work offers only indirect and very limited evidence on how retailer choice varies across households and within households over time. Most research has been limited to using expenditure surveys or scanner data. Surveys typically record spending by disaggregated categories but do not provide information about the retailer from which households purchased these products (e.g. CEX, PSID). Scanner data, on the other hand, often come from a single retailer (e.g. Safeway) or contain only de-identified retailers (e.g. Nielsen), making it difficult to study heterogeneity in retailer choice linked to firm characteristics.

In this paper we use transaction-level data from a large personal finance online aggregator that allows us to comprehensively observe both household income and spending in detail. This class of data is increasingly used for applications in questions of household finance and empirical macroeconomics, but has not been leveraged to investigate questions involving the firms that households interact with. We utilize this data to analyze how retailer choice within several sectors varies both across and within households. Each transaction is associated with a textual description which contains information that allows us to identify the retailer while protecting the anonymity of the household. For over half of household retail spending in our sample, we are also able to link retailers to external information from third parties such as Yelp, Orbis, Compustat, and CRSP. Since the data span both private and public retailers, we are able to study heterogeneity by ownership type as well as other firm characteristics.

This paper makes several contributions to the literature. First, we document new cross-sectional heterogeneities in consumer retailer choices, both across and within retailer categories. Second, we show how retailer choice responds to income changes within households over time. Third, we construct an index of retailer quality and show that households adjust the average quality of their retail spending quickly in response to income changes. Finally, we explore how these choices on the part of households interact with differences in firm characteristics, driving aggregate financial and macroeconomic outcomes.

Cross-sectionally, we find that higher-income households frequent a larger number of unique retailers per month and that they tend to substitute away from larger retailers. This pattern is not just a function of persistent attributes (e.g., location or preferences), but also holds within households over time as household income changes. We show that households are also more likely to experiment with a retailer they have never visited before following an increase in income (e.g. trying out a new restaurant). This suggests that the 'willingness to experiment' increases with income (both cross-sectionally and dynamically), consistent with 'learning about demand' that prevents young firms from growing quickly in size (Foster, Haltiwanger, and Syverson, 2016).

Moreover, these shifts often occur along a retailer quality gradient. Not only do households shift their level of spending, but they also change where they shop. We find that the average quality of retailer that they visit responds strongly to income patterns in both the long- and short-run. This result is most similar to that found in Coibion, Gorodnichenko, and Hong (2015) who use scanner data to show that consumers substitute to lower-priced grocery stores during economic downturns. With our ability to directly observe the true retailer being patronized, we are able to extend this analysis by investigating whether these changes in retailer choice are correlated with firm characteristics. Importantly, if changes in retailer choice are correlated with firm characteristics, then changes in retailer patronage do not average out when aggregated across all households and can lead to real effects on firms and the economy.

For instance, we find that after an increase in income, households systematically shift their spending to publicly traded retailers (affecting the volatility and riskiness of cashflow), to retailers with lower current profitability but higher R&D investments, retailers with higher advertising expenditures, retailers with higher measures of quality, and retailers with higher betas. Cross-sectionally, we find that retailers with higher-income customers have higher betas than those with lower income customers. These demand-side findings therefore complement a recent literature that uses plant-level Census data to document significant differences in the volatility of employment growth between private and public firms (e.g., Davis, Haltiwanger, Jarmin, and Miranda (2006), Davis and Kahn (2008)) and a similar literature in finance that studies recent changes in firm-level volatility (e.g., Campbell, Lettau, Malkiel, and Xu (2001), Fama and French (2004)).

The effect on key macroeconomic outcomes such as employment is more nuanced. Likely due to shifts along the aforementioned quality gradient, we find that an income decrease is associated with households shifting to less labor intense retailers *within* a specific sector (i.e., "trading down"; Jaimovich, Rebelo, and Wong, 2017). However, households also tend to substitute from less to more labor intense retail sectors following a decline in income. Since cross-sector substitution dominates within-sector substation, the net effect is an increase in retail labor intensity.[1]

Our paper relates to several strands of literature in finance and macroeconomics. Recent research in finance studies how firm heterogeneity and corporate decision-making affect expected returns. A large and influential literature surveyed in Fama and French (1992, 2008) explores factors that predict return differences across firms, and most of these studies have focused on supply-side explanations.[2]

Our paper proposes a new mechanism to explain firm heterogeneity: differences in the customer base or "customer capital" and in the elasticity of consumer choices across retailers. Our study therefore contributes to a smaller but complementary finance literature that relates *demand-side* differences to firm heterogeneity – both to intermediate outcomes such as endogenous firm characteristics (e.g., capital structure, organizational form) and to firm performance (e.g., profitability, excess returns).[3]

[1]The net effect on total employment in the economy of course depends not only on the labor intensity of retailers but also on the labor intensity of the products purchased at those retailers, i.e., the entire supply chain.

[2]A non-exhaustive list of recently studied supply-side factors for explaining firm performance heterogeneity includes organizational capital, management skill and management practices (Adams, Almeida, and Ferreira (2009), Eisfeldt and Papanikolaou (2013)); price rigidity and capital structure (Gorodnichenko and Weber (2016), D'Acunto, Liu, Pflueger, and Weber (2017)); product market competition and production networks (Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2017), Bustamante and Donangelo (2017), Herskovic (2018)); and many more.

[3]Demand-side factors studied in previous research that explain excess returns include luxuries vs. basic goods (Ait-Sahalia, Parker, and Yogo (2004)), durable vs. non-durable goods (Gomes, Kogan, and Yogo (2009)), good-specific habit formation (Van Binsbergen (2016)), and shifts in demand elasticity (Stroebel and Vavra (2019), Nevo and Wong

With growing access to new micro-level transaction data, macroeconomists increasingly move beyond studying macroeconomic aggregates and instead explore the macroeconomic implications of various forms of consumer- and firm-level heterogeneities.[4] Our paper connects heterogeneity in consumer demand with supply-side heterogeneities across firms.[5] For instance, our finding that consumers' first-time patronage of stores is positively correlated with income supports customer-base explanations of firm heterogeneity (e.g., price stickiness and firm size).[6]

Finally, our paper belongs to a rapidly growing literature that uses transaction-level data to study firm behavior and markets; see e.g., Einav, Klenow, Klopack, Levin, Levin, and Best (2018) and the literature cited therein.

The paper is organized as follows. In Section 2, we describe our data and measures of retailer characteristics. Sections 3 and 4 document cross-sectional facts and dynamic responses of retailer choices to income shocks at the household level. They then demonstrate some financial and macroeconomic impacts of retailer choice. Section 5 concludes.

2 Data

2.1 Transaction-Level Linked-Account Data

Online aggregation of financial accounts is a popular service that allows households to easily monitor financial activities from across multiple financial institutions using a single web-page or smartphone app. Account aggregation services often allow features such as budgeting, expense tracking, etc. Dozens of companies currently provide such services and our data comes from one of the

(2018)).

[4]Our cross-sectional facts are related to empirical studies of Engle curves, household budget shares, and product choice (variety and quantity-quality choice); see Deaton (1997, 2016) for surveys. Our dynamic within-household results relate to a large literature on intertemporal consumption choice (e.g., MPCs, intertemporal substitution, home production, and other adjustment margins); see Jappelli and Pistaferri (2017) for a recent survey.

[5]A recent literature explores demand-side explanations of differences in firm size. For instance, Foster, Haltiwanger, and Syverson (2016) focus on homogeneous commodity-like product industries (e.g., ready-mixed concrete, manufactured ice) to control for quality difference and rule out other supply side factors (productivity and cost differences). They conclude that demand side factors must be the main explanation for persistent firm size differences, in particular a learning-about-demand mechanism. Our paper complements this strand of literature by providing direct evidence of this mechanism.

[6]While most macroeconomic research of price stickiness focuses on supply-side explanations (e.g., menu costs, information costs), a few studies explore demand-side factors, in particular sticky customer capital; Blinder, Canetti, Lebow, and Rudd (1998), Rotemberg (2005), Hall (2008), Dupraz (2016). Our paper contributes to this literature by using household-level data and household income variation to document this channel. We study how a retailer's customer base changes with economic conditions.

largest of these services.

Once a user initially signs up for the free service, they are given the opportunity to provide the service with user-names and passwords to a variety of financial accounts (checking, savings, credit card, brokerage, retirement, mortgage, student loan, etc.) from any financial institution, though our particular data is limited to bank and credit card accounts. After signing up, the service automatically and regularly pulls data from the user's financial institutions. The data contains transaction-level data similar to those typically found on monthly bank or credit card statements, containing the amount, date, and description of each transaction. Our sample contains 2.7 million households from 2010 to 2015 and there is very little attrition in our sample.

Since unobserved consumer spending from unlinked credit cards is a potential issue with this dataset, we remove any household who makes excessive credit card payments from the bank account relative to observed spending in the credit card account. Specifically, we remove from the sample any household that, over our entire sample period, spends twice as much on credit card payments than observed credit card spending. A similar restriction could be made for regular transfers from unlinked checking accounts, though these transactions are comparatively rare – American households tend to have a range of credit cards but generally only one or two checking accounts.

The sample is not a random sample of the population, but it appears to be broadly representative with some exceptions. Appendix Table A.1 illustrates how our final sample is located geographically relative to the U.S. Census. As shown, households in our sample are well dispersed geographically, though we have high concentrations of households in the states of California, New York, and Texas. Appendix Figure A.1 illustrates the income distribution of our final sample relative to the U.S. Census. As shown, there is a wide range of income for members of our sample and significant numbers of members from across the United States. Dropping members from any given state (eg. overrepresented states) does not substantially impact our results.

Recent work has also utilized similar transaction-based sources to make inferences about the financial habits of the broader population. For instance, Baker (2017), Baker and Yannelis (2017), and Kueng (2018) also utilize data from an online personal financial platform. They perform a multitude of validity tests comparing to data sources such as Census Retail Sales, home price data from Zillow, the Survey of Consumer Finance, and the Consumer Expenditure Survey. They find a close parallel between household-level financial behaviors and distributions in these sources relative to that found among users of the online platform they utilize. That is, conditional on basic demographic types, selection into the online platform did not predict differential financial behavior or characteristics.

