Why Do Retail Prices Fall During Seasonal Demand Peaks?*

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Abstract

Examining all widely-sold products in a large, national scanner database, we find that seasonality in demand is large, pervasive across product categories, and heterogeneous in its timing. Yet at seasonal frequencies prices fluctuate little, and typically, countercyclically, falling as demand peaks. A possible explanation for this pattern is that demand becomes more elastic as its level peaks. We find, indeed, that for most seasonal products, demand becomes more elastic when demand levels peak. Quantitatively, the estimated seasonal elasticity changes can roughly rationalize observed countercyclical pricing. A likely mechanism for time-varying elasticities is seasonal shifts in the composition of buyers, as extensive margin responses account for nearly the entirety of seasonal demand shifts.

JEL codes: D40, L11, L81
Key words: seasonality, countercyclical pricing, demand, price elasticity of demand, optimal pricing

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Seasonal fluctuations in quantities can be enormous, so much so that seasonal fluctuations in GDP growth are larger than those associated with business cycles (Barsky and Miron 1989). Seasonal fluctuations in prices, however, are small and may even be countercyclical; meaning prices appear to fall during periods of peak demand (e.g., Warner and Barsky (1995); MacDonald (2000); Chevalier et al. (2003); Hosken and Reiffen (2004a); Nevo and Hatzitaskos (2005)). As many instances of the seasonal fluctuations in quantities appear demand-driven, systematic countercyclical pricing seasonally would be puzzling. Exploring how microeconomic models can generate countercyclical prices is the focus of many recent studies in industrial organization, which focus on a handful of product categories with obviously seasonal demand such as soup and ice cream (Guler et al. 2014; Bayot and Caminade 2015; Kwon et al. 2018; Haviv 2019). Despite a growing number of explanations, no comprehensive assessment of the prevalence of countercyclical pricing exists, as compositional effects—arising from substitution to cheaper products during demand peaks—may account for the measured price declines (Nevo and Hatzitaskos 2005; Perrone 2016), and existing evidence focuses on only a small number of product categories and retailers. In this paper, we provide the first comprehensive assessment on the extent and path of seasonal fluctuations in demand and prices. We look at a broad set of widely available food products which span dozens of categories, we address compositional effects, and we investigate the ability of simple models of optimal pricing to rationalize the observed seasonal patterns.

Our investigation uses UPC-level data for 1,353 widely available UPCs (hereafter, “products”) in 38 categories, sold in food, drug, and mass merchandise stores in the contiguous U.S. The 24,500 stores in our sample collectively generate $191 billion in annual revenue, and therefore constitute a meaningful share of the population of retailers. These data offer several advantages for studying seasonal fluctuations in demand and prices. First, as we will show, seasonality is a central factor in the demand facing these retailers, leading to large quantity fluctuations across a broad array of product categories. Second, the observed seasonal fluctuations in quantities are very likely demand driven. For the products we study, there is little seasonal variability in availability, quality, or new offerings, ruling out many possible supply-side explanations (Pashigian and Bowen 1991; Einav 2007; Cooper and Haltiwanger 1993). Finally, our scanner data are highly detailed, letting us observe prices at the store-week-product level, so we can quantify price changes that are free of compositional effects that result from aggregation in the time series or cross-section.

We have four results. Our first result is that seasonality in demand is pervasive, substantial, and heterogeneous. We measure seasonality in demand product-by-product by regressing log
quantity on a set of month-of-year dummies, product-store-year fixed effects, and log price interacted with month-of-year dummies. The estimated month-of-year effects measure the month-to-month variation in quantities, adjusting for possible price differences. Our measure of seasonality in demand is the difference between the maximum and minimum quantity month. We find that, for the median product at a fixed price, demand varies by 24 log points from seasonal trough to peak, and by 10 log points at the 10th percentile. These fluctuations are large relative to, for example, quantity fluctuations induced by the business-cycle. Using business-cycle induced fluctuations as a benchmark, we estimate that three-quarters of products are seasonal in the sense that seasonal fluctuations are larger than the fluctuations due to the Great Recession. We find clear seasonality in demand in obvious categories like soup and frozen novelties, but also in less obvious categories like cookies. Not only are seasonal fluctuations in demand large, they are heterogeneous both in their magnitude—cookies are less seasonal than soup—and also in their timing. While many products exhibit demand peaks in January, several peak in June, July, and August.

Our second result is that seasonal fluctuations in prices are small and typically, though not always, countercyclical. We measure seasonality in prices by comparing how prices change from the month of trough demand to the month of peak demand. A negative price change means that prices fall when demand peaks and therefore indicates countercyclical pricing. We find that roughly two-thirds of seasonal products exhibit countercyclical pricing. Our approach looks within store-product-year cells, and therefore is free of compositional effects. In fact, we show that not adjusting for compositional shifts within product categories does result in larger measures of countercyclical prices (Nevo and Hatzitaskos, 2005). As further evidence of countercyclical pricing, we find that the peak demand month is particularly likely to be the trough price month, meaning not only do prices fall when demand peaks, but they often fall to their lowest point over the year. Despite clear evidence that countercyclical pricing is common, however, we find that these seasonal price changes are small: the median price change (between demand trough and peak) is only about 2 log points. Furthermore, these price changes come from a combination of more frequent promotional prices (i.e., sales) and lower base prices, without any meaningful change in the depth of promotional pricing.

Countercyclical pricing is a puzzle for perfectly competitive models of supply-and-demand,
but it is easily rationalized if firms have market power. In that case, prices depend on demand elasticities. And, countercyclical pricing can be rationalized if demand elasticities fall (i.e., become more negative) during seasonal demand peaks. Our third result shows that for a majority of seasonal products, demand indeed becomes more elastic during seasonal demand peaks, and demand elasticities are especially likely to be at their most negative in precisely the months when prices are lowest. Quantitatively, we find that the seasonality in elasticities matches well with the seasonality in prices: looking across product categories, observed prices move roughly one for one with the predicted change in prices, given estimated changes in elasticities. Overall, these results suggest that seasonal pricing patterns—small and typically countercyclical price changes—are roughly optimal.\footnote{The optimal prices of a simple benchmark indicates scope for even larger countercyclicality in prices than what we observe. Furthermore, we estimate that the differences between the observed price changes and optimal prices implied by a simple benchmark are economically small, in the sense that retailers are giving up little profit (see Appendix Section D).}

Our fourth and final result probes the mechanism underlying the observed countercyclical elasticities: changing consumer composition. Using household-level panel data, we decompose observed seasonal fluctuations into an extensive margin component (i.e., does the household purchase?) and an intensive margin component (i.e., conditional on purchase, how much is purchased?). We find the extensive margin is large, explaining nearly the entirety of seasonal fluctuations in demand for the median category. The large extensive margin response means that the identity of the marginal customer during periods of peak demand is potentially quite different than the marginal customer during periods of trough demand. To the extent that the marginal customer in periods of peak demand has a higher price sensitivity than the marginal customer in other times of the year, this would lead to retailers facing more elastic demand during these periods.

These results contribute to three literatures. First, we contribute to a long-standing literature in industrial organization that explores seasonal fluctuations in demand and prices. The key question in this literature has been about the existence of and reasons for countercyclical pricing. Early explanations for countercyclical prices included tacit collusion, which is harder to sustain during periods of overall high demand (Rotemberg and Saloner 1986), or changing search intensity, as people might search more for competitive prices in preparation for their larger shopping trips (e.g., on the weekends) (Warner and Barsky 1995). Both models explain the potential for countercyclical pricing during periods of high aggregate demand, with all products’ prices falling during...
these periods. Later empirical work, most prominently Chevalier et al. (2003), tested this implication using data from Dominick’s supermarkets in Chicago. They found that products differ in their timing of demand peaks (e.g., beer in the summer, soup in the winter, tuna at Lent), and prices tend to fall when product-specific demand peaked, rather than during aggregate peaks—in particular, Thanksgiving and Christmas for grocery stores. In related work, MacDonald (2000) used national aggregate time series information of price and quantity, to show that for many products with large seasonal fluctuations in demand prices are countercyclical. Consistent with these findings, Hosken and Reiffen (2004a) show—using the BLS CPI data—that most of the seasonal variation in prices is tied to the frequency of sales, with more popular products typically being selected to be put on sale. These authors concluded that alternative (supply-side) explanations like “loss-leader” pricing strategies Lal and Matutes (1994; Chevalier et al., 2003) or informational advertising MacDonald, 2000; Hosken and Reiffen, 2004a best explain countercyclical pricing. An important limitation of this early work, however, is its reliance on category-level (or, national) price indices to document countercyclical pricing. As Nevo and Hatzitaskos (2005) argued, however, aggregate price indices could be countercyclical if people substitute towards cheaper products during periods of peak demand even if posted prices are unchanged.4

A more recent set of empirical papers, which overcome this concern by studying product-level prices, investigates single, highly seasonal product categories (such as ice cream, soup, champagne, or tuna), in an effort to recover aspects of demand that provide incentives for countercyclical pricing (Guler et al., 2014; Bayot and Caminade, 2015; Perrone, 2016; Kwon et al., 2018; Haviv, 2019). Explanations from this work center on the role of heterogenous consumer segments (Guler et al., 2014; Bayot and Caminade, 2015), stockpiling and endogenous consumption (Kwon et al., 2018), and changing incentives to search (Haviv, 2019). These explanations typically share the reduced-form implication that the demand facing retailers becomes more elastic during seasonal demand peaks, with some emphasizing the role of the changing composition of consumers.

We complement and extend this literature in three ways. First, our analysis of countercyclical pricing is much more general, examining the widest combination of products, categories, and retailers, and not selecting a sample based on its likely seasonality. This broader coverage of products and categories is important because the existing literature leaves it unclear whether, for typical products (rather than highly seasonal ones), prices trough during aggregate demand peaks.

4In contemporaneous work, Meza and Sudhir (2006) finds some of the observed countercyclical pricing in the tuna and beer categories result from manufacturer trade promotions.
or during idiosyncratic ones. The broader coverage of retailers is important because prices tend to be highly correlated within retailer but not across retailers [Adams and Williams, 2019; DellaVigna and Gentzkow, 2019; Hitsch et al., 2019], meaning a single retailer’s pricing patterns may not be representative of broader trends. Second, our findings on countercyclical demand elasticities (driven by time-varying composition of shoppers), provides reduced form support from a broad and representative set of products for the category-specific structural models. Third, to study such a wide set of products, we developed a tractable but flexible estimation approach that may be useful for future researchers.

Second, we contribute to an emerging literature exploring pricing puzzles. Several papers have documented that prices appear highly uniform despite large demand variation (Orbach and Einav, 2007; Cho and Rust, 2010; Gagnon and López-Salido, 2019). This literature includes the work by DellaVigna and Gentzkow (2019) and Hitsch et al. (2019), whose empirical setting is very comparable to our own. Many of these papers argue that the observed low variability in pricing is inconsistent with profit maximization (Orbach and Einav, 2007; Cho and Rust, 2010; DellaVigna and Gentzkow, 2019). Our results show that large variations in the level of demand need not be accompanied by large variation in its elasticity, meaning that near-uniform pricing can be optimal even in the face of large demand fluctuations.

Finally, our results contribute to two different strands of the macroeconomics literature. First, they contribute to the literature on the construction aggregate price indexes for policies like cost of living adjustments. Important work in this literature has shown that quality adjustment and shifts in preferences are likely to contribute to biases in the construction of aggregate price indexes like the CPI (Broda and Weinstein, 2010; Redding and Weinstein, 2019). These issues have typically presented themselves through the constant entry and exit of products. Our results indicate, however, that seasonal demand shifts also contribute to CPI biases, because such shifts are negatively correlated with prices. Second, we contribute to a long standing debate on the flexibility (or “stickiness”) of prices, and the appropriate way to handle temporary price discounts in assessing that flexibility (e.g., Bils and Klenow, 2004; Hosken and Reiffen, 2004b; Nakamura and Steinsson, 2008, 2013). Our results indicate a large amount of nominal price changes through discounts and changes to their frequency still are likely to represent well planned ahead and possibly fixed price schedules in anticipation of seasonal demand fluctuations, which are otherwise orthogonal to business cycle considerations.
1 Data

We create our analysis data set with three goals in mind. First, we want to investigate the demand conditions and pricing decisions of as many retailers across as many markets as possible. Second, we want to investigate a representative set of product categories. By not selecting product categories based on their perceived or measured seasonal fluctuations in demand, our analysis offers the first credible assessment of the extent of seasonal demand and how this relates to the seasonal fluctuations in prices. Third, we want to investigate all the products within those categories that are widely available. Focusing on widely available products is critical towards interpreting fluctuations in quantities as driven by demand, as well as useful for any analysis that hopes to measure seasonal fluctuations in the price elasticity of demand.

The best available data to meet all of these goals is the Nielsen Retail Scanner data (RMS). The strengths of this dataset include that it provides high frequency information on both price and quantity for a large set products across many geographical markets over a sustained period of time. In particular, the RMS dataset contains information for a panel of as many as 41,000 retail stores from across the country over the period of 2006–2014. The stores within Nielsen make up over 50 percent of the revenue coming from all food and drug stores, and about a third of the revenue from mass merchandise \cite{Nielsen2018}. For each store, information on units sold and revenue for every week and product is reported, as well as other information such as chain affiliation and physical location.

1.1 Sample selection

Selecting retail formats, chains, and stores There are three criteria a chain or store must satisfy to be included in our sample. First, we focus our analysis to stores and chains for which grocery sales represent a major component of overall sales, and thus, for which the pricing decisions of those products are particularly salient to the retailer. Second, we limit the analysis to stores for which we have an accurate measure of its chain affiliation. Having an accurate chain affiliation for each store is important both for our identification strategy (to be described below in the \textit{Identification Section} \ref{sec:identification}), and allows us to at least partially overcome the fact that Nielsen does not report information on a store’s prices for products that experience zero sales in a particular week. Third, we limit our analysis to stores for which we can consistently use both the Nielsen RMS and the Nielsen Consumer Panel (HMS), which provides household trip level information—used in our extensive
Table 1: Store and product-level summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Stores</th>
<th>Chains</th>
<th>States</th>
<th>Total yearly revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food stores</td>
<td>9,834</td>
<td>69</td>
<td>48+DC</td>
<td>$134bn</td>
</tr>
<tr>
<td>Drug stores</td>
<td>11,180</td>
<td>2</td>
<td>48+DC</td>
<td>$23bn</td>
</tr>
<tr>
<td>Mass merchandisers</td>
<td>3,436</td>
<td>6</td>
<td>48+DC</td>
<td>$34bn</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>No. of products</th>
<th>No. of categories</th>
<th>Yearly revenue by store</th>
<th>Weekly average price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample of products</td>
<td>1,356</td>
<td>38</td>
<td>$533K</td>
<td>$1.87</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(627K)</td>
<td>(0.51)</td>
</tr>
</tbody>
</table>

Notes: This table reports final sample characteristics. Yearly revenue is aggregate sales divided by 9 years. Yearly revenue by store is the total revenue from sample products for a given store, divided by the number of years the store is in the sample.

