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Abstract

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JEL Classification: D12, D14

Keywords: price dispersion, grocery shopping, consumer saving, store expensiveness, consumer basket

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Store expensiveness and consumer saving: Insights from a new decomposition of price dispersion*

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July 2022

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1 Introduction

There is considerable evidence of substantial dispersion in the prices of grocery store goods. Prices for identical products vary across stores at any given point in time, and across time in any given store. Some stores are cheaper than other stores overall, but not all products are cheaper in those stores. In principle, price-sensitive consumers can exploit this variation in order to purchase their desired basket of goods at a lower overall cost. Does this happen in practice? Can consumers achieve significant savings simply by shopping from cheap stores? Or do they need to engage in time-consuming price comparisons in order to fully exploit the available saving potential?

The intertemporal dimension of saving has been explored in a literature going back at least twenty years in economics and even further in marketing.[1] The basic idea is that temporary price promotions are an instrument of intertemporal price discrimination between consumers with varying tendencies to shift purchases across time. A more recent literature has focused on the multi-product and multi-store nature of grocery shopping. Consumers shop for many products from multiple stores, choosing some products from one store and other products from another. This allows consumers with low search costs to save relative to those who shop from a single store or do not compare prices across stores.

To what extent do consumers exploit the different channels of saving? Kaplan and Menzio (2015, henceforth KM) investigate heterogeneity in the prices consumers pay for identical products. Using a decomposition method, they attribute variation in a household price index to three sources: the *store component*, which captures variation due to store choice; the *transaction component*, capturing variation due to the timing of purchases; and the *store-specific good component* (we call it *store-good component* for short), which captures variation due to cross-store shopping (purchasing each product from the store where it is cheapest). KM's key finding of interest is that cross-store shopping is the single largest source of variance, accounting for about 50% of the variation in prices paid by households. Store choice accounts for 40% of the variation and only 10% is due to purchase timing.[2] KM conclude that there seems to be "significant variation in households' abilities to systematically take advantage of persistent price differences for the same good at different stores by purchasing each good at the store where that particular good is, on average, cheaper".[3]

The KM findings are intriguing because of the large role attributed to cross-store shopping. The implication is that people who achieve substantial savings do so by engaging in price

[1] The literature is discussed in section 2.

[2] These fractions are approximate averages across several specifications.

[3] Kaplan and Menzio (2015), p. 24.

comparisons across stores, a time-consuming activity. At the same time, the small size of the transaction component indicates surprisingly little variation in the tendency to shift purchases across time. This finding seems at odds with both the large intertemporal price variation observed in the KM data and with the rich extant literature on sales promotions and intertemporal price discrimination. KM explain these results with a simple model where consumers differ in their tendency to compare prices across stores but have similar abilities of exploiting temporary price reductions. Yet it is not clear why consumers should be heterogeneous in their static behavior but homogeneous in the temporal dimension.

We propose that these findings are due to the fact that the KM decomposition is too coarse and lumps together different effects. In particular, we show that the store-good component conflates two distinct behaviors: purchasing each good where it is cheapest (cross-store shopping) and choosing the cheapest store *for one's basket* (basket-based store choice). The latter behavior differs from store choice in KM, which is driven by a store's *overall* expensiveness. Our key insight is that store expensiveness is not universal, but may differ across consumers depending on the basket they consume. This is a natural consequence of the fact – documented by KM – that not all products are cheapest in the same store. In our data, 26% of consumer baskets cost less in a store that is more expensive according to a general price index.

Based on this insight, we propose a finer decomposition of the household price index that distinguishes cross-store shopping from basket-based store choice. When we apply our method – the CCM decomposition – we find that cross-store shopping explains a substantially smaller fraction of the variation in prices consumers pay, less than half what the KM decomposition finds in the same dataset.[4] With the CCM decomposition, most of the variance is explained in roughly equal parts by store choice and by our new component capturing basket-based store choice. We conclude that the degree to which households differ in their ability to capture price differences for the goods they purchase at the stores they visit is not as large as KM found. Rather, households differ more in their ability to save by selecting stores that are cheap *for the basket they purchase.* Price-sensitive households can capture most of the potential savings just by selecting the right store, without having to resort to costly cross-store shopping.

Although the decomposition methodology is atheoretical, our results can inform the literature on consumer search in grocery store shopping. Any consumer search protocol will leave a footprint in the data in terms of the size of the various components. By analyzing the

[4] We use the IRI Marketing Data Set, which is similar to the Kilts-Nielsen Consumer Panel used by KM (see section 3).

components, we can rule out some search models and find support for others. For example, consider the implications of different shopping models when applied to each product category separately.[5] In the KM model of consumer shopping (developed further in Kaplan, Menzio, Rudanko, and Trachter, 2019, henceforth KMRT), shoppers compare prices of all products across stores. In Thomassen, Smith, Seiler, and Schiraldi (2017, henceforth TSSS) consumers use an alternative search protocol where they concentrate expenditure for each product category in a single store. The two protocols have different implications for the size of the components at the category level. If all consumers adopt the KM/KMRT protocol, the size of the components at the category level should be similar to the size of the aggregate ones. If consumers follow the TSSS protocol, there should be no cross-store shopping at the category level, since consumers do not shop around within category.[6]

When we apply the CCM decomposition separately to each of our five product categories, a similar pattern emerges: cross-store shopping is less important than in the aggregate decomposition, while for most categories basket-based store choice is more important and store choice less important. The decrease in the role of cross-store shopping across the board is consistent with the TSSS search protocol, where consumers shop for categories rather than individual goods. But cross-store shopping does not disappear altogether, suggesting that some consumers do compare prices of the same good across stores, as in the KM/KMRT model.

Our paper introduces a new consumer search protocol that has not, to our knowledge, been used in the literature. Existing models specify different behaviors with a range of search intensities. 'Busy' or 'loyal' consumers do not search at all. Searching consumers may purchase their entire basket from a single store; they may shop for categories, as in TSSS; or they may shop for individual products, as in KM/KMRT. We show that a different search protocol, where consumers shop from a single store chosen on the basis of its expensiveness for their basket, has substantial explanatory power and is a useful addition to our existing arsenal of models of consumer behavior.

Our work elucidates the inner workings of the KM decomposition methodology and clarifies its economic interpretation. Our exposition of the methodology uses an alternative formulation based on hypothetical price indexes that correspond to different shopping protocols. For example, we defined the store-good hypothetical price index, which is the cost of the consumer's basket had she bought each item at the average price of the store she purchased it from. Other price indexes are defined in similar ways. The decomposition is then defined

[5] We discuss the link between the decomposition and the search literature further in section 4.3.

[6] These implications derive formally from Proposition 1 in section 4.

as the sum of differences between pairs of price indexes, which represent differences in the cost of the consumer's basket under different protocols. The formulation in terms of price indexes allows for an intuitive interpretation of the results and provides useful economic insights. It is also flexible and general; it is easy to define new price indexes in order to analyze different dimensions of heterogeneity in consumer saving, as we did with our store-basket price index. We believe that our exposition helps make the methodology more transparent and accessible. Our analysis also provides support for the usefulness of the methodology. We find that most of the KM findings carry through to a different data set and are robust to a variety of different assumptions. An important exception is the transaction component, which is significantly higher in our data than in the KM data (see section 5.6). This finding survived a barrage of robustness tests and remains a puzzle for further exploration.

The rest of the paper is organized as follows. Section 2 briefly summarizes the literature on price dispersion and consumer saving. Section 3 explains the data and provides descriptive statistics. Section 4 presents the variance decomposition methodology and uses a simple example to illustrate our notion of the store-basket price index and to highlight the differences between the KM and CCM approaches. It also discusses the link between the methodology and the consumer search literature. The main results from applying both methodologies are presented in Section 5, along with several robustness tests. Section 6 concludes.

2 Literature

In an early contribution, Pratt, Wise, and Zeckhauser (1979) noted the existence of different prices in markets they describe as 'almost competitive'. Systematic evidence of price dispersion began to accumulate in the 2000s with studies of small numbers of products (Sorensen, 2000; Lach, 2002). The increased availability of large and detailed datasets has made it possible to study price dispersion using thousands or even millions of products. The grocery sector has been the subject of many of these studies, such as Hosken and Reiffen (2004), Kaplan and Menzio (2015), Dubois and Perrone (2019), Moen, Wulfsberg, and Aas (2020), and Hitsch, Hortaçsu, and Lin (2021). They all document large and persistent price dispersion for narrowly defined products sold in grocery stores.

