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Goods Prices and Availability in Cities

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Abstract

This paper uses detailed barcode data on purchase transactions by households in 49 U.S. cities to calculate the first theoretically-founded urban price index. In doing so, we overcome a large number of problems that have plagued spatial price index measurement. We identify two important sources of bias. Heterogeneity bias arises from comparing different goods in different locations, and variety bias arises from not correcting for the fact that some goods are unavailable in some locations. Eliminating heterogeneity bias causes 97 percent of the variance in the price level of food products across cities to disappear relative to a conventional index. Eliminating both biases reverses the common finding that prices tend to be higher in larger cities. Instead, we find that price level for food products falls with city size.

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1 Introduction

The variation in prices and price indexes across locations is as central to economic geography and international economics as inflation is to macroeconomics. However, the methods used to construct prominent spatial price indexes are significantly cruder than those used to construct inflation rates and other inter-temporal price indexes. While the U.S. Consumer Price Index (CPI) compares the relative prices over time of identical goods sold in the same store, regional price indexes compare different (but similar) goods purchased in different stores.[1] Moreover, the U.S. CPI accounts for product entry and exit. Evidence suggests that product availability varies across locations as well as over time, yet even the latest spatial price indexes do not account for these differences.[2]

This paper uses detailed barcode data documenting purchase transactions by households in 49 U.S. cities to overcome these obstacles in spatial price index measurement. In order to give some sense of the magnitude of the heterogeneity and variety biases in standard indexes, we focus on two phenomena: the spatial variation in price indexes, which is itself the subject of the purchasing power parity (PPP) debate, and the correlation of price indexes with population, which yields a common agglomerating force across many New Economic Geography (NEG) models. Our use of better data enables us to replicate prior results from these areas and demonstrate a number of novel findings.

First, we precisely measure prices of *identical* goods sold in comparable stores across 49 U.S. cities to properly estimate spatial price differences. While standard price indexes show a positive correlation between average prices and city sizes, this correlation almost entirely disappears when we compare transaction prices of identical products purchased in the same stores. If we define purchasing power parity (PPP) deviations as differences in the average price of traded goods, we find that 97 percent of the variance in PPP deviations for groceries across U.S. cities can be attributed to heterogeneity biases in the construction of price indexes.

Second, while average product prices do not vary much across space, we find dramatic differences in product availability. The detail of our transaction-level data allows us to quantify these differences. We estimate the number of varieties of products available in each city and find that a doubling in city size is associated with a 20 percent increase in the number of available products.

[1]The ACCRA (American Chamber of Commerce Researchers Association) index of U.S. urban prices, used in important papers such as Chevalier (1995), Parsley and Wei (1996), Albouy (2009), and Moretti (2013), is an example of such an index.

[2]The Bureau of Economic Analysis (BEA) recently released regional price (RPP) indexes for the U.S. The RPP methodology, outlined in Aten (2005) and Aten and Martin (2012), makes some headway towards adjusting for product and store heterogeneity. Product heterogeneity has also been partially addressed in the latest Penn World Table (PWT), which compares quality-adjusted prices across countries (Feenstra et al., 2012). Data limitations mean that neither the PWT or the BEA's RPP indexes compare identical goods in different markets (which is critical for the approach used in this paper), nor do they adjust for variety differences.

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Finally, we use data on the purchase quantities, as well as transaction prices, to demonstrate that the differences in variety availability yield economically significant variation in the price level across cities.[3] When we use the data to construct a theoretically rigorous price index that corrects for product, purchaser, and retailer heterogeneity *and* accounts for variety differences across locations, we find that the price level is actually lower in larger cities. Consumers spend less, on average, to get the same amount of consumption utility in larger cities.

The association between city population and price levels plays an important role in many urban and NEG models. NEG models typically predict that price indexes over tradable goods are lower in larger cities (see, *e.g.,* Fujita (1988); Rivera-Batiz (1988); Krugman (1991); Helpman (1998); Ottaviano et al. (2002); Behrens and Robert-Nicoud (2011)). This prediction is at odds with empirical work demonstrating that prices are higher in larger cities (DuMond et al., 1999; Tabuchi, 2001). One reason that these studies have not been deemed fatal for the theory is that it is easy to modify NEG models to generate higher housing prices in cities (see, *e.g.,* Helpman (1998)). Our paper suggests data problems in the construction of urban price indexes are sufficiently large to explain the seemingly contradictory evidence: variety- and heterogeneity-adjusted price indexes are lower in larger cities.

A key difference between this paper and earlier work is that we work with barcode data, so the prices we compare are for *identical* goods. Our dataset includes the prices for hundreds of thousands of goods purchased by 33,000 households in 49 cities in the U.S. Critically, the data indicate the price of each good, where it was purchased, and information about the purchaser. Consistent with earlier analyses, if we aggregate our data and compare the prices of *categories of goods*, we find that the elasticity of the grocery price level with respect to population is 0.042. This implies that New Yorkers (population 21.2 million) pay 16 percent more than people in Des Moines (population 456,000) for similar, but not necessarily identical, groceries. However, when we adjust this index, step-by-step, for the various biases we identify in the standard methodology, we end up with our final estimate for the correct elasticity: -0.011. When estimated properly, grocery price indexes do not rise, but rather fall, with population.

One of the most important classes of bias are "heterogeneity biases," which arise from not being careful about which prices are being compared. For example, the price of an item like a "half-gallon of whole milk" can vary enormously depending on a number of sources of underlying heterogeneity. "Product heterogeneity biases" arise because there are many varieties of whole milk that differ in price, *e.g.,* name brand vs. store brand, organic vs. non-organic, etc.[4] "Retailer heterogeneity biases" arise because high-amenity stores may systematically charge different prices to low-amenity stores for the same good. Finally, "purchaser heterogeneity

[3] We use the word "price" to refer to the price of a particular good and the term "price level" to refer to a price index, or some weighted average of relative prices across goods.

[4] Just to give one simple case of this, in Westside Market in New York on August 18, 2013, a half gallon of Farmland whole milk sold for $2.47 while a half gallon of Sky Top Farms whole milk sold for $6.59.

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biases" arise because shoppers who search intensely for the lowest price can often purchase the same good in the same store for less. Regional price indexes typically do not correct for these biases because without barcode data it is difficult to find the same good in the same store chain in two different locations.[5] To get some sense of the magnitude of these biases among goods that are available in more than one location, we regress disaggregate log prices against log population with product, purchaser characteristic, and store controls. We find that controlling for these heterogeneity biases reduces the elasticity of price with respect to population from 0.042 to 0.006 (86 percent). This indicates that the large positive elasticity in the aggregate data is due to the fact that consumers in large cities tend to purchase higher quality varieties in nicer stores and shop less intensely (presumably because rich people have a higher opportunity cost of time). Although statistically different from zero, the elasticity that remains after controlling for heterogeneity is not economically meaningful; it implies prices of commonly-available goods are approximately equal in large and small cities. Indeed, between 95-97 percent of the variance in PPP deviations across cities disappears once we correct for these biases.

A second major source of bias is variety bias. Variety biases arise because consumers do not have access to the same set of products in all locations. These biases have been studied in the context of the CPI by Broda and Weinstein (2010), but there is reason to believe that they are much more important in the regional context. The difference in product availability between New York and Des Moines, for example, is likely to be much greater than the difference in product availability in the U.S. economy from one year to the next. In order to quantify this effect, we adapt some well-developed statistical procedures to the problem of estimating the number of varieties in cities. Our results indicate very large differences in variety availability. We estimate that there are approximately four times more types of grocery products available in New York than in Des Moines.

In order to quantify the variety bias we need to put more structure on the problem. We use a spatial variant of the Constant Elasticity of Substitution (CES) exact price index developed in the seminal work of Feenstra (1994). The CES structure is commonly employed in NEG models and is well suited for our data.[6] When calculated over varieties available in more than one city and using prices adjusted for product, purchaser, and store heterogeneity, the theoretically-rigorous CES index yields almost the same elasticity of price with respect to population as the price regression above. An advantage of the CES framework is that it enables us to make an additional adjustment for the fact that small cities offer consumers substantially fewer purchase

[5]The food component of the BEA RPP is based on BLS data. The BLS is careful to keep products and stores constant over time, but uses random sampling to select the stores and products for which prices are collected in each location. ACCRA provides field agents with detailed instructions to collect prices for products and in stores meeting certain specifications. These instructions leave a large scope for product and store heterogeneity in prices.

[6]Recent NEG models have also used the quadratic linear framework developed by Ottaviano et al. (2002). While quadratic linear framework is tractable for theoretical analysis, it is difficult to estimate and, therefore, not well-suited for price index measurement.

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options. Given the important difference in product availability across locations, we find that variety bias is extremely important economically. Correcting for the variety bias further lowers the elasticity of price with respect to city size to -0.011. In other words, when we correct for heterogeneity and variety biases, the standard result that prices rise with city size is reversed.

This paper complements large literatures studying international price and variety differences. Simonovska (2010) and Landry (2013), for example, use micro price data to document international price differences of identical products. Barcode price data has also been used extensively in the study of PPP convergence (see a recent survey by Burstein and Gopinath (2013)) and PPP convergence (see, *e.g.*, Broda and Weinstein (2008); Burstein and Jaimovich (2009); Gopinath et al. (2011)). Hummels and Klenow (2005) document that larger countries export more varieties of products; while Bernard et al. (2007) and Eaton et al. (2011) document that larger countries import more varieties of products.

There is less work on intranational price and variety differences. Parsley and Wei (1996) use the ACCRA data to examine convergence to the law of one price in the U.S. Crucini and Shintani (2008) use similar data from the Economist Intelligence Unit, to examine the persistence of law of one price deviations for nine U.S. cities. This work on deviations from the law of one price does not address the question of how much of the difference in observed prices across cities reflects unobserved heterogeneity in products or retailers. The only other paper, to our knowledge, to compare prices of identical goods within countries is Atkin and Donaldson (2012), who use spatial price differences as a proxy for intranational trade costs in developing countries.

A nascent literature has documented that larger and more dense areas in the U.S. have more varieties of restaurants (Schiff, 2012). Unfortunately, the lack of price data and the inability to control for quality differences across restaurants in different locations make it difficult to accurately measure the welfare implications of these variety differences. Recent work by Couture (2013) uses household travel patterns to estimate the substitution between restaurants but, without an additional price or quality measure, he cannot separately identify price from quality, and so he must assume that these two factors are perfectly correlated.

In complementary work, Handbury (2012) uses the same data as the current paper to calculate variety-adjusted city-specific price indexes for households at different income levels and finds that high-income households face relatively lower price indexes in cities with higher per capita incomes. Consistent with the PPP variance results here, Handbury (2012) finds that these intra-income differences are driven entirely by variety differences across cities. Both papers point towards the relevance of the extensive variety margin in explaining PPP deviations across cities.

The rest of the paper is structured as follows. Section 2 describes the data. Sections 3 and 4 explore how identical goods prices and goods availability vary across cities. In Section 5 we

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summarize these results using an urban price index that adjusts for the heterogeneity and variety biases in standard indexes. Section 6 concludes.

2 Data

The primary dataset that we use is taken from the Nielsen Homescan database. These data were collected by Nielsen from a demographically representative sample of approximately 33,000 households in 52 markets across the U.S. in 2005.[7] Households were provided with Universal Product Code (UPC) scanners to scan in every purchase they made including online purchases and regardless of whether purchases were made in a store with scanner technology.[8] Each observation in our data represents the purchase of an individual UPC (or barcode) in a particular store by a particular consumer on a particular day. We have the purchase records for grocery items, with information on the purchase quantity, pre-tax price, and date; the name or type of the store where the purchase is made; and demographic information on the household making the purchase.[9]

Figure 1 presents the basic structure of our data. A barcode, u, uniquely identifies a product. For example, "Horizon 1% Milk in a Half-Gallon Container" has a different barcode than "Horizon 2% Milk in a Half-Gallon Container." Nielsen provides product characteristics for each barcode, including its brand, a detailed product-type description that Nielsen refers to as a "module," and a more aggregate product-type description that Nielsen refers to as a product "group." For example, "Horizon 1% Milk in a Half-Gallon Container" is sold under the "Horizon" brand in the "Milk" module within the "Dairy" product group. We group barcodes with the same brand and in the same module into "brand-modules." For example, "Horizon Milk," "Horizon Butter," and "Breakstone Butter," constitute three different brand-modules in the "Dairy" product group, the first of which is in the "Milk" module and the latter two are in the "Butter" module. The 2005 Homescan sample we consider contains transaction records for almost 350,000 UPCs that are categorized into 597 modules, 27,853 brands, and 55,559 brand-module interactions and 63 product groups.[10] Detailed descriptions of the Nielsen data and the

[7]The Nielsen sample is demographically representative within each market.

[8]In cases where panelists shop at stores without scanner technology, they report the price paid manually. Since errors can be made in this reporting process, we discard any purchase records for which the price paid was greater than twice or less than half the median price paid for the same UPC, approximately 250,000 out of 16 million observations.

[9]Nielsen provides a store code for each transaction in the data. For all but 800,000 of 16 million transactions, the store code identifies a unique store name. For the remaining observations representing 4.4 percent of sales in the data, Nielsen's store code refers to one of approximately 60 store categories, such as "Fish Market," "Cheese Store," "Drug Store," etc.

[10]This sample excludes the "random weight" product group. The quality of random weight items, such as fruit, vegetables, and deli meats, varies over time as the produce loses its freshness. We cannot control for this unobserved quality heterogeneity.

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sampling methods used can be found in Broda and Weinstein (2010).

Figure 1: Terminology

Universal Product Code (UPC) or Barcode ($u \in U_g$)	$\subset$	Brand-Module ($b \in B_g$)	$\subset$	Product Group ($g \in G$)
e.g. Horizon 1% Milk in a Half-Gallon Container		*e.g.* Horizon Milk		*e.g.* Dairy
N=348,646		$N = 55,559$		$N = 63$

Although the Nielsen dataset contains data for 52 markets, we classify cities at the level of Consolidated Metropolitan Statistical Area (CMSA) where available and the Metropolitan Statistical Area (MSA) otherwise. For example, where Nielsen classifies urban, suburban, and ex-urban New York separately, we group all three together as the "New York-Northern New Jersey-Long Island CMSA". We use population, income distribution, and racial and birthplace diversity data from the 2000 U.S. Census and 2005 retail rents from REIS.[11,12] The population and retail rents for the cities included in the analysis are listed in Table A.1, along with market IDs we will use to identify cities in the charts below. There are two cases in which Nielsen groups two MSAs into one market. In these cases, we count the two MSAs as one city, using the sum of the population and the population-weighted mean retail rents.

3 Measuring Retail Prices in Cities

While our ultimate goal is to construct a theoretically-founded urban price index, we begin by exploring the data. Variation in the price index across cities is driven by differences in the prices of identical goods and the variety availability. Our reduced-form analysis explores each of these factors. In this section, we focus only on the price data. We address goods availability and the construction of an urban price index in Sections 4 and 5, respectively.

3.1 Evidence From Categories of Goods

A common method to compare price levels across cities within countries relies on unit value indexes such as those published by the Council for Community and Economic Research (formerly

[11]Specifically, we use the combined effective rents for community and neighborhood shopping centers. Effective rents adjust for lease concessions.

[12]We replicated the analysis below using total manufacturing output and food manufacturing output as alternative measures of city size and reached the same qualitative conclusions. This is not surprising, as the data for total manufacturing output and food manufacturing output from the 2007 U.S. Economic Census were highly correlated with population across the cities in our sample, with coefficients of 0.70 and 0.73, respectively.

