Informational Rigidities and the Stickiness of Temporary Sales

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We use unique price data to study how retailers react to underlying cost changes. Temporary sales account for 95% of price changes in our data. Simple models would, therefore, suggest that temporary sales play a central role in price responses to cost shocks. We find, however, that, in response to a wholesale cost increase, the entire increase in retail prices comes through regular price increases. 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. We present institutional evidence that sales are complex contingent contracts, determined substantially in advance. We show theoretically that these institutional practices leave little money "on the table": in a price-discrimination model of sales, dynamically adjusting the size of sales yields only a tiny increase in profits.

Keywords: Regular Retail Prices, Retail Sales, Trade Deals.

JEL Classification: E30, L11, M30.

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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 vastly different empirical characteristics than "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. As we discuss later in the paper, the institutions of price-setting in the consumer packaged goods industry are such 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. We use a detailed dataset 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 both.[1] Because temporary sales account for 95% of all price changes in our data, one might think 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.

[1] We show that both outcomes are predicted by Hendel and Nevo's (2013) model.

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, we find no response of sales. Second, we provide evidence that temporary sales fail to react to changes in local unemployment rates. Third, we use BLS micro data 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 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 sales prices. We use Hendel and Nevo's (2013) model of sales to study the profit losses 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

[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.

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 the retailer is "spending down" when he holds a sale, observed movements in wholesale prices associated with such trade deals may not reflect true reductions in marginal cost (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? This is because doing so is a contractual obligation 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 the manufacturers require evidence that the retailer actually put the product on sale before they will release the allocated funding from the trade deal budget.

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: (a) the response to commodity cost shocks, (b) the response to changes in local unemployment rates, or (c) the BLS micro data. 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 (2011) 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 (forthcoming) 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. Finally, Guimaraes and Sheedy (2011) develop a model in which temporary sales are used for price discrimination.[4] 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.

A more empirically-focused literature has also blossomed, with a key question being whether temporary sales respond to aggregate information. Using US CPI micro data, Klenow

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

[4] Chevalier and Kashyap (2014) also develop a price-discrimination model. They use it to explore the implications of temporary sales for constructing price indices.

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) find that the frequency of sales is correlated with unemployment in the UK.[5] On the other hand, Coibion et al. (2015) find that US retailers' use of sales does not vary with unemployment, while Berardi et al. (forthcoming) 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 comes 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. (forthcoming) and McShane et al. (forthcoming) who report findings using different datasets. The data used in this paper contains 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.[6] For this sample, we have data on the number of units sold each week for each product at the Stock

[5] Kryvtsov and Vincent (2014) also present some evidence for the US for a subset of the time period we study. See section 6 for a discussion of this evidence.

[6] 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 Mid-West and East Coast states. Because they are in different "price zones," the Regular Retail Price and the Retail Price (including temporary sales) for an SKU in a given week differs across stores.

Keeping Unit (SKU) level at each store.[7] The dataset 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.

The dataset has two unique features that are crucial to our analysis. First, the Regular Retail Price variable is reported directly in our dataset. This allows us to avoid using a "sale filter" to identify sales, as in other scanner datasets.[8] Second, our measure of wholesale prices is the "Base Wholesale Price" excluding trade deals. This is an important departure from earlier work (e.g., Eichenbaum et al. 2011) that focused on wholesale prices including trade deals. The reason we believe it is preferable to exclude trade deals is that, as we explain in detail in section 8, variation in wholesale costs associated with trade deals may not reflect variation in marginal cost faced by the retailer. The retail response to such trade promotions is typically part of a complex contingent contract.[9] 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 underlies the Consumer Price Index. We discuss these additional data sources, as well as several additional details regarding our scanner price dataset in Appendix A.

3. The Importance of Sales in Scanner Data

Figure 1 illustrates three price measures using a representative item in our dataset: the Retail Price, Regular Retail Price, and Base Wholesale Price. The figure reveals that Wholesale and Regular Retail Prices exhibit similar dynamics, adjusting both infrequently and persistently,

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[7] 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 direct store delivery (DSD) categories in Appendix A.

[8] 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, forthcoming). These imputation algorithms will, however, naturally introduce some noise into the regular price variable.

[9] 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.

while Retail Prices adjust much more frequently due to 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).[10] Over 95% of the price changes in our dataset are due to temporary sales. The weekly frequencies of price change for Base Wholesale and Regular Retail Prices are 0.74% and 1.11% respectively; while 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 should expect to see both increases in Regular Retail Prices and reductions in the size and frequency of sales. 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.

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 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 there no unit was sold of the item 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

[10] 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).

37,981 events yields a total panel sample of 2,147,676 observations.

We estimate the following equation,

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

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).[11] To prevent over-identification we omit the dummy variable measuring week 0, the week before the wholesale price change. We estimate the model using weighted OLS, where the observations are weighted by the revenue of the SKU in the store. The standard errors are clustered at the item level, to account for any correlation in the errors across events, stores and/or SKUs that share the same item number.

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).

Results

Figure 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

[11] 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 5 week intervals. The exception is Week 0, which identifies the 1 week before the cost change.

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 increases. Panel A of Figure 2 shows, however, that there is also a sharp and immediate response of Regular Retail Prices.[12] The immediate "pass-through" of Wholesale Prices into Regular Retail Prices is roughly "cent-for-cent." Recall that the series are all indexed against the same base (the average Regular 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 (forthcoming) and Hendel and Nevo (2013) present models in which regular prices and sales both respond to underlying changes in marginal costs.

Panel B of Figure 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.

Recall that the model includes time fixed effects. Therefore, the lines in the figures 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 is getting eroded relative to other products in the sample. This explains the negative trends that arise before and after week "0" in Figure 2. These trends are absent in Appendix Figure A1, which shows the results for the model with no time fixed effects.

[12] 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.

Table 2 presents the results in tabular forms, with the average short-term price response (weeks -20 to -1 versus weeks 1 to 20), the average medium term response (weeks -40 to -21 versus week 21 to 40) and the average long-term price response (weeks -50 to -41 versus weeks 41 to 50).[13] 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 Component. Instead, the increase in Retail Prices is almost completely attributable to an increase in the Regular Retail Price.

The evidence that the Discount Component 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 Component, this would lead to accumulated increases in the Discount Component over time. Eventually the Discount Component would reach its natural limit: discounts all of the time. The fact that we do not see this requires that increases in the Discount Component 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 "cent-for-cent" pass-through (not an equal percentage change). 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 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

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[13] These results were estimated by re-estimating Equation 1 using separate dummy variables identifying these sets of weeks.

usually announced in advance).[14]

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, while the remaining 17% do not. 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 price change—substantiating the view that the increase in sales is intended to mask the increase in regular retail prices.

In the long-run, the wholesale cost increase has no impact on sales in either the case with or 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.

Wholesale Price Decreases

For completeness we also analyze how the retailer responds to wholesale price decreases.

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[14] 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.

Wholesale price decreases are relatively rare events, and so this analysis should be treated cautiously, as it is a study of outliers. In Table A1 of the appendix we report 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. In 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. As a result, it is perhaps unsurprising that we do not see significant changes in either the Regular Price Index or the Discount Index (similar findings are also reported by Anderson et al. (forthcoming) and McShane et al., forthcoming).

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

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.