A different strand of the literature focused on intertemporal price variation in the form of sales promotions of specific products. The review article by Neslin (2002) is a good source for the large marketing literature on this topic. Pesendorfer (2002) was an early contribution to the economics literature. Dynamic inventory models for the problem of intertemporal optimization of storable good purchases were later developed by Erdem, Imai, and Keane

(2003) and Hendel and Nevo (2006, 2013). Seiler (2013) and Pires (2016) developed inventory models that incorporated the decision to engage in costly search. Clerides and Courty (2017) showed that consumers often miss opportunities to buy cheap – even in cases when the search cost appears minuscule – and attribute this behavior to inattention. The emphasis in this literature is on price comparisons over time and/or across brands, but not across stores within the same time period.

Griffith, Leibtag, Leicester, and Nevo (2009) explore four ways in which consumers can save: by buying on sale; in bulk; generic; and from low-price outlets. Using data from the UK, they calculate the amount each household saves from each saving channel relative to a benchmark "full" price. They conclude that "the average consumer realizes significant savings from the four dimensions of choice that we study, and that the savings are comparable in magnitude."[7]

DellaVigna and Gentzkow (2019) have shown that U.S. chains in a broad range of retail sectors charge nearly uniform prices across their stores. In the grocery sector, Hitsch, Hortaçsu, and Lin (2021) have shown that prices vary across stores within the same market but less so across stores within the same retail chain. In other words, prices are set at the chain level and do not adjust to local conditions. KMRT document that a significant source of price dispersion across stores is due to persistent differences in the price that different retailers set for a good relative to the price they set for other goods; they call this type of price variation *relative price dispersion*. KMRT develop a model that delivers relative price dispersion as an equilibrium outcome. Sellers in the model are homogeneous while buyers are heterogeneous. One type of buyer (the 'busy' type) has a high valuation for the goods and purchases all the goods at the same location. The other type of buyer (the 'cool' type) has a low valuation for the goods and is able to purchase different goods at different locations.

KMRT build on a theoretical literature of price search dating back at least to Varian's (1980) classic model of sales. A notable example of the more recent empirical literature is TSSS, who develop a multi-category, multi-seller demand model and estimate it using grocery store data from the UK. Stores in their model sell different categories of products, such as household goods, drinks, fruits and vegetables, meat, etc. Consumers select one store for each category; that is, they shop around for categories rather than for individual goods. Some consumers tend to shop in a single store; the existence of these consumers is important because they generate relatively large cross-category effects and therefore have a greater pro-competitive impact.

[7] Griffith, Leibtag, Leicester, and Nevo (2009), p. 100.

3 Descriptives

3.1 Data

We use the well-known IRI Marketing Data Set.[8] The dataset provides store level sales and price information for 30 product categories in 47 U.S. markets over the 12-year period 2001-2012. For two of those markets (Eau Claire, Wisconsin and Pittsfield, Massachusetts) additional data on consumer purchases are available through the Behavior Scan panel. A total of about ten thousand distinct households are represented on the panel, with an average of roughly five thousand households every year. Behavior Scan includes information on every shopping trip made by each participating panelist during the sample period.[9] For each trip, it records the number of units purchased of each good (defined as a unique UPC) and the unit price.

We work with the top five product categories in terms of total purchase count: carbonated soft drinks, milk, salty snacks, yogurt, and cold cereal. The sixth and seventh categories (soup and frozen dinners) could not be used because they had missing product characteristic values that prevented us from accurately sorting UPCs into unique products. The five categories selected cover 55% of all purchases in the dataset; adding a few more product categories would only marginally increase this figure. The online data appendix explains how we merged UPCs into unique products and how we removed products, stores and panelists with few purchases.

Table 1 provides some summary information about the panelists, products and purchases in our final sample. Panelists stay on average about six years in Behavior Scan. Each quarter, they visit on average 2.2 stores, buy eighteen distinct products from four of the five categories, and make close to thirty purchases total. The summary statistics are broadly similar in Eau Claire and Pittsfield. The most notable difference is in the number of stores visited: Pittsfield residents visit 2.41 different stores per quarter, versus 2.00 for Eau Claire residents.

[8] See Bronnenberg, Kruger, and Mela (2009). The dataset has been widely used in this literature, including recently by Pires (2016) and Ching and Osborne (2020). It is similar in structure and content as the *Nielsen* dataset used by KM, though it is not as extensive.

[9] We use the terms panelist, consumer and household interchangeably.

Table 1: Information about the final IRI sample

	Eau Claire	Pittsfield
Observation count		
Quarters	48	48
Goods	3,812	3,836
Purchases	3,862,540	3,977,461
Panelists	5,609	5,144
Stores	6	7
Averages across panelists		
# quarters panelists remain in the dataset	23.31	24.98
# distinct goods bought per quarter	17.82	18.49
# categories purchased per quarter	3.94	3.96
# stores visited per quarter	2.00	2.41
# purchases per quarter	26.94	29.04

3.2 Store visits, product availability, and price comparisons

Consumers' ability to save from cross-store comparison shopping depends on the number of stores they visit and on the availability of products in these stores.[10] This section presents four stylized facts establishing that consumers can find the majority of the products they purchase in most of the stores they visit.

1. *Although store availability varies greatly across products, a significant share of products is available in all stores.*

   For each market-quarter pair, we counted the number of stores each product was sold in. The median product was available in 5 stores in both towns (out of 6 stores in Eau Claire and 7 in Pittsfield); 27.4% of all products are available in all stores of a market. Only 9.3% of products are available in a single store, and this is similar in the two markets. This figure drops to 2.66% when we compute availability at the transaction instead of product level.[11]

2. *Consumers visit few stores and do most of their spending in their top two stores.*

   27.9% of consumers visit a single store in a given quarter and 84.1% visit at most

[10] We say that a product is available in a given store and quarter if the store records a positive quantity for that product-quarter (see online appendix).

[11] The difference with the product level computation is that at the transaction level a product that is purchased many times will be counted every time, as opposed to just once per market-quarter. There is substantial variation in product availability across markets (lower in Pittsfield than in Eau Claire), product categories (lower for milk and yogurt, higher for carbonated soft drinks) and product popularity (higher for products with larger market shares).

3 stores. On average, consumers do 77.3% of their spending in the single store they frequent most, and 94.1% in two stores.[12]

3. *Most purchased products are available in most visited stores.*

   For each product purchased, we computed the fraction of stores in which the product was available among those stores visited by the consumer in the same quarter. The average of this fraction over all purchases is 90.9%; a full 80% of transactions are available in all stores visited. The figures suggest that, for the large majority of instances, consumers had an opportunity to purchase the same product in another store they visited in the same quarter. There is little variation across consumers with respect to this finding. The vast majority of consumers (95%) can find the majority of the products they purchase (74.8%) in all stores they visit.[13]

4. *The main reason some consumers cannot compare prices across stores is that they visit a single store.*

   For 32.7% of transactions, the consumer cannot make a price comparison. In most cases (73.0%), this occurred because the consumer visited a single store. Among the consumers who visit multiples stores, price comparisons are possible for 88.5% of transactions. One price comparison is possible in 42.9% of transactions, two in about 27.4% and more than two in about 18.2%.

We conclude that product availability in not a major impediment to price comparisons. The reason why price comparison is not possible for about a third of the transactions is that almost one third of consumers visit a single store.

4 Methodology

This section presents the decomposition methodology and discusses its economic interpretation. Our exposition departs from KM in constructing the decomposition in terms of the actual and counterfactual household price indexes (HPIs). We discuss the links between the decomposition and the consumer search literature and present a stylized consumer shopping

[12] The average is across consumer-quarter. TSSS report very similar figures for their UK data: 71% and 94%.

[13] Another way to measure the extend to which store unavailability prevents price comparison, it to use the notion of pairwise price comparison. A pairwise price comparison is possible for a purchased product and a store visited different from the one where the product was purchased, if the product is available in that other store. The ratio of all possible pairwise price comparisons, to the maximum number of possible pairwise price comparisons, were purchased products available in all stores visited, is 80.2%. This demonstrates that product availability does not prevent consumers from comparing prices.

model that helps clarify the main concepts and highlights the difference between the KM and CCM decompositions.

4.1 Household price indexes (HPIs)

The *actual* HPI is defined as in Aguiar and Hurst (2007) and Kaplan and Menzio (2015) as the ratio of the actual cost of a consumer's basket to the cost of the same basket at the average market price of each product. In addition, we define *hypothetical* HPIs that give us the cost of the consumer's basket under different shopping plans. The calculations for the indexes are fairly complex and explaining them in full detail would require some cumbersome notation. To simplify things as much as possible, in the exposition below we show how to construct the HPIs using consumer purchases in a single market and a single period (set to a quarter). We use the term HPI, omitting the qualifier actual or hypothetical, when this is obvious from the context.

With these simplifications, an observation is indexed by $i = 1 \dots I$ for panelist, $j = 1 \dots J$ for good, and $s = 1 \dots S$ for store. Two variables contain all pertinent information: $q_{i,j,s}$ is the number of units of good j purchased by individual i at store s; and $P_{i,j,s}$ is the average unit price paid. With temporal price variation, the average unit price may vary across households, and this could be due to either chance (some households happen to purchase when the price is low, others when the price is high) or choice (household heterogeneity, such as bargain hunters versus loyal consumers in the price discrimination literature).