Ganong and Noel (2017) and Olafsson and Pagel (2018) perform similar exercises using data taken from JPMorgan Chase customers and the population of Iceland, respectively. Across a range of financial indicators, they find strong evidence of external validity of their results using their sample population. Such results point to the fact that, while these types of bank-derived sources will mechanically exclude financial activity by the unbanked, transactional level financial data can produce accurate portrayals of aggregate economic activity and household behavior.

2.1.1 Retailer Identification

We choose to focus on household decision-making regarding retail spending because it offers a setting in which a large number of potential providers are competing for a household's business. Relative to household spending on medical care, housing, education, or other services, there are generally a multitude of retailers within a given category (e.g. clothing, groceries) in a single location that span a wide range of bundles of goods and quality of service.

To perform our analysis, we must aggregate individual textual descriptions of transactions to particular retailers. We approach this retailer identification in two stages. First, we clean each transaction description string to remove common text such as 'Inc', 'Corp', and various other punctuation marks. We also remove long numerical series which represent 'transaction ID' unique to that household-retailer transaction. Second, we aggregate retailer- or categorical-level data to a household-month level, depending on the particular specification being utilized.

The reason for this cleaning procedure is the sheer number of unique textual transaction descriptions in our database. While some retailers' transaction descriptions are consistent across the sample, many retailers have a large number of individual transaction descriptions associated with them, especially those retailers that are highly geographically dispersed. For instance, the grocery store 'Safeway' has 713 unique descriptions associated with it, even after stripping out generic strings and numeric transaction ID numbers. This is because each individual Safeway location typically has a unique string description that includes both 'safeway store' as well as the location of the store or a numerical store identifier (e.g. 'safeway store fairfax' or 'safeway store canyon way').

Following this cleaning procedure, we are able to identify spending at specific retailers across households and across time and can also examine characteristics of retail spending within particular categories. In particular, each retailer is categorized into one of several categories of retail such as Groceries, Restaurants and Dining, Clothing and Shoes, Specialty Retail, General Merchandise, Gasoline and Fuel, Personal Care, and Home Improvement. For the purposes of most of our analysis, we focus the four largest categories of retailers: Groceries, Restaurants and Dining, Clothing and Shoes, and General Merchandise.

2.2 Measuring Retailer 'Quality'

As one method of how households systematically shift between different retailers over time, we attempt to construct a data-driven measure of retailer 'quality'. We proceed under the assumption that, in the cross-section, higher quality retailers will have a more affluent customer base. Retailer 'quality' is then measured as the average household income of a store's patrons.

2.2.1 Comparing Customer Bases Across Retailers

We start from the perspective of individual retailers, seeking to measure the extent to which the income distribution of a retailer's customers differs from the income distribution in the cross-section of households. We first calculate the annual income of each household across all observable months that they remain in our sample and, subsequently, the overall household income distribution of the sample.

If all households shopped at all retailers in equal proportions, the fraction of revenue retailers would derive from households in a given income bin would simply be equal to the fraction of total spending that that income bin makes up in the economy. For instance, if households who make \$50,000–\$51,000 constitute 1.5% of total retail spending, a retailer would be expected to receive 1.5% of their revenue from this group of households.

Figure 3 plots the difference between the observed distribution of retailer income and the 'neutral' or 'expected' distribution for a number of retailers. Households are binned by \$1,000 of annual income. Each panel plots the over- or under-representation of revenue from households for a selected sample of retailers at each point along the income distribution relative to the cross-sectional income distribution (i.e. the 'excess mass' of the customer base income distribution for retailers of the same category). For instance, a value of positive 0.01 means that the named retailer received 1 percentage point more revenue from that portion of the income distribution than would be expected if all households shopped at all retailers with equal likelihood.

We find large differences in the income distribution of customers between retailers within the same retailer category. For instance, in the bottom-left panel, we find that Walmart has a large relative surplus of lower-income customers, while Costco sees a deficit of such households and a surplus of higher-income customers. Similarly, Jack-in-the-Box, Panda Express, Waffle House, Dollar General, and Ross tend to cater to lower-income households relative to their competitors: Panera Bread, PF Chang's, Corner Bakery, REI, and Nordstrom.

From these distributions, we can construct this measure of retailer quality by computing the average income, weighted by spending, of the retailers' customers.

We conduct this exercise for retailers belonging to four primary categories: General Merchandise, Groceries, Restaurants/Dining, and Clothing/Shoes. For example, the computed quality measures of selected General Merchandise retailers include: Walmart ($67,792), Target ($84,460), Barnes and Noble ($87,686), and Bed Bath and Beyond ($92,710). The computed quality measures of selected Grocery retailers include: Kroger ($78,434), Safeway ($87,588), Publix ($81,111), Whole Foods ($107,377), and Trader Joe's ($90,871). The computed quality measures of selected Restaurants/Dining retailers include: McDonald's ($66,651), Starbucks ($83,636), Chick-fil-a ($78,740), Chipotle ($79,359), Denny's ($62,673) and PF Chang's ($90,315). The computed quality measures of selected Clothing/Shoes retailers include: Macy's ($89,163), Kohl's ($84,593), JC Penney ($73,721), and Nordstrom ($111,415).

While this algorithm yields a continuous measure of retailer quality for all retailers in the sample, it does not capture other dimensions of retailer quality, such as customers' perceptions of quality. To validate our data-driven measure with a more 'objective' metric of quality, we merge in information from the online review website Yelp.com for each retailer in our sample. Yelp.com publishes information regarding the price range that each retailer sets and denotes these prices by a number of one to four dollar signs ($-$$$$). [7]

[7] Appendix Table A.2 shows a significant positive relationships between our measure of retailer quality and the Yelp.com price level, providing external validity of our data-driven quality measure. This positive relation holds across all categories of retailers, with high-priced retailers having a significantly more affluent customer base on average.

2.2.2 Households' Average Retailer Quality

We will hereafter refer to this variable as the merchant's *quality*. Higher-end merchants will attract richer households, which will be reflected in a higher quality measure. One nice feature of this quality measure is that is easily computed for all merchants in our database, whether the merchant is publicly traded or private and without regard to whether they can be linked to an external data source such as Compustat. While the measure links retailer quality to household income in the cross-section, within household variation in income does not mechanically drive the quality of retailers that a household patronizes.

To determine the average quality of a household's portfolio of retailers for a given month, we proceed by calculating the dollar-weighted average of these retailer-level quality measures. For example, if a household spent $200 at Walmart (with quality computed as $67,792) and $400 at Target (with quality computed as $84,460) in a given month, the household's average quality in that month would be computed as:

$$\frac{\$200}{(\$200+\$400)} \times \$67,792 + \frac{\$400}{(\$200+\$400)} \times \$84,460 = \$78,904.$$

We compute measures of quality at the household-month level for our four retailer categories (General Merchandise, Groceries, Restaurants/Dining, and Clothing/Shoes) as well as an aggregate measure across retailers in all four categories. Summary statistics for these variables are presented in Table 1.

2.3 Retailer Financial Statements

For results related to understanding how retailer substitution within households is related to firm characteristics reflected by firm financial statements, we limit our analysis to firms that we are able to match to Compustat and Orbis. Unfortunately, this can only be conducted for a subset of retailers in our sample.

We define a retailer's labor intensity as the ratio of the number of employees a retailer has to its sales, in millions of dollars. We take an average of this value for a given retailer, using data from 2010-2015, where available. This approach yields a retailer-level measure of labor intensity.

To construct a time-varying household-level measure of average retailer labor intensity, we take an approach similar to that which we utilized to create the retailer quality variable in the previous section. Again, this is computed at a household-month level for our four retailer categories (General Merchandise, Groceries, Restaurants/Dining, and Clothing/Shoes) as well as an aggregate measure across retailers in all four categories.

In addition, we employ Compustat measures of annual profitability, advertising, R&D expenditures, and other financial attributes, by retailer. Most of these measures are normalized at a firm level by total assets and averages are taken by firm across our sample years, 2010-2015.

3 Retailer Choice Elasticity Across and Within Households

To the best of our knowledge, this is the first comprehensive analysis of retailer choice using household-level transaction data.[8] We therefore start by examining the cross-sectional properties of households' choice of retailers. In particular, we seek to better understand how retailer choice along several dimensions differs between households of different types. We then characterize changes in retail choice *within* a household as household income changes over time.

3.1 Comparing Retailer Choices Across Households

We first study differences in shopping behavior across the household income distribution, finding large differences in a number of dimensions. First, the top panel of Figure 1 plots the average number of retail transactions per month per household, the average number of unique retailers per month that a household visits, and the average monthly number of retailers that a household has never been observed patronizing in previous months (eg. visits to a store that is 'new' to that household). All three series show a positive and monotonic relationship with income. Households in the top decile of household income visit twice as many retailers as those in the bottom decile. This relationship tends to hold throughout each retailer category, with the higher income quantiles visiting more unique retailers and new retailers for every category of retailer in our sample.[9]

[8]There is a large literature in marketing and related fields that studies retailer and store attributes that determine retailer choice (see e.g., Pan and Zinkhan (2006) for a survey), but we are not aware of other works that use comprehensive customer-level financial data to study how households choose between retailers.

[9]In the Appendix, we examine the overlap of retailers across households of different income bins and geographic areas. While households of different incomes exhibit significantly different retailer choice, on average, there remains a substantial degree of overlap in retailers that they patronize, especially for households living in similar geographical areas.

The bottom panel of Figure 1 denotes the distribution of dollar-weighted average retailer size for each quantile and for three categories of retailers – Restaurants, Grocery Stores, and General Merchandise. 'Size' for a particular retailer is measured as the dollar-weighted number of transactions conducted at that retailer across all individuals and all months in our sample. Thus, a retailer with more outlets and more sales will be classified as a larger firm. Here, we find that while the average size of retailer varies across the income distribution, the effect is markedly different for different types of retailers.

For instance, the average restaurant size that the top decile visits is over 40% smaller than the average size restaurant that the bottom decile visits. Meanwhile, the average size of grocery stores hardly varies across the income distribution. The average size of general merchandise retailers exhibits a hump-shaped relationship, with both the top and bottom deciles of the income distribution patronizing smaller sized stores than the middle of the income distribution.

This negative relationship between customer income and average retailer size provides novel *direct* evidence based on household-level data of the 'learning about demand' channel proposed by Foster, Haltiwanger, and Syverson (2016) to explain the wide size distribution of firms in the U.S. After ruling out supply-side explanations using plant-level Census data, the authors conclude that "these patterns do not reflect productivity gaps, but rather show differences in demand-side fundamentals" such as building a customer base. Much of the declines in firm size among the higher income households tend to reflect movement away from big box retailers (eg. Walmart and Target) and large restaurant chains (eg. McDonald's and Chili's) and towards more local firms.

