Concentration in Food Retailing, Prices, and Inflation

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Abstract

This paper examines the extent to which the recent surge in food prices is associated with market concentration in a sample of urban Core-Based Statistical Areas in the United States. We construct Herfindahl-Hirschman Index to measure market concentration using sales information from a census of food retail establishments obtained from the National Establishment Time Series dataset. We also construct panel price indices for select food product categories (produce and non-alcoholic beverages) using IRI InfoScan point-of-sale scanner data between 2010-2021. Using the data, we use panel data methods to estimate the effect of market concentration on price levels and changes in price levels comparing the historical period to 2021, when food prices rose substantially in the wake of the COVID-19 pandemic. Our preliminary results show a positive and significant association between market concentration and price levels during the study period. Whereas we do not find any significant association between market concentration and changes in price levels in our sample CBSAs when comparing 2010-2020 to 2021. This study is the first attempt to evaluate the relationship between food retail concentration and price inflation using novel data merging and panel data methods. Additional analyses we intend to carry out will evaluate the price-HHI relationship at alternative, more geographically granular levels of consumer markets.

Keywords**:** Food retailing prices, market concentration, HHI, Inflation
JEL Classifications: L11, E31, L16

Introduction

U.S. food price inflation has recently been at its highest levels in over three decades. In 2022, the consumer price index (CPI) for food at home increased by 11.8 percent, almost five times its 20-year historical average of 2.4 percent (Figure 1).[1] Fast-rising food prices are a pressing economic problem due to social and economic consequences such as the disproportionate welfare impacts on low-income households and their potential to increase food insecurity but reducing buying power among low-income households. However, factors affecting the recent food price inflation are many and complex, and a growing literature is devoted to the topic (see, e.g., Ball et al., 2022; Cai, Çakır, and Dong, 2023; Cerrato & Gitti, 2022; Cline, 2023). This paper focuses on the relationship between price inflation and the structural features of retail markets. Specifically, we examine the degree to which market concentration is associated with high food prices and inflation in local markets in a sample of urban Core-Based Statistical Areas in the United States.

The trends of increasing concentration in retail food markets over time and across markets are well documented (Çakır et al. 2020; Crespi and MacDonald 2022; Zeballos, Dong, and Islamaj 2022). For instance, Çakır et al. (2020) investigate local and national concentration trends in food retailing using the Herfindahl-Hirschman Index (HHI). They find that the HHI increased by more than five percentage points nationally from 1990-2015. They also show that the supercenters' entry is positively associated with an increased market concentration in the same period. Similarly, Crespi and MacDonald (2022) document that sales by the 20 largest food retailers increased from 35 percent in 1990 to 65.1 percent in 2019, with the top four retailers accounting for one-third of all grocery sales.

[1] Data source: U.S. Bureau of Labor Statistics. https://www.bls.gov/bls/news-release/cpi.htm#2022. Accessed on May 12, 2023.

There is a historically large literature examining the relationship between market concentration and prices, dating back to the studies of the Structure-Conduct-Performance paradigm in the 1950s (see Schmalensee 1989 for a review). However, recent studies on the relationship between food retailing concentration and prices are sparse (e.g., Hovhannisyan and Bozic 2016; Hovhannisyan, Cho, and Bozic 2019; Biscourp, Boutin, and Vergé 2013). Hovhannisyan, Cho, and Bozic (2019) examine grocery retailer concentration and prices in 16 U.S. metropolitan markets between 2008 and 2012, finding that a 5 percent increase in HHI leads to an 18 percent increase in food prices. While previous studies have struggled to find an identification strategy to evaluate the relationship between food prices and HHI, Hovhannisyan et al. (2019) overcome this issue by using a novel instrumental variable fixed-effects model to correct for endogeneity inherent in the price-HHI relationship. In a more recent study, Dong, Balagtas, and Byrne (2023) show that rising fixed costs in food retail have increased market concentration with little impact on prices, yet this study is conducted at the national level, so it cannot evaluate the level of concentration that consumers face in localized markets. Our first objective contributes to this literature by examining how increasing local/regional concentration in food retailing affects food price levels using a unique combination of datasets comprising a near census of retail establishments and a sample of point-of-sale food purchases from selected CBSAs across the United States.

