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Are poor neighborhoods "retail deserts"?

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ABSTRACT

Poor urban neighborhoods are often referred to as "food deserts", lacking in grocery stores and healthy food vendors. However, most empirical studies of food deserts have been small scale, focusing on limited geographies and a narrow range of products. Standard retail location models, which often assume that consumers have identical preferences and are uniformly distributed through space, provide little insight into the relationship between local income and retail patterns. In this paper, we examine the relationship between neighborhood income and retail density for several types of goods and services in 58 large U.S metropolitan areas. We combine detailed data from the National Establishment Time-Series database on retail establishments and employment, by industry category and firm type, with Census data on ZCTA income, poverty and demographics. Results indicate that retail patterns do vary by neighborhood income, along many dimensions. High poverty neighborhoods have lower employment density for retail overall, supermarkets, drugstores, food service and laundry facilities, driven largely by reduced employment in chain establishments. Average establishment size increases with median income for all retail types. Neither income levels nor poverty rates consistently predict retail employment growth, but neighborhoods that experience income upgrading do see larger gains in retail employment.

1. Introduction

Poor urban neighborhoods are often referred to as "food deserts" with few grocery stores and only fast food restaurants (see, for instance, Moore, 2010; Osen, 2010; Powell et al., 2007; Shaffer and Gottlieb, 2007; Sloane et al., 2005). According to popular media accounts and a few academic studies, the arrival of upscale eateries and "boutique" shopping venues is one of the most visible signs of a shift in a neighborhood's income or demographics (Bruni, 2010; Zukin et al., 2009). Certainly some formerly low-income neighborhoods that have gentrified, such as New York's Lower East Side, DC's Adams Morgan and San Francisco's Mission District, are now known for their trendy shops, restaurants and bars. Collectively, these anecdotes suggest that retail establishments are more prevalent in affluent neighborhoods than poor ones.[1] However, high-income households may not view all types of retail as amenities; Big Box stores, for example, have occasionally incurred local opposition (see, for instance, Beaumont, 1997; Mitchell, 2006; Scroop, 2008). To date there has been little empirical research on how neighborhood income (and related characteristics) affects the location of retail establishments within urban areas. In this paper, we take a first step beyond anecdotes to look systematically at the relationship between income and local retail markets. Specifically, we examine whether low-income neighborhoods have less access to a variety of retail goods and services, as implied by the term "retail deserts".

An extensive theoretical literature exists on retail location decisions, beginning with Hotelling's (1929) simple spatial model of firm location in a linear city and its later modifications (see, for instance, Salop, 1979 and Stern, 1972). More recent research focuses on spatial and price competition between firms, often within a game-theoretic framework (for instance, Chamorro-Rivas, 2000; Karamychev and van Reeven, 2009; Pal, 1998). De Palma et al. (1994) develop a more flexible model that allows for consumer heterogeneity, non-price competition in the form of retail "variety" and less constrained market boundaries. However, most formal models of retail location assume that consumers have identical income and homogeneous preferences, and yield few predictions about how spatial variations in income may affect retail patterns. A notable exception is Porter (1995), who argues that although low-income households individually have limited purchasing power, because they tend to live in denser neighborhoods, collectively poor areas should be profitable for retailers.

For our analysis, we combine ZCTA (ZIP Code Tabulation Area) level employment data on retail establishments, by industry category, firm structure and size, from the National Establishment Time-Series (NETS) database, with Census data on household incomes and other

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[1] According to industry classifications, food service is a separate industry from retail (NAICS codes 72 and 44–45, respectively). However, in this paper we include food and beverage services in our general discussion of retail.

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characteristics for 58 large metropolitan areas across the United States. We regress retail employment measures on residential income measures in three models: levels on levels, changes on levels, and changes on changes. Most theoretical models of retail location – and conventional wisdom in the real estate industry – assume that retail establishments take as given the distribution of consumers when deciding where to open new establishments (that is, firm location follows consumers). However we recognize that, at least at the margin, households may sort across neighborhoods based on the presence of retail and services, setting up the possibility of reverse causation. Our data and empirical strategy do not allow us to determine the direction of causality, nor can we identify the mechanisms through which income affects retail patterns. Rather, we document the ways in which retail patterns vary by neighborhood characteristics.

Results suggest that high-poverty neighborhoods have lower retail employment density for retail overall and several types of retail, including supermarkets, drugstores, food service and laundry. For most of these categories, the lower retail employment density is driven by reduced employment in chain establishments. Median household income is associated with increased retail employment for retail as a whole, primarily in chain establishments, but income is not a significant predictor of employment density for most retail categories. Income is positively associated with establishment size across retail types, while high-poverty status is associated with smaller establishments for several types, including supermarkets, drugstores, food service and laundry. The results on supermarkets indicate that whether poor neighborhoods are considered "food deserts" depends in part on the choice of retail metric: high-poverty neighborhoods have a higher density of supermarket establishments, but lower employment density, smaller establishments and fewer chain supermarkets. There is some evidence that income levels are positively associated with retail employment growth, although these results are less robust. Neighborhoods that experience income upgrading, relative to the metropolitan area, see larger gains in retail employment, while high poverty neighborhoods in which poverty increases experience smaller employment gains (or larger losses).

The paper proceeds in the following way. The following section summarizes the relevant theoretical and empirical literature. Section 3 describes the data and our empirical strategy, Section 4 discusses the results, and Section 5 concludes and discusses policy implications.

2. Previous literature

In this section we consider what predictions may be drawn from theoretical models of retail location about the relationship between the spatial distribution of retail and underlying neighborhood characteristics. We first consider how the characteristics of the local neighborhood, in particular income, are related to the density and composition of local retail markets. We then review the relatively limited empirical literature on the topic.

2.1. Neighborhood-level determinants of retail density

The Hotelling model and its variants suggest that the density of stores depends on customer density, store fixed costs, and transportation costs. For local (i.e. neighborhood) retail services, potential customers will primarily be local residents or employees at local firms.[2] Therefore, retail store networks will be denser in neighborhoods with higher residential and employment densities. Spatially, these are likely to be closer to the central business district (CBD), where employment density (and often residential density as well) is high.[3] Retail density will also vary by product type: store density should be higher for establishments that sell goods that are highly standardized, frequently consumed or involve high transport costs due to perishability or other reasons, so that consumers will not be willing to travel long distances to purchase them (Berry, 1967; Huff, 1964; Reilly, 1931). Based on this logic, some categories of retail that are most likely to serve the immediate neighborhood include grocery and convenience stores, pharmacies, laundry services, coffee shops and limited service restaurants, gyms, video rental outlets, and beauty salons/barber shops (West et al., 1985; Ryan et al., 1990).

Market areas for stores will be smaller for retailers with low fixed costs, so neighborhood characteristics that affect fixed costs will affect retail density.[4] For instance, rents are likely to be higher in high-income neighborhoods, while insurance and security costs increase with neighborhood crime rates. If we assume that labor markets correspond to metropolitan areas (MSAs), then wages for similar positions (sales clerk or shelf stocker) may be relatively similar across neighborhoods. However, there is some anecdotal evidence that employee turnover or training needs are higher in low-income neighborhoods (International Council of Shopping Centers, 2004), increasing average labor costs in those areas. Land use regulations and characteristics of the local building stock also vary across neighborhoods, contributing to neighborhood differences in fixed costs. Specifically, restrictions against or incentives for retail occupancy can increase or reduce costs associated with initial setup. Similarly, the inherent nature of the building stock will determine the feasibility and costs associated with adapting the particular retail business to the existing commercial space. For example, grocery stores often require enough space and a robust enough infrastructure to support freezers, while restaurants require venting from stoves and ovens (International Council of Shopping Centers, 2004; Barragan, 2010). Availability of suitable land parcels for development may be particularly important for large chains that have a preferred model for their stores (i.e. Big Box), often a model derived in a suburban or low-density context.

Nearly all theoretical models of retail location discuss density in terms of the number of establishments, with the implicit assumption that size of establishments within retail categories is constant. In reality, there is considerable variation in the size of establishments even within narrowly defined NAICS industry classifications, which raises concerns about using establishment counts or densities as reliable metrics of retail access: a neighborhood with 10 small bodegas presumably has "less" grocery store retail than a neighborhood with 10 large, full-service supermarkets, a distinction that would be lost using establishment counts. Therefore in our empirical analysis, our primary measure of retail density will be the density of retail employment, which takes into account variation in establishment counts and size (number of employees per establishment). In Section 4 we will discuss some of the implications of using these different metrics. In addition to examining the relationship between neighborhood income and retail employment density, we also explicitly look at how establishment size varies by income, to assess whether retail markets in low income neighborhoods exhibit a different industry structure.

2.2. Should neighborhood income affect quantity, size or type of retail?

The primary focus of our current analysis is the relationship between local income and the *quantity* of retail, as measured by employment

[2] Customers are also comprised of non-resident and non-employee commuter or tourist populations. In order to keep the framework simple, we assume that these customers are shopping at a select and limited number of retail centers, many of which correspond with the central business district(s).

[3] This formulation assumes a monocentric model of urban development; in the case of a polycentric metropolitan area, the single CBD might be replaced by several employment subcenters. The same relative density predictions hold however.