We also explore the extensive margin of household retailer choice: the frequency with which households visit retailers that they have never previously visited. Figure 2 shows the distribution of spending at 'new' retailers across several categories as a function of household income. For each household-month, we calculate the fraction of spending done within a particular category at a retailer that the household has not previously shopped at.

A value of 1 means that all of the household's shopping in that retailer category was done at a retailer the household has not previously visited, while a value of 0 means that all of a household's spending of that type was at retailers they have shopped at before. The first 12 months of a given household are excluded to 'burn-in' previously-visited retailers. Each panel in the top row above shows a histogram of these values across all household-months in our sample. The bottom row mirrors the top row but excludes values of 0 and 1 to provide more detail.

We find that trying out a new retailer for only a portion of your monthly spending is rare; spending at new retailers is concentrated around 0% or 100% of monthly spending within a category.[10] However, household spending at new restaurants is much less concentrated at the tails of the distribution relative to spending at general merchandise retailers and grocery stores. That is, households do a much larger proportion of restaurant spending at places they've never visited before. In contrast, monthly spending at general merchandise and grocery retailers is more commonly done entirely at retailers a household has patronized in previous months (yielding a value of 0) or entirely shifted to a new retailer (yielding a value of 1).

3.2 Comparing Retailer Choices Within Households

Now we turn to examining how households change their choice of retailers over time, following changes in household income. Each panel of Table 2 shows income elasticities ϵ_x of different outcome variables x_{it} after controlling for period (τ_t) and household fixed effects (α_i),

$$\ln(x)_{it} = \epsilon_x \ln(\text{income})_{it} + \alpha_i + \tau_t + u_{it}. \tag{1}$$

Column 1 provides the overall elasticity across all retailers, and Columns 2–5 break it down by retailer category (General Merchandise, Groceries, Restaurants/Dining, and Clothing/Shoes).

This panel approach produces similar qualitative patterns as the cross-sectional analysis in the previous section. However, the magnitudes of the effects are substantially reduced within-household relative to those measured across households. This is largely driven by two factors. First, these within-household results measure short-run elasticities while households experiencing changes in long-run income converge only gradually to the retailer choices of a household with a different average income. Second, different geographic areas have both different average income and different choice sets of retailers, so a household may be unable to 'take advantage' of a higher level of income by shopping at different retailers without moving its physical location.

Panel A looks at the relationship between household income and household retail spending at a monthly level. Overall, we find that the elasticity of monthly retail spending with respect

[10] Much of the concentration at the tails is driven by months in which households only have one or two transactions in a particular category (eg. going out to eat only twice or visiting the same grocery store a few times). Restricting this analysis to months in which there is a minimum threshold of spending in a given category reduces the tail outcomes, 0% or 100% of spending at a new retailer, while leaving the interior distributions relatively unchanged.

to income is approximately 0.2. That is, for a 1% increase in household income, retail spending tends to increase by 0.2% in the same month, consistent with a large literature that estimates short-run marginal propensities to consume (MPCs) out of income changes (see Jappelli and Pistaferri (2017) for a survey). We find that different types of retail spending have significantly different elasticities. Spending at General Merchandise tends to be the most responsive, while spending at grocery stores and clothing retailers has the smallest short-run response.

In Panel B we begin to examine other elements of household retailer choice in response to income changes. Mirroring our cross-sectional approach, we test whether households tend to visit more unique retailers when household income increases. We find that this is the case across all categories, with the number of unique retailers increasing between 0.4% and 1% following a 10% increase in household income. This fact can also be expressed a decline in the dollar-weighted Herfindahl-Hirschman index (HHI) of household spending. Panel C shows the HHI declining by approximately 1% for every 10% increase in household income. Both panels reflect an increasing desire for variety across a range of retailers as households become richer.

Panel D demonstrates that the average size of retailer that households frequent (as measured by retailer sales or the number of transactions observed at that retailer) declines when household income increases. This reflects, at least in part, a decline in shopping at big box stores and national fast food chains and an increase in shopping at more local and boutique retailers. Households are more likely to spend their additional income at smaller retailers and at retailers that they have never frequented before. This supports demand frictions proposed by Foster, Haltiwanger, and Syverson (2016) who speculate that "new businesses are small because demand for their product is low, and demand is low because of informational, reputational, or other frictions."

A move away from larger stores may also be reflected in the changes observed in average retailer quality as household income increases. Consistent with this channel, Panel E shows that retailer quality is positively associated with income, even within household over time.

We might worry that short-run impacts of changes in income on retailer choice may be reversed in the longer run. In Appendix Table 3, we show that these effects on spending and retailer choice are not reversed; they tend to increase in magnitude over time. The dynamic specification adds three leads and six lags of household income to equation (1) to observe household responses in advance of and following changes in household income.

We find generally small impacts in advance of any change in income, suggesting that most of the variation in income that we are utilizing is relatively unanticipated by the household. However, we find large and significant impacts in the months following changes in household income and no evidence of reversals in the direction of the effect. This is consistent with changes in spending and retailer choice evolving over time, with impacts after six months being, on average, more than twice as large as the contemporaneous effects.

In addition, we examine the response to a more plausibly unanticipated change in household income: unemployment. Appendix Table A.4 mirrors Table 2 using a sample of only households within 6 months of an unemployment spell (eg. six months prior to spell, entirety of UI period, and six months afterwards). Looking at income changes within these households produces similar responses across all variables except store size which sees more unstable results. In general, responses to changes in income associated with unemployment produce somewhat larger magnitudes of response relative to those utilizing the entire sample.

Overall, households who see changes in income immediately adjust not only their levels of spending, but also the composition of retailers that they visit. For increases in income, households shift towards a greater variety of distinct retailers, smaller and more local retailers, and retailers of higher quality. These changes are most pronounced among restaurants and general merchandise retailers.

3.3 Retailer Financial Characteristics

In addition to affecting levels of spending at retailers overall, the extent to which income fluctuations induce households to shift spending towards or away from retailers with particular financial characteristics has the potential to significantly shift average firm characteristics over the business cycle.

3.3.1 Matching Retailer Transactions to Retailer Characteristics

Most of our analysis has employed statistics regarding household retailer choice across *all* retailers that households in our sample visit. However, to analyze how these choices of retailers affect are related to the financial- and labor-characteristics of retailers, we must impose some restrictions on the data. To gain such information about retailers in our sample, we must match the cleaned textual transaction descriptions to retailer names and identifiers in Compustat and Orbis.

We start by conducting an algorithmic matching process (based on a Levenshtein distance operator) that assigns similarity scores to each transaction description in our sample relative to each retailer. This set of potentially matched retailers is taken as the entirety of retailers who are categorized as being in the retail industry by Compustat as well as a large set of private retailers. Large private retailers number approximately 250 retailers and are identified from a range of sources which aim to identify the largest non-public retailers according to annual sales, number of stores, or estimated value.

We supplement the automated approach with some hand-matching of the largest private and publicly traded retailers to insure thorough coverage. The types of transactions that hand matching typically identified were those in which a description included an abbreviation of a retailer that differed substantially from the full retailer name (e.g. ‘TGT’ rather than ‘TARGET’) or one in which there may have been a change in a parent firm-subsidiary firm relationship over time. Overall, we successfully match our data to 124 publicly traded retailers and to 239 other large private retailers that were targeted. In our entire sample of matched retailers, the mean number of unique text descriptions associated with a given retailer is 157 and the median number is 34.

Appendix Table A.3 shows the fraction of total observed retail spending in our sample is captured by the matched sample of retailers. Firstly, we posit that the total spending we observe approximates the total retail spending done by these households, given the completeness of the data and our sampling restrictions. Overall, the retailers we are able to match constitute about 57% of total retail spending. The fraction is highest for General Merchandise (68%) and lowest for Restaurants (24%). Intuitively, this makes sense as restaurants tend to have a longer tail of single-location retailers while General Merchandise spending is more highly concentrated in big-box stores.

3.3.2 Retailer Choice and Firm Characteristics

Table 5 examines the extent to which we can observe shifts in average firm characteristics by looking at changes in income within a household. The dependent variables in these regressions take the form of averages of the noted variables for a household-month, weighted by the amount of spending done at each retailer by that household (i.e., by the retailer-specific expenditure share of each household). For instance, the dollar-weighted average profitability of retail firms for household i

in month t is given by:

$$\text{Profitability}_{it} = \sum_{f=1}^{F} \text{Profitability}_f \times \frac{\text{Spending}_{ift}}{\text{Spending}_{it}},$$

where Profitability_f is taken as the *average* level of profitability for retailer f for the entirety of our sample period, 2010-2015. Each dependent variable of Panels B–E are normalized such that the standard deviation is equal to one.

In Panel A, we find that households spend a larger share of their income at public retailers when their income is higher. Looking within individual categories of retailers, we find the reverse; each category sees a reduction in the proportion in spending at public retailers after an income increase. This is consistent with households patronizing smaller and more local (and hence, generally private) retailers as their income increases. The increase that we find in aggregate spending is driven by a relative substitution towards the general merchandise category, where the fraction spent at public retailers is highest, and away from the grocery and restaurant categories, where the fraction of spending at public retailers is the lowest.

While these effects are highly significant and robust across demographic groups, locations, and time, they are, for the most part, economically small shifts in choices across public and private retailers. A doubling of monthly income only increases the proportion of spending done at public retailers by approximately 1% relative to the average proportion. The largest effect that we find here is for restaurants, where a doubling of income drives a fall in spending at publicly traded restaurants of approximately 10% relative to the average proportion.

Panels B–E take a similar approach for financial characteristics of retailers that households patronize. Because of the variables in question, we can calculate these measures solely for spending done at public retailers based on Compustat data. Here we see that, as household income rises, households shift spending towards retailers with higher levels of R&D intensity, higher levels of labor intensity, and higher levels of profit. These trends seem to hold true both across categories of retailer as well as within categories, though shifts across grocery stores do not follow a similar pattern in terms of advertising and R&D.

