University of Cyprus
Department of Economics

Working Paper 02-2020

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

Sofronis Clerides, Pascal Courty and Yupei Ma

Department of Economics, University of Cyprus, P.O. Box 20537, 1678 Nicosia, Cyprus
Tel.: +357-22893700, Fax: +357-22895028, Web site: http://www.ucy.ac.cy/econ/en

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

Sofronis Clerides† Pascal Courty‡ Yupei Ma§

March 18, 2020

Abstract We build on recent work analyzing consumers' ability to save by exploiting price dispersion in grocery stores. We show that store expensiveness is not universal but varies across consumers depending on the basket they consume. We incorporate this insight into a decomposition of price variance that is a refinement of Kaplan and Menzio's (2015) approach. Our analysis finds that the ability to choose the right product at the right store is much less important than Kaplan and Menzio found; rather, the ability to choose the cheapest stores for one's basket is the main source of variance in consumer savings.

Keywords: Price dispersion, grocery shopping, consumer saving, store expensiveness.

JEL Classification: D12, D14.

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 not all products are always cheaper in the same stores. In principle, price-sensitive consumers can exploit this variation in order to purchase their desired basket of goods at a lower overall cost. We are interested in the extent to which this occurs in practice: how much do consumers save by exploiting different prices for different products across stores? Which channels of saving do consumers exploit more successfully? A number of recent papers have used detailed consumer level data to shed some light on these questions. We aim to contribute to this literature with a different data set and a refinement of existing methodology that offers a more nuanced answer to the issues of interest.

Our key insight is to recognize that store expensiveness is not universal, but may differ across consumers depending on the basket they consume. In other words, one consumer's typical basket

*We thank Marina Antoniou and Ružica Savčić for research assistance. We gratefully acknowledge funding by the University of Cyprus (internal research grant "Consumer Planning") and Mitacs through its Globalink Research Internship program.

†University of Cyprus and CEPR; s.clerides@ucy.ac.cy (corresponding author).

‡University of Victoria and CEPR; pcourty@uvic.ca.

§University of British Columbia; yupei.ma@alumni.ubc.ca.

may be cheaper in store A while another consumer's basket may be cheaper in store B. The first step of our analysis shows that this is indeed the case. We construct a consumer-specific index of store expensiveness that is based on the basket of goods purchased by the consumer. We compute this index for the top two stores visited by the consumer and compare it with a general index that is based on all products sold in each store. For about 26% of consumers in our data, the rankings do not match: these consumers would spend less if they purchased their entire basket in a store that is *more* expensive according to the general index. This shows that store expensiveness is basket-dependent.

We demonstrate the significance of this insight with an adaptation of the decomposition methodology of Aguiar and Hurst (2007) and its extension by Kaplan and Menzio (2015, henceforth KM). KM construct a household-specific price index, a measure of how much households pay for their basket of goods relative to the average market price. They decompose the index into three components: (i) the *store component*, which is due to the overall expensiveness of the store as measured by the market basket; (ii) the *store-specific good component* (store-good component for short), due to the expensiveness of the basket relative to overall store expensiveness; and (iii) the *transaction component*, due to the expensiveness of the consumers' transactions relative to the overall expensiveness of the transacted products in the store. The variance of the household price index is the sum of the variances of the three components and the covariance terms between them. KM's key finding of interest is that the store-good component is nearly as important as the store component in explaining the variance in the household price index; about 50% of the variance is due to the store component, 40% to the store-good component, and only 10% is due to the transaction component. They 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".[1]

We refine the KM decomposition by introducing an additional component based on our idea of a basket-specific measure of store expensiveness. The resulting extended decomposition (which we call the CCM decomposition) effectively breaks up the KM store-good component into two parts, the *pure store-good component* and the *store-basket component*. The pure store-good component is due to the expensiveness of the consumer's basket at the stores she visits – while keeping fixed her choice of which store to purchase each product from – relative to the expensiveness of those stores evaluated on the basis of her basket. We call this the *pure* store-good component because it measures variation in consumer ability to choose the right product in the right store on the basis of the consumer's basket rather than the overall market basket. The store-basket component is due to the average cost of the consumer's basket at the stores she visits relative to the average expensiveness of those stores. It captures variation in the extent to which the cost of a consumer's basket is representative of the expensiveness of the average store she visits.

[1] Kaplan and Menzio (2015), p. 25.

We apply both the KM and the CCM decompositions to a consumer level dataset similar to the one used by KM.[2] We find that the KM store-good component is even more substantial in our dataset; in fact it is larger than the KM store component. When we apply the CCM decomposition, however, we obtain a much more modest pure store-good effect, a bit less than half the size of the KM store-good effect. The rest of the variance is accounted for by our store-basket effect. Hence 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 not expensive *for the basket they purchase.*

A second contribution of the paper is to examine whether the main findings of the variance decomposition using KM's method carry through to a different data set. The analysis shows that most findings go through 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. This finding survived a barrage of robustness tests and remains a puzzle for further exploration.

Our findings have important implications for our understanding of consumers' ability to save by exploiting price dispersion. If the store-good component is as large as what KM found, it would imply that consumers wishing to maximize savings would have to do a lot of comparison shopping in order to identify the store with the lowest average price for each product. If the store-basket component is as large as our analysis suggests, then choosing the right store (the one that is cheapest for one's basket) is enough to capture most of the available savings.

The rest of the paper is organized as follows. Section 2 summarizes the literature on price dispersion and consumer saving. Section 3 presents the KM methodology and introduces our refinement. Section 4 presents a simple example to illustrate our notion of the store-basket price index and highlight the differences between the two methodologies. Section 5 describes the data and presents our findings, 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 based on a small number of products (Sorensen, 2000; Lach, 2002). Another strand of the literature focused on intertemporal price variation in the form of sales promotions of specific products (Pesendorfer, 2002; Hendel and Nevo, 2006a,b). The increased availability of large and detailed datasets in the last few years 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

[2] KM use the Nielsen Homescan data and we use the IRI BehaviorScan; section 5 describes the datasets.

Perrone (2017), Hitsch, Hortaçsu, and Lin (2019), Kaplan, Menzio, Rudanko, and Trachter (2019), and others. They all document large and persistent price dispersion for narrowly defined products sold in grocery stores.

The existence of price dispersion enables consumers who are willing to spend resources searching for low prices to save relative to non-searchers. A few papers have attempted to quantify the savings consumers can obtain in this way. Griffith, Leibtag, Leicester, and Nevo (2009) identify four ways in which consumers can save: by buying on sale; in bulk; generic; and from low-price outlets. Using detailed consumer level from the UK, they calculate the amount each household saves by exploiting each of the four dimensions. 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."[3]

Kaplan and Menzio (2015) use the Nielsen Homescan data and employ an adaptation of the variance decomposition methodology of Aguiar and Hurst (2007) to explore the extent of price dispersion in US grocery stores. They apply the methodology both to actual store prices and to a household-specific price index (a measure of how much households pay for their basket of goods relative to the average market price). The decomposition of store price dispersion indicates that "only 10% of the variance of prices is due to variation in the expensiveness of the stores at which a good is sold, whereas the remaining 90% is due, in approximately equal parts, to differences in the average price of a good across equally expensive stores and to differences in the price of a good across transactions at the same store."[4] Our work does not focus on their decomposition of price dispersion but rather on their decomposition of the household-specific price index, which we introduce – and contrast with to our modified decomposition – in the next section.

Dubois and Perrone (2017) study both spatial and temporal price dispersion for a selection of narrowly defined products sold in French supermarkets. They find evidence of substantial price dispersion in both dimensions. Berardi, Sevestre, and Thébault (2017) reach similar conclusions in another study of French supermarket prices with a much more extensive dataset covering about one thousand products. Hitsch, Hortaçsu, and Lin (2019) analyze price dispersion in US supermarkets using the Nielsen RMS retail scanner data, which include a much larger number of prices than the Homescan data used by KM. Their analysis emphasizes temporal price dispersion in the form of promotions. In related work, DellaVigna and Gentzkow (2019) show that U.S. food, drugstore, and mass-merchandise chains charge nearly uniform prices across stores; that is, there is price dispersion across chains but not within chain.