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the American Chamber of Commerce Research Association (ACCRA)). ACCRA collects prices in different cities across the U.S. for a "purposive" (*i.e.*, non-random) sample of items that is selected to represent categories of goods. For each item, ACCRA's price collectors are instructed to record the price of a product that meets certain narrow specifications, *e.g.*, "half-gallon whole milk," "13-ounce can of Maxwell House, Hills Brothers, or Folgers ground coffee," "64-ounce Tropicana or Florida Natural brand fresh orange juice," etc. ACCRA takes the ratio of the average price collected for each item in each city and quarter relative to its national average in that quarter. The ACCRA COLI is a weighted average of these ratios, where item weights are based on data from the U.S. Bureau of Labor Statistics 2004 Consumer Expenditure Survey.[13]

There are a host of problems arising from comparing prices of similar (as opposed to identical) products; we deal with these in Section 3.3. As a baseline, we first replicate the standard result that, if one uses the standard ACCRA methodology, the price index for tradable goods rises with population in our data. In order to establish this stylized fact, we obtained the ACCRA COLI data for 2005 and measured the association between log population and four different indexes: ACCRA's aggregate, or composite, cost-of-living index; their grocery index; and two food price indexes that we built using the ACCRA item-level price ratios and weights. We refer to these two constructed indexes as the ACCRA food index and Nielsen food index. The ACCRA food index is a weighted average of item-level relative prices, using ACCRA's price ratios and weights, but only for food items. The Nielsen food index replicates the ACCRA food index by applying the ACCRA methodology to Nielsen price data. To build this index, we first identified the set of UPCs in the Nielsen data whose characteristics match the ACCRA specifications for each food item represented in the ACCRA index. We then calculated the average price observed in the Nielsen data for the set of UPCs matching each item in each city and the ratio of each of these city-specific item unit values to their national average. The Nielsen food index for each city is the weighted average of these Nielsen unit value ratios across items using ACCRA item weights.

Table 1: Category Price Indexes vs. Population

	ACCRA Price Indexes			Ln(Nielsen
	Ln(Composite Index$_c$)	Ln(Grocery Index$_c$)	Ln(Food Index$_c$)	Food Index$_c$)
	[1]	[2]	[3]	[4]
Ln(Population$_c$)	0.132***	0.0727***	0.0718***	0.0423***
	[0.0209]	[0.0167]	[0.0168]	[0.00939]
Constant	2.706***	3.562***	3.541***	3.982***
	[0.306]	[0.245]	[0.245]	[0.138]
Observations	47	47	47	47
R-Squared	0.47	0.30	0.29	0.31

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

[13] See http://www.coli.org/Method.asp for more details.

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We regressed the log of each price index for each city on the log of the city's population and report the results in Table 1. As one can see from the table, there is a very strong positive association between each of these price indexes and population. Although the composite ACCRA index, which includes land prices, rises the steepest with population, we see a very similar pattern for the grocery and food price indexes. A one log-unit rise in city size is associated with a four percent increase in the food price index when we build it using Nielsen data and seven percent when we rely on the ACCRA data. While the magnitude of the slope coefficient varies across the indexes, none of these differences are statistically significant.[14] The coefficients are also economically significant: the smallest coefficient, from the Nielsen price index regression, suggests that a consumer in New York pays 16 percent more for food items than a person in Des Moines.[15]

3.2 Controlling for Product, Buyer, and Retailer Heterogeneity

There are three types of heterogeneity biases that may generate the positive correlations observed above: product heterogeneity bias, retailer heterogeneity bias, and purchaser heterogeneity bias. If consumers in larger cities systematically purchase higher quality (*i.e.,* more expensive) varieties within a product category, then a higher average price level in a city might just reflect the fact that consumers in that city buy more expensive varieties of that product category. Similarly, retailer heterogeneity bias can arise because consumers in large cities might purchase goods in stores that offer systematically higher amenities. For example, some grocery stores, like Whole Foods, offer nicer shopping experiences than mass-merchandisers. Finally, if there is a higher fraction of wealthy people in large cities, and rich people bargain-shop less than poor people, purchaser heterogeneity might mean that purchase prices may reflect different shopping intensities of consumers.

As we mentioned earlier, our objective is obtain a standardized price measure that reflects the prices of identical goods purchased in different locations but at similar stores and by consumers with similar shopping intensities. Essentially, we are trying to do the spatial equivalent of the time-series methodology employed in the construction of the U.S. Consumer Price Index, which measures price changes for identical products, purchased in the same store, by field agents with common shopping instructions.

Our methodology for doing this is quite straightforward. Let P_{ucrh} be the average price that

[14] This partially reflects the fact that the correlation coefficient between the various price indexes ranges from 0.8 to 0.9.

[15] Other indexes show a similar pattern. When we regress the BEA RPP index for goods against log population using our sample of cities, the coefficient on log population is 0.026 and statistically significant at the 1 percent level. There are many potential reasons for the difference between this elasticity and those reported in Table 1, including that the RPP covers a different, broader set of goods than we have in the Nielsen data and partially adjusts for product and store heterogeneity.

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a household h paid for UPC u in store r in city c.[16] We refer P_{ucrh} as the "unadjusted price" and define p_{ucrh} as $\ln(P_{ucrh})$. We can then construct an adjusted price index by running the following regression:

$$p_{ucrh} = \alpha_u + \alpha_c + \alpha_r + \mathbf{Z}_h\beta + \varepsilon_{ucrh} \quad (1)$$

where α_u, α_c, and α_r are UPC, city, and store fixed effects, respectively; $\mathbf{Z}_h$ denotes a vector of household characteristics; and β is a vector of corresponding coefficients. Household demographic dummies are included for household size, as well as the gender, age, marital status, and race of the head of household; in addition, we control for household income, which is correlated with shopping intensity. Our store fixed effects take a different value for each of the approximately 600 retail chains in our sample that serve at least 2 cities. For stores that we observe serving a single city, we restrict α_r to be the same for all stores of the same type, where type is defined in one of seven "channel-IDs": grocery, drug, mass merchandiser, super-center, club, convenience, and other.[17] The α_r are designed to capture store amenities, and the $\mathbf{Z}_h\beta$ capture factors related to purchaser heterogeneity.

The city fixed effects, α_c, can be thought of as city price indexes that control for the types of products purchased, the store in which the purchase occurred, and the shopping intensity of the buyer. We then can test whether standardized urban prices co-vary with population by regressing the city fixed effects on log population, *i.e.*,

$$\hat{\alpha}_c = \alpha + \gamma \ln(Pop_c) + \varepsilon_c, \quad (2)$$

where $\ln(Pop_c)$ is the log of population in city c. In this specification, γ tells us how prices vary with population after we control for the different bundles of products purchased in different cities. An advantage of this two-stage approach as opposed to simply including co-variates of interest in equation (1) is that our city price level estimates are not affected by what we think co-varies with urban prices.[18] Thus, we separate the question of whether urban prices rise with population from the question of how to correctly measure urban prices. We will use this feature of the methodology in Section 5.

[16] Homescan panelists record purchases for each transaction they make while participating the survey and data records are identified using a calendar date. We aggregate the data to the annual frequency, summing purchase values and quantities across transactions in the 2005 sample. The average price paid is, therefore, the sum of the dollar amounts that a household h paid for UPC u in store r over all of the transactions where we observe the household purchasing that UPC in that store, divided by the sum of the number of units that the household purchased across the same set of transactions. We identify the "store" r that a transaction occurs in using Nielsen's store code variable.

[17] We apply the same restriction to stores whose codes refer to store categories (such as "Fish Market," "Cheese Store," etc.) rather than store names.

[18] In the Handbury and Weinstein (2011) we show that we obtain qualitatively similar results if we use a one-step procedure including population in equation 1.

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3.3 Evidence from Barcode Prices

Recall that in Section 3.1 above, we showed that products from the same category were purchased for higher unit values in larger cities. The results in Table 1 indicated that a one log unit rise in city size is associated with a four percent rise in the unit value of groceries. We will now demonstrate that almost all of this effect can be explained by product, retailer, and purchaser heterogeneity biases. In other words, the finding in past studies that there are higher traded goods prices in larger cities arises because big cities have different (less price sensitive) consumers purchasing different (more expensive) varieties of products in different (more expensive) stores.

Table 2 presents results from estimating equations (1) and (2). The first key difference from Table 1 is that we are now gauging price differences between identical products, or UPCs, sold in different cities.[19] In the first column of the table, we present the results from a specification that only adjusts for product heterogeneity. In other words, instead of running the regression specified in equation (1), we compute the city price index by only regressing prices on UPC and city dummies. This method for computing the price index corrects for product heterogeneity, which is contained in the UPC fixed effects, but does not adjust for purchaser and retailer heterogeneity. In the second panel, we report the results from regressing the estimated city dummy coefficients on log population. We obtain a coefficient of 0.0139, which is only one third as large as the coefficient we obtained in Table 1 when we used the ACCRA methodology to generate a price index and regressed that on population. This result indicates that two-thirds of the positive relationship between prices and city size in the unit value index reflects the fact that people in larger cities purchase far more high-priced varieties of goods than residents of small cities.[20]

In Column 2 of Table 2, we adjust the urban price index for both product heterogeneity and purchaser heterogeneity. The positive coefficient on household income indicates that high income households systematically pay more than poorer households for the same goods. Some of this may be due to the fact that high-income households have either a higher opportunity cost of time (and therefore shop less intensively) and/or a greater willingness to shop in high amenity stores. Alternatively, some of this positive association may be due to the fact that stores that cater to richer clientele are able to charge higher markups. While we will disentangle these forces in Section 3.4, for the time being we simply note that controlling for purchaser heterogeneity causes the coefficient on log population to fall by another ten percent.

[19] In all regressions, we weight the data by the transaction value which gives more weight to goods that constitute higher expenditure shares.

[20] One possible concern with these results is that shifts in the weighting of the data or some other factor associated with the shift from the price index methodology to the regression methodology is responsible for the drop. We investigate this possibility as a robustness check and show in the Appendix C of Handbury and Weinstein (2011) that this concern is not warranted.

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Table 2: Identical Product Price Indexes vs. Population

Panel A

	p^1_{ucrh}			
	[1]	[2]	[3]	[4]
Ln(Income$_h$)	-	0.0114***	-	0.00805***
	-	[0.000961]	-	[0.000525]
UPC Fixed Effects	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Household Demographic Dummies[2]	No	Yes	No	Yes
Store Dummies[3]	No	No	Yes	Yes
Observations	15,570,529	15,570,529	15,570,529	15,570,529
Number of UPCs[4]	348,645	348,645	348,645	348,645
R-Squared	0.948	0.948	0.953	0.953

Panel B

	City Fixed Effect Coefficient from Panel A			
	[1]	[2]	[3]	[4]
Ln(Population$_c$)	0.0139***	0.0130***	0.00603***	0.00568**
	[0.00400]	[0.00396]	[0.00215]	[0.00214]
Constant	-0.245***	-0.229***	-0.117***	-0.110***
	[0.0586]	[0.0581]	[0.0315]	[0.0314]
Observations	49	49	49	49
R-Squared	0.916	0.205	0.187	0.143

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1. Panel A standard errors are clustered by city.

Notes:
1. $p_{ucrh} = \ln(P_{ucrh})$ where P_{ucrh} is the total expenditures by household h on UPC u in store r in city c in 2005 divided by the total quantity of UPC u purchased by household h in store r in city c during 2005. Observations in the Panel A regression are weighted by the total expenditure of household h on UPC u in store r.
2. Household demographic dummies are for household size, male and female head of household age, marital status, race, and Hispanic.
3. Regressions with store dummies include one of seven channel-ID dummies in cases where Nielsen does not provide a store name or the store identified only has sales in one city, and a store name dummy otherwise.
4. Random weight UPCs have been dropped from the sample.

Interestingly, controlling for store fixed effects in Column 3 has a much more substantial impact on the elasticity of urban prices with respect to population than controlling for purchaser heterogeneity: more than halving the coefficient. The large impact of controlling for store heterogeneity implies that a second important reason why prices appear higher in larger cities is that residents of large cities disproportionately shop in stores that charge high prices *in all cities.* The most obvious source of this sort of heterogeneity is differences in amenities—rich households living in big cities tend to purchase nicer varieties of goods and shop in nicer stores—but we will also examine the possibility that markup variations are explaining this in Section 3.4.

Finally, if we control for product, purchaser, and retailer heterogeneity in Column 4 the

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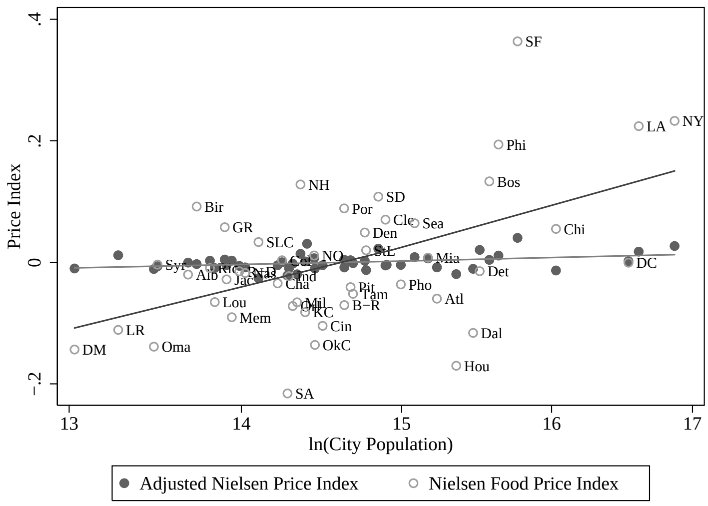
coefficient collapses to only 13 percent of its magnitude in Table 1. Most of this fall arises from adjusting for retailer heterogeneity, which reflects that shoppers in larger cities purchase more items in high-amenity stores. The coefficient on household income remains positive and significant, which means that richer households pay more for the same UPC *even in the same store.* We interpret this as evidence for the impact of purchaser heterogeneity on observed transaction prices. Interestingly, the magnitude of the coefficient on income in Column 4 is about 70 percent as large as in Column 2, indicating that most of the reason why richer households pay more for the same UPC is due to their lower shopping intensity within stores and not to their choosing to shop in nicer stores.

Figure 2: Estimated Price Levels vs. Log City Population



Notes:

1. The market labels on the ACCRA price indexes reference the city represented, as listed in Table A.1.

2. City price indexes are normalized to be mean zero.

Figure 2 presents plots of price indexes computed using the ACCRA methodology in presented in the final column of Table 1 and the price indexes generated in Column 4 of Table 2. The hollow circles indicate the price indexes computed using the ACCRA methodology and the solid circles indicate those computed after correcting for the various forms of heterogeneity in the data. As one can see from the plot, there is a dramatic collapse in the relationship between urban prices and population once one controls for product, purchaser, and retailer heterogeneity. Indeed, the slight positive association that we identified in Table 2 is almost imperceptible, indicating that its economic significance is minor. Moreover, most of the dispersion in city price indexes disappears once we control for heterogeneity yielding relatively small deviations from the fitted line. In fact, adjusting for the various forms of heterogeneity bias, the variance in urban price levels falls by 95 percent. This suggests that purchasing price parity for tradables

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holds almost perfectly across US cities.

3.4 Amenities vs. Mark-ups

One of the important adjustments that we make is for store amenities. Our methodology assumes that if consumers in a given city pay more for identical products when they buy them at one type of store relative to other stores within the same city, the higher price must reflect a difference in store amenities. An alternative explanation is that the higher price reflects a higher markup. If stores that are prevalent in larger cities charge higher markups, our results might be due to the fact that our method of eliminating retailer heterogeneity would be eliminating markup variation across cities and therefore might be understating the high prices in large cities. In other words, if the store effects capture amenities, consumers do not necessarily find big cities to be more expensive because they are getting a higher-quality shopping experience in return for paying a higher price. If the store effects instead reflect markup differences due to differences in market power across stores offering the same shopping experience, then consumers are not getting anything in return for the relatively high prices charged by stores in large cities and will, therefore, perceive these stores as more expensive.

Although we cannot measure markups directly, we can look at store market share information in an attempt to assess how markups might vary in our data, first across cities, and then across retailers and, in particular, across retailers that locate disproportionately in large, relative to small, cities. In many variable markup demand systems involving strategic substitutes, markups positively covary with market shares. For example, Feenstra and Weinstein (2010) show that for the translog system, markups will positively covary with the Herfindahl index in the market. We can compute retailer Herfindahl indexes for each city by aggregating the purchases of consumers in each store. Not surprisingly, Herfindahl indexes are negatively correlated with city size ($\rho = -0.3$) reflecting the fact that consumers in large cities not only have more choices of products, but also more choices of where to purchase those products. This circumstantial evidence suggests that, if anything, we are understating the amenity effect because stores in large cities are likely to face more competition and charge lower markups (which is also consistent with models like Melitz and Ottaviano (2008)).