Finally, Panel E shows how households shift spending across retailers in terms of the weighted average of unlevered betas. That is, does the average dollar of household spending go to a public retailer with a higher level of idiosyncratic volatility when income increases? We find that, across all categories and also at an aggregate level, households experiencing increases in income shift spending towards retailers with higher betas.[11]

Given the propensity of individuals to shift towards higher beta firms after income increases, we next evaluate whether cross-sectional differences in beta across retailers can be explained by the income profile of its shoppers. For low quality retailers (i.e. those with lower income customers), gains from rising aggregate income during periods of economic expansion will partially offset by losses by substitution towards high quality retailers. Conversely, losses from falling aggregate income during periods of economic contraction will partially offset by gains by substitution towards low quality retailers.

In Table 6, we directly test for this predicted positive correlation between beta and firm quality in the cross section among the publicly traded retailers in our sample. In column 1, we regress 5-year unlevered Dimson betas on our firm quality measure. The results are statistically and economically significant. A one standard deviation increase in firm quality is associated with an increase of beta of 0.1 (about ten percentage points). Further, the r-squared in column 1 indicates that our quality measure explains 6.9% of the variation in unlevered betas. In columns 2 and 3 we add controls for firm revenue, category fixed effects. In column 4 we weight observations by average firm revenue. The coefficient on firm quality remains statistically and economically significant throughout each specification. Overall, our findings provide additional granularity and context to the findings of Ait-Sahalia, Parker, and Yogo (2004) and reinforce the importance of substitution across firms as an important source of risk to firms.

4 Retailer Quality and Firm Choice

As in Section 2, we construct measures of firm quality derived solely from our sample of transactional data as the average level of income of customers of a given retailer. One strength of this

[11] We utilize 5-year unlevered 'Dimson betas' to account for nonsynchronous trading in the market index relative to small individual equities. These betas are designed to limit biases for small stocks and for stocks in the early period of the sample. They are computed using the following regression:

$$r_{i,t} = a + b_1 r_{m,t} + b_2 r_{m,t-1} + r_{m,t-2} + \epsilon_{i,t}.$$

For each retailer, the regression is run at the end of every month, using the previous 5 years of daily return data (roughly 1250 trading days). Finally, betas are constructed such that $\beta = b_1 + b_2 + b_3$ and are then unlevered. We take the average across all years in our sample, 2010-2015, for each retailer.

transaction-based approach is the ability to glean more information about private sector firms that was previously unavailable (or only available on a case-by-case base for individual firms, but not the entire retail sector). While data on the characteristics of public firms is readily accessible (eg. from Compustat, CRSP, etc.), details regarding the properties of a wide swath of private firms remain relatively opaque and such a transaction-based approach can yield new insights across the universe of firms that households interact with.

4.1 Quality Smoothing Within Month

Past work has noted that households may not fully smooth even *between* the receipt of periodic income. That is, households do not fully smooth consumption between paychecks, even when both the timing and the amounts of the paychecks are known in advance. Papers such as Shapiro, 2005, Stephens, 2003, and Mastrobuoni and Weinberg, 2009 find evidence for such intra-month consumption cycles for a wide range of households.

In Table 2, we observed that households tend to adjust the average quality of retailer they patronize in response to changes in household income over time. We follow in the vein of the previous literature by testing whether changes in retailer quality also follow an intra-month pattern consistent with households not fully smoothing between paychecks on this dimension.

We construct daily measures of average retailer quality for each household; the weighted average of firm quality given the amount spent at each store on a particular day. Using the online personal financial website's categorization for 'Paychecks', we also map each day to the length of time since the last paycheck was received by that household.[12]

In Table 4, we see that the time since the last paycheck does have a negative and significant relationship with the quality of retailer that a given household is patronizing. For households on a monthly paycheck frequency, the average retailer quality just before receiving their next paycheck is approximately 1.5% lower than the average quality of retailer visited on pay-day itself. For restaurants, this effect is much steeper, with retailer quality among restaurants exhibiting more than twice the decline as for the average retailer.[13]

[12] We limit households in this sample to those who typically receive fewer than 3 paychecks per month. For households receiving more than 3 paychecks per month, it may be difficult to accurately ascertain any lack of smooth due to the short length of time between paychecks. Indeed, if we limit our sample to those who receive many paychecks per month, we find no evidence of shifts in quality of retailers between paychecks.

[13] We note that the observation of consumption, relative to spending, is difficult at such a high-frequency level: most

In columns 6 and 7, we include expand the exercise from columns 1 and 2. Here we mirror our earlier specifications but include interactions with the average marginal propensity to consume out of income that the household exhibited over time (ie. across months) in our sample. Households that have higher MPCs and who tend to smooth retail spending over time may also be those who exhibit the least amount of smoothing in terms of retailer quality in the short-run. We find evidence that households with higher MPCs are the ones that tend to downgrade the quality of the retailers they visit most strongly as the time since their last paycheck increases.[14]

Overall, households in the highest decile of MPCs tend to decrease quality at 2-3 times the rate of the median household. While other work has looked at levels of spending or time spent on home production as avenues to discuss high-frequency consumption smoothing, our work points to the fact that retailer quality is another avenue of consumption adjustment that households take advantage of, as well. Such fluctuations can also have implications for firms, as well. Based on our results, higher quality firms tend to be the most exposed to both unexpected and expected reductions in income and this can translate into higher revenue volatility in both the short- and long-run.

4.2 Macroeconomic Implications of Retailer Choice

Shifts among retailers of different quality can also have implications for the broader macro-economy due to firm attributes that are correlated with this quality gradient. Previous work, such as Jaimovich, Rebelo, and Wong, 2017, has noted that substitution across retailers in the face of fluctuations in household income may exacerbate swings in labor market demand over the business cycle due to variation in the average labor intensity of different retailers.

Panel D of Table 5 directly examines this relationship: whether increases in household income lead to increases in the average labor intensity of the retailers that household visits. We find this to be the case for Grocery Stores, Restaurants, and General Merchandise retailers. However, we find a negative relationship when looking at the same regression for clothing retailers.[15]

purchases are durable to at least some extent over a period of days or weeks. However, the consistent ordering of purchases over this period points to a possible effect on actual consumption. Also reassuring is the fact that we see similar results when restricting solely to restaurant spending, which is likely the least durable spending possible.

[14]We find negative impacts across all categories, though only retaining a statistically significant coefficient for aggregate retail spending and for restaurants.

[15]As in Table 3, we show the dynamics of the average labor intensity of retailers a household visits in Appendix Table A.5. We see similar results, with effects generally building over the few months following the change in income.

Figure 4 demonstrates one channel through which this relationship may operate. We find that, on average, retailers of higher measured quality to be more labor intensive in a given retailer category. This tends to be true across all categories in our sample except for clothing. These results hold true in regression form, as well. Across all matched retailers, we find that increases in firm quality tend to be negatively associated with a firm's labor intensity. This remains true when weighting by retailer size or by censoring the top or bottom 10% of the sample by labor intensity and when running the regression in logs or in levels.

There are two potential substitution channels at work. As consumers' income increases, they might substitute to new retailers with systematically different labor intensities (e.g., from lower- to higher-quality restaurants), and they might spend their additional income differently across retailer categories (e.g., more on restaurants and less on groceries). Due to significant differences in labor intensity across retail sector, the total effect on employment in the retail sector depends on both channels.

To interpret the average magnitudes of these effects, we imagine a scenario where household income doubles for a 12-month period (using coefficient estimates from our dynamic specification). At the end of this period, a household would be visiting restaurants that were, on average, 13% more labor intensive, general merchandise retailers that were 6% more labor-intensive grocery stores that were 0.5% more labor intensive, and clothing retailers that were 8% *less* labor intensive. These results are largely consistent with those seen in Jaimovich, Rebelo, and Wong, 2017, who note 'trading down' to lower quality and lower labor intense firms during recessions.

However, due to changes in the composition of spending across categories, we find that the net effect on the average labor intensity of the bundle of retail spending we observe is reversed. For instance, as income increases, households shift spending away from clothing retailers and towards general merchandise. Since clothing stores tend to be much more labor intensity than general merchandise stores, the decrease in average labor intensity driven by this cross-category substitution dwarfs the within-category trend towards higher quality and more labor intensive retailers. While there is strong evidence that substitution across retailers can significantly amplify the labor demand component of the business cycle *within* a range of industries, understanding how household spending shifts *across* all sectors, not solely retail, is necessary to fully characterize the entire effect.

5 Conclusion

Using transaction-level financial data across hundreds of thousands of households, we illustrate several dimensions of heterogeneity in household firm choice in the context of retailers.

First, we document new facts about the distribution of retailer choice, both in the cross-section of households and also within households as income fluctuates. We find that households with higher incomes spread retail spending across a wider range of firms and are more willing to experiment with new retailers.

We also demonstrate that retailer choice is an important channel of adjustment to fluctuations in household income, much the same as has been studied with home production and searching more extensively for lower prices. Households shift the composition of retailers towards higher quality and more local retailers as income increases and households tend to patronize retailers of lower quality as the time since their last paycheck increases. This last trend is especially true for households that exhibit a high marginal propensity to consume over time.

Finally, we show that substitution across retailers is related to firm characteristics and thus can affect both risk borne by individual firms and also broader business cycle dynamics. Because these changes are not 'neutral' and do not average out across different retailers, retailer choice has important implications for key financial and macroeconomic outcomes such as profitability and labor demand.

While we acknowledge our study is limited in scope to the universe of retailers, they provide the most accessible set of firms interacting with consumers through direct financial transactions. We find it reasonable to believe that our findings would propagate further up the supply chain, but we leave the formal testing of this for future research.

