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Informational rigidities and the stickiness of temporary Sales[☆]

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ABSTRACT

How do retailers react to cost changes? While temporary sales account for 95% of price change in our data, retail prices respond to a wholesale cost increase entirely through the regular price. Sales actually respond temporarily in the *opposite* direction from regular prices, as though to conceal the price hike. Additional evidence from responses to commodity cost and local unemployment shocks, as well as broader evidence from BLS data, reinforces these findings. Institutional evidence indicates that sales are complex contingent contracts, determined substantially in advance. In a standard price-discrimination model, these institutional practices leave little money "on the table".

1. Introduction

The speed of price adjustment to aggregate shocks is a central determinant of the effects of demand shocks on output and in particular the effects of monetary and fiscal policy. In an influential study, Bils and Klenow (2004) show that consumer prices adjust quite frequently. Subsequent empirical work has shown, however, that much of this price flexibility is due to temporary sales, which have empirical characteristics that are vastly different from "regular" price changes (Nakamura and Steinsson, 2008). An important question is to what extent price changes associated with temporary sales contribute to the adjustment of aggregate inflation to aggregate shocks.

A growing literature on sticky information points out that even if prices do change, they may fail to respond to recent economic shocks if the information set on which the price changes are contingent is old (e.g., Mankiw and Reis, 2002; Burstein, 2006). In these cases, the prices may be flexible but follow "sticky plans" whereby pricing decisions are made only periodically. Section 8 discusses how the institutions of price setting in the consumer packaged goods industry are such

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that the timing and magnitude of sales are determined by trade promotion budgets and schedules that are largely set at low frequencies.

Motivated by this institutional evidence, we investigate to what extent temporary sales reflect sticky plans as opposed to playing an important role in how retailers respond to cost shocks. The paper uses a detailed data set on retail and wholesale prices from a large US retailer over the period 2006–2009. Our main empirical exercise is to study how the retailer responds to wholesale cost increases. If both regular prices and sales are equally flexible margins of adjustment, then in response to a wholesale cost increase, the retailer might (1) raise the regular price, (2) decrease the frequency or size of sales, or (3) both.[1] Because temporary sales account for 95% of all price changes in our data, one might think that sale prices account for a large share of retail price adjustment to cost shocks.

Our findings contrast strongly with this prediction. In a substantial fraction of cases, when the base wholesale price increases, the regular retail price responds quickly and completely. In the remaining cases, the regular retail price responds more incompletely and with some delay. However, in neither of these cases do we find any evidence of a decrease in the frequency or size of temporary sales. To the contrary, we find that discounts temporarily *increase* when regular retail prices increase in response to a wholesale price increase–suggesting that the retailer is trying to mask the associated regular price increase.

We present three additional pieces of evidence for our central finding that sales do not play an important role in how prices respond to macroeconomic shocks. First, we provide evidence that temporary sales fail to react to commodity cost shocks. While the frequency of regular price increases roughly quadrupled in response to the sharp commodity price increases in the middle part of our sample (i.e., the Great Recession), we find no response in sales. Second, we provide evidence that temporary sales fail to react to changes in local unemployment rates. Third, we use BLS microdata to show that time variation in sale prices does not contribute to the variance or cyclicality of inflation, or to the response of inflation to an identified monetary policy shock in a vector autoregression (VAR).[2] This generalizes our finding that retailers do not use sales to respond to shocks beyond just a single retailer.

We conclude the paper by asking two questions. First, we ask why retailers respond to cost and demand shocks by adjusting regular prices instead of sale prices. We use Hendel and Nevo's (2013) model of sales to study the profit losses that firms face in not adjusting their discounts in response to cost shocks. In this model, the optimal response to higher costs is for the retailer to raise regular prices and reduce discount depth. However, the profit advantage to the retailer from optimally adjusting the magnitude of discounts in response to changes in marginal costs is miniscule: two orders of magnitude smaller than the benefits of price discrimination per se. While the use of sale prices to price discriminate is crucially important, varying the extent of price discrimination in response to a cost shock is not.

Second, given that 95% of the price variation in our data is explained by sales, are sale prices truly flexible? We present institutional features of retail and wholesale pricing for consumer packaged goods that indicate that sale prices are governed by sticky plans. Most sales are "funded" out of trade promotions budgets and planned substantially in advance according to a "trade promotions calendar." Both the trade promotions budget and the calendar are revised only infrequently. Hence, although the trade promotion system yields price variation, the system itself is not easily varied.

These institutional features also help to reconcile our findings with previous results reported by Eichenbaum et al. (2011) (henceforth, EJR). In particular, the finding that retailers respond to cost increases using the regular price instead of sale prices may at first appear to be at odds with EJR, who find that the vast majority of sales are associated with a change in wholesale prices. Does this imply that sales are, in fact, a key part of the response to wholesale price movements? Not necessarily. EJR's measure of wholesale prices includes manufacturer trade deals. Our discussion of the institutions of pricing in consumer packaged goods highlights two institutional features of trade deals that suggest we need to be cautious when interpreting variation in sale prices in response to trade deals as a measure of whether retailers use sale prices to respond to cost shocks. First, since reductions in wholesale prices during trade deals are often "funded" from trade deal budgets, which retailers are "spending down" when they hold a sale, observed movements in wholesale prices associated with such trade deals may not reflect true reductions in marginal costs (much like plane tickets purchased with frequent flyer points are not free). But if marginal costs do not change at the time of trade deals, why do retailers change the retail price at these times? They do so because a contractual obligation is associated with receiving the trade deal funds—the second institutional feature of trade deals we wish to emphasize in this context. Trade deals are jointly planned well in advance, and manufacturers often require evidence that the retailer actually put the product on sale before they will release the allocated funding from the trade deal budget. These institutional features of trade deals help to explain why EJR's estimates of cost pass-through from wholesale prices (including trade deals) are so much higher than estimates of the pass-through of underlying manufacturer costs (see, for example, Nakamura and Zerom, 2010, and Hong and Li, 2017).

Although trade deal budgets are generally stable, we recognize that they are not completely inflexible. Manufacturers may occasionally adjust their trade deal budgets, and these events could be interpreted as cost shocks to the retailer. Moreover, we cannot rule out the possibility that such adjustments are sometimes influenced by macroeconomic conditions. However, we see no evidence of this in our investigation of (1) the response to commodity cost shocks, (2) the response to changes

[1] Section 7 shows that both outcomes are predicted by Hendel and Nevo's (2013) model.

[2] There is some evidence of a lower-frequency relationship between the level of discounts and unemployment, as emphasized by Kryvtsov and Vincent (2014), but even there, the magnitude of the cyclical fluctuations in the discount is very small. See our discussion at the end of Section 6.

in local unemployment rates, or (3) the BLS microdata. All three pieces of evidence are inconsistent with the view that manufacturers use trade promotions to respond to macroeconomic shocks and that this variation is passed on by retailers through their sale prices.

It is also important to acknowledge that even if retailers do not respond to macroeconomic shocks by adjusting the size or frequency of sales, *consumers*' use of sales may still respond. Indeed, a number of recent papers emphasize this effect.[3] This type of consumer response is, nevertheless, fundamentally different from a firm-level response, since it is entirely consistent with the presence of important price adjustment frictions.

Our paper is related to several recent papers that study the behavior of regular prices and sales from a macroeconomic perspective. Recent theoretical papers investigate why it may be important to distinguish between regular prices and sales in measuring the flexibility of prices. EJR show that weekly grocery prices change frequently but fluctuate around "reference prices" that remain constant for some time. To rationalize these findings, they develop a model of "price plans": firms choose a small set of prices that they can freely move between, but a menu cost applies whenever the plan is changed. In this model, the effects of monetary policy are more tightly tied to the behavior of reference prices than to all prices. Similarly, Kehoe and Midrigan (2015) point out that even if temporary sales completely respond to movements in underlying costs, the temporary nature of sales implies that they contribute much less to the adjustment of the aggregate price level than do regular price changes. Guimaraes and Sheedy (2011) develop a model in which temporary sales are used for price discrimination. In their setup, sales are strategic substitutes, implying that they tend to average out in the cross section and have little impact on aggregate prices. Chevalier and Kashyap (2014) also develop a price-discrimination model. They use it to explore the implications of temporary sales for constructing price indices.

A more empirically focused literature has also blossomed, with a key question being whether temporary sales respond to aggregate shocks. Using US consumer price index (CPI) microdata, Klenow and Willis (2007) argue that the size of sale-related price changes is more responsive to inflation than is the size of regular price changes. Kryvtsov and Vincent (2014) show that the frequency of sales is correlated with unemployment in the United Kingdom. They also present some evidence for the United States for a subset of the time period we study. See Section 6 for a discussion of this evidence. On the other hand, Coibion et al. (2015) find that US retailers' use of sales does not vary with unemployment, while Berardi et al. (2015) find, using French CPI data, that aggregate inflation and unemployment have less effect on price changes associated with sales than they do on regular price changes.

The paper proceeds as follows. Section 2 describes the data. Section 3 illustrates the importance of sales in explaining retail price fluctuations in our data. Section 4 presents our main analysis of how regular prices versus sales respond to changes in the base wholesale price. Section 5 presents our evidence on price responses to the commodity cost run-up and relative unemployment rates. Section 6 presents our broader analysis of the BLS data. Section 7 presents our analysis of the Hendel and Nevo (2013) model of price discrimination. Section 8 discusses the institutions of manufacturer and retail pricing, and their implications for the role of different price-setting mechanisms in the responsiveness of prices. Section 9 concludes.

2. Data

The scanner price data that we use in the paper come from a large retailer that sells products in the grocery, health and beauty, and general merchandise categories. Data from this retailer have been used in other published studies, including Anderson et al. (2015) and McShane et al. (2016), who report findings using different data sets. The data used in this paper contain 195 weeks (15 quarters) of store transactions at a sample of 102 stores. The 195 weeks extend from the first quarter of 2006 through the end of the third quarter of 2009. The stores were selected as a control group for a pricing test conducted by the retailer and are considered representative of the retailer's stores. The stores are located in 14 Midwest and East Coast states. Because they are in different "price zones," the Regular Retail Price and the Retail Price (including temporary sales) for a stock keeping unit (SKU) in a given week differ across stores.