To achieve these criteria we apply a set of screens, that are further detailed in Appendix Table A.1, that proceed with the following steps. First, we exclude all convenience stores and gas stations, each of which do not have grocery sales represent a major component of overall sales. Next, we impose restrictions at the chain- and store-level. We define a chain as a unique combination of parent-code (company) and retailer-code found in the Nielsen dataset. This has the effect of treating stores with different banner names (e.g., Safeway and Jewel-Osco), but the same parent holding company (e.g., Albertson’s), as different chains. Then, we drop stores that either: (i) switch chains, (ii) are in the data for only one year, or (iii) do not show up in the Nielsen Consumer Panel (HMS). At the chain level, we drop a chain if it does not appear in at least eight of the nine years of our panel, or if its chain affiliation appears invalid. In the Nielsen data, sometimes a given retailer-code is assigned to multiple parent-codes. In such cases, we keep only the modal parent-code–retailer-code combinations, and we drop all parent-code–retailer-code combinations in which the modal combination accounts for less than 80 percent of stores. While these screens are helpful in facilitating our empirical analysis, they do not substantially diminish the coverage of the total amount of revenue that is covered by the final sample of stores. The top panel of Table 1 reports the summary statistics at the store-level for our final sample of stores, which collectively

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5At the product-level, we also limit to chain-years in which we are always able to impute missing prices (as described in Section 1.2).
generated $191 billion yearly revenue, or about 85% of total revenue in the Nielsen RMS data.

**Selecting categories and products** In selecting product categories, we elected to use the 40 product categories (i.e., Nielsen’s modules) used by DellaVigna and Gentzkow (2019)—a contemporary study of uniform pricing across retail chains that also uses the Nielsen RMS data. These categories include a variety of products including canned soup, toilet paper, and cat food (e.g., see Appendix Table A.2), and make up as much as 30 percent of overall revenue in the Nielsen data for our sample of stores. Within these product categories, we limit our analysis to the set of products that are widely available (described below). This selection of categories and products suits our investigation for at least two reasons. First, these product categories represent a broad and diverse set that were originally selected—by DellaVigna and Gentzkow (2019), with no intention of investigating seasonal demand. Second, they represent a set of product categories which are common across many chains, and across many markets. Both of these features allows us to credibly measure and assess the overall prevalence of seasonal fluctuations of demand and countercyclical pricing in retail markets.

We define the availability of a product in a given year and format (food/drug/mass merchandise) as the number of store-weeks with positive sales divided by the number of store-weeks with any sales in the category. We define widely available products as ones with greater than 80 percent availability in at least one format and year. Focusing on widely available products moderates the prevalence of missing prices which occur in periods when no units are sold in a store. Alternative solutions to this problem include aggregating over heterogenous products, or aggregating over stores and/or weeks, or dropping observations with zero sales. These alternatives are less appealing in our context as they result in either compositional effects, or biases in price elasticity estimates as units purchased are much more likely to be zero during periods of above average prices. Our definition of widely available products means that private label (or store brand) products are not included in the analysis. Our final sample comprises of 1,356 products, which make up 31.7 percent of total revenue across our set of categories. The bottom panel of Table 1 reports
the summary statistics of our final sample of products, which accounts for half a million dollars of revenue per store-year.

1.2 Quantities, prices, base prices, and promotions

Quantities—units sold—are directly reported in the Nielsen data. In weeks with zero units sold, Nielsen reports a missing value for quantities, which we impute as zero. We have chosen a sample of stores and products to minimize the likelihood of having zero sales, leaving on average 0.32 percent of store-weeks with no reported sales for each product.

Prices are not directly reported by Nielsen, but revenue is. We define price as revenue per unit sold at the store-week-UPC level. Average per unit revenue is likely close but not exactly equal to posted prices. There are two sources of discrepancy, as Einav et al. (2010) explain, and has been documented in other scanner datasets (e.g., Eichenbaum et al. (2014)). First, some shoppers use loyalty cards to get a discount. Second, the Nielsen week is Sunday to Saturday, but some stores change prices midweek, so average per unit revenue is a quantity-weighted average of the two posted prices occurring during that seven-day period. As we do not observe prices for store-weeks with zero sales, we impute prices in those weeks as the median price of other stores in the same chain-state-week. This imputation is likely accurate given the near-uniform pricing within stores of the same chain (DellaVigna and Gentzkow (2019); Hitsch et al. (2019)). This imputation fills in prices for nearly all zero quantity weeks.[11]

In some of the analysis, we distinguish between “base prices” and promotional prices. Unlike other commonly used sources for price information (e.g., the microdata underlying the CPI, as well as other select scanner databases), Nielsen does not identify promotional prices.[12] To over-

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11 In most specifications, we work with the log of quantity, which means the zero quantity weeks are dropped. We use the imputed prices in these weeks when estimating seasonality in prices and in specifications that work with the inverse hyperbolic sine of quantity instead of the logarithm.

12 Most of the literature on price rigidity relies on the distinction between sales and regular prices reported by the BLS (e.g., Bils and Klenow (2004). Nakamura and Steinsson (2008, 2013)). For a selection of about 20 percent of stores, Nielsen reports “feature” and “display” flags at the product level. While correlated, these activities are not directly linked to running a promotional price—or discount.
come this issue, we developed an algorithm to identify base and promotional prices. The basic idea is that, given a store’s time series of observed prices, the base price should be common and high, whereas promotional prices should be intermittent and low. Thus, in each week the algorithm looks for the base price as the highest price in prior and subsequent weeks. To avoid sensitivity to measurement error in prices, we apply a filter to the time series of prices that resembles a mini-max program. We select the width of the window of the filter to ensure a low false negative rate for base price changes. Given a measure of a store’s base price for every week from the algorithm, we define promotion periods as ones when actual prices are at least 10 percent below the base price.

The algorithm yields sensible results in our data. Appendix Table B.1 show that the median store-year has four base prices in the data, which means it changes base prices three times a year. Base prices therefore change relatively infrequently, consistent with other findings in the literature (e.g., Nakamura and Steinsson (2013)). Additionally, products are on promotion on average 22% of the time with an average discount being 24%. While these statistics mask the underlying variation that exists in the promotional practices across stores and categories, they are consistent with the comprehensive assessments reported within the CPI for food items, as well as fall mostly in line with the promotional frequency statistics reported by Hitsch et al. (2019).

We believe this algorithm is an improvement over prior approaches, which include: defining “sales” as prices below a researcher-specified threshold such as $1 (e.g., Hendel and Nevo (2013)), or the modal value over a particular horizon like a quarter or a year or two (e.g., Hendel and Nevo (2003); Hosken and Reiffen (2004b); Hendel and Nevo (2006b); Eichenbaum et al. (2011)); as well as the existing “sales filter” algorithms that have been used in the price rigidity literature (e.g., Nakamura and Steinsson (2008); Klenow and Kryvtsov (2008); Chahrour (2011); Kehoe and Midrigan (2015)). Such procedures may work well for the pricing strategies of some retailers for some products, but are overly restrictive for a study of thousands of products across many different retailers where prices might be missing and subject to measurement error. Our approach to calculating base prices can be implemented efficiently, can accommodate base prices that change over time and at a variety of frequencies, as well as is fairly robust to measurement error in prices (both positive and negative). Hitsch et al. (2019) also report developing an algorithm for identifying base prices and promotion periods in the Nielsen RMS data, and provide figures like Figure B.1 in the appendix. We took inspiration from their approach, but we differ from them in three respects. First, we impute missing prices as the median price of stores in the same chain-state-week based on the uniform pricing within them, before implementing the base price algorithm. Second, we provide validation of the algorithm in the form of a simulation study and a verification with actual promotion data. Third, our approach is simple, which allows for the efficient estimation of base prices for many stores.

Full details can be found in Appendix B. We checked the performance of the algorithm, using the Dominick’s scanner data which reports promotional activities. We show under conservative assumptions that the algorithm has less than 10 percent rate of both Type I and Type II errors. We have also simulated many time series for prices which are roughly realistic with those found in our sample, but with known base prices and promotions, and verified that the algorithm accurately recovers base prices and promotions.

Klenow and Kryvtsov (2008) report that 15 percent of all prices for the underlying food items in the CPI are promotional prices. Over a larger set of products, Hitsch et al. (2019) report promotional frequencies of 0.011 at the 5th percentile (of products) to 0.37 at the 95 percentile, with an average of 0.147. Some of the increase in promotional frequency present in our sample is likely attributable to our focus on widely available products, as retailers often promote the more popular products within a category (Hosken and Reiffen, 2004a).
1.3 Representativeness of our sample

Our selection of widely available products may cause us to understate the prevalence and size of seasonal demand fluctuations, as well as the rate of countercyclical pricing. Products that are available year round but sold rarely in off-season—sunscreen or mittens, for example—are not present in our sample, but they likely have seasonal demand fluctuations well above average. Products that are seasonally unavailable are also excluded from our sample, and during the off-peak season their price is essentially infinite (and hence their prices are highly countercyclical). Thus we think that our sample selection approach is, if anything, conservative for measuring seasonality, and it is all the more remarkable that we end up finding a great deal of seasonality.

Those considerations aside, empirical evidence indicates our selection of widely available products is unlikely to have led to a terribly unrepresentative set of products within the selected categories. First, the selected products make up a considerable amount of overall revenue for these product categories, up to 31%. For the median product category our sample of products make up 18% of category level revenue. In only a quarter of the categories–mostly concentrated in the refrigerated categories–does the sample of products make up less than 10% of total category revenue. Second, the sample of widely available products appears broadly similar to the rest of the products in the category on other dimensions like price. The average price of the products in our sample of products tracks the average price of the other branded products quite closely. In the median product category, the widely available products in the sample are 2 log points lower than the other branded products in the category.

One way that our sample of products is unrepresentative is that we omit private label brands. We believe this is appropriate, for three reasons. First, for the products where the grocery chain private label brand itself is a critical non-price attribute of the product (e.g., Kroger Private Selection), we only have a single retailer that providing it. For these products, we cannot distinguish product-specific from retailer-specific factors. Second, to avoid disclosing the identity of any individual chain, all private label products for a similar product (e.g., vanilla ice cream) are given the same product name. Thus, to have multi-retailer observations for a particular private label product would require aggregating across different UPCs across retailers that we are not able to directly identify. Given the evidence that most variation in demand characteristics, even at the

\[16\] Specifically, our sample of products make up less than 10% of revenue in the following categories: dog food, ice cream, lunch-meat, refrigerated entrees, shredded cheese, refrigerated milk, fresh eggs, light beer, liquid detergents, and pain remedies.
local market level, exist across retail chains as opposed to across stores within the same chain \cite{DellaVigna and Gentzkow 2019, Hitsch et al. 2019}, we view it best to avoid the same compositional issues that have fraught the previous investigations of countercyclical pricing that would arise from including these products. Finally, the consequence of omitting private label brands is unlikely to have a large impact on our analysis as those products make up a total of 16% of revenues in our product categories, and in the median category private label brands make up 12% of category revenue.

2 Empirical approach to measuring seasonality

2.1 A benchmark model

We begin by considering a simple model of seasonal pricing, for a firm with some market power. The model guides our empirical analysis, and is therefore intended to be applicable to a wide variety of products. We deliberately abstract from some salient features of the retailer’s pricing decision (e.g., storability). We do this in the hope of attaining a simple model that still captures the key aspects of seasonal price changes for many product categories.

We assume the residual demand curve for a given product facing a single-product firm at time $t$ takes the following form

$$\ln q_t(p_t) = \alpha_t + \eta_t \ln p_t.$$  

The quantity $\alpha_t - \alpha_{t'}$ measures seasonal shifts in the level of demand between $t$ and $t'$, and $\eta_t - \eta_{t'}$ measures seasonal shifts in the elasticity of demand. Given marginal cost $c_t$, the profit-maximizing price is

$$\ln p^*_t = \ln c_t + \ln \left( \frac{\eta_t}{\eta_t + 1} \right).$$

Seasonal fluctuations in optimal prices reflect changes in marginal cost $c_t$ or demand elasticities $\eta_t$, but not variations in the level of demand at a fixed price, $\alpha_t$.

The change in prices between any two periods $t$ and $t'$ is

$$\Delta_{t,t'} \ln p^* = \left[ \ln c_t - \ln c_{t'} \right] + \left[ \ln \left( \frac{\eta_t}{\eta_t + 1} \right) - \ln \left( \frac{\eta_{t'}}{\eta_{t'} + 1} \right) \right].$$

The change in prices can stem from changes in demand elasticities or changes in marginal costs (because of time-varying or non-constant marginal costs). Our analysis maintains the assumption
that marginal costs are constant across seasons (and do not change with quantity). The assumption that marginal costs are constant in quantity and over the year is standard in the retail pricing literature (e.g., Guler et al. (2014); Bayot and Caminade (2015); Kwon et al. (2018); Haviv (2019)), and is consistent with evidence that wholesale prices and input prices do not systematically vary over the year (MacDonald, 2000; Chevalier et al. 2003; Hosken and Reiffen, 2004b; Anderson et al., 2017). Moreover, we view it as plausible in our context, because the majority of products we study are consumer packaged goods, which are mass produced and likely do not depend on seasonal inputs. One concern is that, plausibly, the economic marginal cost of a good does vary over the year, as the opportunity cost of shelf space changes with aggregate shopping intensity. However, this cost is common to all products, and we will show that the timing of demand peaks varies from one product to the next. Therefore, it is difficult to argue that the opportunity cost of shelf space could jointly explain the seasonal fluctuations in quantities across all our products. The assumption that marginal costs do not depend on quantity is more ambiguous, but we would expect, if anything, that marginal costs increase with quantity. This would imply that prices rise with seasonal demand, however, and we typically observe the opposite.

The benchmark model implies that to understand seasonal pricing and how it relates to demand, we should estimate seasonal shifts and rotations of the demand curves, the \( \alpha_t \) and \( \eta_t \) terms, and relate the term \( \ln \left( \frac{\eta_t}{\eta_{t-1}} + 1 \right) \) to the seasonal shifts in prices. This is exactly the approach we take in our empirical analysis, which we describe next.

### 2.2 Seasonality in demand

To measure seasonality in demand, we estimate the empirical analog of our demand equation, separately for each product \( i \) in the data. Letting \( j \) index stores and \( t \) weeks, our approach to measuring seasonality in demand starts with the following regression:

\[
\ln q_{ijt} = \sum_{m=1}^{12} \alpha_{im} 1 \{ \text{Month}_t = m \} \\
+ \eta_i (\ln p_{ijt} - \ln p_{ijy}) + \sum_{m=1}^{12} \eta_{im} 1 \{ \text{Month}_t = m \} (\ln p_{ijt} - \ln p_{ijy}) \\
+ \eta_t \text{unemployment}_j + \theta_{ijy} + \varepsilon_{ijt}.
\]

(1)

\(^{17}\)An important exception is fresh fruit and vegetables. We show below that this category also exhibits unusual seasonal patterns in our analysis below, and our results are stronger if we exclude it.
This regression involves regressing log quantity \( \ln q_{ijt} \) on a set of month-of-year dummy variables, log price \( \ln p_{ijt} \) (demeaned relative to the store-product-year average, \( \ln \bar{p}_{ijy} \)), a set of interactions between month-of-year dummies and log price, and the local unemployment rate, as well as a product-store-year fixed effect. All coefficients are product specific. We estimate product-by-product and cluster standard errors at the chain level. Below we discuss the product-month specific elasticities and explain why we control for the local unemployment rate.

In estimating this equation, we use two normalizations: we set \( \sum m \alpha_{im} = 0 \) and \( \sum m \eta_{im} = 0 \). These normalizations imply that the \( \alpha_{im} \) terms can be interpreted as the monthly deviation from store-year average demand, and the \( \eta_{im} \) terms as the monthly deviation from store-year average elasticities. Both normalizations are natural in the context of seasonality (e.g., Suits (1984)), and also facilitate our application of the Empirical Bayes procedure (discussed further below).

