



Price dynamics, retail chains and inflation measurement

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ABSTRACT

We use a large scanner price dataset to study grocery price dynamics. Previous analyses based on store scanner data emphasize differences in price dynamics across products. However, we also document large differences in price movements across different grocery store chains. A variance decomposition indicates that characteristics at the level of the chains (as opposed to individual stores) explain a large fraction of the total variation in price dynamics. Thus, retailer characteristics are found to be crucial determinants of heterogeneity in pricing dynamics, in addition to product characteristics. We empirically explore how the price dynamics we document affect price index measures.

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1. Introduction

Price index specialists are involved in defining, compiling and assessing the measures of inflation that central bankers and macro-economists rely on. Price dynamics have implications for the choice of a true target index for inflation. The nature of price dynamics is an important determinant also of the data collection methodologies adopted for price index programs.² For instance, sectors or products that exhibit more volatile prices (e.g., fresh fruit and vegetables) are typically sampled more frequently than product categories with more stable prices. As well, certain types of price dynamics can cause the selected measures for a target index to be biased.³ Ivancic et al. (2009) and Haan and van der Grient (2009) explain, for example, that the chain drift bias problem is caused by a particular sort of price dynamics known as

“price bouncing”, and they provide empirical evidence of this bias problem for Australia and The Netherlands.⁴

Temporary sales are a recognized source of price bouncing, and there is some evidence that the frequency of temporary sales has been increasing in the United States.⁵ The US Bureau of Labor Statistics (BLS) collects prices regardless of whether they are identified as “sale” or “regular” prices. The same is true for Statistics Canada.⁶ Thus the BLS and Statistics Canada are interested in evidence about the severity of chain drift price index bias and ways of reducing this problem. In contrast, Germany, Italy and Spain do not include price discounts for seasonal sales periods in their Consumer Price Index (CPI) data collection.⁷ Thus the statistical agencies in those nations are interested in empirical evidence about whether the movements of regular prices and sale prices are redundant for measuring trends and business cycle fluctuations in inflation.

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¹ The views expressed here are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Philadelphia or of the Federal Reserve System.

² See ILO (2004) and IMF (2004), the new International CPI and PPI Manuals.

³ A price index formula used for evaluating a target consumer price index is said to be biased if the expected value differs from the target index.

⁴ For other sorts of price dynamics that can cause price index bias, see Diewert et al. (2009), Diewert and Nakamura (1993), Feenstra and Shapiro (2003) and Sobel (1984). The paper of Ivancic and Fox (2010) also contains related material.

⁵ See Pashigian (1988) and Nakamura and Steinsson (2008).

⁶ Statistics Canada (1996, p. 5): “Since the Consumer Price Index is designed to measure price changes experienced by Canadian consumers, the prices used in the CPI are those that any consumer would have to pay on the day of the survey. This means that if an item is on sale, the sale price is collected”.

⁷ See the Technical Appendix in Dhyne et al. (2005).

Many previous analyses of retail price dynamics have focused on heterogeneity in pricing behavior across products, of which there is a great deal. One reason for this focus is that data broken down by product category has been more readily available. For example, the database of prices underlying the CPI for the United States is collected and organized according to product category. Also, numerous studies of retail price dynamics have used the Dominick's database at the University of Chicago Graduate School of Business which is for one retail chain.

In contrast, in this paper, we use a dataset consisting of millions of price observations per year at a large number of grocery stores in numerous retail chains to document the nature and dispersion of high frequency price dynamics across stores and chains (in addition to products). We document a vast amount of heterogeneity across retailers in the nature of pricing behavior even for identical products. While some chains exhibit frequent price drops associated with temporary sales and “high–low” pricing schemes, others exhibit more price stability such as those associated with “everyday low prices”. We find that pricing patterns at the level of chains (as opposed to individual stores) play a particularly large role in accounting for price dynamics. There is far more variation in pricing dynamics across chains for a given product than among stores within a given chain. We carry out a variance decomposition to analyze the importance of various determinants of the prevalence of price volatility and temporary sales. Our analysis reveals that the treatment of chains is an important issue for measures of aggregate pricing dynamics. Our analysis also provides a useful reference point for existing studies of individual stores or chains such those based on the Dominick's database.⁸

Our empirical analysis confirms that temporary sales, which occur frequently in many stores, are important determinants of price dynamics in the United States. To investigate the implications of this phenomenon, we compare price index measures calculated using all prices and those calculated using only “regular prices” (i.e., using only prices excluding temporary sales). Our results also confirm the importance for the United States of the chain drift problem documented for Australia by [Ivancic et al. \(2009\)](#) and for The Netherlands by [Haan and van der Grient \(2009\)](#). Our findings indicate that the extent of chain drift is likely to differ significantly across different products and chains.

In the price index area, another contribution of our results is to show that a substantial portion of the price dynamics associated with an individual outlet might be captured by looking at price movements for any representative store from the same chain. This finding is relevant as well for considering how the elemental unit of observation for inflation measurement should be defined. For example, [Diewert \(forthcoming\)](#) suggests that:

“[I]nstead of calculating outlet specific unit values for a commodity, a unit value could be calculated over all outlets in the market area”.

Section 2 presents a simple macroeconomic model of price rigidity as a conceptual framework for our empirical results. We introduce our data in Section 3. In Section 4, we present estimates of the frequency of price change computed with, and without, temporary sales as well as regular prices. We confirm for multiple product categories that the measured frequencies (and

other attributes) of price change differ greatly depending on the treatment of temporary sales. Also in the latter part of Section 4 and then in Section 5, we show that the measured attributes of price change differ greatly not just over products, but over stores, and especially for stores in different retail chains. In Section 6 we directly explore the implications of temporary sales for price index making, and find more evidence that temporary sales matter. Section 7 concludes.