In the first step we divide each price $P_{i,j,s}$ by the average market price P_j to obtain $\mu_{i,j,s}$, the normalized average price paid by panelist i for good j in store s (equations KM1 and KM2):

$$\mu_{i,j,s} = \frac{P_{i,j,s}}{P_j}, \qquad \text{where } P_j = \sum_{i,s} P_{i,j,s} \frac{q_{i,j,s}}{\sum_{i,s} q_{i,j,s}}. \tag{1}$$

In the second step we use the $\mu_{i,j,s}$'s to compute three weighted average normalized prices: μ_j, the average market price that is equal to unity by definition; $\mu_{j,s}$, the average price of good j in store s; and μ_s, the price level of store s relative to the overall price level in the market (KM3-KM5):

$$\mu_j = \sum_{i,s} \mu_{i,j,s} \frac{q_{i,j,s}}{\sum_{i,s} q_{i,j,s}} = 1 \tag{2}$$

$$\mu_{j,s} = \sum_{i} \mu_{i,j,s} \frac{q_{i,j,s}}{\sum_{i} q_{i,j,s}} \tag{3}$$

$$\mu_s = \sum_{j} \mu_{j,s} \frac{\sum_i P_{i,j,s} q_{i,j,s}}{\sum_{i,j} P_{i,j,s} q_{i,j,s}}. \tag{4}$$

The third step computes the expenditure shares $\omega_{i,j,s}$ of each household on product j in store s as a fraction of total household expenditure (KM13):

$$\omega_{i,j,s} = \frac{P_j q_{i,j,s}}{\sum_{j,s} P_j q_{i,j,s}}. \tag{5}$$

The last step computes the price indexes by taking weighted averages of the μ's, with the weight being the expenditure shares. Equation (6) defines the actual HPI p_i, which is the index used by KM and is computed using the normalized price paid by the consumer for her basket:

$$p_i = \sum_{j,s} \mu_{i,j,s} \omega_{i,j,s} = \frac{\sum_{j,s} P_{i,j,s} q_{i,j,s}}{\sum_{j,s} P_j q_{i,j,s}}. \tag{6}$$

Equivalently, p_i can be computed (as in KM12) as the ratio of the actual cost of household i's shopping basket, $\sum_{j,s} P_{i,j,s} q_{i,j,s}$, and the cost of the same basket had the household paid the average market price for each item, $\sum_{j,s} P_j q_{i,j,s}$. As such, this index is a measure of the household's ability to save: a household saves when $p_i < 1$, meaning that it disproportionately purchases products with lower relative prices. The household dissaves when $p_i > 1$. There is no saving or dissaving on average across all households: the average HPI, using household expenditure as weights, is equal to one.[14] For the sake of brevity, we will be talking about household saving, keeping in mind that all statements equally apply to dissaving.

Next we define the counterfactual HPIs, which are alternative ways of calculating the cost of the consumer's basket using hypothetical prices rather than actual ones. First, p_i^m is the cost of the consumer's basket had she bought each item at the average market price. It is equal to unity by definition:

$$p_i^m = \sum_{j,s} \mu_j \omega_{i,j,s} = 1 \tag{7}$$

[14] $\sum_i \alpha_i p_i = 1$ for $\alpha_i = \frac{\sum_{j,s} P_j q_{i,j,s}}{\sum_{i,j,s} P_j q_{i,j,s}}$.

Second, p_i^{sg} is the cost of the consumer's basket had she bought each item at the average price of the store she purchased it from:

$$p_i^{sg} = \sum_{j,s} \mu_{j,s}\omega_{i,j,s} \tag{8}$$

Third, p_i^s is the cost of the consumer's basket on the basis of the average expensiveness of the stores she purchases each item from; put differently, it is the average expensiveness of the stores the consumer visits, evaluated on the basis of her basket:[15]

$$p_i^s = \sum_s \mu_s\omega_{i,\cdot,s} \tag{9}$$

Fourth, p_i^{sb} is the cost of the consumer's basket had she purchased all items in her basket in each of the stores she visits in proportion to her overall spending in each store; it measures the expensiveness of the panelist's basket at the stores visited.

$$p_i^{sb} = \sum_s p_{i,s}\omega_{i,\cdot,s} = \sum_{j,s} \mu_{j,s}\omega_{i,\cdot,s}\omega_{i,j,\cdot}, \tag{10}$$

where $p_{i,s} = \sum_j \mu_{j,s}\omega_{i,j,\cdot}$ is the cost of consumer i's basket in store s.[16] These hypothetical indexes are not explicitly defined in KM. The first three appear implicitly in KM14, while the fourth one is the new index introduced in this paper in order to capture the idea of consumer-specific store expensiveness.

4.2 Decompositions in terms of price indexes

The KM decomposition of the HPI (KM14) can be written in terms of the price indexes as follows:

$$p_i = p_i^m + \underbrace{(p_i - p_i^{sg})}_{\text{transaction}} + \underbrace{(p_i^{sg} - p_i^s)}_{\text{KM store-good}} + \underbrace{(p_i^s - p_i^m)}_{\text{store}}. \tag{11}$$

Casting the KM decomposition in terms of price indices allows for an intuitive interpretation of the components. Each price index gives the cost of the consumer's basket under a specific shopping plan. By comparing price indexes, we can calculate the savings the consumer can

[15] A dot '$\cdot$' in a variable's subindex means that the variable is summed over that subindex, i.e. $\omega_{i,\cdot,s} = \sum_j \omega_{i,j,s}$.

[16] Store-specific baskets in this calculation are reweighed to account for partial product availability; Appendix A explains how this is done.

make by adopting one shopping plan over another. For example, the difference $p_i - p_i^{sg}$ (transaction component) tells us the cost of the consumer's basket relative to its cost had she paid the average store price for each item. Therefore the difference tells us how much she (dis)saved by timing her purchases.

Since our emphasis is on the store-good component $p_i^{sg} - p_i^s$, we will suppress the transaction component for the main part of the analysis.[17] We rewrite equation (11) as

$$p_i^{sg} - p_i^m = \underbrace{(p_i^{sg} - p_i^s)}_{\text{KM store-good}} + \underbrace{(p_i^s - p_i^m)}_{\text{store}}, \tag{12}$$

The left-hand side is the difference between the cost of the consumer's basket at the average price of the store she purchased it from and the cost of the basket at the average market price. This difference is attributed to the store and KM store-good components. The store component measures the expensiveness of the stores visited by the consumer relative to the market. It therefore tells us how much the consumer (dis)saves by shopping in the selected stores (store choice). The KM store-good component is the expensiveness of the household's basket in those stores relative to overall store expensiveness. It measures how much the consumer (dis)saves by selecting the right product (in terms of price) from the right store among the stores visited (cross-store shopping).

We argue that, if our objective is to assess the household's ability to choose cheap products, then p_i^s is not the best benchmark to compare p_i^{sg} to. The reason is that p_i^s is based on a measure of store expensiveness, μ_s, that is calculated on the basis of *all* products. It is more appropriate to compare p_i^{sg} to our proposed new index p_i^{sb}, which is calculated using a *household-specific* measure of store expensiveness, $p_{i,s}$. Thus, our innovation is to introduce p_i^{sb} and use it to define a finer decomposition of $p_i^{sg} - p_i^m$:

$$p_i^{sg} - p_i^m = \underbrace{(p_i^{sg} - p_i^{sb})}_{\text{pure store-good}} + \underbrace{(p_i^{sb} - p_i^s)}_{\text{store-basket}} + \underbrace{(p_i^s - p_i^m)}_{\text{store}}, \tag{13}$$

Essentially, we have broken down the KM store-good component into two: the *pure store-good component* and the *store-basket component*. The former is our measure of the household's ability to choose cheap products from the stores it visits (cross-store shopping). The latter measures the extent to which the household purchases a basket that is representative of the expensiveness of the stores it visits (basket-based store choice). The pure store-good component is zero in three benchmark cases worth discussing in further detail. Proposition

[17]We bring back the transaction component when we discuss robustness in section 5.6.

1 formally describes the three cases (see Appendix B for the proof and further discussion).