Figure 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.[15] The diesel price variable is the 12-month change in diesel prices, lagged by one quarter.[16]

Figure 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). In conversations with managers at the retailer, 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.

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).[17] Table 4 presents results from the following weighted OLS regression,

$$Y_{ist} = \sum \mu_i + \sum \mu_t + \beta_1 \textit{Change in Unemployment}_{st} + \varepsilon_{ist}, \quad (2)$$

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

15 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.

16 Lagging the change by a quarter recognizes that there is a lead-time between the timing of the diesel price change, the timing of wholesale and retail pricing decisions, and the implementation of those decisions.

17 Core Based Statistical Areas 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 people and the surrounding areas that are linked to the core by a high degree of social and economic integration as measured by commuting patterns. Core Based Statistical Areas are defined by the Office of Management and Budget.

the Discount Index. We do not report the results for the Wholesale Price Index as this variable is determined almost exclusively at the national level, implying that there is little variation across regions.

The *Change in Unemployment$_{st}$* variable is defined in a similar way to the change in diesel prices in the previous section. In particular, it is calculated as the 12-month change in the monthly unemployment rate in that CBSA, lagged by one quarter. We use the same sample of approximately 5 million observations 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 changes in unemployment on retail prices solely using variation in regional unemployment (where the regions are represented by the store locations) relative to the average unemployment rate.

Table 4 shows that a one percentage point increase in the relative 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.[18]

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 U.S. retailers? To investigate this question, we use BLS micro data on prices underlying the Consumer Price Index. 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. Appendix A describes other important features of the data construction.

[18] 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.

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.[19] This 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.

Figure 4 plots "posted" and "regular" price inflation alongside the unemployment rate. Posted price inflation is the conventional inflation rate based on observed prices, while regular price inflation is the inflation rate for regular prices excluding sales.[20] We HP-filter all series to remove low-frequency trends[21] 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.

Table 5 presents some key moments of posted, regular, and "sale-related" inflation; the latter being the difference between regular and posted inflation. Our focus is primarily on the elasticity of the respective inflation series to various measures of the business cycle. The elasticity is calculated by running a regression of the (log) inflation rate on unemployment or (log) GDP; all variables HP-filtered.[22] A positive (semi-)elasticity of sale-related inflation with respect to unemployment -- or a negative elasticity with respect to GDP -- would indicate that the magnitude of sale-related discounts tends to rise during recessions. Note that this cyclical elasticity is a covariance measure, so depends on both the correlation of sales with the cycle and the magnitude of the discount due to sales.

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

[20] 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 Appendix A for more details.

[21] Regular price inflation is higher, on average, than posted price inflation over our sample. This 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)).

[22] 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 Table 5 results were qualitatively unchanged.

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 5A shows that sale-related inflation is essentially acyclical for the food category. The cyclical elasticity of posted price inflation (including sales) with respect to the unemployment rate is -0.99 versus -0.91 for regular prices, while the cyclical elasticity of sale-related inflation 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 5B presents the results for all sectors of the economy. Again, the cyclical elasticity with respect to unemployment and GDP is similar for posted price and regular price inflation, and statistically insignificant and economically small for sale-related inflation. 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. Figure 5 presents the impulse response to a +25 basis point monetary policy shock using a standard four-variable VAR, including the unemployment rate, posted (or regular) price inflation, commodity price inflation and the Federal Funds Rate.[23] The shock is identified using a standard Cholesky factorization, where the variables are ordered as above. Figure 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.[24]

The findings in Figures 4 and 5 and Table 5 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 macro-economic shocks. If retailers used sale prices to respond to macro-economic shocks, then we would expect there to be substantial differences in the

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[23] For commodity prices, we use the PPI: Crude Materials for Further Processing, and for the Federal Funds Rate, we use the Wu and Xia (2014) Shadow Rate. We also considered using GDP growth rather than unemployment and the results changed little.

[24] The quarter-one response of sale-related inflation is 0.007 (s.e. 0.008), compared to -0.026 (s.e. 0.018) for posted price inflation.

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 regular prices, rather than by adjusting their sale prices. Time-variation in the frequencies and sizes of sales do 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 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 A2) 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.

Figure 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 and makes somewhat different assumptions about several details of data construction.[25] 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.[26] 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

[25] Our picture looks somewhat different from the one reported in Kryvtsov and Vincent (2014) due to a number of differences in weighting, the definition of sales, and sample selection. We discuss these differences in more detail in Appendix A. However, the qualitative findings are the same.

[26] Note that the discount variable reported in Table A2 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.

at an elevated level in the last few years despite the fall in unemployment after the recession. This helps 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 consumers: storers and non-storers. These consumers have perfect foresight about the path of product prices. However, there demand is random. There is a mass ω^S of storers in the population (and a mass $\omega^{NS} = 1 - \omega^S$ of non-storers).

For non-storers, the model generates inverse demand functions of the form:

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

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

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

If $p_t \leq p_{t+1}$ and they have nothing in storage, then storers purchase for two periods: $2Q^S(p_t)$; while 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 the second. Given the perfect foresight assumption, only non-storers purchase in the second period. The firm solves the following optimization problem:

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

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 have a higher price elasticity than the non-storers: ω^{NS}=0.137172, β^{NS}= -1.413173, β^{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?

Figure 7 addresses the first question. We denote the price when only non-storers buy as the "Regular Price" and the price when storers also buy as the "Sale" price. The green and blue lines show the regular and sale prices respectively in the firm's optimal pricing policy. For comparison, the red line shows the price the firm would set if it was unable to price 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 have a higher price elasticity than the non-storers). Given this, one might expect that sales would play a part in price adjustment, even if their main role is to facilitate price discrimination.

Table 6 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-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), while the non-storers 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").[27] 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 non-storers 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 inter-temporal price-discrimination, Hendel and Nevo (2013) refer to them as "Non-Discriminatory" policies.

The first row of Table 6 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 6 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 as 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 sales price is 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.

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[27] 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.

We can investigate how robust these findings are to varying the parameters in the model. In particular, in Table 6 we report several variations to the Hendel-Nevo parameters:

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

Lower non-storer price sensitivity: $\beta^{NS} = -0.413173$

Higher non-storer price sensitivity: $\beta^{NS} = -2.413173$

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

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

Twice as many non-storers: $\omega^{NS} = 0.274344$

Half as many non-storers: $\omega^{NS} = 0.068586$

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 have 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.[28]

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

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

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.[29] 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.

A. 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.[30]

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

[29] 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.

[30] See for example Anderson and Simester (2001) and Anderson, Fitzsimmons and Simester (2006).

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."[31]

B. 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.[32] This amount will be allocated 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, as 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 flying 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

[31] 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.

[32] 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 25% gross margin but substantially greater unit volume.

spending down a finite resource (the trade deal budget). An implication of this is that the wholesale price variables in scanner price datasets 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.

C. 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," i.e., 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 contingent contracts. Manufacturers require retailers to verify "performance" in order to receive trade deals funds, by providing evidence that they have discounted, promoted and/or featured the product in in-store displays. As part of this verification they may be required to submit examples of advertisements together with scanner price data.

As we discuss in the introduction, we believe that facts B and C 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 due to trade deals. Fact C implies that retailers are often contractually required to reduce retail prices when they take trade deal funding, even though reductions in wholesale price due to trade deals, arguably, do not constitute true changes in the retailer's marginal cost (Fact B).