Our second objective is to examine the relationship between local/regional food retail concentration and food price inflation. While some studies suggest that lower concentration can lead to lower prices due to increased competition (Vardges Hovhannisyan, Cho, and Bozic 2019; Biscourp, Boutin, and Vergé 2013), the extent to which market concentration affects not only price levels but also changes in price levels, including during inflationary periods such as what has occurred in the last two years, remain unclear. To our knowledge, this study is the first to investigate the latter relationship.

To achieve our objectives, we first construct HHI for several geographic definitions of the market using the National Establishment Time Series (NETS) store-level data.[2] The data provides information on sales, employment, and store location of each establishment in the United States between 1990 and 2020 on an annual basis. Then, we construct panel price indices from retail food stores in the IRI scanner data for select food categories using point-of-sale scanner data and index number methods to measure changes in price levels (Çakır et al., 2018; 2022). In particular, the panel price indices allow us to consistently estimate temporal and spatial price changes for each food category across markets. Last, we use panel data methods in a two-step estimation procedure to estimate the effect of market concentration on price levels and changes in price levels.

Our preliminary analysis investigates the association between market concentration in 21 Core Based Statistical Areas (CBSAs) and prices of two product categories: produce and non-alcoholic beverages. We find that the association between market concentration and price levels is positive and significant. However, we do not find any significant association between market concentration and changes in price levels for 2021. Our ongoing work will expand the analysis to cover all markets in the United States and incorporate alternative and more granular geographic market definitions and more food categories. Our results shed new light on the role of concentration in food retail pricing and whether structural factors played any role in driving food price inflation that occurred in 2021 in the wake of the COVID-19 pandemic.

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[2] NETS is a propriety dataset acquired by the Economic Research Service of the USDA to conduct policy-related research.

The paper proceeds as follows. The next section introduces the dataset and discusses its unique aspects. The subsequent section presents our index number methods to construct panel price indices and the econometric model for estimation. Then, we present the results, and the last section concludes.

Data

We obtain data from two primary sources: the National Establishment Time-Series (NETS) and the store scanner data collected by Information Resources, Inc. (IRI)—both datasets purchased by the Economic Research Service (ERS) of the U.S. Department of Agriculture for use in food policy research. The NETS dataset includes information on sales, address, employment, and NAICS codes, at the establishments level between 1990–2020. The dataset also provides retailer names, which is particularly useful when identifying food retailers that cannot be identified via NAICS codes, such as dollar stores. Additionally, the address information enables us to estimate the HHI for alternative geographic definitions of the markets, such as Zip Code, County, or CBSA. For the present analysis we are limited to evaluating the relationship between prices and HHI at the CBSA level, but future work will evaluate the relationship in these more granular geographic areas.

Our second source of information is the scanner data from Information Resources Inc (IRI), which provides weekly purchase information at the Universal Product Code (UPC) level. Our sample includes sales and quantity information for produce and non-alcoholic beverage categories from retailers in 21 CBSAs between 2010 and 2021.[3] These product groups are widely studied in the

[3] The NETS dataset contains over 900 CBSAs. However, in this preliminary analysis, we only use 21 CBSAs for

previous literature. Using the data, we construct monthly panel price indices, which are then aggregated to an annual index to match the frequency of data obtained from NETS. Finally, we also obtain population and poverty data from the census and information on wages from the U.S. Bureau of Labor Statistics. These data are included in our model to control for variability in socioeconomic characteristics that may be correlated with food price levels and/or the placement or prevalence of food retail establishments, which would impact HHI scores across CBSAs.