Proposition 1. *A consumer has zero pure store-good savings, $p_i^{sb} = p_i^{sg}$, when: (a) she visits a single store; (b) store-good prices $\mu_{j,s}$ do not vary across stores visited; or (c) she purchases the same share of each good in all stores visited ($\frac{\omega_{i,j,s}}{\sum_j \omega_{i,j,s}}$ constant across s).*

Although the proposition only states sufficient conditions, it highlights benchmark cases discussed in the literature. Statement (a) says that consumers who visit a single store (about one third of consumers in our sample – see section 3.2) cannot save by comparing prices across stores. This is important because the KM decomposition incorrectly attributes the savings of these consumers to cross-store shopping (the store-good component; see our example in section 4.4). An illustration of part (b) is a consumer who is loyal to a retail chain. This is relevant because the literature has shown that uniform pricing tends to hold within a chain, but not for stores belonging to different chains (DellaVigna and Gentzkow, 2019; Moen, Wulfsberg, and Aas, 2020; Hitsch, Hortaçsu, and Lin, 2021). Again, such a consumer will have a zero pure store-good component. Statement (c) is an illustration of the 'naive' or 'busy' consumers in the price discrimination literature (Lal and Matutes, 1989; Kaplan, Menzio, Rudanko, and Trachter, 2019). These consumers have high search costs and do not take the time to compare relative prices at the stores they visit; they visit multiple stores but the baskets they purchase from each store are composed of the same goods purchased in the same proportions. To summarize, a high store-good component requires a consumer to visit multiple stores, prices to vary across stores visited, and the consumer to systematically collect and compare the different prices.

4.3 Shopping models and search frictions

The decomposition methodology is not directly derived from theory, but its results can still be used to inform the consumer search literature on how to narrow down the type of model (search protocol) that is consistent with actual consumer behavior. A model of consumer search leaves a footprint in the data in terms of the size of the various components. To conceptualize this, consider a frictionless, homogeneous world where all stores carry the same products and charge identical prices, and all individuals purchase their basket from a single randomly-chosen store. In this 'no-search' world there will be no variation in the prices consumers pay, and no store, store-good, or store-basket components to speak of.

To see how each component may arise, we have to introduce heterogeneity in consumer search. Suppose that stores have different price levels: all products have higher prices in an expensive store than in a cheap store. Consumers purchase the same basket, but some pay a search cost to discover the cheap store while others select a store randomly. Consumers who shop at the more expensive store(s) will pay higher prices. There will be a store component but no store-good component (since there is no reason to shop from multiple stores) or store-basket component (since all consumers purchase the same basket).

Next, we slightly modify the above model to obtain variability in both the store and store-basket components. Assume consumers have different baskets and a basket may be cheap in some stores and expensive in others. Some consumers pay a fixed cost to find out where their basket is cheap while others randomly select a store to purchase their basket. This heterogeneity in search generates variability in the store and store-basket components but not in the store-good component (recall that Proposition 1 says that there is no store-good component when consumers visit a single store).

To obtain a store-good component, we introduce KMRT's notion of relative price dispersion (RPD). RPD occurs when some stores charge different prices for some goods relative to the price they charge for other goods. To keep matters simple, assume that all consumers purchase the same basket and visit the same two stores. There are two types of consumers: the busy purchase the same basket in both stores while the shoppers pay a search cost to find the store where each good is cheap. There is variation in the store-good component (because the shoppers pay less than the busy for the same basket) and no store-basket component because all consumers purchase the same basket.

Finally, note that the covariance between components will be non-zero when some consumers do well on one component but others do well on another. To illustrate, the covariance between the store-basket and store-good components is negative in the example presented in the next section and this is because some consumers do best on the store-good component but others do best on the store-basket component (see last two columns of Table 3).

4.4 An illustrative example

We have constructed a stylized consumer shopping model that helps clarify the main concepts and highlights the difference between the KM and CCM decompositions. The point of the example is to narrow the analysis down to the KM store-good and CCM pure store-good components: by design, there is no transaction component (the model is static, so there is no intertemporal price variation) and no store component (because stores are perfectly symmetric).

Consider a market with two stores selling the same two products, say bread and milk. One store specializes in bread (call it a bakery) and the other specializes in milk (a dairy). Both stores offer lower prices on their specialty products. Letting $P_{i,j}$ denote the price of good $i \in \{b, m\}$ in store $j \in \{B, D\}$, we have $P_{b,B} < P_{b,D}$ and $P_{m,D} < P_{m,B}$. Consumers differ in two dimensions: the composition of their basket and their shopping behavior. One fifth of consumers are shoppers and the other four fifths are loyals. Loyals have a basket containing half a unit each of bread and milk. They buy from a single store that could be chosen, say, on the basis of location, and are evenly split across the two stores. Shoppers buy each item in their basket at the lowest available price. They come in three types of equal size: bread shoppers purchase one unit of bread from the bakery, milk shoppers one unit of milk from the dairy, and all-shoppers purchase a half-unit of milk from the dairy and a half-unit of bread from the bakery. Table 2 describes the consumer types and their purchases $q_{i,j,s}$.

Table 2: Consumer types and their choices

	(Stores)		Bakery		Dairy	
	(Products)		Bread	Milk	Bread	Milk
	Consumer type	*Frac.*	*Quantity purchased* q_{ijs}			
1	Bread shopper	1/15	1	0	0	0
2	Milk shopper	1/15	0	0	0	1
3	All-shopper	1/15	1/2	0	0	1/2
4	Dairy loyal	6/15	0	0	1/2	1/2
5	Bakery loyal	6/15	1/2	1/2	0	0
	Quantity purchased		3/10	1/5	1/5	3/10

In order to calculate the HPIs we need prices. Suppose $P_{b,B} = P_{m,D} = 1.0$ and $P_{b,D} = P_{m,B} = 1.1$. Table 3 reports the HPIs and the components from the two decompositions with these prices. Since the store component $p^s - p^m$ is zero by construction, the KM decomposition attributes price dispersion for all consumers entirely to the KM store-good component (equation (12)). This is appropriate for the all-shoppers (type 3) because these consumers save by purchasing the goods in their basket from the stores where these goods are cheap. But the nonzero KM store-good component for consumer types 1, 2, 4, and 5 is problematic. For example, consumers 1 and 2 have a negative KM store-good component because the cost of their single-item basket is lower than the overall expensiveness of the store they visit. Yet there is no basis on which to conclude that these consumers buy the right product from the right store, which is the KM interpretation of a nonzero store-good component, as they only purchase a single item from a single store. In contrast, the CCM pure store-good component is zero for types 1, 2, 4, 5 (each type satisfies one of the conditions stated in Proposition 1). Consumers 1 and 2 have a negative store-basket component because

Table 3: Consumer price indexes and decompositions

	Price indexes					Components			
Cons. type	p	p^m	p^s	p^{sg}	p^{sb}	store KM/CCM $p^s - p^m$	store-good KM $p^{sg} - p^s$	pure store-good CCM $p^{sg} - p^{sb}$	store-basket CCM $p^{sb} - p^s$
1	0.96	1.00	1.00	0.96	0.96	0.00	-0.04	0	-0.04
2	0.96	1.00	1.00	0.96	0.96	0.00	-0.04	0	-0.04
3	0.96	1.00	1.00	0.96	1.01	0.00	-0.04	-0.05	0.01
4	1.01	1.00	1.00	1.01	1.01	0.00	0.01	0	0.01
5	1.01	1.00	1.00	1.01	1.01	0.00	0.01	0	0.01
Market level decomposition						0%	100%	39%	72%

Note: The CCM decomposition adds up to 100% once the covariance term, $cov(p^{sb}-p^m, p^{sg}-p^{sb}) = -5.5\%$, is included.

they choose the right store for their basket. Consumers 4 and 5, on the other hand, have a small positive store-basket component because their basket contains a larger fraction of the expensive good (in value terms) than the market basket.

The subtle difference between the store-good and store-basket components leads to a striking difference between the two decompositions, as reported on the last line of Table 3. The KM decomposition attributes 100 percent of the dispersion to the KM store-good component while the CCM decomposition attributes only 39 percent to the pure store-good component, with 72 percent being attributed to the store-basket component. The conclusion from the CCM decomposition is that differences in prices consumers pay is primarily due to variation in consumers' ability to select stores on the basis of the expensiveness of their basket in these stores, and less so to the ability of selecting the cheapest products across stores.

4.5 Store expensiveness is basket-specific

In the above example, the store-basket HPIs of consumers 1 and 2 are low relative to their store HPIs ($p^{sb} = .96 < 1 = p^s$). These consumers' baskets are cheap at the stores they shop at, and this is what explains the high store-basket component. To further motivate the CCM decomposition, we present direct evidence that store expensiveness is basket-specific in our sample of households.