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 reduction in marginal cost, an optimizing retailer would simply respond by stocking up on inventory at the lower wholesale price.

D. *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.[33] 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.[34] 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

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[33] 61% (77%) of SKUs generate over 90% (80%) of their revenue at the regular retail price (McShane et al., forthcoming).

[34] 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.

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.[35]

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 dataset 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 where 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—i.e., 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 micro data 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.

[35] 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 suggests. 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.

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 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 their 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.

Appendix A: Data Sources

Scanner Price Data

As in other scanner price datasets, each of the price measures in our dataset represents a weighted average over all of that week's retail transactions for the item in that store. This implies that if the Regular Retail Price changes in the middle of the week then the price we observe is an average of the price before and after the change, weighted by the number of items purchased at the different price levels. Similarly, if an item is temporarily discounted but customers only receive the discount if they present the retailer's frequent shopping card then the Retail Price will represent a weighted average of the price paid by customers who receive the discount and those who do not. To avoid double-counting price changes that occur mid-week when calculating the frequency of price changes, we exclude price changes less than 1-cent in magnitude and price changes that are in the same direction as a price change in the immediately preceding week.[36]

Many items have multiple color or flavor variants (e.g. orange versus mint flavored 1oz tic tac candy). The individual flavors of 1oz tic tac candy are identified at the SKU-level, while all of the flavors of 1oz tic tac candy share a common item-number. All SKUs under a single item-number have the same Regular Retail Price at a store in any week. They also share any temporary discounts and generally have the same Wholesale Price (although in some cases there is small variation in the Wholesale Price across different SKU numbers that share the same item-number). In our analysis we will cluster standard errors at the item level to account for the interdependence in price movements across stores and/or across SKUs that share the same item number.

Direct Store Delivery

Direct Store Delivery (DSD) refers to the practice of manufacturers bypassing the retailer's distribution system and delivering certain goods directly to individual retail stores. In

[36] If a price reduction occurs in the middle of week t and continues in week t+1 then the average price paid will be *both* lower in week t than week t-1, and lower in week t+1 than week t. This introduces a risk of double-counting price changes. Excluding price changes in the same direction as a price change in the immediately preceding week addresses this.

the analysis we omit DSD categories, primarily alcohol, beverages, and dairy.[37] There are important institutional differences in how pricing decisions are made in DSD categories, which imply that both the Wholesale Price and the Regular Retail Price measures – key features of our dataset – cannot be interpreted in the same way in these categories as in other categories.

Most important for our purposes, accrual accounts are not used to "fund" temporary discounts in DSD categories. In the case of alcohol, this is the result of legal restrictions. In the other categories, it may be because the incentive problems accrual accounts are designed to solve are not as severe in the case of DSD items since retailers hold no inventory apart from what is on the shelf at each time (so "forward buying" in response to discounts is not possible) and since the manufacturer can better monitor performance.

Manufacturers play a more direct role in setting retail prices in DSD categories.[38] Temporary sales on DSD items are often funded by temporary reductions in the Wholesale Price. Moreover, temporary price fluctuations are often coded as movements in the Regular Retail Price in the DSD category and discounts are more persistent. Approximately 20% of the Retail Price changes on DSD items arise because of long sales of 13 weeks or more, compared to just 1% to 2% for non-DSD items.

For non-DSD categories, we have argued that institutional features of how prices are set – arising because of incentive problems associated with the implementation of temporary sales – imply that Regular Prices respond to cost and demand shocks, while temporary sales do not and are instead purely associated with intertemporal price discrimination. It may be that managers use a similar two-part approach to setting prices in DSD categories. Unfortunately, for the institutional reasons discussed above, this decomposition does not coincide with the Regular Retail Price vs. Retail Price distinction as it does in non-DSD categories, so our data are not able to speak to this issue.

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[37] Firms cannot legally store alcohol unless they are a bonded wholesaler, which in practice requires that wholesalers deliver directly to stores. As a consequence, alcohol items are always DSD items.

[38] Perhaps for this reason, in DSD categories, both Wholesale and Retail prices vary much more across stores in response to regional competition. Regular Retail Prices and Retail Prices may vary at the region level in DSD categories, rather than at the "pricing zone" level for other products. In addition, whereas for almost all other products Wholesale Prices are constant across the national chain, Wholesale Prices for DSD items may also vary at the regional level.

Commodity Price Data

In our analysis of the reaction of retail and wholesale prices to underlying costs and regional unemployment, we use additional data on the spot price of a gallon of diesel and CBSA-level unemployment rates. The diesel price data was downloaded from the US Energy Information Administration website and is for the Los Angeles price of a gallon of ultra-low-sulfur number 2 diesel fuel.

Unemployment Data

The CBSA-level unemployment rates were obtained from the Bureau of Labor Statistics Local Area Unemployment Statistics program. In cases where the stores in our main dataset are located in rural areas that are not part of a CBSA for which an unemployment rate is available, we manually match the store with the closest CBSA, and use the unemployment rate for that CBSA.

BLS Data

We use the micro data underlying the non-shelter portion of the CPI, which is about 70 percent of the CPI based on BLS expenditure weights.[39] The BLS surveys about 85,000 items a month in its *Commodities and Services Survey*; prices are collected at approximately 23,000 retail outlets across 87 large urban areas. Prices are collected *monthly* in the three largest urban areas and for food and fuel items in all areas, but every two months otherwise. We use all the data, but our results are little changed if we restrict our sample to only monthly data. Our sample period is October 1988 through November 2014.[40]

We construct all of our statistics using (expenditure) weighted averages of individual prices (and price changes). The BLS defines approximately 300 categories of consumption as Entry Level Items (ELIs), and they provided us unpublished annual ELI weights based on Consumer Expenditure Surveys. We normalize the ELI weights so that they sum to one across the ELIs each year, and we then construct an average weight over our sample period for each

[39] Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) provide thorough descriptions of this data set. Here, we focus on the features most relevant for our analysis.

[40] The data actually starts in January 1988, but because our construction of regular prices involves "filling forward" past prices when a sale occurs, it takes a few months before the count of admissible observations stabilizes.

ELI -- these weights also sum to one across ELIs. Finally, the CPI-RDB also contains relative weights for each price within an ELI in each month, which we use.[41]

We use constant rather than time-varying ELI weights because we're more interested in whether retailers change their use of sales over time than we are in the share of household expenditures purchased on sale. That is, we want to know if retailers put more items on sale in a recession, not whether households shift their consumption in recessions from, say, goods to services, which have fewer sales. That said, we did construct our measure with both types of weights, and our results do not change qualitatively.

The BLS labels each price as either a "sale" price or "regular" price. For sale prices, we construct a regular price by "filling forward" the previously reported regular price for the item. This would be fairly straight-forward for a balanced panel of data but requires some explanation because of the BLS's rotating sample – specifically, each item is priced for up to five years, after which it is rotated out of the sample – as well as missing observations. Our approach is as follows. First, we drop observations for which there is no previous regular price; for example, when an item is newly introduced to the sample.[42] Second, "forced item substitutions" occur when an item has been discontinued from its outlet and a similar replacement item (e.g., new model) has been identified to price going forward. In this case, we use BLS quality adjustment factors to adjust previous regular prices that are filled forward. Third, about 12 percent of prices the BLS attempts to collect are unavailable in a given month, either because they are out-of-season (5 percent) or temporarily unavailable (7 percent). Out-of-season observations are treated as missing, and when the item comes back into season, its previous regular price is set equal to the last regular price before it was out-of-season. On the other hand, we treat temporarily unavailable items as available at the previously collected (posted and regular) price.

