Market Concentration, Market Shares, and Retail Food Prices: Evidence from the U.S. Women, Infants, and Children Program

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Abstract: We explore pricing in local food-retailing markets where supermarkets operate *versus* those occupied solely by smaller food retailers. Using data from the Women, Infants and Children program in the Greater Los Angeles area, we show that supermarkets do not raise prices in the concentration of local markets or as a function of market shares. Smaller food retailers charge substantially higher prices on average. Their prices increase with market concentration and shares of sales, especially when small retailers face no direct competition of supermarkets. Given the dominance of small retailers in low-income areas, our findings have important implications regarding local market power, food costs, and supermarket entry.

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Introduction

The effects of market structure and market power on retail food prices have drawn widespread interest in the United States and elsewhere. Longstanding concerns have been heightened by the worldwide "supermarket revolution", wherein traditional small-scale retailers have been replaced by supermarket chains that are often international in their geographic scope (Reardon et al. 2003), and by an increase in retail food price volatility beginning in 2007-08 (McCorriston 2014).

Measures of seller concentration in food retailing rely on the distribution of store-level market shares, most often by computing the sum of shares for the four largest sellers in the market —i.e., the four-firm concentration rate (CR4). Richards and Pofahl (2010) estimated the four-firm concentration ratios (CR4) for major metropolitans in the United States: Atlanta 81.9%, Chicago 60%, Dallas 63.7%, Los Angeles 59.1%, and New York 63.8% — all well above threshold levels of CR4 often considered as suggestive of seller market power (Connor et al. 1985).[1]

Yet, no consensus in theory or empirics has been reached as to how market concentration within a relevant market area affects food costs. On one hand, classic theories of imperfect competition suggest that high market concentration reduces effective competition and allows sellers to increase prices (Clarke, Davies, and Waterson 1984; Cotterill 1986), a result supported empirically by studies that find evidence of positive relationship between general or category-specific market shares of supermarkets and food retail prices (Lamm 1981; Nevo 2001; Aalto-Setälä 2002; Bonnet and Dubois 2010; Smith and Thanassoulis 2015).

On the other hand, there are plausible reasons for retail food prices not to be higher in more concentrated markets, particularly in today's diversified food retailing landscape. Firstly,

[1] The Richards and Pofahl (2010) estimates coincide closely with our own metropolitan statistical area average CR4 of 63% based on Nielsen TDLinx data.

economists have long found evidence of a positive concentration-efficiency relationships across industries (Bain 1954; Salop and Stiglitz 1977). Lower operational costs in turn keep prices down in concentrated markets, although the mark-up may increase.

More recently, researchers have established theoretically and empirically that higher concentration of food retailing markets may not be associated with higher prices (Gaudin 2017). A growing literature seeks to explain why supermarkets may not exercise their market power to raise prices. Thomassen et al. (2017) show that cross-category competition can make supermarkets relatively unresponsive in adjusting prices according to the structure of local markets. Because consumers may buy multiple categories of products in a single store, complementary cross-category pricing effects tend to be internalized by supermarkets, reducing their exercise of market power in any given category. DellaVigna and Gentzkow (2017) show that supermarket chains often set uniform prices across broad geographic areas or zones (e.g., a metropolitan area) regardless of substantial variation in demand elasticities and competitive structure in local markets, effectively foregoing opportunities to increase store-level profits.

Supermarkets, especially supercenters, can also impose significant price impacts on their rivals. For example, the presence of supercenters such as Walmart may have a procompetitive effect on prices charged by competing retailers (Basker 2007; Hausman and Leibtag 2007; Volpe and Lavoie 2008; Csipak, Rampal, and Josien 2014). However, other work suggests that some traditional supermarkets have sought to differentiate themselves with higher quality products, store amenities, and services rather than compete directly on price (Matsa 2011; Courtemanche and Carden 2014). This *differentiation strategy* may cause prices of supercenter competitors to increase on balance.

Despite the extensive research that has been conducted on pricing behavior of supermarkets, the role of smaller food retailers (SFR) has been largely ignored. Perhaps SFR are simply assumed to be too powerless to set prices above their costs. A practical empirical limitation on studying SFR pricing is that data are generally unavailable, because these stores are normally not included in food-retail scanner datasets. Nevertheless, SFR can affect food costs and hence consumers' welfare in a significant way, especially in food desert areas where median incomes are low, supermarkets do not exist, and, thus, they may hold considerable market power.[2] We have essentially no knowledge of how SFR respond in settings if they possess market power.

We address that limitation in this paper, wherein we utilize a unique transaction-level dataset to examine the effects of market concentration and store-level market shares on food prices charged by both supermarkets and SFR. We tackle three specific questions. First, how do market concentration and retailer market shares for specific bundles of staple food items affect prices of those bundles? Second, how do price effects differ when market power is held by supermarkets *versus* by SFR? Third, how does the presence of supermarkets and supercenters in the local market areas affect the pricing behavior of competitors including SFR?

Our transaction data come from the California Women, Infants and Children Supplemental Nutrition (WIC) Program from 2009 to 2013. Nearly all large grocers in California participate in the WIC program, and, importantly, so do many smaller retailers. WIC data hence provide unique transaction records of food prices charged by SFR. WIC participants receive vouchers, which contain food packages based on their nutritional needs, and can redeem them at no cost for eligible foods at authorized retailers. Retailers are reimbursed for costs of WIC foods by state WIC

[2] An estimated 18.3 million people in the U.S. lived in food-desert Census Tracts in 2010 (USDA 2016). Dutko, Ver Ploeg, and Farrigan (2012) identified 4,175 urban Census Tracts out of 50,784 as food deserts.

agencies and cannot charge prices to WIC customers that differ from the prices to other customers. Thus, redemption rates for WIC food packages provide an accurate indication of prices for the foods to all consumers.

We study the four most frequently redeemed WIC food packages or food instruments (FI) from October 2009 to December 2013 for the greater Los Angeles area (GLA) in Southern California. Nearly half of the State's WIC participants live in GLA. We focus on GLA because it contains a wide variety of food retailers, local food-retailing market structures, as well as two prominent supercenter chains.

We define local grocery markets within GLA at the zip code level. Although zip codes may not coincide perfectly with relevant geographic markets for food shopping, the area of a typical zip code match closely with average travel distances to shop for food in urban areas. Specifically, the average area of the zip codes in the sample is seven square miles which equals a circle with a radius of 1.5 miles. Charreire et al. (2010), for example, review studies on the relationship between access to food outlets and nutrition intake of urban residents which all consider a half-mile to two-mile vicinity around home as the relevant food environment.