2. Index number theory and models of price rigidity

The measures of price change studied by price index specialists, as well as central bankers and macroeconomists, have traditionally been defined in the context of utility theoretical models. In the economic theory of index numbers, the study of household price indexes focuses on the [Konüs \(1939\)](#) true cost of living index. This index is defined as the ratio of the minimum cost of achieving a certain reference utility level in a base period, given the prices prevailing at that time, versus at a later “current” period given the prices then. The target national price index for consumer products is a generalization of the Konüs true cost of living index for a single household (see [Pollak, 1980, 1981](#) and [Schultze and Mackie, 2002](#)). [Diewert \(1998\)](#) explains that in the index number literature, individuals, individually and collectively, are typically viewed as maximizing utility subject to exogenously given prices and incomes.

One puzzle for central bankers and macroeconomists is that the economic circumstances faced by businesses are in constant flux, but prices for most products change relatively infrequently.⁹ Menu cost models were created as an aid to understanding the observed price rigidity. Utility maximizing households play a central role in these models, much as in the models that price index specialists specify in defining a target consumer price index. However, instead of treating the prices and incomes as exogenously determined, a general equilibrium framework is used.

To illustrate the role of price dynamics in macroeconomic models, we sketch out a simple menu cost model with utility maximizing households and profit maximizing decision makers for grocery stores, chains, and the producers of the products sold in retail grocery stores. The model is a simple version of standard models in the monetary economics literature. A key feature is that retailers must pay fixed costs – “menu costs” – in order to make nominal price changes. Related models of price rigidity are widely used by macroeconomists as well as policymakers for analyzing the effects of monetary policy. Parameters such as the frequency of price change have important effects on the predictions of such models for the evolution of macroeconomic variables, and for their prescriptions for optimal monetary policy. Here, we have adapted the model to recognize the existence of chains, stores, and products with potentially different menu costs and idiosyncratic shocks.¹⁰ We should note that, while we view it as a useful starting point, there are important limitations of this simple model's ability to fit retail price dynamics.¹¹

Households are assumed to consume a continuum of differentiated products represented by the vector z . Element i, s, c of z represents the volume of product i bought at store s in chain c . That

⁹ See [Nakamura and Steinsson \(2008\)](#) and [Klenow and Kryvtsov \(2008\)](#) for recent analyses of this phenomenon.

¹⁰ See, for example, [Goloso and Lucas \(2007\)](#), [Midrigan \(2008\)](#) or [Nakamura and Steinsson \(2009\)](#) for recent examples of menu cost models in the monetary economics literature. The model we present here is adapted from the model analyzed in [Nakamura and Steinsson \(2009\)](#).

¹¹ For example, simple versions of this model do not generate temporary sales. See e.g., [Keohoe and Midrigan \(2008\)](#) for an extension of the menu cost model designed to fit this feature of the data.

⁸ Influential studies based on the Dominick's database include [Chevalier et al. \(2003\)](#). Many other studies of pricing and inventory behavior use descriptive statistics computed using the Dominick's data. For example, [Woodford \(2009\)](#) makes use of statistics reported for the Dominick's database by [Midrigan \(2008\)](#), and [Kryvtsov and Midrigan \(2008\)](#) calibrate their model based on statistics computed using the Dominick's database.

is, a particular value of z represents a particular product (e.g., a 2 L bottle of Coca Cola) purchased from a particular store in a particular chain. The composite consumption good, C_t , is a Dixit–Stiglitz index of the differentiated product–store–chain combinations defined as:

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz \right]^{\frac{\theta}{\theta-1}}, \tag{1}$$

where $c_t(z)$ denotes household consumption in period t , and θ denotes the elasticity of substitution for the differentiated goods.

For any given level of spending in period t , households are assumed to choose the consumption bundle that yields the highest level of the index C_t . This implies that household demand for z is

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta} \tag{2}$$

where $p_t(z)$ is the price vector for z in t . The price level for the economy, P_t , is

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz \right]^{\frac{1}{1-\theta}}, \tag{3}$$

and the households are assumed to maximize their discounted expected utility given by

$$E_t \sum_{j=0}^{\infty} \beta^j \left[\frac{1}{1-\gamma} C_{t+j}^{1-\gamma} - \frac{\omega}{\psi+1} L_{t+j}^{\psi+1} \right], \tag{4}$$

where E_t is an expectations operator conditional on information known at time t , C_t is household consumption, and L_t is household labor supply. As is typical for menu cost models, we assume that households discount future utility by a factor β per period, have constant relative risk aversion equal to γ , and have parameters ω and ψ that determine the level and convexity, respectively, of the disutility of labor.

On the producer side, we assume that the production function for each product–chain–store combination is

$$y_t(z) = A_t(z)L_t(z), \tag{5}$$

where, for period t , $y_t(z)$ denotes the output level which in equilibrium will equal consumption $c_t(z)$, and $L_t(z)$ denotes the quantity of labor employed for the production of z in period t . $A_t(z)$ is an “idiosyncratic shock” to the marginal cost of producing one unit (in quality adjusted terms) of the product–store–chain combination z . This term is a stand-in for all factors generating a desire for stores to adjust their prices. We assume that $A_t(z)$ has a distribution with mean 1 and variance $\sigma^2(z)$. Notice that our specification allows for the possibility that these idiosyncratic shocks may vary across the different product–store–chain combinations.