[4] Many retail firm costs are not "fixed" in the traditional sense, but are also not exactly marginal. For instance, building rents are often fixed over lease terms, which may be five or ten years long but may offer some flexibility between leases, depending on negotiations between tenant and landlord. Likewise contracts with suppliers, insurance, utilities, etc., may be fixed over a short period of time (1–2 years), and so cannot be directly reduced with marginal productivity.

density. Most directly, higher household income implies greater purchasing power among local residents.[5] If we assume that retailers are motivated in their location decisions by profit maximization, retail employment density should be increasing in the potential for local consumption, or income. Even if higher incomes do not translate into a greater number of purchases, but rather better quality products and services consumed, this still implies rising consumption expenditures and thus should induce higher retail employment density. On the other hand, if higher income residents associate retail with nuisances like noise and traffic, and are able to exclude undesirable land uses from their immediate vicinity, then retail employment density may be decreasing with respect to household income.[6] These contrasting hypotheses raise the possibility that the relationship between local income and retail employment density is non-linear, and potentially non-monotonic, exhibiting a positive correlation for low and middle parts of the income distribution and weakening or becoming negative at the high end. Due to the attention on poor neighborhoods as "food deserts", an area of particular interest is whether neighborhoods at the low end of the income distribution are relatively deprived of retail. For instance, there could be a minimum income below which retail is not profitable, or retailers may be deterred from entering high-poverty neighborhoods because of perceived crime, inability to obtain credit or other unfavorable market conditions. Our empirical analysis will examine the direction and strength of the relationship between income and retail employment density at various points along the income distribution, testing for such non-linearities.

We further propose that income and retail density will have a differential relationship depending on the *type* of retail (e.g. grocery versus drug store versus restaurant) and the *size* of the retail establishment. Here, we use size to represent two defining features of local retail stores: the physical space the business occupies and the scope of the business, i.e. the range (and diversity) of goods sold. If proximity to retail in general is a normal or luxury good, then retail employment density overall should be increasing in income, but density may be decreasing in income for specific types of retail that are less desirable. The reverse would hold if proximity to retail in general is an inferior good but some products or services are normal or luxury goods. Specifically, establishments such as specialized grocery stores or upscale restaurants are more likely to locate in high-income neighborhoods, while establishments selling inferior goods (convenience stores and fast food restaurants) will locate in lower-income areas. Teh (2007) provides an example with liquor stores: she finds that alcohol outlets located in low-socio-economic-status (SES) neighborhoods are seen as disamenities, whereas alcohol outlets located in high-SES neighborhoods – which were more likely to be large grocery stores or upscale wine and liquor stores – were valued by homeowners.[7]

Income may also be correlated with preferences over the physical size and architectural design of retail establishments, as illustrated in the debate over Big Box Retailers. Anecdotal evidence demonstrates that more affluent communities often protest larger chain retailers, citing loss of neighborhood character (Li, 2009). If high-income communities have a preference for smaller, locally owned business, retail establishment size should decrease with household income (Zukin et al., 2009). Hausman and Leibtag (2005) show that consumer surplus from increased superstore access is greater for low-income households compared to high-income households. In addition, if higher income households prefer to live in less dense communities (and therefore have more access to car transportation) then retail establishment size will decrease in household income. On the other hand, larger retail establishments may be of value to households, because they can potentially carry a greater variety of goods and offer lower prices (Basker et al., 2007 provide evidence for this). Furthermore, the relationship between income and retail employment density could vary by establishment size: if larger retailers tend to serve larger markets, retail patterns might be less sensitive to neighborhood income for larger establishments than for smaller establishments whose customer base is more localized.

2.3. Empirical literature

The empirical literature on the relationship between retail presence and local market characteristics is limited. Much of the existing work on retail focuses on a single sector and/or a single geographic area. In addition, the research questions typically center on labor market outcomes rather than linkages between retail presence and consumption markets. Here we summarize the existing research that informs the latter relationship.

A handful of studies consider the role of population size, income and related characteristics in retail location at the city or MSA level. Berry and Waldfogel's (2003) research on product quality and market fragmentation suggests that as market size (defined as city population) increases, the range of product variety and quality widens. They also find that the number of high-quality products grows with market size. Dinlersoz (2004) uses an establishment-level dataset on alcoholic beverage retailers in California to test the difference in the organization of chain versus stand-alone stores. He does find variation across the two types of stores: chain stores expand their scale as city population increases, whereas stand-alone stores tend to grow the number of establishments as city population increases.

Glaeser et al. (2001) explore the role of urban density, and in particular commercial density, in facilitating the growth of consumption centers. Generally they find that high-amenity cities have grown faster than low-amenity cities and that, between 1970 and 1990, neighborhoods in Manhattan that are closer to the CBD or a major consumption center have become richer than neighborhoods relatively farther away. These results suggest that households value access to commercial services and that this preference has strengthened over time. Frankel and Gould (2001) examine whether the income distribution within a city affects retail prices, and conclude that greater income inequality – defined as the relative absence of lower-middle income households – leads to higher prices.

A few studies examine similar relationships between population size and retail markets at the neighborhood level. Davis (2006) looks at the relationship between the distribution of consumers and movie theaters. He finds that demand for the theater (and ticket sales) increases with the number of people living within five miles of the cinema; this increase is less pronounced at further distances. Waldfogel (2008) exploits the variation in consumer characteristics and empirically tests the relationship between the mix of commercial services and heterogeneity in consumer preferences. He demonstrates that there is considerable heterogeneity across consumer preferences for such services as restaurants and media, and that preferences are strongly correlated with observable population characteristics, such as educational attainment and race/ethnicity. Using 5-digit ZIP-code level data on food and drinking establishments and population characteristics and proprietary data on consumer patronage behavior, he finds that there is an association between the mix of locally available chain restaurants and demographic mix by race and education.

[5] Cash income is not a perfect proxy for purchasing power, especially among lower-income households, who may receive non-cash benefits such as food stamps or housing assistance, and may engage in reciprocal exchange of services in lieu of cash payments. And purchasing power depends not only on current income but also on lifetime income if people smooth consumption over time relative to income fluctuations. Still, income is the most practical empirical indicator of purchasing power.

[6] Besides income, customer preferences are likely driven by characteristics such as race, ethnicity, age and socioeconomic status, which may be correlated with income (Waldfogel, 2008).

[7] We do not address zoning in the current analysis, but we acknowledge that sorting of retail establishments by product quality may be reinforced by zoning if certain types of food establishments (like bars or fast food places) might attract undesirable crowds or other disamenities.

Table 1
Variable definitions and sources.

Variable	Definition	Source(s)
Retail metrics		NETS (1992–2006), census (2000)
Emp/sq mi	Employees per sq mi (by retail category)	
Ind emp/sq mi	Employees in independent retail estabs per sq mi	
	Employees in multi-establishment (chain) retail estabs per sq mi	
Chain emp/sq mi		
Est/sq mi	Establishments per sq mi (by retail category)	
Ind est/sq mi	Independent establishments per sq mi	
Chain est/sq mi	Chain establishments per sq mi	
Emp/estab	Avg employees per establishment (by retail category)	
Ind emp/estab	Avg employees per independent establishment	
Chain emp/estab	Avg employees per chain establishment	
Emp growth	Average annual employment growth	
Demographic & economic characteristics		Census (1990, 2000)
Income	Median household income	
Δ ZCTAinc/MSAinc	Change, 1990–2000, (ZCTA median household inc/MSA median HH inc)	
Poor	=1 if poverty rate >20%	
Pop dens	Population/sq mi	
Dist CBD	Distance from ZCTA centroid to CBD	
BA plus	% population with BA or graduate degree	
Owner occ	% housing units that are owner-occupied	
Central city	=1 if ZCTA in designated central city, 0 otherwise	OMB (2000)
Black	% non-Hispanic black population	
Hispanic	% Hispanic population (any race)	
Kids	% population under 18 years	
Old	% population 65+ years	
Foreign born	% population foreign born	
Hsg < 1940	% housing built prior to 1940	

A sizable literature in public health and economic development explores the differences in the locational decisions of establishments across neighborhoods within a city. Powell et al. (2007), Zenk et al. (2005) and Alwitt and Donley (1997) demonstrate that various retailers (namely banks and supermarkets) opt not to locate in poorer ZIP codes even after controlling for purchasing power – leading the authors to conclude that retail locational decisions may hinge on a host of factors in addition to an area's market potential. Interestingly, Alwitt and Donley found that fast food restaurants were least likely to discriminate across neighborhoods, whereas Block et al. (2004) and Sloane et al. (2005) found that fast food restaurants were more likely to locate in poorer, predominately minority neighborhoods. Meltzer and Schuetz (2012) find that although high-income neighborhoods in New York City have a higher density of retail employment and more chain restaurants, low-income and predominantly black or Latino neighborhoods have a much higher share of unhealthy fast food restaurants.

Chapple and Jacobus (2009) and Kolko (2009) offer the most relevant evidence, both using data from the National Establishment Time-Series (NETS) dataset and the Neighborhood Change Database (NCDB). Chapple and Jacobus use ZIP-code level data on retail businesses and Census tract-level data on neighborhood economic and demographic characteristics for the San Francisco Bay area to examine the link between retail revitalization and neighborhood change. They classify neighborhoods into five categories of relative income change and show with descriptive crosstabs that retail revitalization is most strongly associated with gains for middle-income neighborhoods. They hypothesize that this is, in part, due to their greater ability to attract start-up businesses. While they construct a nuanced definition of neighborhood change, their methods are primarily bivariate and leave out controls for neighborhood characteristics that might influence both retail and residential revitalization.

Kolko (2009) looks at the relationship between employment and gentrification at the neighborhood level. He uses the NETS and NCDB data to measure the impact of employment location on neighborhood gentrification during the 1990s for metropolitan areas across the U.S. He finds that, at the tract level, average household income change is positively correlated both with the change in average pay for nearby jobs and with the start-year average pay for nearby jobs. While Kolko focuses on the impact of overall employment on neighborhood change, we focus on retail presence exclusively and explore the reverse relationship: how well changes in neighborhood income explain changes in local retail presence (as measured by employment density). This reverse relationship is particularly appropriate for analyzing retail employment since retail product markets have smaller geographic scope than the markets for many other goods and services. Retail establishments are more likely to follow population than industries that serve other businesses; industries in which output is intangible and can be delivered electronically; industries in which transport costs are low relative to agglomeration economies; and industries that must locate near natural resources.