We interpret Equation 1 as the residual demand curve facing a given retailer, the empirical analog of the demand curve in our benchmark model. This interpretation requires that seasonal variability in quantities reflects changing demand and not changing costs. Costs can only affect quantities, however, through their effect on prices. As Equation 1 adjusts for prices, the remaining variation in quantities reflects demand rather than cost side factors.

Given the demand curve, a natural measure of the seasonality in demand for product \( i \) is

\[
\text{Amplitude}_i = \max_m \alpha_{im} - \min_m \alpha_{im}.
\]

This is the difference in log quantities between the month with maximal sales and the month with minimal sales, for a given product-store-year, holding prices fixed at their product-store-year mean. We can also use the estimates to obtain peak and trough demand months:

\[
\overline{m}_i = \arg\max_{m} \{ \alpha_{im} \} \quad (2)
\]
\[
\underline{m}_i = \arg\min_{m} \{ \alpha_{im} \}. \quad (3)
\]

These are the months when the level of demand achieves its minimum or maximum.

This approach has several appealing features. First, like MacDonald (2000), we let the data indicate the timing of seasonal peaks and troughs, rather than impose a functional form or assume

\(^{18}\)Demeaning prices by their product-store-year mean does not affect the estimated elasticities, because we control for product-store-year fixed effects. Instead, we demean so that we can interpret the month fixed effects as the change in demand at the average price (which would otherwise be \( \alpha_{im} + \ln \bar{p}_{ijy} \)).
that seasonal fluctuations in demand are tied to temperature or holidays, as Chevalier et al. (2003) do. This data-driven approach is especially valuable when studying seasonality across a wide array of products, like we do, because it would be difficult a priori to specify the seasonal patterns for over a thousand products. A potential limitation of a data-driven approach, however, is that it risks conflating price-induced shifts along the demand curve with seasonality-induced shifts in demand. Our specification addresses this possibility by explicitly adjusting for prices shifts, with month-specific coefficients. Finally, because we estimate Equation 1 product-by-product, we obtain granular estimates of seasonality, which is especially valuable for measuring changes in prices that are free of compositional effects, as we explain below.

The estimation of Equation 1 must overcome two challenges: price endogeneity and estimation error. The price endogeneity challenge is the usual concern that differences in prices could themselves be driven by demand shocks that are unobserved to the econometrician, and is one we address through an instrumental variables approach we describe in Identification Section 2.5. The second challenge our approach faces is estimation error, which can lead to bias in estimates of seasonal amplitudes.

To see why, note that the natural plug-in estimator for the seasonal amplitude is:

\[ \text{Amplitude}_i = \max_m \hat{\alpha}_{im} - \min_m \hat{\alpha}_{im}, \]

where \( \hat{\alpha}_{mi} \) is the estimated value of the month-of-year effect. Even in the absence of any seasonal effects, so that \( \alpha_{mi} = 0 \) for every month, estimation error will generally mean that some \( \alpha_{mi} \) are positive and some are negative, producing a positive estimate of seasonality. More generally, estimation error increases the expected difference between estimated \( \alpha \)'s, biasing seasonal amplitudes upward.

To address this challenge, we use Empirical Bayes shrinkage. We briefly summarize our approach here, and provide more details in Appendix C. This process yields shrunk coefficients \( \tilde{\alpha}_{im} \), defined as weighted averages of \( \hat{\alpha}_{im} \) and 0 (the value of \( \alpha_{im} \) under the null of no seasonality). The weights we use depend on the variability of the coefficients (across months) and the estimated variance of the estimates (i.e., the standard errors); the noisier are the individual estimates, the more weight is put on the null of zero. We then estimate seasonal amplitudes as

\[ \text{Shrunk Amplitude}_i = \max_m \tilde{\alpha}_{im} - \min_m \tilde{\alpha}_{im}. \]
In the extreme case when all variability is due to estimation error, the shrinkage procedure shrinks all the estimates to their mean, and so we obtain an amplitude of zero. In general, this procedure tightens the range of seasonal coefficients, adjusting for the fact that selecting the maximum and minimum of a set of noisy estimates will generally result in too large a range. Throughout our empirical analysis, we focus on results based on the shrunk estimates. However, we also present as a robustness check the set of results which use the estimates before shrinkage as well. These results show more seasonality in quantities, more variable elasticities, and almost no change in the cyclicality of prices. Thus, the shrunk estimates are conservative and more precise.

**Using unemployment effects as a benchmark** Ideally, we would have a benchmark to assess whether observed seasonal fluctuations are large. We obtain such a benchmark by including as an additional regressor the local (county-specific) unemployment rate, a natural measure of the stage of the business cycle. Using the local unemployment rate as a measure of the business cycle has been used in many other settings including those examining scanner data (e.g., Coibion et al. (2015)). Including this regressor does not substantially affect any of our estimates, but the size of its effects provides a useful benchmark, letting us compare the size of fluctuations driven by seasonal shifts in demand to those induced by business cycle considerations.

**Abstracting from holiday effects** In estimation, we exclude all weeks that include a major holiday. The major holidays include New Years, the Superbowl, Memorial Day, July 4, Labor Day, Thanksgiving, and Christmas. We abstract from them for several reasons. First, for certain holidays and products (such as ketchup and mustard during July 4, or Turkeys during Thanksgiving), we are concerned about the possibility of “loss leaders”—temporary deep sales on a particular product in an effort to pull in people to a retailer (e.g., Lal and Matutes (1994); Chevalier et al. (2003); DeGraba (2006)). Such effects would be difficult to detect empirically (because they would rely on cross-category demand elasticities), but they are likely not representative of seasonal pricing, because (as we show) many products exhibit seasonal peaks in demand, and it is unlikely that every product could be focal enough to act as a loss leader. A second reason to abstract from holidays is that fairness constraints may make it difficult for retailers to suddenly and sharply raise prices (Kahneman et al. (1986)). We expect that such constraints do not, however, prevent retailers from seasonally adjusting their pricing strategies over the course of the year. Thus, the price response to holidays need not be representative of the general pricing patterns over the year. A final

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19 Given its role as a benchmark to seasonal fluctuations, we use the seasonally adjusted measure of the unemployment rate.
reason to abstract from holiday effects is that it is difficult to identify holiday-specific demand elasticities for every product. This is because our empirical strategy uses within product-chain-year price variation, essentially looking at chain-wide discounts; not all products are discounted on holidays, making it impossible to identify holiday shifts in price elasticities.

2.3 Seasonality in prices

We are interested in how seasonal price fluctuations compare to seasonal demand fluctuations. In particular, we want to measure the sign and size of price changes between peak and trough demand. To do so, we estimate

$$\ln p_{ijt} = \sum_{m=1}^{12} \beta_{im} 1 \{\text{Month}_t = m\} + \tau_{i} \text{unemployment}_{jt} + \mu_{ijy} + \epsilon_{ijt}. \quad (5)$$

This is a regression of log price on a set of month-of-year dummies (with $\sum_{m} \beta_{im}$ normalized to zero), plus a product-store-year fixed effect. Again, we estimate product-by-product and cluster standard errors at the chain level. As with our quantity estimates, we do not work directly with the estimated month-of-year effects, but instead work with their shrunk values, $\tilde{\beta}_{im}$, to avoid estimation error leading us to overstate the extent of seasonal fluctuations.

We use Equation 5 to assess the cyclicity in prices, and specifically, how it compares to demand. Therefore, we use the peak and trough months of demand, and compare the prices observed during these periods. In particular, we calculate

$$\Delta p_i \equiv \tilde{\beta}_{im_i} - \tilde{\beta}_{im_t}. \quad (6)$$

This is the difference in (shrunk) month-of-year coefficients from the price equation, but comparing the months when demand peaks and troughs (see Equations 2 and 3). For example, if we estimate for product $i$ that price-adjusted quantities peak in December and trough in July, then we would take the difference $\beta_{12i} - \beta_{7i}$. If prices are countercyclical, we would expect this difference to be negative. A second use of these estimates is to calculate the peak and trough price months, as we do with quantities. Countercyclical pricing would imply that a given product’s peak demand month is its trough price month.

We emphasize that we implement this approach product-by-product, and obtain product-specific measures of pricing patterns. We therefore avoid the potential problem of confounding
the composition effect highlighted by Nevo and Hatzitaskos (2005). The composition effect could arise if during peak demand periods, people substitute towards low-price varieties. Here, we hold fixed the product, and so avoid compositional shifts affecting our measures of countercyclical pricing.

2.4 Seasonality in elasticities

Our benchmark model implies that how optimal prices fluctuate seasonally depends crucially on if there are seasonal changes in elasticity of demand. Therefore, we also investigate how demand elasticities vary over the year, and in particular how they might vary between peak and trough demand. Our baseline specification, Equation 1, yields an estimate of a product-level elasticity \( \hat{\eta}_i \), as well as product-month specific deviations, \( \tilde{\eta}_{im} \). As with our other estimates, we focus on the shrunk values of the monthly deviation, \( \tilde{\eta}_{im} \), to avoid spuriously inflating seasonal fluctuations.

Given these shrunk values, we can find the seasonal difference in elasticities as

\[
\Delta \eta_i = \tilde{\eta}_{im} - \tilde{\eta}_{im},
\]

or the difference in elasticities between peak and trough demand months (with peak and troughs defined by price-adjusted demand levels). \( \Delta \eta_i \) is interesting because it is informative about the optimality of seasonal pricing.

The change in elasticities is informative about the sign of optimal price changes, but not directly their magnitude. We therefore also consider another object, the change between trough and peak demand months in the optimal price implied by our benchmark model:

\[
\Delta p_i^* = \ln \frac{\hat{\eta}_i + \tilde{\eta}_{im}}{\hat{\eta}_i + \tilde{\eta}_{im} + 1} - \ln \frac{\hat{\eta}_i + \tilde{\eta}_{im}}{\hat{\eta}_i + \tilde{\eta}_{im} + 1}.
\]

\( \Delta p_i^* \) is the (log) change in optimal price for a single-product monopolist experiencing an all-else-equal elasticity change from \( \hat{\eta}_i + \tilde{\eta}_{im} \) to \( \hat{\eta}_i + \tilde{\eta}_{im} \). It is therefore a useful benchmark not only for the sign but also for how large a price change we should expect to see for product \( i \). Of course, richer models would imply that other factors (such as cross-price, or other products’ own price elasticities) also influence the optimal price. We view this as a useful benchmark, however, rather than a definitive pricing rule.
2.5 Identification

We interpret $\alpha_{im}$ and $\eta_{im}$ as measuring the level and elasticity of the residual demand curve facing a retailer in a given month. This interpretation is justified under the assumption that prices in other stores (in a given chain outside the DMA and conditional on product-store-year and product-month fixed effects) are uncorrelated with unobserved shocks to demand. This assumption is plausible because price variation over time within a chain-product largely reflects the promotional pricing strategies that are pre-negotiated between manufacturers and retailers, and not temporary changes in local demand conditions.

Thus, we interpret our estimates as measuring the level and slope of the residual (log) demand curve facing a given retailer. A limitation of our estimates is that we assume a single elasticity (at a point in time). In practice, elasticities may differ for short- and long-lasting price changes (for example because of storability) and they may differ for single-product price changes relative to category-wide price changes. Assuming away these rich complications lets us estimate elasticities month-by-month for over 1,000 products.

Although our specification is already tightly controlled—product-store-year fixed effects control for a great deal of demand heterogeneity—we address price endogeneity using an instrumental variables approach. We instrument for the price of a product in given store-week using the prices of that product in the same chain and week but in stores in other markets, specifically all other DMAs. These are within-chain versions of the Hausman (1996) instruments. The justification for this instrument is that for a given product and week, prices are highly correlated within a chain, and so a given chain’s out-of-market prices are informative for local prices, but are unlikely to correlated with local demand conditions. Past work using the instrument has found it to be strong and to produce sensible demand elasticities, a finding which we confirm in our sample as well. Additionally, we include a set of specifications estimated via OLS and find similar results (e.g., see Robustness Section 5).

This instrument corrects for two other potential endogeneity problems that relate to the measurement error in prices that might result from misaligned store-weeks and loyalty cards. The misalignment is that Nielsen weeks are defined as Saturday-Saturday, but some stores change prices midweek. If people buy more during the low price week, there is a mechanical price-quantity

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20Specifically, we instrument for the price-month interactions with a series of interactions between within chain out-of-market prices and month-of-year dummies.
correlation. The loyalty card problem is that we do not observe discounts for using loyalty cards, and greater loyalty card use generates both greater quantities and lower prices, again creating a mechanical price-quantity correlation. Our instrument solves both these problems by using other stores’ prices, breaking the mechanical link between prices and quantities.

However, a reasonable concern is that the confounding influences of other prices—either past prices or competitor’s current price—might affect our estimates. There are three potential concerns. First, we estimate Equation 1 product by product and do not account for other products’ prices. To the extent that price changes are coordinated, we may underestimate the own-price elasticity. We address this concern in two robustness specifications that control for the average of other (log) prices of products in the same category, and the minimum log price of other products in the same category. (DellaVigna and Gentzkow (2019) and Strulov-Shlain (2019) also use this strategy to address this concern.) A second concern is that we do not adjust for the price that competing retailers are charging. To address this concern, in a robustness test, we include a control for the average log price of other chains in the same market (DMA). Finally, a third concern is that some products are storable, in which case past prices influence current demand. We address this concern in a final robustness test by including a control for “weeks since last promotion,” following Hendel and Nevo (2003) and Strulov-Shlain (2019).

3 Seasonality in demand, prices, and elasticities

3.1 Seasonality in demand

We begin by describing seasonal fluctuations in demand. For these and all subsequent results, we exclude products with extremely large standard errors. For these products, it is impossible for us to reliably measure seasonality. We exclude products if, for any month, the standard error of its demand level ($\alpha_{im}$), demand elasticity ($\eta_{im}$), or price level ($\beta_{im}$) is larger than two. Applying this filter removes 178 products, bringing our final sample down to 1,353. Inspection of the excluded products reveal they are usually products sold in relatively few chains, and with limited price variation.

We present the distribution of peak-to-trough amplitudes for price-adjusted log quantities in

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21 We take a store-weighted average price, to avoid compositional biases.

22 In particular, we have determined that high standard errors arise for two reasons. First some products are widely available but only in drug or mass merchandise stores. This results in high standard errors because there are few drug and mass merchandise chains in the Nielsen data, and we cluster our standard errors on chain. Second, some products have limited within chain-year price variation, making it impossible to precisely estimate time varying elasticities.
Figure 1: Seasonality in demand

**A. Amplitude**

- Min = 0.00
- p10 = 0.10
- p50 = 0.24
- p90 = 0.63
- Max = 1.38
- 78.9% seasonal

**B. Peak month**

- 41% of peaks December-February
- 37% of peaks June-August

Notes: Panel A plots the distribution of estimated amplitudes, across products, defined as the difference in shrunk log quantity (adjusted for price) between the peak and trough (of demand) month. Panel B plots the distribution of peak demand months.

Panel A of Figure 1. This figure shows the magnitude of the seasonal fluctuations in quantities for the final 1,353 products across 38 categories, and therefore gives a comprehensive sense of the size and scope of seasonal fluctuations of demand. Seasonal fluctuations in demand are large for most products. For example, the 10th percentile is 10 log points, the median is 24 log points, and the most seasonal products have fluctuations above 63 log points. The breadth of the seasonal fluctuations in demand that we are finding further underscored by the design of our product selection. Unlike past work, our sample selection was not pre-disposed towards seasonal or non-seasonal products, and so we view these results as providing the first comprehensive assessment of the overall size of seasonal demand fluctuations facing retailers.