Methods

Herfindahl-Hirschman Index

The HHI requires information on market shares of all firms in a market and is one of the most used indicators of market concentration in the industrial organization literature.[4] The HHI is calculated by taking the sum of the squared market shares of all individual firms in a market. Formally, let *r* index retailer, the HHI in market *m* in period *t* is given as:

$$H_{mt} = \sum_{r} s_{rmt}^{2}, \qquad (1)$$

where s_{rmt} is the market share of retailer *r* in market *m* at time *t,* and is calculated using establishment-level annual sales data as:

$$s_{rmt} = \frac{\sum_{i \in I_r} x_{imt}}{\sum_i x_{imt}},$$

where x_i is the food sales of establishment *i,* and I_r is a partition of stores owned by the retailer *r.*[5] In our preliminary analysis reported below, we calculate the HHI at the establishment level, which

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which Burau of Labor Statistics reports at least one price index. Our set of CBSAs includes the largest metropolitan areas, such as New York City and Los Angeles, and are relatively less concentrated. Therefore, the average HHI of our sample is not representative of the average HHI of all CBSAs.

[4] The U.S. Federal Trade Commission regularly uses the HHI to conduct a competitive analysis of a proposed merger or acquisition in a relevant antitrust market (U.S. Department of Justice and Federal Trade Commission 2010).

[5] We adjust sales of each establishment in our data by the food sales ratios provided by the Economic Census.

assumes each store is a competitor even if the same retailer owns them. Our ongoing work will calculate HHI at the more preferred retailer level.

Table 1 reports descriptive statistics of estimation data by CBSA. Notably, the average market concentration in our sample of CBSAs are low. Theoretically, HHI takes values between zero and ten thousand, i.e., $HHI \in (0{,}10{,}000]$, with HHI=10,000 representing a monopoly market. Our calculated average HHI from 2010-2021 ranges from 14 in Los Angeles to 249 in Minneapolis, indicating highly competitive markets over the period under study.[6]

Panel Price Indices

To obtain prices for different food categories and their estimates of temporal and spatial changes, we construct panel price indices using index number methods that are widely applied with scanner data (Çakır et al. 2018; 2022; Li and Çakır 2013). Specifically, we use the rolling window GEKS index to obtain temporal indices (Ivancic, Erwin Diewert, and Fox 2011), the Minimum Spanning Tree method to obtain spatial indices(Hill 1999), and the Chronological Graph (CG) method to link the temporal and spatial indices and get the panel price index (Hill 2004). The GEKS method is calculated by taking the geometric mean of the ratios of all bilateral indices between the two periods being compared, with each period ($l = 1, \dots, T$) in the sample serving as the base. The GEKS index formula for the comparison of periods j and k can be expressed as follows:

$$P_{GEKS}^{j,k} = \prod_{l=0}^{T} \left[P^{j,l} \times P^{l,k}\right]^{1/(T+1)}, \qquad (2)$$

[6] Because our reported HHIs are calculated at the establishment level and for the largest CBSAs, they are comparably lower than those published in the prior literature (e.g., Çakır et al. 2020; Zeballos, Dong, and Islamaj 2022), which are calculated at the retailer level.

where $P^{j,l}$ and $P^{l,k}$ are bilateral Törnqvist indices given as:

$$P_T^{0,t} = \prod_{i=1}^{N} \left(\frac{P_i^t}{P_i^0}\right)^{\frac{s_i^0+s_i^t}{2}},$$

where s_i^0 and s_i^t are the expenditure shares of item i in periods 0 and t (years), respectively. The unit value of good i in period t is represented by P_i^t. The rolling window GEKS method allows adding new periods without the need to revise reported values for previous periods. Formally, let $W + 1$ denote the window length, then the rolling window GEKS going from period 0 to period $T > W + 1$ can be expressed as:

$$P_{RWGEKS}^{0,T} = P_{GEKS}^{0,W} \times \prod_{t=W+1}^{T} \prod_{t=T-W}^{T} [P^{t,T-1}/P^{t,T}]^{1/(W+1)} \tag{3}$$

Following Ivancic, Erwin Diewert, and Fox (2011), we calculate the index using 13 months window length, i.e., $W = 12$.

We construct spatial indices for each period using Hill's (1999) MST approach, which accounts for price and expenditure similarities between any two CBSAs in constructing the overall index. Then, we combine the temporal and spatial price indices using the CG method to obtain the panel price index (Hill 2004). The CG method links the temporal price indices, which are chronological, with a spatial reference comparison. Because the choice of the reference index could lead to different results, we use the geometric mean of spatial indices in all periods as the reference index. Figure 2 presents monthly CBSA-level panel price indices for produce and beverages between 2010–20221.