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

[4]Kaplan and Menzio (2015), abstract. They extended this work on price dispersion in Kaplan, Menzio, Rudanko, and Trachter (2019).

3 Methodology

We describe the key elements of the decomposition methodology developed by Aguiar and Hurst (2007) and Kaplan and Menzio (2015). Indexes are as follows: $j = 1 \dots J$ stands for good; $s = 1 \dots S$ for store; $w = 1 \dots W$ for week; $i = 1 \dots I$ for panelist (household); $k = 1 \dots \infty$ for trip; $m = 1 \dots M$ for market; and $t = 1 \dots T$ for quarter. Two variables contain store level information: $Q_{j,s,w}$, the number of units of good j sold at store s in week w; and $P_{j,s,w}$, the average unit price of good j at store s in week w. At the individual panelist level, transaction information is given by $q_{j,k}$, the number of units of good j purchased on shopping trip k made by panelist $i(k)$ in store $s(k)$; and $P_{j,k}$, the unit price paid for the good j on shopping trip k.

3.1 Price indexes

Table 1 summarizes how we follow KM to construct household price indexes. We start from the raw data to construct normalized prices $\bar{P}_{j,m,t}$ and $p_{j,s,w}$. $\bar{P}_{j,m,t}$ is the sales-weighted average price paid for good j in market m in quarter t; $p_{j,s,w}$ is the price of good j in store s in week w as a fraction of the mean market-quarter price $\bar{P}_{j,m,t}$. We take the sales-weighted average of the weekly prices $p_{j,s,w}$ to obtain the normalized store price for good j in quarter t, $\mu_{j,s,t}$. The sales-weighted average of the latter over goods gives the store average price $\mu_{s,t}$.

The normalized prices are used to construct the household's overall price index $p_{i,t}$, as well as several specific indexes. The store price index $p^{s}_{i,t}$ is the overall price index of stores visited by the household. The store-good price index $p^{sg}_{i,t}$ is the price index for stores visited by the household based on products purchased by the household. We also define $p^{m}_{i,t} = 1$ as the normalized average market cost of consumer i's purchases, which is equal to one by construction.

We augment the KM methodology by computing an additional price, the store-basket average price $\mu_{i,s,t}$ defined in Table 2. It measures the cost of consumer i's basket in store s: the total cost of the basket had the consumer purchased all of it from store s instead of the actual stores where the purchases were made. After weighing each store visited by its share of total expenditure, we obtain the consumer's store-basket price index $p^{sb}_{i,t}$ as given in Table 2. According to the store-basket counterfactual spending, the consumer substitutes her purchases across the stores she visits holding good and store expenditure shares constant; that is, the consumer purchases her entire basket in each of the stores she visits in proportion to her overall spending in each store.

3.2 Decompositions

We are now in a position to define KM's decomposition and our proposed modification, which we will refer to as CCM for brevity. We start with an overall decomposition of the panelist's price

Table 1: Normalized prices, price indexes and household price indexes

Normalized prices		
$\bar{P}_{j,m,t}$	KM2	$\bar{P}_{j,m,t} = \sum\limits_{s,w \in m \cap t} P_{j,s,w} \frac{Q_{j,s,w}}{\sum\limits_{s,w \in m \cap t} Q_{j,s,w}}$
$p_{j,s,w}$	KM1	$p_{j,s,w} = \frac{P_{j,s,w}}{\bar{P}_{j,m(s),t(w)}}$
Weighted average prices		
Market average	KM3	$\mu_{j,m,t} = \sum\limits_{s,w \in m \cap t} p_{j,s,w} \frac{Q_{j,s,w}}{\sum\limits_{s,w \in m \cap t} Q_{j,s,w}} = 1$
Store-good average	KM4	$\mu_{j,s,t} = \sum\limits_{w \in t} p_{j,s,w} \frac{Q_{j,s,w}}{\sum\limits_{w \in t} Q_{j,s,w}}$
Store average	KM5	$\mu_{s,t} = \sum\limits_{j \in s \cap t} \mu_{j,s,t} \frac{R_{j,s,t}}{\sum\limits_{j \in s \cap t} R_{j,s,t}}$
Store-good revenues	KM6	$R_{j,s,t} = \sum\limits_{w \in t} P_{j,s,w} Q_{j,s,w}$
Household price indexes		
Household expenditure	KM11	$\bar{X}_{i,t} = \sum\limits_{j,k \in i \cap t} \bar{P}_{j,m(i),t} q_{j,k}$
Household exp. shares	KM13	$w_{i,j,k,t} = \frac{\bar{P}_{j,m(i),t} q_{j,k}}{\bar{X}_{i,t}}$, $w_{i,j,s,t} = \sum\limits_{k \in i \cap j \cap s \cap t} w_{i,j,k,t}$
Household price index	KM12	$p_{i,t} = \sum\limits_{j,s,w \in i \cap t} p_{j,s,w} w_{i,j,s,t}$
Store-good	KM14	$p^{sg}_{i,t} = \sum\limits_{j,s \in i \cap t} \mu_{j,s,t} w_{i,j,s,t}$
Store	KM14	$p^{s}_{i,t} = \sum\limits_{s \in i \cap t} \mu_{s,t} w_{i,.,s,t}$
Market	KM14	$p^{m}_{i,t} = \sum\limits_{j,k \in i \cap t} \mu_{j,m,t} w_{i,j,k,t} = 1$

Note: The second column provides the reference to the equation number in Kaplan and Menzio (2015). Notation '.' in a variable's subindex means that the variable is summed over that subindex: $w_{i,.,s,t} = \sum\limits_{j} w_{i,j,s,t}$.

Table 2: Household basket prices

Store-basket average price		
$\mu_{i,s,t}$	Store-basket price	$\mu_{i,s,t} = \sum\limits_{j \in i \cap t} \mu_{j,s,t} w_{i,j,\cdot,t}$
Household store-basket price index		
$p^{sb}_{i,t}$	Household store-basket price index	$p^{sb}_{i,t} = \sum\limits_{s \in i \cap t} \mu_{i,s,t} w_{i,.,s,t} = \sum\limits_{j,s \in i \cap t} \mu_{j,s,t} w_{i,j,\cdot,t} w_{i,\cdot,s,t}$

index as

$$p_{i,t} - p^m_{i,t} = \underbrace{(p_{i,t} - p^{sg}_{i,t})}_{\text{transaction}} + \underbrace{(p^{sg}_{i,t} - p^{sb}_{i,t})}_{\text{pure store-good}} + \underbrace{(p^{sb}_{i,t} - p^{s}_{i,t})}_{\text{store-basket}} + \underbrace{(p^{s}_{i,t} - p^{m}_{i,t})}_{\text{store}}. \tag{1}$$

The interpretation of each difference is as follows:

$p_{i,t} - p^m_{i,t}$ is the difference between the price paid by the consumer and the price she would have paid for the goods in her basket, had she paid the average market price.

$p_{i,t} - p^{sg}_{i,t}$ is the *transaction* component. It is the difference between the actual normalized price paid for each good and the average price for the same good at the store she purchased that good. It measures the panelist's ability to take advantage of temporal changes in price.

$p^{sg}_{i,t} - p^{sb}_{i,t}$ is the *pure store-good* component. It is the difference between the average cost of the goods she purchases at the stores where each purchase is made and the cost of her basket at the stores she visits. It measures the panelist's ability to purchase each good in her basket at the store where that good is relatively cheaper within the set of stores visited.

$p^{sb}_{i,t} - p^{s}_{i,t}$ is the *store-basket* component. It is the difference between the average cost of the panelist's basket at the stores she visits and the average expensiveness of the stores she visits. It measures the extent to which the panelist purchases a basket that is representative of the expensiveness of the stores she visits.