3. Data and methodology

We analyze the relationship between neighborhood income and retail presence with three basic estimation strategies, regressing retail measures on household income measures: levels on levels, changes on levels, and changes on changes.[8] All retail metrics are constructed using the NETS database, described below, while all right-hand side variables are taken from GeoLytics' normalized Census data, which presents decennial Census data for geographically consistent boundaries. Specific variable definitions and sources are shown in Table 1; summary statistics for all variables are shown in Table 2. Our sample includes the 58 largest MSAs in the U.S., all those with population over 700,000 as of 1990. The sample was chosen to include urban areas that had sufficiently large and dense populations that they could plausibly support neighborhood-level retail for multiple geographic submarkets within the cities. We define “neighborhood” as ZIP Code Tabulation Area (ZCTA), an approximation of U.S.

[8] Another typical approach to measure the amenity value of a specific attribute is to include that amenity as a right-hand variable in hedonic regressions of housing prices. We do not use that approach because we lack neighborhood measures of several key variables, namely school quality and crime rates, which would lead to omitted variable bias in such estimations.

Table 2
Summary statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Emp/sq mi	13,542	294.56	1,526.62	0.00	56,792.75
Emp/estab	13,542	8.24	20.43	0.00	1,759.25
Emp growth	13,542	1.27	7.52	−33.33	33.33
Income	13,542	51,940	21,351	2,583	206,724
Δ ZCTAinc/MSAinc	6,766	−0.01	0.29	−3.85	5.32
Poor	13,542	0.14	0.35	0.00	1.00
Pop dens	13,542	4,049	14,027	0	808,000
Dist CBD	13,542	19.33	15.38	0.00	238.66
Owner occ	13,542	67.48	20.95	0.00	100.00
Central city	13,542	0.25	0.43	0.00	1.00
BA plus	13,542	24.52	16.70	0.00	100.00
Black	13,542	10.67	19.26	0.00	100.00
Hispanic	13,542	9.83	16.35	0.00	100.00
Kids	13,542	25.30	6.52	0.00	86.45
Old	13,542	11.83	6.56	0.00	100.00
Foreign born	13,542	9.51	11.87	0.00	100.00
Hsg<1940	13,542	17.11	17.82	0.00	100.00

Note: Retail metrics for all retail (44–45). Comparison of retail categories in Table 3.

Postal Service ZIP codes created by the Census Bureau. [9] We chose ZCTAs rather than Census tracts for neighborhood level analysis for two main reasons. First, in urban areas ZCTAs are generally larger than Census tracts and therefore are a more appropriate size for estimating locally oriented retail markets: the median population of a ZCTA in our sample is 13,700, while tracts are designed to have populations of roughly 4000 inhabitants. Second, ZCTAs (or ZIP codes, depending on the data source) have been frequently used to define neighborhood market areas in the existing literature on retail activity, so our choice of geography makes our results more directly comparable to prior analyses. Because ZCTAs are not entirely contiguous with place or MSA boundaries, we assigned ZCTAs entirely to the place and MSA that includes more than half of the ZCTA's population.[10] Therefore our place and MSA boundaries are not exactly consistent with official definitions but are internally consistent, and avoid the quandary of apportioning retail metrics or demographics across ZCTAs that straddle multiple places or MSAs. Because we only have ZCTA-level data on income for two years – 1990 and 2000 – we cannot take full advantage of the annual reporting of retail metrics from the NETS dataset, described below, and simply estimate pooled regressions using retail metrics from the year closest to each Census year (1992 and 2000). Similar pooled regressions using the average of retail metrics over each time period (1992–2000 and 2001–06) produced largely similar results.

The general form of the regression for the pooled cross-sectional analysis is shown below:

$$Empland_{ijt} = \alpha Income_{it} + \beta X_{it} + MSA + Yr2000 + \varepsilon_{ijt}$$

where *i*, *j* and *t* index the ZCTA, retail category and year, respectively. *Empland* is the retail employment density, *Income* represents one or more variables describing ZCTA income, *X* is a vector containing population density and a variety of economic, demographic and locational characteristics of the ZCTA (described in more detail below), *MSA* is a set of fixed effects for MSAs, *Yr2000* is a dummy variable for year (1990 is the base year).

All retail metrics are created from the National Establishment Time Series (NETS) database. The NETS is a longitudinal, establishment-level database covering nearly all businesses in the U.S. It is constructed by Walls and Associates from the Dun & Bradstreet business register. Unlike publicly available government data on employment, the NETS includes no suppression of employment in small industry or geographic cells and provides full street address information for each establishment, which we geocoded in order to generate ZCTA-level counts. In addition, industry is reported at the 6-digit NAICS level, and a headquarters identifier permits classification of establishments according to firm size and structure. Finally, because the NETS are longitudinal, we can measure gross employment changes at the establishment level, not just net employment changes.

The primary retail metric is density of employment, calculated by dividing the number of employees in the ZCTA-industry category by total land area of the ZCTA. As described in Section 2, we believe that employment density most fully captures differences in access to retail, because it reflects both the number of establishments and the number of employees per establishment. To examine whether income also affects establishment size and density, we also calculate establishment density, using the count of establishments per ZCTA-category and total land area of the ZCTA, and the average establishment size, measured as total employment divided by total establishments. These metrics are calculated separately for all establishments, for those in single-establishment ("independent") firms and those belonging to multi-establishment ("chain") firms.[11] Because our main research focus is on retail that primarily serves the residents of the immediate neighborhood (rather than the type of retail that might attract customers from across the city), and because we are interested in quality of life implications, we have chosen to focus on several industry categories that meet these criteria: supermarkets (NAICS 6-digit code 445110), pharmacies and personal care stores (NAICS 3-digit code 446), clothing stores (NAICS 3-digit code 448), food service establishments (NAICS 3-digit code 722), and laundry facilities (NAICS code 812). To provide some context we also look at the total number of establishments in retail (NAICS 2-digit 44–45). Note that our "all retail" measure includes many retail industries that we do not look at separately; it also excludes the food service establishments and laundry facilities industries.

An important concern is how best to model the shape of the relationship between neighborhood income and retail density. If retail purchases are normal goods, then we would expect to see a positive correlation between household income and retail employment density, conditional on other factors. Although we expect a positive slope, we do not have strong priors about the shape of the relationship, so use a number of techniques to explore empirically what functional form best fits the data. The literature on food deserts, financial services and other neighborhood retail activity suggests very low-income neighborhoods are deprived of certain retail and service establishments, relative to middle-and upper-income neighborhoods, which may suggest that there is some minimum income threshold below which retail is unsustainable. It is also possible that very affluent neighborhoods are more sensitive to potential disamenities of commercial activity or better able to block unwanted development, which would result in lower levels of retail at the top of the income distribution. Both of these hypotheses suggest there may be non-

[9] ZCTA's were defined by the Census in 2000 only, not 1990. The 1990 Census data are from GeoLytics' "1990 Long Form in 2000 Boundaries" product. Our ZCTA-level measures therefore reflect consistent boundaries over time, both for Census- and NETS-derived measures.

[10] Some ZCTAs in our sample were split among three places, but in these cases all had greater than 50% in one place and so were assigned to that place. Assignments were based on the MABLE/Geocorr engine, available at http://mcdc2.missouri.edu/websas/geocorr2k.html.

[11] From NETS data we can identify firm ownership in three ways: single-establishment firms (which we call "independent" for brevity), headquarters of multi-establishment firms (briefly called "chains") and non-headquarters establishments of multi-establishment firms. Ideally we would like to exclude any establishments that do not carry out direct retail (interaction with consumers), or perform little retail relative to other corporate functions, such as personnel or marketing. However, it is likely that some headquarters establishments carry out direct consumer activity while many non-headquarters establishments also carry out general corporate functions, so the headquarters distinction may not be that useful. We estimate our equations both for non-headquarters establishments only and for all establishments belonging to chains. The results are not significantly different, so we present results grouping headquarters and non-headquarters collectively as "chain" establishments.

linear or non-monotonic relationships between median household income and retail density. To test for non-linear and potentially non-monotonic relationships between income and retail density, we explored a number of different functional form, including log-linear models (natural logarithm of median household income as the explanatory variable), quadratic income terms, piecewise linear splines and cubic splines. A comparison of these functional forms provides some evidence of non-linearity: the relationship between income and retail employment density is strongest at low values of median household income and declines as income increases, but is consistently positive. However, the magnitude of the change in slope as income increases is very small, so we do not sacrifice much in terms of substance by using a simple log-linear model, which is presented throughout our results.[12]

Median household income is a good proxy for average purchasing power but is of limited use in examining the very low end of the income distribution, where we would most expect to see a threshold effect. In our sample, the fifth percentile of median ZCTA income is approximately $24,000. (Of course the distribution of median *ZCTA* income has a much smaller variance than the distribution of median *household* income.) While this is well below the national median, it is roughly 140% of the federal poverty line, and so will not allow us to identify a threshold at very low incomes. Therefore we cannot rely solely on median income to test the “retail deserts” hypothesis. To explore the low end of the distribution more accurately, we include a dummy variable for high poverty neighborhoods (poverty rate greater than or equal to 20%) in addition to the log of median income. The poverty dummy may also help indicate whether retailers are sensitive not just to the level of neighborhood income but to the distribution of income within a neighborhood. Controlling for median income, a large share of poor households in a neighborhood may act as a deterrent to retailers, perhaps serving as an indicator of neighborhood crime or social problems that we cannot directly observe. The choice of a dummy variable for poverty and the selection of 20% as a threshold follow extensive testing of functional form, similar to testing of income (linear poverty rate, dummy variables with differing cutoffs, linear and cubic splines). There appears to be no relationship between ZCTA poverty rate and retail employment density below 20% poverty, nor does there appear to be much variation in the size of the impact above this threshold, therefore a simple dummy variable is sufficient to model the relationship.[13]

Besides income and poverty, our models include a variety of controls for other factors expected to influence retail density. As described in Section 2, we would expect retail density to increase with residential density, representing larger potential consumer base, therefore we include a measure of population density. We control for distance from the CBD, as a proxy for employment density.[14] In a sense, the analysis tests hypotheses that retail density is determined by the *quantity* of potential consumers (population and employment density) versus the *quality* or type of potential consumers (income and other characteristics). Distance from CBD should also be correlated with travel costs and accessibility, important cost factors. To control for differences in consumer preferences, we control for a variety of demographic characteristics, namely percent of population with college or graduate degrees, share non-Hispanic black, share Hispanic, share under 18, share over 65, and share foreign born. As noted earlier, if retail activity brings some disamenities, such as noise or congestion, then residents may try to block retailers from entering a neighborhood. On the assumption that homeowners wield disproportionate power relative to renters in local land use decisions (see Fischel, 2001), we include the share of owner-occupied housing in the ZCTA. Finally, we include the share of housing stock built before 1940; prior research has suggested the age of housing is an indicator of residential gentrification (Rosenthal, 2008; Brueckner and Rosenthal, 2009), which may be accompanied by commercial growth or upgrading.