For each panelist-quarter observation, we select the top two stores (s_1, s_2) in terms of overall expenditure, and rank them in two ways: according to their basket-specific price level $p_{i,s}$

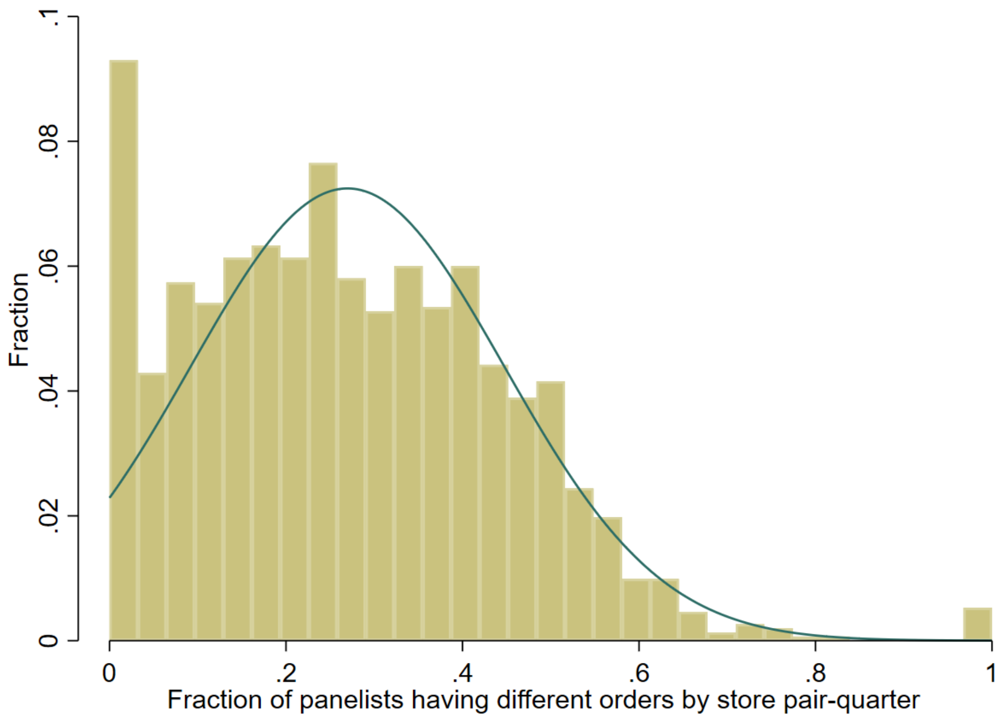

Figure 1: Distribution of disagreement (fraction of panelists with $Sign(p_{i,s_1} - p_{i,s_2}) \neq Sign(\mu_{s_1} - \mu_{s_2})$) by store pair-quarter

and according to their overall price level μ_s. For each store-pair quarter triplet, we compute a measure of disagreement over store ranking defined as the fraction panelists who have different orderings with the two store price indexes, $Sign(p_{i,s_1} - p_{i,s_2}) \neq Sign(\mu_{s_1} - \mu_{s_2})$. Figure 1 plots the distribution of the disagreement measure.[18]

If store expensiveness was not basket-specific, we would expect a large spike at zero. Instead, we find that in only 5% of store-pair quarter observations do households agree (they all rank the two stores the same for both measures).[19] The distribution of disagreement over store ranking has a wide support. On average, store preference is basket-specific for 26 percent of panelists. This evidence supports using a basket-specific measure of store expensiveness as done in the CCM decomposition.

[18]There are 1517 store-pair-quarter observations: both stores in the pair are one of the top two stores by expenditure for at least one panelist in that quarter (the upper bound is 36 store-pairs times 48 quarters = 1728). After filtering out store pair-quarters with fewer than 50 panelists, we end up with 954 observations.

[19]The spike at zero on Figure 1 says that a bit more than 9% of store-pair quarters have 3.2% (bin size of .032) or fewer panelists having different rankings.

5 Empirical results

5.1 Descriptive statistics on HPIs

We first report distributional statistics on the HPIs in Table 4. The two columns under the heading *Nielsen (KM)* are copied from KM (Table 2, column 2 on page 9 and Table 6, column 1 on page 22 respectively). They report expenditure-weighted averages across markets and quarters of measures of dispersion for the price $\mu_{i,j,s}$ and the actual HPI p_i. The 90-10 ratio is the ratio of the price at the 90th percentile to the price at the 10th percentile; the other ratios are defined in a similar way. The next two columns report the statistics for the same variables in our IRI dataset.

Table 4: Average statistics of price and HPIs

	Nielsen (KM)		IRI				
	Price	p_i	Price	p_i	p^{sg}	p^s	p^{sb}
Std dev.	0.21	0.09	0.16	0.07	0.04	0.03	0.04
90-10 ratio	1.79	1.22	1.54	1.18	1.10	1.07	1.09
90-50 ratio	1.29	1.09	1.20	1.08	1.05	1.04	1.04
50-10 ratio	1.38	1.12	1.29	1.09	1.05	1.04	1.04

The two columns under the heading *Nielsen (KM)* are copied from KM. The next two columns provide the same statistics with our IRI data, and the last three give statistics on the hypothetical price indexes.

The variation in our data is somewhat smaller – the average standard deviation is 21% with the Nielsen data and 15% with the IRI data – but the overall patterns are similar. Some panelists spend a significantly larger amount on grocery relative to others: in our IRI data, the panelist at the 90th percentile spends 18% more on groceries than the panelist at the 10th percentile. The equivalent figure for the Nielsen data is 22%. The last three columns report the same statistics for the store-good, store, and store-basket indexes respectively. The standard deviations of the store-good and store-basket price indexes are greater than the standard deviation of the store price index.

5.2 Decomposition results

Table 5 shows the results of applying the CCM and KM decompositions to our data. The CCM decomposition is presented in column 2 on the left panel. The KM decomposition is presented in the second to last line of the right panel, where the components are obtained by summing the appropriate terms (marked by 'X') in each column. We follow KM in computing statistics for each of the 96 market-quarters (excluding all good-market-quarters with fewer than 25 transactions) and then aggregating them by taking expenditure-weighted averages across markets and quarters.

Table 5: The KM and CCM decompositions

CCM decomposition		KM decomposition		
		store	store-good	cov
Pure store-good	24%		X	
Store-basket	46%		X	
Store	49%	X		
2*covar(store-basket, pure store-good)	-15%		X	
2*covar(store, pure store-good)	4%			X
2*covar(store, store-basket)	-7%			X
sum = var(overall)	100%	49%	55%	-3%
			sum = 100%	

Note: All variances and normalized by the total variance, $var(p^{sg}_{i,t} - p^{m}_{i,t})$. The CCM decomposition is reported on the left. The KM decomposition is reported on the second to last line and computed as vertical sums of the relevant terms from the CCM decomposition.

Looking first at the CCM decomposition, note that the store-basket component accounts for a bit less than half of the overall variance (46%). This confirms the result from the previous section that store expensiveness and store-basket expensiveness are not the same thing. The store component accounts for about half (49%) of the overall variance. The pure store-good component is the smallest of the three, contributing 24% to the overall variance.

The KM store-good component is more than double the size of the CCM pure store-good component (55% vs 24%). This difference in the estimated store-good components can be seen in detail in Figure 2, where we display the distributions of the KM and CCM components over all consumer-quarter-markets. The left panel plots the distribution of the two KM components while the right panel plots the distributions of the CCM store-basket and pure store-good components (the CCM store component is the same as the KM one). Some interesting patterns emerge. About a third of consumers have a CCM pure store-good component that is close to zero, as evidenced by the large spike.[20] The majority of these consumers visit a single store. The distribution of the store-good component obtained from the KM method has no such spike and is much more spread out. This is reminiscent of the example in section 4.4, where the variation in the KM store-good component was much

[20] Across all market-quarters, 29% of consumers have a zero store-good component. Note that the bar at zero has been trimmed in order to display the rest of the distribution more clearly – see graph.

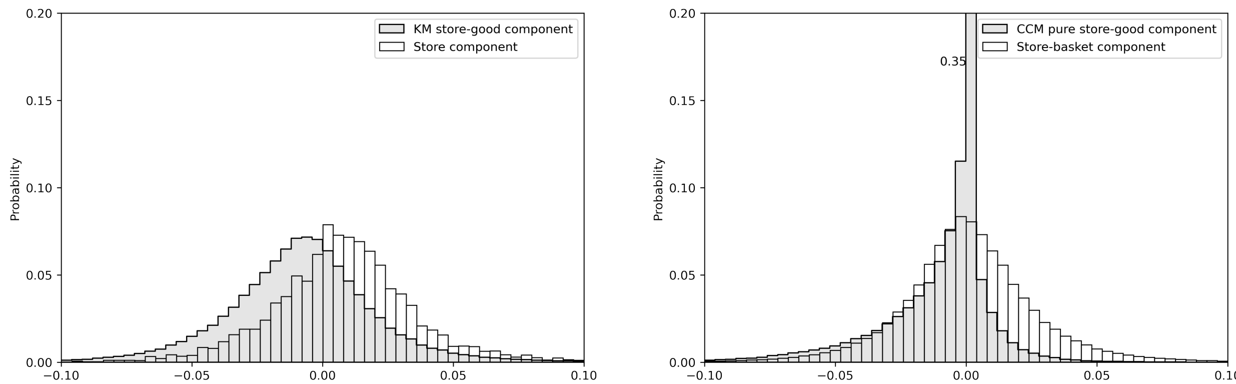

Figure 2: KM and CCM component distributions. The figures plot the average distribution across all market-quarters. The bar at zero on the right panel has been trimmed.

larger than the CCM pure store-good component (see Table 3). Finally, the KM/CCM store components and the CCM store-basket component have a long tail of consumers with dissaving of at least 5 percent. This is not the case for the CCM store-good component. The distribution is skewed to the left with a small fraction of consumers dissaving. The reason is that no consumer would deliberately try to purchase each good in their basket at a visited store where it it relatively more expensive. The default search method is to randomly purchase across stores, which costs about the same as purchasing all goods from a single store.