$p^{s}_{i,t} - p^{m}_{i,t}$ is the *store* component. It is the difference between the average cost of the stores visited by the panelist and the average store in the market. It measures the panelist's ability to select cheap stores.

By merging the second and third components in equation (1), we obtain KM's decomposition:

$$p_{i,t} - p^m_{i,t} = \underbrace{(p_{i,t} - p^{sg}_{i,t})}_{\text{transaction}} + \underbrace{(p^{sg}_{i,t} - p^{s}_{i,t})}_{\text{KM store-good}} + \underbrace{(p^{s}_{i,t} - p^{m}_{i,t})}_{\text{store}}. \tag{2}$$

The first and last terms on the right hand side of equation (2) are the same terms as in equation (1). The middle term is the KM store-good component, which is the sum of the pure store-good and store-basket components from equation (1). It is important to take note that we have introduced two distinct store-good components: the pure store-good component defined in equation (1), and the KM store-good component, defined in equation (2).

Since our focus in on the relative magnitudes of the store and store-good components in the KM and CCM decompositions, and in order to simplify the exposition, we will suppress the transaction component for the main part of the analysis.[5] We rewrite equation (2) as

$$p_{i,t}^{sg} = p_{i,t}^{m} + \underbrace{(p_{i,t}^{sg} - p_{i,t}^{s})}_{\text{KM store-good}} + \underbrace{(p_{i,t}^{s} - p_{i,t}^{m})}_{\text{store}}, \tag{3}$$

In this simplified version of the KM decomposition, the store-good price index is broken down into the market index ($p_{i,t}^{m} = 1$) and the store and KM store-good components. The store component measures the expensiveness of the stores visited relative to the market. The KM store-good component is the expensiveness of the household's basket in those stores relative to overall store expensiveness. Similarly, the CCM decomposition can be obtained from equation (1) after removing the transaction component:

$$p_{i,t}^{sg} = p_{i,t}^{m} + \underbrace{(p_{i,t}^{sg} - p_{i,t}^{sb})}_{\text{pure store-good}} + \underbrace{(p_{i,t}^{sb} - p_{i,t}^{s})}_{\text{store-basket}} + \underbrace{(p_{i,t}^{s} - p_{i,t}^{m})}_{\text{store}}, \tag{4}$$

3.3 Formal comparison of the two decompositions

The two decompositions will coincide when the pure store-good component is zero, $p_{i,t}^{sg} = p_{i,t}^{sb}$, or when the store-basket component is zero, $p_{i,t}^{sb} = p_{i,t}^{s}$. Combining the definition of $p_{i,t}^{sb}$ in Table 2 with equation KM14, the former condition is written

$$p_{i,t}^{sg} - p_{i,t}^{sb} = \sum_{j,s \in i \cap t} \mu_{j,s,t} \left(w_{i,j,s,t} - w_{i,\cdot,s,t} w_{i,j,\cdot,t} \right). \tag{5}$$

This expression equals zero when $w_{i,j,s,t} = w_{i,\cdot,s,t} w_{i,j,\cdot,t}$, meaning that each consumer purchases the same basket shares in all stores visited but purchases different amounts of that basket in different stores. The relative chance of purchasing a product in one store over another is independent of the good purchased, $\frac{w_{j,s,t}}{w_{j,s',t}} = \frac{w_{j',s,t}}{w_{j',s',t}}$ for any (j, j', s, s').

Combining the definition of $p_{i,t}^{sb}$ in Table 2 with equations KM5 and KM14 we obtain

$$p_{i,t}^{s} - p_{i,t}^{sb} = \sum_{j,s \in i \cap t} \mu_{j,s,t} w_{i,\cdot,s,t} \left(\frac{R_{j,s,t}}{\sum\limits_{j \in s \cap t} R_{j,s,t}} - w_{i,j,\cdot,t} \right). \tag{6}$$

The two indexes are the same when the above sum, which is a non-linear function of the primitives (transaction prices and quantities), equals zero. This occurs in three cases worth mentioning: (i) the trivial case when there is a single product or single store; (ii) when the store-good prices are constant across stores, $\mu_{j,s,t} = \mu_{s,t}$; and (iii) when the share of each good purchased by each consumer is equal to the share sold by each store $w_{i,j,\cdot,t} = \frac{R_{j,s,t}}{\sum\limits_{j \in s \cap t} R_{j,s,t}}$. The next proposition formalizes these

[5] We bring back the transaction component when we discuss robustness in section 5.4.

insights.

Proposition 1. *The KM and CCM decompositions are identical if any of the following four conditions hold:*

(a) Consumers select stores independently of the product purchased: For all i, $\frac{w_{j,s,t}}{w_{j',s,t}} = \frac{w_{j,s',t}}{w_{j',s',t}}$ *for any* (j, j', s, s').

(b) There is a single store $(S = 1)$ *or single product* $(J = 1)$.

(c) Uniform store prices: $\mu_{j,s,t} = \mu_{s,t}$, $j = 1 \ldots J$; *a sufficient pair of conditions for this to hold is:*

  (c1) Stores sell the same relative quantity of products, $\frac{\sum_w Q_{j,s,w}}{\sum_w Q_{j',s,w}} = \frac{\sum_w Q_{j,s',w}}{\sum_w Q_{j',s',w}}$ *for any* (j, j', s, s'); *and*

  (c2) The same holds for sales, $\frac{R_{j,s,t}}{R_{j',s,t}} = \frac{R_{j,s',t}}{R_{j',s',t}}$ *for any* (j, j', s, s').

(d) Uniform store-basket prices: $\mu_{i,s,t} = \mu_{s,t}$, $i = 1 \ldots I$; *both (c2) and condition (d1) below must hold:*

  (d1) Consumers spend the same share of total expenditure on each good, $w_{i,j,\cdot,t} = w_{i',j,\cdot,t}$ *for any* (i, i', j).

Proof. See appendix. □

Condition (a) says that each consumer purchases in each store the same normalized (up to scaling factor) basket, which may be different across consumers, with the consequence that a consumer's normalized basket is the same basket as the one used to construct the consumer's store-basket price index. The intuition for condition (b) is straightforward. With a single product, the market basket and each consumer's basket are the same, hence there can be no difference between the store and store-basket price indexes. When there is a single store, that store's overall expensiveness has to be equal to 1, regardless of which basket of goods we are considering. Hence again store and store-basket indexes will coincide.[6]

Conditions (c1) and (c2) are statements about store scalability: store and store-basket indexes will be the same if stores are replicas of each other up to some scaling factor. Condition (c1) says that store quantities sold can be written as the product of a store and product component, $Q_{j,s,t} = \alpha_j \beta_s$, where α_j and β_s are positive numbers less than one and each sum up to one. Each store controls the same share of each product, where β_s is the market share or scale, of store s and

[6] The store and store-basket may differ even when there is a single consumer. To see why, note that the weights $\frac{R_{j,s,t}}{\sum\limits_{j \in s \cap t} R_{j,s,t}}$ and $w_{1,j,\cdot,t}$ in equation (6) may not be equal even with a single consumer.

each store sells the same portfolio of products, where α_j is the share of product j in the common portfolio. Condition (c2) makes the same statement about revenue instead of quantity.

Condition (d) says that all consumers purchase the same basket and all store also sell the same basket up to a scaling factor. The cost of a consumer basket in a given store, $\mu_{i,s,t}$, which is evaluated using the store-good prices, ends up being the same as the measure of store expensiveness, $\mu_{s,t}$, because the store sells goods in the same proportions as what the consumer purchases, and we obtain $p_{i,t}^{sb} - p_{i,t}^{s} = \sum_{s \in i \cap t} (\mu_{i,s,t} - \mu_{s,t}) w_{i,\cdot,s,t} = 0$.

4 An illustrative example

We present a simple example to help clarify the main concepts and highlight the difference between KM's methodology and ours. 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 second one 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 $p_{m,B} > p_{m,D}$.