Letting $D_{t,t+j}$ denote the producer discount factor for time period t versus $t+j$, the expected discounted profits are given by

$$E_t \sum_{j=0}^{\infty} D_{t,t+j} \Pi_{t+j}(z), \tag{6}$$

where profits in t are given by

$$\Pi_t(z) = p_t(z)y_t(z) - W_t L_t(z) - K(z)I_t(z). \tag{7}$$

$I_t(z)$ is an indicator variable that equals 1 if the firm changes its price in period t and 0 otherwise, $K(z)$ is the “menu cost” (i.e., the fixed cost of price adjustment for product i in store s and chain c) and W_t is the wage rate. For simplicity, we assume that W_t is common to all firms, and that all idiosyncratic cost factors are incorporated in the idiosyncratic shock, $A_t(z)$. The producer is assumed to maximize the discounted expected sum of profits, given by Eq. (6), subject to Eq. (5) which is the production function,

as well as product demand and the evolution of wages, all of which may depend on the state of the macroeconomy.

Central bankers and macroeconomists are interested in determining when and how monetary policy can be used to tame inflation. Thus, they are interested in how exogenous price shocks are, or are not, passed on. In the model described above, the key parameter in determining how rapidly underlying shocks are passed on to prices is the magnitude of the menu cost $K(z)$. Standard models of how monetary policy affects the economy, including the workhorse policy models of central banks, build in assumptions about the frequency of price change based on estimated values reported in empirical studies. A key question, therefore, is what determines this cost, and whether it varies over time and across different firms in the economy.

3. Data

Our analysis is based on proprietary scanner price data, consisting of weekly price and quantity observations for product sales at grocery stores across the United States.¹² The scanner dataset we use is from a national sample of hundreds of grocery stores belonging to numerous grocery chains. The dataset represents over 20 billion dollars of retail sales annually for thousands of UPCs, with tens of millions of observations per year. Thus, we are working with a dataset that, in multiple dimensions, is orders of magnitude larger than the typical micro price data analyzed by the BLS.¹³ The retail stores covered by our data are a sample of grocery stores, including some supercenters, but excluding drug stores. These data are for the years 2001 through 2005. We focus on three categories of products: coffee, cold cereal, and soft drinks. Each product category contains a large number of distinct products identified by individual UPCs.

We construct weekly average prices (i.e., unit prices) for products defined at the Universal Product Code (UPC) level by dividing store level dollar sales by the sales volumes.¹⁴ Recent evidence indicates that what we refer to as temporary sales, or simply as sales, account for a large fraction of the volatility in unit prices.¹⁵ Our dataset includes a flag for whether a given price–quantity observation is associated with a temporary sale.¹⁶

Numerous previous studies have been carried out using scanner data for one or for a small number of stores or chains. For example, a number of important studies are based on the Dominick’s database, maintained by the University of Chicago Graduate School of Business, which is for a single retail chain. However, without broad store and chain coverage, it is impossible to properly address some of the questions taken up in our study.

¹² Our analysis is based on Information Resources, Inc. (“IRI”) data, as analyzed and interpreted by us, which are a subset of the data described in Bronnenberg et al. (2008). IRI has neither reviewed nor approved of any analyses or conclusions described in this paper.

¹³ It should be noted, however, that the store and chain coverage for the data are determined by the data provider instead of by a statistical sampling procedure of the type used by the BLS.

¹⁴ A UPC is an exact identifier of a product. This type of product identifier is much more specific than the product categories typically used by national statistical agencies (such as the ELI system used by the BLS or the European COICOP system). Our unit prices are for products identified by their UPC codes. This is the situation in which the use of unit values is said to be ideal, unlike some other uses made of unit values to describe price movements for mixed groups of products (see Diewert, forthcoming). For more on retail sector measurement, see Nakamura (1999).

¹⁵ For more on the importance of temporary sales for explaining retail price dynamics, see Pesendorfer (2002), Hosken and Reiffen (2004a,b) and Nakamura and Steinsson (2008).

¹⁶ The temporary sales are identified using a standardized algorithm, implemented by the data vendor, which identifies cases in which prices decline temporarily by substantial amounts. This algorithm is similar to the one described in Kehoe and Midrigan (2008).

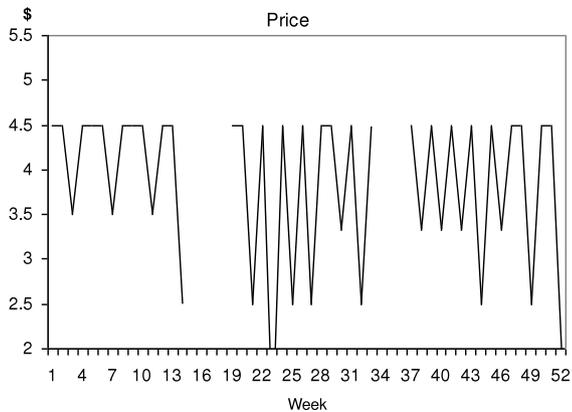


Fig. 1. Prices, “regular” prices and sales. The figure plots a price series for 12-packs of a particular soft drink UPC in the dataset. The frequent “V” shaped price movements are temporary sales.