It is possible that households who choose to live in urban and suburban areas have different preferences over the mix of uses in their environment, with suburban households preferring greater separation of residential and commercial uses. Therefore, in some models, we interact income with other measures, including a dummy variable indicating whether the ZCTA is located in one of the central cities within the MSA, the distance from CBD, the share of the MSA that is mixed residential and commercial use, the overall employment density gradient in the MSA, and the MSA population size.[15] As shown in Appendix A, few of these interactions produced results that are statistically different from zero, and even those with statistical significance were of very small magnitude.

As discussed previously, the income elasticity of demand will differ for various retail goods and services. Similarly, some categories of retail or establishment types may be viewed by neighborhood residents as amenities while others are disamenities. By estimating separate regressions for several different retail categories, we can begin to tease out these distinctions. We might expect that density of establishments selling “necessity” goods and services, such as grocery stores, drugstores, and laundry facilities, will be less sensitive to income: the income elasticity of demand for these goods is presumably less than one, so expenditures would increase with income but at a declining rate. Conversely, goods such as clothing and restaurants may represent “luxury” goods, with high income elasticity of demand. Even within these categories, some establishments such as fast food restaurants or convenience stores may represent “inferior goods” with negative income elasticities. Similarly, the income elasticity for firm type may vary, although it is not immediately obvious in what direction. Some large national (or international) chains are clearly in the luxury market (Barney's clothing or Wolfgang Puck's restaurant chains) while others are more mass-market (Payless Shoes or McDonald's). Therefore we separate establishments based on firm type – chain versus independent – for all retail categories examined.

Although we use employment density as the primary measure of retail access, we also calculate average establishment size to test for differences in market structure by neighborhood income. That is, a network of a few large stores or many small stores could yield the same overall employment density, but provide differential access to consumers. A priori it is unclear whether households with different incomes would prefer different retail networks. Anecdotal evidence suggests that higher-income households may have preferences for small, locally owned stores with more distinctive “character” than large, corporate stores (Zukin et al., 2009). Smaller stores may also offer a higher level of customer service, which high income households might prefer. And many discount stores targeting lower-income consumers tend to use a large store format, or may

[12] Results of functional form tests are available from the authors upon request.

[13] The correlation coefficient between the high poverty dummy and log median income is 0.61, so inclusion of both variables does not raise concerns about excess collinearity.

[14] To identify the CBD, we calculate total employment density in each ZCTA using the NETS data and land area from the Census. The ZCTA within the MSA's primary central city with the highest employment density is designated as the CBD. We then calculate the pairwise distance between each ZCTA and the CBD using latitude and longitude coordinates from the Census for the centroid of each ZCTA. Even if our MSAs are not perfectly monocentric, they all have declining employment density gradients with distance from CBD, so as a first approximation of employment density, this seems reasonable. We run robustness checks stratifying the sample by MSA density gradient, with largely similar results, as shown in Appendix A.

[15] We obtain overall employment density gradients for each MSA by estimating regressions of total employment density (in all industries) against distance from CBD. The coefficient on distance from CBD is then used in the interaction with ZCTA income. For the mixed-use share of the MSA, we calculate the ratio of total employment to population for each ZCTA. ZCTAs with job-population ratios between 0.25 and 0.8 (approximately the 25th and 75th percentiles of the whole sample) as designated as mixed use, and the share of land area within the MSA that is contained by mixed-use ZCTAs is our MSA-level indicator.

prefer lower-rent locations because of their need for large spaces. Alternatively, if low-income households have less access to cars, they may be more dependent on stores within closer proximity, suggesting a higher density of small establishments in low income neighborhoods. The theoretical predictions are ambiguous, but can be tested empirically with our data, by estimating the same basic model for employment density but using average establishment size (employees per establishment) as the dependent variable. We also include results on establishment density in Appendix Table B (in some cases but not all, the relationship between income and establishment density can be directly inferred from coefficients on employment density and establishment size).

Besides examining the cross-sectional relationship between income and retail, we regress retail employment *changes* on neighborhood income levels and changes in order to understand how the retail landscape might change as neighborhoods upgrade economically. We estimate models of the change in retail density first as a function of initial income level and then as a function of simultaneous change in income. The reasons to estimate both two types of models is that is unclear to what extent retail growth is forward-looking – firms make location, hiring and investment decisions for the future based on current observable neighborhood characteristics – and to what extent firms can make simultaneous adjustments to changing neighborhood conditions. Particularly for fine levels of geography, retail firms (like researchers) have limited access to reliable data on income and other consumer attributes in between census years; and even with perfect data, retail firms may not make investment decisions until neighborhood change proves to be persistent rather than a temporary fluctuation. The length of time required for new construction or decisions about long-term leases for commercial space also suggest that retail markets may be "sticky", so future growth may rely on lagged neighborhood characteristics. However, if retailers have access to more recent data on neighborhood change and are able to make quick assessments and adjustments, then the contemporaneous relationship between retail employment changes and neighborhood changes may be more appropriate. For the changes-on-levels models, we again pool both time periods, looking at retail changes during the 1990s and 2000s as a function of prior income. For the changes-on-changes models, we can only use the first time period, because ZCTA income is not available after 2000. The general form of the two-period pooled regression for the changes-on-levels analysis is shown below:

$$\Delta Employment_{ijt,t-1} = \alpha Inc_{it-1} + \beta X'_{it-1} + MSA + Yr2000 + \varepsilon_{ijt}$$

where *i, j* and *t* index ZCTAs, retail categories and years, respectively. $\Delta Employment$ is the average annual employment growth rate, *Inc* is the log of median household income in the baseline year, *X* is a vector of demographic and economic characteristics the baseline year, MSA is a set of fixed effects for MSAs and Yr2000 is a dummy variable for the second period. The first period of retail change is calculated between 1992 (the first year data are available) and 2000, the second period of retail change is 2000–2006 (the latest year available). Baseline years for income and other neighborhood characteristics are 1990 and 2000, respectively.

Employment growth rate is calculated using a standard measure:

$$g_{ijt} = \frac{\frac{(Emp_{ijt} - Emp_{ijt-1})}{0.5*(Emp_{ijt} + Emp_{ijt-1})}}{t-(t-1)}$$

in which Emp_{ijt} is the number of employees in ZCTA i in industry j in time t. As discussed in several previous papers that have used this measure, this growth rate provides a symmetric growth rate that is useful for estimation and, by using a two-year average employment level rather than a single year of employment in the denominator, reduces potential measurement error associated with large single-year deviations from average employment (see Davis et al., 1996; Haltiwanger et al., 2010 for more discussion). Because the number of years for which we have data on employment varies by period (1992–2000, 2000–2006), we annualize the measure by dividing by the number of years. Calculations were also made of the compound annual growth rate using beginning and ending year employment; regressions using both growth rates are very similar, so we followed standard practice by using the measure described above. Note that the growth rate uses net change in employment.

In addition to the changes-on-levels models, we estimate a changes-on-changes model: change in retail employment as a function of changes in neighborhood income (and other characteristics). Conceptually the changes-on-changes model is similar to the levels-on-levels model with the addition of ZCTA fixed effects. The dependent variable is the annual employment growth rate described above, while the key independent variable is a measure of relative change in income between 1990 and 2000. The relative change measure is calculated as follows:

$$\Delta ZCTAInc = \frac{Inc_{ikt}}{Inc_{kt}} - \frac{Inc_{ikt-1}}{Inc_{kt-1}}$$

where Inc_{ikt} is the median household income in ZCTA i in MSA k in year t, Inc_{kt} is median household income in MSA *k* in year *t*. Essentially this measure indicates the change in ratio of ZCTA household income to MSA household income between 1990 and 2000. We use a relative income change measure to indicate upgrading of the neighborhood, relative to the surrounding MSA; this should capture whether a ZCTA is becoming more affluent (thus a more desirable location for retailers), compared to other ZCTAs within the MSA. Intuitively, if a neighborhood's absolute income rises but at a similar or slower pace than surrounding neighborhoods, it is less likely to attract additional retailers than if a neighborhood which experiences smaller absolute gains (or even losses) but whose income growth outpaces other neighborhoods within the MSA. Several recent papers on gentrification or neighborhood change have used relative income gain (or loss) measures (see Ellen and O'Regan, 2008; Bostic and Martin, 2003; McKinnish et al., 2010). The base regression models were also estimated using several other income change measures, including a simple log of change in median household income, percentage change in income, and difference between percentage change of ZCTA income and MSA income. All regressions also include MSA fixed effects, so results are nearly identical in sign and significance regardless of income measure. Besides the change in income, right hand side variables include prior level of income and changes in the same demographic variables described in the cross sectional model (except distance to CBD and central city status, which do not change over time).

All regressions include metropolitan area fixed effects and robust standard errors clustered by Census place, to account for any spatial autocorrelation by political jurisdiction (such as city-wide zoning rules or business start-up fees). All regressions are weighted by ZCTA population, due to large variation in ZCTA size (this reduces distortion of results by sparsely populated ZCTAs on the urban fringe).