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 both bread and milk. They buy from a single store that could be chosen, say, on the basis of location. Shoppers buy each item in their basket at the lowest available price. They come in three types of equal size. One type has only bread in their basket ("bread shoppers"), another type has only milk ("milk shoppers"), and the third type has both ("all-shoppers"). Table 3 describes the consumer types and their purchase shares in each store. Bread shoppers purchase only from the bakery, milk shoppers only from the dairy, and all-shoppers purchase milk from the dairy and bread from the bakery. Loyals are evenly split between the bakery and the dairy.

Table 3: Consumer types and their choices

	(Stores)		Bakery		Dairy	
	(Products)		Bread	Milk	Bread	Milk
	(Prices)		$p_{b,B} = 1.0$	$p_{m,B} = 1.1$	$p_{b,D} = 1.1$	$p_{m,D} = 1.0$
	Consumer type	*Frac.*	*Expenditure shares* w_{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	Bakery loyal	2/5	0	0	1/2	1/2
5	Dairy loyal	2/5	1/2	1/2	0	0
	Quantity purchased		3/10	1/5	1/5	3/10

By design, there is no intertemporal price variation. Suppose that posted prices in the stores are $p_{b,B} = p_{m,D} = 1.0$ and $p_{b,D} = p_{m,B} = 1.1$. The sales-weighted average price is the same for both goods, $\bar{P}_b = \bar{P}_m = 1.04$. The weighted average store-good prices vary in opposite fashion across stores, $\mu_{b,B} = \mu_{m,D} = 0.96$ and $\mu_{m,B} = \mu_{b,D} = 1.06$, and the same holds for revenues ($R_{b,B} = R_{m,D}$ and $R_{m,B} = R_{b,D}$). The implication is that the two stores are equally expensive with respect to the market basket, $\mu_B = \mu_D = 1$. Thus, this example has neither transaction nor store components. The point is to narrow the analysis down to the KM store-good and CCM pure store-good components.

Table 4 reports the consumer price indexes and the components from the two decompositions. The first three indexes are the ones constructed by KM: the market index p^m, store index p^s and store-good index p^{sg}. The fourth price index is our store-basket index p^{sb}. The market index is $p^m = 1$ by construction. As mentioned above, the store index is also equal to one ($p^s = 1$) for all consumers. The store-good index p^{sg} is the average price of the goods each consumer purchases at the store where those purchases are made. Shoppers (consumers 1, 2 and 3) purchase goods from stores where they are cheap while loyals (consumers 4 and 5) purchase from relatively expensive stores. The store-basket index p^{sb} is the average cost of the consumer's basket at the stores she visits. The index is low for single-item shoppers (consumers 1 and 2) because they only visit the store that is cheap for the sole item in their basket. It is higher for the other three consumer types because they have both items in their basket, therefore calculation of p^{sb} will include high-priced items.

Table 4: Consumer price indexes and decompositions

	Price indexes				Components			
Consumer type	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	1.00	1.00	0.96	0.96	0.00	-0.04	0	-0.04
2	1.00	1.00	0.96	0.96	0.00	-0.04	0	-0.04
3	1.00	1.00	0.96	1.01	0.00	-0.04	-0.05	0.01
4	1.00	1.00	1.01	1.01	0.00	0.01	0	0.01
5	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.

The components of interest are reported in the last four columns of Table 4, first for each consumer and then, on the last line, for the entire market. The store component, which is common to both decompositions, is zero in all cases (column 6). This is expected, as the price of the market basket is the same in both stores. As a result, the KM decomposition attributes price dispersion for all consumers entirely to the KM store-good component. This is appropriate for the all-shoppers (consumer type 3) because these consumers save by purchasing the goods in their basket in the stores where these goods are cheap. They have a KM store-good component $p^{sg} - p^{s} = -0.04$, and a CCM pure store-good component of a similar magnitude, $p^{sg} - p^{sb} = -0.05$. Hence the two decompositions lead to similar conclusions with respect to type 3 consumers. They differ, however, with respect to the other four types. The KM store-good component is nonzero for the remaining four consumers (types 1, 2, 4, and 5). We argue that this is problematic. 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, since consumers 1 and 2 only purchase a single item from a single store.[7]

In contrast, the CCM pure store-good component is zero for the four consumer types: these consumers' store-good price index is equal to their store-basket price index. For consumers 1 and 2 we get instead a negative store-basket component because their basket is cheaper than overall store expensiveness, while for consumers 3 and 4 we get a small positive store-basket component because their basket is more expensive than overall store expensiveness.

This explains the striking difference between the two decompositions reported on the last line of Table 4. As expected, neither decomposition attributes any of the dispersion in price index to the store component. 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, while 72 percent being attributed to the store-basket component. The conclusion from the CCM decomposition is that consumer price dispersion is primarily due to variation in consumers' ability to select stores on the basis of the expensiveness of their basket in these stores.

5 Data and analysis

5.1 Data

We use the well-known BehaviorScan consumer panel provided by the market research company IRI.[8] The panel tracks consumers in two markets (Eau Claire, Wisconsin and Pittsfield, Massachusetts) over a period of twelve years, 2001-2012. A total of about ten thousand distinct households are represented on the BehaviorScan panel, with an average of roughly five thousand households every year. Unless stated otherwise, we follow KM to compute statistics that apply to the entire dataset. We first calculate statistics for each market quarter and then aggregate them by taking the expenditure-weighted averages across markets and quarters.

[7] Consumer 4 and 5 have a small positive KM store-good component because they do not purchase goods proportionally to the store-good revenue shares at the store they visit. See footnote 6.

[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 (2017).

Table 5: Information about the dataset

	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
Average 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

BehaviorScan contains about 30 product categories. We ranked categories by total purchase count, and selected the top 5 categories (carbonated soft drinks, milk, salty snacks, yogurt, cold cereal). The sixth (soup) and the seventh (frozen dinner) categories 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 and adding a few more product categories would only marginally increase this figure. The online data appendix explains how we merge UPCs into unique products, and delete products, stores and panelists with few purchases. Table 5 gives some summary information about the subset of panelists, products and purchases used in this paper. Panelists stay on average about six years in BehaviorScan. Each quarter, they visit on average two stores, buy eighteen distinct products from four of the five categories, and make close to thirty purchases total. The summary statistics are very similar in Eau Claire and Pittsfield. The two IRI markets do not reveal the existence of market heterogeneity, although one should be cautious in drawing conclusions based on two observations.

Tables 10 and 11 in the Appendix replicate some of the KM results with the IRI dataset. Table 10 reports a value of 0.09 for the standard deviation in the overall price index across panelists ($p_{i,t}$ from equation 1) for KM and the slightly lower value of 0.073 in IRI. Table 11 replicates KM's price decomposition (KM equation 7, p.13). For the sake of comparability, we report KM's results from Table 3 (p14) in the last two columns. The results are fairly similar although the transaction component is slightly higher in the IRI dataset.

Table 6 reports some statistics on the household price indexes defined in section 3. The three columns give measures of dispersion for the store-good, store, and store-basket indexes respectively and report the same statistics as those reported in KM's Table 2. As expected, the standard deviation of the store-good price index, 0.039, is greater than the standard deviation in the other two indexes. The panelist who save can save a significant amount relative to those who don't: the panelist at the top 10 percentile of spenders spend about 10% more on groceries that the panelist at the top 10 percentile of savers.

Table 6: Household price indexes

	p^{sg}	p^{s}	p^{sb}
Standard deviation	0.039	0.023	0.037
90-10 ratio	1.098	1.060	1.089
90-50 ratio	1.047	1.027	1.043
50-10 ratio	1.049	1.033	1.044

5.2 Store preferences

For each panelist-quarter observation, we select the top two stores (s_1, s_2) in terms of overall expenditure. We rank the stores in two ways: according to their household-specific price level $\mu_{i,s,t}$ and according to their overall price level $\mu_{s,t}$. We then aggregate this information for 954 store-pair quarters.[9] For each store-pair quarter triplet (s_1, s_2, t), we compute the fraction of panelists who have different orderings with the two store price indexes:

$$Pr[(\mu_{i,s_1,t} - \mu_{i,s_2,t})(\mu_{s_1,t} - \mu_{s_2,t}) < 0]. \tag{7}$$

The order under KM's store index is the same for all panelists for a given store pair-quarter. Figure 1 shows the distribution of the fraction of panelists having different orderings using our store-basket index. For about 26 percent of panelists the expensiveness ranking of the two stores where they spend the most is different with the average store price index than with a price index specific to their own basket. This demonstrates that preferences over stores are consumer specific for a significant fraction of panelists.