5.3 Single-store shoppers

Table 5 includes consumers who visit a single store (see discussion in section 3.2). These consumers, who make up 27.9% of the total and account for 23.5% of purchases, have no store-good component (Proposition 1). Can the small pure store-good component in the CCM decomposition be explained by the large fraction of households visiting a single store? We computed the CCM decomposition separately for consumers visiting a single store and those visiting multiple stores and report the results in Table 6. The store-good component is higher for multi-store shoppers than for the entire sample (32% versus 24%). Still it is smaller than the store-good component from the KM decomposition (32% versus 55%) and the store-basket component (32% versus 43%). Thus, the conclusion that the store-good component is small relative to the store-basket component in CCM is not driven by the existence of consumers visiting a single store.

Households visiting a single store have about the same store and store-basket components (58% and 52% respectively). For these households, the store-basket component is at-

Table 6: The CCM decompositions for households visiting single and multiple stores

	Entire sample	Multiple stores	Single store
Pure store-good	24%	32%	0%
Store-basket	46%	43%	52%
Store	49%	45%	58%
2*covar(store-basket, pure store-good)	-15%	-19%	0%
2*covar(store, pure store-good)	4%	5%	0%
2*covar(store, store-basket)	-7%	-6%	-10%
sum = var(overall)	100%	100%	100%

Note: All variances and normalized by the total variance, $var(p_{i,t}^{sg} - p_{i,t}^{m})$.

tributed to the store-good component under the KM decomposition. The misallocation of the 52% store-basket component to the store-good component for 27.9% of households explains roughly half of the 31% difference in store-good components between the KM and CCM decomposition.

5.4 Decomposition by product category

We can obtain additional insights into consumer behavior by examining each product category separately. To see how, we review two benchmark models of relative price comparison that rely on different search protocols.

Under one view, consumers compare prices of all products across all visited stores, independently of product category. There is a fixed cost of comparing prices for a given product that may differ across consumers but does not depend on the category the product belongs to. We call this the KMRT view because category does not play a role in their theory of relative price dispersion. Under this view, the decomposition should produce the same results when categories are examined together or separately. Under the second view, consumers source all products of a given category from a single store but may source different categories from different stores. This is the search protocol adopted in TSSS. Under this view, the decomposition by category should have a zero pure store-good component (see Proposition 1). In such a scenario, a non-zero aggregate pure store-good component could arise because of variation in ability to correctly choose a store for each category.

The two views outlined above have different implications for how household expenditure shares, and saving decompositions, should change when disaggregating purchases by categories. We now confront these implications to the data, starting with the evidence on store expenditure shares. Recall from Section 3.2 that (across all categories) consumers spend 77.3% of their expenditure in their top store and 16.8% on their second store. Looking at expenditure category by category and taking average across categories, these figures are 86.7% and 12.5% respectively. Although consumers are more likely to concentrate their spending on a single store at the category level, which is consistent with the TSSS view, multiple-store sourcing does not disappear within category.[21]

Table 7 presents the results of applying the decomposition separately for each product category. The share of the store-good component decreases for all categories, by about one to two thirds depending on the category. For the majority of categories, the share of the store-basket component increases while the share of the store component decreases.

Table 7: The CCM decomposition by product category

	Carbonated soft drinks	Cereal	Milk	Salty snacks	Yo-gurt
Pure store-good	11%	15%	16%	13%	8%
Store-basket	43%	53%	69%	47%	64%
Store	56%	41%	33%	49%	31%
2*covar(store-basket, pure store-good)	-7%	-8%	-17%	-6%	-2%
2*covar(store, pure store-good)	2%	3%	2%	3%	0%
2*covar(store, store-basket)	-5%	-4%	-3%	-6%	-2%
sum = var(overall)	100%	100%	100%	100%	100%

Note: all variances and normalized by the total variance, $var(p^{sg}_{i,t} - p^{m}_{i,t})$.

The evidence from Table 7 is consistent with the interpretation that consumers take advantage of relative price differences both within and across categories. The pure store-good component explains 24% of the variance in consumer savings across all categories. Turning to the decompositions category by category, this figure falls to 8-16% depending on the category. This decrease in the role of the store-good component is consistent with the TSSS view, but the fact that it is not zero supports the KM/KMRT hypothesis that at least some consumers compare prices of the same good across stores.

5.5 Robustness

We conducted a wide array of robustness tests in order to ensure that our findings are not the result of special circumstances. We provide a summary here. Table 8 replicates

[21]Interestingly, TSSS find a smaller role for multi-store sourcing at the category level: "Across all consumers (whether one- or multi-stop) the share of category spending in the category's second store is 4 percent (panel A3, p.2317)."

the decomposition presented in Table 5 and reports the results of seven robustness tests. For each of these tests, the variances of the KM store-good and the CCM pure store-good components are reported in the last two rows. The 'Baseline' scenario (first column in Table 8) corresponds to the CCM decomposition from Table 5.

Table 8: Robustness check of the CCM decomposition

	Baseline	Filter	PL	Eau	Pitts	SW2	SW3	1VD
Pure store-good	24%	23%	23%	18%	31%	40%	33%	28%
Store-basket	46%	42%	45%	36%	60%	44%	36%	46%
Store	49%	52%	49%	61%	31%	49%	49%	50%
2*covar(sb, psg)	-15%	-16%	-15%	-12%	-19%	-30%	-15%	-20%
2*covar(s, psg)	4%	4%	4%	7%	0%	32%	3%	3%
2*covar(s, sb)	-7%	-7%	-7%	-10%	-3%	-35%	-6%	-8%
Sum	100%	100%	100%	100%	100%	100%	100%	100%
Variances of the pure store-good and store-good components:								
CCM pure-store good	24%	23%	23%	18%	31%	40%	33%	28%
KM store-good	54%	50%	53%	42%	72%	54%	54%	54%

Note: *s*, *sb* and *psg* in the covariance names stand for store, store-basket and pure store-good respectively.

The 'Filter' column reports results obtained when we filter out panelist-quarter observations with fewer than 20 purchases per quarter. The concern being addressed is that the average purchase count in IRI is smaller than in Nielsen. We want to check that the results do not change when we increase the purchase count per panelist-quarter.

A limitation of the data is that we cannot tell if two private label (PL) UPCs with the same characteristics but sold in two different stores are the same product or not (see detailed explanation in Section A.6 of the online appendix.) The baseline column assumes that they are the same product. Alternatively, we could assume that they are different products, although it is important to keep in mind that doing so is unlikely to change our main results because PL purchases represent a small fraction (less than 11 percent) of all purchases for most product categories (the exception is milk for which 37.6 percent of purchases are PL). The results do not change when we merge only non-PL products (see column 'PL').[22]

Columns 'Eau' and 'Pitts' show results for each of the two markets separately. Nielsen contains 54 geographically dispersed markets. One concern is that our two markets may not be representative of the average Nielsen market. Although we are limited in what we can do

[22]We also merge the PL products sold in stores that belong to same chain (this applies to two pairs of stores in Pittsfield). All remaining PLs (PLs from different chains) are treated as different products.

about this, we can at least check that the results are not driven by a single market. Both markets point to the same conclusion: the KM store-good component is more than twice the size of the CCM pure store-good component.

Columns 'SW2' and 'SW3' report estimates using alternative store-good weights to the weight $w_{i,j,\cdot,t}$ and $w_{i,\cdot,s,t}$ used in the definition of $p_{i,t}^{sb}$ (equation (10)) to weight the store-good prices in the calculation of the store-basket price index. A problem with these weights is that they overestimate the store-basket price index if a good in the panelist's basket has an abnormally high price in a store visited by the panelist. The good may never be bought by the panelist in that store, and for that matter, by most consumers. SW2 assumes that the panelist purchases each good in her basket proportionally to how the average consumer in the market would purchase the good among the stores visited by the panelist. This method takes care of the problem presented above. Another concern is that the panelists' baskets vary from quarter to quarter because the one-quarter window is too short. SW3 computes the weights for the goods in a consumer's basket, $w_{i,j,.,t}$, using a centered three-quarter window.