For this sample, we have data on the number of units sold each week for each product at the SKU level at each store. The data set reports three price measures: (1) the Regular Retail Price, (2) the Retail Price that was actually paid (including any temporary sales), and (3) the Base Wholesale Price of the item. The Retail Price reflects the average price actually charged by the retailer and excludes potential confounds such as employee discounts and manufacturer coupons. We exclude private label items and "Direct Store Delivery" (DSD) categories (primarily alcohol, beverages, and dairy). DSD categories and private label items have very different institutional features. We discuss the implications of excluding the DSD categories in the Appendix.

The data set has two unique features that are crucial to our analysis. First, the Regular Retail Price variable is reported directly in our data set. This allows us to avoid using a "sale filter" to identify sales, as in other scanner data sets.[4] Second,

[3] Nevo and Wong (2014) find that a greater share of household grocery expenditures were purchased on sale during the Great Recession, while Stroebel and Vavra (2014) document that, when house prices fall, the expenditure share on sale items increases for homeowners, whereas it decreases for renters. Coibion et al. (2015), however, show that, at the universal product code (UPC) level, the share of goods bought on sale is acyclical. These results can be reconciled by noting that, during recessions, consumers may be shifting expenditures toward UPCs that have, on average, more sales.

[4] For example, syndicated data providers such as Symphony IRI and Nielsen have created algorithms to impute the regular price from the observed average prices. Analogous sale filters have been adopted by academics (e.g., Nakamura and Steinsson, 2008; Chahrour, 2011; Kehoe and Midrigan, 2015). These imputation algorithms will, however, naturally introduce some noise into the regular price variable.

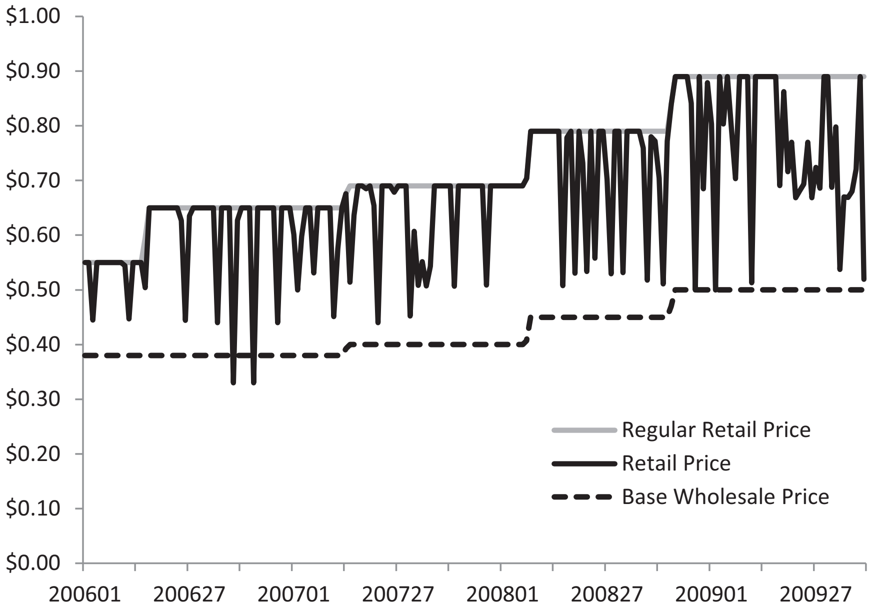


Fig. 1. Price series: example
This figure reports the price trends for the three price variables for an arbitrarily chosen SKU at a single store that had sales of the SKU in all 195 weeks of the sample period.

our measure of wholesale prices is the "Base Wholesale Price" excluding trade deals. This is an important departure from earlier work (e.g., EJR) that focused on wholesale prices including trade deals. We believe it is preferable to exclude trade deals because, as we explain in detail in Section 8, variation in wholesale costs associated with trade deals may not reflect variation in marginal costs faced by the retailer. The retail response to such trade promotions is typically part of a complex contingent contract.[5] Another advantage of our data is that the wholesale price measure is a true "marginal cost" as opposed to an "average acquisition cost."

We use several additional sources of data: commodity cost data, unemployment data, and the BLS price data that underlie the CPI. We discuss these additional data sources, as well as several additional details regarding our scanner price data set, in the Appendix.

3. The importance of sales in scanner data

Fig. 1 illustrates three price measures using a representative item in our data set: the Regular Retail Price, Retail Price, and Base Wholesale Price. The figure reveals that Wholesale and Regular Retail Prices exhibit similar dynamics, adjusting both infrequently and persistently, whereas Retail Prices adjust much more frequently because of the presence of temporary sales.

Table 1 reports the average weekly frequency and average size of price changes for all three price measures, weighted by total revenue for each SKU–store combination (calculated using all 195 weeks). The average absolute size of the price changes is measured as a percentage of the average regular price (calculated for that SKU in that store across the entire 195-week period). Over 95% of the price changes in our data set are a result of temporary sales. The weekly frequencies of price change for Base Wholesale and Regular Retail Prices are 0.74% and 1.11%, respectively, whereas the frequency of retail price change including sales is 21.16% per week.

Although these findings are well established, they provide important motivation for the analysis that follows. Does the prevalence of temporary sales mean they are responsible for the lion's share of the retail price response to a wholesale cost increase? In the next section, we investigate this question empirically.

4. Do sales respond to wholesale costs?

If sales represent an additional dimension of flexibility for retailers to respond to underlying movements in costs over and above changes in Regular Retail Prices, then when wholesale costs increase, we might expect to see both increases in Regular Retail Prices and reductions in the size and frequency of sales. Further, one might expect that sales would be responsible for a large fraction of the responsiveness of prices to costs, given that they account for 95% of all price changes.

[5] For example, the retailer that we study uses the Base Wholesale Price (without trade promotions) as its measure of marginal product cost. It tracks promotion "funding" separately through a stand-alone system that is used solely for trade promotion planning and evaluation.

Table 1
Frequency and size of wholesale and retail price changes.

	Average weekly frequency	Average absolute size
Base wholesale price		
Any change	0.74%	
Increases	0.63%	4.67%
Decreases	0.11%	7.14%
Regular retail price		
Any change	1.11%	
Increases	0.91%	8.41%
Decreases	0.20%	10.10%
Retail prices (including temporary sales)		
Any change	21.16%	
Increases	10.70%	22.64%
Decreases	10.46%	22.31%

This table reports the average weekly frequency of price changes and the average absolute percentage size of the price changes. The average absolute size of the price changes is measured as a percentage of the average regular price (calculated for that SKU in that store across the entire 195-week period). The unit of observation is a SKU at a store in a week, and the sample size is 5,394,146 for the frequency measures. Not all items have price changes in every week, and so the sample sizes for the absolute size measures range from a low of 6052 (wholesale price decreases) to a high of 602,678 (retail price decreases). The observations are weighted by total revenue for the SKU-store combination (calculated across all 195 weeks).

To investigate this hypothesis, we consider the evolution of retail prices surrounding changes in the Base Wholesale Price. We initially focus on the effects of wholesale price increases but will later also extend the analyses to wholesale price decreases. We identify 37,981 Base Wholesale Price increase events, representing a cost increase on an item in a week in a store. We construct a sample that for each event includes the week of the event, the prior 50 weeks, and the subsequent 50 weeks. For some cost increase events, several observations are missing, either because no units of the item were sold in one of these weeks or because the cost increase event occurred too close to the start or end of the sample period. Pooling across the 37,981 events yields a total panel sample of 2,147,676 observations.

We estimate the following equation:

$$Y_{ist} = \sum \mu_i + \sum \mu_t + \sum \beta Period_{est} + \varepsilon_{ist}, \tag{1}$$

where Y_{ist} refers to the relevant price measure (for item i in store s in week t). The μ_i terms are item fixed effects, and the μ_t terms are time fixed effects. The $\beta Period_{est}$ term refers to a set of dummy variables identifying blocks of weeks before and after the cost increase event (e).[6] To prevent overidentification, we omit the dummy variable measuring week 0, the week before the wholesale price change. We estimate the model using weighted ordinary least squares (OLS), where the observations are weighted by the revenue of the SKU in the store.

The standard errors are clustered at the manufacturer x category level, to account for any correlation in the errors across events, stores, or SKUs (or some combination of these) that share the same manufacturer and category number. This approach recognizes that price changes tend to be coordinated across the items that a manufacturer sells in the same category.[7] As a robustness check, in the Appendix we also report standard errors clustered at several different levels (see Table A1). The results are reassuringly robust to using these different approaches.

We analyze the response of four different price measures:

$$Wholesale\ Price\ Index_{ist} = \frac{Wholesale\ Price_{ist}}{Average\ Regular\ Price_{is}}$$

$$Retail\ Price\ Index_{ist} = \frac{Retail\ Price_{ist}}{Average\ Regular\ Price_{is}}$$

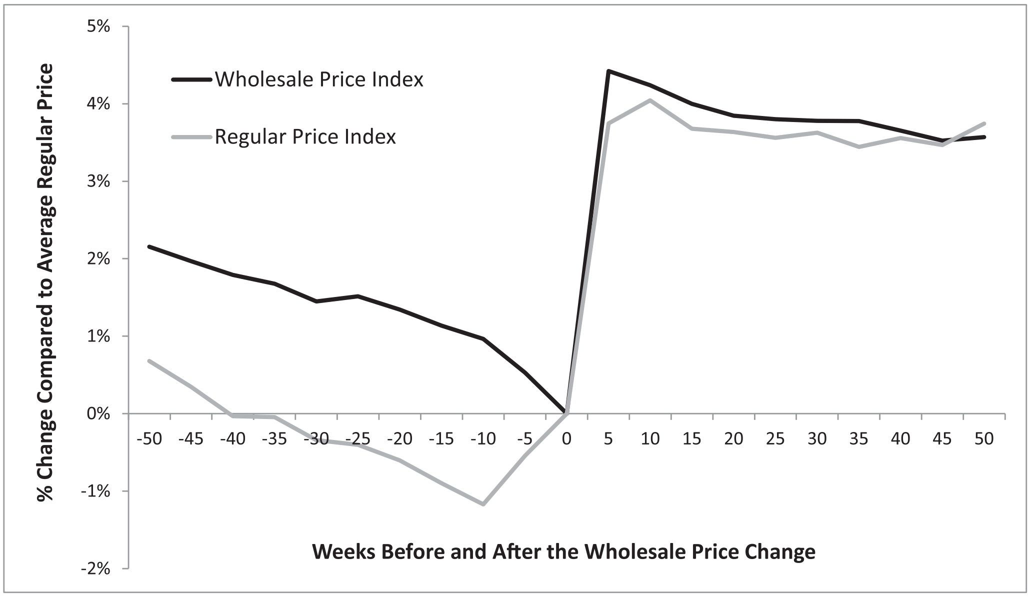
$$Regular\ Price\ Index_{ist} = \frac{Regular\ Price_{ist}}{Average\ Regular\ Price_{is}}$$

$$Discount\ Index_{ist} = \frac{Average\ Discount_{ist}}{Average\ Regular\ Price_{is}}.$$

Note that our measure of discounts is defined such that $Retail\ Price_{ist} = Regular\ Price_{ist} - \ Average\ Discount_{ist}$. Each price index is normalized using the average Regular Price (calculated using the entire 195-week data period).