A key advantage of the scanner dataset we use relative to other potential data sources, such as the CPI Research Database used in a number of studies (e.g., Hosken and Reiffen, 2004a; Bils and Klenow, 2004), is that it includes many different store quotes for most UPCs. In contrast, for the CPI Research Database, an average of just seven price quotes are collected per month for each product category and geographical area. Moreover, BLS price collection methods often result in different UPCs being collected at different stores so prices for a given UPC are only available for a single store in a particular geographical area. Even for questions that can be appropriately addressed using data for one store or chain, or for a small number of stores or chains, our data permit a check on the generality of the prior results.

4. Basic statistics on retail price dynamics

Fig. 1 depicts a typical price series from our dataset. The regular price of the product remains unchanged throughout the time interval despite frequent sales. In addition, there are missing price observations that arise due to stock-outs and in periods when a product was available but no units sold.

In principle, price changes are readily observable: one simply looks for differences in value for successive prices. However, to calculate the frequency of price change for data series like the one in Fig. 1, a procedure is needed for dealing with missing observations. We are also interested in studying the frequency of price change separately for regular prices and those including temporary sales.

One approach to measuring the frequency of price change is to focus only on contiguous pairs of observations. Fig. 2 shows how price changes are recognized for this procedure. The frequency of price change is the number of contiguous pairs of price observations (regular, or regular and sale prices, as specified) that have different values (i.e., the number of price changes for contiguous pairs) divided by the total number of contiguous pairs (including those with no price change).

A second procedure involves “filling in” the last observed price of any sort through periods with missing prices when computing the frequency of price change including sales, or filling in the last observed regular price through periods with missing prices and/or sale prices when computing the frequency of price change excluding sales.¹⁷ This procedure has the advantage that it yields many more observations for calculating the frequency of price change.

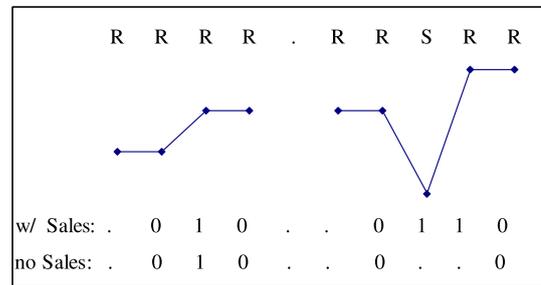


Fig. 2. Frequency of price change calculation for contiguous observations. Note: The figure illustrates that the first procedure can be used to estimate the frequency of price change in the presence of sales and missing values. The top row gives the sale flag value (“R” a regular price while “S” indicates a sale price). The “w/Sales” row toward the bottom gives the values of an indicator variable set equal to 1 for an observed price change (including price changes due to sales) and is set equal to 0 otherwise. The very bottom row gives the values for an analogous indicator for observed price changes excluding changes due to sales. The graph illustrates our approach based on “contiguous observations”. As explained in the text, we also consider an approach based on filling in missing prices, but that approach is not illustrated in this figure.

Tables 1 and 2 present results on the frequency of price change based on both procedures explained above for dealing with missing observations.¹⁸ The reported average weekly frequency and size of price change figures are weighted means, with the weights set equal to the dollar revenue figures for the included UPC–store–chain combinations.

In Table 1, significant differences are evident across the product groups in terms of the flexibility of prices. Also, the frequencies of price change including temporary sales are much higher than when the temporary sales prices are omitted. This indicates that a large fraction of retail price variability arises from temporary sales.

Table 2 presents an analogous set of statistics for the average absolute value of log price changes. These results can be interpreted as giving roughly the average percentage change in individual prices conditional on adjustment. These percentage change figures when sales prices are included (columns 1 and 3) are high relative, say, to aggregate inflation which averaged around 2% in the United States over 2001–2005. This finding suggests that the vast majority of grocery price movements are idiosyncratic to particular products, stores or chains as opposed to being common to the whole economy. Notice also that the absolute size of price change including sales is much larger than the absolute size of price change with sale prices excluded. The two procedures discussed yield similar qualitative results, as others have also found. Hence, in the rest of our tables, we present only results based on the “filled-in” procedure.

Column 1 of Table 3 reports the fractions of weeks when products in the different categories were on sale. Though substantial, all these fractions are less than half. Yet, the second column of Table 3 shows that sales account for more than three fourths of the price changes.¹⁹

We next provide evidence on the variation in price dynamics across stores for a given product. Columns 1 and 2 of Table 4 report the standard deviation for the frequency of price change across UPCs within each product category, with and without including temporary sales prices. The estimated standard deviations when

¹⁷ See Nakamura and Steinsson (2008) for a detailed discussion of the differences between “filled-in” and contiguous observations.

¹⁸ Both types of procedures are sometimes used by the BLS in dealing with missing observations in the calculation of aggregate price indexes. The BLS does not make use of the “fill-in” procedure for compilation of the CPI except in exceptional cases, but this is often used by the BLS in the construction of import and export price indexes.

¹⁹ The statistic is calculated by comparing the frequency of sale and non-sale price change reported in Table 1.

Table 1
Summary statistics on frequency of price change.

Category	"Filled-in" prices		Contiguous observations	
	Including temp. sales (%)	Excluding temp. sales (%)	Including temp. sales (%)	Excluding temp. sales (%)
Coffee	30.2	6.83	33.8	13.1
Cold cereal	26.0	5.98	27.5	8.81
Soft drinks	54.2	7.21	57.2	27.2

Note: The table reports the weighted mean frequency of price changes for each of the product categories discussed in the paper. The weights are the total dollar sales for each UPC–store combination.

Table 2
Summary statistics on absolute size of price changes.