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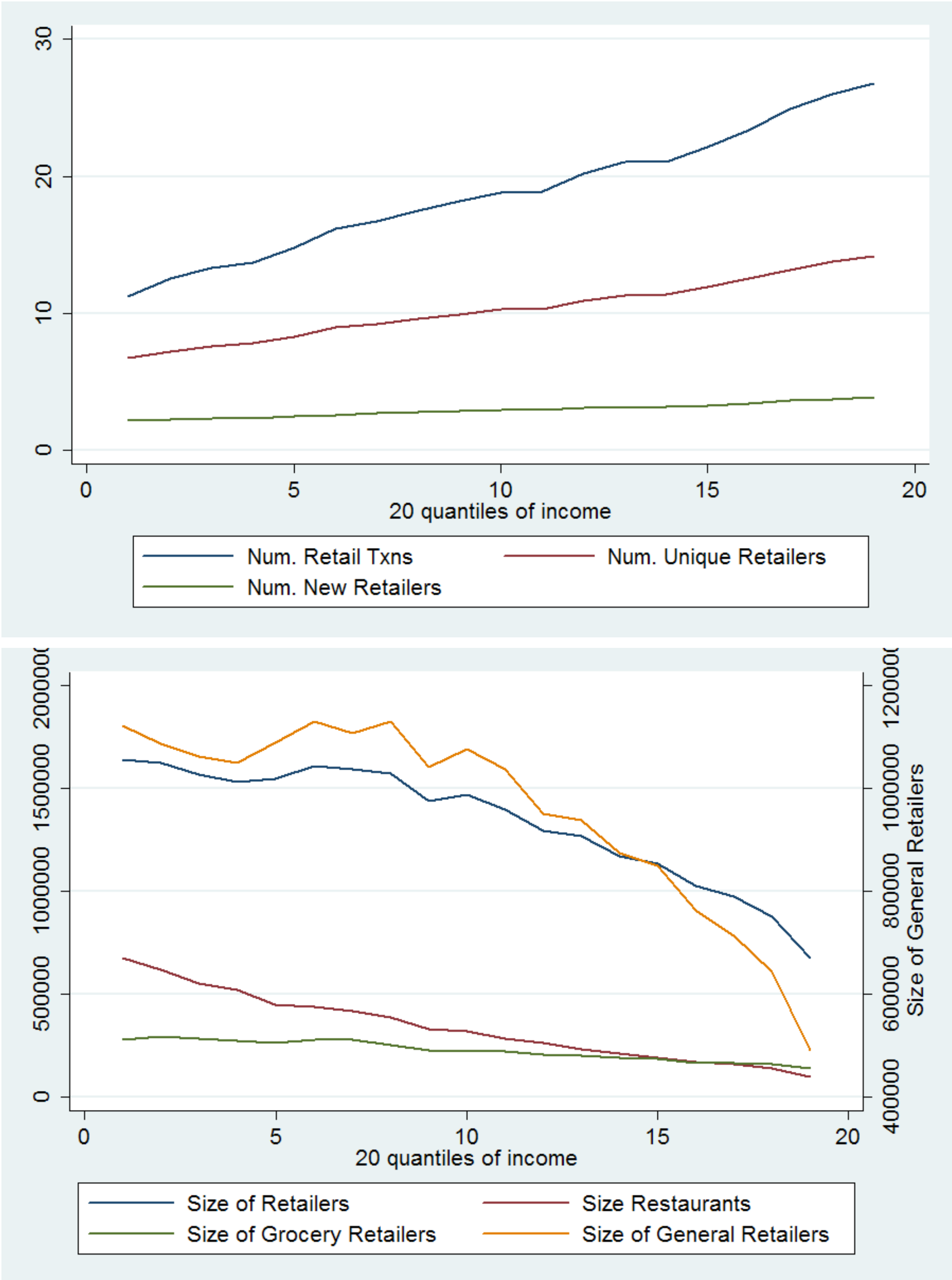
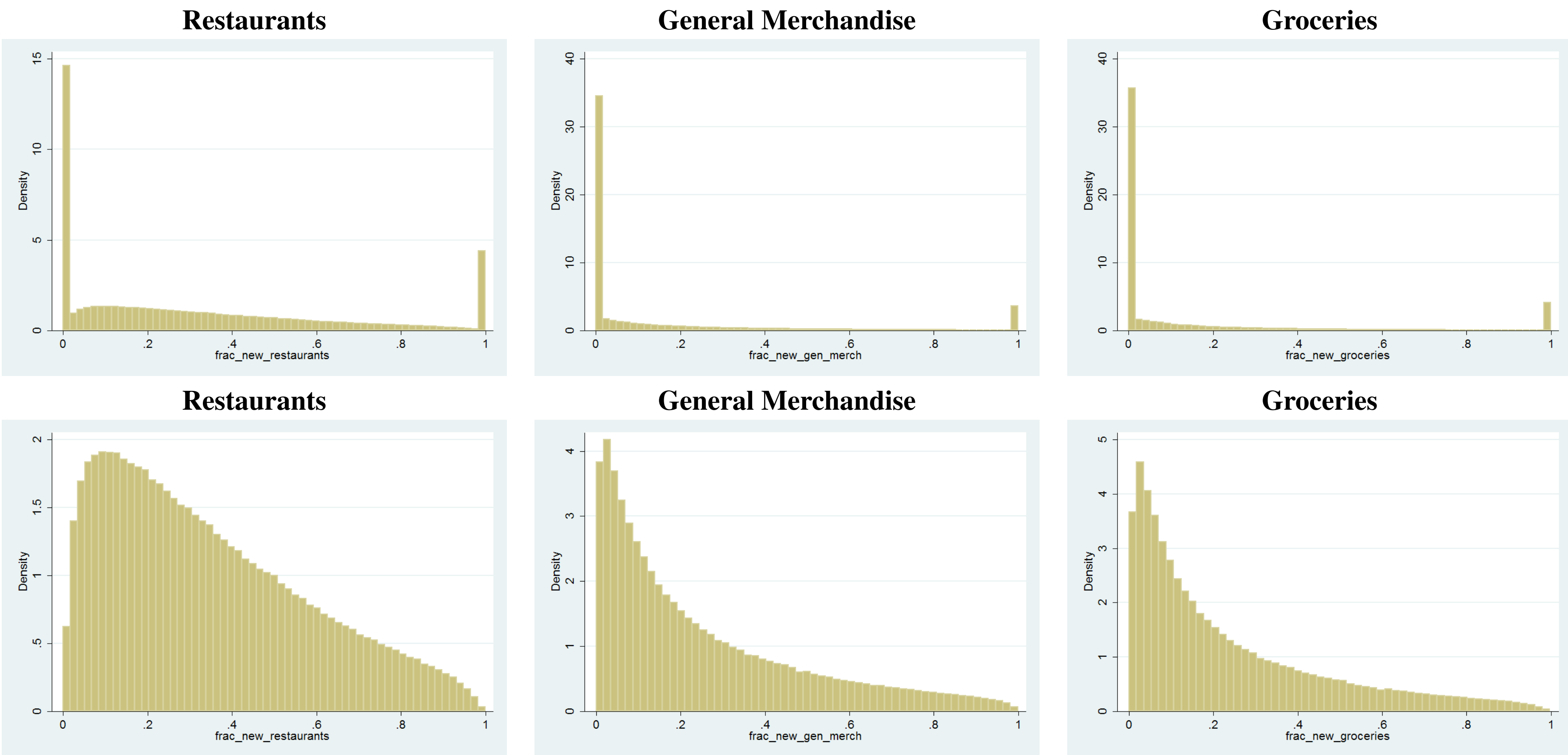
Figure 1: Retailer Choice Across Income Distribution



Notes: Both figures denote average values of a particular variable across 20 quantiles of observed household income. The top panel plot three series: the average number of retail transactions per month per household, the average number of unique retailers per month that a household visits, and the average monthly number of retailers that a household has never been observed patronizing in previous months. The bottom panel denotes the distribution of dollar-weighted average firm size for each quantile and for three categories of retailers – Restaurants, Grocery Stores, and General Merchandise. Firm 'Size' for a particular firm is measured as the dollar-weighted number of transactions conducted at that firm across all individuals and all time in our sample. Thus, a firm with more outlets and more sales will be rated as a larger firm.

Figure 2: Fraction ‘New’ Spending (inclusive and exclusive of 0 and 1)

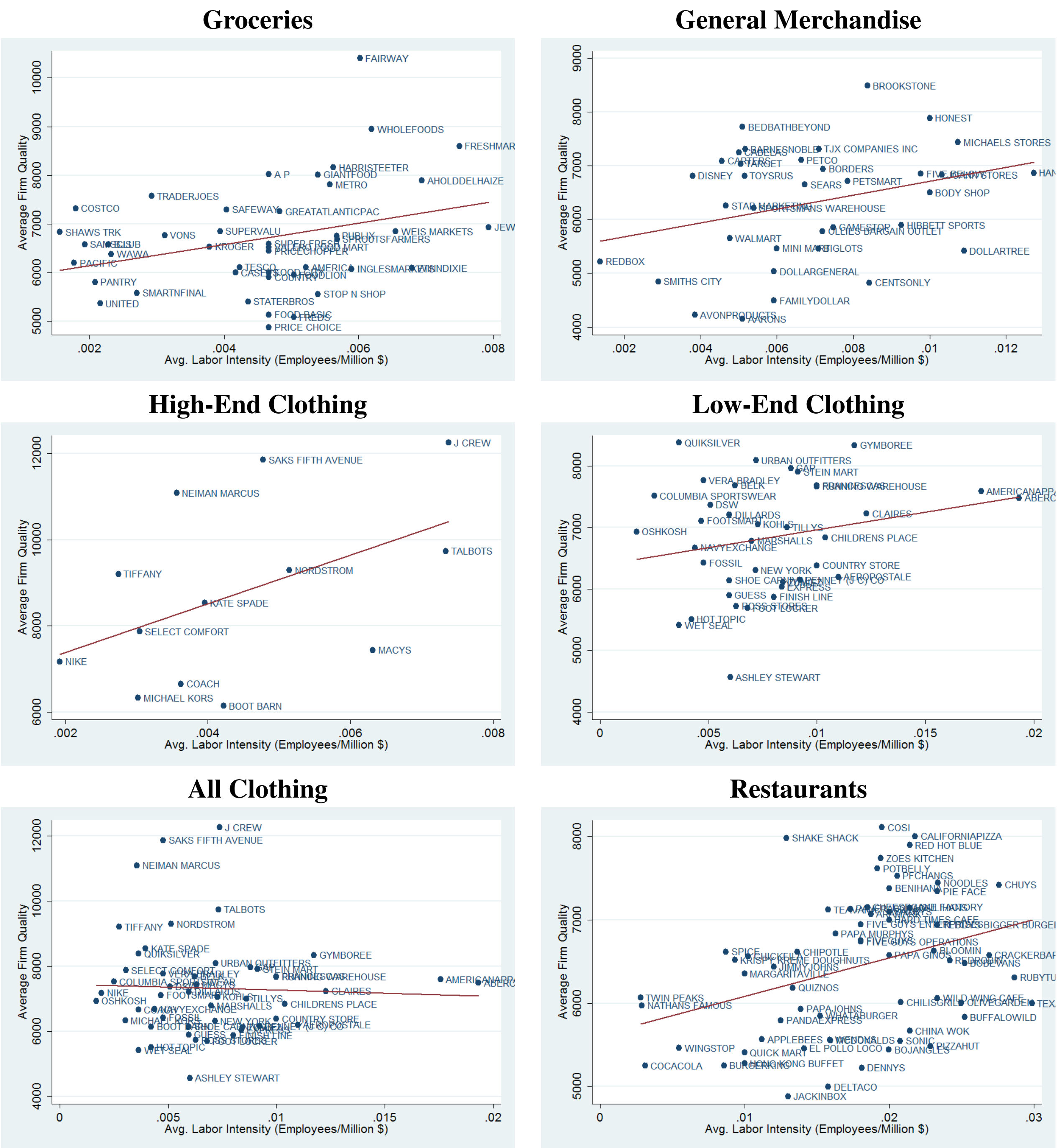


Notes: For each household-month, we calculate the fraction of spending done within a particular category at a retailer that the household has not previously shopped at. A value of ‘1’ means that all of the household’s shopping in that retailer category was done at a retailer the household has not previously visited while a value of ‘0’ means that all of a household’s spending of that type was at retailers they have shopped at before. The first 12 months of a given household are excluded to ‘burn-in’ previously-visited retailers. Each figure above shows a histogram of these values across all household-months in our sample. The bottom row mirrors the top row but excludes values of ‘0’ and ‘1’ to show more detail.