The finding that the store rankings are different suggests that store preference may be basket specific for some consumers. Thus, the large store-good component found in KM may be due to the their decomposition underestimating the role of the store component. After accounting for the fact that the store component is consumer specific, as proposed in the CCM decomposition, the relative roles of the store and store-good components may change.

5.3 Decomposition results

Table 7 shows the results of applying the CCM and KM decompositions to our data. The CCM decomposition is presented in column 2. The KM decomposition is presented in the second to last line of the right panel. The components are obtained by summing terms in each column. Looking

[9] 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 time 48 quarters=1728). After filtering out store pair-quarters with less than 50 panelists, we end up with 954 observations.

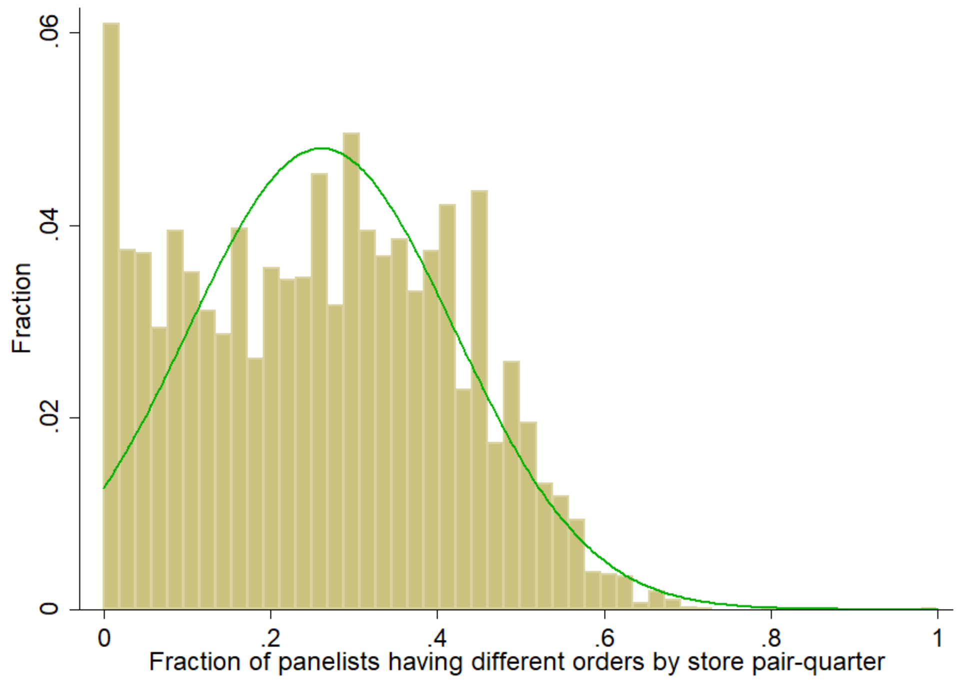

Figure 1: Distribution of the fraction of panelists with different expensiveness rankings by store pair-quarter

first at the CCM decomposition, note that the store-basket component $(p^{sb}_{i,t} - p^{s}_{i,t})$ accounts for about half the overall variance (48%). This confirms the result from the previous section that store expensiveness and store-basket expensiveness are not the same thing. The next important component is the store component $(p^{s}_{i,t} - p^{m}_{i,t})$, which accounts for about 41% of the overall variance. The pure store-good component $(p^{sg}_{i,t} - p^{sb}_{i,t})$ is the smallest of the three, contributing 27% to the overall variance.

The KM store-good component is more than double the size of the CCM pure store-good component (57% to 27%). This difference in the estimated store-good components can be seen clearly in Figure 2, which plots their full distributions for an indicative market-quarter.[10] Using the CCM method, there is a large spike at zero: almost 40% of consumers have a zero pure store-good component. The distribution using the KM method has no such spike and is much more spread out. This is reminiscent of the illustrative example reported in Table 4, which showed that the KM store-good component is much larger than the CCM pure store-good component.

[10] Since the variance is computed by market-quarter, it is not possible to show the distributions for all market-quarters in a single graph. The distributions displayed are for Eau Claire 2001:1.

Table 7: The KM and CCM decompositions

CCM decomposition		KM decomposition		
		Store	Store-good	Cov
$var(p^{sg}_{i,t} - p^{sb}_{i,t})$	27%		X	
$var(p^{sb}_{i,t} - p^{s}_{i,t})$	48%		X	
$var(p^{s}_{i,t} - p^{m}_{i,t})$	41%	X		
$2cov(p^{sb}_{i,t} - p^{s}_{i,t}, p^{sg}_{i,t} - p^{sb}_{i,t})$	-17%		X	
$2cov(p^{s}_{i,t} - p^{m}_{i,t}, p^{sg}_{i,t} - p^{sb}_{i,t})$	3%			X
$2cov(p^{s}_{i,t} - p^{m}_{i,t}, p^{sb}_{i,t} - p^{s}_{i,t})$	-1%			X
Sum=$var(p^{sg}_{i,t} - p^{m}_{i,t})$	100%	41%	57%	2%
			Sum=100%	

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

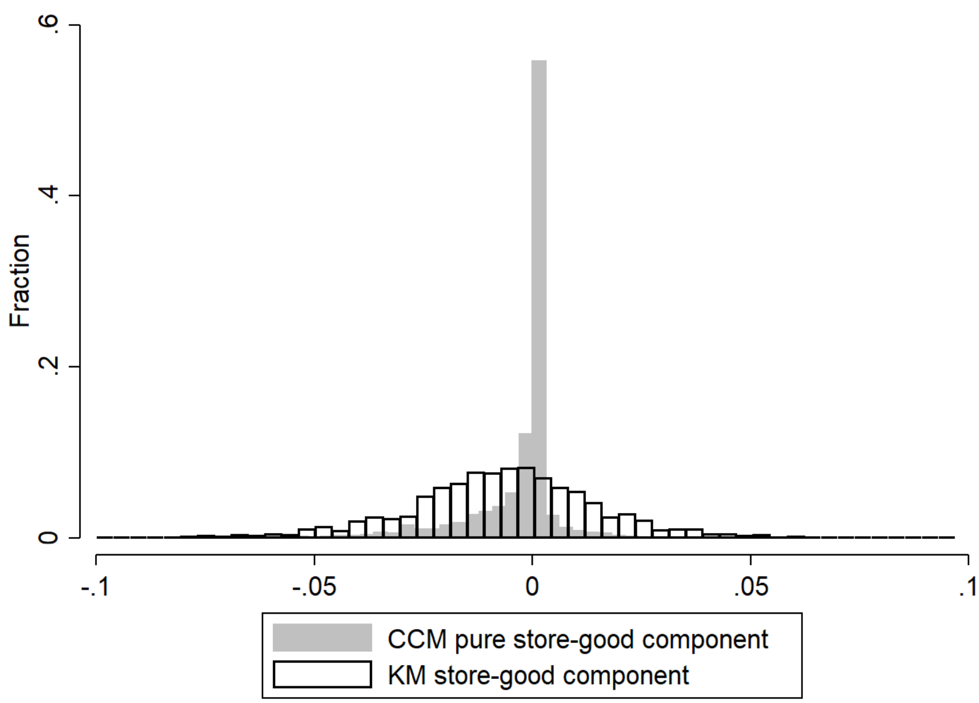

Figure 2: The distribution of the KM store-good component and the CCM pure store-good component in an indicative market-quarter

5.4 Robustness

We conducted a wide array of robustness tests in order to ensure that our finding is not the result of special circumstances. We provide a summary here and a more detailed explanation in the Online Appendix. Table 8 replicates the full decomposition presented in the second column of Table 7 for seven robustness checks. Table 9 reports the variances of the KM store-good and the CCM pure store-good components for the same robustness tests. The 'Baseline' scenario (first column in Table 8 and first row in Table 9) corresponds to the CCM decomposition from Table 7.