We also can try to strip out the market power effect from our estimates more directly. In order to do this we control for differences in markups across retail chains, or types, by including store market shares in the regression where we estimate the store effects (α_r).[21] Specifically,

[21] Recall that r denotes the store code for each transaction. Most store codes uniquely identify retail chains or standalone stores; others refer to one of 60 store categories. If a store only has sales in one city or we do not have the store name, we restrict α_r to be equal across stores with the same "channel-ID," which can take one of seven values: grocery, drug, mass merchandiser, super-center, club, convenience, and other. We do not group stores in this manner when calculating market shares: $Share_{rc}$ represents the sales share of store code r in city c.

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we add the market share of each store in each city to equation (1) and estimate

$$p_{ucrh} = \alpha_u + \alpha_c + \alpha_r + \mathbf{Z}_h\beta + \gamma Share_{rc} + \varepsilon_{ucrh}, \tag{3}$$

where $Share_{rc}$ is store r's market share in city c and γ is a parameter to be estimated. We interpret $\hat{\alpha}_r$ in this specification as the component of the store's idiosyncratic price that cannot be explained by its market power. We then subtract these $\hat{\alpha}_r$ estimates from observed prices, adjusting prices for the component that is potentially related to differences in amenities, but not the component related to differences in markups via market power. We regress these adjusted prices against city fixed effects to estimate urban price indexes that control for differences in amenities across stores, but still allow for price differences resulting from differences in market power:

$$p_{ucrh} - \hat{\alpha}_r = \alpha_u + \tilde{\alpha}_c + \mathbf{Z}_h\beta + \tilde{\varepsilon}_{ucrh}, \tag{4}$$

The dependent variable is the store amenity-adjusted price and $\tilde{\alpha}_c$ is an urban price index that reflects systematic differences in prices across stores with different market shares, but not those related to unobserved heterogeneity between retail chains.

Table 3 presents the results of this exercise. The estimates for equation (3), in Column 1, suggest no significant relationship between a store's market share in a city and the price it charges there.[22] The coefficient on market share is positive but not statistically significant, indicating that the capacity of a retailer to exercise market power is quite limited in most cities. This result is consistent with the previous literature on retailer market power in the U.S. grocery sector which finds that stores do not exploit market power in their pricing decisions. For example, Ellickson and Misra (2008) demonstrate that "stores in a particular market do not use pricing strategy as a differentiation device but instead coordinate their actions" and find that "firm size is not the primary determinant of pricing strategy."

Column 2 presents the results of estimating the price indexes according to equation (4), and Column 3 presents the results of regressing the resulting adjusted city fixed effects, $\tilde{\alpha}_c$, against population. Not surprisingly, given the lack of a significant effect in Column 1, we do not find that adjusting for market share qualitatively affects our results. The city price indexes that have been purged of these market power effects have almost the same association with population as we saw in Table 2, which suggests that most of what is being captured in the store fixed effects reflects store amenities and not market power.

One might be concerned that market shares and prices are determined endogenously. Both could, for example, be correlated with unobserved productivity differences across retailers (more productive stores can charge lower prices and attain higher market shares even while

[22]We also tried non-linear specifications linking store shares with market power by including quadratic and cubic terms without finding a significant link.

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Table 3: Are prices higher in larger cities, controlling for market power?

	p_{ucrh}[1]	p_{ucrh} - $\hat{\alpha}_r$	City Fixed Effect from Column 2 ($\hat{\alpha}_c$)
	[1]	[2]	[3]
Ln(Income$_h$)	0.00876***	0.00877***	-
	[0.000572]	[0.000560]	-
Store Share$_{rc}$	0.00128	-	-
	[0.00977]	-	-
Ln(Population$_c$)	-	-	0.00604**
	-	-	[0.00238]
Constant	0.549***	0.550***	-0.112***
	[0.0151]	[0.0113]	[0.0348]
UPC Fixed Effects	Yes	Yes	N/A
City Fixed Effects	Yes	Yes	N/A
Household Demographic Dummies[2]	Yes	Yes	N/A
Store Dummies[3]	Yes	No	N/A
Observations	15,570,529	15,570,529	49
Number of UPCs[4]	348,645	348,645	N/A
Number of Cities	49	49	N/A
R-Squared	0.934	0.933	0.121

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1. Column 1 standard errors are clustered by city.

Notes:
1. $p_{ucrh} = \ln(P_{ucrh})$ where P_{ucrh} is the total expenditures by household h on UPC u in store r in city c in 2005 divided by the total quantity of UPC u purchased by household h in store r in city c during 2005. Observations in Columns [1] and [2] are weighted by the total expenditure of household h on UPC u in store r.
2. Household demographic dummies are for household size, male and female head of household age, marital status, race, and Hispanic.
3. Regressions with store dummies include one of seven channel-ID dummies in cases where Nielsen does not provide a store name or the store identified only has sales in one city, and a store name dummy otherwise.
4. Random weight UPCs have been dropped from the sample.

charging higher mark-ups). In our specification, these productivity differences should be captured by the retailer fixed effects and so should not generate a bias. A given retail chain will have more market power in markets where consumers demand more of its output or it faces less competition.

4 Do Larger Cities Have More Varieties?

Many NEG models predict not only that the price level of tradable goods should be lower, but also that larger cities should offer consumers more varieties because more firms can profitably enter in larger markets. This prediction also has implications for the price level in cities since varieties that are unavailable in locations are effectively priced at their reservation levels. In this sense, we can think of the variety bias as an extreme form of the well-known substitution

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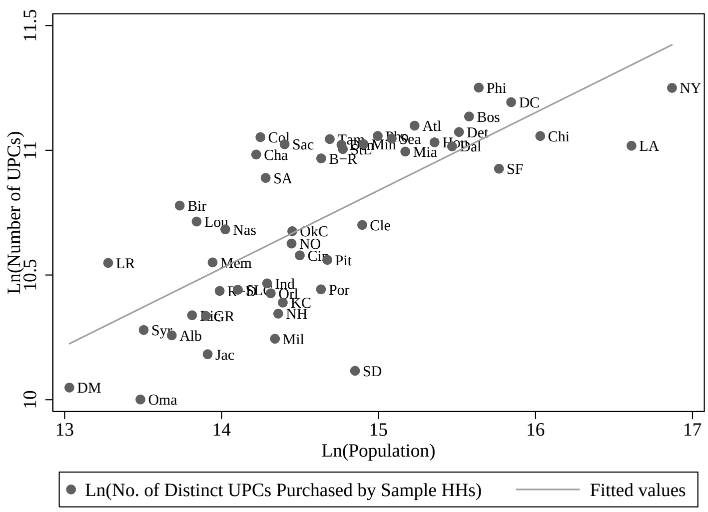
bias that plagues fixed-weight price indexes—if prices are so high that goods are not consumed in small cities, fixed-weight indexes will understate the true cost of living because high-priced goods that are not consumed will receive a weight of zero in the index. We will deal with both the substitution and variety biases in Section 5. In this section we examine the underlying evidence on variety availability.

4.1 Data Overview

The simplest way to document that consumers in larger cities consume more varieties is to examine whether we observe more varieties being purchased in larger cities. Figure 3 shows the relationship between the log of the number of UPCs observed in the Nielsen sample for each city against log population. This relationship is upward sloping with a coefficient of 0.312 and standard error of 0.043. We cannot interpret this estimate as the elasticity of variety with respect to city size, however, because Nielsen tends to sample more households in larger cities, so part of the reason why more goods are purchased in larger cities is due to the greater sample sizes in those cities.

Figure 3: Log Number of Distinct UPCs in Each City Sample vs. Log City Population



Notes:

1. Numbers on plots reference the market ID of the city represented, as listed in Table A.1.

One way to deal with this bias is to instead examine whether the number of different varieties consumed by an equal number of households varies with city size. The basic idea is that any two households are less likely to purchase the same product in cities where there are more products to choose from. If there is less overlap in the varieties purchased by different households in larger cities, we expect to see equally-sized samples of households from these cities purchasing larger numbers of unique varieties.

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Here, we restrict ourselves to only looking at 25 cities in which Nielsen sampled at least 500 households and compare the number of varieties purchased by a random sample of 500 households in each of these cities.[23] Figure 4 plots the aggregate number of *different* UPCs purchased by these randomly-selected households against the size of the city in which the households live. The results show a clear positive relationship between the variety of UPCs purchased by 500 households in a city and the population of the city. The slope of the linear regression fit is 0.033 with a standard error of 0.017. The large amount of noise in the 500-household variety counts indicates that this estimate may be subject to attenuation bias.[24]

These results are certainly suggestive of the notion that the number of varieties available in a location rises with number of inhabitants in that location, but neither provides a reliable estimate of the elasticity. In the next section, we take a more direct approach to estimating the variety-city size relationship: we use all of the information at hand to estimate the total number of varieties available in each location and then examine how these aggregate variety estimates vary with city size.

4.2 Estimating the Number of Varieties in Cities

The principle challenge that we face in measuring the number of varieties in a city is that our data is not a census of all varieties purchased in a city but rather a count of varieties based on a random sample of households. Fortunately, our problem is isomorphic to a well-studied problem in biostatistics: estimating the number different species in a general area based on the number of species identified in certain locations (see Mao et al. (2004, 2005)). Prior work in this area has solved the problem using parametric and structural approaches that yield very similar results in our data. Since the parametric approach is significantly simpler to explain, we focus

[23]There is a trade-off between the number of households that we consider and the number of cities that can be included in the sample. As we decrease the number of households selected, we increase the number of cities in our sample (adding small cities disproportionately). However, as we work with smaller samples of households, we have a lot more noise because the number of barcodes purchased by a small sample of households can vary a lot depending on the households picked. This results in attenuation bias.

[24]We have replicated this analysis looking at the purchases of different fixed numbers of households and, consistent with the attenuation bias hypothesis, we find that the estimated variety-city size relationship is increasing in the number of households under consideration. For example, the coefficient on city size is statistically zero when we consider the number of varieties purchased by samples of 116 households in all 49 cities, but increases to 0.05, statistically significant at the 5 percent level, when we look at the number of varieties purchased by 750 households, in the 23 cities where this is possible.

One reason why it is difficult to identify differences in the number of varieties available in a city in the purchases of small samples of households is due to the fact that many households purchase "popular" goods that other households in their city also purchase. To see the intuition here, suppose that all households purchase $N+1$ products, N of which are the same across households in a city and one of which is drawn at random from the set of varieties available in the city. Regardless of how many varieties are available for purchase in a city, we can at most expect to see $N+1$ unique varieties purchased by one household, $N+2$ by two households in the same city, $N+3$ by three, etc. The number of varieties purchased in a city will range from N to N plus the number of households sampled in a city.

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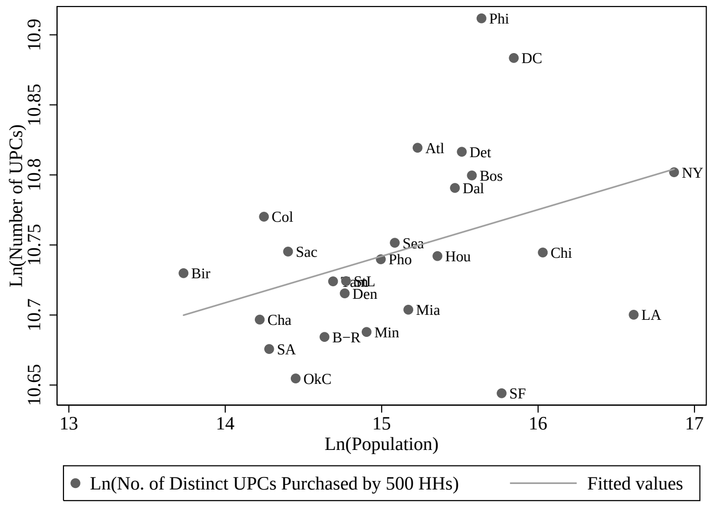
Figure 4: Log Number of Distinct UPCs Purchased by 500 Households in Each City vs. Log City Population



Notes:
1. Numbers on plots reference the market ID of the city represented, as listed in Table A.1.

on the parametric approach and relegate the structural approach to Appendix A as a robustness check.

In order to obtain some intuition for this methodology, assume that the expected number of different products purchased by one household in city c is denoted by $S_c(1)$. The expected number of distinct products purchased in a sample of n households can be denoted by the "accumulation curve," $S_c(n)$. Accumulation curves must be concave because every time the sample size rises by one household the probability of finding good that has not been purchased by any of the other households falls. Moreover, a critical feature of accumulation curves is that as the number of households surveyed rises, the number of observed varieties in a city must approach the true total number of varieties in a city. We can write this formally as $\lim_{n\to\infty} S_c(n) = S_c^T$, where S_c^T is the total number of distinct varieties available in the city.[25] In other words, the asymptote of the accumulation curve is the estimate for the total number of goods available in the city.

Estimation of S_c^T requires us to know the expected value of distinct varieties for each sample of households, *i.e.*, $(S_c(1), S_c(2), S_c(3), \ldots)$, and also the functional form of $S_c(n)$. Estimating the expected number of distinct varieties purchased by a sample of n households, $S_c(n)$ is straightforward. The only econometric issue we face is that the number of distinct varieties we observe being purchased, $S_c(n)$, in a sample of n households is going to depend on exactly which households are in the sample. For example, our measure of $S_c(1)$, how many different

[25]This property is based on the assumption that all types of varieties have a positive probability of being purchased.

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goods one household purchases, depends on which household is chosen. In order to obtain an estimate of the expected number of goods purchased by a sample of n households, Colwell and Coddington (1994) propose randomizing the sample order I times and generating an accumulation curve for each random ordering indexed by i. The expected value of the number of varieties purchased by n households can then be set equal to the mean of the accumulation curves over I different randomizations, *i.e.*,

$$S_c(n) = \frac{1}{I}\sum_{i=1}^{I} S_{ci}(n).$$

We set $I = 50$.[26]

Once we have our estimates for each $S_c(n)$, we can turn to estimating the asymptote, $S_c(H_c) = S_c^T$. Unfortunately, theory does not tell us what the functional of $S_c(n)$ is, so we follow Jimenez-Valverde et al. (2006) by estimating the parameters of various plausible functional forms and use the Akaike Information Criterion (AIC) goodness-of-fit test to choose between a range of functional forms that pass through the origin and have a positive asymptote.

4.3 Results

We can get a clear sense of how this methodology works by simply plotting the accumulation curves. Figure 5 presents a plot of accumulation curves for the twelve cities for which we have the largest samples. As one can see from the picture, the average sample of 1000 households in Philadelphia (population 6.2 million) purchased close to 70,000 different varieties of groceries. By contrast, the average sample of a 1000 households in Saint Louis (population 2.6 million) purchased closer to 50,000 different varieties. Moreover, these curves reveal that the four highest curves correspond to Philadelphia, D.C.-Baltimore, New York, and Boston, which are all among the five largest cities in our sample. In other words, this limited sample indicates that a given number of households tends to purchase a more diverse set of goods when that sample is drawn from a city with a larger population.

We can examine this more formally by estimating the asymptotes of the accumulation curves. Since we are not sure how to model the functional forms of these accumulation curves, we tried five different possible functional forms—Clench, Chapman-Richards, Morgan-Mercer-Flodin, Negative Exponential, and Weibull. The Weibull was a strong favorite with the lowest AIC score in the majority of cities for which we modeled UPC count accumulation curves, and so we decided to focus on this functional form.

Once again, we can get intuition for how this methodology works by showing the fit for a sub-sample. Figure 6 plots the raw data and the estimated Weibull accumulation curve for our

[26]The resulting estimates are less noisy, and their correlation with city size less subject to attenuation bias, than the 500-household variety counts studied in Section 4.1 above, each of which is just a single point on a single accumulation curve for each city.