By comparison, Los Angeles County is 4,751 square miles and the city of Los Angeles is 503 square miles, both of which are clearly too large to be considered as a relevant local urban food market. This illustrates the more general point that food-retailing concentration measured at the level of metropolitan statistical areas (MSAs) or core based statistical areas (CBSAs) (Hosken, Olson, and Smith 2018) is far too broad for the analysis of behavior in local food retailing markets.[3]

[3] Alternatively, census blocks or tracts have been used in some studies on the spatial distribution of food retailing (e.g., Ver Ploeg, Nulph, and Williams 2011; Lamichhane et al. 2013). These units, however, are typically too small in urban areas to constitute geographic markets for analysis of concentration and market power. Tracts are designed for a population ranging from 1,200 to 8,000, whereas the average GLA zip code in our data has nearly 40,000 people.

The empirical model specifies a redemption rate for a WIC food package as a function of market structure variables including local market concentration and store market shares of WIC sales for that food package, indicator variables to denote whether the redeeming store is an SFR, supermarket, or supercenter, indicators for the presence of at least one supermarket in the local market area and the competition in the local market from supercenters, and other control variables. Market concentration is measured by the Herfindahl-Hirschman Index (HHI) using Nielsen TDLinx data. HHI is preferred relative to CR4 as a measure of concentration because HHI incorporates all sellers, not just the top four, and differentiates based on shares of individual firms. The data sample is broken into two periods, October 2009-April 2012 and May 2012-December 2013, in order to capture impacts of key program changes implemented by California in May 2012 intended to restrain the pricing of SFR.

Estimation results show that price effects of market concentration and market shares are highly heterogeneous depending on whether the store is an SFR, supermarket, or supercenter, and whether a supermarket is competing in the local market. High concentration within the local market area does not result in higher prices, unless no supermarket operates in the market area, in which case SFR increase prices as a function of HHI and their individual market shares. The May 2012 policy change was effective in restraining SFR from charging high prices or adjusting prices to market structure. Supermarkets charge considerably lower prices than SFR and do not set prices as a function of HHI or market shares. Supercenters charge still lower prices. We find no evidence, however, to support additional "yardstick-of-competition" effect for supercenters beyond what appears to exist for supermarkets in general.

The California WIC Program

To provide context for the empirical analysis, it is important to convey some brief background on the WIC program. It is the third largest food assistance program in the nation measured by expenditure, providing in-kind food assistance to women, infants and children in low-income households. [4] WIC participants are assigned food packages (FI) based on their nutritional needs.

The WIC program is administered by the U.S. Department of Agriculture's (USDA) Food and Nutrition Service (FNS), although substantial operational control is delegated to state, territorial, and tribal government WIC agencies. California has the largest WIC program in the United States, with the largest number of authorized stores.

FNS regulations mandate the establishment of store (also called as vendor) peer groups for agencies that use commercial stores to dispense WIC foods, as nearly all do (7 CFR §246.12(4)). These peer groups are designed for purposes of program cost containment, but local agencies have considerable discretion in the design of peer groups. California operated 16 peer groups of stores during the time of our study defined by geographic location and store size, as measured by the number of cash registers (hereafter, registers). The program calculated a biweekly maximum allowable redemption rate (MARR) for each WIC food package and each store peer group.[5] These MARRs acted as price ceilings for each food package for authorized program stores.

Stores receiving more than 50% of their food revenues from WIC sales are classified by FNS as "Above-50" (A-50) stores. These stores constituted 20% of program stores and 37% of

[4] Since 2008, the WIC program costs to the federal government have been six to seven billion dollars annually. In recent years, over eight million people have participated in the program each month. The program benefits half of all infants in the nation.

[5] California calculated MARRs using the rolling 12-week average redemption rate for each food package within each peer group, plus an allowance based on the standard deviation of redemption rates within the peer group for the food package for the same time period.

program sales in California during the study period. A-50 stores face stringent MARRs mandated by FNS and intended to ensure that their presence does not raise program food costs above the statewide average. The redemption rates charged by A-50 stores almost perfectly coincided with the ceiling price (Saitone, Sexton, and Volpe 2014), meaning that A-50 redemption rates were determined by regulation instead of market forces. Accordingly, A-50 transactions were excluded from the empirical analysis, although we account for potential competitive effects in local markets due to the presence of A-50 stores in the empirical analysis.

Unlike the price ceilings faced by A-50 stores, the price ceilings for the other peer groups were seldom binding before May 2012 (Saitone, Sexton, and Volpe 2014), meaning that redemption rates were determined by market forces amenable to econometric modeling. Starting from May 2012, California changed its peer group regulations and imposed much stricter MARRs for stores with 1-4 registers, which had historically charged the highest redemption rates for WIC FIs (Saitone, Sexton, and Volpe 2015). New price ceilings tied the redemption rates of these stores to the redemption rates charged by stores with 5+ registers. The policy significantly reduced the MARRs, causing them to effectively bind for many of the 1-4 register stores.[6]

The WIC and Nielsen TDLinx Data

We study WIC transaction records in the GLA area from October 2009 through December 2013, 51 months in total. Each observation contains information on the food package (FI) being redeemed, the redemption rate (i.e., summation of the prices charged for each product in the FI),

[6] We use the term "effectively bind" in recognition of the fact that, with the combination FIs and broad product choices in many instances, it is very difficult for retailers to set prices for individual products, so that the MARR exactly binds for a given FI.

date of the transaction, the number of registers in that store at which the transaction took place, and the zip code of the store.

The empirical analysis focuses on four WIC food instruments: FIs 1011, 6003, 6011, and 6012. FI 1011 allows participants to purchase four 12.5-oz cans of infant formula. Infant formula is the largest single item in the WIC program measured by value of sales, and FI 1011 was the fourth most redeemed FI during the period of study.[7] All states, including California, sign a sole-source supply contract with a formula manufacturer in exchange for a rebate from the manufacturer, which supplements program funding (Davis 2012). Enfamil was the exclusive formula supplier for California at the time of the study and formula, thus, represents a perfectly homogeneous product in the empirical analysis.

The other three FIs are the largest FIs by frequency of redemption and accounted jointly for 31% of total WIC redemptions by value during the study period. Each of these FIs consist of a combination of three to four food items as detailed in table 1. FI 6012 consists of low-fat milk, choice among standard cheeses, eggs, and beans, lentils or peanut butter. FIs 6003 and 6011 both contain low-fat milk and whole grains. FI 6003 includes breakfast cereal, while FI 6011 includes bottled or concentrated juices.

Table 1. *Food Items Contained in FIs 6003, 6011, and 6012*

				Choose either				Choose either	
FI No.	Low/nonfat milk	Whole grains	Breakfast cereals	Bottled juice	Concentrated juice	Eggs	Cheese	Dry beans	Peanut butter
6003	1 gl	16 oz	36 oz	--	--	--	--	--	--
6011	1 gl	16 oz	--	64 oz	11.5/12 oz	--	--	--	--
6012	1 gl +1 qt	--	--	--	--	1 dz	16 oz	16 oz	16-18 oz

Source: USDA (2017b).