These seasonal fluctuations are large relative to other cyclical variations, especially variations attributable to business cycles. We estimate, for example, that movements in the local unemployment rate has a relatively small effect on the sales of most products. The median effect (across products) of a 1-percentage point increase in unemployment on quantities is -2 log points. As unemployment rates rose by about 4.5 percentage points during the Great Recession in the av-

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We report in Appendix Figure A.1 the distribution of unemployment coefficients.
verage county, our estimates imply the median product’s demand declined by about 9 log points during the Great Recession—small relative to the typical seasonal fluctuation. As a benchmark, if a product’s seasonal (price adjusted) quantity amplitude change is greater than 4.5 times its unemployment effect, we define the product as having seasonal demand. By this measure, about three quarters of the products in our sample are seasonal. While this share may seem large, it is remarkably similar to the share of goods the BLS classifies as requiring seasonal adjustment at 65 percent—which of course includes an even broader array of goods (U.S. Bureau of Labor Statistics 2020b). The prevalence of seasonal demand products, as measured by this benchmark, partly reflects the fact that grocery shopping in general is more sensitive to seasonal factors (MacDonald 2000; Chevalier et al. 2003), and less sensitive to business cycles (Coibion et al. 2015). Nonetheless, our results indicate substantial and heterogeneous seasonality in demand.

Significant seasonal fluctuations in demand is not limited to a select set of product categories. We report several dimensions of the seasonality in demand by product category (Nielsen’s module measure) in Appendix Table A.2. The product categories with the most seasonal demand are canned soup and frozen novelties, as might be expected given their obvious connection to the outside temperature. Even a not-so-obvious seasonal category such as cookies, however, exhibits fairly high seasonality: 80 percent of products within the category are seasonal, with an average amplitude of 28 log points. Of course, cookies are much less seasonal than canned soup. It is not the case, however, that our method simply finds large seasonal amplitudes for all products. For example, we find that dog food, cat food, and pain remedies all have very modest seasonal amplitudes in demand—a feature one might have expected.

The heterogeneity in seasonal demand appears not only in the size of fluctuations but also in their timing. We measure the timing of seasonality by the month in which demand peaks, and we plot the distribution of peak demand months in Panel B of Figure 1. The modal peak demand month is January, which is broadly consistent with the findings in MacDonald (2000), although our estimates control for price changes. There is a clear second mode in the summer, however, when demand peaks for seasonal products like ice cream, hot dogs, beer, and juice and water.

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24 Conditioning on the food items within the CPI, BLS classifies 86 percent of products as requiring seasonal adjustment (U.S. Bureau of Labor Statistics 2020b).

25 This relative insensitivity to the business cycle also translates to the prices. For example, Coibion et al. (2015) find the stage of the business cycle has minimal effects on both regular/base prices as well as the frequency of sales, nor the volume of purchases during sale prices.

26 These categories also have little business cycle variation, so some of their products do still have larger seasonal components than business cycle components, and are thus deemed seasonal.

27 We report, for each category, the mode peak month (when it is unique) in Appendix Table A.2.
The heterogeneity in the timing of demand peaks is important for the rest of our analysis for at least two reasons. First, the variation in demand peaks across products indicates it is unlikely that any variation in marginal cost that is common to all products (e.g., cost of shelf space) could be the primary driver for the quantity fluctuations we are observing. This supports the view that our empirical approach is picking up seasonal fluctuations in demand, and not movements along a demand curve. Second, the variation in demand peaks indicates that it is also unlikely that a common (or aggregate) shock to demand for all retail products (e.g., increased shopping intensity around Christmas) can explain the overall size and breadth of seasonal demand fluctuations across products.

Thus, the results reveal that seasonal fluctuations in demand are large, common, and heterogeneous in magnitude and timing. This finding is important because it indicates that seasonal fluctuations in demand are a central part of the retail sector, and a likely economically important dimension in the effectiveness of their pricing decisions. The results also reveal the importance of a broad examination; studies focusing on individual product categories, even obviously seasonal ones, are likely to miss much of the seasonality in demand facing retailers.

3.2 Countercyclical prices

How do movements in prices relate to these large seasonal fluctuations in quantities? We measure the seasonality in prices by looking at how prices change between the peak and trough of demand. We plot the distribution of these price changes in Figure 2, looking separately at seasonal and non-seasonal products. For the typical product—seasonal or not—prices move very little at seasonal frequencies, less than 2 log points. For the 1,067 seasonal products, between peak and trough demand months the average price change is negative and small, about -3 log points. This negative price change indicates that for the average seasonal product, prices are countercyclical, in that they fall when demand peaks. Indeed, prices are countercyclical for a majority of seasonal products, about two-thirds. There is, however, a heavy left-tail of products with larger countercyclical price movements. At the 10th percentile of seasonal products, for example, prices decline by 13 log points from trough to peak demand months. Even this, however, is a relatively small price change when judged against the benchmark of quantity changes, where the median change is 23 log points. Countercyclical pricing, limited though it may be, is a common prop-

28To this point, it is also important to note that are empirical estimates of the seasonal fluctuations in demand abstract from holiday weeks.
Figure 2: Distribution of seasonal price changes

Notes: This figure plots the distribution of observed price changes between peak and trough demand months, separately for seasonal and non-seasonal products. Seasonal products are those with a peak-trough difference in demand greater than the implied effect of a 4.5 percentage point increase in unemployment.

Prior research has found that countercyclical movements in the average price paid largely reflect changing composition of the set of products purchased (Nevo and Hatzitaskos, 2005; Perrone, 2016). Our estimates of price changes are free from this problem because we look at price changes on a UPC-by-UPC basis. This finding does not mean, however, that compositional changes are unimportant. To illustrate the importance of compositional changes, we re-estimate our demand and price equations, but using data aggregated to the category level, and look at cyclicality in the sales-weighted average price. We find that category-level prices are much more countercyclical than are product-level prices. For the average category, category-level prices fall by 2.5 log points between peak and troughs of demand, whereas the fall in product-level prices is only 1.4 log points. Looking across categories, Appendix Figure A.3 shows the scatter plot of category-level price cyclicality against product-level cyclicality (averaging up to a given product category). Although there is a strong association, points are typically below the 45-degree, especially for
products with the most countercyclical prices, reflecting that category-level prices are more countercyclical than product-level prices (see, e.g., Nevo and Hatzitaskos (2005)).

Thus, prices often fall when demand peaks, although rarely by a large amount. This is one indication that prices are countercyclical. An alternative indication is: how often are prices at their trough when demand peaks? We answer that question in Figure 3. In this figure, we divide up the seasonal products according to the month when demand peaks. Then, for each demand peak month, we plot the distribution of what month prices for those products reached their trough. For example, the top left panel of the figure is limited to the 257 products in which demand peaks in January. For those products, we plot the distribution of the price trough month. If prices are strongly countercyclical, we should see that they tend to trough in exactly the month when demand peaks. That is the pattern we find, with some exceptions. For products with a demand peak in a particular month, we find that there is a clearly elevated probability of having a price trough in that month. To show this more clearly, in each panel, we also plot the distribution of trough price months for products with peak quantities in all other months. To quantify the patterns in the figures, we make a product-month data set, and regress an indicator for “trough price month” on an indicator for “peak demand month”, and obtain a coefficient of 0.10 (with a standard error of 0.01, clustering on product), meaning there is a 10 percentage point increase in the likelihood that a given month is the trough price month if it is also the peak demand month. Since the base rate is 1/12, this is about a 100 percent increase.

The observed seasonal price changes could be because of falling base prices, deeper sales, or greater frequency of promotional prices. We decompose the sources of countercyclical pricing in Table 2. The table reports the distribution of changes in log price, log base price, frequency of promotional price discounts, and depth of promotional price discounts, between trough and peak demand months. On average base price changes account for about half of the countercyclical price change, although they account for less than a quarter of the median product’s price change. The balance of countercyclical pricing is accounted for by an increased frequency of promotional prices. The average seasonal product has promotional prices 4.6 percentage points more often during peak quantity periods, relative to trough periods, and for the median product the difference is 2.9 percentage points. The depth of promotional price discounts varies little at seasonal frequencies.
Figure 3: Timing of price troughs, given timing of demand peaks

Notes: This figure plots the distribution of observed trough price months, among seasonal products, separately by the timing of peak demand months (e.g., in the top left, we plot the distribution of price trough months among products whose demand peaks in January). The hollow bars plot the distribution of timings for other products (e.g., those that do not peak in January). See notes to Figure 2.
Table 2: Sources of seasonal price changes

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<th>Median</th>
<th>90th percentile</th>
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<td>0.029</td>
<td>0.157</td>
</tr>
<tr>
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<td>-0.044</td>
<td>-0.000</td>
<td>0.033</td>
</tr>
</tbody>
</table>

Notes: This table reports statistics on the distribution (across products) of changes in the indicated price component, between peak and trough demand months, for seasonal products. Seasonal products are those with a peak-trough difference in demand greater than the implied effect of a 4.5 percentage point increase in unemployment.

Overall, we find that when demand peaks, prices typically fall, in equal parts because of more frequent pricing promotions and lower base prices. Furthermore, prices are especially likely to reach their trough in months of peak demand.\(^{29}\) However, the price changes are fairly small for the typical product, and there are some seasonal products that do not show countercyclical pricing. Thus, case studies of individual product categories could easily reveal pro- or countercyclical pricing, and any assessment of whether prices are countercyclical requires a broad perspective.

### 3.3 Demand elasticities are often countercyclical

The results so far show that many products exhibit large seasonal fluctuations in demand, with little corresponding price changes. What price changes we do observe are often countercyclical, in the sense that prices often fall when demand peaks. This finding is counterintuitive when viewed through a perfectly competitive, simple (upward sloping) supply and demand framework, which would imply that prices should remain steady or rise with demand. However, a perfectly competitive model likely does not adequately describe the retail sector, as retailers likely have considerable market power. For a firm with market power, the optimal prices depends crucially on the price elasticity of demand. We therefore investigate seasonality in demand elasticities.

Our baseline specification, Equation 1, yields demand elasticities that vary by month-of-year.\(^{30}\) We calculate how these (shrunk) estimates change between trough and peak quantity months, and we report the distribution of changes in elasticities in Panel A of Figure 4. We look separately

\(^{29}\)We emphasize that our measure of peak month of demand is price adjusted, so it is not caused by the price changes we describe here.

\(^{30}\)We plot the distribution of estimated elasticities (across products; not the monthly deviations) in Appendix Figure A.2. The elasticities appear sensible. The mean and median are -2.64 and -2.51. Every one of our 1,353 products has a negative elasticity, and all but 8 are elastic (i.e. less than -1).
at seasonal and non-seasonal products. For seasonal products, demand elasticities are typically countercyclical, meaning that demand usually becomes more elastic when demand peaks. About 70 percent of seasonal products exhibit countercyclical elasticities, and for the average seasonal product, the elasticity falls by 0.4 between peak and trough demand months. For non-seasonal products, the seasonal changes in elasticities are smaller and nearly symmetric around zero.

These estimated demand elasticities broadly rationalize the observed price patterns of the previous section. Demand becomes more price sensitive during demand peaks, providing an incentive for retailers to decrease their prices. About 70 of products show countercyclical prices, and about 70 percent show countercyclical elasticities. However, the results so far do not necessarily indicate that the observed magnitude of price changes is consistent with elasticity changes, because (in a our benchmark model) the optimal price is a nonlinear function of the elasticity. We therefore report in Panel B of Figure 4 the distribution of implied changes in the benchmark price, defined as $\ln \frac{\eta}{\eta + 1}$, where $\eta$ is the shrunk elasticity estimate.\[31\] For seasonal products, the mean change in benchmark price is -0.15 and the median change is -0.04. Although the mean change in $\ln p^*$ is larger than the observed change in prices, the median is close. For most products, the change in the benchmark price is both small and not too different from what is observed.

\[31\] This is undefined for products with elasticities greater than -1. Following DellaVigna and Gentzkow (2019), we use winsorized elasticities to calculate optimal prices, winsorizing at -7 and -1.2. This winsorizing explains why there are fewer negative benchmark price changes than elasticity changes (because it sometimes results in exactly zero change).
Figure 5: Timing of elasticity troughs, given trough price month

Notes: This figure plots the distribution of observed trough elasticity months, among seasonal products, separately by the timing of trough price months (e.g., in the top left, we plot the distribution of elasticity trough months among products whose prices trough peak in January). The hollow bars plot the distribution of timings for other products (e.g., those that do not trough in January). Seasonal products are those with a peak-trough difference in demand greater than the implied effect of a 4.5 percentage point increase in unemployment.
3.4 Interpreting our results relative to a simple benchmark

We present two further pieces of evidence that low and typically countercyclical price changes are consistent with our simple pricing benchmark. First, we show that the elasticities are particularly likely to reach their trough when prices do as well, so the timing of changes in prices and elasticities line up. We show in Figure 5 the distribution of trough (most elastic) elasticity months, among products with a given trough price month, analogous to our exercise for the timing of prices and demand levels. The figure reveals more noise in the timing of elasticity changes than what we observed for prices. Nonetheless, there is a clear pattern for elasticities to trough when prices trough, and indeed we find in a regression framework that the trough price month is 4.1 percentage points more likely to be the trough elasticity month (standard error, clustered on product, of 0.01), a 50 percent increase over the base rate.

Our second piece of evidence that price changes are consistent with optimal pricing comes from comparing the magnitude of price changes across categories to the implied benchmark price change. We aggregate to the category level because the noisiness in the product-level elasticity estimates makes it difficult to assess their correlation with product-level price changes. To aggregate, we take the simple average, across products in a category, of the estimated seasonal price change and benchmark price change. We plot the benchmark price change against the observed price change in Figure 6. Our benchmark models implies that these price changes should be perfectly correlated with a 1:1 relationship. Measurement error (especially in the elasticity estimates) will attenuate the correlation. Nonetheless, the figure shows a clear connection between observed price changes and benchmark price changes, with one important exception: fresh fruit-remaining. Our simple benchmark model assumes that demand fluctuations are the only reason for price changes, but this assumption is likely to be a poor one for fresh fruit, where harvest conditions are likely to be just as seasonal (or more) as demand. Excluding fresh-fruit, we estimate a strong relationship between observed price changes and benchmark seasonal price changes, with a slope coefficient of 2.05. This magnitude means that benchmark prices are strongly correlated with seasonal prices, and on average move more than one for one. While this might indicate that seasonal prices do not move enough, relative to an optimal benchmark, it is only marginally significantly different from 1 (p-value = 0.06), i.e., meaning we cannot necessarily reject the hypothesis that prices move one for one with those implied by our benchmark. We view this evidence as showing that countercyclical elasticities can roughly quantitatively rationalize countercyclical prices. If
anything, observed prices are not as countercyclical as our elasticity estimates say they should be.