Econometric Model

A primary challenge to estimating the price-HHI relationship is the endogeneity problem inherent between market concentration and prices. Prior literature addressed the issue using the instrumental variable approach (e.g., (Hovhannisyan, Cho, Bozic 2019; Singh and Zhu 2008)). To fix ideas, consider the following price-concentration model:

$$P_{imt} = X_{mt}\theta + \alpha HHI_{mt} + \lambda_i + \lambda_m + \epsilon_{imt}, \quad (4)$$

where *P* is the price index of product category *i* in market *m* and time *t (year)*, X is a vector of CBSA socioeconomic characteristics, *HHI* is the Herfindahl - Hirschman index measuring market concentration, λ_i and λ_m are product and market fixed effects, respectively, and ϵ is the error term.[7]

The OLS estimate of α in this model is biased due to the potential endogeneity of the *HHI with prices*. The HHI might be endogenous because of the simultaneity problem, as prices affect market structure. Also, market concentration is a function of output which is correlated with unobserved determinants of price; hence $COV(\epsilon, HHI) \neq 0$. To address the endogeneity problem, Singh and Zhu's (2008) used a two-step estimation procedure. An underlying assumption of the two-step model is that the observed market structure is an outcome of a strategic game between potential entrants. Hence, in the first stage, a model of firm entry is estimated to obtain correction terms which are then inserted into equation (4) to correct for the correlation between the error term and the HHI. The intuition is that the correction terms are proxy variables representing the firm's long-term entry decisions without affecting short-term prices. While there are many alternative firm-entry models, in a typical model, the probability of observing *n* firms in a market is estimated as a function of exogenous demand and cost shifters (Bresnahan and Reiss 1990). This paper reports

[7] Note that our price data includes 2021 but the HHI data ends in 2020. Therefore, our measures of price index and concentration are not contemporaneous.

the results of our preliminary analysis based on estimating (4) using OLS. However, in our ongoing work, we use a combination of Evans, Froeb, and Werden's (1993) panel data technique and Singh and Zhu's (2008) two-step estimation method to estimate the model. Furthermore, for robustness, the model will be estimated for alternative geographic definitions of the market.

We also estimate the effect of retail concentration on food price inflation by replacing the price variable in equation (4) with its first difference, i.e., ΔP_{imt}, where $\Delta P_{imt} = P_{im,t} - P_{im,t-1}$, and adding an interaction of HHI with a dummy for the period of high inflation, i.e., $D = 1, if\ t \in [January\ 2021, December\ 2021]$, and $D = 0$, otherwise.

$$\Delta \mathrm{P}_{imt} = X_{mt}\theta + \alpha HHI_{mt} + \beta D * HHI_{mt} + D + \lambda_i + \lambda_m + \epsilon_{imt}. \qquad (5)$$

The coefficient of interest β measures whether the rate of price changes is correlated with market concentration.

Preliminary Results

Table 2 presents our results. Models 1-3 present the estimates of equations (4), while models 4-6 present the estimates of equation (5). We add product and market fixed effects for each set of estimates sequentially. Model (1) does not include product and CBSA fixed effects and shows no statistically significant association between HHI and prices. Model (2) adds product fixed effects. While this raises the R-squared from 0.1 to 0.36, the estimated coefficient on HHI remains statistically insignificant. Finally, model (3) adds CBSA fixed effects. This model explains 67 percent of the price variation and shows a statistically significant and positive association between HHI and prices at a ten percent significance level. The estimated coefficients of population and wages in Model (3) are also statistically significant and positive, while the estimated coefficient on poverty is not statistically significant.

In a similar procedure, we estimate equation (5), adding fixed effects sequentially. However, estimates presented in models 4-6 show that HHI has no statistically significant association with price changes. Furthermore, the coefficient on the interaction of HHI with the 2021 dummy is also insignificant, indicating that market concentration had no discernible effect on the recent surge in food prices in the United States.