Category	"Filled-in" prices		Contiguous observations	
	Including temp. sales (%)	Excluding temp. sales (%)	Including temp. sales (%)	Excluding temp. sales (%)
Coffee	19.0	7.98	18.7	7.40
Cold cereal	27.1	4.12	27.2	4.12
Soft drinks	20.0	8.75	20.0	8.60

Note: The table reports the weighted mean absolute size of price changes for each of the four categories discussed in the paper. The weights are the total dollar sales for a given product–store combination.

Table 3
Summary statistics on prevalence of temporary sales.

Category	Frequency of temp. sales (%)	Fraction of price changes due to temp. sales (%)
Coffee	24.4	77.4
Cold cereal	17.8	77.0
Soft drinks	44.0	86.7

Note: The table reports the weighted mean frequency of temporary sales for each of the four categories discussed in the paper. The weights are the total dollar sales for a given product–store combination. Missing observations are filled in.

sale prices are included are substantially larger than when sale prices are excluded (a range of 10%–20% versus 3%–7%). We see, therefore, that a substantial fraction of the cross-sectional variation in the frequency of price change arises from variation in the prevalence of temporary sales.

Columns 3 and 4 of Table 4 show the values for the standard deviation for the frequency of price change across stores. The ranges of values in column 3 (with sale prices included) and column 4 (with sale prices excluded) are similar to the ranges of values in column 1 and column 2, respectively. However, the standard deviation for the frequency of price change across stores *within* chains (columns 5 and 6) is much smaller than for the frequency of price change across all stores (columns 3 and 4). Looking now at Table 5 and comparing the column 3 figures (for variation across stores within chains) with the columns 1 and 2 figures, we see that a substantial amount of the variation in the prevalence of sales across stores is accounted for by differences among chains.

We next investigate the extent to which the variability in price dynamics across stores and products can be related to differences in product popularity and store size. Table 6 reports the results of regressions of the frequency of price change and of temporary sales on total sales revenue for given UPCs. The analysis answers the question of whether UPCs tend to exhibit different price adjustments depending on the volumes sold (e.g., the volumes for Coke versus less popular soft drink products). We find a robust positive relationship between UPC sales volumes and price flexibility. For the product categories we study, an increase in total sales volume of one hundred thousand dollars is associated with an increase in the frequency of price change when temporary sales prices are included of 0.5%–1% points, an increase in the frequency of price change when temporary sales prices are excluded of 0.04%–0.2% points, and an increase in the frequency of temporary

sales of 0.4%–0.7% points. In all cases but one, the estimated relationship is statistically significant.²⁰

In addition, we also ran OLS regressions of the frequency of price change and temporary sales on the size of the store, where the latter is measured by the estimated annual total sales volume for all products for a store, in millions of dollars. In our dataset, the annual store sales volumes range from around 5 million dollars to over 40 million dollars. The results are reported in Table 7. We find that larger stores tend to have more frequent price changes and temporary sales. These effects are statistically significant in all categories considered.

5. Variance decompositions

To more formally analyze the role of products, stores, and chains in explaining cross-sectional variation in price dynamics, we next decompose the observed price variation into two broad classes: (1) variation common to all UPCs within a given product category (such as coffee), and (2) variation common only to all items with the same UPC.²¹ Within each of these broad classes, we further decompose the cross-sectional variation into variation common across all stores, variation common only to stores within a chain, and variation for items sold at specific stores. In formal terms, we estimate the following nested random effects model,

$$f_{csi} = \alpha_i + (\varphi_c + \varphi_{ci}) + \gamma_{cs} + \varepsilon_{csi}, \quad (8)$$

where f_{csi} is the frequency of price change for UPC i sold at store s which is part of chain c , and α_i , φ_c , φ_{ci} , γ_{cs} and ε_{csi} are random effects assumed to be identically and independently normally distributed; i.e., $\alpha_i \sim N(\mu_{\alpha_i}, \sigma_{\alpha_i}^2)$, $\varphi_c \sim N(\mu_{\varphi_c}, \sigma_{\varphi_c}^2)$, and so on.

The model specified allows for a wide variety of correlation structures across products, stores and chains. The first component, α_i , is common to all retail stores selling a given UPC. The second component, $\varphi_c + \varphi_{ci}$, is common to all stores in a chain.²² The third term, γ_{cs} , is common only to a particular store in a given chain. Finally, the residual, ε_{csi} , picks up all remaining variation in the frequency of price change which is specific to both a particular store (within a given retail chain) and a particular

²⁰ This regression illustrates a statistical relationship between the frequency of retail sales and UPC sales volumes; not a causal relationship. Indeed, more frequent retail sales are one potential cause of increased UPC sales volume.

²¹ Nakamura (2008) carries out a related variance decomposition using a much more limited dataset.

²² Here φ_c is common to all UPCs while the second term, φ_{ci} , applies only to a particular UPC.

Table 4
Cross-sectional variation in price flexibility.

Category	Across UPCs		Across stores		Across stores within chains	
	Including temp. sales (%) (1)	Excluding temp. sales (%) (2)	Including temp. sales (%) (3)	Excluding temp. sales (%) (4)	Including temp. sales (%) (5)	Excluding temp. sales (%) (6)
Coffee	12.3	3.54	19.0	4.15	4.80	1.60
Cold cereal	11.1	3.13	10.6	5.35	3.88	1.34
Soft drinks	20.8	6.68	13.7	4.10	5.48	2.26

Note: The table reports the cross-sectional standard deviation in the frequency of price change across stores and across stores within particular retail chains. These statistics are calculated by first calculating the cross-sectional standard deviation in the frequency of price change across stores (or across stores within chains), and then calculating the weighted mean value of this statistic. Missing observations are filled in.