Figure 3: Income Heterogeneity in Retailers' Customer Base

Notes: Figures show the over- or under-representation of retailer revenue from households at each point along the income distribution for a selected sample of firms. First, the overall household income distribution of the sample is calculated. For each firm, the difference in the revenue from of households from a particular point of the income distribution is calculated relative to the overall distribution and plotted in $2,500 bins. For instance, a value of positive 0.01 means that the named retailer received 1 percentage point more revenue from that portion of the income distribution than would be expected if all households shopped at all retailers with equal likelihood. Household income spans $0 to $300,000. Retailers are a selected sample of large retailers.

Figure 4: Firm Quality and Labor Intensity



Notes: Each panel shows all matched retailers in a given retailer category and plots their firm 'quality' and the labor intensity of the firm. 'Quality' is measured as the dollar-weighted average household income of a retailers customers in our data. Labor intensity is measured as employees per million dollars in sales across all matched years in the data (2010-2015). A line of best fit is also plotted. From top to bottom and right to left, figures denote values for grocery stores, general merchandise retailers, 'high quality' clothing and shoes retailers, 'low quality' clothing and shoes retailers, and restaurants.

Table 1: Summary Statistics

	Conditional		Unconditional	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Demographic Variables				
Monthly Income	$5,114	$4,616	$3,729	$4,550
Monthly Credit Card Payments	$1,753	$2,640	$1,208	$2,337
Monthly Credit Card Purchases	$2,192	$2,899	$998	$2,240
Has Any Credit Card?	78%	42%	78%	42%
Spending Statistics (monthly)				
Aggregate	$764	$729	$759	$730
Clothing/Shoes	$203	$269	$109	$221
General Merchandise	$367	$413	$317	$404
Groceries	$310	$342	$240	$328
Restaurants	$149	$151	$127	$149
Quality Statistics (annual)				
Aggregate	$78,417	$10,712	$78,417	$10,712
Clothing/Shoes	$82,415	$14,457	$82,415	$14,457
General Merchandise	$76,970	$9,776	$76,970	$9,776
Groceries	$81,203	$12,636	$81,203	$12,636
Restaurants	$73,947	$11,818	$73,947	$11,818
Labor Intensity (employees per $1M sales)				
Aggregate	0.00712	0.00349	0.00712	0.00349
Clothing/Shoes	0.00705	0.00176	0.00705	0.00176
General Merchandise	0.00486	0.00143	0.00486	0.00143
Groceries	0.00413	0.00167	0.00413	0.00167
Restaurants	0.01609	0.00377	0.01609	0.00377

Notes: This table shows basic summary statistics for households in our sample. The unit of measure is the household month. Both unconditional values as well as values conditional on non-zero values are shown. Monthly Income is the observed total household income for the household. Monthly Credit Card Payments is the sum of payments to credit card companies. Spending data are limited to spending identified as retail spending (rather than, for instance, bills or mortgage payments or various services). Firm 'quality' is determined by the dollar-weighted average household income of customers at a given retailer. Labor intensity data refers to employees per million dollars of sales and is restricted to retailers in our data able to be matched to the Compustat database.

Table 2: Retailer Choice Elasticity Using Customer-Level Income Changes

	Agg	Rest	Groceries	Gen Merch	Clothes
Panel A. **Aggregate Spending**					
ln(Income)	0.230***	0.180***	0.139***	0.215***	0.130***
	(0.00157)	(0.00180)	(0.00219)	(0.00220)	(0.00309)
Observations	1,300,499	1,150,360	1,036,070	1,118,010	676,405
R^2	0.516	0.487	0.513	0.435	0.278
Panel B. **Unique Stores**					
ln(Income)	0.103***	0.0903***	0.0365***	0.0600***	0.0326***
	(0.000939)	(0.000995)	(0.000806)	(0.000847)	(0.00103)
Observations	1,300,499	1,150,360	1,036,070	1,118,010	676,405
R^2	0.592	0.582	0.448	0.443	0.258
Panel C. **Spending Concentration Across Retailers (HHI)**					
ln(Income)	-0.0660***	-0.0858***	-0.0308***	-0.0515***	-0.0392***
	(0.00104)	(0.00113)	(0.000914)	(0.000963)	(0.00129)
Observations	1,300,499	1,150,360	1,036,070	1,118,010	676,405
R^2	0.463	0.545	0.405	0.369	0.270
Panel D. **Average Store Size**					
ln(Income)	-0.0176***	-0.0624***	-0.0418***	0.0387***	-0.0251***
	(0.00291)	(0.00430)	(0.00528)	(0.00497)	(0.00638)
Observations	1,300,499	1,150,360	1,036,070	1,118,010	676,405
R^2	0.494	0.526	0.472	0.409	0.294
Panel E. **Average Firm Quality**					
ln(Income)	0.00411***	0.00521***	0.00353***	0.00273***	0.00269***
	(0.000171)	(0.000215)	(0.000263)	(0.000238)	(0.000403)
Observations	1,300,499	1,150,360	1,036,070	1,118,010	676,405
R^2	0.719	0.635	0.646	0.594	0.476
Year-Month FE	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES

Notes: The dependent variable for each specification varies by panel. Each column varies the set of retailers that the given variable spans (eg. Aggregated across retailers, solely restaurants, solely grocery stores, etc.). Each specification includes household and period fixed effects as well as logged household income. Panel A considers logged spending, panel B considers the logged number of unique retailers, panel C's dependent variable is the HHI within category of retailer, panel D looks at the weighted average of store size that a household shops at (as measured by logged number of total transactions across our sample at a given retailer), and panel E measures the weighted average of firm quality for a household-month.

Table 3: Dynamic Responses to Income Changes

Dynamic Responses			
	(1)	(2)	(3)
VARIABLES	Spending	Uniques	HHI
ln(Income) = F,	0.00555**	0.00374***	-0.00492***
	(0.00233)	(0.00142)	(0.00161)
ln(Income) = F,	0.0142***	0.00708***	-0.00433**
	(0.00245)	(0.00149)	(0.00169)
ln(Income) = F,	0.0223***	0.0125***	-0.00934***
	(0.00248)	(0.00150)	(0.00171)
ln(Income)	0.148***	0.0625***	-0.0361***
	(0.00249)	(0.00151)	(0.00172)
ln(Income) = L,	0.101***	0.0448***	-0.0275***
	(0.00248)	(0.00151)	(0.00171)
ln(Income) = L,	0.0384***	0.0144***	-0.00701***
	(0.00248)	(0.00151)	(0.00171)
ln(Income) = L,	0.0111***	0.00282*	-0.00202
	(0.00248)	(0.00150)	(0.00171)
ln(Income) = L,	0.0147***	0.00440***	-0.00240
	(0.00246)	(0.00149)	(0.00169)
ln(Income) = L,	0.00538**	0.00193	-0.00180
	(0.00243)	(0.00147)	(0.00167)
ln(Income) = L,	0.00789***	0.00468***	-0.00251
	(0.00231)	(0.00140)	(0.00160)
Observations	813,341	811,023	821,324
R^2	0.557	0.636	0.500
Year-Month FE	YES	YES	YES
Household FE	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Logged income is measured at a household-month level and incorporates all observable income for the household. 3 leads of logged income and 6 lags of logged income are included alongside contemporaneous logged income. ‘Spending’ refers to household logged spending across all retail categories. ‘Uniques’ refers to unique retailers that a household visits in a given month across all retail categories. ‘HHI’ refers to the Herfindahl-Hirschman index of dollars of retail spending for a household across all retailers and is calculated by squaring the fraction of total spending of the household done at each retailer and summing across all retailers. A lower HHI indicates a greater amount of dispersion in spending across multiple retailers.

Table 4: Individual MPC and Intra-Month Changes in Retailer Quality

VARIABLES	(1) Qual - All	(2) Qual - Rest	(3) Qual - Gen	(4) Qual - Groc	(5) Qual - Cloth	(6) Qual - All	(7) Qual - Rest
Months Since Paycheck	-0.0150***	-0.0315***	-0.00319**	-0.0100***	-0.00619*	0.00251	-0.0355***
	(0.000909)	(0.00139)	(0.00138)	(0.00171)	(0.00337)	(0.00330)	(0.00509)
Months Since Paycheck*MPC						-0.0335*	-0.0854***
						(0.0188)	(0.0292)
Observations	11,040,170	5,305,626	5,000,604	3,500,327	919,307	11,040,170	5,305,626
R^2	0.455	0.499	0.416	0.594	0.457	0.436	0.484
Period FE	YES	YES	YES	YES	YES	YES	YES
Indiv FE	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: ‘Months since Paycheck’ denotes the time since the last receipt of income that is coded as a paycheck for a given individual. Regressions are run at a daily level. Each column’s dependent variable is the logged weighted average in of firm ‘quality’ for a given type of retailer. Each specification includes individual and period fixed effects. ‘MPC’ is a household’s average marginal propensity to consume out of income at a monthly level as calculated across the entire sample period (excluding the first 3 months of each household’s data).