Note: Niche products such as free-range eggs or organic milk are not eligible under WIC. The eligible foods in whole grains include whole wheat bread, buns and rolls; whole grain bread, buns and rolls; other whole grains, i.e., brown

[7] Other WIC formula FIs contain differing amounts of the same product.

rice, bulgur, oatmeal, and whole-grain barley without added sugars, fats, oils, or salt; soft corn or whole wheat tortillas; whole wheat macaroni products. Eligible breakfast cereals must contain at least 51% whole grains or meet other nutritional standards regarding folic acid or fiber, while eligible juices must contain 100% juice and at least 120% vitamin C. Cheese purchases are restricted to one-pound blocks or rounds of Colby, cheddar, jack, mozzarella, or blends of these cheeses. "dz" stands for dozen, "gl" for gallon, "qt" for quart, and "--" for not available.

The variation in redemption rates, therefore, can be driven by both price variation for each food item and variation in the quality or brands of food items in the three non-formula FIs. The variety of offerings may be impacted by market structure because retailers compete in product variety as well as price (Richards and Hamilton 2006). However, it is not possible to specify variables in the econometric model to account for price effects due to quality, brands, or package sizes chosen by the participant because FI redemption data do not specify the particular brands, products, or package sizes purchased.

Fortunately, many of the staple foods offered through the WIC program, such as low-fat milk, standard cheeses, eggs, and beans or lentils, are largely homogeneous products. California WIC consumers are not allowed to purchase niche versions of staple products. For example, free-range eggs or organic milk are not eligible. Cheese purchases are restricted to one-pound blocks or rounds of Colby, cheddar, jack, mozzarella, or blends of these cheeses[8]. Among the three non-formula FIs, FI 6012 contains most homogenous food items.

Given the limited product heterogeneity in the three FIs, therefore, the variation in redemption rates should be predominantly driven by prices. Note that, if retailers carry multiple brands of these products and engage in differentiated pricing among them, the impact of markups associated with discriminatory brand pricing strategies and markups associated simply with seller

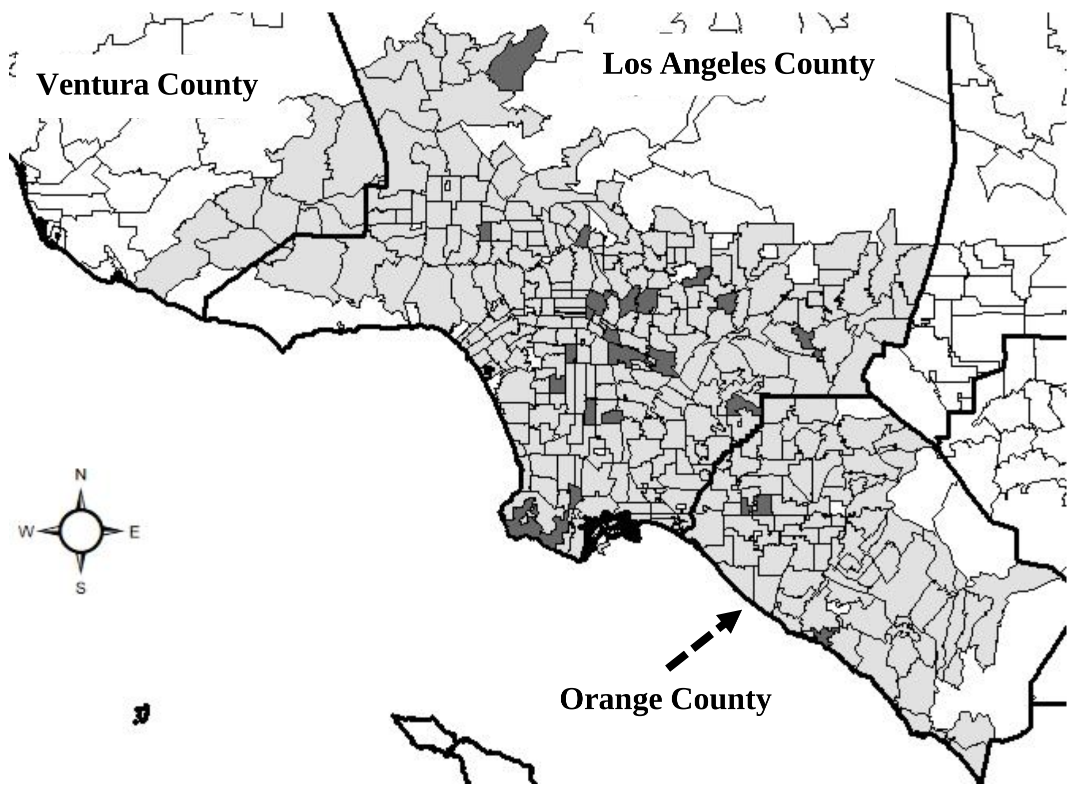
[8] Relative to many other states, though, California does allow WIC participants wide latitude to select among store offerings within each product category. Some states specify that participants must choose the least-cost brand in some product categories, such as milk, cheese, and eggs.

market power are observationally equivalent. Either can impact prices of WIC FIs, and either is reflective of the retailer's pricing power.

Define local food markets

As noted, we define local retail food markets according to zip code. To be included in the sample, zip codes must be entirely located in Los Angeles, Orange, or Ventura Counties, have WIC redemption data, and be below the 90th percentile in geographical areas among all zip codes in GLA (see figure 1).[9] The last requirement removes zip codes that are geographically too large to constitute meaningful markets for food retailing. Changing this size threshold to 95% had no significant impact on the empirical results.

Figure 1. *Map of Sampled Zip Codes in the Greater Los Angeles Area*



[9] Formally zip codes consist of a collection of addresses and do not have defined boundaries *per se*. The Census Bureau constructs interpretive boundaries of zip codes for purposes of reporting area, population, and other demographic statistics. This information is from the 2010 Census and was obtained from ArcGIS online maps.

Note: The base map is obtained from https://www.arcgis.com/home/index.html. The Projected Coordinate System is NAD_1983_UTM_Zone_10N. The thick black lines are county boundaries. The thin lines are zip code boundaries. Light gray areas are zip codes contained in the sample. The 22 dark gray zip codes are sampled zip codes that did not have supermarkets operating for some months over the study period of October 2009 to December 2013.

Based on these criteria, 315 zip-code market areas are included in the sample. The number of zip codes in each month varies slightly over time due to entry and exit of authorized stores from the WIC program. The average size of zip codes is 6.92 square miles, varying from 0.22 to 42.28. The median size is 4.68, with 98% of the zip codes having sizes within the range of 0.86 square miles (e.g., a circle with a radius of 0.5 mile) to 40.46 (e.g., a circle with a radius of 3.6 miles) square miles. Such dimensions of a typical zip code align well with the average travel distances to shop for food in urban areas (Charreire et al. 2010). Specifically for the GLA area, Wu, Saitone, and Sexton (2017) found average travel distances of 3.2 miles for WIC participants living outside of food-desert areas and 3.6 miles for food-desert participants.