Finally, the last column considers a different way to aggregate the variance decompositions across markets and quarters. The method reported in the baseline column follows KM's approach: the variance decomposition is conducted by quarter and then aggregated over quarters. The method reported in column '1VD' computes a single variance decomposition for all panelist-quarter observations.

The results are broadly similar across all seven columns in Table 8. In the last two rows we see that in every case, the variance of the CCM pure store-good component is substantially smaller than the variance of the KM store-good component, about half the size in several cases. Overall, the large number of robustness tests reported here, along with additional unreported tests we have carried out, do not produce any evidence against our main conclusions.

5.6 The full decomposition

All of the variance decompositions presented thus far are calculated from the simplified versions of the KM and decompositions (equations (12) and (13)) that exclude the transaction component defined in equation (11). This does not mean any loss of generality because all variance decompositions are normalized and what interests us is the relative magnitude of the variances of the KM store-good component and the CCM pure store-good component. Whether we include or not the transaction component does not change this relative magnitude. For the sake of completeness, we have applied the full KM and CCM decompositions (including the transaction component) to the IRI dataset. Table 11 in Appendix C.2 provides the results and a discussion. The main conclusion from the previous analysis stands: each of the store and store-basket components accounts for twice as much of the variation in the HPI than the pure-store good component (same as in Table 5). Cross-store shopping accounts for just 10% of the variation, compared to the 53% reported by KM.

The decompositions with the IRI and Nielsen data diverge in one significant aspect. With the IRI data, the transaction component is 51% (in both the KM and the CCM decompositions), which is substantially larger than the 16% found by KM with the Nielsen data. We carried out a careful data investigation and conducted a barrage of robustness checks to ensure that the difference is not due to any error on our part or to the methodology; the 51% result survived. The explanation comes down to the use of different data sets, even though it is not clear why consumers in the different panels would behave so differently. We believe that the 51% transaction component that we find is consistent with the recent literature on promotions and its emphasis on heterogeneous consumer behavior (Pesendorfer, 2002; Hendel and Nevo, 2006, 2013; Griffith, Leibtag, Leicester, and Nevo, 2009). Nonetheless, the divergence in estimates of the transaction component remains a puzzle for future exploration.

6 Concluding remarks

Price dispersion provides price-conscious consumers with the opportunity to save by shopping around for the best deals. Recent work has documented substantial price dispersion in grocery stores. Combined with the fact that many households spend a significant fraction of their income in grocery stores, this suggests that the scope for savings from grocery shopping is considerable. Consumers can save by searching for the lowest price for identical products both across stores and over time. They can also save by buying in bulk, consuming generic brands or using coupons.

In order to understand the different ways in which consumers save, we adopt and modify the variance decomposition methodology of Aguiar and Hurst (2007) and Kaplan and Menzio (2015). Our modification incorporates the insight that store expensiveness is consumer-specific: one store may be the cheapest place to buy a specific basket of goods, but another store may be the cheapest for a different basket. In practical terms, it amounts to a refinement of the decomposition that breaks down the store-good component into two parts that we call pure store-good component and store-basket component. This allows us to address the following question: do (many) consumers really choose the right store for the right product, as KM conclude? Or are they actually just choosing the right store for their basket?

The results from our decomposition suggest that the latter is the case. A large fraction of the variance in consumer saving is due to variation in consumers' ability to choose the best store for their basket, and a smaller part is due to variation in ability to choose the right subset of products from the each store. We conclude that the definition of store expensiveness, whether it is consumer specific or common to all consumers, has a significant impact in understanding consumer savings.

Our work adds to a growing literature that attempts to make sense of supermarket pricing and consumer shopping behavior. A branch of this literature mines large store and household datasets to establish stylized facts about pricing and demand. The importance of consumer baskets has long been recognized in the literature on grocery shopping. The latest research – including this paper – is now establishing that consumers vary in their ability to shop for baskets. Conversely, baskets are constrained by the products assortments one can find at the stores one visits. Hitsch, Hortaçsu, and Lin (2021) find that assortments across stores tend to be specialized, and that a similar store assortment within a chain is associated with a similar degree of price dispersion and similar demand elasticities. Understanding how stores tailor product assortments and prices to target specific consumer baskets is an interesting topic that warrants further investigation.

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Appendices

A Computations of consumer store baskets weights

To compute the store-basket price index, we first compute a store-specific household price index, $p_{i,s}$ (see equation (10) for the definition). To deal with the case where a product purchased by consumer i, is not available in another store visited by consumer i, we assume that the consumer purchases the goods in her basket that are available each store visited, in the same relative proportions as the basket's proportions (see Table 9).[23]

Table 9: Store-basket weights with partial product availability

J_i	Consumer basket	$J_i = \{j \ s.t. \ \omega_{i,j,s} > 0 \ for \ some \ s\}$
S_i	Stores visited	$S_i = \{s \ s.t. \ \omega_{i,j,s} > 0 \ for \ some \ j\}$
$J_{i,s}$	Basket availability	$J_{i,s} = \{j \ s.t. \ \omega_{i,j,s} > 0 \ for \ s \in S_i\}$
$\omega_{i,j,\cdot\|s}$	Store basket weights	$\omega_{i,j,\cdot\|s} = \frac{\omega_{i,j,\cdot}}{\sum_{j \in J_{i,s}} \omega_{i,j,\cdot}}$
$p_{i,s}$	Store-specific basket	$p_{i,s} = \sum_{j \in J_{i,s}} \mu_{j,s} \omega_{i,j,\cdot\|s}$

B Proof of proposition 1

Proposition 1. *A consumer has zero store-good savings, $p_i^{sb} = p_i^{sg}$, when: (a) she visits a single store; (b) store-good prices $\mu_{j,s}$ do not vary across stores visited; or (c) she purchases the same share of each good in all stores visited ($\frac{\omega_{i,j,s}}{\sum_j \omega_{i,j,s}}$ constant across s).*

Proof. Combining the definitions of p_i^{sg} and p_i^{sb} (equations (8) and (10)), we obtain

$$p_i^{sg} - p_i^{sb} = \sum_{j,s} \mu_{j,s} \left(\omega_{i,j,s} - \omega_{i,\cdot,s} \omega_{i,j,\cdot} \right).$$

To prove claim (a), denote by s_i the single store visited by consumer i. We have $\omega_{i,j,s_i} = \omega_{i,j,.}$, $\omega_{i,j,s} = 0$ for $s \neq s_i$, and $\omega_{i,\cdot,s_i} = 1$. We obtain $p_i^{sg} - p_i^{sb} = \sum_j \mu_{j,s_i} \left(\omega_{i,j,s_i} - \omega_{i,\cdot,s_i} \omega_{i,j,\cdot} \right) = \sum_j \mu_{j,s_i} \left(\omega_{i,j,.} - \omega_{i,j,\cdot} \right) = 0$.

[23] As a technical point, the consumer may not purchase goods in the same proportion in the store-basket and store-good indexes.

Condition (b) says that $\mu_{j,s} = \mu_j$ for all (j,s). We obtain $p_i^{sg} - p_i^{sb} = \sum_j \mu_j \left(\sum_s (\omega_{i,j,s} - \omega_{i,\cdot,s}\omega_{i,j,\cdot}) \right) = \sum_j \mu_j (\omega_{i,j,\cdot} - \omega_{i,j,\cdot}) = 0$.

To prove claim (c) note that condition $\frac{\omega_{i,j,s}}{\sum_j \omega_{i,j,s}}$ constant across s is equivalent to $\omega_{i,j,s} = \omega_{i,\cdot,s}\omega_{i,j,\cdot}$. We conclude that $p_i^{sg} = p_i^{sb} = \sum_{j,s} \mu_{j,s} (\omega_{i,j,s} - \omega_{i,\cdot,s}\omega_{i,j,\cdot}) = 0$. □

The conditions stated in Proposition 1 are influenced by both consumer and store behavior, in the sense that the attribution of consumer savings to the store-basket or store-good component depends on the number of stores visited and on store pricing and product assortment policies. To illustrate, consider a simplified market where: (a) products are sold at normalized prices that vary across products and stores and can take only one of two values, $\mu_{j,s} = c$ for cheap or $\mu_{j,s} = e$ for expensive, and (b) all stores sell the same expenditure share of expensive products.[24] This latter assumption implies $\mu_s = 1$ for all stores and there is no store component, $p^s = 1$.[25]

With this as background, we now consider a consumer who buys n cheap products from n different stores. We have $p^{sg} = c$ and the consumer savings are $p^s - p^{sg} = 1 - c$. In one scenario, each product is cheap in only one of the visited stores. If the consumer spends the same amount on each product, we obtain that her store-specific basket (see equation (5)) is composed of $\frac{1}{n}$ and $\frac{n-1}{n}$ of cheap and expensive products respectively in any of the stores she visits, and $p^{sb} = \frac{1}{n}c + \frac{n-1}{n}e$.[26] The store good component, $p^{sb} - p^{sg} = \frac{n-1}{n}(e-c)$, increases