4. Results

4.1. Descriptive statistics

Fig. 1 shows the relationship between neighborhood retail employment density and distance from the CBD, estimated with kernel-weighted local polynomial smoothing to allow for variation in the shape of the relationship at different distance bands. As predicted by the monocentric city model, all retail employment categories have negative density gradients moving away from the CBD, but the rates

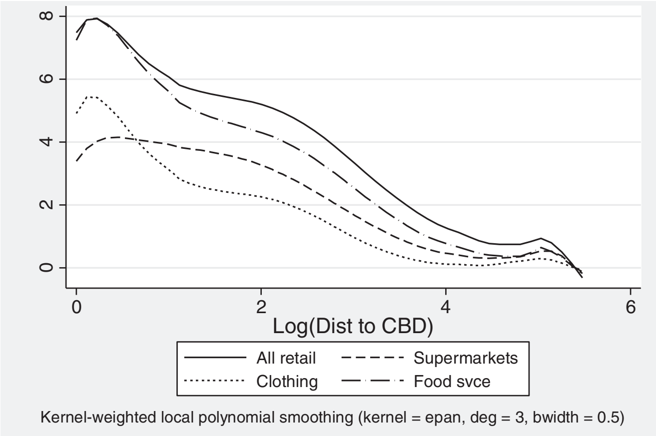

Fig. 1. Retail employment density gradient.

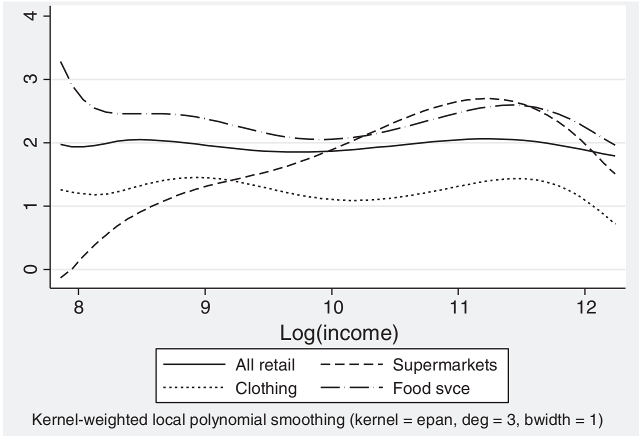

Fig. 3. Retail establishment size and income.

of decline differ by category. Food service and retail overall have the steepest slopes, consistent with food service being oriented towards high levels of general employment in the CBD or possibly "destination" restaurants that draw consumers from across the metro area. It is also plausible that residents near the CBD live in smaller housing units and therefore are more likely to eat out. In contrast, supermarkets have the flattest density gradients, consistent with similar demand in all residential neighborhoods for necessity items.

Plotting the relationship between retail employment density and neighborhood income (Fig. 2) shows a less obvious pattern. All categories except supermarkets show an initially declining relationship between income and employment density, then a gradual flattening out, while supermarket employment density initially increases with income, then declines gradually. The steepness of the slopes varies by retail category. However the raw correlations may be misleading because they do not control for confounding factors, such as underlying population density or intra-metropolitan location. Additionally, very few ZCTAs fall into the lowest income range (median income up to $24,000 or logged values below 10), so it is unclear how robust the estimates are for low income ranges. Fig. 3 shows the average establishment size increasing with income for supermarkets, with indeterminate slopes for other categories.

Table 3 shows the mean for all retail metrics across categories and by firm type (chain versus independent). For comparison purposes, we also include the mean for all industries. Of our retail categories, food service has by far the highest density of employment and establishments, with an average of 174 employees and 10 establishments per square mile. Looking at the categories broken out by firm type, independents dominate in establishment density for all categories, but chains dominate in employment density for most (laundry and food service are the only categories with higher employment density in independent establishments) – because chain establishments have more employees, on average, than independent establishments. The ratio of independent to chain employment varies considerably across categories, however. Looking at the average size of establishments, we find that overall retail establishments are quite small, around 8.25 employees, smaller than average size for all industries, and size varies widely by category. Notably, the average size for supermarkets is just under 25 employees, although independents are much smaller (7.65) while chains are much larger (45.87). This suggests that the NAICS category for supermarkets captures many small stores, such as corner bodegas, as well as full service supermarkets. The average size of clothing stores is perhaps surprising; these appear smaller than would be expected of stores in typical suburban malls.[16] The last column of Table 3 compares employment growth by category. Employment in the retail sector overall grew somewhat more slowly than employment in all industries. Supermarkets had much less employment growth than the retail sector overall, laundry slightly less growth, drugstores and clothing slightly more and restaurants approximately 2.5 times the growth.

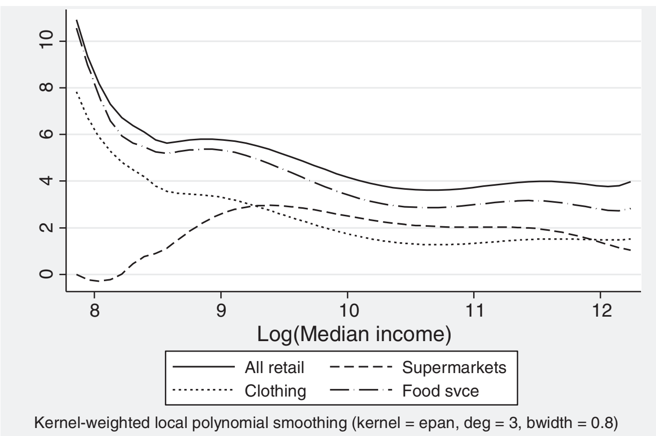

Fig. 2. Retail employment density and income.

4.2. Results of cross-sectional analysis: retail overall

The results in Table 4 show that there is a positive relationship between neighborhood income and employment density in the retail sector overall, controlling for neighborhood characteristics, while high poverty neighborhoods have significantly lower retail employment density. A simple bivariate regression, including only year and MSA fixed effects, indicates a significant negative relationship between median household income and employment density, similar to the one shown in Fig. 2. This likely reflects the spatial distribution of income across MSAs: higher income households tend to live farther from the CBD in lower-density neighborhoods, both of which should be associated with lower retail density. Once we control for population density and distance to CBD in column 2, the coefficient on income becomes positive and significant. In order to compare magnitudes of coefficients for the three variables, we estimate standardized betas (with variables normalized to mean zero and standard deviation of one), the coefficient on population density has largest magnitude, 0.72 compared to 0.09 for income and 0.19 for distance

[16] The data on establishment size does not distinguish between full-time and part-time employees, so should be read as total employees on the payroll, not FTEs.

Table 3
Comparison of retail metrics by category.

	Emp/sq mi	Emp share by firm type	Emp/sq mi	Emp share by firm type	Emp/estab	Emp growth
All industries	5660.44		304.13		13.15	1.52
Independent	2150.32	38.0%	248.94	81.9%	6.96	
Chain	3510.13	62.0%	55.19	18.1%	43.85	
All retail	299.89		34.47		8.25	1.27
Independent	133.79	44.6%	27.90	81.0%	4.79	
Chain	166.10	55.4%	6.56	19.0%	20.84	
Supermarkets	33.79		2.15		24.70	0.56
Independent	12.01	35.5%	1.83	85.3%	7.65	
Chain	21.78	64.5%	0.32	14.7%	45.87	
Drugstores	14.59		1.43		7.88	1.80
Independent	5.81	39.8%	0.93	65.2%	4.27	
Chain	8.79	60.2%	0.50	34.8%	10.99	
Clothing	37.00		4.45		4.56	1.78
Independent	14.00	37.8%	3.21	72.1%	2.59	
Chain	23.00	62.2%	1.24	27.9%	6.93	
Food svce	174.04		10.14		13.48	3.07
Independent	110.09	63.3%	8.45	83.3%	10.40	
Chain	63.95	36.7%	1.69	16.7%	21.91	
Laundry	7.50		1.60		3.53	1.06
Independent	6.05	80.7%	1.47	91.5%	3.16	
Chain	1.45	19.3%	0.14	8.5%	2.96	

Notes: All retail includes NAICS 44–45, does not include food service or laundry. Table shows mean values for all ZCTA-year observations (n = 13,542). Employment density, establishment density, and establishment size are shown for 1992 and 2000. Employment growth is calculated as the annualized average employment change in each period, 1992–2000 and 2000–2006.

to CBD (standardized betas not shown but available upon request). The coefficient on population density also has the strongest statistical significance and in bivariate regressions yields the highest R-squared. The coefficient on distance from CBD is negative and significant, as expected. Overall these results are consistent with predictions that retail density is quite sensitive to density of employment and population, as well as to income.

In Column 3 we add a set of standard demographic and economic characteristics, which reduces the magnitude of the income coefficient slightly relative to Column 2, but still yields a positive and strongly significant result. Most controls perform as expected. The negative coefficient on share of owner-occupied housing is consistent with an interpretation that homeowners tend to resist commercial development. Retail density declines with share of black and Hispanic

Table 4
How does retail density vary by neighborhood income?