Conclusion

This paper investigates two relationships in food retail markets: one between market concentration and price levels and the other between market concentration and the changes in price levels. While the first relationship has a relatively long, historical literature, few studies have evaluated the second relationship. Notably, whether the recent surge in food prices differs by the level of market concentration in geographical granular food retail markets is unknown. We address these questions using the National Establishment Time Series (NETS) near census of food retail establishments and IRI point-of-sales scanner data for 2010-2021 for 21 urban CBSAs. The NETS data allows us to calculate HHI for alternative urban geographic markets, while the IRI data allows us to construct panel price indices at the product level across markets, which, in turn, allows us to estimate temporal and spatial price changes. Our preliminary analysis uses data for 21 CBSAs and two product categories, non-alcoholic beverages and produce. The results show that although there is some evidence of a statistically significant association between HHI and price levels, the association between HHI and changes in price levels is statistically insignificant.

It is worthwhile to highlight some of the important caveats of our preliminary results. First, the results are based on 21 CBSAs which are among the largest in the U.S. and are not representative of all CBSAs, and they do not necessarily represent larger markets in which consumers typically shop. Furthermore, our sales data has a higher coverage for urban markets than rural markets, which means it may not accurately reflect highly concentrated markets typically found in rural areas (Çakır et al., 2020). Similarly, our analyses are also limited to examining produce and non-alcoholic beverages. Our ongoing work addresses these issues by expanding our sample data.

Second, we estimate the models in a single step using OLS. These models typically suffer from the endogeneity of HHI, and the estimates are potentially biased. Our ongoing work searches for valid instruments to implement the two-step procedure, as discussed in the modeling section. Last, the latest available data only extends until the end of 2021. Consequently, our analysis accounts for the price surge in the second half of 2021, but not the more significant surge that occurred throughout 2022.

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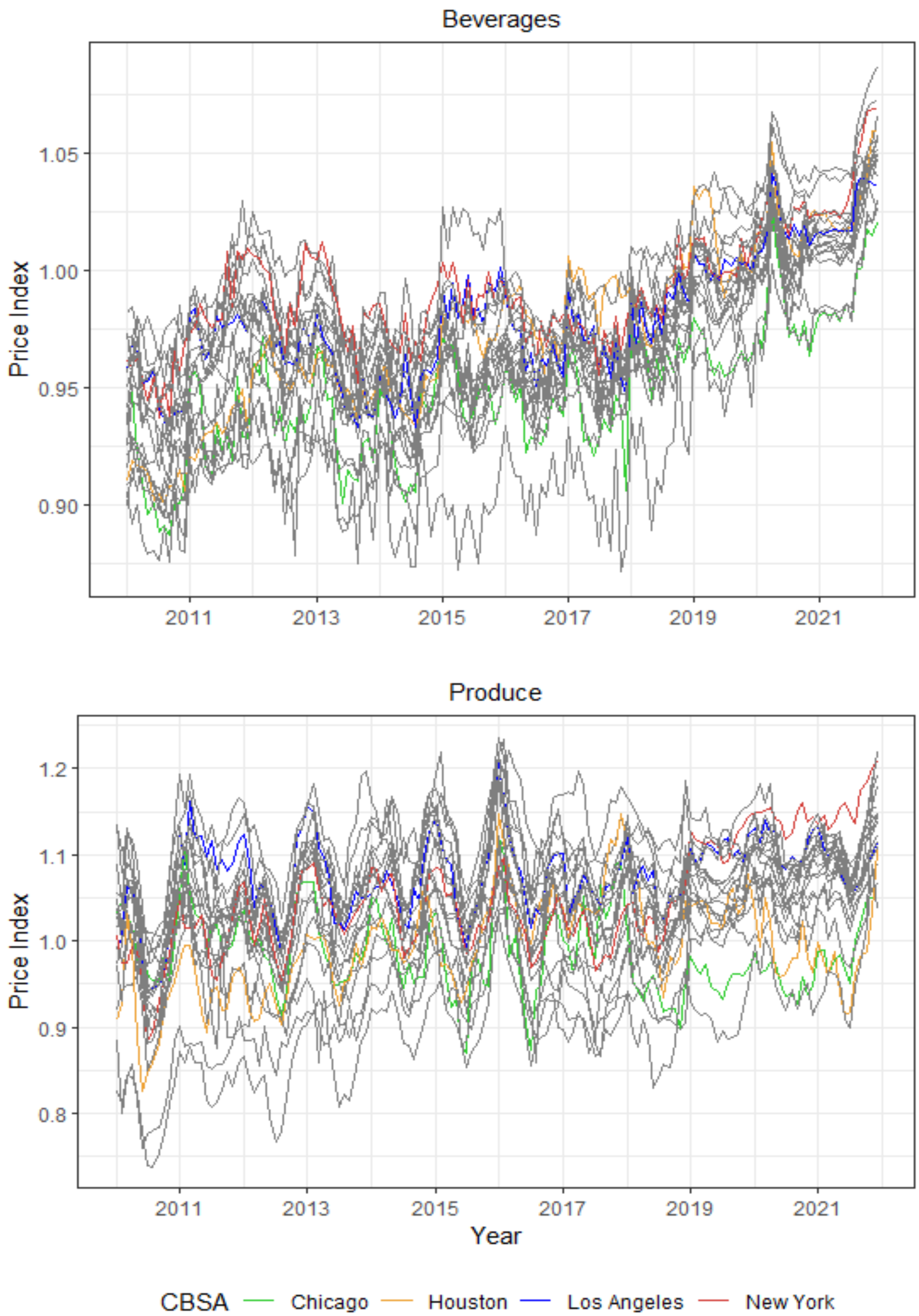
Figure 1: Food at Home Consumer Price Index, 2010-2023