[24]Normalized prices take only two values in the following example: (a) all stores pay the same cost for each product, possibly varying from product to product, and then each store chooses a markup for each product that may be low or high; and (b) stores sell the same quantity share of low and high products. Since there is no temporal variation, we can omit without loss of generality the i sub-index on the transaction price $P_{j,s}$, and we also have $\mu_{i,j,s} = \mu_{j,s}$. Statement (a) says that stores charge price $P_{j,s} = c_j\alpha_e$ for expensive products and $P_{j,s} = c_j\alpha_c$ for cheap ones, where c_j is the cost of product j and $\alpha_e > \alpha_c$ are the markups. Denote by E_j the set of stores where product j is expensive. Applying KM2 (see equation (1)), we have $P_j = c_j(\alpha_e x_e^j + \alpha_c(1 - x_e^j))$, where $x_e^j = \frac{\sum_{i,s \in E_j} q_{i,j,s}}{\sum_{i,s} q_{i,j,s}}$ is the quantity share of product j sold at an expensive price. According to statement (b) x_e^j is constant across j, $x_e^j = x_e$. Applying KM1, we obtain that the normalized prices are $\mu_{j,s} = \frac{\alpha_e}{x_e\alpha_e + (1-x_e)\alpha_c} \equiv e$ for expensive products and $\mu_{j,s} = \frac{\alpha_c}{x_e\alpha_e + (1-x_e)\alpha_c} \equiv c$ for cheap ones.

[25]To show that $\mu_s = 1$, applying equation (4), we have $\mu_s = e\frac{\sum_{i,j \text{ s.t. } s \in E_j} P_{j,s}q_{i,j}}{\sum_{i,j,s} P_{j,s}q_{i,j,s}} + c\frac{\sum_{i,j \text{ s.t. } s \notin E_j} P_{j,s}q_{i,j,s}}{\sum_{i,j} P_{j,s}q_{i,j,s}}$ which does not depend on s because the expenditure share of expensive products, $\frac{\sum_{i,j,s \in E_j} P_{j,s}q_{i,j,s}}{\sum_{i,j} P_{j,s}q_{i,j,s}}$, is constant across stores. Moreover, plugging the above formula for μ_s in the weighted average $\sum_s \frac{\sum_{i,j} P_{j,s}q_{i,j,s}}{\sum_{i,j,s} P_{j,s}q_{i,j,s}}\mu_s$, we obtain that $\sum_s \frac{\sum_{i,j} P_{j,s}q_{i,j,s}}{\sum_{i,j,s} P_{j,s}q_{i,j,s}}\mu_s = 1$ and conclude that $\mu_s = 1$.

[26]The store-specific basket price index is $p_{i,s} = \sum_j \mu_{j,s}\omega_{i,j,\cdot}$ and by assumption $\omega_{i,j,\cdot} = \frac{1}{n}$ for n products and $\omega_{i,j,\cdot} = 0$ for the remaining ones. We also have $\mu_{j,s} = c$ for a single purchased product j and $\mu_{j,s} = e$ for the remaining $n-1$ products in the consumer's basket. The store-specific basket is $p_{i,s} = \frac{1}{n}c + \frac{n-1}{n}e$ for each store and this is also the value of p_i^{sb}.

as the consumer visits more stores. This is as it should be, since buying cheap products requires more cross-store shopping as the number of stores visited increases. In an alternative scenario, where cheap products are cheap in all stores visited, consumer savings are explained by the store-basket component alone, since there is no pure store-good component, $p^{sg} - p^{sb} = 0$. This demonstrates that the attribution of consumer savings to the store-basket and store-good components depends both on consumer behavior (store visited and purchase choices) and store pricing policies (whether store prices are correlated across stores).

C Replication of KM decompositions

We replicate (using the IRI dataset) the KM decompositions for the transaction prices (KM equation 7 in Section 3) and for the household price indexes (KM equation 14 in Section 4, corresponding to equation (11) using CCM notation).

C.1 Replication of KM price decomposition

Table 10 reports the results of the KM price decomposition with the IRI data (column 1) and with the Nielsen data (column 3, copied from KM p. 14, Table 3, column 3). Columns 2 and 4 re-normalize the variances and covariance after ignoring the transaction component.

Table 10: Decomposition at transaction level

	IRI		Nielsen	
	With tran	Without tran	With tran	Without tran
Transaction	65%	–	62%	–
Store-good	31%	89%	30%	81%
Store	4%	11%	7%	19%
2cov(tran, sg)	0%	–	0%	–
2cov(tran, s)	0%	–	0%	–
2cov(sg, s)	0%	1%	0%	0%

Note: the columns do not add up to 100% due to rounding.

The price decompositions are fairly similar across the two datasets. The share of the transaction component is large in both datasets (65% in IRI versus 62% in Nielsen), and similar in both IRI markets (63% in Eau Claire and 66% in Pittsfield), suggesting that promotions play a similar role for our five products categories as it does for the much wider set of products included in KM's analysis.

C.2 Replication of KM household price index decomposition

Table 11 replicates the KM decomposition with the transaction component using the IRI data. Column 1 presents the result for the decomposition with the transaction and store-basket components (a combination of equations 11 and 13). Column 2 re-normalizes the components to obtain the KM decomposition (equations 11). For comparison purposes, column 3 copies the values of these components using the data from Nielsen (see KM p. 25, Table 7, column 3). The main difference between the KM decomposition applied to the two different datasets is a significantly higher transaction component in the IRI dataset (51% instead of 16%). This was pointed out in the introduction and was discussed further in section 5.5.

Table 11: Decomposition with transaction component

<table>
<tr><th>Components</th><th>CCM-IRI</th><th>Components</th><th>KM-IRI</th><th>KM-Nielsen</th></tr>
<tr><td>Transaction</td><td>51%</td><td>Transaction</td><td>51%</td><td>16%</td></tr>
<tr><td>Pure store-good</td><td>10%</td><td rowspan="2">Store-good</td><td rowspan="2">22%</td><td rowspan="2">53%</td></tr>
<tr><td>Store-basket</td><td>19%</td></tr>
<tr><td>Store</td><td>20%</td><td>Store</td><td>20%</td><td>39%</td></tr>
<tr><td>2cov(tran, sg)</td><td>8%</td><td rowspan="2">2cov(tran, sg)</td><td rowspan="2">9%</td><td rowspan="2">5%</td></tr>
<tr><td>2cov(tran, sb)</td><td>1%</td></tr>
<tr><td>2cov(tran, s)</td><td>0%</td><td rowspan="2">2cov(tran, s)</td><td rowspan="2">0%</td><td rowspan="2">1%</td></tr>
<tr><td>2cov(sb, sg)</td><td>-6%</td></tr>
<tr><td>2cov(s, sg)</td><td>2%</td><td rowspan="2">2cov(s, sg)</td><td rowspan="2">-1%</td><td rowspan="2">-13%</td></tr>
<tr><td>2cov(s, sb)</td><td>-3%</td></tr>
</table>

Note: the columns do not add up to 100% due to rounding.

Table 12 shows that the large transaction component is present in both markets and in all five categories. The first column copies column 2 from Table 11 as a baseline. Columns 2 and 3 report the decomposition for the two markets separately. The next five columns replicate the baseline column for the five product categories (carbonated soft drinks, cold cereal, milk, salty snacks and yogurt). The transaction component has the same magnitude in all columns. The same holds if we filter out panelist-quarter observations with fewer than 20 purchases per quarter.

It is difficult to explain why the temporal component explains a larger share of consumer saving in the IRI dataset. Section C.1 has shown that the temporal component explained the same share of price variation in the two datasets. It is not the case that households can take advantage of greater temporal variations (e.g. more frequent or deeper promotions) for the set of products selected from IRI dataset. One explanation could be that households

Table 12: Decomposition with transaction component (robustness)

	KM-IRI	Eau	Pitts	cate1	cate2	cate3	cate4	cate5
Transaction	51%	45%	57%	52%	54%	60%	57%	63%
Store-good	22%	19%	25%	21%	23%	26%	22%	22%
Store	20%	29%	11%	25%	16%	13%	19%	10%
2cov(tran,sg)	9%	9%	9%	3%	7%	2%	3%	6%
2cov(tran,s)	0%	0%	-1%	0%	0%	0%	0%	0%
2cov(sg,s)	-1%	-1%	-1%	-1%	0%	-1%	-1%	-1%

Note: the columns do not add up to 100% due to rounding.

represented in the IRI dataset are more heterogeneous in their ability to take advantage of promotions.