Table 5: Elasticity of Firm Attributes in Response to Customer-Level ΔIncome

	Agg	Rest	Groceries	Gen Merch	Clothes
Panel A: **Fraction Public**					
ln(Income)	0.00505***	-0.0506***	-0.00830***	-0.0333***	-0.0259***
	(0.000899)	(0.00117)	(0.000990)	(0.00101)	(0.00173)
R^2	0.445	0.297	0.682	0.226	0.461
Panel B: **Profitability**					
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	0.0282***	0.0192***	0.00861***	0.00122	-0.000796
	(0.000956)	(0.00125)	(0.00114)	(0.00101)	(0.00186)
R^2	0.288	0.272	0.656	0.282	0.279
Panel C: **R&D Intensity**					
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	0.0334***	0.00960***	-0.00428***	0.0313***	0.00239
	(0.000933)	(0.00129)	(0.00163)	(0.000965)	(0.00206)
R^2	0.344	0.253	0.439	0.369	0.157
Panel D: **Labor Intensity**					
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	-0.0298***	0.00603***	0.0194***	0.0197***	-0.00606***
	(0.000998)	(0.00102)	(0.00132)	(0.00104)	(0.00200)
R^2	0.294	0.270	0.673	0.336	0.346
Panel E: **Betas**					
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	0.0143***	0.0168***	0.0106***	0.0263***	0.0198***
	(0.000875)	(0.00125)	(0.00115)	(0.000894)	(0.00182)
R^2	0.423	0.251	0.688	0.444	0.374
Observations	4,623,454	3,085,676	2,682,893	4,325,129	2,439,531
Year-Month FE	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable for each specification varies by panel. Each column varies the set of retailers that the given variable spans (eg. Aggregated across retailers, solely restaurants, solely grocery stores, etc.). Each specification includes household and period fixed effects as well as logged household income. Panel A covers both private and public firms, looking at the fraction of spending done at public firms. For all other panels, the dependent variable is an average of a particular firm financial characteristic, weighted by dollars of spending, across all public firms that the household conducts spending at in a given month. Panel B looks at the ratio of gross profits to total assets, panel C looks at the ratio of R&D spending to total assets, panel D looks at the ratio of employees to revenue, and panel E looks at the average beta of public firms, as measured by 5-year unlevered Dimson betas.

Table 6: Firm Quality and Stock Market Betas

VARIABLES	(1) Stock Beta	(2) Stock Beta	(3) Stock Beta	(4) Stock Beta
ln(Firm Quality)	0.546***	0.615***	0.520**	0.535***
	(0.185)	(0.182)	(0.202)	(0.201)
ln(Revenue)		-0.0490**	-0.0556**	-0.0572**
		(0.0192)	(0.0268)	(0.0266)
Observations	120	120	120	120
R^2	0.069	0.119	0.268	0.273
Category FE	NO	NO	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variables are the average betas of public firms across our sample period, as measured by 5-year unlevered Dimson betas. Firm quality is determined by the dollar-weighted average household income of customers at a given retailer and is averaged across our sample period. Also included is the logged average annual firm revenue taken from Compustat. Column 4 weights observations by firm revenue.

Online Appendix of

Income Fluctuations and Firm Choice

A Retailer Choice Overlap Across Households

To quantify the extent to which households in different income groups shop at different sets of retailers, we develop a measure of 'retailer overlap' across the ten deciles of household income. Table A.6 enumerates the results of this exercise. To compute this table, we first collapse our data to the level of household income deciles. That is, for each income decile, we compute the amount of spending done at every retailer observable in our sample (e.g., a random household in the 10th (lowest) income decile spent \$9.57 per month at Kroger's on average during our sample period). We then convert these amounts into retailer-specific expenditure shares by dividing by total spending of each income decile (e.g., total monthly retail spending at identifiable retailers for a random household in the 10th income decile is \$367, such that the expenditure share of the 10th income decile at Kroger's is 2.6%).

We then compute a metric of total retailer 'overlap' across two income deciles i and j by summing up the intersections of their expenditure shares across all retailers $r \in R$ in our data:

$$\text{Overlap}_{ij} = \sum_{r=1}^{R} \min \left\{ \frac{\text{Spending}_{ir}}{\text{Spending}_i}, \frac{\text{Spending}_{jr}}{\text{Spending}_j} \right\}.$$

If the expenditure shares of two income deciles are the same at each retailer, then this measure equals 1.

We compute this value across all households in our sample (top panel), but also comparing only households residing in the same state (bottom panel). Overall, we see that households shop at increasingly similar retailers as their incomes converge. When comparing two neighboring income deciles, households tend to spend about 50% of their income at the same retailers.

We find a significantly larger overlap in retailer patronage when looking at only households within the same state. In fact, when comparing a household in the 1st decile of income with one in the 10th decile of income across states (e.g., overlap of 0.247), having the household increase their income to the 6th decile (e.g., overlap of 0.434) would have a similar effect as the household simply moving to the same state as the higher income household (e.g., overlap of 0.432).

Much of the difference in retailer choice attributable to income is driven by geographic dispersion in retailer prevalence. This is especially true when looking at the overlap in spending between the extreme ends of the income distribution. While the overlap between the shopping habits of the top few income bins increases only marginally when restricting to within-state households, the overlap between the top and bottom income bins increases by 50-100%.

Table A.1: Geographic Distribution of the Sample

	% Households Residing in				% Households Residing in		
State	Data	US Census	(Data - Census)	State	Data	US Census	(Data - Census)
Alabama	0.4%	1.5%	-1.2%	Montana	0.1%	0.3%	-0.2%
Alaska	0.2%	0.2%	-0.1%	Nebraska	0.2%	0.6%	-0.4%
Arizona	1.5%	2.1%	-0.6%	Nevada	1.1%	0.9%	0.3%
Arkansas	0.3%	0.9%	-0.7%	New Hampshire	0.2%	0.4%	-0.2%
California	23.3%	12.1%	11.2%	New Jersey	2.5%	2.8%	-0.4%
Colorado	0.8%	1.6%	-0.9%	New Mexico	0.4%	0.7%	-0.3%
Connecticut	1.2%	1.2%	0.0%	New York	22.2%	6.3%	15.9%
Delaware	0.1%	0.3%	-0.1%	North Carolina	1.9%	3.1%	-1.2%
D.C.	0.3%	0.2%	0.2%	North Dakota	0.1%	0.2%	-0.2%
Florida	7.9%	6.1%	1.8%	Ohio	0.6%	3.7%	-3.2%
Georgia	2.5%	3.1%	-0.7%	Oklahoma	0.5%	1.2%	-0.7%
Hawaii	0.3%	0.4%	-0.1%	Oregon	0.6%	1.2%	-0.6%
Idaho	0.1%	0.5%	-0.4%	Pennsylvania	1.1%	4.1%	-3.0%
Illinois	5.2%	4.2%	1.1%	Rhode Island	0.2%	0.3%	-0.2%
Indiana	0.3%	2.1%	-1.8%	South Carolina	0.8%	1.5%	-0.7%
Iowa	0.1%	1.0%	-0.9%	South Dakota	0.0%	0.3%	-0.2%
Kansas	0.4%	0.9%	-0.5%	Tennessee	0.8%	2.1%	-1.3%
Kentucky	0.2%	1.4%	-1.2%	Texas	10.1%	8.1%	1.9%
Louisiana	0.4%	1.5%	-1.1%	Utah	0.2%	0.9%	-0.7%
Maine	0.1%	0.4%	-0.3%	Vermont	0.0%	0.2%	-0.2%
Maryland	2.2%	1.9%	0.3%	Virginia	2.9%	2.6%	0.3%
Massachusetts	2.3%	2.1%	0.2%	Washington	1.1%	2.2%	-1.1%
Michigan	0.8%	3.2%	-2.4%	West Virginia	0.1%	0.6%	-0.5%
Minnesota	0.3%	1.7%	-1.4%	Wisconsin	0.2%	1.8%	-1.6%
Mississippi	0.2%	1.0%	-0.8%	Wyoming	0.0%	0.2%	-0.1%
Missouri	0.7%	1.9%	-1.3%				

Notes: This table shows the geographic distribution of the households in the sample relative to the 2010 U.S. Census.

Table A.2: Firm Quality Index and Yelp Ratings

Firm Quality Index and Yelp Ratings

	(1)	(2)	(3)	(4)	(5)
Dep. Var = Quality	All Stores	Groceries	Restaurants	General Merch.	Clothing
Yelp - $$	753.1***	250.0	761.8***	505.9***	1,412***
	(232.6)	(190.6)	(204.2)	(177.0)	(366.2)
Yelp - $$$-$$$$	2,565***	2,033***	1,425***	2,925***	2,896***
	(318.7)	(314.3)	(479.3)	(573.0)	(1,023)
Observations	253	46	63	87	41
R^2	0.409	0.384	0.238	0.428	0.277

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations are individual retailers from our sample able to be matched to Yelp. Independent variables are indicators for a firm's price range in Yelp, where the excluded category is Yelp '$'. Coefficients denote the average difference in firm 'quality' corresponding to different Yelp price categories. Firm 'quality' is determined by the dollar-weighted average household income of customers at a given retailer.

Table A.3: Total Retail Spending and Fraction Matched Retail Spending

Category	Matched Spending ($)	Total Spending ($)	% Matched Spending
Clothing	$688,001,444	$1,161,744,033	59%
General Merchandise	$4,417,609,344	$6,503,408,754	68%
Groceries	$1,337,016,923	$2,520,792,995	53%
Restaurants	$480,185,427	$2,031,692,191	24%
All Categories	$6,922,813,137	$12,217,637,972	57%

Notes: Matched spending represents the amount of spending done at retailers in a given category that were affirmatively matched to outside databases like Compustat and Orbis (both private and public firms) across all households in our final sample from 2010-2015. Total spending represents the total amount of spending done by households in our sample at *all* firms in a sample, whether they were matched to outside data or not.