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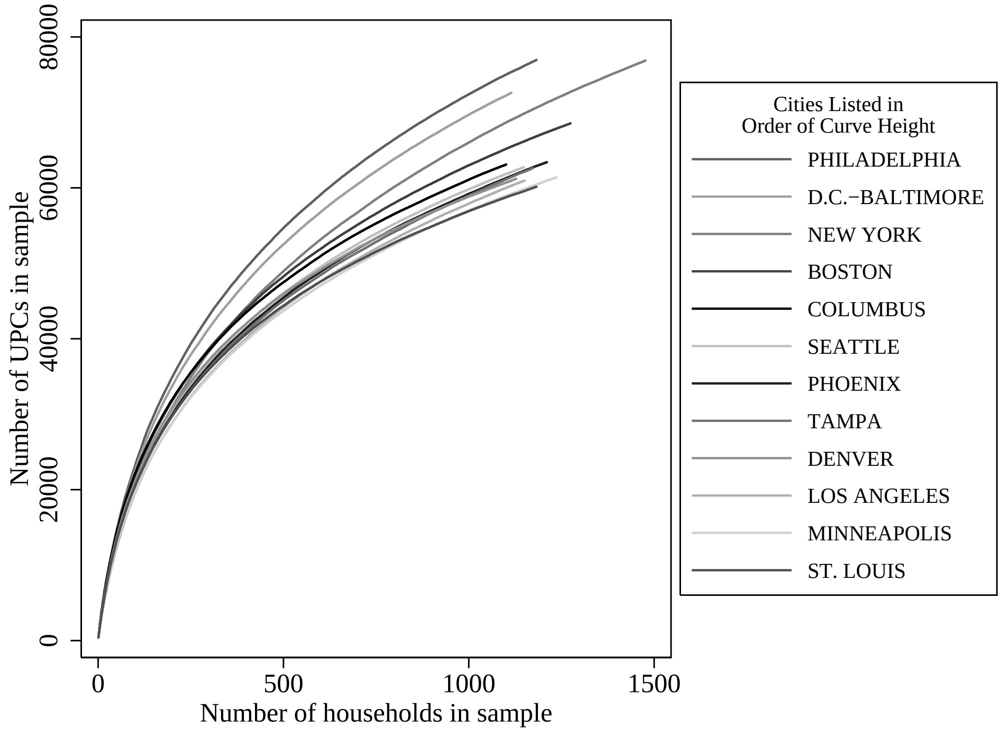
Figure 5: UPC Accumulation Curves for cities with 12 Largest Samples



largest city, New York. A typical sample of 500 random households buys around 49,000 unique UPCs, and a sample of 1000 households typically purchases around 66,000 different goods. As one can see from the plot, the estimated Weibull distribution fits the data extremely well. The estimated asymptote is approximately 112,000 varieties, which is 35,000 more than we observe in our sample of 1500 New York households.[27]

Figure 7 presents a plot of the log of the estimated Weibull asymptotes for each city against the log population in the city. As one can see, there is a clear positive relationship between the two variables—we estimate that households in larger cities have access to more varieties than households in smaller ones. It is interesting that the relationship between city size and the total number of varieties in a city is much stronger than the relationship between city size and the number of varieties purchased by a fixed sample of cities observed in Figure 4. This is consistent with the pattern observed in Figure 5: the cross-city dispersion in the number of unique UPCs purchased by n households in each city increases with n. Overall, the data support the relationship between the size of a city and the number of available varieties hypothesized by NEG models. Residents of New York have access just over 110,000 different varieties of groceries, while residents of small cities like Omaha and Des Moines have access to fewer than

[27] Since the number of households in a city is large, we obtain almost identical results regardless of whether we set the number of varieties equal to $S_c(H_c)$ or $S_c(\infty)$.

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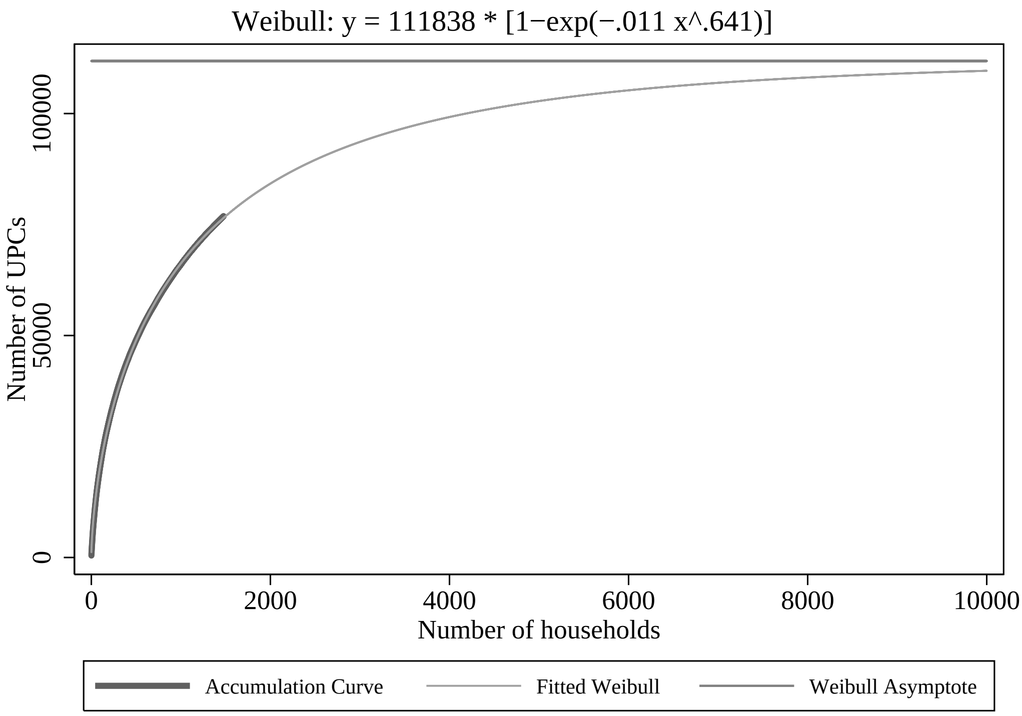
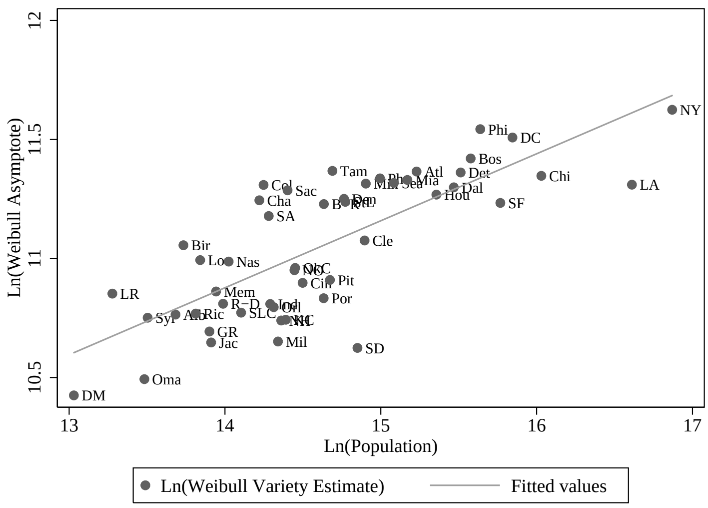
Figure 6: Fitted UPC Accumulation Curve for New York



24,000.

Figure 7: Log Weibull Variety Estimate vs. Log City Population



Notes:

1. Acronyms on plots reference the city represented, as listed in Table A.1.

We test this relationship between city size and variety abundance formally in Table 4. Table 4 presents the results from regressing the log estimated number of varieties in a city on the log

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of the population in the city. The first three columns of the table present regressions of the log sample counts of varieties in each city on the log of the city's population. The next three columns present regressions of the log estimate of number of varieties based on the Weibull asymptotes on city size. As one can see from comparing Columns 1 and 4, the elasticity of variety with respect to population is slightly less using the Weibull estimate presumably because the Weibull corrects for the correlation between sample size and population in the Nielsen data. What is most striking, however, is that we observe a very strong and statistically significant relationship between the size of the city and the number of estimated varieties. Our estimates indicate that a city with twice the population as another one typically has 20 percent more varieties.

Table 4: Do larger cities have more UPC varieties?

	Ln(Sample Count$_c$)			Ln(Weibull Asymptote$_c$)		
	[1]	[2]	[3]	[4]	[5]	[6]
Ln(Population$_c$)	0.312***	0.338***	0.281***	0.289***	0.317***	0.321***
	[0.0432]	[0.0678]	[0.0971]	[0.0373]	[0.0582]	[0.0841]
Ln(Per Capita Income$_c$)	-	-0.155	-0.043	-	-0.032	-0.038
	-	[0.341]	[0.369]	-	[0.293]	[0.319]
Income Herfindahl Index	-	-0.952	-0.289	-	-1.302	-1.338
	-	[3.132]	[3.246]	-	[2.689]	[2.809]
Race Herfindahl Index	-	0.064	0.115	-	0.147	0.145
	-	[0.411]	[0.417]	-	[0.353]	[0.361]
Birthplace Herfindahl Index	-	0.006	0.029	-	0.068	0.067
	-	[0.282]	[0.285]	-	[0.222]	[0.225]
Ln(Land Area$_c$)	-	-	0.087	-	-	-0.005
	-	-	[0.106]	-	-	[0.0919]
Constant	6.158***	7.474**	6.275*	6.835***	6.790**	6.856**
	[0.632]	[3.391]	[3.704]	[0.546]	[2.911]	[3.205]
Observations	49	49	49	49	49	49
R-squared	0.53	0.53	0.54	0.56	0.57	0.57

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

One concern with these results is that they might be biased because larger cities have more diverse populations. It is possible that the reason larger cities have more diverse sets of goods reflects their greater consumer diversity and not the market-size effect postulated in some economic geography models. In order to control for the impact of consumer heterogeneity on product variety, we constructed a number of Herfindahl indexes based on the shares of MSA population with different income, race, and country of birth. These indexes will be rising in population homogeneity. In addition, we include the per capita income in each city. As one can see from Columns 2 and 5 in Table 4, the coefficient on population is almost unaffected by adding controls for population diversity and urban income. These suggest that population, and neither consumer diversity or income, is the main explanation for the relationship between the number available products and city size.

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Finally, we were concerned that our results might be due to a spurious correlation between city population and urban land area. If there are a constant number of unique varieties per unit area, then more populous cities might appear to have more diversity simply because they occupy more area. To make sure that this force was not driving our results, we include the log of urban land area in our regressions. The coefficient on land area is not significant in any of the specifications, while the coefficient on population remains positive and very significant. These results indicate that controlling for land area and demographic characteristics does not qualitatively affect the strong relationship between city size and the number of available varieties. The R^2 of around 0.5 to 0.6 indicates that city size is an important determinant of variety availability. Thus, the number of tradable goods varies systematically with city size as hypothesized by the NEG literature.

5 The Price Level in Cities

5.1 Constructing an Exact Urban Price Index

A theoretically sound urban price index must correct for the heterogeneity biases discussed in Section 3, the product availability differences discussed in Section 4, and make adjustments for substitution biases. Progress can only be made by putting some more structure on the problem, and so we will assume that one can use a CES representative agent utility function to measure welfare in cities. In doing so, we abstract away from heterogeneity or non-homotheticities in preferences. To the extent that the product diversity in larger cities exists to suit the diversity of preferences in these locations, we are likely to understate the welfare gains from varieties in larger cities because we do not take into account the fact that their diverse populations are more likely to value greater numbers of varieties than the homogeneous populations in smaller cities.

Specifically, we modify the variety-adjusted, nested CES utility function developed in Broda and Weinstein (2010) for time-series analysis so that it can be used with our data. Instead of working with two time periods, we change the notation of the basic theory so that we can compare two locations. We express the price level in each city as its level relative to the price level a consumer would face if the buyer faced the average price level in the U.S. and had access to all the varieties.

5.1.1 Notation

Before actually writing down the price index, we need to set forth some notation corresponding to the organization of the data presented in Figure 1. Let $g \in \{1, ..., G\}$ denote a product "group", which we define in the same way as Nielsen to capture broadly similar grocery items. Let B_g

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and U_g respectively denote the set of all "brand-modules" and UPCs in a product group g, and U_b be the set of all UPCs in brand-module b.

We now define the subsets of UPCs that we observe being purchased in each city. Let v_{uc} denote the value of purchases of UPC u observed in city c.[28] Define $U_{bc} \equiv \{u \in U_b | v_{uc} > 0\}$ as the set of all UPCs in brand-module b that have positive observed sales in city c, $U_{gc} \equiv \{u \in U_g | v_{uc} > 0\}$ as the set of all UPCs in product group g that have positive observed sales in city c, and $B_{gc} \equiv \{b \in B_g | \sum_{u \in b} v_{uc} > 0\}$ as the set of all brand-modules that have positive sales in city c in product group g.

We next need to measure the share of available goods both within brand-modules and within product groups. Let s_{bc} be share of *national* brand-module b expenditures that is spent on the set of UPCs U_{bc} that are sold in city c, *i.e.*,

$$s_{bc} \equiv \frac{\sum_{u \in U_{bc}} \sum_c v_{uc}}{\sum_{u \in U_b} \sum_c v_{uc}}. \tag{5}$$

s_{bc} tells us the expenditure share of UPCs within a brand-module that are available in a city using *national* weights. The numerator is the total amount spent nationally on the brand-module b UPCs available in city c, while the denominator gives the total spent on brand-module b nationally. This share will be useful as a measure of the quality-adjusted count of unavailable varieties in a city. s_{bc} is less than one whenever a UPC from brand-module b is unavailable in city c. s_{bc} rises with the number of available UPCs in a city and will be smaller if varieties with a high market share are unavailable. It is easiest to see what moves s_{bc} by considering an extreme case. If all varieties had the same price and quality and therefore the same market share, s_{bc} would equal the share of all varieties within a brand-module that are available in city c. In general, however, two cities with the same number of UPCs available in brand-module b will have equal values of s_{bc} if their unavailable varieties have the same aggregate importance in national consumption or national expenditure share.

Analogously, s_{gc} is the share of *national* product-group g expenditures that is spent on the set of brand-modules U_b that are sold in city c, *i.e.*,

$$s_{gc} \equiv \frac{\sum\limits_{b \in B_{gc}} \sum\limits_c v_{bc}}{\sum\limits_{b \in B_g} \sum\limits_c v_{bc}}, \text{ where } v_{bc} = \sum_{u \in U_b} v_{uc}, \tag{6}$$

[28]The national average price of a UPC is the total value of purchases of that UPC across all cities in the Homescan sample divided by the total quantity that these purchases represent. In all of the analysis below, we work with nationally-representative values and quantities for each UPC, scaling the value and quantity of purchases in each city by the population in that city divided by the total number of household members represented in the Nielsen sample for that city (*i.e.*, the sum of the household sizes for the Nieslen sample households).

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The numerator of s_{gc} is the total amount spent nationally on the product group g brand-modules available in city c, and its denominator is the total spent on product group g nationally. While s_{bc} tells us about the availability of UPCs within brand-modules, s_{gc} tells us about the availability of brand-modules themselves.

Finally, it is useful to discuss the price data we use in the index. In our preferred specification, we will work with "adjusted prices" that correct for product, purchaser, and retailer heterogeneity biases. In the simplest case, where we only control for product heterogeneity biases, we set the adjusted price, $\tilde{P}_{ucrh}$, equal to the the actual price: $\tilde{P}_{ucrh} \equiv P_{ucrh} = \exp(p_{ucrh})$. However, at other times we may want to correct for product and purchaser heterogeneity biases in the collection of price data that we documented in Section 3. In this case, we will set $\tilde{P}_{ucrh} \equiv \exp\left(p_{ucrh} - \mathbf{Z}_h\hat{\beta}\right)$, or to additionally correct fo retailer heterogeneity biases we will set prices equal to $\tilde{P}_{ucrh} \equiv \exp\left(p_{ucrh} - \hat{\alpha}_r - \mathbf{Z}_h\hat{\beta}\right)$. Similarly, we can write the adjusted value of UPC u purchased in city c as $\tilde{v}_{uc} \equiv \sum_{h\in H_c}\sum_{r\in R_c} \tilde{P}_{ucrh} q_{ucrh}$, where q_{ucrh} is the quantity that household h in city c purchases of UPC u in store r. $q_{uc} \equiv \sum_{h\in H_c}\sum_{r\in R_c} q_{ucrh}$ is the quantity of UPC u purchased in city c.