Using our simple benchmark prices, we can also provide a quantitative sense as to just how large are the deviations between the benchmark and observed prices by calculating the amount of profits retailers forgo by not pricing more countercyclically. Appendix Section D provides the full description of our approach and the results. It is important to emphasize that we view our benchmark price as a simple quantitative benchmark, not as the optimal price, as that would require far more considerations including cross-category effects, and local competition to name just two. However, given the difficulty retailers have in determining differences in demand conditions across stores [Hitsch et al., 2019], we view this benchmark pricing scheme as fully achievable by the retailers given their current IT and pricing strategies. Our resulting lost profits indicate that retailers are not losing much in the way of profit through their seasonal pricing practices. Across our set of products, we find that the median chain loses about $260,000, or 0.5% of yearly revenue. Given this rough quantitative assessment of how large are the deviations between our benchmark and observed prices, we view that it is difficult to argue the seasonal pricing practices of retailers are not optimal.
4 Seasonality on the intensive and extensive margin

We find that most products exhibit countercyclical price fluctuations, and these fluctuations are broadly consistent with a simple benchmark pricing model, because the demand curve facing retailers becomes more elastic during periods of demand peaks. What explains this time-varying elasticity? A natural candidate is that the identity of shoppers in a given category changes over the year. For example, the average soup buyer in July may be quite different than the average soup buyer in February. If people who only purchase during peak demand periods have more elastic demand, than the aggregate demand curve facing a retailer will become more elastic during peak demand periods, even if at an individual level the demand curve has a time-invariant elasticity. Several researchers have proposed and investigated versions of this explanation for countercyclical-pricing for particular products (e.g. Guler et al. (2014); Bayot and Caminade (2015); Perrone (2016); Kwon et al. (2018); Haviv (2019)). Here, we test an implication of this idea, using a wide range of products. Specifically, for this compositional explanation to be correct, it must be true that categories with larger seasonal shifts in demand experience large extensive margin shifts, i.e., large changes in the fraction of people purchasing any products in the category at all.

We use a simple decomposition to show the importance of the extensive margin for overall seasonality.\footnote{This decomposition, and how it relates to Tobit analysis was discussed by McDonald and Moffitt (1980), and used in a very similar manner using retail scanner data by Hastings and Washington (2010).} Specifically, the change in average quantity purchased (at the individual level) between two months $m$ and $m'$, can be written as

\[
E[q|m] - E[q|m'] = (1/2) \left( E[q|q > 0, m] + E[q|q > 0, m'] \right) \left( Pr(q > 0|m) - Pr(q > 0|m') \right) \\
\equiv \Delta Pr \\
+ (1/2) \left( Pr(q > 0|m) + Pr(q > 0|m') \right) \left( E[q|q > 0, m] - E[q|q > 0, m'] \right). \\
\equiv \Delta ECOP.
\]

This is the difference in probability of any purchase (which we call $\Delta Pr$), scaled by the expected amount purchased conditional on making a purchase, plus the change in the expected amount purchased conditional on making a purchase (which we call $\Delta ECOP$). We therefore define the extensive margin share as

\[
\text{Extensive share}_{m,m'} = \frac{\Delta Pr \left( E[q|q > 0, m] + E[q|m'|q > 0, m'] \right) / 2}{E[q|m] - E[q|m']}.
\]
If changes in the composition of consumers drive changes in the store-level elasticity, then we should observe that the extensive share accounts for a large share of seasonal changes in quantities, i.e. a large share of the peak-trough difference $E[q_m] - E[q_m]$.

Figure 7: The extensive margin accounts for most of the seasonal variation in demand

![Graph showing the distribution of extensive margin shares across categories.]

Notes: This figure reports the distribution, across categories, of the extensive margin’s contribution to seasonal amplitudes. We estimate the extensive margin share using Equation 9 and Nielsen’s Consumer Panel.

To estimate the extensive share, we use Nielsen’s household level dataset, the Consumer Panel. We aggregate to the household-week-category (i.e., Nielsen module) level and record total purchases, whether a household has any purchases, and the amount purchased if positive. Then for each month we calculate the empirical analogs of $E[q|Month = m]$, $Pr(q > 0|Month = m)$, and $E[q|q > 0, month = m]$, and we use these to seasonal amplitudes and the extensive margin share.

33 For consistency with our main analysis, we exclude holiday weeks. However, in the household data we do not adjust for prices or other factors because there is not a straightforward way to measure the price a customer faces when she buys no product. We show in Figure A.4 in appendix, however, that seasonality in the household data is very similar to (price-adjusted) seasonality in the retail scanner data.
demand peaks. These intensive margin declines are consistent with both large extensive margin shifts and considerable consumer heterogeneity, with the marginal customers who purchase during only peak periods having much lower demand than the consumers who purchase during demand troughs. Thus, seasonal shifts in demand are accompanied by large shifts in the composition of buyers. As these buyers have less attachment to the product category, it is likely that they are more price sensitive and hence, much more elastic. These extensive margin response therefore help explain why we find that retailers face time-varying elasticities.

5 Robustness

Our approach to measuring the seasonality of demand and its relationship to countercyclical pricing made several assumptions that require further inspection. In this section, we discuss a set of robustness checks that focus on addressing the possibility that (i) cross store competition, (ii) within category substitution, (iii) storability, or (iv) our sample selection might affect our primary results.

For each alternative empirical specification, we report the distribution of demand amplitudes in Appendix Table A.3, seasonal price changes from these alternative specifications in Appendix Table A.4, and seasonal changes in elasticity in Appendix Table A.5. Additionally, we show the robustness of our observed price-benchmark price association to these alternative specifications in Appendix Table A.6. Broadly speaking, our key findings are robust to these alternative specifications. Seasonal fluctuations in demand are substantial and pervasive (in many cases more so than reported in our main results), and are typically accompanied by countercyclical pricing, that is more modest in magnitude, and mostly rationalized by estimates of countercyclical elasticities. In what follows, we discuss in more detail the specifics of each of these robustness checks.

5.1 Cross store competition

An important facet of the grocery retail industry is the localized nature of competition (Smith, 2006). In our primary results, we attempt to avoid confounding variation in local competition through a set of product-store-year fixed effects. Even with that set of fixed effects, our results could confound differences in local competition across retailers and/or markets to the extent that

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34We do not consider robustness of the elasticity or benchmark price results to the inverse hyperbolic sine specification, because this specification yields an elasticity which depends on quantity and, hence the price level itself.
this competition varies within the year. As entry and exit in the grocery retail industry are rare and likely uncorrelated with seasonal demand fluctuations for individual products, their influence on the results is likely to be small, and they would not be able to explain all of our results given the heterogeneity in the timing of these demand fluctuations. Changes in local competition, however, could manifest through variation in the degree of price competition (e.g., Rotemberg and Saloner (1986)).

To address this concern, we estimate an alternative set of specifications where we include in the demand for product \( i \) in store \( j \) the (fixed-weight) average price charged for \( i \) in all the other stores located in that \( j \)'s DMA. While this approach has its shortcomings, and we would not view the coefficient estimates on the average of other stores’ prices as causal, it does provide a measure of how sensitive our results are to the possibly time varying distribution of prices from other local stores. Allowing for cross store competitive effects has minimal effect on our estimates. We find very similar results for this specification (reported in the second row of Appendix Tables A.3-A.6): seasonal fluctuations in demand are large, the typical seasonal product exhibits countercyclical pricing, and the seasonal fluctuation in prices is typically small relative to seasonal fluctuations in demand.

The fact that the local prices of other stores has minimal effects on our primary results is consistent with other findings in the literature, as well. Arcidiacono et al. (2020) use the specific timing of Walmart Supercenter store openings to show that while incumbent stores’ revenues decline by as much as 16% immediately following Walmart’s entry, this entry is not met with any price response on the part of the incumbents (preemptively, or otherwise). Given Walmart’s every-day-low-price (EDLP) strategy and well established cost advantages as well as the salience of a Walmart entry for local incumbents, this result might seem surprising. Regardless, the results do indicate that the nature of local market competition in grocery retail as it relates to price might be limited, and instead are primarily on other dimensions (e.g., entry/exit). Hitsch et al. (2019) provide systematic evidence of the degree of pricing coordination within and across chains and markets for an expansive set of products. They find that after controlling for the share of stores within the same chain and market that are running a promotional price on a product, that the share of stores in other chains in that market has no relationship with a store running a promotion. Given our

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35 A couple of the shortcomings of this approach include that we only observe the local prices of the stores that report to Nielsen. Additionally, the prices of other local stores is surely endogenous, and we do not instrument for this set of prices.

36 Hitsch et al. (2019, pg. 30) report the median effect of going from no stores in other local chains running a promotion to all of them leads to a -0.1 percentage point decline a store running a promotion. Close to 90 percent of product-store
identification strategy of using the prices charged in other stores in the same chain and state as an instrument, the results of Hitsch et al. (2019) indicate the promotional price activity of other stores locally is conditionally independent of an individual stores pricing decision for a product. Altogether, we view this combination of evidence makes it very difficult to argue that local competition considerations could explain or strongly affect our primary set of results.

5.2 Cross-product substitution

For almost all product categories, retailers typically carry a variety of different individual products. For many categories (e.g., dried pasta), this variety of products includes some from the same brand name (e.g., Barilla brand Penne and Rotini pasta), while others might come from competing brands (e.g., De Ceco), or the chain’s private label. The degree of substitution across products within a category is likely to be very heterogeneous across categories, retailers, and possibly markets. Trade promotion deals between retailers and manufacturers only further complicates the analysis.

For many of these considerations, our set of product-store-year fixed effects mitigates the possibility that these factors may confound our elasticity estimates, to the extent they remain constant over the year for a particular store and product. For example, product assortment available at different stores varies systematically across retail chains, while remaining quite similar within them (Hwang et al., 2010). For some research questions, such as ones focusing on competitive effects, cross-product substitution would be important to model explicitly (e.g., Nevo, 2001). Given our research questions, and the overall breadth of the products and markets in our analysis we instead resort to absorbing all brand and availability effects through our rich set of fixed effects.

A remaining concern is the possibility that time-varying prices of substitute products influence our main estimates. We note that it would likely be difficult for time-varying substitute prices to account for our main results on seasonality, given that fluctuations in prices are so low relative to fluctuations in the level of demand. Despite these considerations, it is possible that coefficient estimates are not statistically distinguishable from zero.

Interestingly, Hitsch et al. (2019) also report results on the unconditional independence of chains promotional activities. Here, they find distribution that is largely still concentrated near zero—or independence—but that has a right skew, which they hypothesize could be the consequence of seasonal demand.

Put differently, to explain the seasonal fluctuations we see we would need cross-price elasticities to be on the order of 5-10, or larger than own-price elasticities. This appears implausibly large. For example, the cross-price elasticities estimated from multi-product differentiated demand systems for the ready-to-eat cereal (Hausman, 1996; Nevo, 2001), light-beer (Miller and Weinberg, 2017), soft-drinks (Hendel and Nevo, 2013), and laundry detergent (Hendel and Nevo, 2006a) are all an order of magnitude smaller than the own-price elasticities—and in some cases two orders of magnitude smaller.
the magnitude of our elasticity estimates (and hence their countercyclicality) could be sensitive to cross-product substitution.

We therefore estimate two alternative set of demand specifications that adjust for competitor products’ prices. In particular, we re-estimate our primary demand specification but including either: (i) the (fixed weight) average of all other prices in the category for that store, or (ii) the minimum price for all other prices in the category. These two approaches can be interpreted as estimating a constant elasticity of substitution (CES) demand system where across many products that have some degree of substitution across all the products of the category (in the case of the average), or are perfectly substitutable (in the case of the minimum). They therefore span a range of substitution patterns. This approach is admittedly restrictive, but should pick up systematic seasonal changes in the relative position of product’s price relative to others in the category, and has been used in other large-scale investigations using scanner data (Strulov-Shlain, 2019). Allowing for cross product substitution effects of either form has essentially no effect on our estimates. Across both specifications (shown in the third and fourth rows of Appendix Tables A.3-A.6), we continue to find large seasonal fluctuations in demand, and that the seasonal variation in elasticities can roughly rationalize the countercyclical pricing that does exist across products.

The limited affect of allowing for cross product substitution on our main results is supported by other findings in the literature. Hitsch et al. (2019) include an even richer set of other products in their demand system, in a demand specification that is otherwise similar in spirit to ours (though does not allow for time varying elasticities). Hitsch et al. (2019) report a median cross-price elasticity that is positive but fairly small (0.153 for the primary competitor), alongside a large fraction of estimates that are negative, and a majority that are not statistically different from zero. We share the view of Hitsch et al. (2019) in that: “estimating cross-price effects at the brand/store level with weekly data... is daunting,” and that short of a well tailored demand model with fewer parameters is unlikely to find such effects will be found to be important (at least with any amount of precision). Thus, while we hold the view that cross-price elasticities are important, and indeed play a vital role in the competition that occurs within product categories, we find it difficult to argue that there exists empirical evidence that indicates this factor is changing dramatically within the year for many product categories and doing so in a way that could fully explain our main

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Given that retailers make the pricing decisions of all the products within a category jointly, the price indices of other products in the category might suffer from the same classic endogeneity concerns that the own price might. While we do not use an instrumental variable for these other price indices, and would be cautious in interpreting the estimated coefficients themselves as causal, we think the likely bias of these coefficients is small.
results.

5.3 Storability

The storability of a good could affect our estimates if consumers are forward looking and stock up on a product while it’s on sale for future consumption. In effect, the role of stockpiling for future consumption might lead to a distortion of our price elasticity estimates. Hendel and Nevo (2013) and Chevalier and Kashyap (2019) show that retailers might use discounts as a means to price discriminate amongst consumers of varying willingness to pay and ability to stockpile. We explore the sensitivity of our estimates to storability considerations by including time-since-last sale as an additional control variable across our empirical specifications (fifth row of Appendix Tables A.3-A.6). This approach towards controlling for the possibility of consumer stockpiling has been used before in the literature (Hendel and Nevo, 2003; Strulov-Shlaim, 2019), and is the most practical in an investigation of over a thousand products, across hundreds of markets, especially when the analysis is being done at the individual product level.

Across each of our set of results, controlling for time since last sale does not appear to dramatically affect the distribution of estimates. The lack of any discernible effect might be surprising, as the previous literature has found that the level of elasticity estimates for storable products can be sensitive to the handling of sales (e.g., Hendel and Nevo, 2013; Haviv, 2019). There are two explanations. First, we find that the difference in elasticities between seasonal peaks and troughs is robust to controlling for time-since-last sale. Second, many of our products are not storable and some are perishable. To this point, we show in Appendix Table A.7 that store purchases are much more sensitive to time-since-last sale for storable products than for perishable ones. These additional results confirm the validity of time-since-last sale as a proxy for capturing the possible price discrimination incentives retailers might practice for storable products. With that said, these incentives and their influence on the pricing strategies of retailers appear unable to fully explain the prevalence of seasonal demand fluctuations and its relationship with countercyclical pricing.

5.4 Other considerations

We consider several other specification checks. First, although our base specifications for measuring seasonality in the level of demand uses instrumental variables to adjust for price changes, we also consider specifications that use OLS, or forgo the price adjustment entirely. We show in
rows 7 and 8 of Appendix Tables A.3 that using OLS instead of IV does not substantially change our estimated seasonality. Failing to price adjust at all does not produce larger estimates of seasonality, because prices are countercyclical, and therefore amplify seasonal demand shifts. We also consider inverse hyperbolic transformations rather than log; this produces larger seasonality in the level of demand and in prices (shown in row 6 of Appendix Tables A.3 and A.4). Finally, we show how our estimates change when we do not use the Empirical Bayes shrinkage procedure. Without shrinkage, we classify more products as seasonal, we find larger amplitudes and more varied elasticity changes, consistent with expectations that shrinkage reduces bias and noise in our estimates. The effect of shrinkage on the price estimates are smaller because these estimates are more precisely estimated. These results confirm our expectation that failing to shrink our estimates would produce even more seasonality.