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[41] Differential weights within an ELI reflect relative probabilities that an item is purchased versus sampled at an outlet. Our results do not change if we instead simply assign equal weight to all items within an ELI-month.

[42] It's clear why this is necessary if the first observation(s) of an item is a sale price. We drop the first observation of *every* item, even those whose first observation is a regular price, to avoid selection bias. Because the number of new items varies over time, including those that enter at a regular price but not those on sale would lead to fluctuations in the fraction of goods on sale due solely to our selection.

Once we have posted and regular prices for each item, we compute the item-specific (i) log difference between the regular and posted price and (ii) log difference between the *t* and *t-1* posted price and regular prices, respectively.[43] Although the BLS requires its price collectors to explain large price changes in order to minimize measurement error, some price changes in the dataset appear implausibly large. We exclude (posted or regular) price changes that exceed a factor of five in either direction (up or down). These account for less than one-tenth of one percent of all price changes. We similarly exclude sales for which the posted price is less than one-fifth of our constructed regular price. Finally, if the posted price is greater than the constructed regular price, we set their log difference to zero; in other words, "sales" must be price discounts.

We then take the weighted average of these measures across items in each month to construct time series of (i) the discount due to sales, (ii) posted price inflation, and (iii) regular price inflation, respectively. We similarly construct a times series of the (weighted average) frequency of sales by calculating the expenditure share on items whose posted price is less than their constructed regular price. We then seasonally adjust these time series by taking out monthly dummies, and finally take averages of the 3 months within each quarter to produce quarterly time series.

Comparison of Figure 6 to Kryvtsov and Vincent (2014)

Kryvtsov and Vincent (2014) present statistics on the frequency of sales for a subset of the years presented in Figure 6. For the years of overlap, the figure differs somewhat for the following three reasons. First, we use stable item weights over the whole sample period, as opposed to time-varying weights, as in the rest of our analysis—this is appropriate given that we wish to measure the producer response of sales to unemployment. Time-varying weights largely eliminate the upward trend in the frequency of sales that otherwise arises in the BLS data. BLS product weights put less weight on products with a high frequency of sales in more recent time periods. Second, our definition of sales requires both that the BLS sale flag be active and that the posted price is less than the regular price, whereas Kryvtsov and Vincent (2014) define sales using the BLS sale flag alone. Our definition is necessary because we are ultimately interested in

[43] For bi-monthly observations, we calculate monthly inflation by dividing the log difference by 2.

the total discount from sales, not just their frequency. Third, and for a similar reason, we drop observations that are out-of-season, don't have a lagged regular price, or have a sale that is larger than an 80% discount.

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Table 1
Frequency and Size of Wholesale and Retail Price Changes

	Average Weekly Frequency	Average Absolute Size
Base Wholesale Price Changes		
Any Change	0.74%	
Increases	0.63%	4.67%
Decreases	0.11%	7.14%
Regular Retail Price Changes		
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%

The 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 6,052 (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).

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%**	2.18%**	1.54%**
	(0.25%)	(0.31%)	(0.29%)
Retail Price Index	3.22%**	3.13%**	3.05%**
	(0.36%)	(0.40%)	(0.50%)
Regular Price Index	4.57%**	3.77%**	3.11%**
	(0.30%)	(0.39%)	(0.45%)
Discount Index	1.35%**	0.64%*	0.06%
	(0.36%)	(0.28%)	(0.36%)

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 -21 to -40 with weeks 21 to 40, 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 item level and reported in parentheses. *Significantly different from zero, $p < 0.05$, ** Significantly different from zero, $p < 0.01$.

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%**
		(0.24%)	(0.26%)	(0.26%)
	Retail Price Index	3.89%**	3.23%**	2.98%**
		(0.45%)	(0.47%)	(0.54%)
	Regular Price Index	5.42%**	3.88%**	2.91%**
		(0.34%)	(0.48%)	(0.54%)
	Discount Index	1.57%**	0.65%*	-0.07%
		(0.41%)	(0.32%)	(0.43%)
No Nearby Regular Price Change	Wholesale Price Index	3.55%**	3.68%**	2.95%**
		(0.59%)	(0.99%)	(0.90%)
	Retail Price Index	-0.46%	2.41%*	3.43%*
		(0.54%)	(0.97%)	(1.67%)
	Regular Price Index	-0.23%	2.73%*	3.40%*
		(0.39%)	(1.15%)	(1.45%)
	Discount Index	0.23%	0.32%	-0.03%
		(0.48%)	(0.49%)	(0.82%)

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 -21 to -40 with weeks 21 to 40, 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 1,834,682 (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 item level and reported in parentheses. *Significantly different from zero, $p < 0.05$, ** Significantly different from zero, $p < 0.01$.

Table 4
Regional Variation in Unemployment and the Frequency of Price Changes

	Retail Price Index	**Regular Price Index**	**Discount Index**
Change in Unemployment	-0.170%**	-0.156%**	0.014%
(3 month lag)	(0.039%)	(0.037%)	(0.022%)
R^2	0.278	0.251	0.280

The table reports coefficients from estimating Equation 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 5,394,146. Observations are weighted by Total Revenue for the SKU in that Store (calculated across all 195 weeks). Standard errors are clustered at the item level and reported in parentheses. *Significantly different from zero, $p < 0.05$, ** significantly different from zero, $p < 0.01$.

Table 5A
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	-0.57
		(0.02)	(0.08)
Cyclical Elasticity wrt U	-0.99	-0.91	0.08
	(0.34)	(0.30)	(0.06)
Correlation with U	-0.38	-0.40	0.13
	(0.09)	(0.09)	(0.10)
Cyclical Elasticity wrt GDP	0.59	0.53	-0.06
	(0.25)	(0.21)	(0.05)
Correlation with GDP	0.35	0.36	-0.15
	(0.09)	(0.09)	(0.10)

Table 5B
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	-0.36
		(0.02)	(0.09)
Cyclical Elasticity wrt U	-0.32	-0.37	-0.04
	(0.25)	(0.24)	(0.05)
Correlation with U	-0.10	-0.12	-0.08
	(0.10)	(0.10)	(0.10)
Cyclical Elasticity wrt GDP	0.42	0.45	0.03
	(0.20)	(0.18)	(0.05)
Correlation with GDP	0.19	0.22	0.07
	(0.10)	(0.10)	(0.10)