Table 5
Cross-sectional variation in prevalence of retail sales.

Category	Across UPCs (%)	Across stores (%)	Across stores within chains (%)
Coffee	10.7	8.31	3.88
Cold cereal	8.20	7.55	2.94
Soft drinks	16.0	10.8	6.12

Note: The table reports the cross-sectional standard deviation in the frequency of temporary sales across stores and across stores within particular retail chains. These statistics are calculated by first calculating the cross-sectional standard deviation across stores (or across stores within chains), and then calculating the weighted mean value of this statistic. Missing observations are filled in.

Table 6
Effect of total UPC sales volume on price flexibility.

Category	Freq. including sales	Freq. excluding sales	Freq. of temporary sales
Coffee	0.934 (0.075)	0.181 (0.023)	0.678 (0.067)
Cold cereal	0.692 (0.032)	0.152 (0.011)	0.367 (0.030)
Soft drinks	0.592 (0.046)	0.039 (0.016)	0.490 (0.035)

Note: The table reports the coefficient of total UPC sales volume (in hundreds of thousands) on percentage frequency of price change or temporary sales. Standard errors are in parentheses. Missing observations are filled in.

Table 7
Effect of store size on price flexibility.

Category	Freq. including sales	Freq. excluding sales	Freq. of temporary sales
Coffee	0.282 (0.047)	0.129 (0.018)	0.139 (0.039)
Cold cereal	0.396 (0.053)	0.184 (0.027)	0.136 (0.041)
Soft drinks	0.397 (0.072)	0.030 (0.023)	0.161 (0.059)

Note: The table reports the coefficient of store size (in millions) on percentage frequency of price change or temporary sales. Standard errors are in parentheses. Missing observations are filled in.

UPC. The parameters of the model are estimated using maximum likelihood.²³ These estimated model parameters were used to decompose the sources of variation in the frequency of price change across products and retail outlets. This decomposition was carried out separately for each product category.²⁴

Table 8 shows the decomposition results for all prices. Looking across the rows of Table 8 for each of the product categories, the column 1 value is the fraction of the variation common to all stores selling a particular UPC (α_i), the column 2 value is the fraction common to all UPCs for all the stores in a given chain (φ_c), and

Table 8
Variance decomposition of price flexibility (including sales).

Category	UPC (%) (1)	Retail chain (%) (2)	UPC–retail chain (%) (3)	Retail store (%) (4)	UPC–retail store (%) (5)
Coffee	37.2	20.4	27.1	5.62	9.58
Cold cereal	42.0	30.1	19.8	3.39	4.72
Soft drinks	53.7	12.9	24.4	1.42	7.50

Note: The variance decomposition is estimated using the average frequency of price change for prices including sales by store and UPC. Missing observations are filled in.

Table 9
Variance decomposition of price flexibility (excluding sales).

Category	UPC (%) (1)	Retail chain (%) (2)	UPC–retail chain (%) (3)	Retail store (%) (4)	UPC–retail store (%) (5)
Coffee	16.4	18.1	28.1	8.30	29.1
Cold cereal	9.42	39.7	24.6	9.65	16.6
Soft drinks	32.6	8.62	33.7	2.69	22.5

Note: The variance decomposition is estimated using the average frequency of price change for prices excluding sales by store and UPC. Missing observations are filled in.

Table 10
Variance decomposition of prevalence of retail sales.

Category	UPC (%) (1)	Retail chain (%) (2)	UPC–retail chain (%) (3)	Retail store (%) (4)	UPC–retail store (%) (5)
Coffee	38.2	15.2	30.2	4.05	12.4
Cold cereal	36.8	26.0	28.4	2.74	5.99
Soft drinks	48.2	13.9	23.1	1.71	13.1

Note: The variance decomposition is estimated using the average frequency retail sales by store and UPC. Missing observations are filled in.

the column 3 value is the fraction of the variation common only to a particular UPC for a particular chain (φ_{ci}). The remaining two columns pertain to the fraction of the variation common only to a particular store. Column 4 gives the fraction common to all UPCs at a particular store (γ_{cs}), and column 5 gives the residual variation common only to a particular UPC and store (ε_{csi}).

We also carried out similar variance decompositions for prices excluding temporary sales. These results, shown in Table 9, are broadly similar to the Table 8 results for prices including sales. Also, Table 10 presents the corresponding estimates of the components of cross-sectional variation in the frequency of temporary sales. Similar patterns again emerge. There is far more variation in the frequency of temporary sales across chains for a given product than among stores within a given chain. Chain-wide decisions or shocks dominate the pricing dynamics. These results suggest it is important that statistical agencies collect price observations from a representative selection of retail chains. Price dynamics variation across chains is likely to also lead to variation in the number of observations needed in a product category to calculate an accurate price index, and to variation in the importance of certain measurement problems.

²³ See e.g. Baltagi (2005) for an excellent survey of these methods.

²⁴ We include in the sample we use for estimation all cases in which a UPC is sold in at least two retail stores and is present for all five years of the dataset.