Data: BLS

Figure 2: Monthly Panel Price Indices for Non-alcoholic Beverages and Produce across Twenty-one Core Based Statistical Areas, 2010-2021



Beverages
Price Index
1.05
1.00
0.95
0.90
2011
2013
2015
2017
2019
2021
Produce
Price Index
1.2
1.1
1.0
0.9
0.8
2011
2013
2015
2017
2019
2021
Year
CBSA
Chicago
Houston
Los Angeles
New York

Table 1. Descriptive Statistics by CBSA, 2010-2021

CBSA		Poverty All Ages (%)	Average weekly wages ($)	Population (Millions)	HHI (Out of 10,000)
Atlanta	Mean	14.31	1104	5.73	22.17
	Min	11.53	946	5.30	21.00
	Max	16.88	1342	6.14	24.00
	SD	1.90	113	0.29	0.82
Baltimore	Mean	9.14	1126	2.79	152.69
	Min	8.27	979	2.72	102.77
	Max	9.87	1366	2.84	193.44
	SD	0.54	119	0.04	30.76
Boston	Mean	9.69	1281	4.78	31.10
	Min	8.36	1081	4.57	26.01
	Max	10.77	1613	4.94	41.08
	SD	0.86	164	0.12	5.12
Chicago	Mean	10.22	1047	9.52	23.79
	Min	8.54	909	9.45	21.61
	Max	11.70	1260	9.60	27.15
	SD	1.07	102	0.04	1.71
Dallas	Mean	10.96	1106	7.11	29.80
	Min	8.97	946	6.40	19.49
	Max	12.47	1340	7.77	41.90
	SD	1.35	117	0.46	8.09
DC, Washington	Mean	8.34	1343	6.09	28.95
	Min	7.35	1199	5.68	25.09
	Max	8.96	1614	6.39	35.00
	SD	0.53	131	0.22	3.11
Denver	Mean	8.41	1156	2.81	52.91
	Min	6.86	981	2.55	37.78
	Max	10.21	1447	2.97	78.02
	SD	1.24	142	0.15	15.47
Detroit	Mean	12.29	1103	4.32	32.86
	Min	10.18	957	4.29	30.26
	Max	14.43	1303	4.39	40.39
	SD	1.40	105	0.03	2.64
Houston	Mean	12.61	1053	6.65	35.97
	Min	10.82	910	5.95	22.58
	Max	14.36	1195	7.21	52.11
	SD	1.26	85	0.43	10.00
Los Angeles	Mean	13.93	1176	13.11	14.33
	Min	11.10	1016	12.84	12.00
	Max	16.25	1464	13.27	21.00
	SD	1.84	138	0.14	3.24
Miami	Mean	15.10	999	5.95	17.43
	Min	12.67	868	5.58	15.72
	Max	17.20	1271	6.16	19.60
	SD	1.70	120	0.20	1.56
Minneapolis	Mean	7.85	1080	3.54	248.50
	Min	6.50	958	3.36	50.00