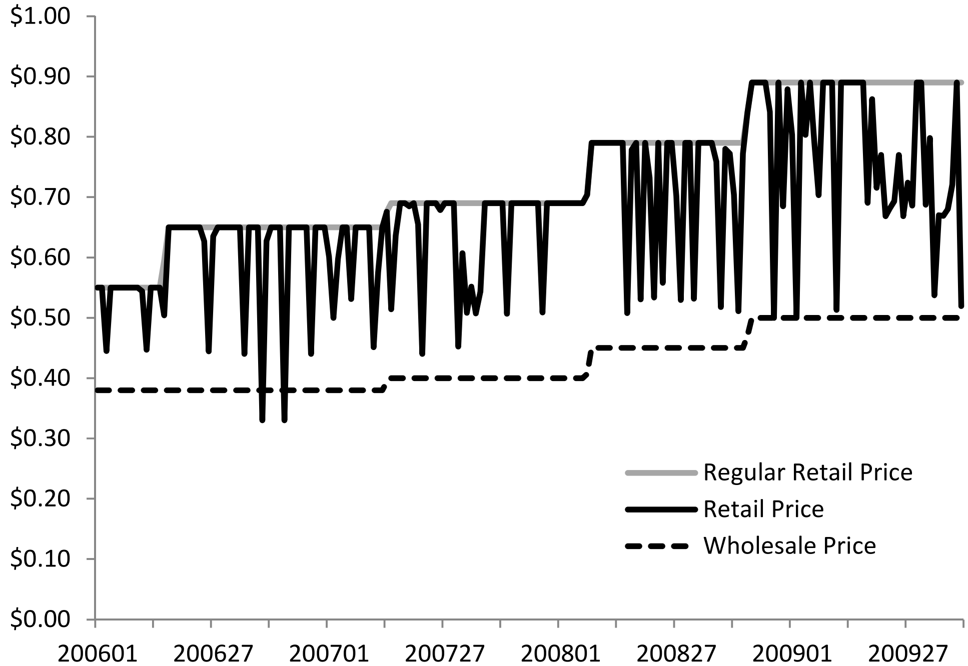
Inflation series constructed from the CPI-RDB, using data on food items (Panel A) and all non-shelter items (Panel B) in all areas from 1988q4 through 2014q3. Posted Prices include sale prices, whereas Regular Prices replace sale prices with previous regular price. Inflation is the weighted average of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

Table 6
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 Non-Storer Price Sensitivity	0.00%	0.01%	0.00%	0.01%
Higher Non-Storer 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 Non-Storers	0.01%	0.16%	0.99%	1.12%
Fewer Non-Storers	0.01%	0.42%	6.37%	6.79%

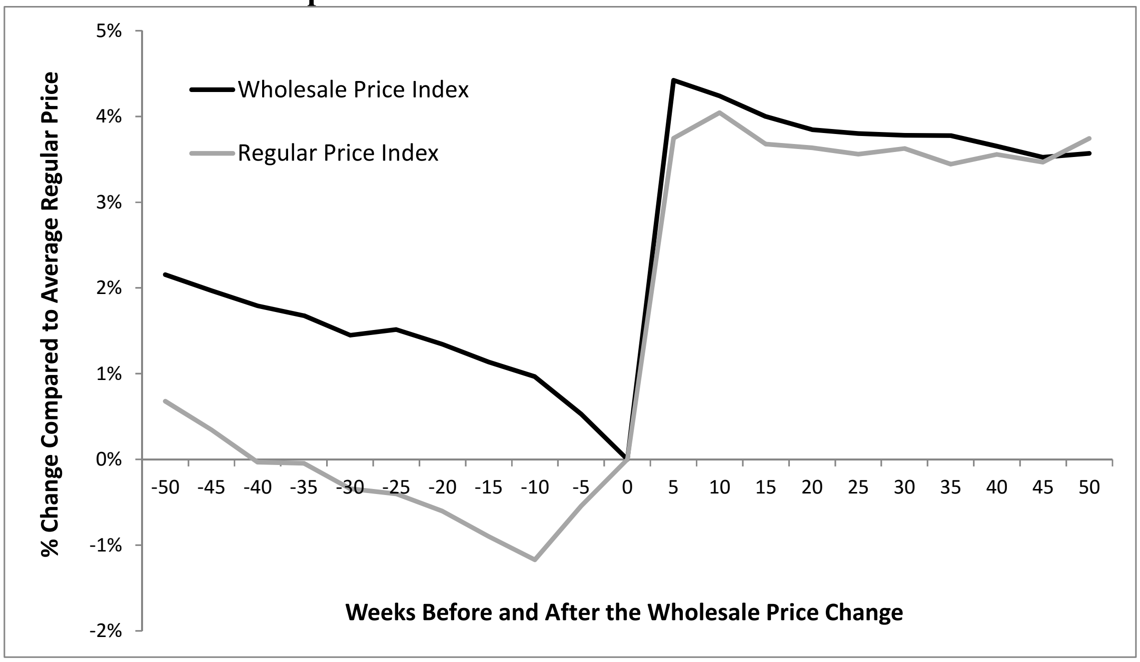
The table reports the loss from fixing each price component, as a percentage of the profit earned under the "flexible sales policy" (which allows both regular prices and sales prices to be optimized). The "fixed discount" policy allows the firm to adjust the regular price in response to the cost shocks, 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 2-period model.

Figure 1
Price Series: Example

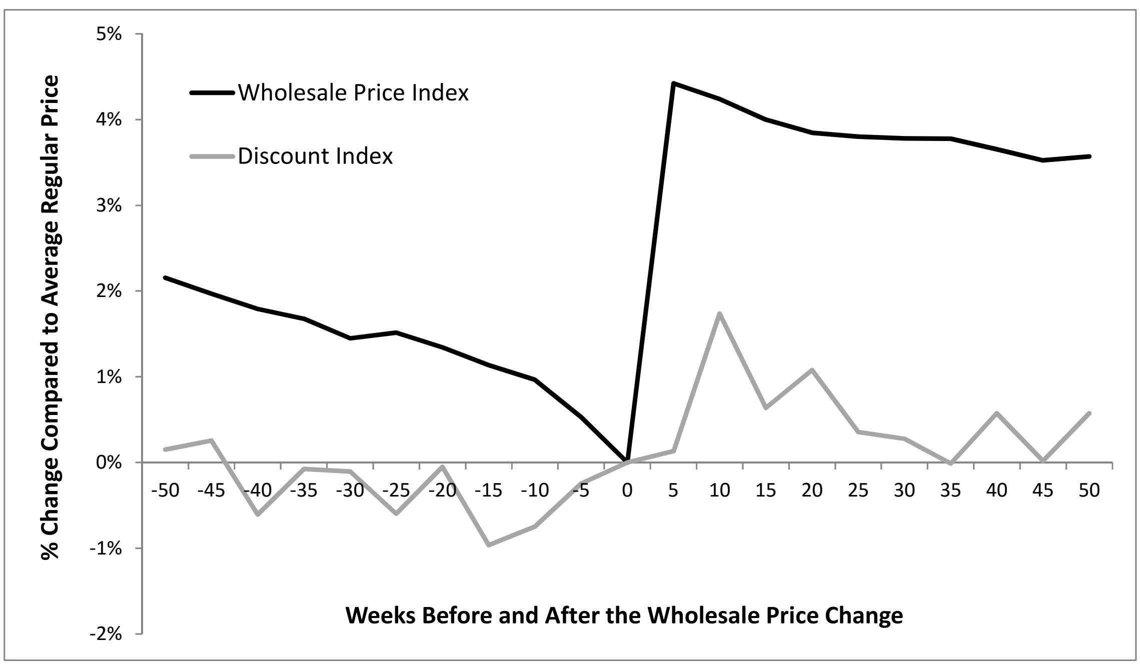


The figure reports the price trends for the three price variables for an arbitrarily chosen SKU at a single store that had sales of the SKU in all 195 weeks of the sample period.