[6] For example, week –50 corresponds to weeks –50 to –46, week –45 corresponds to weeks –45 to –41, and so on, for weeks –50 to 50, in five-week intervals. The exception is week 0, which identifies the week immediately before the cost change.

[7] Manufacturers tend to negotiate Wholesale Price changes for all of their items in a category at the same time. Moreover, a single manager at the retailer makes decisions about Regular and Retail Price changes for all of a manufacturer's items in a category. Both observations suggest that errors will be correlated across items that share the same manufacturer and category. Consistent with this interpretation, additional analysis reveals that price changes tend to be coordinated across items sold by a manufacturer within a category.



Panel A: Wholesale Price and Regular Price Index

Panel B: Wholesale Price and Discount Index

Fig. 2. Response to a base wholesale price increase
These figures report the coefficients identifying the weeks before and after a wholesale price increase. Week 0 identifies the week before the wholesale price increase. The coefficients are obtained from estimating Eq. (1) on each dependent variable. Fixed effects identifying each item and each time period were included in the model but are not reported. The sample sizes are all 2,147,676. Observations are weighted by total revenue for the SKU in that store (calculated across all 195 weeks).

4.1. Results

Fig. 2 presents the results. Recall that we omitted the dummy variable identifying week 0 (the week immediately before the cost change), and so all of the coefficients measure the change in the indexed price series relative to this week. This also ensures that the plots of the coefficients pass through zero at week 0. The sharp increase in the Wholesale Price index after week 0 is therefore by construction—we have selected these instances precisely as periods when the wholesale price

Table 2
Change in price indices around the wholesale price increase events.

	Short-Term Comparison	Medium-Term Comparison	Long-Term Comparison
Wholesale Price Index	3.18%** (0.32%)	2.18%** (0.42%)	1.54%** (0.39%)
Retail Price Index	3.22%** (0.47%)	3.13%** (0.42%)	3.05%** (0.63%)
Regular Price Index	4.57%** (0.36%)	3.77%** (0.53%)	3.11%** (0.58%)
Discount Index	1.35%** (0.42%)	0.64%* (0.30%)	0.06% (0.44%)

This table reports the change in the four price indices in the periods after the Wholesale Price increase events compared to the corresponding periods before the events. Week 0 identifies the week before the wholesale price increase. The "Short-Term Comparison" compares weeks -20 to -1 with weeks 1 to 20, the "Medium-Term Comparison" compares weeks -40 to -21 with weeks 21 to 40, and the "Long-Term Comparison" compares weeks -50 to -41 with weeks 41 to 50. Positive values indicate that the price index was higher after the event. The sample sizes are all 2,147,676. Observations are weighted by Total Revenue for the SKU in that store (calculated across all 195 weeks). Standard errors are clustered at the manufacturer *x* category level and reported in parentheses. *Significantly different from zero, $p < 0.05$, ** significantly different from zero, $p < 0.01$.

increases. Panel A of Fig. 2 shows, however, that there is also a sharp and immediate response of Regular Retail Prices.[8] Recall that the series are all indexed against the same base (the average Regular Retail Price), and so movements in each series represent the same dollar-for-dollar change.

If sales and regular prices play a similar role in the price adjustment process, one might expect to see a decline in the frequency and size of sales around the time of the wholesale price increase. For example, Kehoe and Midrigan (2015) and Hendel and Nevo (2013) present models in which regular prices and sales both respond to underlying changes in marginal costs.

Panel B of Fig. 2 presents the response of discounts following the wholesale price increase. Sales do not respond strongly. In fact, if anything, there is a temporary *increase* in sales following the wholesale cost increase. In other words, sales actually *hinder* the increase in retail prices following the cost increase, as opposed to accelerating the speed of the price adjustment. One potential interpretation of this pattern is that the retailer increases discounts following the regular price increase so as to make it more difficult for the consumer to notice the price increase.

Further investigating reveals that the short-term increase in the Discount Index in Table 2 results from an increase in both the frequency and depth of discounts. However, only the change in the discount depth is statistically significant.

Recall that the model includes time fixed effects. Therefore, the lines in Figs. 2A and B should be interpreted as prices of products contingent on a wholesale cost increase in week 0 *relative* to what we would have expected without this contingency. The trend in the sample is positive, since prices generally increase over time. Hence, in the weeks before and after week 0 when the cost change occurs, the product's price erodes relative to other products in the sample. This explains the negative trends that arise before and after week 0 in Fig. 2. These trends are absent in Appendix Figure A1, which shows the results for the model with no time fixed effects.

Table 2 presents the results in tabular form, with the average short-term price response (weeks -20 to -1 versus weeks 1 to 20), the average medium-term price response (weeks -40 to -21 versus weeks 21 to 40), and the average long-term price response (weeks -50 to -41 versus weeks 41 to 50). These results were estimated by re-estimating Eq. (1) using separate dummy variables identifying these sets of weeks. The table shows that in the short term, the Wholesale Price increased by 3.2%, which led to a 3.2% increase in the Retail Price. Regular Retail Prices rose by 4.6%, but this was offset by a 1.4% increase in discounts. In the long term, there was no change in the Discount Index. Instead, the increase in Retail Prices is almost completely attributable to an increase in the Regular Retail Price.

The evidence that the Discount Index returns to its pre-event level in the long run is perhaps unsurprising. If every Wholesale Price increase led to permanent increases in the Discount Index, this would lead to accumulated increases in the Discount Index over time. Eventually the Discount Index would reach its natural limit: discounts all of the time. The fact that we do not see this requires that increases in the Discount Index are not permanent.

Notice that in the short run, pass-through is one-for-one, whereas in the long run, the increase in wholesale prices is considerably less than the increase in retail prices (1.5% vs. 3.1%). Recall that these percentage statistics are taken relative to the same base (the average regular retail price). An equal change for wholesale and retail prices thus corresponds to a "cent-for-cent" pass-through (not an equal percentage change).[9] Therefore, the one-for-one increase we observe in the short run reflects a decline in the markup in percentage terms. If this response occurred systematically, then over time this would lead to gradual erosion in retail markups in percentage terms. Hence, the greater relative adjustment of retail prices in the long run depicted in Table 2 reflects the retailers' efforts to maintain their percentage margins. The larger pass-through

[8] This result is consistent with the results of Nakamura and Zerom (2010) and Goldberg and Hellerstein (2013), who find that retail prices respond quickly to wholesale price changes.

[9] Note that this is the result of two processes. First, regular prices do not always respond to wholesale price changes (i.e., no pass through). Second, in our data, when they do respond the dollar change in regular price exceeds the dollar change in wholesale prices. The net of these two effects in our data is cent-for-cent pass through.

Table 3
Change in price indices around the wholesale price increase events conditional on whether there was a nearby regular price change.

		Short-Term Comparison	Medium-Term Comparison	Long-Term Comparison
Nearby regular price change	Wholesale Price Index	3.08%**	1.87%**	1.21%**
		(0.33%)	(0.36%)	(0.32%)
	Retail Price Index	3.85%**	3.23%**	2.98%**
		(0.57%)	(0.53%)	(0.65%)
	Regular Price Index	5.42%**	3.88%**	2.91%**
		(0.44%)	(0.66%)	(0.69%)
	Discount Index	1.57%**	0.65%	−0.07%
		(0.46%)	(0.36%)	(0.52%)
No nearby regular price change	Wholesale Price Index	3.55%**	3.68%**	2.95%**
		(0.68%)	(1.13%)	(0.97%)
	Retail Price Index	−0.46%	2.41%	3.43%
		(0.81%)	(1.32%)	(1.87%)
	Regular Price Index	−0.23%	2.73%	3.40%
		(0.63%)	(1.57%)	(2.07%)
	Discount Index	0.23%	0.31%	−0.03%
		(0.61%)	(0.69%)	(0.68%)

This table reports the change in the four price indices in the periods after the Wholesale Price increase events compared to the corresponding periods before the events. Week 0 identifies the week before the wholesale price increase. The "Short-Term Comparison" compares weeks −20 to −1 with weeks 1 to 20, the "Medium-Term Comparison" compares weeks −40 to −21 with weeks 21 to 40, and the "Long-Term Comparison" compares weeks −50 to −41 with weeks 41 to 50. Positive values indicate that the price index was higher after the event. The sample sizes are all 1834,682 (Nearby Regular Price Change) and 312,994 (no nearby regular price change). Observations are weighted by total revenue for the SKU in that store (calculated across all 195 weeks). Standard errors are clustered at the manufacturer *x* category level and reported in parentheses. *Significantly different from zero, $p < 0.05$, ** significantly different from zero, $p < 0.01$.

in the long run than in the short run arises from a combination of both anticipatory and delayed price responses to the wholesale price increase (changes in the Base Wholesale Price are usually announced in advance).[10]

4.2. With and without a nearby regular price change

One might ask whether the reason that sales fail to play any role in the adjustment to a wholesale cost increase is precisely *because* regular retail prices adjust so completely. Perhaps if regular retail prices did not increase, then sales would adjust in their stead. Table 3 addresses this question by considering the effect of wholesale price increases in two cases: those with a nearby regular price change and those without a nearby regular price change (where "nearby" is defined as within 10 weeks of the event).