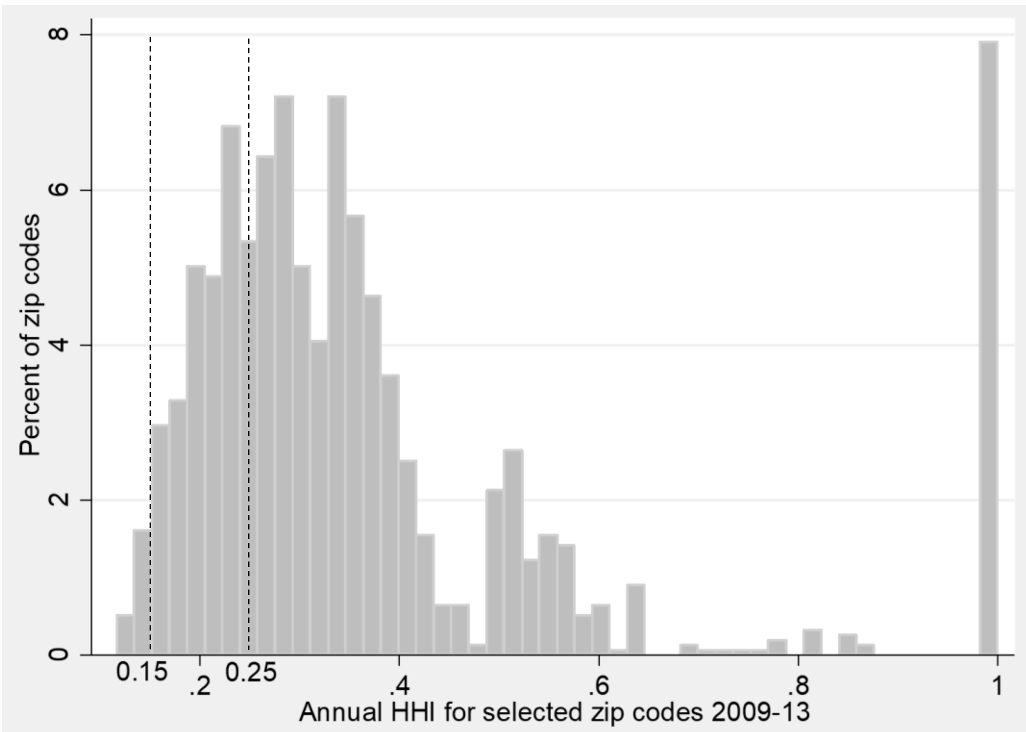
Importantly, the geographic size of a zip code is inversely related to its population density, with the correlation coefficient equal -0.53 in our dataset. The most populous zip codes and smallest in land area are concentrated in the urban core and correspond to areas where residents are least likely to travel far for grocery shopping due to the lack of access to a private vehicle or simply the transactions costs of navigating through urban congestion. This linkage between zip code areas and population density further supports using zip codes to define relevant geographic markets for food retailing.

Market concentration in each zip-code market was computed from Nielsen TDLinx data. The TDLinx dataset consists of store-level data for a comprehensive listing of food retailers in the

United States. Key attributes included are store names, ownership structure, location according to multiple geographic identifiers, and categorical annual food revenues.[10]

Market concentration is measured by HHI, calculated as the sum of squared total-food-revenue shares within a zip code for the 10 largest grocery stores based on food revenue in each year from 2009 to 2013. In our dataset, the value of HHI ranges from 0.12 to 1.00. Its mean is 0.38 and median is 0.32. The distribution does not vary significantly before and after the price-ceiling policy was implemented in May 2012.

Figure 2. *Distribution of HHI in Local Food Retailing Markets in GLA*



Source: Authors' calculation.

Note: The horizontal axis measures the value of HHI, ranging from 0.1 to 1. The vertical axis is the percentage of zip codes for each bin of HHI values. The left dashed line is at the value of 0.15, and the other dashed line at the value of 0.25. The DOJ classifies markets with HHI larger than 0.15 as medium concentration and with HHI larger than 0.25 as high concentration.

[10] To use revenues for constructing HHI, we took the midpoint of each revenue category. The largest category consists of stores with more than $100,000,000 in annual revenues, and for this category we report $100,000,001. While this may introduce measurement error for the largest chains, these stores only constitute 0.66% of the stores in the sample.

The distribution of HHI values is displayed in figure 2. Over 70% of the zip-code markets have HHI values higher than 0.25 in a year and hence are considered highly concentrated markets under the U.S. Department of Justice (DOJ) and Federal Trade Commission (FTC) merger guidelines (2010).[11] Only a few zip codes have HHI lower than 0.15 and are considered markets of low concentration under the DOJ-FTC underlines.

Empirical Strategy

Our goal is to estimate price effects of market concentration measured by HHI, retailer market shares for specific WIC FIs, and the presence of supermarkets and supercenters in the market area, while paying close attention to possible differences in pricing behavior among supermarkets, supercenters, and SFR.

Summary statistics for the key variables defined below are provided in table 2. The dependent variable is the redemption rate (*Redemp*) measured in USD for each transaction of the four WIC FIs. Though WIC participants are required to fully redeem formula FIs and have little reason not to obtain all the costless items in other three FIs, they sometimes partially redeem the FIs by purchasing only a subset of the products in the food voucher (Furey, Klerman, and Grindal 2018). Whether a redemption is full or partial, however, cannot be discerned directly from the data.

To ensure that the variation in *Redemp* is driven by the variation in price not by quantity sold, it is important to reduce the presence of partial redemptions without eliminating low-cost full redemptions. In the base analysis, we excluded redemption rates that are lower than 1.5 standard deviations from the mean of each FI. This rule was applied separately to the pre- and post-policy

[11] An alternative measurement of HHI utilized by the DOJ and FTC relies upon percentage market shares rather than proportional market shares, in which case its range is $HHI \in (0, 10{,}000]$ instead of is $HHI \in (0, 1]$ as in this study.

change subsamples, because the reduced MARRs for stores with 1-4 registers in the post-policy period reduced the standard deviation of redemption rates. Applying this rule caused the exclusion of from 1.1% to 3.8% of observations across FIs. The number of observations ranged from 765,086 for FI 1011 to 7,925,255 for FI 6012. We also conducted the empirical analysis for cut points set at 1.0 and 2.0 standard deviations below the mean. Results are highly robust to the alternative cut points and available from the authors.

Market concentration is measured by HHI $\epsilon(0, 1]$. Standard theory posits an increasing relationship between HHI and prices due to greater ease of coordinated behavior among sellers as the market shares of key players increase or simply due to the exercise of unilateral market power. However, these classic theories are based on single-product sellers and do not account multiproduct nature of pricing decisions (Thomassen et al. 2017) or possible zone-pricing strategies of supermarket chains (DellaVigna and Gentzkow 2017), factors that can attenuate or even eliminate the positive link between market concentration and pricing.