6 Conclusions

We have provided new evidence on the extent of seasonal fluctuations in demand that is substantially broader than previous work, and have shown that these fluctuations are typically accompanied by increases in the price elasticity of demand, and in so doing largely rationalizing the once apparent pricing puzzle of countercyclical pricing. Seasonal fluctuations in demand are large, pervasive, and heterogeneous. The typical product experiences demand swings of 25 log points or more, and most products are seasonal in the sense that their seasonal demand fluctuations are larger than their business cycle fluctuations. The timing of these fluctuations is heterogeneous: for a plurality of products, demand peaks in the winter, but many products show a summer peak. Despite these large demand fluctuations, prices vary little at seasonal frequencies, and prices are typically countercyclical. For the average seasonal products, prices fall by a few percent from demand trough to demand peak, and peak demand months are usually trough price months. Roughly half of the countercyclical price changes come from greater frequency of promotional prices. These price changes are for a fixed product and therefore avoid compositional bias, which we show results in even greater measured countercyclicality.

We show that the simplest model of optimal pricing can roughly account for countercyclical prices. The model implies that prices depend on demand elasticities rather than levels, and we find that, indeed, demand elasticities typically become more negative when the level of demand peaks. Elasticity and price movements are temporally closely aligned; we find that demand is
often most elastic in the month when prices are most negative. Quantitatively, we find a roughly one-for-one relationship between seasonal price changes and seasonal changes in the theoretical benchmark price, looking across product categories. Our benchmark model in fact implies that prices should be somewhat more countercyclical than they are. Although observed seasonal price changes are not exactly equal to our benchmark, the lost profits from misprinting relative to our benchmark are a small share of revenue. Thus despite abstracting from many important features such as varying marginal cost, intertemporal considerations, or competitive effects, the simple pricing model can rationalize seasonal pricing patterns. Key to this rationalization is the fact that demand becomes more elastic during seasonal peaks. We argue that the mechanism behind this countercyclical elasticity is a changing composition of consumers. People who buy soup in summer likely have a strong attachment to soup and low price sensitivity, while people who buy soup only in winter are likely more price sensitive. In support of this mechanism, we show using household-level data that nearly the entirety of seasonal fluctuations in quantities comes from the extensive margin, shifts in the fraction of people buying any product in a given month and category.
References


A  Additional results

Table A.1: Selecting chains and stores

<table>
<thead>
<tr>
<th>Restriction imposed</th>
<th>No. of Stores</th>
<th>No. of Chains</th>
<th>No. of States</th>
<th>Total yearly revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial sample of stores</td>
<td>40,070</td>
<td>398</td>
<td>49</td>
<td>$225bn</td>
</tr>
<tr>
<td>Food, drug, and mass merchandise only</td>
<td>38,052</td>
<td>390</td>
<td>49</td>
<td>$222bn</td>
</tr>
<tr>
<td>Stores do not switch chain</td>
<td>34,519</td>
<td>133</td>
<td>49</td>
<td>$208bn</td>
</tr>
<tr>
<td>Stores ≥ 2 years</td>
<td>33,595</td>
<td>121</td>
<td>49</td>
<td>$208bn</td>
</tr>
<tr>
<td>Stores in Household panel</td>
<td>33,595</td>
<td>121</td>
<td>49</td>
<td>$208bn</td>
</tr>
<tr>
<td>Chain present ≥ 8 years</td>
<td>24,597</td>
<td>79</td>
<td>49</td>
<td>$194bn</td>
</tr>
<tr>
<td>Valid chain</td>
<td>24,471</td>
<td>77</td>
<td>49</td>
<td>$191bn</td>
</tr>
<tr>
<td>Base price algorithm (baseline sample)</td>
<td>24,450</td>
<td>77</td>
<td>49</td>
<td>$191bn</td>
</tr>
</tbody>
</table>

Notes: The table shows the breakdown of stores and chains as we refine our samples. This table follows Table 1 of DellaVigna and Gentzkow (2019) except the last panel aggregates over all types of stores, not just food stores. Total yearly revenue is the aggregate sales divided by 9 years.
Notes: Figure plots the distribution (across products) of estimated coefficients on the local unemployment rate (measured on a 0-100 scale), from Equation 1.
Figure A.2: Elasticity distribution, across products

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-2.64</td>
</tr>
<tr>
<td>Min</td>
<td>-6.53</td>
</tr>
<tr>
<td>p10</td>
<td>-3.69</td>
</tr>
<tr>
<td>p50</td>
<td>-2.51</td>
</tr>
<tr>
<td>p90</td>
<td>-1.66</td>
</tr>
<tr>
<td>Max</td>
<td>-0.37</td>
</tr>
</tbody>
</table>

1345/1353 of elasticities < -1
1353/1353 elasticities < 0

Notes: Figure plots the distribution of estimated elasticities, across products, from Equation 1.
Figure A.3: Category-level seasonal aggregate price changes vs. product-level seasonal price changes

Notes: Figure illustrates how composition bias can lead to greater countercyclicality in category level average prices than in the individual prices. To do so, we estimate Equation 1 on data aggregated to the category-store-week level, yielding an estimate of peak and trough quantity months. We then estimate Equation 5 using category-store-week log average price as the dependent variable (using a revenue weighted average). $\Delta p$ at the category level is the difference in log average price between peak and trough months. We plot that against the category level average of the product level $\Delta p$ (averaging these using equal weights). Composition bias makes the category level price change more negative than the product level price change.
Table A.2: Seasonality by category

<table>
<thead>
<tr>
<th>Category</th>
<th>Products</th>
<th>% Seasonal</th>
<th>Amp</th>
<th>Mode peak month</th>
<th>Share at Mode</th>
<th>Share Jan peak</th>
<th>ln p</th>
<th>ln base price</th>
<th>promo rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOUP-CANNED</td>
<td>79</td>
<td>1.00</td>
<td>.71</td>
<td>1.00</td>
<td>.68</td>
<td>.68</td>
<td>-.15</td>
<td>-.06</td>
<td>.19</td>
</tr>
<tr>
<td>FROZEN NOVELTIES</td>
<td>22</td>
<td>1.00</td>
<td>.63</td>
<td>1.00</td>
<td>.55</td>
<td>0</td>
<td>-1.06</td>
<td>-1.06</td>
<td>.11</td>
</tr>
<tr>
<td>BATTERIES</td>
<td>5</td>
<td>1.00</td>
<td>.53</td>
<td>1.00</td>
<td>.8</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>.02</td>
</tr>
<tr>
<td>FRUIT DRINKS-OTHER CONTAINER</td>
<td>101</td>
<td>.91</td>
<td>.44</td>
<td>1.00</td>
<td>.41</td>
<td>.04</td>
<td>-.08</td>
<td>-.06</td>
<td>.05</td>
</tr>
<tr>
<td>FRESH FRUIT-REMAINING</td>
<td>1</td>
<td>1.00</td>
<td>.43</td>
<td>1.00</td>
<td>.5</td>
<td>0</td>
<td>-1.02</td>
<td>-1.02</td>
<td>.06</td>
</tr>
<tr>
<td>FRANKFURTERS-REFRIGERATED</td>
<td>18</td>
<td>.83</td>
<td>.39</td>
<td>1.00</td>
<td>.67</td>
<td>0</td>
<td>-.08</td>
<td>-.04</td>
<td>.09</td>
</tr>
<tr>
<td>WATER-BOTTLED</td>
<td>30</td>
<td>.83</td>
<td>.38</td>
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<td>.23</td>
<td>.17</td>
<td>-.02</td>
<td>-.01</td>
<td>.03</td>
</tr>
<tr>
<td>YOGURT-REFRIGERATED</td>
<td>90</td>
<td>.96</td>
<td>.38</td>
<td>1.00</td>
<td>.3</td>
<td>.02</td>
<td>0</td>
<td>0.00</td>
<td>.08</td>
</tr>
<tr>
<td>CANDY-NON-CHOCOLATE</td>
<td>27</td>
<td>.93</td>
<td>.37</td>
<td>1.00</td>
<td>.3</td>
<td>0</td>
<td>-.02</td>
<td>-.02</td>
<td>0</td>
</tr>
<tr>
<td>CANDY-CHOCOLATE</td>
<td>87</td>
<td>.95</td>
<td>.37</td>
<td>1.00</td>
<td>.22</td>
<td>.05</td>
<td>-.03</td>
<td>-.02</td>
<td>.02</td>
</tr>
<tr>
<td>BAKERY-CAKES-FRESH</td>
<td>9</td>
<td>1.00</td>
<td>.35</td>
<td>1.00</td>
<td>.33</td>
<td>.22</td>
<td>-.03</td>
<td>0.00</td>
<td>.09</td>
</tr>
<tr>
<td>BEER</td>
<td>6</td>
<td>1.00</td>
<td>.34</td>
<td>1.00</td>
<td>.67</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>ICE CREAM - BULK</td>
<td>17</td>
<td>.94</td>
<td>.29</td>
<td>1.00</td>
<td>.47</td>
<td>0</td>
<td>-.04</td>
<td>-.01</td>
<td>.08</td>
</tr>
<tr>
<td>COOKIES</td>
<td>85</td>
<td>.82</td>
<td>.28</td>
<td>1.00</td>
<td>.15</td>
<td>.13</td>
<td>-.03</td>
<td>-.01</td>
<td>.06</td>
</tr>
<tr>
<td>PAPER TOWELS</td>
<td>10</td>
<td>.60</td>
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<td>0</td>
<td>.05</td>
<td>.03</td>
<td>-.06</td>
</tr>
<tr>
<td>LIGHT BEER (LOW CALORIE/ALCOHOL)</td>
<td>6</td>
<td>.83</td>
<td>.28</td>
<td>1.00</td>
<td>.67</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>SNACKS - TORTILLA CHIPS</td>
<td>53</td>
<td>.51</td>
<td>.27</td>
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<td>.36</td>
<td>.36</td>
<td>-.01</td>
<td>0.00</td>
<td>.01</td>
</tr>
<tr>
<td>CEREAL - READY TO EAT</td>
<td>194</td>
<td>.80</td>
<td>.27</td>
<td>1.00</td>
<td>.3</td>
<td>.3</td>
<td>-.02</td>
<td>-.01</td>
<td>.04</td>
</tr>
<tr>
<td>CHEESE - SHREDDED</td>
<td>7</td>
<td>1.00</td>
<td>.26</td>
<td>1.00</td>
<td>.71</td>
<td>.71</td>
<td>.02</td>
<td>0.00</td>
<td>-.01</td>
</tr>
<tr>
<td>BLEACH - LIQUID/GEL</td>
<td>11</td>
<td>.91</td>
<td>.23</td>
<td>1.00</td>
<td>.64</td>
<td>0</td>
<td>-.01</td>
<td>0.00</td>
<td>.02</td>
</tr>
<tr>
<td>LUNCHEMEAT-DELI POUCHES-REFRIGERATED</td>
<td>21</td>
<td>.81</td>
<td>.23</td>
<td>1.00</td>
<td>.43</td>
<td>0</td>
<td>-.01</td>
<td>0.00</td>
<td>.03</td>
</tr>
<tr>
<td>SNACKS - POTATO CHIPS</td>
<td>79</td>
<td>.52</td>
<td>.22</td>
<td>1.00</td>
<td>.39</td>
<td>.05</td>
<td>-.01</td>
<td>0.00</td>
<td>.03</td>
</tr>
<tr>
<td>EGGS-FRESH</td>
<td>2</td>
<td>.50</td>
<td>.22</td>
<td>1.00</td>
<td>.1</td>
<td>0</td>
<td>.03</td>
<td>.01</td>
<td>-.03</td>
</tr>
<tr>
<td>DETERGENTS - HEAVY DUTY - LIQUID</td>
<td>21</td>
<td>.52</td>
<td>.22</td>
<td>1.00</td>
<td>.38</td>
<td>.38</td>
<td>0</td>
<td>0.02</td>
<td>0</td>
</tr>
<tr>
<td>SOFT DRINKS - LOW CALORIE</td>
<td>66</td>
<td>.76</td>
<td>.22</td>
<td>1.00</td>
<td>.27</td>
<td>.27</td>
<td>.01</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>GROUND AND WHOLE BEAN COFFEE</td>
<td>17</td>
<td>.53</td>
<td>.21</td>
<td>1.00</td>
<td>.29</td>
<td>.06</td>
<td>.01</td>
<td>.01</td>
<td>.01</td>
</tr>
<tr>
<td>ENTREES - ITALIAN - 1 FOOD - FROZEN</td>
<td>33</td>
<td>.94</td>
<td>.21</td>
<td>1.00</td>
<td>.3</td>
<td>.3</td>
<td>-.03</td>
<td>0.00</td>
<td>.07</td>
</tr>
<tr>
<td>TOILET TISSUE</td>
<td>27</td>
<td>.70</td>
<td>.2</td>
<td>1.00</td>
<td>.37</td>
<td>.3</td>
<td>.01</td>
<td>.01</td>
<td>-.01</td>
</tr>
<tr>
<td>FRUIT JUICE - ORANGE - OTHER CONTAINER</td>
<td>39</td>
<td>.33</td>
<td>.2</td>
<td>1.00</td>
<td>.44</td>
<td>.44</td>
<td>0</td>
<td>0.00</td>
<td>.01</td>
</tr>
<tr>
<td>LUNCHEMEAT-SLICED-REFRIGERATED</td>
<td>13</td>
<td>.69</td>
<td>.19</td>
<td>1.00</td>
<td>0</td>
<td>.31</td>
<td>0</td>
<td>0.00</td>
<td>.01</td>
</tr>
<tr>
<td>ENTREES-REFRIGERATED</td>
<td>3</td>
<td>.33</td>
<td>.18</td>
<td>1.00</td>
<td>0</td>
<td>0</td>
<td>.02</td>
<td>.02</td>
<td>.03</td>
</tr>
<tr>
<td>SOFT DRINKS - CARBONATED</td>
<td>73</td>
<td>.66</td>
<td>.18</td>
<td>1.00</td>
<td>.22</td>
<td>.22</td>
<td>0</td>
<td>-.01</td>
<td>-.01</td>
</tr>
<tr>
<td>PIZZA-FROZEN</td>
<td>25</td>
<td>1.00</td>
<td>.18</td>
<td>1.00</td>
<td>.6</td>
<td>.6</td>
<td>-.02</td>
<td>-.01</td>
<td>.03</td>
</tr>
<tr>
<td>DOG FOOD - DRY TYPE</td>
<td>8</td>
<td>.88</td>
<td>.14</td>
<td>1.00</td>
<td>0</td>
<td>.25</td>
<td>.02</td>
<td>.01</td>
<td>-.05</td>
</tr>
<tr>
<td>PAIN REMEDIES - HEADACHE</td>
<td>2</td>
<td>.50</td>
<td>.14</td>
<td>1.00</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>.01</td>
</tr>
<tr>
<td>CAT FOOD - WET TYPE</td>
<td>54</td>
<td>.70</td>
<td>.08</td>
<td>1.00</td>
<td>0</td>
<td>.22</td>
<td>0</td>
<td>0.00</td>
<td>.01</td>
</tr>
<tr>
<td>DAIRY-MILK-REFRIGERATED</td>
<td>4</td>
<td>0.00</td>
<td>.06</td>
<td>1.00</td>
<td>1</td>
<td>1</td>
<td>-.01</td>
<td>-.01</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Notes: Sorted by amplitude. Table reports, for each category, the number of products, the mean seasonal amplitude ("amp"), the modal peak quantity month (if unique, otherwise missing), the share of products who share the modal peak quantity month, and the share of products whose peak month is January, as well as the seasonal change in log price, log base price, promotional price rate, and benchmark optimal price.
### Table A.3: Robustness table for seasonal quantity amplitudes