Dep var	Ln(Emp/sq mi)				Ln(Emp/estab)
	(1)	(2)	(3)	(4)	(5)
Log(income)	−0.957***	0.468***	0.385***	0.299***	0.217***
	(0.102)	(0.059)	(0.092)	(0.099)	(0.042)
Poor				−0.093**	−0.070***
				(0.042)	(0.019)
Log(Pop dens)		0.829***	0.773***	0.770***	0.036***
		(0.034)	(0.034)	(0.035)	(0.011)
Log(Dist CBD)		−0.395***	−0.418***	−0.424***	−0.092***
		(0.061)	(0.053)	(0.054)	(0.017)
Owner occ			−0.014***	−0.014***	−0.006***
			(0.002)	(0.002)	(0.001)
Central city			−0.092**	−0.090**	−0.027
			(0.040)	(0.040)	(0.018)
BA plus			0.000	0.001	−0.002*
			(0.001)	(0.002)	(0.001)
Black			−0.006***	−0.006***	−0.002***
			(0.001)	(0.001)	(0.000)
Hispanic			−0.003**	−0.002**	0.000
			(0.001)	(0.001)	(0.001)
Kids			−0.022***	−0.020***	−0.005**
			(0.003)	(0.004)	(0.002)
Old			0.016***	0.016***	0.002
Foreign born			0.001	0.001	−0.001
			(0.001)	(0.001)	(0.001)
Hsg < 1940			−0.011***	−0.011***	−0.010***
			(0.002)	(0.002)	(0.001)
Fixed effects	Year & MSA	Year & MSA	Year & MSA	Year & MSA	Year & MSA
Observations	13,542	13,542	13,542	13,542	13,542
R-squared	0.249	0.736	0.773	0.774	0.248

Robust standard errors, clustered by place, in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5
Does relationship between income and retail employment vary by retail industry?

Dep var	Ln(Emp/sq mi)					
Industry	All retail	Supermarkets	Drugstores	Clothing	Food svce	Laundry
	(1)	(2)	(3)	(4)	(5)	(6)
Log(income)	0.299***	−0.124	−0.096	0.162	0.158	0.076
	(0.099)	(0.107)	(0.104)	(0.145)	(0.129)	(0.084)
Poor	−0.093**	−0.142***	−0.156***	−0.021	−0.079*	−0.068**
	(0.042)	(0.044)	(0.045)	(0.058)	(0.042)	(0.034)
Log(Pop dens)	0.770***	0.640***	0.490***	0.409***	0.681***	0.382***
	(0.035)	(0.031)	(0.023)	(0.026)	(0.032)	(0.020)
Log(Dist CBD)	−0.424***	−0.267***	−0.289***	−0.359***	−0.484***	−0.195***
	(0.054)	(0.045)	(0.036)	(0.052)	(0.055)	(0.037)
Owner occ	−0.014***	−0.007***	−0.008***	−0.015***	−0.014***	−0.009***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
Central city	−0.090**	0.022	−0.024	−0.068	−0.022	−0.059*
	(0.040)	(0.040)	(0.035)	(0.061)	(0.039)	(0.035)
BA plus	0.001	0.004**	0.002*	0.010***	0.005***	0.006***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Black	−0.006***	−0.004***	−0.006***	−0.002	−0.008***	0.003***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Hispanic	−0.002**	0.001	−0.005***	−0.001	−0.001	−0.002*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Kids	−0.020***	−0.005	−0.017***	−0.026***	−0.048***	−0.018***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)
Old	0.016***	0.017***	0.019***	0.020***	0.007	0.007***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)
Foreign born	0.001	0.003	0.005***	0.008***	−0.004**	0.005***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Hsg<1940	−0.011***	−0.003**	0.002*	−0.004*	−0.008***	0.007***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Fixed effects	Yr & MSA	Yr & MSA	Yr & MSA	Yr & MSA	Yr & MSA	Yr & MSA
Observations	13,542	13,542	13,542	13,542	13,542	13,542
R-squared	0.774	0.665	0.703	0.613	0.766	0.752

Robust standard errors, clustered by place, in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

population, consistent with some prior research that shows that minority populations generally have less access to retail. To frame the magnitude of the income coefficient, we use the coefficients from Column 4 to calculate the predicted employment density for neighborhoods with household incomes of $25,000 and $75,000 (assuming mean values for all other variables, 1992 for year and using Akron, Ohio, as the reference MSA). The lower-income neighborhood is predicted to have 80 employees per square mile, compared to 122 employees per square mile in the higher income neighborhood.

Because we are particularly interested in ZCTAs at the bottom of the income distribution, in Column 4 we add a dummy variable for high-poverty neighborhoods. The coefficient is negative and significant, indicating that even controlling for median household income, high poverty neighborhoods have less retail employment, consistent with a hypothesis of “retail deserts”. Inclusion of the poverty dummy decreases the magnitude of the coefficient on median income somewhat, but it is still strongly significant. Robustness checks on the functional form of both income and poverty, including different cutoff points for the poverty dummy, are generally consistent with the results that high rates of neighborhood poverty are associated with lower retail density.

Besides examining retail employment density, a general measure of retail quantity, we test whether the size of retail establishments differs by neighborhood income or poverty. The last column in Table 4 suggests that establishment size is increasing in median income and is significantly lower in high poverty neighborhoods, even controlling for income. The positive relationship between income and establishment size would be consistent with higher income neighborhoods offering greater demand for a wide range of products and services within a single store, or with higher fixed costs (such as rent or obstacles to development) causing retailers to operate larger stores. The negative coefficient on poverty is consistent with anecdotal evidence that low-income neighborhoods are dominated by small, primarily mom-and-pop stores.

4.3. Cross-sectional results by retail category

Next we examine the relationships between income, poverty and employment density for a variety of retail categories (Table 5). The results suggest that high poverty neighborhoods have lower employment density for retail overall and four of five categories examined, but that there is not a statistically significant association between median income and employment for several types of basic retail. As discussed earlier, the retail sector as a whole includes several sub-categories not examined separately in our analysis, and excludes food service and laundry. The coefficient on “All retail” (Column 1) reflects relatively large, statistically significant positive correlations between income and employment density on several of these other sub-categories, notably department stores (NAICS 4521), automobile dealers (4411) and automotive parts (4413), building materials (4441) and home furnishings (4422).[17] Establishments in these categories are likely to serve a larger market area than the immediate neighborhood, and so are less relevant for the current analysis. We hypothesize that although these categories do not depend primarily on neighborhood residents, when choosing locations within a city or MSA, they prefer to locate in higher-income areas. That is, high income neighborhoods will contain

[17] To check which retail sub-categories were driving the “All retail” coefficient, we estimated the model from Table 5 on employment density for all 4-digit NAICS groups within the retail sector. Results available from authors upon request.

Table 6
Relationship between income and employment density, by firm type.

Dependent var	Ln(Emp/sq mi)			Ln(Emp/estab)
Firm type	All firms	Independents	Chains	All firms
All retail				
Log(income)	0.299***	0.080	0.422***	0.217***
	(0.099)	(0.074)	(0.158)	(0.042)
Poor	−0.093**	−0.002	−0.212***	−0.070***
	(0.042)	(0.035)	(0.059)	(0.019)
Supermarkets				
Log(income)	−0.124	−0.431***	0.179	0.459***
	(0.107)	(0.096)	(0.165)	(0.097)
Poor	−0.142***	0.130***	−0.383***	−0.211***
	(0.044)	(0.039)	(0.080)	(0.040)
Drugstores				
Log(income)	−0.096	−0.330***	0.135	0.358***
	(0.104)	(0.091)	(0.150)	(0.069)
Poor	−0.156***	−0.032	−0.194***	−0.119***
	(0.045)	(0.047)	(0.054)	(0.035)
Clothing				
Log(income)	0.162	0.074	0.052	0.219***
	(0.145)	(0.112)	(0.187)	(0.071)
Poor	−0.021	0.033	−0.107	−0.023
	(0.058)	(0.049)	(0.071)	(0.031)
Food svce				
Log(income)	0.158	0.000	0.006	0.288***
	(0.129)	(0.116)	(0.150)	(0.056)
Poor	−0.079*	−0.041	−0.139**	−0.041*
	(0.042)	(0.037)	(0.058)	(0.021)
Laundry				
Log(income)	0.076	0.035	0.093	0.324***
	(0.084)	(0.078)	(0.086)	(0.056)
Poor	−0.068**	−0.076**	−0.023	0.009
	(0.034)	(0.031)	(0.041)	(0.028)

All regressions include controls for population density, distance to CBD, owner-occupied housing share, central city dummy, share with BA or graduate degree, share non-Hispanic black, share Hispanic, share under 18, share 65 and older, share foreign-born, share housing pre 1940, year and MSA fixed effects. N = 13,542. Robust standard errors, clustered by place, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

a larger share of city- or regional-serving retail. In contrast to the generally insignificant coefficients on median income, the coefficients on the high poverty indicator are negative and significant for retail overall and for four categories: supermarkets, drugstores, food service (significant at 10% level) and laundry (Columns 1–3, 5 and 6). Only clothing shows no statistically significant difference in employment density between high and low-moderate poverty neighborhoods. It is notable that the coefficients on other controls, particularly population density, distance from CBD and share of owner-occupancy, are all consistent in sign and significance, although magnitude varies by category. That suggests that retail employment for all categories reflects size of potential market and possible NIMBYism of homeowners, but that income elasticity of demand for (or amenity value of) products and services varies.

Table 6 explores whether the relationship between our two income metrics and employment density varies by retail category and firm structure, and whether income is related to establishment size. The first three columns present the coefficients on median income and poverty for employment density by firm status (all firms, independents and chains). The last column shows the coefficients on income and poverty for establishment size. For the retail sector as a whole, income is positively associated with total employment and chain employment, but has no relationship with employment in independent establishments. Similarly, high poverty ZCTAs have lower overall retail employment, a result driven by decreased employment in chain establishments, but no difference in independent employment. As shown in Column 4, higher income is associated with increased establishment size, while high poverty is associated with smaller establishments. For the retail sector overall, higher employment density does not represent a larger number of establishments: rather, the additional employment is absorbed into larger establishments of all firm types (results on establishment density shown in Appendix Table B). Similarly, while poor ZCTAs have lower overall retail employment, because establishments are smaller, there is no significant reduction in the density of total establishments. High poverty is associated with fewer chain establishments, though.