5.1.2 Definition

We can now rewrite Broda and Weinstein (2010)'s intertemporal price index in a spatial context as follows:

Proposition 1: *If $B_{gc} \neq \emptyset$ for all $g \in G$, then the exact price index for the price of the set of goods G in city c relative to the nation as a whole that takes into account the differences in variety in the two locations is given by,*

$$EPI_c = \prod_{g\in G} \left[CEPI_{gc} VA_{gc}\right]^{w_{gc}}$$

where:

$$CEPI_{gc} \equiv \prod_{u\in U_{gc}} \left(\frac{\tilde{v}_{uc}/q_{uc}}{\sum_c \tilde{v}_{uc}/\sum_c q_{uc}}\right)^{w_{uc}}$$

$$VA_{gc} \equiv (s_{gc})^{\frac{1}{1-\sigma_g^a}} \prod_{b\in B_{gc}} (s_{bc})^{\frac{w_{bc}}{1-\sigma_g^w}}$$

w_{uc}, w_{bc}, and w_{gc} are log-ideal CES Sato (1976) and Vartia (1976) weights defined in Appendix B, σ_g^a is the elasticity of substitution across brand-modules in product group g, and σ_g^w is the elasticity of substitution among UPCs within a brand-module.

We can obtain some intuition for the formula by breaking it up into several components. The term in the square brackets is the exact price index for each product group, and EPI_c is

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just a weighted average of these product group price indexes where the Sato-Vartia weights take into account both the importance of each product group in demand and the ability of consumers to substitute away from expensive product groups. Each product-group price index is composed of two terms. $CEPI_{gc}$ is the conventional exact price index for product group g. It is a sales-weighted average of the prices of each good sold in the city where the weights adjust for conventional substitution effects. One can think of $CEPI_{gc}$ as the correct way of measuring the price level of each product group in city c relative to its national average if all goods were available in the city.

Since some goods are are unavailable in each location, we need to adjust the $CEPI_{gc}$ by VA_{gc}. This variety adjustment is composed of two terms. $(s_{gc})^{1/\left(1-\sigma_g^a\right)}$ corrects the index for the importance of missing brand-modules. s_{gc} provides a quality-adjusted count of the missing brand-modules in city c, and the exponent weights these counts by how substitutable they are.[29] For example, if the Coke soft-drink brand were not available in a city, its importance for the price index would depend on the share of Coke nationally (s_{gc}), and how substitutable Coke is with other soft drinks (σ_g^a). If Coke is highly substitutable with other brand-modules, then σ_g^a will be large, and not having Coke available will not matter much, but if Coke is a poor substitute for other soft drinks, σ_g^a will be small and not having Coke in a location would depress welfare more.

The second variety adjustment term is a weighted geometric average of variety adjustments for each brand-module available in city c, $\prod_{b \in B_{gc}} (s_{bc})^{\frac{w_{bc}}{1-\sigma_g^w}}$. $(s_{bc})^{\frac{1}{1-\sigma_g^w}}$ corrects the index for the fact that even if brand-module b is available in a city, not all of the varieties within that brand-module may be available. Thus, if the two-liter bottle of Coke were not available in a city, the impact on the price index would depend on how important two-liter Coke is (s_{bc}) and how similar two-liter Coke is to other Coke products (σ_g^w). We obtain the elasticities of substitution computed for UPCs within a brand-module and across brand-modules within a product group from Broda and Weinstein (2010).

5.2 Measuring the Share of Commonly Available Goods

Recall that we do not observe the full set of UPCs available in each city. Just as we estimated the raw counts of UPCs available in each city, we now have to estimate the quality-adjusted counts (or national expenditure shares) of available brand-modules (s_{gc}) and UPCs (s_{bc}). In Section 4.2, we built an accumulation curve corresponding to the raw counts of the UPCs represented in different-sized samples of households for each city. We now use the same method to build curves corresponding to the national market shares of the different brand-modules and UPCs

[29]The quality-adjusted count of missing brand-modules weights each brand-module by how important it is in the utility function. In the CES setup, the national expenditure share on a product is the correct way to measure the relative quality of a variety that is unavailable in a specific location.

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represented in a sample. Our estimates of s_{gc} and s_{bc} are simply the asymptotes of these shares accumulation curves in each city. If $s_{gc}(n)$ denotes the national expenditure share of brand-modules within a product group g purchased by n households in city c, our estimate of s_{gc} (the national market share of the brand-modules that are available in a city within a product group) is simply the value we expect $s_{gc}(n_c)$ to take for n_c equal to the number of households in the city. We approximate $s_{gc}(n_c)$ using the asymptote of the accumulation curve or $\lim_{n\to\infty} s_{gc}(n)$. We use the same procedure to estimate the national market share of the UPCs that are available in a city within each brand-module, s_{bc}.

Unfortunately, we are unable to estimate a value of s_{bc} for every brand-module b in each product group g for each city c because household samples are sometimes too small to allow us to observe more than a few purchases of UPCs within many of the brand-modules available in a city. Since we do not want to estimate accumulation curves for brand-modules in which there are very few purchases, we pool the data across brand-modules available in each city and estimate a common s_{bc} within each product group, which we denote $\bar{s}_{gc}$. Since $\bar{s}_{gc}$ does not vary at the brand-module level, this assumption simplifies the variety adjustment in Proposition 1 to:

$$VA_{gc} \equiv (s_{gc})^{\frac{1}{1-\sigma_g^a}} (\bar{s}_{gc})^{\frac{1}{1-\sigma_g^w}} \tag{7}$$

5.3 Price Level in Cities: Evidence

In this section we present our variety-adjusted exact prices for each city. First, however, we illustrate how we estimate the brand-module and UPC share inputs into the variety-adjustment component (s_{gc} and $\bar{s}_{gc}$) using the "bread and baked goods" product group (one of the largest product groups in terms of sales and the number of varieties available nationally) and show how these quality-adjusted counts vary across cities of different sizes.

Figures 8 and 9 plot the share accumulation curves for bread and baked goods using data from two cities with very different populations, New York and Des Moines. Figure 8 shows the s_{gc} accumulation curve, which tells us about the availability of brand-modules, while Figure 9 portrays the same curve for $\bar{s}_{gc}$, which tells us about the availability of UPCs within brand-modules. We estimate s_{gc} and $\bar{s}_{gc}$ for each product group and city as the asymptotes of a Weibull function fitted to each of these curves.[30] By examining the asymptote of the Weibull distribution in the first panel, we can see that New Yorkers have access to a set of bread brand-modules available that constitute 80 percent of national expenditures on bread. By contrast, residents of Des Moines, with a population less than a fortieth as large, have access to bread brand-modules that constitute only 62 percent of national expenditures.

[30]We selected the Weibull since the AIC favored it for the raw count accumulation curves. We find that the AIC favors the Weibull distribution when estimating the share accumulation curves as well.

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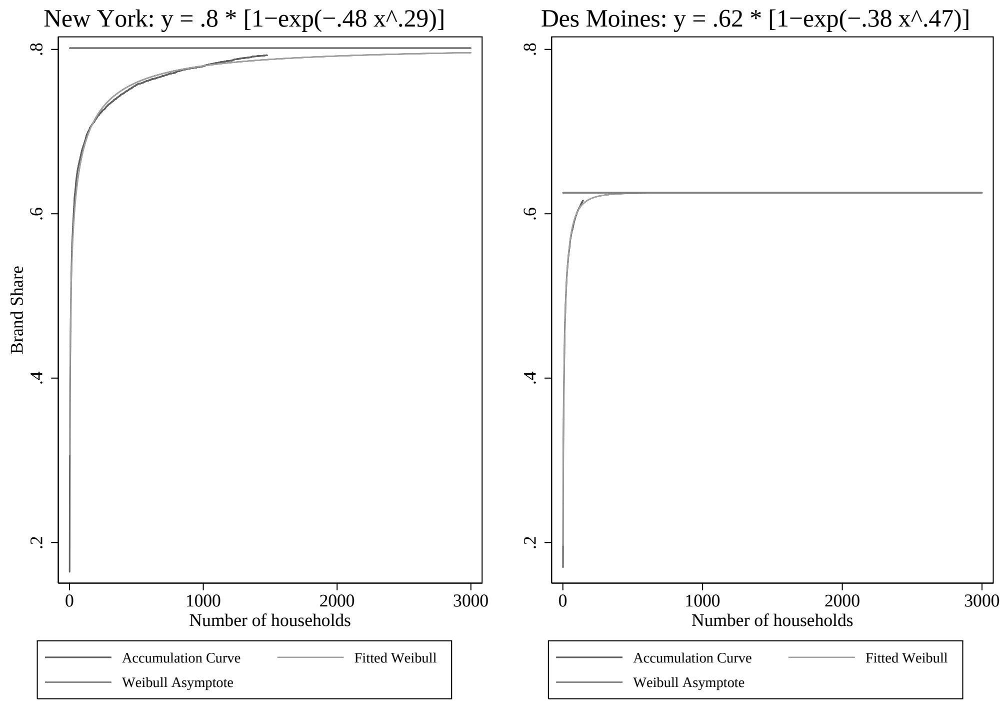
Figure 9 shows that even when brand-modules are available in a city, many of the UPCs that make up these brand-modules are often not available. For example, consumers in New York and Des Moines only had access to bread UPCs that accounted for on average 64 and 43 percent of their brands' national sales in a given module, respectively. This indicates that a firm selling a product in a city does not necessarily mean that all varieties of that product are available there. That said, New Yorkers have access to more varieties per available bread brand-module, on average, than residents of Des Moines.

Figure 8: Brand-Module Share Accumulation Curves for the Bread Product Group



To demonstrate how these differences in the market shares of UPCs and brand-modules available in the two cities affect the exact price index in New York relative to Des Moines, we can calculate the variety adjustments for bread in each city from equation (7). The elasticity of substitution between UPCs within brand-modules in the bread product group is 17.2, so the UPC variety adjustment for New York is $0.64^{1/(1-17.2)}$, or 1.028. The across-brand-module elasticity of substitution for the bread product group is 9.6, so the brand-module variety adjustment for New York is $0.80^{1/(1-9.6)}$, or 1.026. Our estimates imply that someone restricted to only consume the bread varieties available in New York would face a price index that is 5.5 percent higher than someone paying the same prices for available varieties but with access to all national varieties. A similar calculation shows that the variety adjustment for the bread product group in Des Moines is equal to 6.9 percent. The variety adjustment for New York relative to

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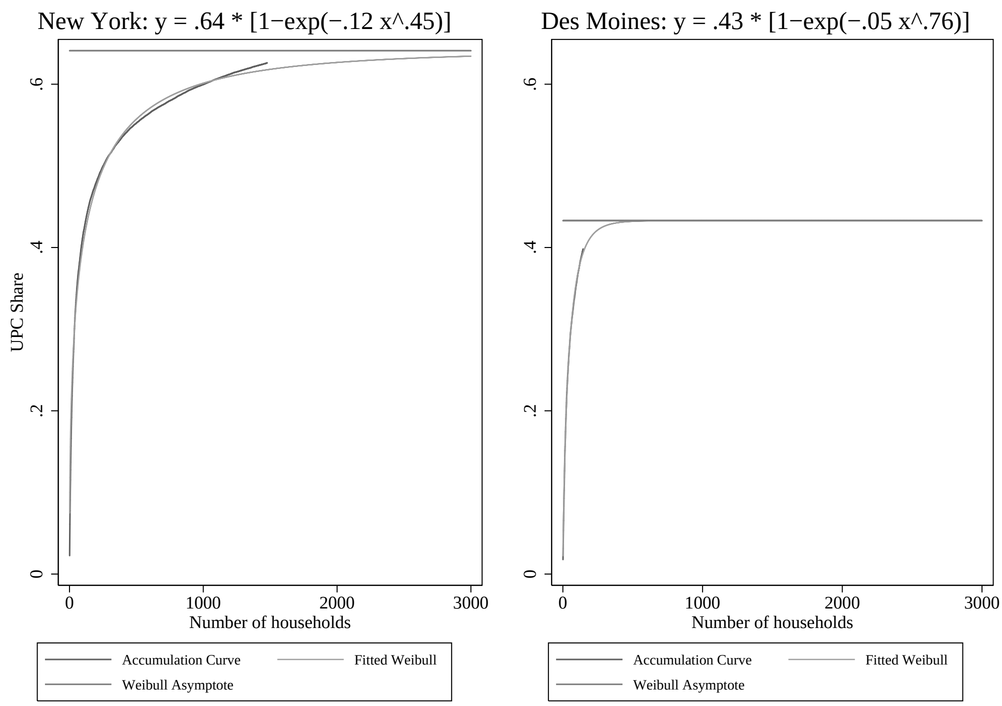
Figure 9: UPC Share Accumulation Curves for the Bread Product Group



Des Moines is equal to 1.055/1.069, or 0.987, implying that if the prices of commonly available varieties are the same in the two cities, people living in New York face 1.3 percent lower costs for bread because they have access to more varieties.

Figures 10 and 11 plot the average asymptotes of the share accumulation curves in each city against the log of the population in each city. As one can see from the figure, there is a strong positive relationship between variety availability and the city's population. On average, consumers spend 5 percent more on brand-modules and UPCs available in the largest cities than they do on those brand-modules and UPCs available in the smallest cities. Once again we see that people in larger cities have access to more varieties and/or more popular varieties, while those in smaller cities have more limited access.

If we compare the results in Figure 10 with those in Figure 7, we can see the importance of adjusting the data for the quality of the unavailable varieties. We saw in Section 4 that New York was estimated to have more than four times as many varieties as Des Moines. However, many of the products available in New York but not in Des Moines have extremely small market shares, implying that consumers do not value these varieties much. In general, both the shares of brand-modules available and products available within a brand-module increase with city-size, but the slope is much lower than we saw with the raw counts. This lower slope reflects the fact that even though larger cities have substantially more varieties, the most popular brand-modules

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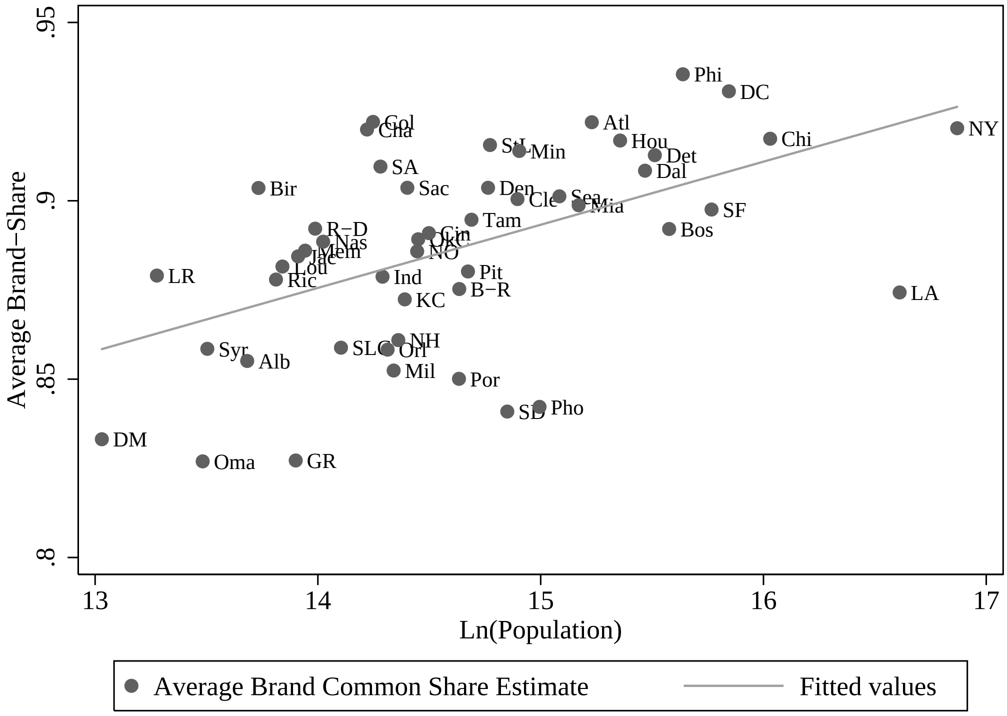
Figure 10: Average Brand-Module Share Estimate vs. Log City Population



Notes:

1. Common shares are averaged across product groups using national product group sales weights.

2. Acronyms on plots reference the city represented, as listed in Table A.1.

and products tend to be available everywhere.