Table A.4: Retailer Choice Elasticity Using Customer-Level Income Changes Near UI Spells

		Panel A. **Aggregate Spending**			
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	0.248***	0.208***	0.130***	0.243***	0.149***
	(0.00469)	(0.00517)	(0.00635)	(0.00617)	(0.00970)
Observations	92,737	83,175	73,170	88,690	43,261
R^2	0.566	0.536	0.568	0.489	0.309
		Panel B. **Unique Stores**			
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	0.119***	0.104***	0.0301***	0.0842***	0.0288***
	(0.00244)	(0.00263)	(0.00221)	(0.00239)	(0.00305)
Observations	187,330	155,678	117,678	172,679	62,296
R^2	0.766	0.713	0.609	0.679	0.418
		Panel C. **Spending Concentration Across Retailers (HHI)**			
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	-0.0762***	-0.0995***	-0.0238***	-0.0658***	-0.0375***
	(0.00281)	(0.00301)	(0.00252)	(0.00268)	(0.00396)
Observations	188,970	157,810	119,321	174,587	65,318
R^2	0.662	0.685	0.573	0.598	0.437
		Panel D. **Average Store Size**			
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	-0.0132**	-0.0351***	0.00336	0.0448***	0.0300*
	(0.00646)	(0.0101)	(0.0126)	(0.00991)	(0.0162)
Observations	182,840	153,461	115,112	169,193	62,278
R^2	0.650	0.618	0.671	0.629	0.490
		Panel E. **Average Firm Quality**			
	Agg	Rest	Groceries	Gen Merch	Clothes
ln(Income)	0.00384***	0.00566***	0.00379***	0.00240***	0.00169
	(0.000467)	(0.000579)	(0.000756)	(0.000607)	(0.00126)
Observations	182,547	153,597	114,696	168,632	62,526
R^2	0.801	0.746	0.760	0.721	0.627
Year-Month FE	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES

Notes: The dependent variable for each specification varies by panel. Each column varies the set of retailers that the given variable spans (eg. Aggregated across retailers, solely restaurants, solely grocery stores, etc.). Each specification includes household and period fixed effects as well as logged household income. Panel A considers logged spending, panel B considers the logged number of unique retailers, panel C's dependent variable is the HHI within category of retailer, panel D looks at the weighted average of store size that a household shops at (as measured by logged number of total transactions across our sample at a given retailer), and panel E measures the weighted average of firm quality for a household-month.

Table A.5: Income and Labor Intensity - Dynamics

Household Income and Labor Intensity

VARIABLES	(1) ln(LI) - Agg	(2) ln(LI) - Groc	(3) ln(LI) - Rest	(4) ln(LI) - General	(5) ln(LI) - Clothes
ln(Income) = F,	0.00100	0.00139	0.00261	0.00112	-0.00260
	(0.00155)	(0.00151)	(0.00207)	(0.00160)	(0.00310)
ln(Income) = F,	-0.00528***	0.00158	0.00798***	0.00451***	-0.00203
	(0.00162)	(0.00157)	(0.00217)	(0.00168)	(0.00324)
ln(Income) = F,	-0.00465***	0.000499	0.00327	0.00727***	-0.000385
	(0.00164)	(0.00159)	(0.00220)	(0.00170)	(0.00328)
ln(Income)	-0.0251***	0.00462***	0.0140***	0.0165***	-0.000414
	(0.00165)	(0.00160)	(0.00221)	(0.00170)	(0.00326)
ln(Income) = L,	-0.0151***	0.00612***	0.00920***	0.00887***	0.000391
	(0.00164)	(0.00159)	(0.00219)	(0.00170)	(0.00324)
ln(Income) = L,	-0.00946***	0.00336**	0.00325	0.00470***	0.00505
	(0.00164)	(0.00159)	(0.00219)	(0.00170)	(0.00325)
ln(Income) = L,	-0.00275*	0.00225	-0.00147	0.00381**	-0.00127
	(0.00164)	(0.00159)	(0.00219)	(0.00170)	(0.00326)
ln(Income) = L,	-0.00627***	0.00163	0.000231	-0.00249	0.00175
	(0.00163)	(0.00157)	(0.00218)	(0.00168)	(0.00324)
ln(Income) = L,	-0.00231	-0.000973	0.000423	-0.000689	-0.0105***
	(0.00161)	(0.00155)	(0.00215)	(0.00166)	(0.00321)
ln(Income) = L,	0.00238	0.00236	-0.00380*	0.00397**	0.00490
	(0.00153)	(0.00149)	(0.00204)	(0.00159)	(0.00307)
Observations	1,593,683	928,376	1,088,843	1,469,119	565,886
R^2	0.381	0.694	0.309	0.407	0.297
Year-Month FE	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variable is logged labor intensity at a household-month level. Labor intensity at a firm level is measured as the number of employees per million dollars of sales at a given firm. For each household-month, a dollar-weighted average of the labor intensity at matched retailers (either across all categories or within a retail category as noted by column headers) is constructed and used in these specifications. Household months with no spending at a matched retailer are excluded for lack of labor intensity data. Standard errors clustered at a household level.

Table A.6: Retailer Overlap Across Income Deciles

All Households

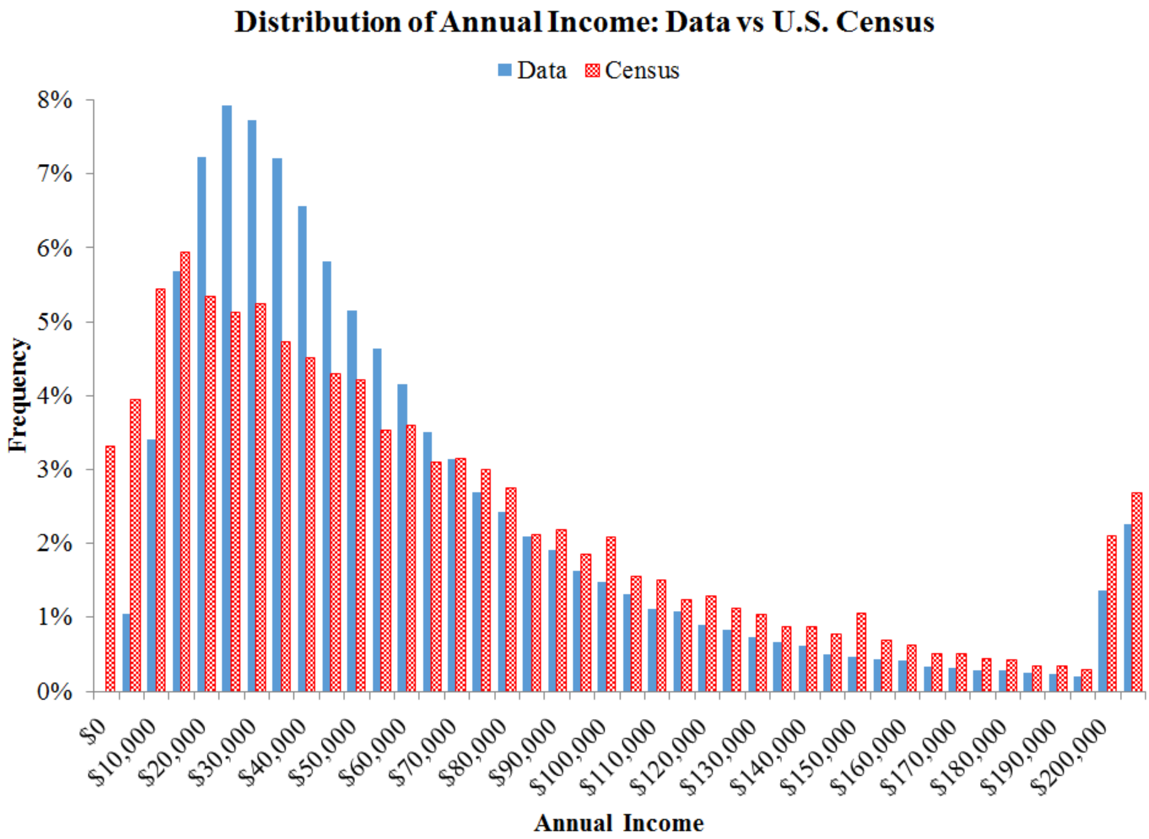
	1	2	3	4	5	6	7	8	9	10
1	-	-	-	-	-	-	-	-	-	-
2	0.508	-	-	-	-	-	-	-	-	-
3	0.460	0.532	-	-	-	-	-	-	-	-
4	0.465	0.519	0.530	-	-	-	-	-	-	-
5	0.434	0.482	0.480	0.507	-	-	-	-	-	-
6	0.418	0.451	0.458	0.494	0.505	-	-	-	-	-
7	0.410	0.429	0.457	0.472	0.492	0.514	-	-	-	-
8	0.371	0.381	0.412	0.444	0.454	0.487	0.523	-	-	-
9	0.341	0.336	0.348	0.406	0.401	0.425	0.458	0.516	-	-
10	0.247	0.222	0.213	0.290	0.264	0.313	0.322	0.381	0.430	-

Within-State Households

	1	2	3	4	5	6	7	8	9	10
1	-	-	-	-	-	-	-	-	-	-
2	0.579	-	-	-	-	-	-	-	-	-
3	0.559	0.615	-	-	-	-	-	-	-	-
4	0.544	0.584	0.635	-	-	-	-	-	-	-
5	0.536	0.567	0.619	0.639	-	-	-	-	-	-
6	0.525	0.561	0.600	0.624	0.652	-	-	-	-	-
7	0.498	0.534	0.579	0.595	0.620	0.654	-	-	-	-
8	0.505	0.544	0.569	0.585	0.612	0.638	0.667	-	-	-
9	0.482	0.501	0.524	0.532	0.551	0.585	0.612	0.661	-	-
10	0.432	0.443	0.456	0.444	0.465	0.485	0.511	0.547	0.610	-

Notes: Panels list the fraction of overlap in spending at individual retailers across households in different income deciles. For a given pair of deciles, the overlap in retailer spending is given as: $\text{Overlap}_{ij} = \sum_{r=1}^{R} \min \left\{ \frac{\text{Spending}_{ir}}{\text{Spending}_{i}}, \frac{\text{Spending}_{jr}}{\text{Spending}_{j}} \right\}$ where i, j are income deciles and r denotes an individual retailer. If the expenditure shares of two income deciles are the same at each retailer, then this measure equals 1. Top panel displays results for all households in our sample, split by income deciles. Bottom panel restricts to comparing income deciles of households within a single state.

Figure A.1: Income Distribution of Sample and Census Data



Notes: This figure compares the distribution of annual income of households in our sample relative to the 2010 U.S. Census. Data are binned into $5,000 buckets. For households in the sample for multiple years, we take the average across all observed years.