Based on this definition, 83% of our wholesale cost increase events do exhibit a nearby regular price change, whereas the remaining 17% do not.[11] When there is a nearby change, the Regular Retail Price responds quickly and completely. In the remaining cases, the Regular Retail Price responds incompletely and with some delay.

In neither of these cases do we find any evidence that a decrease in the frequency or size of temporary sales helps accelerate the adjustment to the wholesale price increase. In the former case, where the Regular Retail Price increases, we observe a transitory increase in sales, as we discuss above. However, this does not occur in the case without a nearby Regular Retail Price change—substantiating the view that the increase in sales is intended to mask the increase in Regular Retail Prices.

This interpretation that the retailer uses sales to mask the increase in Regular Retail Prices suggests that we should also see an increase in discounts following a Regular Retail Price increase that is not accompanied by a Wholesale Price increase. Further investigation confirms that this is the case; we also see short-term increases in the Discount Index after these events.

In the long run, the wholesale cost increase has no impact on sales in either the case with or the case without the nearby regular price increase. The long-run increase in the Retail Price is also very similar in the two cases. In the latter case with no nearby price change, the increase in the Regular Retail Price occurs outside the short-term window. Notably, even in these situations, the retailer does not use temporary sales as a way of adjusting prices in the short term.

4.3. Wholesale price decreases

For completeness we also analyze how the retailer responds to wholesale price decreases. Wholesale price decreases are relatively rare events, and so this analysis should be treated cautiously because it is a study of outliers. In Table 4, we report

[10] To see the intuition for this result, it is helpful to look at the results with no time fixed effects (in Figure A1). Here, it is clear that, for retail prices, the long-run response is much larger than the short-run response; but for wholesale prices, the short- and long-run responses are similar.

[11] We can also ask the inverse question: in weeks with a Regular Retail Price increase, there is a Wholesale Price increase in 35.44% of the weeks. In contrast, in weeks without a Regular Retail Price change, there is a Wholesale Price increase in just 1.23% of the weeks. Regular Retail Price changes are often associated with Wholesale Price changes; however, the association is not perfect.

Table 4
Change in price indices around the wholesale price decrease events.

	Short-Term Comparison	Medium-Term Comparison	Long-Term Comparison
Wholesale Price Index	−2.68% (1.65%)	−0.34% (0.90%)	−0.07% (1.02%)
Retail Price Index	−0.99% (1.81%)	0.19% (0.97%)	1.43% (1.99%)
Regular Price Index	−0.52% (2.01%)	2.22% (1.82%)	2.49% (2.37%)
Discount Index	0.47% (0.55%)	2.04% (1.06%)	1.07% (0.85%)

This table reports the change in the four price indices in the periods after the wholesale price decrease events compared to the corresponding periods before the events. The "Short-Term Comparison" compares weeks − 20 to − 1 with weeks 1 to 20, the "Medium-Term Comparison" compares weeks − 40 to − 21 with weeks 21 to 40, and the "Long-Term Comparison" compares weeks − 50 to − 41 with weeks 41 to 50. Positive values indicate that the price index was higher after the event. The sample sizes are all 274,031. Observations are weighted by total revenue for the SKU in that store (calculated across all 195 weeks). Standard errors are clustered at the manufacturer *x* category level and reported in parentheses.

the equivalent of Table 2 for cost decreases, comparing the short-, medium-, and long-term change in the different price indices. These results are calculated using 6,052 events, representing a reduction in the Base Wholesale Price in a store in a week. For comparison, the analysis of the response to wholesale price increases uses 37,981 events.

We see that none of the price indices change significantly in any of the three time periods. Even the Wholesale Price Index is not significantly lower in the 20 weeks after the wholesale price reduction, compared to before the price reduction. Further investigation reveals that many of the wholesale price decreases are short-term events, and the wholesale price quickly recovers to its pre-event levels. Given the transitory nature of the effect on wholesale prices, it is perhaps not surprising that we do not see significant changes in either the Regular Price Index or the Discount Index in response to these wholesale price decreases.

An asymmetric response to increases versus decreases is also in line with earlier work by Anderson et al., (2015), McShane et al., (2016) and Peltzman (2000). Aside from the transitory nature of the shock, retailers may respond more to cost increases than decreases in an environment with menu costs and trend inflation (intuitively, cost increases are more likely to be persistent). Moreover, if demand is relatively inelastic to retail price decreases (Hoch et al., 1994), this reduces the short-term incentive to lower retail prices when costs decrease. Finally, the benefits of lowering prices (higher demand) may be more salient to managers than the benefits of raising prices (higher margins). All of these explanations are, however, highly speculative. Understanding fully why retailers respond differently to cost increases than they do to cost decreases remains an important unanswered research question.

4.4. Summary

We have shown that the retailer we study responds to most wholesale price increases by increasing its regular retail price quickly and completely. In other cases, it still increases its regular price, though the response may be delayed. We find no evidence that wholesale price increases yield a systematic reduction in discounts. To the contrary, if anything the retailer increases its discounts in an apparent attempt to mask the regular price increases.

In the remainder of the paper, we reinforce the findings in this section through a series of additional analyses. These additional results help to generalize the findings beyond a single retailer and a single type of cost shock. They also offer an explanation for why retailers respond through their regular prices instead of their sale prices. We begin by examining how this retailer responded to changes in commodity prices and regional employment.

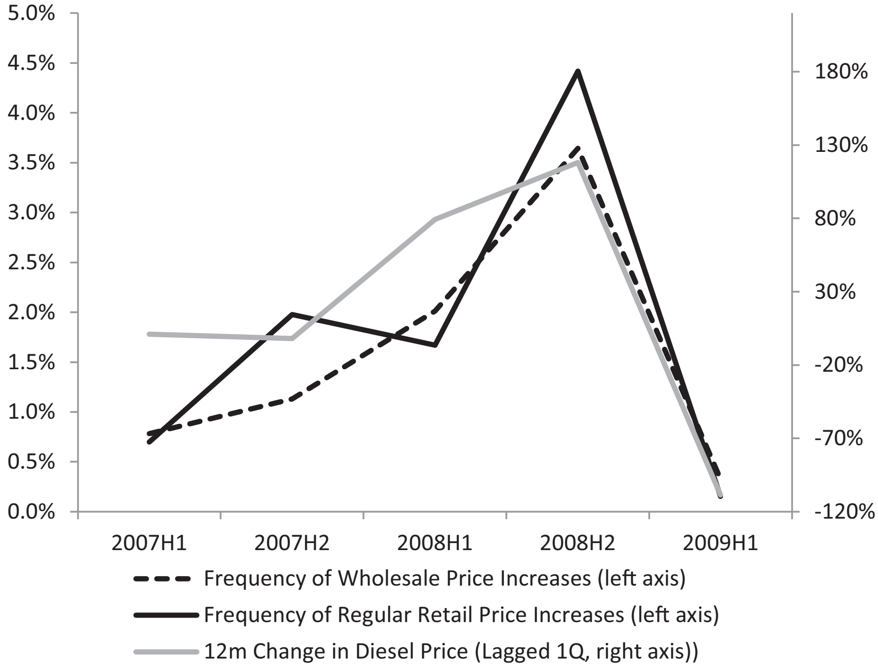
5. The response of prices to commodity costs and unemployment rates

5.1. The effect of the commodity cost boom of 2007–2008

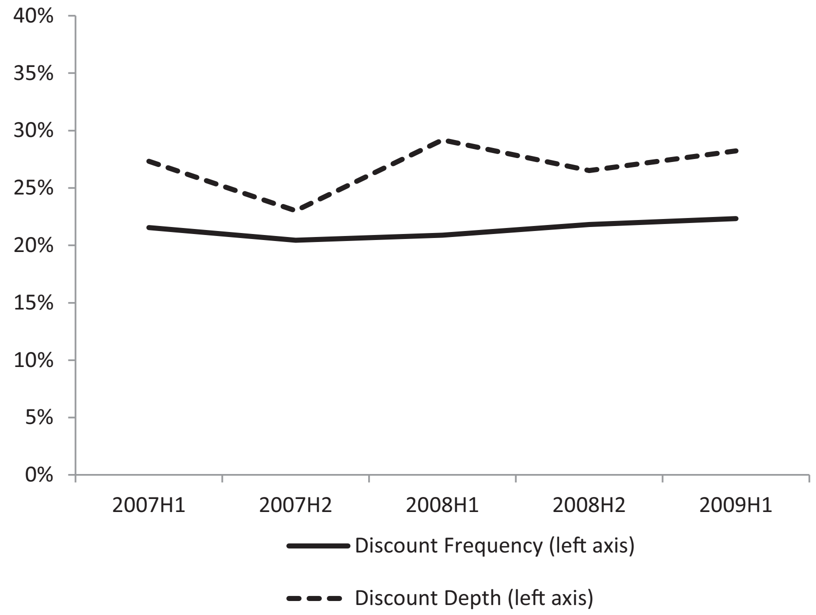
Our sample period coincides with a rapid rise and fall in the price of oil and other commodities in 2007–2008. To the extent that temporary sales are used to respond to underlying movements in production costs, we should expect to see the frequency and depth of discounts change in response to the commodity cost fluctuations.

Fig. 3 (Panel A) plots the average weekly frequency of Regular Retail and Base Wholesale Price increases (left axis), along with changes in diesel prices (right axis) on a biannual basis. Panel B presents analogous statistics for temporary sales. The frequencies of price change are weighted by total revenue and are adjusted for the seasonal pattern observed in 2006.[12] The diesel price variable is the 12-month change in diesel prices, lagged by one quarter. This is meant to recognize the lead time between the timing of the diesel price change, the timing of wholesale and retail pricing decisions, and the implementation of those decisions.

[12] The frequency of price change is considerably higher in the first quarter of the year than in other quarters, consistent with the seasonal pattern found in Nakamura and Steinsson (2008). To adjust for this pattern, we subtract from each frequency statistic the average frequency of price change for that time period in 2006, relative to the overall frequency for that year.



Panel A: Regular Prices and Base Wholesale Prices



Panel B: Temporary Sales

Fig. 3. Price adjustment and diesel prices.