WIC% $\epsilon(0, 100]$ and is the store-level and FI-specific percentage of total WIC sales, including sales by A-50 stores, in a local market for a particular month. WIC% can capture two effects in our data. First is the standard interpretation from industrial organization that the market share indicates unilateral market power for a seller and, accordingly, ability to raise price (Cowling and Waterson 1976). A second interpretation, unique to the WIC program, is due to WIC foods being free of charge to participants, whose demands are, thus, price inelastic for these products. Therefore, the higher the WIC share of total sales for a product, the greater the motivation of a retailer to raise the product's price to exploit WIC consumers' price inelasticity.

Table 2. *Summary Statistics for Key Variables by Food Instrument*

Period of Data		Oct 2009 to April 2012					May 2012 to December 2013				
	Type	No. Obs.	Mean	Std. dev.	Min	Max	No. Obs.	Mean	Std. dev.	Min	Max
FI 1011											
Redemption rates	Continuous	482,414	72.12	17.88	45.34	143.56	282,672	72.43	7.01	60.66	128.28
Store WIC%	Continuous		24.84	26.08	0.08	100		25.38	25.21	0.11	100
SFR trans	Dummy		0.190	0.392	0	1		0.193	0.395	0	1
Supermarket trans	Dummy		0.741	0.438	0	1		0.743	0.436	0	1
Supercenter trans	Dummy		0.020	0.140	0	1		0.082	0.275	0	1
FI 6003											
Redemption rates	Continuous	3,366,662	16.92	4.68	9.49	45.69	2,126,842	16.43	2.05	12.06	30.06
Store WIC%	Continuous		22.75	23.22	0.01	100		23.75	23.15	0.03	100
SFR trans	Dummy		0.186	0.389	0	1		0.198	0.398	0	1
Supermarket trans	Dummy		0.732	0.443	0	1		0.722	0.448	0	1
Supercenter trans	Dummy		0.009	0.093	0	1		0.024	0.153	0	1
FI 6011											
Redemption rates	Continuous	3,213,683	14.50	4.62	7.46	41.54	2,008,063	14.08	1.77	10.63	27.76
Store WIC%	Continuous		22.44	23.10	0.01	100		23.56	23.12	0.02	100
SFR trans	Dummy		0.184	0.388	0	1		0.200	0.400	0	1
Supermarket trans	Dummy		0.732	0.443	0	1		0.718	0.450	0	1
Supercenter trans	Dummy		0.008	0.091	0	1		0.024	0.155	0	1
FI 6012											
Redemption rates	Continuous	4,911,520	14.99	3.31	9.71	37.50	3,013,735	15.39	1.91	11.70	24.07
Store WIC%	Continuous		23.11	23.12	0.01	100		23.96	23.08	0.01	100
SFR trans	Dummy		0.172	0.377	0	1		0.197	0.398	0	1
Supermarket trans	Dummy		0.746	0.435	0	1		0.724	0.447	0	1
Supercenter trans	Dummy		0.009	0.095	0	1		0.028	0.164	0	1

Note: The mean of *Supcnt Comp* is 0.10 (0.29) and 0.26 (0.44) for FI 1011 pre and post May 2012, respectively. For the other three FIs, it is 0.12 (0.32) and 0.30 (0.46) pre and post May 2012, respectively. Standard deviations are in parentheses.

Notably, WIC% is an imperfect proxy for either of the two effects. Ideally, we would measure unilateral market power by a seller's market share of total sales, not just WIC sales, in the local market, while we would measure a retailer's "internal" WIC share, i.e., share of sales in a product category to WIC customers, to study the phenomenon of "pricing to WIC." Neither of these variables can be measured directly, given the available data, but WIC% represents a useful proxy for either effect.

Supermarkets are defined as stores operating 7+ registers. Transactions made in supermarkets are indicated by the dummy variable *Supmkt*. If transactions are made in a supermarket belonging to one of the two prominent supercenter chains operating in GLA, the dummy variable *Supcnt* equals one. We expect both *Supmkt* and *Supcnt* to have negative coefficients on redemption rates according to a central finding in a growing literature showing that prices are significantly higher at small convenience stores than at supermarkets (Liese et al. 2007; Ghosh-Dastidar et al. 2014).

If a local market (i.e., a zip code) has at least one supermarket operating, the dummy variable *Supmkt Exist* equals one. If a store is faced with competition in its local market from a supercenter, the dummy variable *Supcnt Comp* equals one. Both *Supmkt Exist* and *Supcnt Comp* are intended to test for "yardstick-of-competition" effects in a market area due to the presence of supermarkets or supercenters that operated in the market. The coefficient of *Supcnt Comp* captures any additional "yardstick-of-competition" effect is associated with the presence of a supercenter compared to the price effect due to the presence of at least one supermarket in the local market.

Finally, to control for the inherent differences in the prices charged by small-sized WIC stores, we generate an indicator variable to denote transactions taking place at small-sized, *SFR*, defined as retailers operating with1-4 registers. The default category for our econometric tests is, thus, medium-sized stores with 5-6 registers.

Estimation specification

We distinguish the response of supermarkets and SFR to changes in market structure in two ways. First, we interact HHI and WIC% with the indicator variable, *Supmkt Exist*. The coefficients of HHI and WIC% represent impacts of market structure in those markets without supermarkets operating, while the coefficients on the *HHI×Supmkt Exist* and *WIC%×Supmkt Exist* interaction terms indicate any difference in price effects conditional on the presence of supermarkets. Second, we distinguish price effects of supermarkets and SFR in markets where supermarkets operate. We perform the test by interacting HHI and WIC% with *Supmkt* and use the subsample of markets where supermarkets operate.

Throughout this section, the data are spilt into two periods at May 2012 to account for the change in pricing regulations for SFR implemented by California WIC program. The first period covers 31 months from October 2009 up to April 2012 (referred to as *pre-policy* in following tables), the latter 20 months until December 2013 belong to the second period (referred to as *post-policy* in following tables).

We run the regressions at the transaction level, so that every transaction carries an equal weight and make use of as much price information as possible. For each of the four FIs, the baseline regression model is given by equation (1), where subscripts i, m, and t refer to transactions, zip codes, and year-months, respectively. Equation (1) is estimated separately for FIs 1011, 6003, 6011, and 6012. Standard errors are clustered at the zip code level to account for correlation of errors between stores within the same local market area and the correlation of transactions in a store from month to month.

$$Redemp_{i,m,t} = \alpha + \beta_{11} HHI_{m,t} + \beta_{12} HHI_{m,t} \times Supmkt\ Exist_{m,t}$$
$$+\beta_{21} WIC\%_{i,m,t} + \beta_{22} WIC\%_{i,m,t} \times Supmkt\ Exist_{m,t}$$
$$+\beta_{31} SFR_{i,m,t} + \beta_{32} SFR_{i,m,t} \times Supmkt\ Exist_{m,t} + \ \beta_4 Supmkt_{i,m,t} + \ \beta_5 Supcnt_{i,m,t}$$
$$+\beta_6 Supcnt\ Comp_{i,m,t} + \delta X_m + \gamma T_{m,t} + \mu_{i,m,t} \quad (1)$$

Coefficient β_{11} measures the impact of an increase in HHI on prices charged by stores when no supermarket operates in a market, while $\beta_{11} + \beta_{12}$ measures the impact on retail prices when supermarkets operate in a market. Similarly, the impact of an increase in the store's share of WIC sales in a market where no supermarket operates is measured by β_{21}, while the price effect of WIC% in a market with supermarkets is measured by $\beta_{21} + \beta_{22}$. Given the market structure, coefficients β_{31} and β_{32} measure the price effects of SFR, while β_4 and β_5 measure price effects of supermarkets and supercenters. The price effect of competing with supercenters is captured by β_6.