<table>
<thead>
<tr>
<th>Specification</th>
<th># Products</th>
<th>% Seasonal</th>
<th>Seasonal amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>Baseline</td>
<td>1353</td>
<td>0.79</td>
<td>0.35</td>
</tr>
<tr>
<td>DMA competition</td>
<td>1350</td>
<td>0.77</td>
<td>0.35</td>
</tr>
<tr>
<td>Other product competition - average</td>
<td>1351</td>
<td>0.79</td>
<td>0.36</td>
</tr>
<tr>
<td>Other product competition - minimum</td>
<td>1353</td>
<td>0.79</td>
<td>0.35</td>
</tr>
<tr>
<td>Time since last sale</td>
<td>1334</td>
<td>0.78</td>
<td>0.36</td>
</tr>
<tr>
<td>Inverse hyperbolic sine</td>
<td>1265</td>
<td>0.76</td>
<td>0.50</td>
</tr>
<tr>
<td>OLS with price adjustment</td>
<td>1531</td>
<td>0.80</td>
<td>0.37</td>
</tr>
<tr>
<td>OLS without price adjustment</td>
<td>1531</td>
<td>0.88</td>
<td>0.46</td>
</tr>
<tr>
<td>No shrinkage</td>
<td>1353</td>
<td>0.83</td>
<td>0.37</td>
</tr>
</tbody>
</table>

Notes: Each row is a different specification. For each specification, we exclude products with too-large standard errors, and then report the number of products, the percent seasonal, and statistics on the distribution of seasonal amplitudes in quantities. “DMA competition” controls for the average log price charged by other chains in the same DMA. “Other product competition - average” controls for the average log price of other products in the same category and store. “Other product - minimum” instead controls for the minimum log price of other products in the same category and store. “Time since sale” controls for weeks since the last promotional pricing period. Inverse hyperbolic sine uses the inverse hyperbolic sine, \( \ln \sqrt{q^2 + 1} \), as the dependent variable. OLS with price adjustment is identical to our baseline specification, except we estimate by OLS rather than 2SLS. OLS without price adjustment drops all price controls, and includes only product-month dummies, product-store-year fixed effects, and product-unemployment controls.
### Table A.4: Robustness table for seasonal price changes

<table>
<thead>
<tr>
<th>Specification</th>
<th># Seasonal</th>
<th>Price change, peak q month minus trough q month</th>
<th>% negative</th>
<th>Mean</th>
<th>p1</th>
<th>p10</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>p90</th>
<th>p99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>1067</td>
<td></td>
<td>0.68</td>
<td>-0.03</td>
<td>-0.27</td>
<td>-0.13</td>
<td>-0.06</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.11</td>
</tr>
<tr>
<td>DMA competition</td>
<td>1041</td>
<td></td>
<td>0.70</td>
<td>-0.04</td>
<td>-0.27</td>
<td>-0.13</td>
<td>-0.06</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.09</td>
</tr>
<tr>
<td>Other product competition - average</td>
<td>1073</td>
<td></td>
<td>0.71</td>
<td>-0.04</td>
<td>-0.27</td>
<td>-0.13</td>
<td>-0.06</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.02</td>
<td>0.08</td>
</tr>
<tr>
<td>Other product competition - minimum</td>
<td>1072</td>
<td></td>
<td>0.68</td>
<td>-0.03</td>
<td>-0.27</td>
<td>-0.13</td>
<td>-0.05</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.11</td>
</tr>
<tr>
<td>Time since last sale</td>
<td>1043</td>
<td></td>
<td>0.68</td>
<td>-0.03</td>
<td>-0.25</td>
<td>-0.13</td>
<td>-0.06</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.10</td>
</tr>
<tr>
<td>Inverse hyperbolic sine</td>
<td>966</td>
<td></td>
<td>0.69</td>
<td>-0.04</td>
<td>-0.25</td>
<td>-0.13</td>
<td>-0.06</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.02</td>
<td>0.09</td>
</tr>
<tr>
<td>No shrinkage</td>
<td>1129</td>
<td></td>
<td>0.68</td>
<td>-0.03</td>
<td>-0.25</td>
<td>-0.12</td>
<td>-0.05</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.03</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Notes: Each row is a different specification. For each specification, we exclude products with too-large standard errors, and then report the number of seasonal products, the percent with negative price changes between seasonal trough and peak, and the distribution across products of seasonal price changes. See notes to Table A.3 for an explanation of the different specifications.

### Table A.5: Robustness table for seasonal elasticity changes

<table>
<thead>
<tr>
<th>Specification</th>
<th># Seasonal</th>
<th>Elasticity change, peak q month minus trough q month</th>
<th>% negative</th>
<th>Mean</th>
<th>p1</th>
<th>p10</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>p90</th>
<th>p99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>1067</td>
<td></td>
<td>0.71</td>
<td>-0.38</td>
<td>-3.50</td>
<td>-1.19</td>
<td>-0.58</td>
<td>-0.18</td>
<td>0.00</td>
<td>0.20</td>
<td>1.00</td>
</tr>
<tr>
<td>DMA competition</td>
<td>1041</td>
<td></td>
<td>0.69</td>
<td>-0.37</td>
<td>-3.40</td>
<td>-1.13</td>
<td>-0.58</td>
<td>-0.17</td>
<td>0.02</td>
<td>0.20</td>
<td>0.98</td>
</tr>
<tr>
<td>Other product competition - average</td>
<td>1073</td>
<td></td>
<td>0.71</td>
<td>-0.36</td>
<td>-3.38</td>
<td>-1.09</td>
<td>-0.57</td>
<td>-0.16</td>
<td>0.01</td>
<td>0.18</td>
<td>0.97</td>
</tr>
<tr>
<td>Other product competition - minimum</td>
<td>1072</td>
<td></td>
<td>0.70</td>
<td>-0.38</td>
<td>-3.35</td>
<td>-1.16</td>
<td>-0.58</td>
<td>-0.19</td>
<td>0.00</td>
<td>0.18</td>
<td>0.98</td>
</tr>
<tr>
<td>Time since last sale</td>
<td>1043</td>
<td></td>
<td>0.70</td>
<td>-0.39</td>
<td>-3.67</td>
<td>-1.11</td>
<td>-0.59</td>
<td>-0.19</td>
<td>0.00</td>
<td>0.19</td>
<td>0.98</td>
</tr>
<tr>
<td>No shrinkage</td>
<td>1129</td>
<td></td>
<td>0.73</td>
<td>-0.58</td>
<td>-4.34</td>
<td>-1.72</td>
<td>-0.98</td>
<td>-0.40</td>
<td>0.04</td>
<td>0.44</td>
<td>1.53</td>
</tr>
</tbody>
</table>

Notes: Each row is a different specification. For each specification, we exclude products with too-large standard errors, and then report the number of seasonal products, the percent with negative elasticity changes between seasonal trough and peak, and the distribution (across products) of seasonal elasticity changes. See notes to Table A.3 for an explanation of the different specifications.
### Table A.6: Robustness table for price-benchmark price association

<table>
<thead>
<tr>
<th>Demand specification</th>
<th># Categories</th>
<th>Constant (SE)</th>
<th>Slope (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>37</td>
<td>-0.08 (0.02)</td>
<td>2.05 (0.53)</td>
</tr>
<tr>
<td>DMA competition</td>
<td>37</td>
<td>-0.05 (0.03)</td>
<td>2.22 (0.54)</td>
</tr>
<tr>
<td>Other product competition - average</td>
<td>37</td>
<td>-0.06 (0.02)</td>
<td>1.78 (0.44)</td>
</tr>
<tr>
<td>Other product competition - minimum</td>
<td>37</td>
<td>-0.07 (0.02)</td>
<td>2.10 (0.51)</td>
</tr>
<tr>
<td>Time since last sale</td>
<td>37</td>
<td>-0.13 (0.05)</td>
<td>1.83 (0.68)</td>
</tr>
</tbody>
</table>

Notes: Table reports the results of a category level regression of the (category average) change in benchmark price against the (category average) observed change in price, among seasonal products and excluding fresh fruit. Each row uses a different specification to determine the change in benchmark price and benchmark price. See notes to Table A.3 for an explanation of the different specifications.

### Table A.7: Time-since-sale matters much more for storable products than for perishable products

<table>
<thead>
<tr>
<th>Product grouping</th>
<th>Average $\Delta \eta$, Baseline</th>
<th>Average $\Delta \eta$, controlling for weeks-since-sale</th>
<th>Average coefficient on weeks-since-sale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perishable</td>
<td>-0.033</td>
<td>-0.026</td>
<td>0.0004</td>
</tr>
<tr>
<td>Storable</td>
<td>-0.407</td>
<td>-0.431</td>
<td>0.0012</td>
</tr>
</tbody>
</table>

Notes: Table shows the validity of the weeks-since-sale control as a proxy for storability incentives. While the estimated change in elasticities is robust to controlling for weeks-since-sale, we see that weeks-since-sale has a much stronger effect on quantities for storable products than for perishable ones, as we would expect from a model of storability. Table reports the average $\Delta \eta$ (across products) in the baseline specification and in the robustness specification, and the average coefficient on week-since-sale. The storable products are defined as canned soup, toilet tissue, soft drinks (carbonated or low calorie), and detergent. The non-storable products are orange juice, yogurt, and milk.
Figure A.4: Seasonal amplitudes are highly correlated between the Retail Panel and Consumer Panel.

Notes: Figure plots seasonal amplitudes in quantities estimated in the household data (at the category level) against seasonal amplitudes estimated in the retail panel (aggregated to the category level). The estimation of the retail panel amplitudes is described in the text; it is based on shrunken monthly differences in log quantities. To estimate seasonal amplitudes in the household data, we look at the difference in the level of weekly purchases between the peak and trough month, scaled by the average purchase amount across those months (so that the scale is comparable to the retail panel scaling).
B Base Price Algorithm

B.1 Overview

We suggest a simple and straightforward algorithm to construct “base” prices allowing for time-varying base prices. Traditionally (e.g., Hendel and Nevo (2003, 2013)), ad-hoc procedures have been used to establish these base prices (e.g., single base price over a predetermined time period), and thus subsequently the promotional periods that are further inferred from price deviations (e.g., beyond a threshold) from the base price. For example, Hendel and Nevo (2003) establish the base price at a particular period to be the modal price observed for that product over the two years, and define a “promo” as any period where the price is 5 percent below this level. Our algorithm is different from the literature in three ways. First, we do not predetermine the number of base prices over a fixed length of time. Second, the algorithm is robust to various depth of either price dips or jumps (i.e., we do not need to take a stance on the minimum/maximum price difference between base and non-base prices). Third, selection of the parameters for the algorithm can be guided by documented practices of grocery retailers, as well as the price path and promotion activity for stores with information on both.

The algorithm is robust to instances of retailers in the Nielsen retail scanner dataset which have pricing schedules that do not align with the Nielsen reporting week. For those retailers and weeks with multiple prices our base price algorithm is likely to be less prone to incorrectly inferring changes in the base price, because of the algorithms built in accommodation for measurement error in prices.

Figure B.1: Example of base and actual prices

Notes: The figure plots the weekly time series of the observed price per unit of a 10.75 oz can of Campbell’s Chicken Noodle Soup, and the imputed base price, for the largest store in our data, given $\gamma_1 = 5$ and $\gamma_2 = 7$. Our data use agreement prohibits us from disclosing the price of individual UPCs, so we cannot label the y-axis of this figure.
Table B.1: Base Price Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>% missing</td>
<td>0.0032</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>No. of base price</td>
<td>4.46</td>
<td>3</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>% p &gt; base price</td>
<td>0.07</td>
<td>0</td>
<td>0.06</td>
<td>0.12</td>
</tr>
<tr>
<td>% promo</td>
<td>0.22</td>
<td>0.08</td>
<td>0.21</td>
<td>0.35</td>
</tr>
<tr>
<td>Promo depth (%)</td>
<td>-0.25</td>
<td>-0.3</td>
<td>-0.24</td>
<td>-0.18</td>
</tr>
</tbody>
</table>

The table reports the summary statistics of base price and promotion per store-year given $\gamma_1 = 5$ and $\gamma_2 = 7$.

As an example, Figure B.1 plots observed prices and the imputed base prices for canned soup for the store with the most canned soup sales in our data. Inspection of the figure reveals that each year has one or two obvious base prices (except 2009), and the algorithm correctly identifies these as such. In some years price is a base price but in other years it is a promotional price, and the algorithm successfully distinguishes between these cases. Our algorithm does well at avoiding false negatives, and successfully distinguishes between promotions and base prices that occur at the same dollar value. On the other hand, the algorithm has trouble with long-lasting spells of promotional prices; for example, in 2006 and 2007, the algorithm detects a base price drop where there is (likely) none. Implementing the algorithm requires that we specify hyperparameters that let us trade off these false negatives and false positives. In selecting these hyperparameters, we have erred on the side of caution, with a low false negative rate for base price changes.

### B.2 Base price algorithm in detail

From a time series of observed weekly prices, $(p_t)^{T}_{t=\tau}$, for each product and each store, the algorithm constructs a time series of “base” prices, $(b_t)^{T}_{t=\tau}$, over the same set of weeks. The algorithm requires two parameters—the maximum consecutive weeks allowed for a promo period ($\gamma_1 - 1$) and the minimum length of weeks required for non-promo period ($\gamma_2$).

To present in more detail the specifics of the algorithm, an example time series of prices $(p_t)$ is presented in the second column of table B.2. The price path exhibited in table B.2 indicates that a typical price dip lasts one week. From $p_t$, it is evident that there are likely two sets of base prices. The first base price is 1.0 during weeks 1-3 and 8-11. The second base price is 0.8 during weeks 4-7. Among these base prices, a promotional price of 0.4 is run during week 4, and 0.6 during week 6. Akin to what would be experienced in the price paths of the Nielsen dataset, it appears that a modest deviation from the base price is experienced during week 9 when the observed price increases to $1.1 for just one week. Ideally, the base price algorithm would be able to distinguish between the two base prices of a 1.0 and 0.8, without incorrectly attributing the other prices observed in the time series to base prices.

The first step of the algorithm detects smooth base prices during price dips. We use the hyperparameter ($\gamma_1$) and construct the lower envelope of both a “forward” and “backward” $\gamma_1$-period cumulative maximum of the observed time series of prices to construct the candidate time series of base prices. In the example, we let $\gamma_1 = 2$ based on the observation that price dips last one week typically. The “forward” 2-period cumulative maximum $(p_f^1)$ is reported in the third column, while the “backward” 2-period cumulative maximum $(p_b^1)$ is reported in the fourth column.