In the context of the theoretical model presented in Section 2, variation in the frequency of price change across stores is viewed as arising from a combination of variation in menu costs $K(z)$ and the volatility of idiosyncratic shocks $\sigma^2(z)$ that motivate variation in the desired price. Our empirical results suggest that the variation in these parameters across stores arises primarily from variation at the chain level. Variation in menu costs $K(z)$ at the chain level could reflect chain-level variation in the cost-effectiveness of pricing decision making. Or it could arise from chain-specific differences in the technology for implementing price changes, including even the approach used to put price stickers on product items. Similarly, chain-level differences in the volatility of idiosyncratic shocks $\sigma^2(z)$ could arise from variation in bargaining ability at the chain level. It is well-known that much of the negotiation over wholesale prices for grocery products takes place at the chain level (as opposed to the store level). If some grocery chains are more successful at negotiating stable wholesale prices from producers, this could lead to lower variation in desired prices and a lower frequency of price change for those chains (e.g., the Wal-Mart “every day low pricing” policy).²⁵ Finally, inventory management technologies could be another source of chain-level variation in $\sigma^2(z)$ and hence in the volatility of desired prices.

6. Price dynamics implications for price index construction

We now take up the implications of our results for consumer price index making. The (fixed base) period t Laspeyres price index (P_L^t) can be written as follows:²⁶

$$P_L^t \equiv \sum_i w_i^0 (p_i^t / p_i^0), \quad (9)$$

where p_{i0} is the base period price of product i , p_{it} is the price of product i in period t for $t = 1, \dots, T$, and w_i^0 is good i 's share of total expenditure in period 0.²⁷ Eq. (9) aggregates unit value indexes by using base period share weights. The period t Paasche price index (P_P^t) can similarly be written as follows:

$$P_P^t \equiv \left[\sum_i w_i^t (p_i^0 / p_i^t) \right]^{-1}, \quad (10)$$

where w_i^t is product i 's share of total expenditure in period t , for $t = 0, \dots, T$. The Fisher index formula is the geometric mean of the Laspeyres and Paasche indexes; i.e.,

$$\text{Fisher}_t = [\text{Paasche}_t \times \text{Laspeyres}_t]^{1/2}.$$

Sometimes expenditure data are not available. One way of proceeding in this case is to set all of the weights in the Fisher index equal to the reciprocal of the sample size. We refer to the resulting index hereafter as the *unweighted Fisher*.²⁸

We first consider how price indexes differ depending on whether they are constructed using only regular prices or all prices.²⁹ We also present evidence regarding the chain drift bias

problem that can result from temporary sales activity. Chained price index measures are usually recommended as one way of mitigating the product attrition problems that plague price index programs. However, it has been shown in the price measurement literature that price bouncing, of the sort caused by temporary sales, can cause chain drift bias. This part of our study builds on the related research of Ivancic et al. (2009) (IDF) and Haan and van der Grient (2009) (HG). IDF show for Australia and HG show for The Netherlands that price bouncing combined with the use of chained price indexes can lead to unacceptably large chain drift.³⁰ We also consider how price indexes differ depending on whether prices are averaged only across stores within chains versus across all stores.

Tables 11–13 compare the values of the price indexes depending on whether they are calculated using all prices or using only regular prices. All three of these tables present results for both the weighted and unweighted Fisher index.³¹

Table 11 is for the case of no item aggregation across stores; that is, the unit values used to construct the index numbers are the raw price data. The results are different for the index of all prices and the index with only regular prices. For the regular Fisher index, this difference ranges from 2%–20%. The difference is smaller for the unweighted Fisher index, ranging from 1%–10%. We would not expect such substantial differences in the absence of chain drift since once a temporary sale is finished, the price returns to the regular price in effect before the sale began.³²

Table 12 is for the case of item aggregation across all stores; i.e., in this case the unit values used to construct the index numbers are averages across all stores for a given UPC. As noted by HG and IDF, this procedure may ameliorate chain drift bias by reducing “bouncing” in prices and quantities. In all of the categories we consider, averaging across stores also reduces the difference between the indexes based on all prices and those based on just regular prices. For the weighted index, the difference between the index based on all prices and the index based only on regular prices falls to between 1% and 6%. For the unweighted index, the difference between the two indexes falls to between 0.6% and 6%. This finding is related to our findings in Sections 4 and 5 that there is a large amount of heterogeneity in pricing dynamics across stores even after controlling for the UPC. This implies that averaging across stores should yield smoother price series than using the raw data. However, IDF note that this procedure has the disadvantage that the unit values are calculated as averages across potentially heterogeneous products if consumers view differences in the locations and shopping experiences offered by different stores as changing the value to them of the purchased grocery products.

Another approach suggested by IDF is to aggregate across stores within retail chains. The results for this approach are presented in Table 13. With this approach, the difference between the indexes of all prices versus just regular prices does not diminish as much as with aggregation across all stores. This finding is consistent with our earlier finding in Sections 4 and 5 that a large fraction of the heterogeneity in pricing behavior across stores is due to differences across chains.

²⁵ See, for example, Fishman (2003).

²⁶ See Diewert (forthcoming) for further details and references.

²⁷ The prices are unit values for product classes for each period t of the specified unit time period.

²⁸ Erwin Diewert pointed out to us that in the international Consumer Price Index Manual (ILO, 2004, p. 361, Paragraph 20.43), this index is labeled as P_{CSWD} ; that is, it is labeled as an index that was suggested by Carruthers et al. (1980) and Dalen (1992, p. 140) in the elementary index context. But this index was also suggested by Fisher (1922, p. 472) as his formula 101 and he observed that it was very close to the unweighted geometric mean Jevons index and stated that these two indexes were his best unweighted indexes.

²⁹ This is a particularly relevant exercise considering that a number of statistical agencies including Germany, Italy and Spain explicitly do not collect sale prices as part of the CPI, as was noted in Section 2.