Fig. 3 (Panel A) shows that the increase in diesel prices in 2008 was matched by a sharp rise in the frequency of Wholesale Price increases (the correlation between the two series is 0.91). Conversations with managers at the retailer revealed that they attributed the spike in the frequency of Wholesale Price increases in 2008 to the commodity price changes. The frequency of Regular Retail Price increases also spikes sharply at this time. In stark contrast, Panel B shows that the frequency and depth of temporary sales were unaffected by the huge run-up and subsequent fall in diesel and other commodity prices.

Table 5
Regional variation in unemployment and the frequency of price changes.

	Retail Price Index	Regular Price Index	Discount Index
Unemployment (three-month lag)	−0.065%** (0.018%)	−0.051%** (0.013%)	0.013% (0.013%)
R^2	0.278	0.251	0.280

This table reports coefficients from estimating Eq. (2) on each dependent variable. The coefficients reflect the percentage point increase in the dependent variable. Item and week fixed effects (and a constant) are included but omitted from the table. The unit of observation is an item x week, and the sample sizes are 5394,146. Observations are weighted by Total Revenue for the SKU in that store (calculated across all 195 weeks). Standard errors are clustered at the manufacturer x category level and reported in parentheses. *Significantly different from zero, $p < 0.05$, **significantly different from zero, $p < 0.01$.

5.2. The effect of unemployment rates

Next we study the responsiveness of the different forms of price change to variation in unemployment across different Core Based Statistical Areas (CBSAs).[13] Table 5 presents results from the following weighted OLS regression:

$$Y_{ist} = \sum \mu_i + \sum \mu_t + \beta_1 Unemployment_{st} + \varepsilon_{ist}, \tag{2}$$

where the μ_i terms are item fixed effects and the μ_t terms are time fixed effects. We use three different outcome measures, Y_{ist}, including the Retail Price Index, the Regular Price Index, and the Discount Index. We do not report the results for the Wholesale Price Index because this variable is determined almost exclusively at the national level, implying that there is little variation across regions.

The $Unemployment_{st}$ variable is the monthly unemployment rate in that CBSA, lagged by one quarter. We use the same sample of approximately 5 million observations that we used in Table 1, weighted by the total revenue of the SKU in the store. The inclusion of the time fixed effects means that we identify the impact of unemployment on retail prices solely by using variation in regional unemployment (where the regions are represented by the store locations) relative to the average unemployment rate.

We again report standard errors clustered at the manufacturer *x* category level. In addition, we report alternative clusters of the standard errors in Appendix Table A2 (including the CBSA *x* month, which is the level at which unemployment varies). The findings are robust to all of these clustering approaches.

Table 5 shows that a 1 percentage point increase in the regional unemployment rate led to significantly lower retail prices. However, this reduction arose entirely from regular prices, as opposed to sales. The change in the unemployment rate had no effect on the Discount Index.[14]

The empirical findings in the previous three sections are constructed using pricing data from a single retailer. Even though the retailer sells consumer packaged goods in a very broad range of categories, the restriction to a single retailer is an obvious limitation. We address this limitation in the next section using BLS data.

6. Broader analysis using BLS data

How representative are our findings of other US retailers? To investigate this question, we use BLS microdata on prices underlying the CPI. These data have the advantage of being highly representative of the economy as a whole. In these data, temporary sales are identified using a "sale flag" that indicates whether a product was on promotion. We aggregate these data to a quarterly frequency for a sample covering 1988q4 to the present. The Appendix describes other important features of the data construction.

Since the BLS data do not include direct information on costs, we are not able to directly study the response of regular prices versus sales to cost shocks. We are, however, able to study how regular prices versus sales vary over the business cycle. If sales were highly responsive to shocks, we would expect that including temporary sales in measures of inflation would have a substantial effect on the cyclicality of measured inflation.[15] This approach allows us to investigate the generalizability of the key finding in the previous sections. If retailers respond to shocks by adjusting their temporary sales, then including or excluding temporary sales in measures of inflation should yield important differences.

Fig. 4 plots "posted" and "regular" price inflation alongside the unemployment rate. Posted price inflation is the conventional inflation rate based on observed prices, whereas regular price inflation is the inflation rate for regular prices excluding

[13] CBSAs are geographic areas consisting of a county or set of counties that include a core urban area with a population of at least 10,000 and the surrounding areas that are linked to the core by a high degree of social and economic integration as measured by commuting patterns. CBSAs are defined by the Office of Management and Budget.

[14] This result is consistent with Coibion et al. (2015), who also find no impact of the unemployment rate on the frequency of sales for the US. In contrast, Kryvtsov and Vincent (2014) do find an increase in sales during the Great Recession in the UK and US.

[15] Klenow and Malin (2011) also construct and contrast measures of inflation with and without sales, but they do not focus on the cyclical behavior of these series or their responsiveness to aggregate shocks.

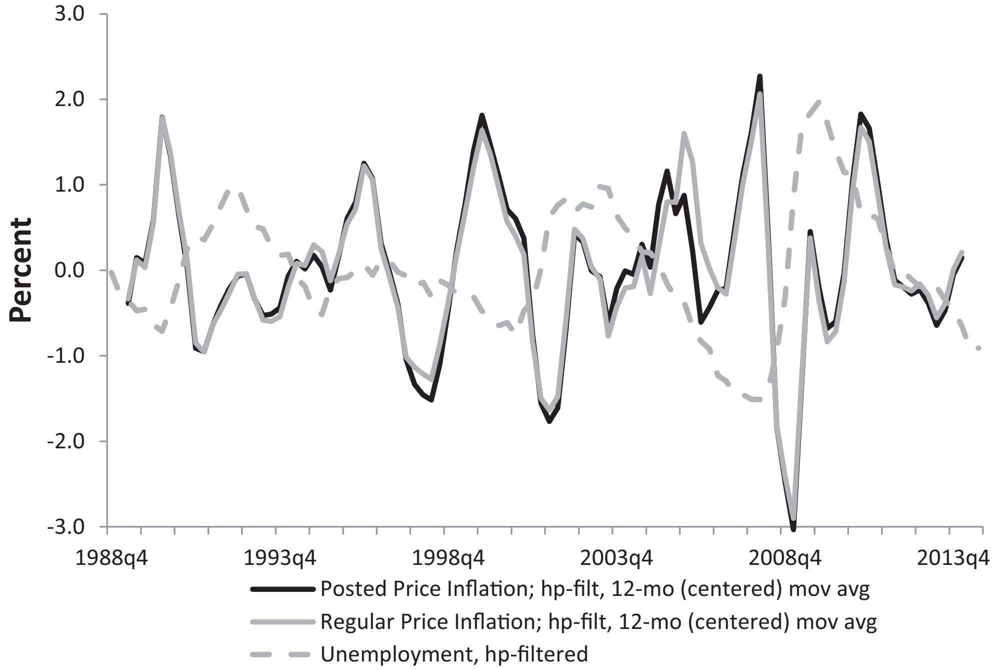


Fig. 4. Posted versus regular price inflation.

Table 6A
Inflation cyclicality: food.

	Posted price inflation	Regular price inflation	Sale-related inflation
Relative Variance	1.00	0.78	0.06
Correlation with posted	1.00	0.98 (0.02)	−0.57 (0.08)
β^{U}	−0.99 (0.34)	−0.91 (0.30)	0.08 (0.06)
Correlation with U	−0.38 (0.09)	−0.40 (0.09)	0.13 (0.10)
β^{GDP}	0.59 (0.25)	0.53 (0.21)	−0.06 (0.05)
Correlation with GDP	0.35 (0.09)	0.36 (0.09)	−0.15 (0.10)

sales.[16] We HP-filter all series to remove low-frequency trends[17] and plot the 12-month (centered) moving average of the inflation series to remove very high-frequency fluctuations. Foreshadowing some of our results, the inclusion or exclusion of sales yields inflation rates that exhibit almost identical cyclicality.

Tables 6A and 6B present some key moments of posted, regular, and “sale-related” inflation, the latter being the difference between regular and posted inflation. We primarily focus on the co-movement of the respective inflation series and various measures of the business cycle. Specifically, we regress the respective inflation rate on unemployment or (log) GDP; all variables are HP-filtered.[18] A positive unemployment coefficient—or a negative GDP coefficient—in the sale-related inflation regression would indicate that the magnitude of sale-related discounts tends to rise during recessions. Note that the regression coefficient is a covariance measure, and so depends on both the *correlation* of sales with the cycle and the *magnitude* of the discount.

Let us start by discussing the features of food price inflation, since these products have the greatest overlap with those sold by the retailer we focus on in our earlier analysis. Table 6A shows that sale-related inflation is essentially acyclical for the food category. Regressing posted price inflation (including sales) on the unemployment rate yields a coefficient of −0.99 versus −0.91 for regular price inflation, whereas the coefficient in the sale-related inflation regression is statistically insignificant and economically small (+0.08, s.e. 0.06). The results are qualitatively similar if we use GDP as our measure of the business cycle: 90% of the cyclical movement in posted price inflation is due to movement in regular price inflation. Table 6B presents the results for all sectors of the economy. Again, posted and regular price inflation have similar responses to unemployment and GDP, respectively, and the response of sale-related inflation is statistically insignificant and econom-

[16] We use the BLS sale flag to identify sales and “fill-forward” the previously observed regular price through these sale episodes to construct the regular price series. See the Appendix for more details.

[17] Regular price inflation is higher, on average, than posted price inflation over our sample. This discrepancy is due to a trend increase in the frequency (and size) of sales over our sample period, as we will show later (see also Nakamura and Steinsson, 2008, and Kryvtsov and Vincent, 2014).

[18] As an alternative to the HP-filter, we used a band-pass filter to focus on fluctuations of frequency between 6 and 32 quarters. The results in Table 6 were qualitatively unchanged.

Table 6B
Inflation cyclicality: all products.

	Posted Price Inflation	Regular Price Inflation	Sale-Related Inflation
Relative variance	1.00	0.91	0.03
Correlation with posted	1.00	0.99 (0.02)	−0.36 (0.09)
β^{U}	−0.32 (0.25)	−0.37 (0.24)	−0.04 (0.05)
Correlation with U	−0.10 (0.10)	−0.12 (0.10)	−0.08 (0.10)
β^{GDP}	0.42 (0.20)	0.45 (0.18)	0.03 (0.05)
Correlation with GDP	0.19 (0.10)	0.22 (0.10)	0.07 (0.10)

Inflation series constructed from the CPI-RDB, using data on food items (Panel A) and all nonshelter items (Panel B) in all areas from 1988q4 through 2014q3. Posted Prices include sale prices, whereas Regular Prices replace sale prices with previous regular price. Inflation is the weighted average of individual log price differences, and weights are constant as described in the Appendix. Sale-Related Inflation is obtained by subtracting Posted Price Inflation from regular price inflation. Inflation series are seasonally adjusted and HP-filtered (parameter = 1600). "β^{GDP}" ("β^{U}") is obtained by regressing (log) inflation on (log) GDP (unemployment); all variables are HP-filtered and Newey–West standard errors are reported.