The asymptotes of the share accumulation curves, in conjunction with our price data and sales weights, enable us to estimate exact price indexes for each city. Proposition 1 defines the exact price index in terms of product group-specific conventional exact price indexes ($CEPI_{gc}$) and variety adjustments (VA_{gc}). We aggregate across product groups to obtain values for each of these components for each city. Rearranging terms in the exact price index definition from Proposition 1, we can see that the exact price index is the product of each of these aggregate components:

$$EPI_c = \prod_{g \in G} [CEPI_{gc} VA_{gc}]^{w_{gc}} = \prod_{g \in G} [CEPI_{gc}]^{w_{gc}} \prod_{g \in G} [VA_{gc}]^{w_{gc}} = CEPI_c VA_c.$$

Table 5 presents our estimates for how the conventional exact price index ($CEPI_c$), the variety adjustment (VA_c), and their product, the exact price index (EPI_c), vary across cities. The first three columns in the table use unadjusted prices to compute the index. As we saw in Table 2, unadjusted prices are higher in larger cities, and these results translate into a common exact price index that rises with city size. These higher prices, however, are offset by an even stronger

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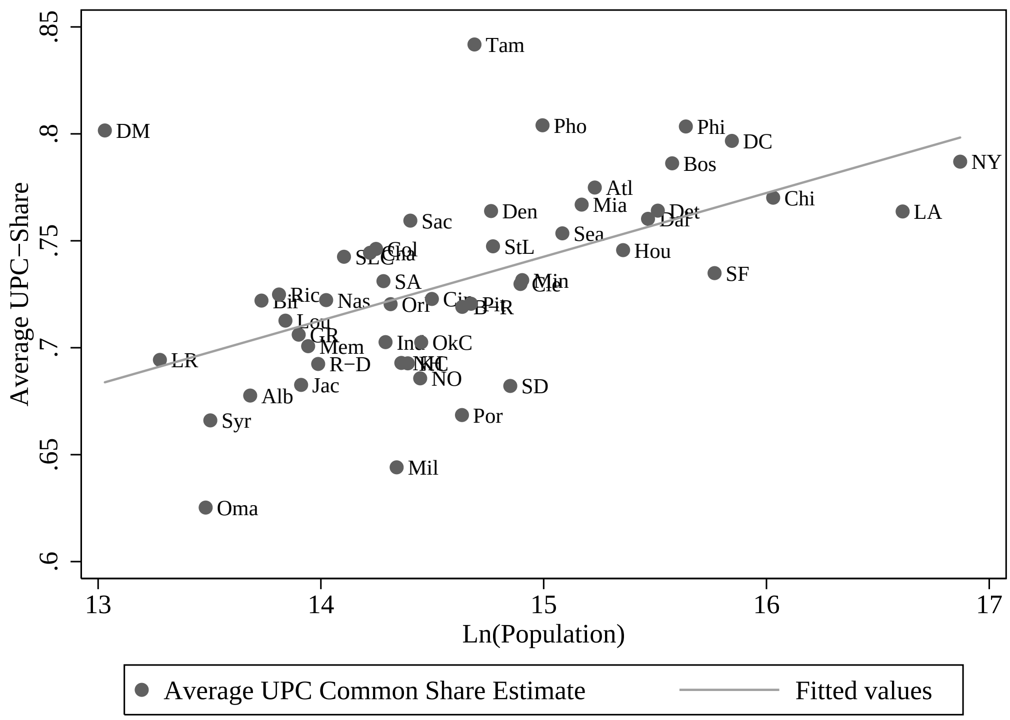
Figure 11: Average UPC Share Estimate vs. Log City Population



Notes:

1. Common shares are averaged across product groups using national product group sales weights.

2. Acronyms on plots reference the city represented, as listed in Table A.1.

variety adjustment to prices arising from the greater availability of varieties in larger cities, leading to an exact price index that falls slightly, but not significantly with city size.

Table 5: Are price indexes higher in larger cities?

	Unadjusted Prices			Prices Adjusted for Purchaser Heterogeneity			Prices Adjusted for Purchaser and Store Heterogeneity		
	$CEPI_c$	VA_c	EPI_c	$CEPI_c$	VA_c	EPI_c	$CEPI_c$	VA_c	EPI_c
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Ln(Population$_c$)	0.012***	-0.016***	-0.0025	0.012***	-0.016***	-0.003	0.0041**	-0.015***	-0.011***
	[0.0035]	[0.0028]	[0.0050]	[0.0034]	[0.0028]	[0.0050]	[0.0018]	[0.0028]	[0.0036]
Constant	0.82***	1.31***	1.11***	0.82***	1.31***	1.12***	0.94***	1.31***	1.24***
	[0.051]	[0.042]	[0.074]	[0.050]	[0.042]	[0.073]	[0.027]	[0.042]	[0.053]
Observations	49	49	49	49	49	49	49	49	49
R-squared	0.206	0.394	0.005	0.201	0.394	0.007	0.096	0.388	0.167

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Notes:

1. The dependent variables in the above regressions are indexes. These indexes are calculated using unadjusted prices or prices that have been adjusted as indicated above, using estimates from the regression in Column [4] of Panel A in Table 2.

2. $EPI_c = CEPI_c VA_c$ which implies that $\log(EPI_c) = \log(CEPI_c) + \log(VA_c)$. Note that the dependent variables in the above regressions are in levels, not logs, so the coefficients on log population in the $CEPI_c$ and VA_c regressions do not add to the coefficient on log population in the EPI_c regression.

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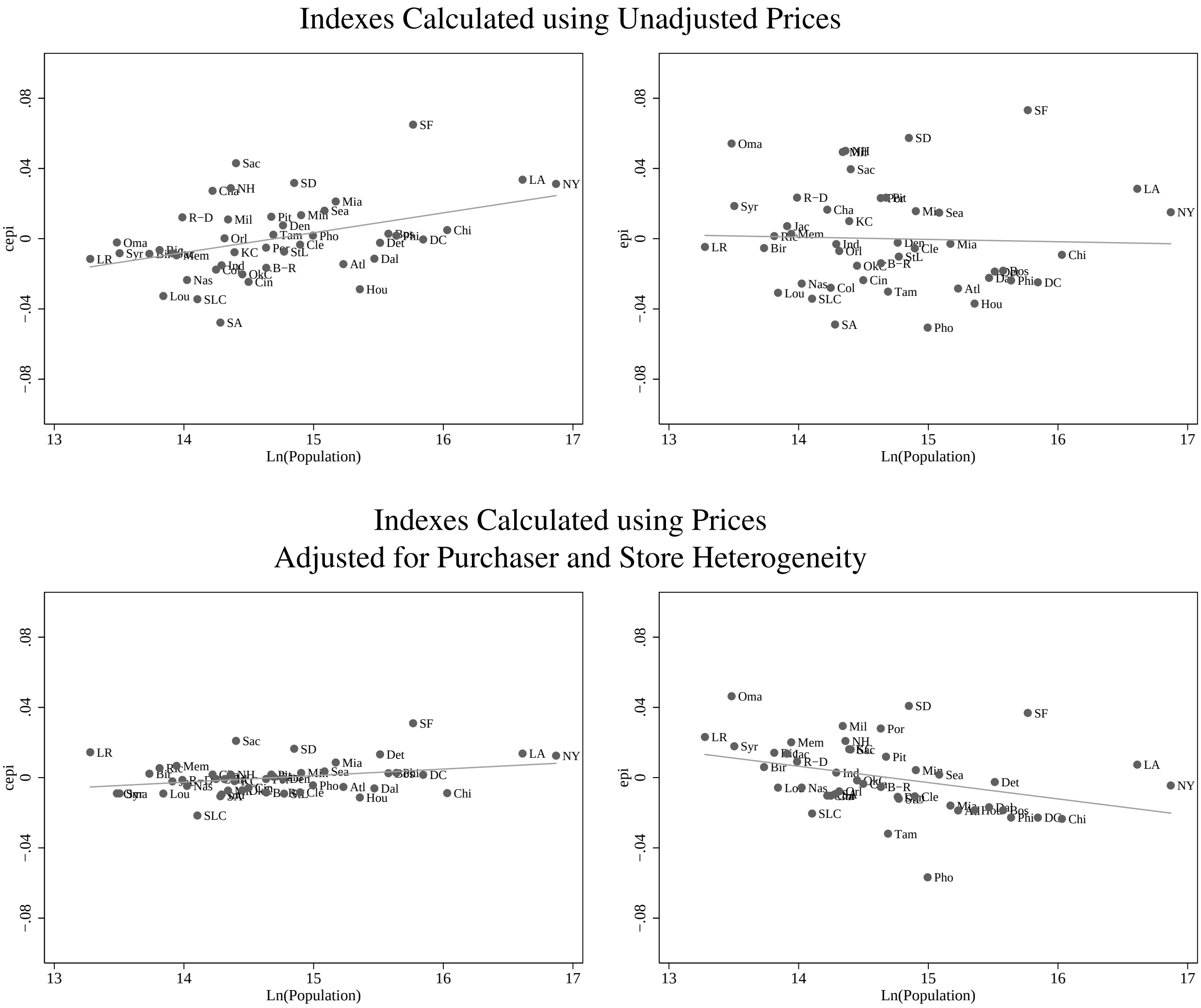
Figure 12: City Price Indexes vs. Log City Population



Notes:

1. Acronyms on plots reference the city represented, as listed in Table A.1.
2. City price indexes are normalized to be mean zero.

As we argued in Section 3.3, the unadjusted prices are problematic because they do not correct for the store in which the goods are purchased or the type of household making the purchase. We therefore use adjusted prices in the subsequent columns. Our price adjustments are based on the estimates from Column 4 of Table 2. Adjusting for purchaser heterogeneity hardly has any impact in Table 2, and it barely affects our point estimates in Columns 4-6. However, adjusting for retailer heterogeneity has a big impact. Columns 7-9 present results in which we also control for retailer heterogeneity. We still obtain a statistically significant positive association between city size and the common goods price index, but it is economically small in size. On average, a person moving from a small city like Des Moines to New York City would experience the price of commonly available groceries rise by 1.6 percent. However, this

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higher common goods price index would be more than offset by the fact that many goods are not available and are therefore effectively priced at their reservation level, resulting in the exact price index in the small city being 4.2 percent higher.

We can assess the importance of the heterogeneity and variety availability biases visually in Figure 12. The plots on the left shows how the common-goods exact price index varies across cities, and the plots on the right shows how the exact price index varies. As we saw in Figure 2, there is virtually no upward relationship between the $CEPI_c$ and population when we adjust for heterogeneity biases and only a slight upward sloping relationship when we do not. Meanwhile, the negative relationship between city population and the exact price index is robust and clearly not driven by outliers.

Figure 12 also demonstrates how controlling for heterogeneity affects the variance of the price level across cities. The common-goods exact price indexes plotted on the top left are calculated with unadjusted prices. The variance of the price indexes that control for product heterogeneity but not purchaser or store effects is 86 percent lower than the variance in our replication of the ACCRA food price index. When we further control for purchaser and store heterogeneity in the indexes on plotted on the bottom left, the variance falls by an additional 10 percentage points to just 3 percent of the variance of the ACCRA-style index. In sum, 97 percent of the variance in urban price levels disappears when we move from an *ad hoc* price index to a theoretically-justified one that corrects for both heterogeneity and substitution biases. This drop is almost identical to the 95 percent decline in variance that we observed comparing our replication of the ACCRA food price index with the city fixed effects estimated in Section 5.3. The methodological differences between the city fixed effects and the CES indexes, therefore, play only a small role in the drop in variance. We attribute most of the variance in measured PPP of commonly-available food products to heterogeneity biases, rather than substitution biases.[31]

It is also interesting to compare the common-good exact price index, $CEPI_c$, in Table 5, with the coefficient on the city fixed effects, $\hat{\alpha}_c$, in Table 2. Recall that we can think of the city fixed effects as a price index in the sense that they summarize the relative price levels across locations, where relative prices are weighted by the transaction-value weights used in the regressions. An important difference between the two is that the Sato-Vartia weights used to calculate the $CEPI_c$ are theoretically justified if one assumes a CES utility function, whereas the transaction weights used in the estimation of the $\hat{\alpha}_c$'s do not have a theoretical justification but rather serve an econometric purpose: to minimize the influence of errors associated with small transactions on the estimates. Nevertheless, it is reassuring that the associations between these variables and population are so close; the differences are typically around 0.002. This indicates that our results regarding the computation of the price level of available goods in a city are robust to a number of sensible aggregation methods.

[31] These price indexes and their relative variances are listed in Appendix Table A.2.

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Taken together with those in Section 3, these results suggest that conventional price indexes provide a very misleading picture of what the prices of tradables are in cities and also help to explain why. In Column 1 of Table 1, we saw that the elasticity of a conventional urban price index with respect to population was 4.2 percent. However, once we controlled for product heterogeneity, the fact that the standard urban price indexes don't compare the same goods, we see that the elasticity falls to 1.6 percent (Column 1 of Table 2): a loss of two-thirds of its magnitude. Controlling for purchaser and especially retailer heterogeneity more than halves the magnitude of this coefficient, taking it down to 0.6 percent. Further using the common exact price index instead of an *ad hoc* one, which is the principle difference between $CEPI_c$ and $\hat{\alpha}_c$, reduces the coefficient to 0.4 percent (Column 7 of Table 5), which is less than one tenth of its initial magnitude. Finally, the exact price index, which differs from the $CEPI_c$ by correcting for variety availability (an extreme form of substitution bias), flips the sign, suggesting that the elasticity of urban price with respect to population is -1.1 percent (Column 9 of Table 5): a 5 percentage point differential. Thus, the standard result that the prices of tradables are higher in cities is due to a series of measurement issues. If one uses a theoretically sound approach, the result reverses.

5.4 Robustness

One possible concern about these results is that people who live in large cities might not shop in all of the neighborhoods within the city's borders. This might bias our variety adjustment downwards because we may be counting varieties in, say, suburbs that are irrelevant for people who live downtown.

An easy solution to this problem is to make use of the fact that the Nielsen data records the household's county and the zip codes of the stores in which they purchase each UPC. We first assume that a household is located in the zip code in the county where its grocery expenditures are the highest. We then construct the population of the market where households in each zip code shop. For a set of households living in the same zip code, we sum the populations of the zip codes where we observe the set of households purchasing UPCs. This sum tells us the population of the market that is available to households located in that zip code. We average these market populations across the zip codes in each city to yield the average population of the neighborhoods where households in the city choose to shop. We refer to this number as the relevant population.

Table 6 presents results in which we replace the city's population with the relevant population in the neighborhoods in which households actually shop. The results are, if anything, stronger than the results using urban population as the measure of city size. The fact that the results are so similar indicates that understanding where households shop within cities is not

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important for understanding the relationship between city size and prices. The key finding is that the exact price index falls with city size, and this relationship is significant whenever we adjust prices to take into account store amenities and buyer characteristics.

Table 6: Are price indexes higher in larger cities?