Figure 2
Response to a Base Wholesale Price Increase



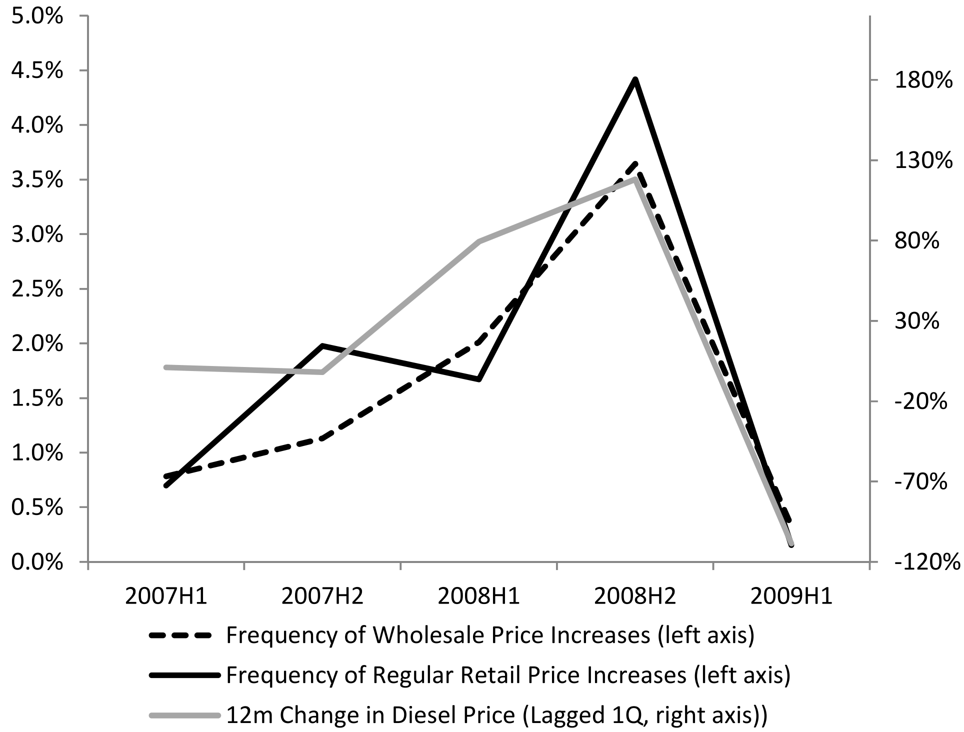
Panel A: Wholesale Price and Regular Price Index



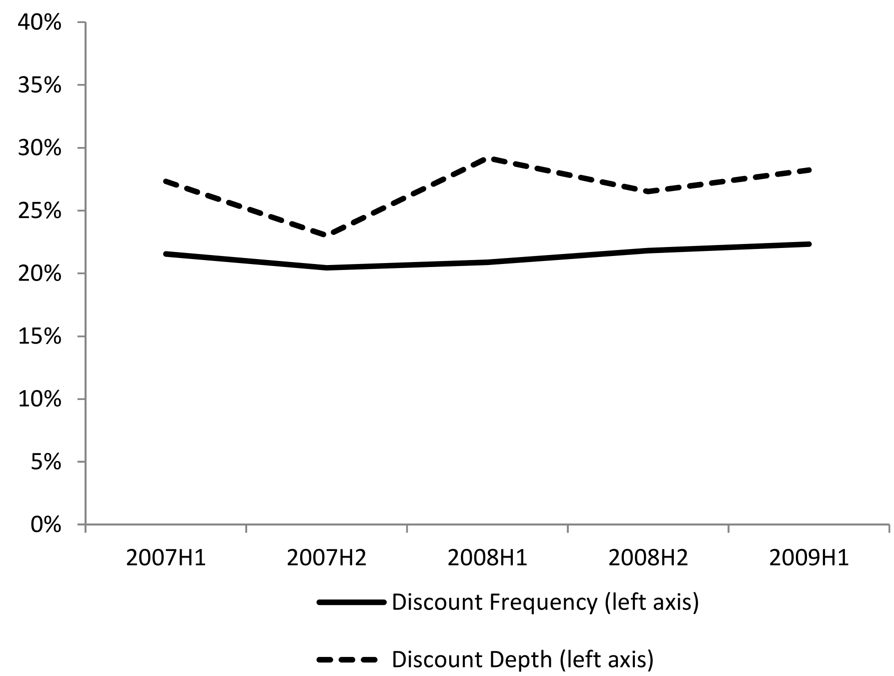
Panel B: Wholesale Price and Discount index

This 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 Equation 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).

Figure 3
Price Adjustment and Diesel Prices



Panel A: Regular Prices and Base Wholesale Prices



Panel B: Temporary Sales

Figure 4
Posted vs Regular Price Inflation

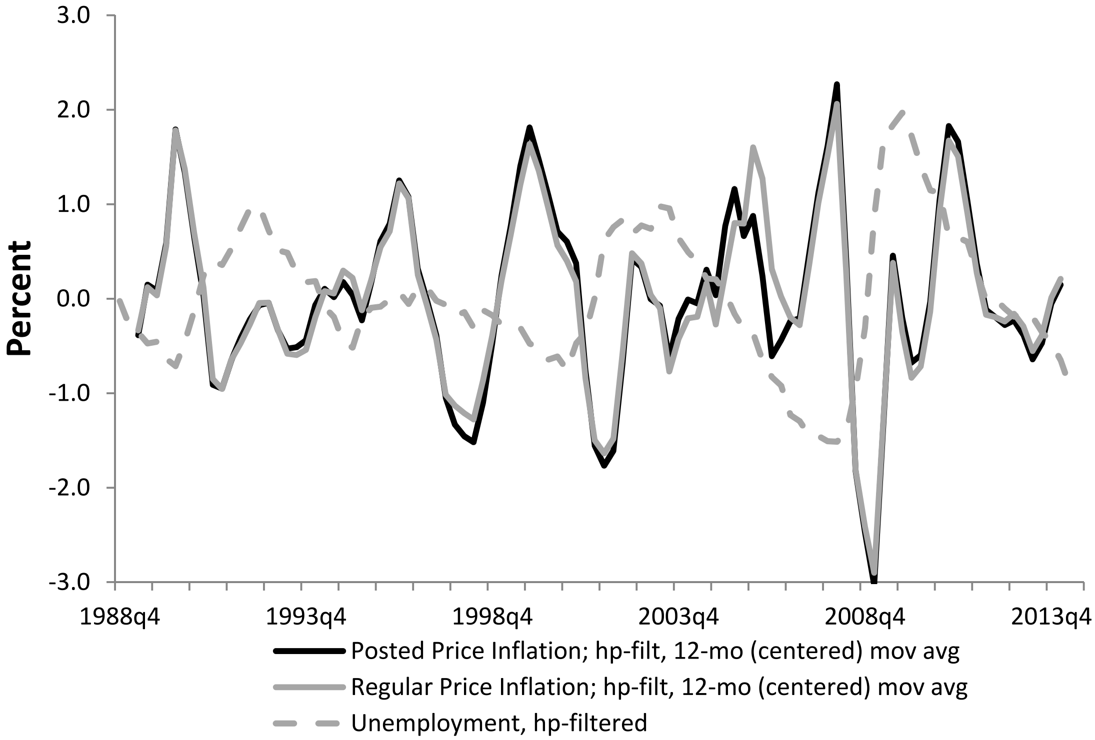
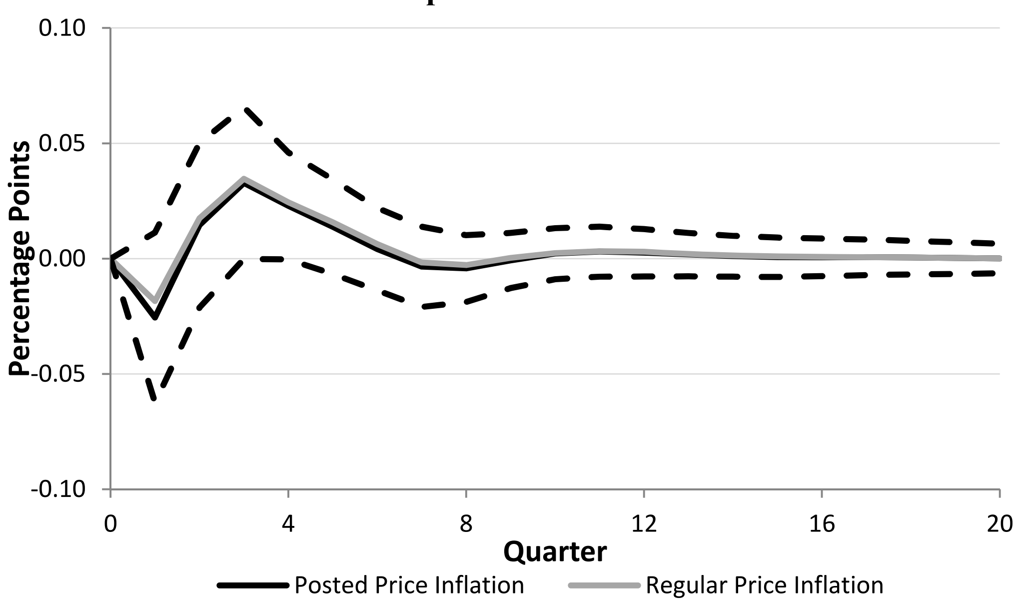