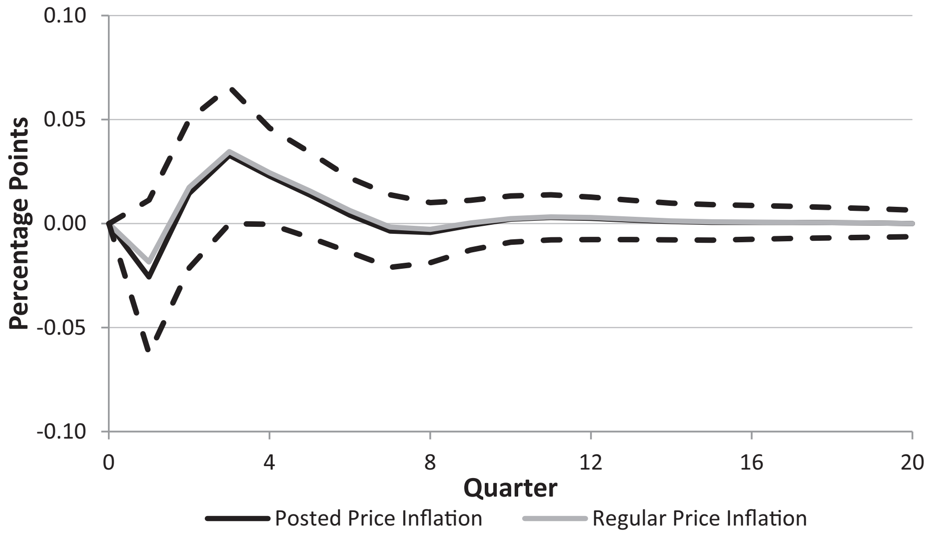


Fig. 5. Inflation response to federal funds rate shock
Impulse response functions constructed from four-lag, four-variable VAR, including unemployment rate, commodity price inflation, posted (or regular) inflation, and federal funds (shadow) rate. The shock is a +25 basis point innovation to the federal funds rate. Dashed lines are 2 * standard error bounds on the *posted* inflation response.

ically small. These findings provide further evidence that incorporating temporary sales into measures of inflation does not appear to influence the cyclicality of these measures.

While we are not able to directly study the effect of cost shocks in the BLS data, we can study the response of inflation to aggregate shocks. Fig. 5 presents the impulse response to a monetary policy shock of +25 basis points using a standard four-variable VAR, including the unemployment rate, posted (or regular) price inflation, commodity price inflation, and the federal funds rate.[19] The shock is identified using a standard Cholesky factorization, where the variables are ordered as above. Fig. 5 shows that the estimated response of posted price inflation is very similar to the estimated response of regular price inflation. A tiny gap appears in the first quarter after the shock, but that response in sale-related inflation is economically small and statistically insignificant: the quarter 1 response of sale-related inflation is 0.007 (s.e. 0.008), compared to −0.026 (s.e. 0.018) for posted price inflation.

The findings in Figs. 4 and 5 and Table 6 provide consistent evidence that incorporating temporary sales in measures of inflation has little impact on the cyclicality of the measures or on their response to macroeconomic shocks. If retailers used sale prices to respond to macroeconomic shocks, then we would expect there to be substantial differences in the inflation measures constructed using regular prices (without sales) versus posted prices (with sales). We interpret the absence of any differences as evidence supporting the generalizability of our earlier findings that retailers respond primarily through

[19] For commodity prices, we use the producer price index (PPI): Crude Materials for Further Processing, and for the federal funds rate, we use the Wu and Xia (2016) shadow rate. We also considered using GDP growth rather than unemployment, and the results changed little.

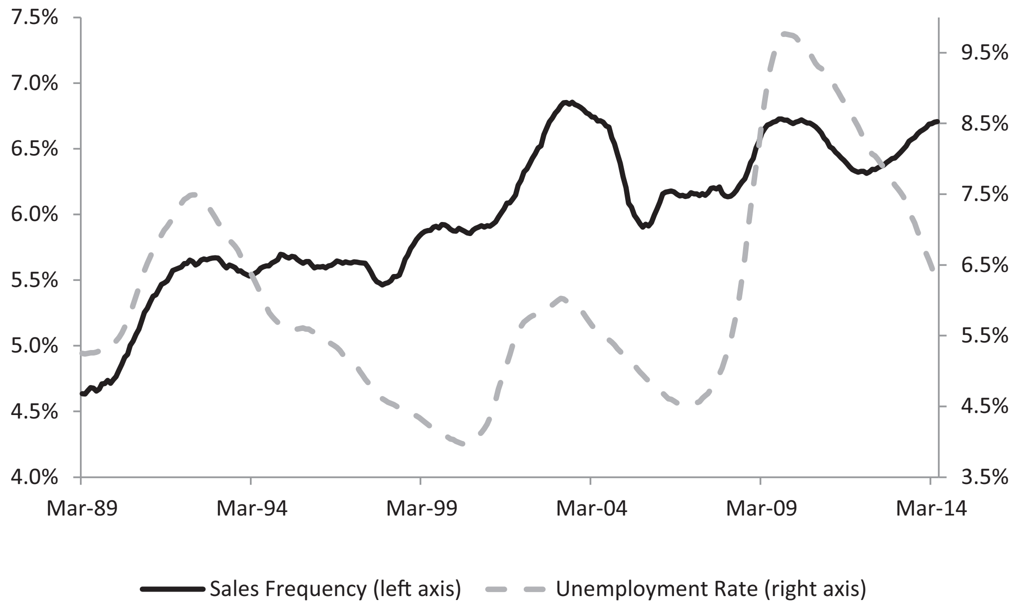


Fig. 6. Frequency of sales and unemployment rate.

regular prices, rather than by adjusting their sale prices. Time variation in the frequencies and sizes of sales does not appear to play an important role in how prices respond to shocks.

In a recent paper, Kryvtsov and Vincent (2014) argue that there is a statistically significant relationship between the frequency of sales in BLS data and the unemployment rate. This argument may seem to conflict with our results above. However, the frequency of sales is more closely related to the *level* of prices than the rate of inflation. We show in the Appendix (Table A3) that it is possible to obtain a statistically significant relationship between sales and unemployment/GDP if one focuses on the HP-filtered *level* of prices as opposed to the inflation rate. However, the magnitude of the cyclicality is small. These results are also somewhat difficult to interpret, since the cyclicality of the posted price itself is small and sometimes (e.g., for food items) goes in the "wrong" direction. This makes it difficult to say whether the discount response is "facilitating" an adjustment that would otherwise have been hampered by the presence of sticky prices. The analysis of inflation rates above suggests, moreover, a mismatch in the precise timing of the acceleration of sales and the timing of recessions.

Fig. 6 plots the (unfiltered) frequency of sales for all items against the unemployment rate. The figure is directly comparable to the figure of sales reported in Kryvtsov and Vincent (2014) but covers a longer time period. We make slightly different choices on a number of details of data construction, but these differences have little impact on our overall conclusions (the Appendix discusses these differences and shows that their impact is small). Several things stand out. First, there is a substantial upward trend in the frequency of sales, and this rise appears to accelerate during the last three recessions.[20] However, the magnitude of the increase in the frequency of sales is small and does not correlate well with the size of the recession (it is much smaller during the Great Recession than the 2001 recession), and the timing lines up imperfectly—in particular, the frequency of sales has remained at an elevated level in the last few years despite the fall in unemployment after the recession. This helps to explain why we found that sale-related *inflation* has been acyclical.

The next two sections focus on explaining the findings in the previous sections. We begin by presenting evidence that holding sale prices fixed, rather than adjusting them in response to shocks, results in only a small opportunity cost for retailers. We then describe several institutional features of trade deal funding for temporary sales and argue that these features help to explain why sales are "sticky plans."

7. The (un)profitability of dynamically adjusting sales

To what extent is our retailer "leaving money on the table" by failing to adjust its sales policy in response to cost shocks? If the profitability of adjusting sales optimally to changes in marginal costs was large, we might find it a priori implausible that a retailer would behave in the way we describe above.

In this section, we investigate the optimal response of temporary sales to changes in costs in a recent two-period price discrimination model of temporary sales developed by Hendel and Nevo (2013). In this model, there are two types of con-

[20] Note that the discount variable reported in Table A3 is the product of the frequency and average size of sales, but the discount variable moves very closely with the frequency because the average size of sales turns out to be acyclical—though growing over time.

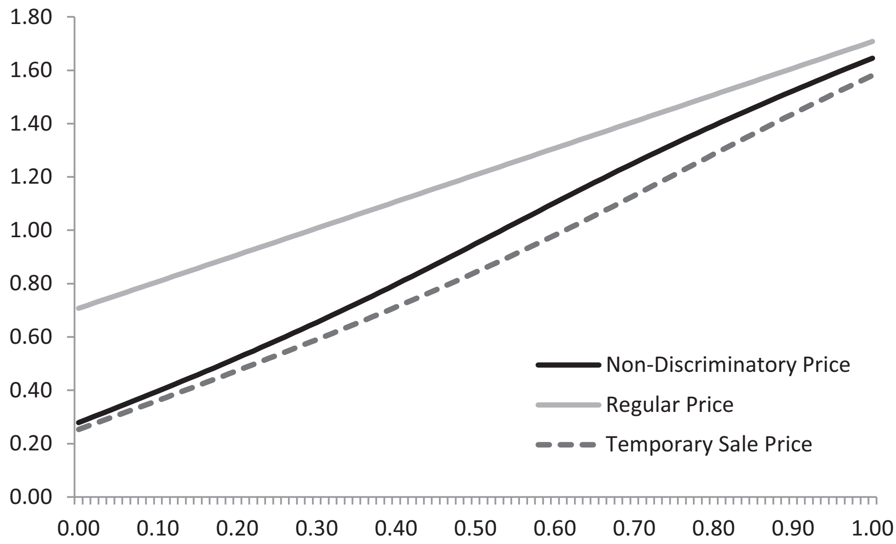


Fig. 7. Discounts and costs in the Hendel–Nevo model
This figure illustrates how the optimal regular and sale prices vary according to the marginal cost in the Hendel and Nevo (2013) model. The sale price is calculated as the regular price less discount. The non-discriminatory price is the price that the firm would charge if it was unable to price discriminate between the two periods (charging the same regular price without discounts in both periods).

sumers: storers and nonstorers. These consumers have perfect foresight about the path of product prices; however, their demand is random. There is a mass ω^S of storers in the population (and a mass $\omega^{NS} = 1 - \omega^S$ of nonstorers).