The literature on "food deserts" has focused particularly on income disparities in two retail categories, namely that poor neighborhoods lack access to supermarkets and have relatively more fast food restaurants. The results on these two categories provide some confirmation of these hypotheses, but also illustrate how the choice of metrics may affect the conclusion. There is no statistically significant association between median income and supermarket employment for all firms and chain stores, while employment in independent supermarkets decreases with rising income. However, high poverty ZCTAs have lower employment in supermarkets for all firms and chains, consistent with the "food desert" hypothesis, but higher employment in independent supermarkets. As shown in Table 3, independent supermarkets are a relatively small share of the retail category, so the increase in independent employment is not enough to offset the decrease in chains. The coefficients on employees per establishment (Column 4) match the pattern of retail overall: establishment size rises with median income and is lower for high poverty ZCTAs. Combining the results on employment density and size produces somewhat unexpected results if we look at establishment density: increased income is associated with *lower* establishment density (both types of firms and aggregate) and high poverty is associated with *increased* establishment density for all firm types and independent supermarkets (Appendix Table B, Columns 1 and 2). High poverty ZCTAs do have lower establishment density of chain supermarkets, but with this exception, the results on establishment density are contrary to the "food deserts" hypothesis. Collectively, the results on employment density, establishment density and size suggest there are notable differences between poor and non-poor neighborhoods in supermarket size and firm structure, but these differences may not be well captured by comparing counts of establishments, as several previous studies have done. Employment density, because it accounts for size differences, may be a better metric of supermarket access.

Turning to the other retail category discussed in the food deserts literature, we find no significant relationship between median income and food service employment, either in the aggregate or broken out by firm type (Columns 1–3). Income is positively associated with size of food service establishments (Column 4), implying a negative relationship between income and establishment density, as confirmed in Appendix Table B. Because eating in restaurants is generally a more expensive substitute to eating at home, it is somewhat surprising that higher neighborhood income does not translate into greater density of food service, although perhaps restaurants are perceived as undesirable neighbors because of their potential to attract noise, traffic or odors. High poverty ZCTAs have a lower density of food service employment, in the aggregate and for chains, and smaller establishments. Poor ZCTAs also have a significantly lower density of food service establishments belonging to chains (Appendix Table B), again somewhat unexpected given the claims that poor neighborhoods are dominated by fast food restaurants.

Results on the remaining three categories confirm that the dynamics between income and retail employment vary by type of firm, as well as product and service. For drugstores, income is negatively associated with employment at independent establishments and positively associated with establishment size. High poverty ZCTAs have significantly less drugstore employment, due to reduced chain employment, and smaller average establishments. Neither income nor poverty are significant predictors of employment in clothing stores for any firm type, although income is positively associated with larger stores. Similarly, income is not significantly associated with employment at laundry facilities, but is associated with larger establishments. High poverty ZCTAs have lower employment density in laundry facilities, primarily in independent establishments (Columns 1–2), which according to Table 3 make up the majority of the category.

Across all retail categories, income is a more robust predictor of establishment size than of employment density (positive and significant in all categories). It is not possible to assess whether the larger size associated with high income neighborhoods indicates a higher prevalence of big-box retailers, but the results are not consistent with a stated preference by high-income households for small, locally owned stores. The results on the relationship between poverty and overall employment density are also quite robust across categories, although the association between poverty and employment by firm type varies. For three categories – supermarkets, drugstores and food service – there is evidence that employment in chain establishments (and the number of establishments) is lower in high-poverty neighborhoods.

4.4. Dynamic regressions

Table 7 provides some evidence that initial neighborhood income is positively correlated with growth in retail employment, although

Table 7
Relationship between retail employment growth and initial neighborhood income.

Dep var	Avg annual retail employment change			
	(1)	(2)	(3)	(4)
Log(income)	2.099***	1.750***	−0.570	−1.395
	(0.328)	(0.343)	(0.712)	(2.042)
Poverty rate	0.006	0.025	−0.030*	0.022
	(0.016)	(0.018)	(0.017)	(0.050)
Log(Pop dens)		−0.576***	−0.594***	−1.552***
		(0.089)	(0.099)	(0.407)
Log(Dist CBD)		0.038	−0.307*	
		(0.172)	(0.168)	
Owner occ			0.010	−0.002
			(0.007)	(0.026)
Central city			0.117	
			(0.178)	
BA plus			0.017*	−0.050*
			(0.010)	(0.027)
Black			−0.013***	−0.074**
			(0.004)	(0.036)
Hispanic			−0.005	−0.029
			(0.007)	(0.037)
Kids			0.057***	0.027
			(0.019)	(0.052)
Old			−0.096***	−0.078
			(0.014)	(0.059)
Foreign born			0.003	0.005
			(0.008)	(0.048)
Hsg<1940			−0.006	−0.062**
			(0.004)	(0.031)
Year = 2000	−1.346***	−1.347***	−1.489***	−1.180***
	(0.260)	(0.256)	(0.234)	(0.392)
Fixed effects	MSA	MSA	MSA	ZCTA
Observations	13,541	13,541	13,541	13,541
R-squared	0.078	0.096	0.109	0.573

Employment growth is calculated as the annualized average employment change during each period, 1992–2000 and 2000–2006. Robust standard errors, clustered by place, in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8
Relationship between retail employment change and income change.

Dependent var	Avg annual emp change		
	(1)	(2)	(3)
Δ ZCTA inc/MSA inc	2.308***	1.668	3.578***
	(0.730)	(1.062)	(1.297)
Δ poverty	−0.015	−0.048	−0.112**
	(0.039)	(0.044)	(0.047)
Log(income)			2.345***
			(0.643)
Poverty			−0.054**
			(0.024)
Δ Pop		0.069***	0.052***
		(0.013)	(0.012)
Δ Owner occ		0.012	−0.006
		(0.021)	(0.021)
Δ BA plus		0.046*	−0.016
		(0.025)	(0.027)
Δ Black		0.008	−0.009
		(0.014)	(0.013)
Δ Hispanic		0.012	0.014
		(0.020)	(0.019)
Δ Kids		0.044	−0.019
		(0.048)	(0.050)
Δ Old		0.027	−0.040
		(0.035)	(0.035)
Δ Foreign born		0.011	0.020
		(0.021)	(0.020)
Δ Hsg<1940		0.045*	0.018
		(0.024)	(0.021)
Fixed effects	MSA	MSA	MSA
Observations	6748	6744	6744
R-squared	0.11	0.135	0.183

Employment growth is calculated as the annualized average employment change. Robust standard errors, clustered by place, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

results are not as robust as the cross-sectional regressions. The simplest regression, pooling both time periods, indicates that initial income is positively correlated with subsequent retail employment change, but there is no significant relationship between initial poverty rate and employment growth (Column 1). Both of these results hold when we add controls for initial population density and distance to CBD (Column 2). However, when we add the full set of demographic and economic controls the coefficient on income becomes negative and statistically insignificant, while the coefficient on poverty is negative and marginally significant (Column 3). In Column 4, we add ZCTA fixed effects as an additional robustness check; coefficients on neither income nor poverty rate are significantly different from zero. In general, the results on retail employment change suggest that employment growth in relatively small geographic areas may be somewhat idiosyncratic and is not easily predicted by initial neighborhood characteristics.[18]

Results from the final set of dynamic models, shown in Table 8, provide some evidence that neighborhoods that experience income gains relative to the MSA see larger net growth in retail employment. The first column estimates the relationship between retail employment growth and changes in relative income (the ratio of ZCTA to MSA income) and poverty rates, controlling only for MSA fixed effects. The coefficient on relative income change is positive and significant, the coefficient on poverty is negative but statistically not different from zero. Once we add controls for changes in population and demographics, coefficients on changes in both income and poverty become insignificant, although still with the expected signs (Column 2). The final column adds controls for initial levels of income and poverty: coefficients on both level and change in income are positive and statistically significant, while coefficients on level and change in poverty are negative in significant. This suggests that ZCTAs that were initially higher income and gained income, relative to the MSA, attracted larger gains in retail employment. ZCTAs with high initial poverty rates which became still poorer lost retail employment rapidly. Not surprisingly, neighborhoods that experience population growth also have larger gains in retail employment, but changes in most demographic variables are not statistically significant and the overall explanatory power of the models is quite low (R-squared values under 0.20 for all models).

[18] Similar regressions were estimated for changes in employment as a function of baseline neighborhood income for all retail categories; results are summarized in Appendix Table C(control variables are included but not shown). The results for most categories are similar to those for the retail sector overall.

5. Conclusions and policy implications

The urban economics literature on neighborhood amenities has focused mainly on public goods, such as schools, parks and safety. Private goods, such as retail and basic household services, can also have important quality of life implications. Except for limited and largely anecdotal evidence on the dearth of some types of retail (grocery stores, banks, non-fast food restaurants) in poor neighborhoods, we have relatively little evidence on whether retail presence within urban areas varies by neighborhood income. In this paper, we have offered a first analysis of the relationship between income and retail density for a variety of retail categories, firm types and sizes.

Our results suggest that retail patterns do vary by neighborhood income. High-poverty neighborhoods have lower retail employment density for retail overall and several types of retail, including supermarkets, drugstores, food service and laundry. For most of these categories, the lower employment density is driven by reduced employment in chain establishments. Median household income is associated with increased retail employment for retail as a whole, primarily in chain establishments, but income is not a significant predictor of employment density for most retail categories. Income is positively associated with establishment size across retail types, while high-poverty status is associated with smaller establishments for several types. The results on supermarkets indicate that whether poor neighborhoods are considered "food deserts" depends in part employment density, smaller establishments and fewer chain supermarkets. Results also suggest that retail density increases with population density and decreases with distance to the CBD, consistent with theoretical models, but decreases with share of owner-occupied housing. The latter result may indicate a NIMBY response of homeowners to commercial uses they perceive as undesirable.

Most of the categories we examined are basic necessities – food, drugstores, and laundry – which might be expected to have a relatively low income elasticity of demand. But it is perhaps somewhat surprising that employment density in two of the categories that might represent more discretionary spending, clothing and restaurants, are also relatively uncorrelated with neighborhood differences in income. One problem with categorizing establishments based solely on NAICS code is that these codes obscure wide variation in the quality and range of goods and services. For instance, we would expect employment in upscale restaurants to be quite sensitive to income, and employment in coffee shops and delis less so.