The "Filter" column reports results obtained when we filter out panelist-quarter observations with fewer than 50 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.

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 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 pure CCM 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 $p_{i,t}^{sb}$ in Table 2 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 consider a different way to aggregate the variance decompositions across markets and quarters. The method reported in the baseline column follows KM's approach. We conduct the variance decomposition by quarter and then aggregate over quarters. The method reported in column $var_{i,m,t}(\Delta_{it})$ computes a single variance decomposition for all panelist-quarter observations.

The full variance decomposition does not change much across the seven columns in Table 8. In Table 9 we see that in every case, the variance of the CCM pure store-good component is

Table 8: Robustness check of the CCM decomposition

	Baseline	Filter	Eau	Pitts	SW2	SW3	$var_{i,m,t}(\Delta_{it})$
$var(p^{sg}_{i,t} - p^{sb}_{i,t})$	27%	27%	19%	36%	41%	38%	31%
$var(p^{sb}_{i,t} - p^{s}_{i,t})$	48%	45%	36%	63%	42%	34%	49%
$var(p^{s}_{i,t} - p^{m}_{i,t})$	41%	44%	50%	28%	41%	41%	39%
$2cov(p^{sb}_{i,t} - p^{s}_{i,t}, p^{sg}_{i,t} - p^{sb}_{i,t})$	-17%	-18%	-11%	-25%	-26%	-16%	-22%
$2cov(p^{s}_{i,t} - p^{m}_{i,t}, p^{sg}_{i,t} - p^{sb}_{i,t})$	3%	3%	6%	-1%	26%	3%	3%
$2cov(p^{s}_{i,t} - p^{m}_{i,t}, p^{sb}_{i,t} - p^{s}_{i,t})$	-1%	0%	0%	-2%	-24%	0%	0%
Sum=$var(p^{sg}_{i,t} - p^{m}_{i,t})$	100%	100%	100%	100%	100%	100%	100%

substantially larger than the variance of the KM store-good component, roughly about double the size.

Table 9: Robustness check of the variances of the pure store-good and KM store-good components

	CCM pure store-good $var(p^{sg}_{i,t} - p^{sb}_{i,t})$	KM store-good $var(p^{sg}_{i,t} - p^{s}_{i,t})$
Baseline	27%	57%
Filter	27%	54%
Eau Claire	19%	44%
Pittsfield	36%	75%
Store weight 2	41%	57%
Store weight 3	37%	57%
$var_{i,m,t}(\Delta_{it})$	31%	58%

Table 12 in the Appendix presents nine additional robustness checks. We use transaction price instead of store prices to compute the normalized prices in order to exactly match KM methodology. We filter out good-market-quarters with few purchases and panelist-quarters with few purchases or with few unique store visits. Finally, we conduct the decomposition separately for our five product categories. The ratios of the store-good to store components are robust to these additional robustness checks.

All of the variances decompositions presented in Tables 7, 8, 9 and 12 are calculated from the simplified version of the KM decomposition (equations 3 and 4) that excludes the transaction component defined in equation (1). This is without loss of generality because all variance decompositions are normalized and what interests us is the relative magnitude of the KM store-good components 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 also attempted to replicate in the IRI dataset the KM decomposition including the transaction component (equation (1)). Tables 13 and 14 in the Online Appendix report the results. The transaction component in our data is substantially larger in our IRI data than in KM's Nielsen data, and this is true independently of whether one follows the KM or CCM decomposition. The Online Appendix rules out several candidate explanations for this difference. A proper evaluation of these explanations requires access to the Nielsen data, which we do not have. The difference in the magnitudes of the transaction components remains a puzzle for future exploration. We emphasize that this does not affect our primary result about the relative magnitudes of the store and store-basket components. The result holds regardless of whether or not we include the temporal component in the decomposition and is robust to many alternative computational and methodological assumptions as demonstrated by Tables 9 and 12.

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 both across stores and over time. They can also save by buying in bulk of choosing generic brands.

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 KM decomposition that breaks down their store-good component into two parts that we call pure store-good component and store-basket component. This allows us to ask 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 product from the right 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 analysis also finds an important role for the temporal component, which is consistent with the recent literature on promotions (Pesendorfer, 2002; Hendel and Nevo, 2006a,b) but comes in contrast with KM, who find a small transaction component. The difference is not due to the methodology, but to our use of a different data set. We discuss several reasons why differences in the two data sets can account for the divergent estimates of the transaction component but leave a proper evaluation of these explanations as a question for future exploration.

References

Aguiar, M., and E. Hurst, 2007, "Life-Cycle Prices and Production," *American Economic Review*, 97(5), 1533–1559.

Berardi, N., P. Sevestre, and J. Thébault, 2017, "The Determinants of Consumer Price Dispersion: Evidence from French Supermarkets," in *The Econometrics of Multi-dimensional Panels: Theory and Applications*, ed. by L. Matyas. Springer, Cham, Advanced Studies in Theoretical and Applied Econometrics, vol 50, pp. 427–449.

Bronnenberg, B. J., M. W. Kruger, and C. F. Mela, 2009, "The IRI Marketing Data Set," *Marketing Science*, 27(4), 745–748.

Ching, A., and M. Osborne, 2017, "Identification and Estimation of Forward-Looking Behavior: The Case of Consumer Stockpiling," Rotman School of Management Working Paper No. 2594032.

DellaVigna, S., and M. Gentzkow, 2019, "Uniform Pricing in U.S. Retail Chains*," *The Quarterly Journal of Economics*, 134(4), 2011–2084.

Dubois, P., and H. Perrone, 2017, "Price Dispersion and Informational Frictions: Evidence from Supermarket Purchases," unpublished manuscript.

Griffith, R., E. Leibtag, A. Leicester, and A. Nevo, 2009, "Consumer Shopping Behavior: How Much Do Consumers Save?," *Journal of Economic Perspectives*, 23(2), 99–120.

Hendel, I., and A. Nevo, 2006a, "Measuring the Implications of Sales and Consumer Inventory Behavior," *Econometrica*, 74(6), 1637–1673.

——— , 2006b, "Sales and Consumer Inventory," *RAND Journal of Economics*, 37(3), 543–561.

Hitsch, G. J., A. Hortaçsu, and X. Lin, 2019, "Prices and Promotions in U.S. Retail Markets: Evidence from Big Data," Becker Friedman Institute Working Paper 2019-117.

Hosken, D., and D. Reiffen, 2004, "Patterns of Retail Price Variation," *The RAND Journal of Economics*, 35(1), 128–146.

Kaplan, G., and G. Menzio, 2015, "The Morphology of Price Dispersion," *International Economic Review*, 56(4), 1165–1206.

Kaplan, G., G. Menzio, L. Rudanko, and N. Trachter, 2019, "Relative Price Dispersion: Evidence and Theory," *American Economic Journal: Microeconomics*, 11(3), 68–124.

Lach, S., 2002, "Existence and Persistence of Price Dispersion: An Empirical Analysis," *The Review of Economics and Statistics*, 84(3), 433–444.

Pesendorfer, M., 2002, "Retail Sales: A Study of Pricing Behavior in Supermarkets," *Journal of Business*, 75(1), 33–66.

Pires, T., 2016, “Costly search and consideration sets in storable goods markets,” *Quantitative Marketing and Economics*, 14(3), 157–193.

Pratt, J. W., D. A. Wise, and R. Zeckhauser, 1979, “Price Differences in Almost Competitive Markets,” *The Quarterly Journal of Economics*, 93(2), 189–211.