The vector X_m contains control variables to account for the population, geographic area, and population density of each zip code in the year of 2010. It also includes county fixed effects and the 2014 median household income for each zip code. Vector $T_{m,t}$ contains *Supmkt Exist*, year-month fixed effects and county-specific time trends. Although A-50 transactions are excluded, we include the percentage of WIC sales in the local market earned by A-50 stores as a control variable to see if there is any impact on pricing at non-A-50 stores due to the extent of competition from A-50 stores.

Focusing on transactions in local markets where at least one supermarket operates, the second specification allows us to see whether supermarkets respond to market structure differently compared with SFR when they compete in the same market.[12] The price effect of HHI for supermarkets is measured by $\beta_{11} + \beta_{12}$, while β_{11} measures the average effect for all SFR and medium-sized stores. Similarly, $\beta_{21} + \beta_{22}$ measure the price effect of WIC% for supermarkets, and β_{21} for other stores. The dummy variables for different sizes of stores and all other control variables in specification (1) are also included.

$$Redemp_{i,m,t} = \alpha + \beta_{11} HHI_{m,t} + \beta_{12} HHI_{m,t} \times Supmkt_{i,m,t}$$
$$+\beta_{21} WIC\%_{i,m,t} + \beta_{22} WIC\%_{i,m,t} \times Supmkt_{i,m,t}$$
$$+\beta_3 SFR_{i,m,t} + \beta_4 Supmkt_{i,m,t} + \beta_5 Supcnt_{i,m,t} + \beta_6 Supcnt\ Comp_{i,m,t}$$
$$+\delta X_m + \gamma T_{m,t} + \mu_{i,m,t} \quad (2)$$

Variation in explanatory variables is limited over time, but is large across stores and markets. To be specific, only 1% of HHI observations vary by more than 0.1 and less than 0.2% by 0.2 or more before the price-ceiling policy was implemented. During the same period, only 3% of stores have had variation in monthly WIC% over 10%.

Entry, exit, merger, and acquisition of stores would typically drive such substantial changes (Hosken, Olson, and Smith 2018) and hence make our interpretation of the estimates fundamentally different if the identification relies on time-series variation in HHI and WIC%. Thus, we use cross-sectional variation for identification. Pooled OLS models are employed to prevent the estimates from being driven by a few stores or markets that experience substantial changes in market concentration or sales shares over time.

[12] As similarly, transactions of redemption rates lower than the mean minus 1.5 times of the standard deviation are excluded for each FI and for periods before and after May 2012, respectively. The cut points used for specification (2) typically differ by \$0.01 or \$0.02 compared with the ones used for specification (1).

Empirical Results and Discussion

Estimation results from specification (1) are provided in table 3. The estimated effects can be interpreted as the causal relationship between market structure and retail prices, albeit with some caution because unobserved store or market characteristics may simultaneously affect market structure and the price. Recall that FI 1011 provides the best estimation of pure price effects due to market structure, because it is a perfectly homogeneous product.

Three patterns stand out in the table. First, estimates of the four FIs exhibit the same signs for coefficients of HHI, WIC%, and other variables of interest. Second, whether supermarkets operate in a market imposes significant impacts, both economically and statistically, on the price effects of market structure variables. Third, the implementation of a price-ceiling in May 2012 had significant impacts on the price effects of market structure variables.

We focus discussion mainly on FI 1011 (columns (1) and (2)). In markets where no supermarket operates every increase of 0.1 in HHI on average brought an increase of $3.0 in the FI price charged by non-supermarket stores or a 4.1% increase from the sample mean prior to May 2012. Every 10% increase in WIC% led to an increase of $5.1 in the FI price charged by non-supermarket stores or 7.0% from the mean. Both coefficients suggest considerable price effects of the structure of local markets.

Taking stores with 5-6 registers as the reference, an SFR (i.e., with 1-4 registers) charged $8.1 more for each can of infant formula or 45% higher than the mean price. This price difference remained constant whether or not there were supermarkets in the market. Once the price-ceiling policy was implemented, the price increment of SFR dropped dramatically to only $1.4 per can of infant formula or 5.8% of the mean price.

Table 3. *Market Structure and WIC Program Redemption Rates*

Dep. Var.	WIC Redemption Rates ($Transaction)							
	FI 1011		FI 6003		FI 6011		FI 6012	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-policy	Post-policy	Pre-policy	Post-policy	Pre-policy	Post-policy	Pre-policy	Post-policy
HHI	30.447***	2.229	10.384**	1.222	13.062**	0.267	6.489[#]	-0.076
	(11.540)	(2.946)	(5.177)	(0.879)	(6.300)	(0.862)	(3.986)	(0.949)
HHI	-31.730***	-3.941	-10.927**	-1.001	-13.657**	-0.094	-6.225	0.955
×Supmkt Exist	(11.796)	(3.249)	(5.223)	(0.962)	(6.343)	(0.921)	(4.033)	(1.048)
WIC%	0.507***	0.020	0.179***	0.012	0.149***	-0.000	0.109***	0.019*
	(0.093)	(0.040)	(0.030)	(0.010)	(0.035)	(0.011)	(0.021)	(0.011)
WIC%	-0.472***	-0.011	-0.168***	-0.014	-0.137***	-0.002	-0.109***	-0.026**
×Supmkt Exist	(0.094)	(0.041)	(0.030)	(0.011)	(0.035)	(0.011)	(0.021)	(0.012)
SFR	32.476***	5.570***	9.873***	1.943***	8.812***	0.914***	7.490***	1.984***
	(7.594)	(0.496)	(2.856)	(0.113)	(3.071)	(0.238)	(2.137)	(0.092)
SFR	-0.191	0.111	-2.155	-1.282***	-1.113	-0.150	-2.793	-1.258***
×Supmkt Exist	(7.882)	(0.751)	(2.863)	(0.275)	(3.079)	(0.297)	(2.132)	(0.224)
Supmkt	-4.103***	-2.816***	-0.541**	-0.544**	-0.583**	-0.581***	-0.643***	-0.647***
	(1.306)	(0.554)	(0.258)	(0.257)	(0.241)	(0.174)	(0.157)	(0.199)
Supcnt	-7.111***	-6.538***	-2.249***	-2.066***	-0.942***	-0.884***	-0.352**	0.107
	(0.537)	(0.387)	(0.154)	(0.092)	(0.148)	(0.069)	(0.146)	(0.110)
Supcnt Comp	-0.177	0.300	0.049	0.176**	-0.048	0.044	-0.083	-0.019
	(0.552)	(0.351)	(0.146)	(0.079)	(0.143)	(0.067)	(0.146)	(0.095)
No. observations	482,414	282,672	3,366,662	2,126,842	3,213,683	2,008,063	4,911,520	3,013,735
R^2	0.708	0.469	0.508	0.127	0.501	0.144	0.416	0.120

Note: Standard errors in parentheses are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1, [#] p=0.105. Pooled OLS models are used. The columns titled *pre-policy* report regression outcomes using data from October 2009 to April 2012, while other columns report regressions using data from May 2012 to December 2013. Year-month and county fixed effects are included, so are county-specific trends. Control variables include the population, geographic area, and population density of each zip code in 2010, the median household income for each zip code in 2014, and monthly percentage of WIC sales in the local market by A-50 stores. Interaction terms of the control variables and *Supmkt Exist* are also included.