	Unadjusted Prices			Prices Adjusted for Purchaser Heterogeneity			Prices Adjusted for Purchaser and Store Heterogeneity		
	$CEPI_c$	VA_c	EPI_c	$CEPI_c$	VA_c	EPI_c	$CEPI_c$	VA_c	EPI_c
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Ln(Relevant	0.0082***	-0.016***	-0.0066	0.0079**	-0.016***	-0.0069*	0.0027*	-0.015***	-0.012***
Population_c)	[0.0030]	[0.0020]	[0.0041]	[0.0030]	[0.0020]	[0.0040]	[0.0016]	[0.0020]	[0.0027]
Constant	0.86***	1.34***	1.18***	0.86***	1.34***	1.19***	0.95***	1.34***	1.29***
	[0.050]	[0.034]	[0.068]	[0.049]	[0.034]	[0.067]	[0.026]	[0.034]	[0.045]
Observations	49	49	49	49	49	49	49	49	49
R-squared	0.137	0.553	0.052	0.133	0.553	0.058	0.06	0.549	0.304

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

Notes:
1. The dependent variables in the above regressions are indexes. These indexes are calculated using unadjusted prices or prices that have been adjusted as indicated above, using estimates from the regression in Column [4] of Panel A in Table 2.
2. $EPI_c = CEPI_c VA_c$ which implies that $\log(EPI_c) = \log(CEPI_c) + \log(VA_c)$. Note that the dependent variables in the above regressions are in levels, not logs, so the coefficients on log population in the $CEPI_c$ and VA_c regressions do not add to the coefficient on log population in the EPI_c regression.

6 Conclusion

In this paper we have shown how the lack of sophistication of standard spatial price indexes can lead to very misleading portraits of how prices vary across space. We find that most of the large dispersion in food prices across space is due to problems in the measurement of prices. 97 percent of the variation in price levels across space in conventional indexes can be attributed to unobserved heterogeneity in the goods being compared. In particular, product and retailer heterogeneity play very large roles. We also show that standard indexes suffer severely from the spatial equivalent of the "new goods bias" that is well known in inflation measurement. Small cities offer consumers a much smaller array of available goods. Building a price index that takes all of these biases into account, we reverse the conventional finding that tradable goods prices rise with city size. The elasticity of tradable goods prices with respect to city population is -0.011.

These results have important implications for a broad class of New Economic Geography models in which agglomeration is driven, at least in part, by pecuniary externalities. In Krugman (1991)'s model of monopolistic competition, these externalities arise when there are positive trade costs between locations; locally-produced goods are cheaper in the local market than they are elsewhere, and larger cities produce more varieties than smaller ones, so consumers in large cities have access to more locally-produced goods and therefore face a lower price index.

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More recent papers propose that other mechanisms are at play here. Behrens and Robert-Nicoud (2011) and Combes et al. (2012) demonstrate that, with quadratic linear preferences and fixed trade costs as in Melitz and Ottaviano (2008), three related phenomena yield lower prices in larger cities: (i) more efficient firms are more likely to locate in, or "select into," larger cities; (ii) firms in larger cities can take advantage of agglomeration economies in those locations; and finally, (iii) larger cities are more competitive so firms charge lower markups in these locations. Finally, Hummels et al. (2009) argue that scale economies in the shipping industry lower costs and increase competition on routes to large markets. Similar economies in domestic transportation could also lower prices in large cities.

While separating the contributions of each of these forces to understanding the spatial distribution of prices is beyond the scope of this paper, our results indicate that the New Economic Geography framework is correct to predict that the price level of tradable goods tends to be lower in larger cities.

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Appendices

Table A.1: Sample City Data

Market Name	Population[1] (thousands)	Sample Household Count[2]	Effective Retail Rent[3] (psf)	Normalized Herfindahl Index[4]
Correlation with Population	1.00	0.57	0.59	-0.30
Omaha (Oma)	717	116	11.70	0.116
Jacksonville (Jac)	1,100	130	12.95	0.157
Albany (Alb)	876	138	-	0.139
San Diego (SD)	2,814	139	23.52	0.116
Des Moines (DM)	456	145	-	0.176
Syracuse (Syr)	732	164	10.77	0.078
Milwaukee (Mil)	1,690	170	13.37	0.220
Hartford-New Haven (NH)	1,725	193	14.53	0.138
Richmond (Ric)	997	194	15.04	0.120
Grand Rapids (GR)	1,089	198	-	0.221
Kansas City (KC)	1,776	220	12.10	0.082
Raleigh-Durham (R-D)	1,188	239	15.25	0.113
Indianapolis (Ind)	1,607	245	12.82	0.109
Orlando (Orl)	1,645	247	15.74	0.203
Salt Lake City (SLC)	1,334	248	14.11	0.092
Portland, Or (Por)	2,265	263	16.76	0.110
Pittsburgh (Pit)	2,359	303	14.07	0.143
Cincinnati (Cin)	1,979	317	12.52	0.201
Memphis (Mem)	1,136	331	11.98	0.155
Little Rock (LR)	584	351	11.11	0.193
Cleveland (Cle)	2,946	362	13.88	0.095
Nashville (Nas)	1,231	403	12.99	0.169
New Orleans-Mobile (NO)	1,878	409	-	0.216
Louisville (Lou)	1,026	454	13.46	0.209
Oklahoma City-Tulsa (OkC)	1,887	528	9.83	0.147
Birmingham (Bir)	921	570	12.81	0.154
Dallas (Dal)	5,222	899	14.05	0.119
San Antonio (SA)	1,592	921	12.48	0.305
San Francisco (SF)	7,039	995	29.90	0.152
Detroit (Det)	5,456	1,001	15.66	0.135
Atlanta (Atl)	4,112	1,038	15.31	0.141
Sacramento (Sac)	1,797	1,052	19.84	0.064
Chicago (Chi)	9,158	1,064	16.92	0.127
Houston (Hou)	4,670	1,070	13.63	0.143
Miami (Mia)	3,876	1,086	20.08	0.286
Columbus (Col)	1,540	1,101	10.97	0.171
Charlotte (Cha)	1,499	1,115	14.89	0.132
Washington, DC-Baltimore (DC)	7,608	1,115	21.49	0.070
Denver (Den)	2,582	1,128	14.70	0.163
Buffalo-Rochester (B-R)	2,268	1,135	11.20	0.176
Seattle (Sea)	3,555	1,149	19.78	0.104
Los Angeles (LA)	16,400	1,151	24.47	0.100
Tampa (Tam)	2,396	1,173	13.11	0.198
St. Louis (StL)	2,604	1,183	12.84	0.107
Philadelphia (Phi)	6,188	1,183	17.02	0.066
Phoenix (Pho)	3,252	1,211	16.27	0.129
Minneapolis (Min)	2,969	1,236	14.99	0.165
Boston (Bos)	5,819	1,275	19.03	0.122
New York (NY)	21,200	1,477	20.13	0.088

Sources and notes:
1. 2000 U.S. Census.
2. 2005 Nielsen HomeScan sample.
3. 2005 Community/Neighborhood Shopping Center Effective Rents from reis.com.
4. Herfindahl indexes measure the concentration of retail chains in each market.

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Table A.2: Price Indexes

Market Name	Population[1] (thousands)	Price Indexes[2]: Nielsen Food Index[3]	Unadjusted: City Fixed Effect[4]	Unadjusted: CEPI[6]	Purchaser-Store Adjusted: City Fixed Effect[4]	Purchaser-Store Adjusted: CEPI[6]	Purchaser-Store Adjusted: EPI[6]
Correlation with Population	1.00	0.49	0.44	0.43	0.42	0.37	-0.19
Coefficient of Variation		6.8%	2.6%	2.2%	1.3%	1.1%	2.0%
Var(Index)/Var(Nielsen Food Index)			0.18	0.13	0.05	0.03	0.12
Des Moines (DM)	717	0.802	0.959	0.968	0.963	0.971	1.039
Little Rock (LR)	1,100	0.872	0.953	0.961	0.969	0.976	1.007
Omaha (Oma)	876	0.924	0.967	0.970	0.973	0.975	1.013
Syracuse (Syr)	2,814	0.973	1.004	1.001	0.996	0.995	1.033
Albany (Alb)	456	0.844	0.927	0.940	0.964	0.974	1.039
Birmingham (Bir)	732	0.847	0.953	0.961	0.967	0.972	1.014
Richmond (Ric)	1,690	0.871	0.969	0.980	0.955	0.965	1.015
Louisville (Lou)	1,725	0.976	0.998	0.998	0.987	0.985	1.019
Grand Rapids (GR)	997	0.849	0.954	0.963	0.976	0.983	1.007
Jacksonville (Jac)	1,089	0.833	0.930	0.938	0.978	0.981	1.016
Memphis (Mem)	1,776	0.840	0.953	0.962	0.975	0.980	1.014
Raleigh-Durham (R-D)	1,188	0.905	0.972	0.981	0.968	0.977	1.003
Nashville (Nas)	1,607	0.836	0.945	0.955	0.964	0.972	1.000
Salt Lake City (SLC)	1,645	0.907	0.961	0.970	0.971	0.975	0.985
Charlotte (Cha)	1,334	0.818	0.928	0.936	0.948	0.957	0.976
Columbus (Col)	2,265	0.834	0.963	0.964	0.978	0.979	1.022
San Antonio (SA)	2,359	0.827	0.973	0.982	0.977	0.982	1.008
Indianapolis (Ind)	1,979	0.844	0.934	0.946	0.969	0.977	0.996
Orlando (Orl)	1,136	0.813	0.946	0.960	0.976	0.987	1.016
Milwaukee (Mil)	584	0.802	0.946	0.958	0.985	0.995	1.019
Hartford-New Haven (NH)	2,946	0.859	0.958	0.966	0.968	0.973	0.988
Kansas City (KC)	1,231	0.806	0.934	0.947	0.965	0.976	0.992
Sacramento (Sac)	1,878	0.877	0.952	0.965	0.980	0.990	1.019
New Orleans-Mobile (NO)	1,026	0.827	0.927	0.938	0.964	0.973	0.993
Oklahoma City-Tulsa (OkC)	1,887	0.830	0.937	0.950	0.964	0.973	0.996
Cincinnati (Cin)	921	0.858	0.948	0.961	0.971	0.982	1.002
Portland, Or (Por)	5,222	0.861	0.945	0.958	0.963	0.974	0.981
Buffalo-Rochester (B-R)	1,592	0.784	0.909	0.923	0.953	0.964	0.982
Pittsburgh (Pit)	7,039	1.031	1.035	1.033	1.014	1.013	1.033
Tampa (Tam)	5,456	0.840	0.958	0.967	0.994	0.999	1.000
Denver (Den)	4,112	0.863	0.943	0.955	0.965	0.974	0.978
St. Louis (StL)	1,797	1.024	1.016	1.011	1.004	1.003	1.014
San Diego (SD)	9,158	0.902	0.968	0.974	0.961	0.966	0.970
Cleveland (Cle)	4,670	0.798	0.925	0.941	0.955	0.966	0.976
Minneapolis (Min)	3,876	0.932	0.981	0.990	0.980	0.986	0.979
Phoenix (Pho)	1,540	0.835	0.941	0.952	0.974	0.980	0.988
Seattle (Sea)	1,499	0.885	0.985	0.996	0.969	0.978	0.984
Miami (Mia)	7,608	0.911	0.965	0.969	0.975	0.978	0.972
Atlanta (Atl)	2,582	0.938	0.973	0.977	0.976	0.981	0.988
Houston (Hou)	2,268	0.859	0.941	0.953	0.965	0.973	0.993
Dallas (Dal)	3,555	0.905	0.987	0.985	0.982	0.983	0.997
Detroit (Det)	16,400	0.952	1.002	1.002	0.991	0.993	1.003
Boston (Bos)	2,396	0.905	0.963	0.972	0.972	0.976	0.963
Philadelphia (Phi)	2,604	0.832	0.952	0.962	0.961	0.969	0.983
San Francisco (SF)	6,188	0.938	0.968	0.971	0.984	0.986	0.979
Washington, DC-Baltimore (DC)	3,252	0.857	0.968	0.971	0.969	0.972	0.941
Chicago (Chi)	2,969	0.900	0.971	0.983	0.969	0.981	0.998
Los Angeles (LA)	5,819	0.937	0.965	0.972	0.977	0.983	0.980
New York (NY)	21,200	1.000	1.000	1.000	1.000	1.000	1.000

Sources and notes:
1. 2000 U.S. Census.
2. All price indexes are relative to the price index for New York.
3. Nieslen food index is replication of ACCRA food index, as described in Section 2.
4. Unadjusted city fixed effects are α_c estimates from equation (2) without purchaser demographic or storetype controls.
5. Purchaser-store adjusted city fixed effects are α_c estimates from equation (2) with purchaser demographic and storetype controls.
6. CEPI and EPI indexes are calculated according to methodology described in Section 5.

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A Structural Variety Estimation

In Section 4, we used a non-structural "accumulation curve" methodology to estimate the number of UPCs available in each city. Here we demonstrate that a structural methodology yields very similar results for how the number of varieties varies across cities.

A.1 Methodology

We first consider a simple case in which all UPCs are purchased by households with the same probability in order to develop the intuition, and then move to a more realistic case in which each UPC has its own purchase probability.

In order to work out the math in the simple case, assume that each household selects only one UPC out of the S UPCs available in the market. If we also assume that each UPC is purchased with a probability π that is identical for all UPCs in the market, then it follows that $\pi = 1/S$. Our task is to estimate S using the number of different UPCs purchased by a sample of H households. To do this, we make one additional assumption: stores have sufficient inventories of goods so that the purchase of a UPC by one household does not reduce the probability of another household buying the same UPC. If household purchases are independent in the cross-section, then the probability that we observe one of the H households in our sample selecting a particular UPC is equal to one minus the probability that none of the H households selects the UPC, or $1-(1-1/S)^H$. The number of different UPCs that we expect to observe in the purchase records of the H households is simply the sum of these probabilities across all of the S available UPCs,

$$S(H) = S[1-(1-1/S)^H] \tag{A.1}$$

It is immediately apparent that equation (A.1) is an accumulation curve that has been derived from a particular set of assumptions. It would be straightforward to obtain an estimate for the number of varieties in the market in this simple case. By equating $S(H)$ to the sample UPC count, $\tilde{S}(H)$, we can derive an estimate for the number of available UPCs that satisfies equation (A.1). Note that the accumulation curve, $S(H)$ should follow the negative exponential function (which a special case of one of the functional forms we considered in Section 4:

$$S(H) = S\left(1-e^{-\ln((1-1/S)H)}\right) \tag{A.2}$$

This simple approach cannot be applied to the data for two reasons. First, households purchase more than one UPC in the course of a year. And second, some UPCs, like milk, are likely to be purchased at higher frequencies than other UPCs, like salt. Hence the probability that we observe the purchase of a UPC will vary across UPCs. We can deal with the first problem by

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allowing the purchase probability, π, to differ from $1/S$. The second problem, however, is more complicated because solving it requires us to know the purchase frequencies not only of every observed UPC but also of the UPCs that we do not observe in our sample. In order to solve this problem, we follow Mao et al. (2005).

We allow for different products to have different purchase probabilities, but we restrict these probabilities to be identical for groups of UPCs that we will refer to as "incidence groups." This is not that restrictive an assumption, as we do not put a limit on the number of incidence groups but only assume that some UPCs from each incidence group are purchased in our data. Grouping UPCs in this way enables us to estimate the purchase frequencies for all of the UPCs in an incidence group even though we may only observe a fraction of the UPCs in the group being purchased.

To put this concretely, suppose that each UPC u has a probability of π_{cu} of being selected by a household in city c, and that there are K different incidence groups, or values that π_{cu} can take in each city c, such that $\pi_{cu} = \pi_{ck}$ for each UPC in incidence group k. We define α_{ck} as the proportion of UPCs in incidence group k in city c, *i.e.*, the proportion of UPCs that are selected with probability π_{ck} in city c. For example, when residents of a particular city choose to purchase a good, the probability that they will purchase any given UPC can take one of K values. The incidence groups do not map directly into the product groups or product modules. The estimated purchase frequency associated with each UPC within a product group or brand-module will vary with the popularity of the UPC, which may be correlated with its brand, container, size, and other characteristics. The UPCs in the high frequency incidence group tend to be the most popular varieties of products that are frequently purchased, *e.g.* 12-packs of some soda varieties, which are purchased by almost a third of the households in our sample. Less popular varieties of soda tend to fall into the lower purchase frequency incidence groups, along with the UPCs in less frequently purchased product categories, *e.g.,* cake yeast.