Sorensen, A. T., 2000, “Equilibrium Price Dispersion in Retail Markets for Prescription Drugs,” *Journal of Political Economy*, 108(4), 833–850.

A Additional results

Columns 3 and 5 in Table 10 are copied from KM and correspond to Table 2 Column 3 (p.9) and Table 6 Column 3 (p.22) respectively.

Table 10: Average statistics of price and $p_{i,t}$

	Price		$p_{i,t}$	
	IRI	Nielsen	IRI	Nielsen
Standard Deviation	0.16	0.21	0.07	0.09
90-10 ratio	1.54	1.79	1.19	1.22
90-50 ratio	1.21	1.29	1.08	1.09
50-10 ratio	1.29	1.38	1.10	1.12

The fourth columns in Table 11 correspond to Table 3 Column 3 in KM (p.14). Columns 3 and 5 renormalize the variances and covariance after ignoring the transaction component.

Table 11: Decomposition at transaction level

	IRI		Nielsen	
	With tran	Without tran	With tran	Without tran
Transaction	80%	–	62%	–
Store-good	28%	88%	30%	81%
Store	3%	9%	7%	19%
2cov(tran,sg)	-12%	–	0%	–
2cov(tran,s)	0%	–	0%	–
2cov(sg,s)	1%	3%	0%	0%

In Table 12, line A replicates the analysis using transaction prices instead of store prices to compute the normalized prices. Line B replicates line A after filtering out goods-market-quarters with fewer than 25 purchases. Line C replicates line B after filtering out panelist-quarters with fewer than 50 purchases. Line D replicates line C after filtering out panelist-quarters with only one store visited. The last five lines replicates line B for our five product categories, that is, carbonated soft drinks, cold cereal, milk, salty snacks and yogurt.

B Proof of proposition 1

Proposition 1. *The KM and CCM decompositions are identical if any of the following four conditions hold:*

(a) *Consumers select stores independently of the product purchased: For all i,* $\frac{w_{j,s,t}}{w_{j',s,t}} = \frac{w_{j,s',t}}{w_{j',s',t}}$ *for*

Table 12: Comparison of the variances of key components using transaction price data

	CCM pure store-good	KM store-good
Baseline	27%	57%
A: transaction price data	24%	55%
B: A and filter goods-market-quarters with fewer than 25 purchases	24%	55%
C: B and filter panelist-quarters with fewer than 50 purchases	21%	47%
D: C and filter panelist-quarters with only one store visited	27%	46%
B for carbonated soft drinks	11%	48%
B for cereal	15%	62%
B for milk	15%	67%
B for salty snacks	13%	54%
B for yogurt	8%	71%

any (j, j', s, s').

(b) *There is a single store* ($S = 1$) *or single product* ($J = 1$).

(c) *Uniform store prices:* $\mu_{j,s,t} = \mu_{s,t}$, $j = 1 \dots J$; *a sufficient pair of conditions for this to hold is:*

(c1) *Stores sell the same relative quantity of products,* $\frac{\sum_w Q_{j,s,w}}{\sum_w Q_{j',s,w}} = \frac{\sum_w Q_{j,s',w}}{\sum_w Q_{j',s',w}}$ *for any* (j, j', s, s'); *and*

(c2) *The same holds for sales,* $\frac{R_{j,s,t}}{R_{j',s,t}} = \frac{R_{j,s',t}}{R_{j',s',t}}$ *for any* (j, j', s, s').

(d) *Uniform store-basket prices:* $\mu_{i,s,t} = \mu_{s,t}$, $i = 1 \dots I$; *both (c2) and condition (d1) below must hold:*

(d1) *Consumers spend the same share of total expenditure on each good,* $w_{i,j,\cdot,t} = w_{i',j,\cdot,t}$ *for any* (i, i', j).

Proof. We prove claim (a) by showing that condition $\frac{w_{j,s,t}}{w_{j,s',t}} = \frac{w_{j',s,t}}{w_{j',s',t}}$ for any (j, j', s, s') implies $p^{sg}_{i,t} = p^{sb}_{i,t}$. Combining the definition of $p^{sb}_{i,t}$ in Table 2 with equation KM14, we obtain

$$p^{sg}_{i,t} - p^{sb}_{i,t} = \sum_{j,s \in i \cap t} \mu_{j,s,t} \left(w_{i,j,s,t} - w_{i,\cdot,s,t} w_{i,j,\cdot,t} \right).$$

Note that condition $\frac{w_{j,s,t}}{w_{j,s',t}} = \frac{w_{j',s,t}}{w_{j',s',t}}$ for any (j, j', s, s') implies $w_{i,j,s,t} = w_{i,\cdot,s,t} w_{i,j,\cdot,t}$. Thus, the expression $w_{i,j,s,t} - w_{i,\cdot,s,t} w_{i,j,\cdot,t}$ on the right hand side of the above equation equals zero and we conclude that $p^{sg}_{i,t} = p^{sb}_{i,t}$.

(b) From KM14 and Table 2: $p^{s}_{i,t} - p^{sb}_{i,t} = \sum_{s \in i \cap t} \mu_{s,t} w_{i,.,s,t} - \sum_{s \in i \cap t} \mu_{i,s,t} w_{i,.,s,t} = \sum_{s \in i \cap t} (\mu_{s,t} - \mu_{i,s,t}) w_{i,.,s,t}$. Thus $\mu_{i,s,t} = \mu_{s,t}$ for all s implies $p^{sb}_{i,t} = p^{s}_{i,t}$. It is thus sufficient to show that

$\mu_{i,s,t} = \mu_{s,t}$. We distinguish the two cases. $(S = 1)$ When there is a single store, we have $\mu_{j,m,t} = \mu_{j,s,t} = 1$. But $\mu_{i,s,t} = \sum\limits_{j \in i \cap t} \mu_{j,s,t} w_{i,j,\cdot,t} = 1$. Moreover $\mu_{j,s,t} = 1$ for all j implies $\mu_{s,t} = 1$. We conclude $\mu_{i,s,t} = \mu_{s,t} = 1$. $(J = 1)$ When there is a single product, we have $\mu_{j,s,t} = \mu_{s,t}$ and $\mu_{i,s,t} = \sum\limits_{j \in i \cap t} \mu_{j,s,t} w_{i,j,\cdot,t} = \mu_{s,t}$.

The proof of claims (c-d) are derived by showing that the conditions stated in these claims imply $p^s_{i,t} = p^{sb}_{i,t}$. To evaluate $p^s_{i,t} - p^{sb}_{i,t}$, put together the definition of $p^{sb}_{i,t}$ in Table 2, $p^{sb}_{i,t} = \sum\limits_{j,s \in i \cap t} \mu_{j,s,t} w_{i,j,\cdot,t} w_{i,\cdot,s,t}$, and KM5 and KM14, $p^s_{i,t} = \sum\limits_{s \in i \cap t} w_{i,.,s,t} \left(\sum\limits_{j \in s \cap t} \mu_{j,s,t} \frac{R_{j,s,t}}{\sum\limits_{j \in s \cap t} R_{j,s,t}} \right)$, to obtain

$$p^s_{i,t} - p^{sb}_{i,t} = \sum_{s \in i \cap t} w_{i,.,s,t} \left(\left(\sum_{j \in s \cap t} \mu_{j,s,t} \frac{R_{j,s,t}}{\sum\limits_{j \in s \cap t} R_{j,s,t}} \right) - \sum_{j \in i \cap t} \mu_{j,s,t} w_{i,j,\cdot,t} \right)$$

or,

$$p^s_{i,t} - p^{sb}_{i,t} = \sum_{j,s \in i \cap t} \mu_{j,s,t} w_{i,\cdot,s,t} \left(\frac{R_{j,s,t}}{\sum\limits_{j \in s \cap t} R_{j,s,t}} - w_{i,j,\cdot,t} \right). \tag{8}$$