³⁰ This is so even when superlative index number formulas are used (see Haan, 2008). For earlier work on this bias problem, see Szulc (1983).

³¹ The tables present the value of the index at the end of 12 months of data for 2004, assuming an initial value of 100 for the first month. Limiting this portion of the analysis to 12 months made the computations manageable without imposing procedures at this point to reduce the sample size. The sample used to calculate these indexes is described in Nakamura (2008). Using 12 months for the calculations in this section also means that the results are roughly comparable with those of IDF who use 15 months for their index measure calculations.

³² Recall from Section 3 that a temporary sale is identified in our data by the data vender as a short-lived drop below the “regular price”.

Table 11
Price indexes based on monthly sale and non-sale prices (no item aggregation over stores).

Category	Chained Fisher			Chained unweighted Fisher		
	Including temp. sales	Excluding temp. sales	Diff	Including temp. sales	Excluding temp. sales	Diff
Coffee	111.3	109.6	1.7	101.7	102.3	−0.6
Cold cereal	95.9	101.8	−5.9	102.1	104.3	−2.2
Soft drinks	91.2	109.8	−18.6	94.4	102.6	−8.2

Note: The table reports the year-end price index based on alternative measurement approaches assuming an initial value of 100. The “Diff” columns show the differences in the indexes with and without temporary sales.

Table 12
Price indexes based on monthly sale and non-sale prices (item aggregation over all stores).

Category	Chained Fisher			Chained unweighted Fisher		
	Including temp. sales	Excluding temp. sales	Diff	Including temp. sales	Excluding temp. sales	Diff
Coffee	104.9	103.6	1.3	101.8	102.4	−0.6
Cold cereal	103.4	103.0	0.4	102.4	103.2	−0.8
Soft drinks	99.0	104.5	−5.5	96.8	102.6	−5.8

Note: The table reports the year-end price index based on alternative measurement approaches assuming an initial value of 100. The “Diff” columns show the differences in the indexes with and without temporary sales.

Table 13
Price indexes based on monthly sale and non-sale prices (item aggregation over stores within chains).

Category	Chained Fisher			Chained unweighted Fisher		
	Including temp. sales	Excluding temp. sales	Diff	Including temp. sales	Excluding temp. sales	Diff
Coffee	112.3	109.7	2.6	101.9	104.1	−2.2
Cold cereal	97.7	101.9	−4.2	102.6	103.3	−0.7
Soft drinks	91.9	109.7	−17.8	96.6	106.0	−9.4

Note: The table reports the year-end price index based on alternative measurement approaches assuming an initial value of 100. The “Diff” columns show the differences in the indexes with and without temporary sales.

7. Conclusion

Our empirical results address questions related to price dynamics that are relevant to central bankers and macroeconomists as well as price index specialists. One key finding is that the treatment of temporary sales matters for inflation measurement, analysis and forecasting purposes. Our results definitely show that the implications of temporary sales for index number measurement cannot be ignored when constructing price indexes.

A second finding is that in addition to the product characteristics emphasized in the measurement and the macroeconomics literature, retailer characteristics are crucial determinants of heterogeneity in pricing dynamics. We show that a substantial fraction of this variation is accounted for by differences across chains, as opposed to among stores within chains.

Our conclusions about the importance of chain-level pricing have potential applicability as well for improving the efficiency of CPI sampling. One implication is that it would be appropriate to sample more chains and fewer stores per chain. In addition, because there are systematic differences in price dynamics between smaller and larger retail outlets, and analogous differences in price dynamics for different UPCs depending on their sales volumes, it also seems important for statistical agencies to recognize that the appropriate sampling methodology may differ depending on the popularity of products and outlets.³³

Because much of the variation in price data is idiosyncratic to particular stores, averaging across stores is likely to ameliorate measurement challenges associated with price bouncing. However, this approach has the downside that it involves averaging prices over stores with potentially heterogeneous quality.

Ivancic et al. (2009) therefore recommend that “statistical agencies that have access to scanner data form their unit values by ...[aggregating over] stores which belong to the same supermarket chain”.

However, our analysis suggests that since retail price dynamics are also more similar within chains, although averaging within chains will ameliorate the chain drift problem, the improvement will be less than for averaging across chains. Of course, this finding does *not* mean that statistical agencies should average prices across potentially heterogeneous retail chains.³⁴ What our results imply is that the chain drift problem will not be solved solely by averaging data across stores within retail chains. A more hopeful solution appears to be the use of drift-free indexes such as the one developed by Ivancic et al. (2009). Our results answer some of the questions considered, but leave others for future study. In a 2004 interview about the development of his own career, Arnold Zellner explained:

“I learned much about measurement and its important role in providing data to test alternative explanations or theories and to stimulate theorists to devise new theories to explain observed properties of the data, a very fundamental role of measurement in science”.

Zellner quoted by Morrissey (2004).

Similarly, we hope our measurement findings will stimulate both other empirical researchers and also theorists to deepen our

³³ Previously, Greenlees and McClelland (2007, 2008) documented the importance of chain competition for outlet bias in CPI measurement (see also Reinsdorf, 1993).

³⁴ Different amounts of transportation and other purchased services and time from household members may be involved when households change where they shop. For instance, a consumer may need to spend more time and use more gasoline driving to a superstore that offers cheaper prices on products they buy compared with a neighborhood grocery store. This type of substitution is difficult to allow for empirically, however, because some of the goods and services involved are bundled and sold together along with the location and other shopping amenities offered by the stores where a consumer chooses to shop.

collective understanding of price dynamics and to develop improved methods for price index measurement that build on this research.

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