We have limited information on some components of store costs that could be correlated with income, and may introduce bias into our results. Examples include crime rates, which affect security and insurance costs; labor costs, including employee training and turnover; transportation access and costs; and suitability of existing structures for commercial uses or availability of land for new development. Local policies such as zoning or tax incentives for businesses may also affect the incentive or ability to operate retail in neighborhoods of differing income. The direction of potential bias from omitting these variables is not immediately obvious, however. For instance, direct labor costs (wages) may be positively correlated with income and negatively correlated with employment density, introducing a negative bias on the income coefficient. By contrast, crime rates should be negatively correlated with both income and employment density, introducing a positive bias on income. Obtaining accurate data on such costs or policies at the neighborhood level is infeasible for a large national study, but might be possible for a single MSA.

Finally, our results cannot directly address a key welfare concern: is there an optimal level of retail, and do low-income neighborhoods fall below that level? However, the findings do raise a number of related questions that invite further research. First, why is there such a consistently strong relationship between income and establishment size? Is this due to differences in operations costs of serving lower income neighborhoods, or reluctance by large firms (especially regional or national chains) to enter markets perceived as more risky or less profitable? Low-income households presumably have the most to gain from lower prices made possible by economies of scale, yet are less likely to benefit from them. Are there differences in household buying patterns that could explain this? For instance, perhaps low income households have less access to cars and are more dependent on smaller local stores, or have less storage space and so make more frequent trips. Our current data do not allow us to tease out alternative explanations, and would likely need to be supplemented by more micro-level data on household buying patterns to answer the question. If local governments wish to encourage more retail (at least for certain categories) in low-income neighborhoods, understanding the reasons behind the existing discrepancies is necessary to design effective economic development policies. Policymakers should also consider whether retail is associated with negative externalities, such as increased noise, pollution or crime, which might counteract the benefits to low-income neighborhoods.

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Appendix A

Appendix Table A
Interactions between income and ZCTA, MSA characteristics.

Dependent var	Ln(Emp/sq mi)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(income)	0.385***	0.460***	0.404***	0.271***	0.385***	0.359***	0.296***
	(0.092)	(0.099)	(0.137)	(0.087)	(0.095)	(0.095)	(0.098)
Log(income)*Cent city		−0.110					
		(0.077)					
Log(income)*Dist CBD			−0.010				
			(0.044)				
linc*MSA % mixed use				0.00176***			
				(0.0004)			
linc*MSA emp density					9.99E−08		
					(0.00001)		
linc*MSA pop						9.24E−09*	
						−5.1E−09	
Log(Pop dens)	0.773***	0.774***	0.772***	0.773***	0.773***	0.772***	0.772***
	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.034)	(0.037)
Log(Dist CBD)	−0.418***	−0.410***	(0.317)	−0.417***	−0.418***	−0.418***	−0.420***
	(0.053)	(0.054)	(0.458)	(0.052)	(0.054)	(0.053)	(0.056)
Owner occ	−0.014***	−0.014***	−0.014***	−0.0138***	−0.014***	−0.0143***	−0.0152***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Central city	−0.092**	1.087	−0.0922**	−0.0917**	−0.0922**	−0.0913**	(0.063)
	(0.040)	(0.834)	(0.040)	(0.039)	(0.040)	(0.040)	(0.042)
BA plus	0.000	−0.001	0.000	0.000	0.000	0.000	0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)

Appendix Table A (*continued*)

Dependent var	Ln(Emp/sq mi)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	−0.006***	−0.006***	−0.006***	−0.006***	−0.006***	−0.006***	−0.00728***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	−0.003**	−0.003**	−0.003**	−0.003**	−0.003**	−0.003**	−0.00278*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Kids	−0.022***	−0.024***	−0.022***	−0.0222***	−0.0221***	−0.0216***	−0.0169***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Old	0.016***	0.0155***	0.0155***	0.0151***	0.0156***	0.0158***	0.0189***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Foreign born	0.001	0.001	0.001	0.001	0.001	0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Hsg<1940	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***	−0.0132***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Fixed effects	Yr & MSA	Yr & MSA	Yr & MSA	Yr & MSA	Yr & MSA	Yr & MSA	Yr & MSA
Other notes							Excludes NYC & LA
Observations	13,542	13,542	13,542	13,542	13,542	13,542	12,441
R-squared	0.773	0.773	0.773	0.775	0.773	0.773	0.747

Robust standard errors, clustered by place, in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table B
Relationship between income and establishment density, by firm type.

Dependent var	Ln(Estab/sq mi)		
Firm type	All firms	Independents	Chains
All retail			
Log(income)	−0.030	−0.077	−0.089
	(0.071)	(0.064)	(0.100)
Poor	−0.023	−0.006	−0.082**
	(0.030)	(0.028)	(0.034)
Supermarkets			
Log(income)	−0.373***	−0.383***	−0.074*
	(0.062)	(0.067)	(0.042)
Poor	0.076***	0.116***	−0.062***
	(0.023)	(0.025)	(0.018)
Drugstores			
Log(income)	−0.235***	−0.225***	−0.124**
	(0.064)	(0.058)	(0.051)
Poor	−0.018	0.010	−0.043***
	(0.028)	(0.029)	(0.016)
Clothing			
Log(income)	0.020	0.007	−0.085
	(0.094)	(0.081)	(0.081)
Poor	0.018	0.030	−0.004
	(0.048)	(0.047)	(0.032)
Food svce			
Log(income)	−0.215**	−0.256***	−0.253***
	(0.083)	(0.079)	(0.068)
Poor	−0.042	−0.022	−0.0547**
	(0.026)	(0.025)	(0.023)
Laundry			
Log(income)	−0.089	−0.100*	−0.001
	(0.057)	(0.057)	(0.028)
Poor	−0.060***	−0.052***	−0.011
	(0.018)	(0.018)	(0.015)

All regressions include controls for population density, distance to CBD, owner-occupied housing share, central city dummy, share with BA or graduate degree, share non-Hispanic black, share Hispanic, share under 18, share 65 and older, share foreign-born, share housing pre 1940, year and MSA fixed effects. N = 13,542. Robust standard errors, clustered by place, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table C
Employment change and neighborhood income, by retail category.

Dependent var	Avg annual employment change, 1992–2006			
	Baseline Income/Poverty			ΔIncome/Poverty
Category	(1)	(2)	(3)	(4)
All retail				
Income	2.301***	1.647***	0.483	1.668
	(0.290)	(0.289)	(0.625)	(1.062)
Poverty	0.491**	0.671***	0.240	−0.048
	(0.215)	(0.220)	(0.223)	(0.044)

(continued on next page)

Appendix Table C (*continued*)

Dependent var	Avg annual employment change, 1992–2006			
	Baseline Income/Poverty			ΔIncome/Poverty
Category	(1)	(2)	(3)	(4)
Supermarkets				
Income	2.760***	2.506***	1.187	0.859
	(0.363)	(0.367)	(0.913)	(0.906)
Poverty	1.182***	1.174***	0.802**	−0.029
	(0.343)	(0.360)	(0.393)	(0.041)
Drugstores				
Income	3.058***	2.630***	0.255	2.951***
	(0.484)	(0.494)	(1.165)	(0.914)
Poverty	0.649*	0.794**	0.138	0.046
	(0.385)	(0.389)	(0.417)	(0.049)
Clothing				
Income	2.435***	2.049***	1.633*	1.934**
	(0.377)	(0.379)	(0.848)	(0.930)
Poverty	2.087***	2.100***	1.081***	−0.001
	(0.352)	(0.353)	(0.405)	(0.034)
Food svce				
Income	2.581***	1.832***	−0.472	1.535**
	(0.359)	(0.363)	(0.791)	(0.769)
Poverty	1.474***	1.776***	0.868**	−0.026
	(0.395)	(0.402)	(0.348)	(0.040
Laundry				
Income	2.656***	1.930***	−0.597	3.033***
	(0.346)	(0.350)	(0.658)	(0.932)
Poverty	0.701**	0.927***	−0.027	0.036
	(0.352)	(0.339)	(0.357)	(0.037)
Controls	Year dummy	Log(Pop), Log(Dist to CBD), year	Full controls	Full controls

Columns 1–3 show coefficients on log(income) high poverty dummy. Column 4 shows coefficients on changes in ZCTA income/MSA income and poverty rate. Controls noted for columns 1–2. Column 3 includes controls for: log(population density), log(distance to CBD), owner-occupied housing share, central city dummy, share with BA or graduate degree, share non-Hispanic black, share Hispanic, share under 18, share 65 and older, share foreign-born, share housing pre 1940. Column 4 includes controls for changes in all variables. All regressions include MSA fixed effects. Columns 1–3: N = 13,542. Column 4: n = 6745. Robust standard errors, clustered by place, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table D
Retail employment share and neighborhood income.

Dep var	Retail share of total emp		
	(1)	(2)	(3)
Log(income)	0.259	0.195	1.989***
	(0.332)	(0.307)	(0.740)
Poor	−3.030***	−2.441***	−1.374***
	(0.379)	(0.361)	(0.341)
Log(Pop dens)		1.529***	1.742***
		(0.132)	(0.149)
Log(Dist CBD)		2.754***	1.714***
		(0.260)	(0.283)
Owner occ			0.010
			(0.012)
Central city			0.127
			(0.284)
BA plus			−0.089***
			(0.012)
Black			−0.035***
			(0.007)
Hispanic			−0.037***
			(0.010)
Kids			0.043*
			(0.024)
Old			0.029
			(0.019)
Foreign born			−0.010
			(0.016)
Hsg < 1940			−0.037***
			(0.012)
Fixed effects	Yr & MSA	Yr & MSA	Yr & MSA
Observations	13,542	13,542	13,542
R-squared	0.058	0.100	0.128

Robust standard errors, clustered by place, in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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