CBSA		Poverty All Ages (%)	Average weekly wages ($)	Population (Millions)	HHI (Out of 10,000)
	Max	9.07	1284	3.71	607.00
	SD	0.84	100	0.12	207.37
New York	Mean	11.17	1226	19.33	44.84
	Min	9.78	1081	18.92	38.92
	Max	12.15	1485	20.10	63.56
	SD	0.80	126	0.31	6.50
Philadelphia	Mean	10.43	1118	6.08	90.58
	Min	9.27	989	5.97	76.00
	Max	11.28	1331	6.24	105.00
	SD	0.58	105	0.08	10.37
Phoenix	Mean	14.71	1008	4.61	25.49
	Min	11.00	876	4.20	23.57
	Max	17.55	1250	4.95	28.75
	SD	2.45	111	0.27	1.57
Riverside	Mean	15.94	855	4.47	47.34
	Min	12.30	753	4.24	42.18
	Max	19.10	1049	4.65	52.91
	SD	2.56	93	0.14	3.29
San Diego	Mean	12.94	1151	3.25	38.14
	Min	9.50	971	3.10	34.23
	Max	15.30	1451	3.33	44.52
	SD	2.09	142	0.08	2.80
Seattle	Mean	10.07	1199	3.77	138.20
	Min	7.80	973	3.45	70.75
	Max	12.57	1574	4.02	230.26
	SD	1.69	187	0.20	67.82
San Francisco	Mean	9.46	1657	4.60	190.76
	Min	7.46	1252	4.34	121.49
	Max	11.24	2413	4.74	309.78
	SD	1.32	341	0.13	72.35
St. Louis	Mean	11.72	939	2.80	53.10
	Min	9.77	827	2.79	38.42
	Max	13.12	1124	2.82	83.66
	SD	1.09	90	0.01	13.89
Tampa	Mean	14.23	879	3.01	31.43
	Min	11.73	763	2.79	28.61
	Max	16.28	1092	3.22	37.91
	SD	1.52	99	0.16	2.88

Table 2. Regression Results

Dependent Variable	(1) Price	(2) Price	(3) Price	(4) Price Change	(5) Price Change	(6) Price Change
Population	0.0276	0.0276	3.6524**	0.0203	0.0203	-2.5160***
	(0.1028)	(0.1029)	(1.6309)	(0.0144)	(0.0145)	(0.4101)
Weekly Wages	0.0092**	0.0092**	0.0110***	-0.0002	-0.0002	0.0009
	(0.0042)	(0.0042)	(0.0037)	(0.0004)	(0.0004)	(0.0011)
Poverty	0.0831	0.0831	0.0311	-0.0147	-0.0147	-0.2246***
	(0.3884)	(0.3888)	(0.1862)	(0.0363)	(0.0363)	(0.0567)
HHI	0.0019	0.0019	0.0134*	0.0029	0.0029	0.0034
	(0.0046)	(0.0046)	(0.0065)	(0.0018)	(0.0018)	(0.0023)
Dummy2021				0.2159	0.2159	0.1531
				(0.3726)	(0.3730)	(0.3941)
Dummy2021*HHI				0.0003	0.0003	-0.0005
				(0.0014)	(0.0014)	(0.0015)
Constant	88.4893***	88.4893***	64.8706***	0.9556	0.9556	17.1899***
	(8.8299)	(8.8388)	(9.2124)	(0.6681)	(0.6689)	(2.6987)
Observations	504	504	504	462	462	462
R-squared	0.101	0.358	0.673	0.010	0.011	0.042
Product fixed effects	NO	YES	YES	NO	YES	YES
CBSA fixed effects	NO	NO	YES	NO	NO	YES

Notes: Standard errors cluster at CBSA level in parentheses, *** p<0.01, ** p<0.05, * p<0.1