Figure 5
Inflation Response to Fed Funds Rate Shock



Impulse response functions constructed from 4-lag, 4-variable VAR, including unemployment rate, commodity price inflation, posted (or regular) inflation, and fed funds (shadow) rate. The shock is a +25 basis point innovation to the Fed Funds rate. Dashed lines are 2 * std error bounds on the p*osted* inflation response.

Figure 6
Frequency of Sales and Unemployment Rate

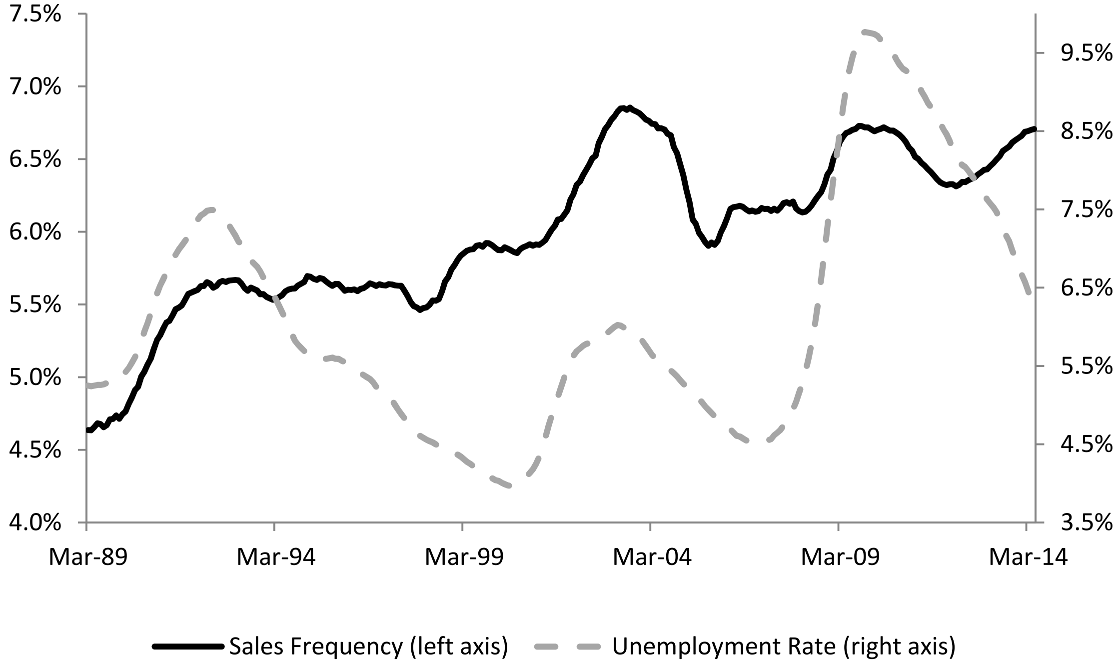
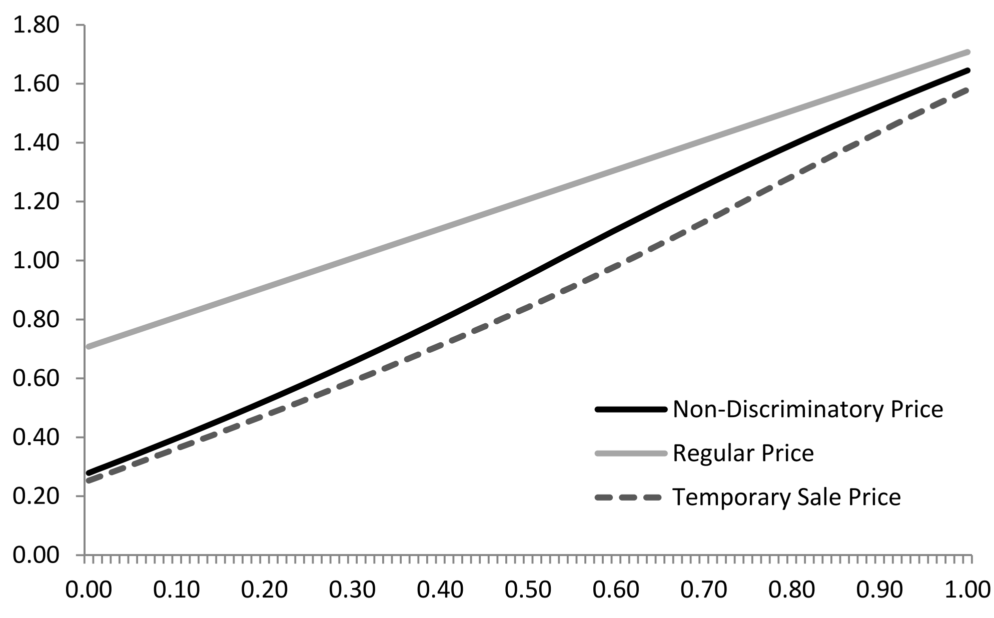


Figure 7
Discounts and Costs in the Hendel-Nevo Model



This figure illustrates how the optimal regular and sales prices vary according to the marginal cost in the Hendel and Nevo (2013) model. The sales 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).