Suppose that there are S_c UPCs available in city c. If we again assume that household purchases are independent in the cross-section, we can express the probability that any of the UPCs in incidence group k available in city c is purchased by one of H_c households as one minus the probability that none of the H_c households selects the UPC, or $1-(1-\pi_{ck})^{H_c}$. Taking the weighted average of these probabilities across incidence groups (using incidence group shares as weights), we can now express the unconditional probability that any one UPC available in city c is observed in the purchases of a sample of H_c households *without knowing its incidence group* as $\sum_{k=1}^{K} \alpha_{ck}(1-(1-\pi_{ck})^{H_c})$. The number of different UPCs that we expect to observe in the purchase records of H_c households in city c is the sum of these probabilities across all of the

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S_c available UPCs, or

$$S_c(H_c) = S_c \sum_{k=1}^{K} \alpha_{ck}(1-(1-\pi_{ck})^{H_c}). \tag{A.3}$$

Mao et al. (2004) note that equation (A.3) can be re-written as:

$$S_c(H_c) = S_c \sum_{k=1}^{K} \alpha_{ck}(1-\exp(C_{ck}H_c)) \text{ where } C_{ck} = -\ln(1-\pi_{ck})$$

Equation (A.3) is therefore referred to as the "generalized negative exponential" (GNE) model. It is straightforward to see that equation (A.2) is a specific case of equation (A.3) in which the selection probability is identical for all UPCs, *i.e.*, $K=1$ and $\pi = 1/S$. Moreover, if we knew the share of all goods in each incidence group, α_{ck}, and the probability that each UPC was purchased, π_{ck}, (A.3) would just give us the equation of a particular accumulation curve for a city.

Fortunately, we can use maximum likelihood estimation to estimate S_c as well as the α_{ck} and π_{ck} for any choice of K. The number of households purchasing product u in city c, h_{cu}, follows a binomial distribution where the probability of observing h_{cu} purchases is given by:

$$P(h_{cu}) = \varphi(h_{cu};\pi_{cu}) = \begin{pmatrix} H_c \\ h_{cu} \end{pmatrix} (\pi_{cu})^{h_{cu}}(1-\pi_{cu})^{(H_c-h_{cu})} \tag{A.4}$$

where H_c is the total number of households in the sample for city c,

$$\begin{pmatrix} H_c \\ h_{cu} \end{pmatrix} \equiv \frac{H_c!}{h_{cu}!(H_c-h_{cu})!}$$

and once again $\pi_{cu} = \pi_{ci}$ for each UPC, u, in category k. Let $\{h_{cu}\}_{u\in U_c}$ be the observed counts of each UPC purchased by our sample of households in a city c, where U_c is the set of UPCs observed in the city c sample. Now, we can define the binomial mixture distribution as follows:

$$\Phi(h_{cu}) = \sum_{k=1}^{K} \alpha_{ck}\varphi(h_{cu};\pi_{ck})$$

This distribution tells us the unconditional probability of observing h_{cu} purchases of *any* UPC u in our data, regardless of its incidence group, given the size and purchase probabilities of each of the incidence groups.

Mao et al. (2005) derive a maximum likelihood methodology for estimating the α's and π's for a given K using data on the number of samples (in our case, households) in which each variety is observed. The variable n_{cj} is defined to be the number of products that are purchased

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by j households in the dataset for city c, *i.e.*, for which h_{cu} equals j. In other words, if 100 UPCs are purchased by no households, 50 UPCs are purchased by 1 household, and 25 UPCs are purchased by 2 households, then we would have $n_{c0} = 100$; $n_{c1} = 50$; and $n_{c2} = 25$. The joint likelihood of the total number of products available in the city and the parameters of the mixture distribution is

$$L\left(S_c, \{\alpha_{ck}, \pi_{ck}\}_{k=1}^{K}\right) = \frac{S_c!}{\prod_{j=0}^{H_c} n_{cj}!} \prod_{j=0}^{H_c} \Phi(j)^{n_{cj}}$$

Note that from equation (A.3), we know that the number of available products, S_c, is a function of the number of observed products, $S_c(H_c) = \sum_{j=1}^{H_c} n_{cj}$, and the parameters of the mixture distribution, $\{\alpha_{ck}, \pi_{ck}\}_{k=1}^{K}$. Therefore, we only need to estimate the parameters of the mixture distribution to derive an estimate for the number of available products. To do so, we will maximize a conditional likelihood function. Let $\tilde{\varphi}(h_{cu}; \pi_{cu})$ be a zero-truncated binomial density, *i.e.*, the probability that a product is purchased by j households conditional on it being purchased by more than one household, and $\tilde{\Phi}(j) = \sum_{k=1}^{K} \alpha_{ck} \tilde{\varphi}(j; \pi_{ck})$ be the mixture distribution over these densities for K incidence groups. If we denote the total number of UPCs that are purchased by at least one household in the sample n_{c+}, the conditional likelihood function is

$$L\left(S_c, \{\alpha_{ck}, \pi_{ck}\}_{k=1}^{K}\right) = \frac{n_{c+}!}{\prod_{j=1}^{H_c} n_{cj}!} \prod_{j=1}^{H_c} \tilde{\Phi}(j)^{n_{cj}} \tag{A.5}$$

Equation (A.5) gives us the likelihood function as a function of the number of incidence groups, K. In order to identify the correct number of these groups, we estimate the parameters of mixture distributions for a range of values for K using the conditional likelihood function. Each distribution implies a different estimate for the total number of UPCs available in a city. We then compute the Akaike Information Criterion (AIC) for each value of K in each city. We choose between the distributions by selecting the number of incidence groups for all cities equal to the K that maximizes the sum of the AICs across all cities. The intuition for this procedure is that each additional incidence group improves the fit but adds parameters, and the AIC provides a way of determining how many groups are likely to exist in the data.[32]

Once we have our estimates for the α's and π's, we can use equation (A.3) to obtain an

[32] We also assume that the sampling is sufficient so that we observe some UPCs purchased in each incidence group. We need this assumption because we cannot say anything about the number of goods in an incidence group that are purchased with such low a probability that no one in the sample ever buys them. In other words, we can only discuss the number of available varieties for observable classes of goods.

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estimate of the total number of varieties as follows:

$$\hat{S}_c = \tilde{S}_c(H_c)\left[\sum_{k=1}^{K}\hat{\alpha}_{ck}(1-(1-\hat{\pi}_{ck})^{H_c})\right]^{-1} \tag{A.6}$$

where variables with circumflexes represent parameter estimates and $\tilde{S}_c(H_c)$ is equal to the sample count of distinct varieties in the city. It is useful to note that when the number of sampled households in the city, H_c approaches infinity, the fact that the α's sum to one implies that our count of the number of distinct products purchased by these households becomes our estimate of the number of varieties.

A.2 Results

With 49 cities, the GNE approach involves the estimation of several hundred parameters, so we do not report all the values here. The AIC indicates that UPCs tend to fall within 10 incidence groups in terms of their purchase frequency. Table A.3 summarizes these estimates across our sample of 49 cities. We see that in all cities there are few UPCs that are purchased with very high frequency—on average, one in ten thousand UPCs are purchased with a frequency of 0.5 by a household. This would correspond to about 8 UPCs in the typical city having a purchase probability of 0.5 over the course of a year by a typical household. However, we also see that the vast majority of UPCs have extremely low purchase probability. 49 percent of UPCs have a purchase probability of approximately one in a thousand. Thus, the product space is characterized by a few UPCs with high purchase probabilities and a vast number of UPCs that are rarely purchased.

Table A.3: Summary Statistics for GNE Parameter Estimates

Incidence	Probability of Purchase (π_{ck})		Share of UPCs (α_{ck})	
Group (k)	Mean	Standard Deviation	Mean	Standard Deviation
1	0.496	0.096	0.00009	0.00006
2	0.332	0.103	0.00041	0.00029
3	0.226	0.085	0.00116	0.00071
4	0.152	0.066	0.003	0.00181
5	0.102	0.052	0.00757	0.0047
6	0.065	0.035	0.01953	0.01045
7	0.038	0.022	0.05083	0.01821
8	0.019	0.011	0.12115	0.01879
9	0.008	0.004	0.30803	0.03277
10	0.001	0.001	0.48823	0.03465

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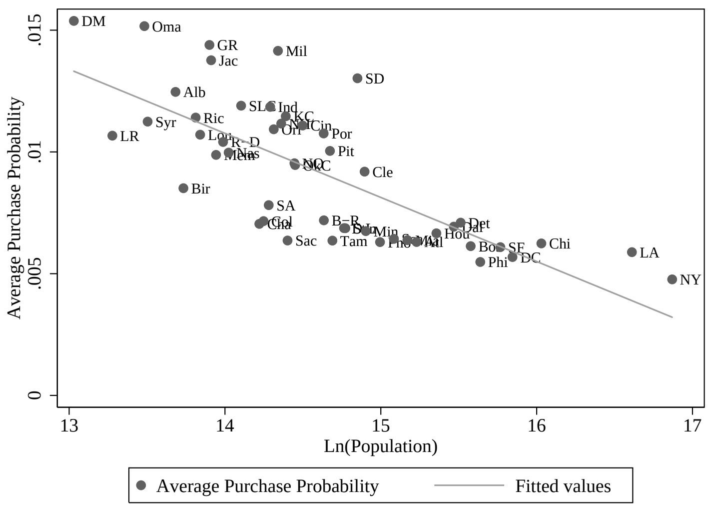
Another way of summarizing the estimates is to examine how the probability that a UPC is purchased varies with city size. We would expect that the probability that any consumer purchases any one UPC would go down as the range of available UPCs in the city increases. Fortunately, this is easy to examine given that our GNE structure enables us to estimate the average probability that a household in city c purchases a UPC by simply calculating

$$\Pi_c = \sum_{k=1}^{K} \hat{\alpha}_{c,k}\hat{\pi}_{c,k}.$$

In Figure A.1, we see that the estimated average probability of purchase (which uses no population data in its estimation) decreases sharply with city size. A UPC sold in our smallest city, Des Moines, has three times the probability of being purchased by any individual household as a UPC sold in New York. The fact that households in larger cities are much less likely to buy any individual UPC is strongly suggestive of the fact that that the parametric estimate of the UPCs available in a city is increasing with city size. We test this directly by using the GNE parameter

Figure A.1: Average Purchase Probability vs. Log City Population



Notes:

1. Average purchase probability is the average of the estimated probability of a household purchasing a UPC in each incidence group weighted by the estimated share of UPCs in the same incidence group, *i.e.*, Average Purchase Probability in City $c = \Pi_c = \sum_{k=1}^{10} \hat{\alpha}_{c,k}\hat{\pi}_{c,k}$.

2. Acronyms on plots reference the city represented, as listed in Table A.1.

estimates to calculate an estimate for total number of varieties in each city and considering how this varies with city size. Figure A.2 plots how the log estimated number of varieties in each city varies with city size. The results in Table A.4 shows that the relative relationship between the estimated number of varieties and city size using the GNE is almost identical to that obtained with the Weibull. The first three columns repeat the regression results reported in Columns 4

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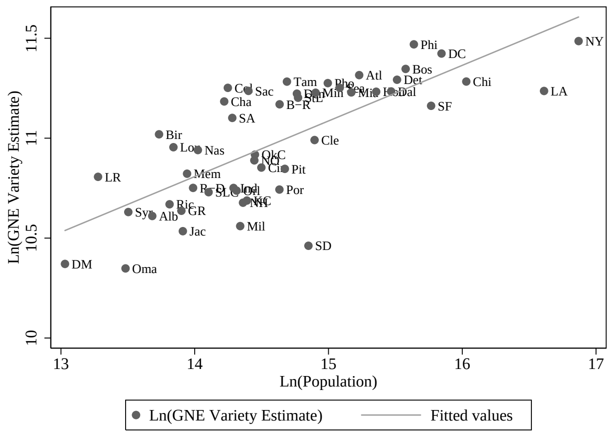
through 6 of Table 4. The last three columns repeat these regressions with the log GNE asymptote instead of the log Weibull asymptote as the dependent variable. The coefficients on log population are almost identical in all three specifications.[33]

Table A.4: Are prices higher in larger cities?

	ln(Weibull Asymptote)			ln(GNE Asymptote)		
	[1]	[2]	[3]	[4]	[5]	[6]
Ln(Population$_c$)	0.278***	0.300***	0.261***	0.281***	0.303***	0.275***
	[0.0364]	[0.0572]	[0.0821]	[0.0340]	[0.0534]	[0.0769]
Ln(Per Capita Income$_c$)	-	-0.137	-0.060	-	-0.129	-0.074
	-	[0.288]	[0.312]	-	[0.269]	[0.292]
Income Herfindahl Index	-	-0.630	-0.178	-	-0.321	0.000
	-	[2.641]	[2.745]	-	[2.466]	[2.568]
Race Herfindahl Index	-	0.074	0.109	-	0.111	0.135
	-	[0.347]	[0.353]	-	[0.324]	[0.330]
Birthplace Herfindahl Index	-	-0.012	0.004	-	-0.028	-0.017
	-	[0.238]	[0.241]	-	[0.222]	[0.225]
Ln(Land Area$_c$)	-	-	0.060	-	-	0.042
	-	-	[0.0898]	-	-	[0.0840]
Constant	6.912***	8.057***	7.240**	6.937***	7.962***	7.381**
	[0.533]	[2.860]	[3.132]	[0.498]	[2.670]	[2.930]
Observations	49	49	49	49	49	49
R-squared	0.55	0.56	0.56	0.59	0.60	0.60

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Figure A.2: Log GNE Estimate vs. Log City Population



Notes:

1. Acronyms on plots reference the city represented, as listed in Table A.1.

[33]This is not surprising, given that the correlation between the Weibull and GNE asymptotes, or variety estimates, is 0.99.

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B Formulas for Sato-Vartia Weights

$$w_{uc} = \frac{\frac{s_{uc}-s_u}{\ln s_{uc}-\ln s_u}}{\sum\limits_{u'\in U_b}\left(\frac{s_{u'c}-s_{u'}}{\ln s_{u'c}-\ln s_{u'}}\right)},\ w_{bc} = \frac{\frac{s_{bc}-s_b}{\ln s_{bc}-\ln s_b}}{\sum\limits_{b'\in B_g}\left(\frac{s_{b'c}-s_{b'}}{\ln s_{b'c}-\ln s_{b'}}\right)} \text{ and } w_{gc} = \frac{\frac{s_{gc}-s_g}{\ln s_{gc}-\ln s_g}}{\sum\limits_{g'\in G}\left(\frac{s_{g'c}-s_{g'}}{\ln s_{g'c}-\ln s_{g'}}\right)}$$

s_{uc}, s_{bc}, and s_{gc} are city-specific expenditure shares defined as follows:

$$s_{uc} = \frac{v_{uc}}{\sum\limits_{u'\in U_b} v_{u'c}},\ s_{bc} = \frac{\sum\limits_{u\in U_b} v_{uc}}{\sum\limits_{b'\in B_g}\sum\limits_{u'\in U_{b'}} v_{u'c}} \text{ and } s_{gc} = \frac{\sum\limits_{b\in B_g}\sum\limits_{u\in U_b} v_{uc}}{\sum\limits_{g'\in G}\sum\limits_{b'\in B_{g'}}\sum\limits_{u'\in U_{b'}} v_{u'c}}$$

s_u, s_b, and s_g are national expenditure shares defined as follows:

$$s_u = \frac{v_u}{\sum\limits_{u'\in U_b} v_{u'}},\ s_b = \frac{\sum\limits_{u\in U_b} v_u}{\sum\limits_{b'\in B_g}\sum\limits_{u'\in U_{b'}} v_{u'}} \text{ and } s_g = \frac{\sum\limits_{b\in B_g}\sum\limits_{u\in U_b} v_u}{\sum\limits_{g'\in G}\sum\limits_{b'\in B_{g'}}\sum\limits_{u'\in U_{b'}} v_{u'}}$$

for $v_u = \sum_c v_{uc}$. G denotes set of product groups, and G_c denotes the set of product groups with products sold in city c. Mathematically, $G_c = \{g \in G | B_g \neq \emptyset\}$. All product groups are sold in every city, so $G_c = G$.

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