For nonstorers, the model generates inverse demand functions of the form

$$Q^{NS}(p_t) = \omega^{NS} \exp\left(\alpha - \beta^{NS} p_t\right),$$

where p_t denotes the price of the product in period t, and Q^{NS} denotes the quantity demanded by nonstorers. The demand function for storers is slightly more complicated. We denote one-period demand for storers as

$$Q^S(p_t) = \omega^S \exp\left(\alpha - \beta^S p_t\right).$$

If $p_t \le p_{t+1}$ and they have nothing in storage, then storers purchase for two periods: $2Q^S(p_t)$; whereas if they have goods in storage, they purchase only for the next period: $Q^S(p_t)$. If $p_t > p_{t+1}$ and storers have goods in storage, then demand is zero; otherwise, they demand $Q^S(p_t)$.

Suppose the firm holds a sale in the first period but not in the second. Given the perfect foresight assumption, only nonstorers purchase in the second period. The firm solves the following optimization problem:

$$max_{p_1 \le p_2}\left(2Q^S(p_1) + Q^{NS}(p_1)\right)(p_1 - c) + Q^{NS}(p_2)(p_2 - c),$$

where c is the firm's marginal cost. We adopt Hendel and Nevo's parameter assumptions in their Coca-Cola example, for which the storers' price elasticity is higher than that of the nonstorers: $\omega^{NS} = 0.137172$, $\beta^{NS} = -1.413173$, $\beta^S = -4.371763$, and $c = 57$ cents.

In the context of this model, we ask two questions: First, what is the optimal response of discounts to an increase in costs? Second, suppose the firm decides to hold fixed its discounts following a cost shock. By how much will its profits be reduced?

Fig. 7 addresses the first question. We denote the price when only nonstorers buy as the "Regular Price" and the price when storers also buy as the "Sale" price. The grey solid and dashed lines show the regular and sale prices, respectively, in the firm's optimal pricing policy. For comparison, the black line shows the price the firm would set if it was unable to price 400 discriminate between the first and second period (i.e., the "Non-Discriminatory" price). The figure shows that the firm does optimally reduce the magnitude of discounts as costs increase in the Hendel–Nevo model (i.e., the top and bottom lines get closer together as costs rise). As costs increase, the fraction of storers buying on sale falls, lowering the overall price elasticity for sale prices (the storers' price elasticity is higher than that of the nonstorers). Given this finding, one might expect that sales would play a part in price adjustment, even if their main role is to facilitate price discrimination.

Table 7 addresses the question of how much profits would be reduced if the firm decided to hold fixed its discounts instead of varying them optimally as costs change. Here, we consider a 20,000-period simulation of the Hendel–Nevo model. In the simulation, marginal costs have a mean of $c = 57$ cents, as in the Hendel–Nevo calibration, and a standard deviation of 2.4 cents (5% of the average cost). We assume that the cost shocks are known by all agents to persist for two periods (the duration of the storage technology). Hence, the simulation is equivalent to 10,000 repetitions of the two-period Hendel–

Table 7
Profit loss from constraining prices.

	Fixed discount	Fixed price	Non-discriminatory flexible	Non-discriminatory fixed
Parameters in Hendel–Nevo	0.02%	0.29%	4.06%	4.32%
Lower nonstorer price sensitivity	0.00%	0.01%	0.00%	0.01%
Higher nonstorer price sensitivity	0.00%	0.53%	1.68%	2.20%
Lower storer price sensitivity	0.01%	0.27%	3.65%	3.91%
Higher storer price sensitivity	0.04%	0.22%	1.22%	1.37%
More nonstorers	0.01%	0.16%	0.99%	1.12%
Fewer nonstorers	0.01%	0.42%	6.37%	6.79%

This table reports the loss from fixing each price component as a percentage of the profit earned under the “flexible sales policy” (which allows both regular prices and sale prices to be optimized). The “fixed discount” policy allows the firm to adjust the regular price in response to the cost shocks, but uses a fixed percentage discount. The “fixed price” policy uses a fixed regular price and fixed sale price (no adjustment for cost shocks). The “non-discriminatory” policies set the same price in both periods. The non-discriminatory price is fixed in one regime and flexible in the other. The findings are obtained from 10,000 simulations of Hendel and Nevo’s two-period model.

Nevo model described above, in which the firm alternates between regular prices and sales, but where the marginal cost changes every other period.

We consider five alternative pricing regimes. In three of the regimes, the firm (optimally) sets a low “sale” price in the first period of each two-period block and sets a higher “regular” price in the second period of each two-period block. Storers only buy at the first-period sale price (storing for the second period), whereas the nonstorers purchase in both periods. In the first regime, the firm can vary both prices in response to the cost shock (“Flexible Sales Policy”). In the second regime, the regular price can respond to the cost shock, but the sale price is a fixed percentage discount of the regular price for all 10,000 periods (“Fixed Discount”).[21] This fixed discount percentage is set at the optimal level for the average marginal cost. In the third regime, the firm chooses both a fixed regular price and a fixed sale price (“Fixed Prices”), where neither price can respond to the (two-period) cost shock. These fixed prices are both chosen to optimize profits at the average marginal cost.

In the final two regimes, the price is held fixed within each two-period block, and so both storers and nonstorers buy each period for just that period’s consumption (without storing). In one regime this fixed price is allowed to vary in response to the cost shock, and in the other regime it is held fixed across the 20,000 periods. Because these regimes rule out intertemporal price discrimination, Hendel and Nevo (2013) refer to them as “Non-Discriminatory” policies.

The first row of Table 7 compares the profits earned under each regime. To ease comparison, the profits are indexed against the Flexible Sales Policy, where complete price flexibility yields the highest profits. Table 7 therefore reports the loss resulting from each pricing restriction as a percentage of flexible price profits. In this model, firms want to vary their prices for two reasons: to price discriminate across consumers within each two-period block and to respond to cost shocks. The biggest loss (4.32%) arises if the firm cannot price discriminate or respond to cost shocks. If it cannot price discriminate but can respond to cost shocks, then the opportunity cost is 4.06%. On the other hand, if it can price discriminate but cannot respond to cost shocks, the opportunity cost is only 0.29%. Conspicuously, if the constraint only applies to the sale price, so that the firm can adjust the regular price in response to cost shocks, but the percentage discount is fixed, then the opportunity cost is miniscule: just 0.02%.

The results confirm that having a sale price is important because it allows for price discrimination. Moreover, allowing the regular price to vary is important because it allows for prices in both periods to adjust to the cost shocks. In contrast, allowing the sale price has a miniscule effect because its role is limited to allowing the extent of price discrimination to vary over time in response to the cost shock.

We can investigate how robust these findings are to varying the parameters in the model. In particular, in Table 7 we report several variations to the Hendel-Nevo parameters:

$$\text{Baseline case (Hendel - Nevo parameters)}: \omega^{NS} = 0.137172, \beta^{NS} = -1.413173, \beta^{NS} = -4.371763$$

$$\text{Lower nonstorer price sensitivity}: \beta^{NS} = -0.413173$$

$$\text{Higher nonstorer price sensitivity}: \beta^{NS} = -2.413173$$

$$\text{Lower storer price sensitivity}: \beta^{S} = -3.371763$$

$$\text{Higher storer price sensitivity}: \beta^{S} = -5.371763$$

[21] Recall that in our analyses of the firm’s response to wholesale price changes, we indexed the price series using the average regular price. For this reason, the Discount Index used in that analysis can be interpreted as a percentage discount off the regular price.

$$\text{Twice as many nonstorers}: \omega^{NS} = 0.274344$$

$$\text{Half as many nonstorers}: \omega^{NS} = 0.068586$$

The findings confirm the robustness of the initial analysis. The firm incurs almost no opportunity cost from failing to adjust its discounts in response to cost shocks. In contrast, failing to either price discriminate between periods or adjust its regular prices in response to a cost shock has impacts that are at least an order of magnitude larger. We conclude that the firm leaves very little money on the table when it forgoes the opportunity to vary its sale prices in response to cost shocks. While it is important to offer sale prices, it is not important to let the size of the discount vary with underlying marginal costs.[22]

8. Institutions of manufacturer trade deals and retailer temporary sales

We have presented evidence from multiple sources that retailers respond to macroeconomic shocks through their regular prices rather than their sale prices. This evidence contrasts with the initial observation that 95% of the price variation in our data is explained by sales. In this section, we reconcile the findings with these observations by discussing the institutional features of trade promotions and sales. These features indicate that sale prices are governed by sticky plans, so that while the system of trade promotions contributes to price variation, the system itself is not easily changed.

The information in this section is based on interviews with both the firm that provided data for this study and a convenience sample of manufacturers and retailers. We should note that the details of the promotion funding mechanisms discussed in this section differ across manufacturers and retailers.[23] However, we know from surveys of manufacturers that a large fraction of these mechanisms share the key features that we emphasize in markets for consumer packaged goods (see, e.g., Acosta, 2012). We have organized our findings into four stylized facts.

8.1. Temporary sales follow "Sticky plans"

From a logistics perspective, temporary sales are complicated events that require a substantial amount of planning and coordination between retailers and manufacturers. For example, when a promotion is run at a retail chain, it may be accompanied by coupons, radio-television advertising, digital marketing, in-store displays, feature advertising, or product sampling. Retailers and manufacturers both understand that these demand-generating activities are highly complementary with temporary sales and thus need to be coordinated carefully. In addition, there is often coordination with the retailer to ensure that sufficient inventory is available (see, for example, Anderson and Simester, 2001, and Anderson et al., 2006).