In sharp contrast, the coefficients of HHI and WIC% fall statistically zero in markets where supermarkets operate in the pre-policy period. This means that when relatively small stores operate under direct competition of supermarkets do not tend to raise prices as a function of the structure of local markets. Nor do supermarkets themselves raise price as a function of the local market structure. We also notice that the coefficient of *Supcnt Comp* is insignificant. Despite findings such as Hausman and Leibtag (2007) that showed a strong price discipline exerted by Walmart on its rivals, we find no additional yardstick effect of supercenters beyond that provided by supermarkets in general.

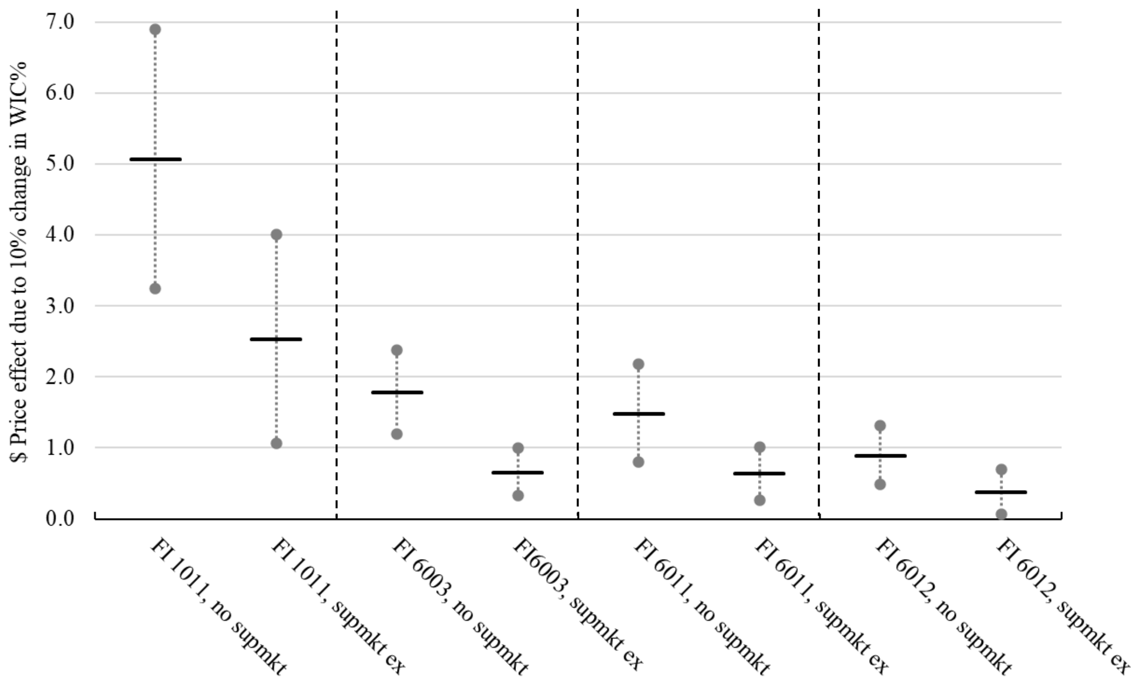
Supermarkets on average charge $1.3 per can less than their medium-sized counterparts—a much smaller price difference than between small and medium-sized retailers. Supermarkets which are supercenters charged even less: a $2.8 discount per can of infant formula or a 3.8% decrease from the mean price. Not surprising, the price differences of supermarkets and supercenters remain largely unchanged by the May 2012 price-ceiling policy which was aimed at restraining the pricing of relatively small WIC stores.

Turning now to the subset of markets where both supermarkets and relatively small stores operate, we estimate specification (2) and report the results in table 4. The goal is to see how stores of different sizes respond to changes in the local market structure when they compete head-to-head. Again, we focus discussion on the estimates of FI 1011 (columns (1) and (2)), given that the four FIs generate estimates of same signs.

First, an increase in concentration in the local market no longer leads to higher prices. Neither supermarkets nor other stores tend to adjust the price when HHI goes up. Second, relatively small stores still raise the price as a function of their WIC sales shares. Compared to the estimates in table 3, however, the magnitude of the coefficient falls by about half. Every 10% increase in

WIC% now implies an increase of $0.6 per can of infant formula. Though the mean values of these two WIC% coefficients differ substantially, they tend not to be statistically different given large standard errors (see Figure 3). Finally, coefficients of all other variables of interest stay consistent with those in table 3. In particular, supermarkets do not increase prices in HHI or WIC% whether the price-ceiling policy is in effect.

Figure 3. *Price Effects of WIC% for Small and Medium-Sized Stores*



Note: Drawn by the authors based on tables 3 and 4. The vertical axis measures the price effect of a 10% increase in WIC% of store with 1-6 registers in zip codes with and without supermarkets, respectively. “No supmkt” refers to markets with no supermarket operating, while “supmkt ex” refers to markets with supermarkets. The horizontal segment for each FI represents the average price effect. The upper grey dot represents the upper bound of the 95% confidence interval, while the lower grey dot is the lower bound of the interval.

Table 4. *Market Structure and WIC Program Redemption Rates for Zip Codes with Supermarkets*