(c) From KM1 and KM2, the normalized price is:

$$p_{j,s,w} = \frac{P_{j,s,w}}{\sum\limits_{s',w' \in m \cap t} P_{j,s',w'} \frac{Q_{j,s',w'}}{\sum\limits_{s'',w'' \in m \cap t} Q_{j,s'',w''}}}.$$

In turn, the store-good average price is obtained from KM4

$$\mu_{j,s,t} = \sum_{w \in t} p_{j,s,w} \frac{Q_{j,s,w}}{\sum\limits_{w \in t} Q_{j,s,w}} = \frac{\sum\limits_{w \in t} P_{j,s,w} \frac{Q_{j,s,w}}{\sum\limits_{w \in t} Q_{j,s,w}}}{\sum\limits_{s',w' \in m \cap t} P_{j,s',w'} \frac{Q_{j,s',w'}}{\sum\limits_{s'',w'' \in m \cap t} Q_{j,s'',w''}}}$$

$$= \frac{\frac{\sum\limits_{w \in t} P_{j,s,w} Q_{j,s,w}}{\sum\limits_{w \in t} Q_{j,s,w}}}{\frac{\sum\limits_{s',w' \in m \cap t} P_{j,s',w'} Q_{j,s',w'}}{\sum\limits_{s',w' \in m \cap t} Q_{j,s',w'}}} = \frac{\sum\limits_{s',w' \in m \cap t} Q_{j,s',w'}}{\sum\limits_{w \in t} Q_{j,s,w}} \frac{R_{j,s,t}}{\sum\limits_{s \in m \cap t} R_{j,s,t}}.$$

Assumptions (c1) and (c2) imply that $\frac{\sum\limits_{w \in m \cap t} Q_{j,s,w}}{\sum\limits_{s,w \in m \cap t} Q_{j,s,w}}$ and $\frac{R_{j,s,t}}{\sum\limits_{s \in m \cap t} R_{j,s,t}}$ are independent of j and this in turn implies that $\mu_{j,s,t}$ is constant across j because the two terms in the last product in the above equation are independent of j. To conclude, rewrite

$$p_{i,t}^{s}-p_{i,t}^{sb}=\sum_{s\in i\cap t}\left(w_{i,\cdot,s,t}\mu_{j,s,t}\left(\sum_{j\in s\cap t}\frac{R_{j,s,t}}{\sum\limits_{j\in s\cap t}R_{j,s,t}}-\sum_{j\in i\cap t}w_{i,j,\cdot,t}\right)\right)=0,$$

where the last equality follows from $\sum\limits_{j\in s\cap t}\frac{R_{j,s,t}}{\sum\limits_{j\in s\cap t}R_{j,s,t}}=\sum\limits_{j\in i\cap t}w_{i,j,\cdot,t}=1.$

(d) A sufficient condition for $p_{i,t}^{sb}=p_{i,t}^{s}$ is $w_{i,j,\cdot,t}=\frac{R_{j,s,t}}{\sum\limits_{j\in s\cap t}R_{j,s,t}}$ for all (i,j,s). Assumption (d1) says that $w_{i,j,\cdot,t}$ is constant across i and assumption (c2) implies that $\frac{R_{j,s,t}}{\sum\limits_{j\in s\cap t}R_{j,s,t}}$ is constant across s. Thus, we only need to show that the two terms are equal. This is indeed the case because the overall expenditure share of good j purchased by consumers, $\frac{\sum_i \bar{X}_{i,t}w_{i,j,\cdot,t}}{\sum_{i,j}\bar{X}_{i,t}w_{i,j,\cdot,t}}$, has to equal to the overall share of good j sold by stores, $\frac{\sum_s R_{j,s,t}}{\sum_{s,j}R_{j,s,t}}$ and we obtain

$$w_{i,j,\cdot,t}=\frac{\sum_i \bar{X}_{i,t}w_{i,j,\cdot,t}}{\sum_{i,j}\bar{X}_{i,t}w_{i,j,\cdot,t}}=\frac{\sum_s R_{j,s,t}}{\sum_{s,j}R_{j,s,t}}=\frac{R_{j,s,t}}{\sum\limits_{j\in s\cap t}R_{j,s,t}}\quad for\ all\ i\ and\ s.$$

and this holds for all j. We conclude that $w_{i,j,\cdot,t}=\frac{R_{j,s,t}}{\sum\limits_{j\in s\cap t}R_{j,s,t}}$ for all (i,j,s) and $p_{i,t}^{sb}=p_{i,t}^{s}$ for all i.

□

A final comment is in order. The proof of claim (c) does not hold when one only assumes that the price ratios are constant across stores $\frac{P_{j,s,w}}{P_{j',s,w}}=\frac{P_{j,s',w}}{P_{j',s',w}}$ for any (j,j',s,s'). One needs to add assumption (c1) saying that the ratio of quantity sold is also constant across stores $\frac{Q_{j,s,w}}{Q_{j',s,w}}=\frac{Q_{j,s',w}}{Q_{j',s',w}}$ for any (j,j',s,s'). These two assumption, which taken together imply assumption (c2), hold for example, when all goods are proportionally more expensive, and sold in proportionally smaller quantity, in more expensive stores.

C Online Appendix

Table 13 replicates in the IRI dataset the KM decomposition including the transaction component. Column 2 presents the result for the full decomposition (equation 1). Column 4 present the results for the KM decompostion applied to IRI. Column 5 presents the results of the KM decomposition applied to Nielsen reported in KM, Table 7, Column 3 (p.25).

Table 13: Full decomposition

	Full decom		KM-IRI	KM-Nielsen
$var(\Delta_{i,t}^{a,sg})$	70%	Transaction	70%	16%
$var(\Delta_{i,t}^{sg,sb})$	8%	Store-good	18%	53%
$var(\Delta_{i,t}^{sb,s})$	15%			
$var(\Delta_{i,t}^{s,m})$	13%	Store	13%	39%
$2cov(\Delta_{i,t}^{a,sg}, \Delta_{i,t}^{sg,sb})$	3%	2cov(tran,sg)	1%	5%
$2cov(\Delta_{i,t}^{a,sg}, \Delta_{i,t}^{sb,s})$	-3%			
$2cov(\Delta_{i,t}^{a,sg}, \Delta_{i,t}^{s,m})$	-3%	2cov(tran,s)	-3%	1%
$2cov(\Delta_{i,t}^{sb,s}, \Delta_{i,t}^{sg,sb})$	-6%			
$2cov(\Delta_{i,t}^{s,m}, \Delta_{i,t}^{sg,sb})$	1%	2cov(s,sg)	1%	-13%
$2cov(\Delta_{i,t}^{s,m}, \Delta_{i,t}^{sb,s})$	0%			
Sum=$var(p_{i,t}^{sg} - p_{i,t}^{m})$	100%		100%	100%

In Table 14, column A replicates the analysis using transaction prices instead of store prices to compute the normalized prices. Column B replicates column A after filtering out goods-market-quarters with fewer than 25 purchases. Column C replicates column B after filtering out panelist-quarters with fewer than 50 purchases. Column D replicates column C after filtering out panelist-quarters with only one store visited. Column 1 to 5 replicate column B for our five product categories, that is, carbonated soft drinks, cold cereal, milk, salty snacks and yogurt.

Table 14: Replication of the full KM decomposition using transaction data

	A	B	C	D	cate1	cate2	cate3	cate4	cate5	Nielsen
Transaction	50%	51%	47%	48%	52%	54%	60%	57%	63%	16%
Store-good	23%	23%	20%	19%	22%	24%	26%	22%	22%	53%
Store	20%	20%	24%	22%	25%	16%	13%	19%	10%	39%
2cov(tran,sg)	10%	9%	11%	12%	3%	7%	2%	3%	6%	5%
2cov(tran,s)	-1%	0%	-1%	-1%	0%	0%	0%	0%	0%	1%
2cov(sg,s)	-1%	-1%	-1%	0%	-1%	-1%	0%	-1%	-1%	-13%