To coordinate these activities, manufacturers and retailers collaborate to determine the timing and depth of temporary sales. For many promotions, manufacturers allow for a "trade deal window" of several weeks where retailers can execute a promotion (see Blattberg and Neslin, 1990, p. 319). This flexibility allows retailers to adjust their promotion plan to local market conditions. For example, if a competing retailer is expected to offer a deep discount on Coke, then a retailer may decide to promote a different carbonated soft drink, such as Pepsi. In a subsequent week, the retailer may take advantage of the trade deal window to promote Coke.

Within the parameters of the trade deal funding offered by the manufacturer, retailers and manufacturers jointly agree up to a year in advance on a "trade promotion calendar"—a schedule for temporary sales and associated promotional activity. This is often decided via an annual planning process. We interpret this promotional calendar as a "sticky plan."[24]

8.2. Temporary sales are funded by "Trade deal budgets"

Most temporary sales are "funded" by trade deal budgets. To understand how this process works, consider the following example. Suppose a manufacturer's product normally has a regular retail price of $2.49, but the manufacturer wants to encourage the retailer to lower the price to $1.99 for one week eight times during the year. To "fund" the $0.50 discount, the retailer may be "paid" $0.35 per unit sold at $1.99 during the eight promotion weeks.[25] This amount will be allocated

[22] Notice that for several of the alternative parameter configurations we consider, the benefits of price discrimination are smaller than in our baseline specification. In two alternative scenarios, the benefits of price discrimination become extremely low: (1) because the storers and nonstorers become sufficiently similar or (2) because it becomes more optimal to sell only to the nonstorers.

[23] Precisely documenting how the promotion funding mechanisms work for every manufacturer and every retailer is extremely difficult. For example, in 2002 two of us (Anderson and Simester) sent an MBA student to intern for 10 weeks at a retailer and document promotion funding. We learned that there was no uniform promotion funding practice among manufacturers selling to the retailer, and the retail category managers could not easily document the flow of promotion funds. The most senior retail managers admitted that the promotion funding process had become extremely complicated and difficult to trace. At that time, determining the true marginal cost of a promoted item proved almost impossible.

[24] In a separate study, two of the authors were involved in manipulating the depth of temporary discounts on a sample of items. Even though they were merely varying the prices (and not which items were to be discounted), the lead time on making these decisions was almost four months.

[25] In many cases, the amount that is paid out of the accrual account (e.g., $0.35 per unit) is designed to keep the retailer satisfied with the total dollar margin during the promoted weeks. So, if the retailer earns a 33% gross margin per unit at the regular price, then the retailer may be happy to run a promotion that yields a 25% gross margin but substantially greater unit volume.

from a manufacturer trade deal budget that is specific to each retail account. In addition to "funding" temporary sales, the trade deal budget can be used to fund advertisements, in-store displays, and other demand-generating activity associated with the temporary sale. The allocation of this funding should not be considered a marginal cost shock, because it is neither an unexpected shock nor, arguably, a change in the true marginal cost of the item. An analogy can be drawn to the allocation of funds from travelers' frequent flyer accounts. When travelers redeem miles for free flights, it would be wrong to interpret the transaction as customers taking advantage of a sudden price shock.

Importantly, the amount of funds in a trade deal budget limits the total amount the retailer can "spend" on temporary sales. If the retailer wants to increase the number of discounts early in the year, it must recognize that there will be fewer funds in the trade deal budget to support discounts later in the planning period. Reductions in the wholesale price associated with trade deals therefore may not reflect reductions in the retailer's marginal cost—since the retailer is spending down a finite resource (the trade deal budget). One implication is that the wholesale price variables in scanner price data sets used in the macroeconomics and industrial organization literatures must be interpreted with great caution, since these variables often include price reductions "paid for" by trade deal funds, and therefore may not reflect true variation in the retailer's marginal cost.

8.3. Manufacturer trade deals are contingent contracts

In the late 1960s and early 1970s, manufacturers would simply offer retailers a temporary discount to the wholesale price. The intent of the manufacturer was to induce the retailer to hold a temporary sale. However, the funding strategy by manufacturers for sales was not incentive compatible. Some retailers would "forward buy," that is, purchase large quantities of the product at the discounted price. They would also not reduce the retail price (i.e., not hold a temporary sale) or execute in-store displays to advertise the product. This "bad behavior" on the part of retailers presumably arose because they understood that the temporary decline in wholesale price did not reflect a commensurate decline in the value of inventory.

Most modern sales are, therefore, designed as explicit or implicit contingent contracts. Manufacturers expect compliance and typically require retailers to verify "performance" in order to receive trade deals funds, by providing evidence that they have discounted, promoted, or featured the product in in-store displays (or some combination of these). As part of this verification, they may be required to submit examples of advertisements together with scanner price data. Non-compliance by a retailer can jeopardize both current and future financial transfers from the manufacturer.

As we discuss in the introduction, we believe that the facts in sub-sections 8.3 and 8.4 help to explain why EJR (2011) find that retail sales almost always coincide with wholesale cost changes, whereas we find little role for sales in responding to wholesale cost increases. Recall that we focus on changes in the Base Wholesale Price as our measure of wholesale cost changes—and do not include wholesale cost changes arising from trade deals. Fact C implies that retailers are often contractually required (implicitly or explicitly) to reduce retail prices when they take trade deal funding, even though reductions in the wholesale price arising from trade deals, arguably, do not constitute true changes in the retailer's marginal cost (sub-section 8.2).

In fact, if trade deals did not constitute contingent contracts, it would be surprising to observe sharp drops in observed wholesale prices associated with sharp contemporaneous drops in retail prices (as EJR document). If such sharp drops in wholesale prices truly reflected reductions in marginal cost, an optimizing retailer would simply respond by stocking up on inventory at the lower wholesale price.

8.4. Managers pay attention to regular prices

A key concern that macroeconomists have had about analyzing data on regular prices is: How do we know that regular prices are relevant in determining the ultimate price faced by the consumer? What if actual prices are set entirely independently from regular prices—making regular prices a vacuous concept?

One way of addressing this concern is to calculate how many transactions occur at the regular price. At this retailer, transactions at the regular price contribute 75% of revenue. The vast majority of revenue on the vast majority of the SKUs occurs at the regular retail price. Specifically, 61% (77%) of SKUs generate over 90% (80%) of their revenue at the regular retail price (McShane et al., 2016). Furthermore, when the regular price is not a retail price (i.e., there is a sale), we find the regular price is almost always related to nearby retail prices. Specifically, an item's time-t regular price is said to be "vacuous" if it is higher than the maximum price paid for the item from week $t-n$ to t. We find that vacuous prices are rare—for $n=26$, only 0.75% of regular prices are vacuous—and in 82% of these cases, the regular price equals a retail price paid in the next 26 weeks.

We can also ask: Which price measures do the firm's senior managers believe are most important? At this firm, Regular Retail Prices and Base Wholesale Prices are clearly viewed as the primary measures of the firm's pricing policy and costs. These two metrics are summarized in monthly pricing reports that are shared among senior leaders in the company. Doubtless, the use of regular prices varies across firms. We believe, however, that the importance of the regular price is likely to hold true for other retailers of consumer packaged goods. The monthly pricing report lists every change in the Base Wholesale Price and the Regular Retail Price (in the "main" pricing zone) that occurred in the calendar month. It then summarizes the impact on profit margins by category and at the aggregate firm level. In this report, the Base Wholesale Prices and the

Regular Retail Prices are interpreted as the true variable cost of a unit and the true price of a unit. Notably, there is no reference to temporary sale prices or the funding of temporary sales by manufacturers. In several years of conducting research with this firm, we (Anderson and Simester) have never observed a regular management report describing temporary sale prices or the amount of manufacturer trade deal funding.

These findings may help to explain the results of interview studies on pricing, such as the seminal work by Blinder et al., (1998) and the many follow-up studies using similar methodologies. These studies interview managers about their pricing practices and find that prices change about once a year—much less than retail price data suggest. The managers in our firm probably would have interpreted such interview questions as referring to the firm's regular price, explaining why the reported frequency of price change is much closer to the frequency of regular price change than the frequency including sales.

9. Conclusion

Sale prices can result in an extremely high frequency of price changes in retail price data. In our data, temporary sales account for 95% of all price changes. A key question is whether these frequent price changes facilitate rapid responses to changing economic conditions or whether they are merely part of a "sticky plan" that is determined substantially in advance and therefore not responsive to changing conditions. We use an exceptionally detailed data set on retail and wholesale prices to investigate this question.

We show empirically that, while regular retail prices respond strongly and immediately to wholesale cost increases, temporary sales play no role in facilitating the upward adjustment of retail prices. This is true even in cases in which regular retail prices fail to respond immediately—even in these cases, there is no immediate response of sales. To the extent that sales do respond, it is the "wrong" direction—that is, sales appear to rise temporarily following regular retail price increases, perhaps to conceal the price increase.

We present three additional pieces of evidence for our central finding that retailers do not use sale prices to respond to shocks. First, we provide evidence that temporary sales fail to react to commodity cost shocks. Second, we provide evidence that temporary sales fail to react to changes in local unemployment rates. Third, we use BLS microdata to show that time variation in sale prices does not contribute to the variance or cyclicality of inflation. This generalizes our finding that retailers do not use sales to respond to shocks beyond just a single retailer.

We then present theoretical and institutional arguments for why retailers behave in this way. We use Hendel and Nevo's (2013) model of price discrimination to show that the benefit to a retailer of dynamically adjusting the size of sales is minimal: two orders of magnitude smaller than the benefits of price discrimination per se. Finally, we highlight four features of the institutions of retail and wholesale pricing for consumer packaged goods, which help to explain our empirical findings. Temporary sales are typically (1) orchestrated substantially in advance according to a trade promotion calendar (i.e., they are "sticky plans"), (2) "funded" out of trade promotion budgets, (3) implemented as part of "contingent contracts" requiring the retailer to lower its price, and (4) the dynamic adjustment of sales is not the main focus of managerial attention. These features imply that wholesale price variables that appear in scanner price data sets often do not provide an accurate representation of the retailer's marginal cost.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2017.06.003.

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