Dep. Var.	WIC Redemption Rates ($/Transaction)							
	FI 1011		FI 6003		FI 6011		FI 6012	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-policy	Post-policy	Pre-policy	Post-policy	Pre-policy	Post-policy	Pre-policy	Post-policy
HHI	-2.100	0.122	-0.370	2.124	-1.187	0.960	-0.201	1.679
	(11.319)	(2.777)	(2.964)	(1.618)	(3.083)	(1.207)	(1.838)	(1.396)
HHI	1.313	-2.149	-0.113	-2.249	0.801	-0.934	0.585	-0.916
×Supmkt	(11.261)	(2.910)	(2.932)	(1.785)	(3.041)	(1.325)	(1.845)	(1.563)
WIC%	0.254***	0.052	0.066***	0.015***	0.064***	0.010***	0.038**	0.005
	(0.075)	(0.034)	(0.017)	(0.005)	(0.019)	(0.004)	(0.016)	(0.004)
WIC%	-0.236***	-0.048	-0.061***	-0.019***	-0.058***	-0.013***	-0.041***	-0.013**
×Supmkt	(0.072)	(0.033)	(0.017)	(0.005)	(0.018)	(0.004)	(0.015)	(0.004)
SFR	33.672***	5.820***	8.073***	0.761***	8.046***	0.840***	5.002***	0.789***
	(2.163)	(0.592)	(0.471)	(0.213)	(0.489)	(0.161)	(0.299)	(0.190)
Supmkt	-0.330	-1.370	0.547	0.431	0.204	-0.071	-0.077	-0.142
	(2.447)	(0.873)	(0.745)	(0.385)	(0.785)	(0.291)	(0.479)	(0.352)
Supcnt	-7.062***	-6.552***	-2.287***	-2.098***	-0.982***	-0.907***	-0.369***	0.077
	(0.582)	(0.387)	(0.152)	(0.083)	(0.142)	(0.065)	(0.136)	(0.106)
Supcnt Comp	-0.171	0.276	0.061	0.152**	-0.043	0.030	-0.073	-0.040
	(0.595)	(0.353)	(0.142)	(0.077)	(0.141)	(0.067)	(0.140)	(0.094)
No. observations	475,971	280,303	3,322,336	2,104,575	3,170,675	1,989,071	4,850,176	2,983,059
R^2	0.711	0.468	0.503	0.134	0.500	0.148	0.413	0.122

Note: Standard errors in parentheses are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. Pooled OLS models are used. The columns titled *pre-policy* report regression outcomes using data from October 2009 to April 2012, while other columns report regressions using data from May 2012 to December 2013. Year-month and county fixed effects are included, so are county-specific trends. Control variables include the population, geographic area, and population density of each zip code in 2010, the median household income for each zip code in 2014, and monthly percentage of WIC sales in the local market by A-50 stores.

Robustness tests

First, it is possible that the intensity of supermarket competition in a market affects supermarkets' "yardstick-of-competition" effect on prices. For example, how much an SFR manages to raise prices as its WIC% goes up might be influenced if it competes with multiple supermarkets relative to competing with only one supermarket. We study the importance of supermarket intensity by adding the number of supermarkets in a local market as a control variable and interact it with $HHI \times Supmkt\ Exist$ and $WIC\% \times Supmkt\ Exist$ in specification (1). Coefficients of these interaction terms on the price are found to be generally insignificant and of small magnitude, leaving our original estimates robust.

Second, we test if relatively small and medium-sized stores (i.e., stores with 1-6 registers) which are chain stores behavior differently compared with the localized ones. As mentioned earlier, one explanation to why chain stores do not adjust prices to local market structure is their "zone-pricing" strategy (DellaVigna and Gentzkow 2017). Prior studies, however, have only looked at chain supermarkets. We take advantage of the WIC data and check if chain stores that are relatively small also tend not to adjust prices to local market structure as much as the localized ones do.

To perform the test, we create an indicator variable, *Chain*, which equals one if there are multiple stores under one store identification number in the GLA area. It turns out that 21% of the non-A-50 small stores in our sample are chain stores, and over 96% the supermarkets are. We interact *Chain* with HHI and WIC. We find that the coefficients of HHI × *Chain* and WIC% × *Chain* are negative but generally insignificant for relatively small stores that operate in markets without supermarket. Thus, there is weak evidence that chain small stores tend to increase prices in HHI and WIC% less than localized ones do if not competing head-to-head with supermarkets.

For relatively small stores competing directly with supermarkets, WIC%$\times$ SFR $\times$ *Chain* has negative and significant coefficients and cancel out the positive coefficient of WIC% $\times$ *SFR*. The estimates indicate that only the non-chain relatively small stores still increase prices in WIC% in markets with supermarkets, which further illustrates the findings in table 4.

Finally, we notice that the distribution of HHI is approximately bimodal with a large portion of zip codes having HHI of 0.2 to 0.35 and another portion having HHI close to 1. Instead of treating HHI as a continuous variable, we define a binary variable, *HHI_Hg*, which equals one is HHI is larger than 0.4 (i.e., the 25% percentile of HHI) and replace HHI with *HHI_Hg* in specification (1). We find that the coefficient of *HHI_Hg* is positive and significant for transactions in markets with no supermarket, but insignificant for those in the other types of markets. Outcomes of robustness tests are available from the authors upon request.

Concluding Remarks

Our study has incorporated a number of features that distinguish it from prior work on the relationships between retail prices and market structure in food markets. It is the first to define local markets and measure market concentration at the zip-code level. Numerous studies have shown that urban consumers travel at most a few miles to do grocery shopping. Using zip codes, therefore, enabled this study to better identify relevant markets for food retailing, compared to prior studies that examined concentration and food pricing at considerably more aggregate levels such as MSAs or CBSAs.

This study is the first to utilize WIC transactions data to analyze pricing by food retailers as a function of local market structure. Use of WIC data enabled us to study pricing behavior at the transaction level for frequently redeemed packages of staple foods and to have data on small food retailers that are generally not included in scanner datasets. These data also avoid issues due to data aggregation that is inherent in scanner data. A disadvantage in our application was that data were recorded at the WIC food-instrument level instead of by UPC code, a shortcoming that is eliminated as state WIC agencies convert to electronic benefit transfer (EBT) by 2020.

Our empirical findings for the Greater Los Angeles area indicate that supermarkets charged relatively low prices and did not tend to raise prices according to local market structure. In contrast, small sized stores charged significantly higher prices than supermarkets whether they were able to exercise market power or not. Furthermore, if unbridled by the presence of supermarket competitors, econometric analysis showed that WIC redemption rates charged by small stores were increasing in both HHI and WIC%, the latter result most likely reflecting a combination of these stores "pricing to WIC" to exploit the inelasticity of WIC customers' demands, and their ability to exploit local market power to raise food prices.

Our findings have important policy implications for the WIC program and for food-desert areas. Retailers who increase food prices by exercising market power and/or pricing to WIC, raise program costs and reduce the program's ability to serve participants. Further, retailers that "price to WIC," raise costs of staple foods for poor consumers who are not included in the program. Those consumers would be particularly vulnerable if constrained to shop at these local retailers due to lack of access to supermarkets.

Despite the potentially important negative externality of the WIC program, the good news from a policy perspective is that supermarkets were present in most of the market areas included in this study. However, the areas where they were not present are generally low-income neighborhoods, where residents may be constrained in their ability to shop outside of the local market area. Our findings suggest the efficacy of former First Lady Michelle Obama's wellpublicized 2011 initiative to encourage supermarket entry in food desert areas as part of her “Let’s Move” campaign. However, the Associated Press (2015) reported that relatively little progress had been achieved in the four years since launch of the campaign and the promise of leading retailers, including Walmart, to join the campaign. The Associated Press’s analysis showed that only 1.4 million of 18 million food-desert residents had experienced entry by a supermarket in the intervening four years, meaning the policy issue remains largely unresolved.

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