Appendix

Table A1.
Change in Price Indices around the Wholesale Price Decrease Events

	Short-Term Comparison	Medium-Term Comparison	Long-Term Comparison
Wholesale Price Index	-2.68%	-0.34%	-0.07%
	(1.59%)	(0.86%)	(0.98%)
Retail Price Index	-0.99%	0.19%	1.43%
	(1.76%)	(0.93%)	(1.97%)
Regular Price Index	-0.52%	2.22%	2.49%
	(1.96%)	(1.78%)	(2.30%)
Discount Index	0.47%	2.04%	1.07%
	(0.58%)	(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 -21 to -40 with weeks 21 to 40, 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 item level and reported in parentheses.

Table A2a
HP-Filtered Price Cyclicality: Food

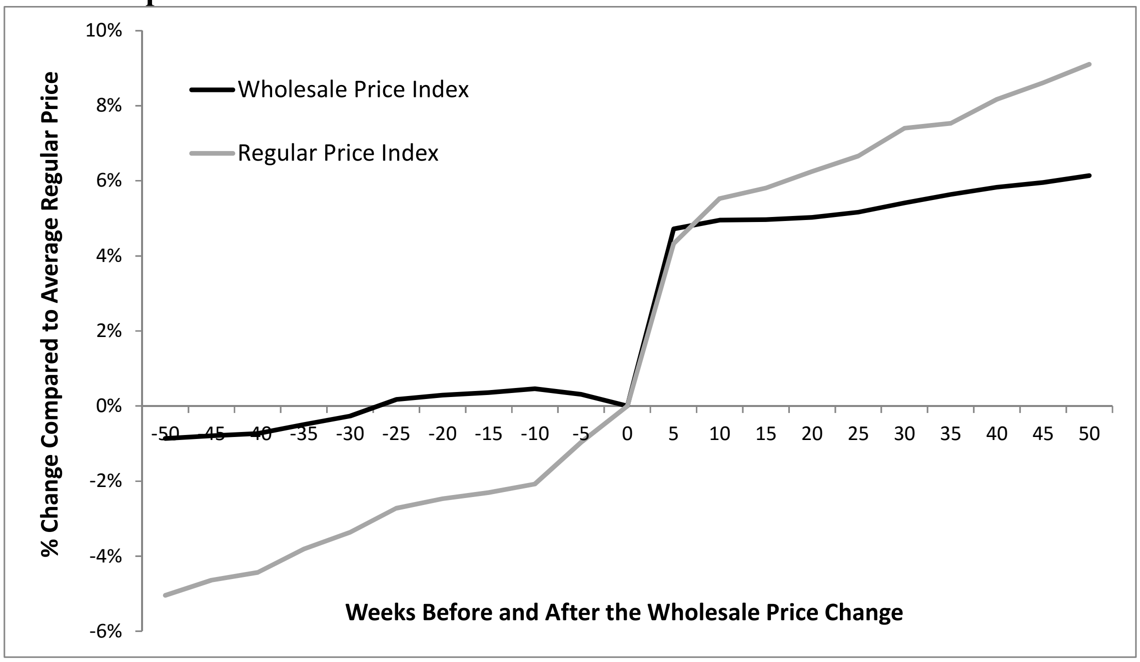
	Posted Price	Discount
Relative Variance	1.00	0.03
Correlation with Posted	1.00	-0.36 (0.09)
Cyclical Elasticity wrt U	0.09 (0.17)	0.10 (0.02)
Correlation with U	0.08 (0.10)	0.55 (0.08)
Cyclical Elasticity wrt GDP	-0.21 (0.10)	-0.05 (0.01)
Correlation with GDP	-0.26 (0.10)	-0.44 (0.09)

Table A2b
HP-Filtered Price Cyclicality: All Products

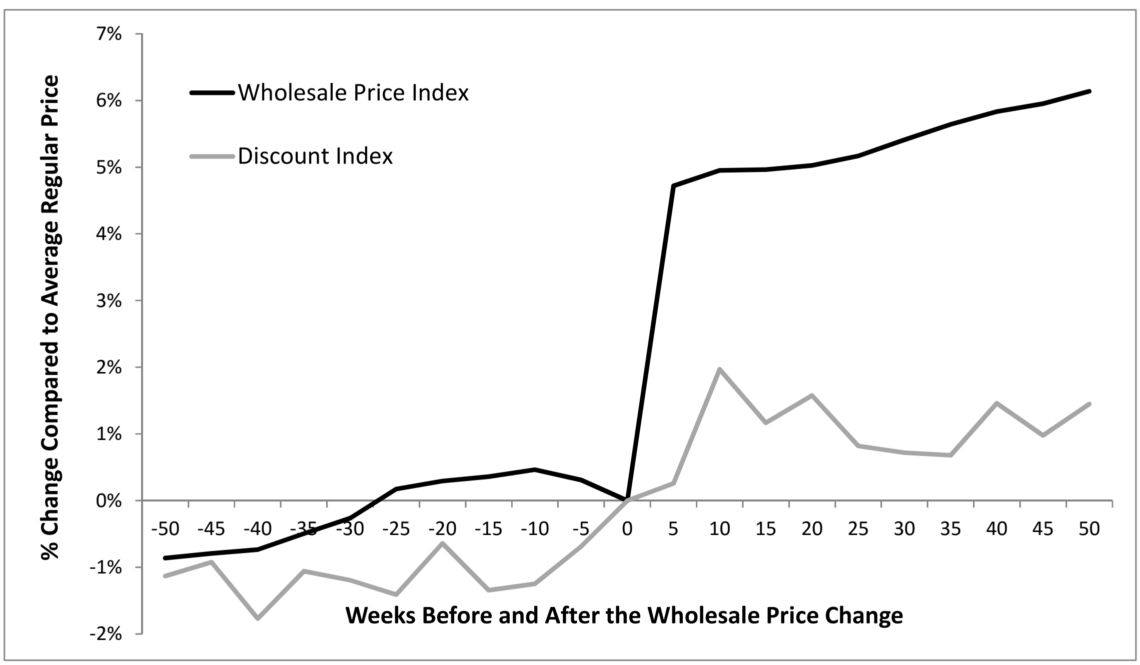
	Posted Price	Discount
Relative Variance	1.00	0.02
Correlation with Posted	1.00	-0.43 (0.09)
Cyclical Elasticity wrt U	-0.27 (0.14)	0.07 (0.01)
Correlation with U	-0.27 (0.10)	0.60 (0.08)
Cyclical Elasticity wrt GDP	0.10 (0.10)	-0.04 (0.01)
Correlation with GDP	0.15 (0.10)	-0.53 (0.09)

Series constructed from the CPI-RDB, using data on food items (Panel a) and non-shelter items (Panel b) in all areas from 1988q4 through 2014q3. Posted Price constructed by cumulating posted-price inflation, which is the weighted average of individual log price differences. Discount is the weighted average log difference of individual regular and posted prices. We use constant weights as described in Appendix A. Series are seasonally adjusted and HP-filtered (parameter = 1600). The cyclical elasticity is obtained by regressing (log) price index on (log) GDP (or unemployment); all regression variables HP-filtered and Newey-West standard errors are reported in parentheses.

Figure A1
Response to a Base Wholesale Price Increase: No Time Fixed Effects



Panel A: Wholesale Price and Regular Price Index



Panel B: Wholesale Price and Discount Index

This figure reports 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 a modified version of Equation 1 on each dependent variable. Equation 1 was modified to remove the time fixed effects. Fixed effects identifying each item 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).