---

40 $(p_t)^{T}_{t=\tau}$ would not have any missing values as they are already imputed by the median chain-state-week prices.
Table B.2: An Example Price Path: Minimax/Maximin filter-smoother

<table>
<thead>
<tr>
<th>t</th>
<th>$p_t$</th>
<th>$p^f_t$</th>
<th>$p^b_t$</th>
<th>$\tilde{b}_t$</th>
<th>$\tilde{b}^f_t$</th>
<th>$\tilde{b}^b_t$</th>
<th>$b_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.0</td>
<td>-</td>
<td>1.0</td>
<td>1.0</td>
<td>-</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>2</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>3</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>0.8</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>4</td>
<td>0.4</td>
<td>1.0</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>5</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>6</td>
<td>0.6</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
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<tr>
<td>7</td>
<td>0.8</td>
<td>0.8</td>
<td>1.0</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>8</td>
<td>1.0</td>
<td>1.0</td>
<td>1.1</td>
<td>1.0</td>
<td>0.8</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>9</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>10</td>
<td>1.0</td>
<td>1.1</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>11</td>
<td>1.0</td>
<td>1.0</td>
<td>-</td>
<td>1.0</td>
<td>1.0</td>
<td>-</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Notes: The table provides an example of the minimax (first) filter-smoother step of the base price algorithm, as well as the maximin (second) filter-smoother step for a hypothetical observed time series path of prices. The second column presents the observed price series ($p_t$). The third column ($p^f_t$) presents the “forward” $\gamma_1 = 2$-period cumulative maximum, while the fourth column ($p^b_t$) presents the “backward” $\gamma_1 = 2$-period cumulative maximum. The fifth column ($\tilde{b}_t$) presents the lower envelope of the two cumulative maximum series by taking the period-wise minimum. The sixth column presents the resulting price series from the first step ($\tilde{b}^f_t$). The seventh column ($\tilde{b}^b_t$) presents the “forward” $\gamma_2 = 2$-period cumulative minimum, while the eighth column ($\tilde{b}^b_t$) presents the “backward” $\gamma_2 = 2$-period cumulative minimum. Finally, the last column ($b_t$) presents the upper envelope of the two cumulative minimum series by taking the period-wise minimum.

To construct the lower envelope of these two price series, we take the period-wise minimum of both of these series to construct the first step’s candidate base price time series. We call this step of the algorithm the minimax filter-smoother step, and report the resulting time series in the fifth column ($\tilde{b}_t$).

In case of price paths where promotions never lasted longer than $\gamma_1 - 1$ periods, the minimax filter-smoother step could almost perfectly identify base prices from promotional prices. However, in the event that small week-to-week deviations in prices occur for likely idiosyncratic reasons tied to measurement or reporting issues, this single step will still yield a modest amount of noise in the construction of the base price. Given the minimax formulation of the first step, positive measurement errors, like the one experienced in week nine, are likely to be the most influential to the base price construction. For example, at the culmination of the minimax step of the algorithm, week nine posits that the base price for that period is 1.1, a price that only occurs once in the time series, and is much more likely to be the consequence of measurement error.

To ameliorate the algorithm’s sensitivity to these sorts of measurement errors, the second step of the algorithm detects smooth base prices during price jumps or short dips. In particular, the maximum length of the autocorrelation of measurement errors will be controlled by the hyperparameter, $\gamma_2$. Another way to view this hyperparameter is the minimum uninterrupted sequence length a base price must have over the duration of its spell.

We let the upper envelope of both a “forward” and “backward” $\gamma_2$-period cumulative minimum of the time series of candidate base prices resulting from the first step ($\tilde{b}_t$) to construct the final candidate time series of base prices, ($b_t$). In our example, data shows that the typical plateau
periods last at least two weeks, and therefore we set $\gamma_2=2$. In table B.2, the “forward” 2-period cumulative minimum of the first step’s base price time series is reported in the sixth column ($\tilde{b}_t^f$). The “backward” 2-period cumulative minimum of the observed time series is reported in the seventh column ($\tilde{b}_t^b$). To construct the upper envelope of these two price series, we take the period-wise maximum of both of these series to construct the second step’s final candidate base price time series, $b_t$. We call this step of the algorithm the maximin filter-smoother step. As was desired, this second step has the effect of smoothing over the short-lived idiosyncratic price increases that are less likely to be base prices and more likely to be the result of measurement error.

In summary, the base price algorithm is a straightforward implementation of two filter-smoother steps that both have the interpretation of a minimax (maximin) approach. Both steps are parameterized by separate hyperparameters, $\gamma_1$ and $\gamma_2$, respectively. The specific details of each step in the algorithm are provided below.

**Steps for Base Price Identification**

For any given observed time series of prices $(p_t)_{t=\tau}^T$ and a set of hyperparameters $(\gamma_1, \gamma_2)$,

1. **Minimax($\gamma_1$) filter-smoother:**
   - Construct $\gamma_1$ period forward cumulative max of the observed price series, $p_t^f$.
     \[ p_t^f = \max\{p_t, p_{t-1}, \ldots, p_{t-(\gamma_1-1)}\}, \quad \forall \tau + (\gamma_1 - 1) \leq t \leq T \]
   - Construct $\gamma_1$ period backward cumulative max of the observed price series, $p_t^b$.
     \[ p_t^b = \max\{p_t, p_{t+1}, \ldots, p_{t+(\gamma_1-1)}\}, \quad \forall \tau \leq t \leq T + (\gamma_1 - 1) \]
   - Take period-wise minimum of the two price series $\tilde{b}_t = \min\{p_t^f, p_t^b\}$.
     \[ \tilde{b}_t = \min\{p_t^f, p_t^b\}, \quad \forall \tau \leq t \leq T \]

2. **Maximin($\gamma_2$) filter-smoother:**
   - Construct $\gamma_2$ period forward cumulative min of the observed price series, $\tilde{b}_t^f$.
     \[ \tilde{b}_t^f = \min\{\tilde{b}_t, \tilde{b}_{t-1}, \ldots, \tilde{b}_{t-(\gamma_1-1)}\}, \quad \forall \tau + (\gamma_1 - 1) \leq t \leq T \]
   - Construct $\gamma_2$ period backward cumulative min of the observed price series, $\tilde{b}_t^b$.
     \[ \tilde{b}_t^b = \min\{\tilde{b}_t, \tilde{b}_{t+1}, \ldots, \tilde{b}_{t+(\gamma_1-1)}\}, \quad \forall \tau \leq t \leq T + (\gamma_1 - 1) \]
   - Take period-wise maximum of the two price series $b_t$.
     \[ b_t = \max\{\tilde{b}_t^f, \tilde{b}_t^b\}, \quad \forall \tau \leq t \leq T \]

The resulting price series, $b_t$, is the base price for the algorithm with hyperparameters $(\gamma_1, \gamma_2)$.

**B.3 Base price algorithm validity check: The Dominick’s dataset**

In this section, we evaluate how closely the base price algorithm mimics the promotion practices of retailers. To provide such an assessment, we leverage the promotional activities reported in an alternative scanner dataset of the now defunct grocery retailer, Dominick’s, that operated
Table B.3: Summary statistics for Dominick’s price of Campbell’s Chicken Noodle Soup

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Overall std.</th>
<th>Within std.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price ($/can)</td>
<td>0.57</td>
<td>0.096</td>
<td>0.094</td>
</tr>
<tr>
<td>Simple discount</td>
<td>0.08</td>
<td>0.281</td>
<td>0.280</td>
</tr>
<tr>
<td>Impute</td>
<td>0.03</td>
<td>0.180</td>
<td>0.168</td>
</tr>
</tbody>
</table>

Source: Kilts Marketing Center University of Chicago, Dominick’s Data. Notes: The table shows summary statistics for the 31,567 store-week observations of prices and promotional activities for the 10.75 oz can of Campbell’s Chicken Noodle Soup. The weekly price observations come from 85 stores over an average of 372 weeks (per store).

about 100 stores in the Chicagoland area until 2013. Much like the Nielsen dataset, the Dominick’s data contains weekly information on the posted price and quantity sold for each product in each store in each week. In contrast to the Nielsen data, the Dominick’s scanner dataset also reports for each product-store-week whether or not the product was on promotion that week. In particular, the dataset provides promotion in three measures—“Bonus Buy,” “Coupon,” or “Simple Price Reduction.” Although we have discovered that sometimes promotional activities are under- or miss-reported in Dominick’s scanner data, this dataset offers a unique opportunity to validate our base price algorithm in a grocery retail environment.

In preliminary analysis, the canned soup category displayed the most variation at seasonal frequencies. Consequently, for this exercise, we focus on one of the most popular items in the canned soup category, Campbell’s Chicken Noodle Soup. The Dominick’s dataset never reports the use of “Coupon” promotional activity. Furthermore, preliminary regressions reveal that “Bonus Buy” promotional activity is not closely linked to changes in per unit prices. In fact, in a regression of the logarithm of the per unit price on indicator for “Bonus Buy” and “Simple Price Reduction,” together with a set of month-price tier fixed effects, the estimated size of the price effect of a product being on “Bonus Buy” in that store-week is less than the benchmark threshold (10 percent) used in our baseline analysis. We also strongly reject the null hypothesis that the effect on prices of the two promotional activities is the same. Given that the objective of our algorithm is to infer promotional activities through changes in prices, we focus our validation exercise in picking up “Simple Price Discounts.”

Table B.3 presents some stylized facts about the prices for Campbell’s Chicken Noodle Soup in the Dominick’s dataset. The sample consists of an unbalanced panel of 85 stores reporting prices and units sold from September 20, 1989 to May 7, 1997. During this time period the average price was 57 cents, and was put on a “simple price discount” in 8 percent of store-weeks, a modest decrease from the frequency of promotion that we found in our main analysis. In the aggregate time series, Campbell’s Chicken Noodle Soup was on discount in at least one Dominick’s store in 8 percent of weeks over the time period of our sample. Lastly, the extent of imputed prices due to a store-week not reporting any sales is minimal comprising 3 percent of store-weeks.

As was documented for retailers more generally by DellaVigna and Gentzkow (2019), Dominick’s also exhibited relatively homogenous pricing at the product level across its 100 stores in any given week. To the extent that there are across-store differences in posted prices of a product for a given week, they are explained by the 12 price zones Dominick’s used to set their prices at

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41This dataset is also made available by the Kilts Center for Marketing at the University of Chicago, and was used in the analysis of Chevalier et al. (2003) and Nevo and Hatziatkos (2005). For more information, see https://www.chicagobooth.edu/research/kilts/datasets/dominicks.
four different price tiers. To this point, while store (price tier) fixed effects explain as little as 4 (2.6)
percent of the variation in prices over the 85 stores and 400 weeks, a set of week-of-sample fixed
effects explains as much 90 percent of the variation. We exploit the almost uniform pricing within
a price tier to infer missing prices before we implement our algorithm.

The assessment of the algorithm is done by three steps. First, for store-weeks in which price is
missing because no quantity is sold, we impute prices with the median price experienced in all the
stores of that price tier. Second, we use our base price algorithm to impute base prices from the
time series of weekly prices for a 10.75 ounce can of Campbell’s Chicken Noodle Soup (our modal
product for the canned soup category) in each of the stores in the Dominick’s dataset. Third, we
compare the implied promotional activities by the algorithm with those reported by Dominick’s
for that product-store-week.

Table B.4 reports the type I and type II error rates of our base price algorithm for three sets of
hyperparameters ($\gamma_1$, $\gamma_2$). We define type I error rates as the percent of weeks defined as a promo
by the algorithm conditional on Dominick’s not reporting that store-week as having a promo-
tion. Type II error rates are defined as the percent of weeks defined as non-promo week conditional on
Dominick’s reporting that store-week as having a promotion. The “Dis-
count” columns report the error rates for all store-weeks, while in the last two columns we restrict
the store-week observations to only those that did not require any price imputation. Due to the
under- or false reporting from Dominick’s, the error rates are likely to be overestimated.

Several clear patterns emerge from table B.4. First, the performance of the algorithm appears
relatively stable across the alternative choices of hyperparameters. The robustness of the algo-
rithm to these hyperparameters is comforting, and was discussed in relation to our baseline sam-
ple in more detail earlier. Second, the type I and II error rates are modest, and given the likely
measurement error in underreporting some promotional activity likely overestimates of the true
false-positives and false-negatives. For instance, as soon as you restrict the evaluation to simple
discounts and periods in which no prices had to be imputed, the maximum error rate (across both
type I and II and sets of hyperparameters) is 10 percent. As we will show next, it’s highly likely
some of these errors of the algorithm are due to measurement error in Dominick’s data.

To provide some casual evidence to support our view that the error rates reported in table B.4
are conservative, we also report some particular instances of the observed time series of prices
Figure B.2: Dominicks case study examples

Source: Kilts Marketing Center University of Chicago, Dominick’s Data. Notes: The figure reports the time series for two stores over several weeks of the observed price of a 10.75 oz can of Campbell’s Chicken Noodle Soup (in blue), together with the base price (in red), as well as gray lines denoting the weeks in which Dominick’s reported that a price discount was used in that store-week.
as well as the imputed base price for a couple of stores. In particular, figure B.2 reports the time series for two stores (stores 2 and 86) over several weeks of the sample, as well as the promotional activity reported by Dominick’s over those weeks.

Several instances of false reporting on the part of Dominick’s are evident from this figure. In particular, a price discount in week 217 for store 2, and week 231 and 233 for store 86, seems is not reported by Dominick’s. Contrast those periods, with the reported price discount that Dominick’s reported as having occurred in week 234 in store 86. Of course, if the $0.65 price in week 234 was in fact a price discount, it seems difficult to reconcile why the remaining weeks of that month would not also have been considered a price discount. These patterns indicate that measurement error may exist in the Dominick’s reporting of promotional activities, resulting in inflated type I and II error rates of our base price algorithm. In this light, we view the stable and strong performance of the base price algorithm in this sample of retailer behavior as providing substantial support for its use more systematically in the Nielsen Retail Scanner dataset used in the baseline analysis.

C Empirical Bayes Shrinkage Procedure Algorithm

Our measures of monthly shifts in quantities \( \alpha_m \), elasticities \( \eta_m \), and prices \( \beta_m \) are estimated with sampling error. If uncorrected, this sampling error means that we overstate the min-max difference and therefore end up with biased estimates of seasonality. We use an Empirical Bayes Shrinkage to adjust for this sampling error. The procedure we use goes back to the economics of education literate (where it is used to adjust differences in teacher- or school-specific value-added measures, see e.g. Kane and Staiger (2008); Jacob and Lefregren (2008); Angrist et al. (2017)). This approach is also used by DellaVigna and Gentzkow (2019) for their store-level elasticity estimates; we follow their implementation and description closely.

Let \( \theta_{im} \) denote a generic parameter estimate \( \alpha_{im}, \eta_{im}, \text{or } \beta_{im} \) for product \( i \) and month \( m \). We define the shrunk estimate \( \tilde{\theta}_{mi} \) as

\[
\tilde{\theta}_{mi} = \left( \frac{\sigma^2_{mi}}{\sigma^2_{mi} + \text{Var}(e_{mi})} \right) \hat{\theta}^i_{m} + \left( \frac{\text{Var}(e_{mi})}{\sigma^2_{i} + \text{Var}(e_{mi})} \right) \bar{\theta}^i,
\]

where \( \bar{\theta}^i \) and \( \sigma^2_i \) are the prior mean and variance (at the category level), and \( e_{jce} \) is the estimation error in \( \hat{\rho}_{jce} \). We define \( \text{Var}(e_{jce}) \) as the estimate of the asymptotic variance of the pass-through, from Equation 1 or 3. We set \( \theta_{im} = 0 \) (which is exactly the sample average of \( \hat{\theta}_{im} \)). We measure \( \sigma^2_i \) as \( \text{Var}(\hat{\theta}_{im}) \) minus the average estimation variance for that product (or zero, if that is larger). This procedure shrinks each product’s month-specific deviation from their annual average towards zero, i.e. the null of zero seasonality.

D Lost Profit Calculations

This section briefly outlines our approach to calculating the lost profits reported in section Section 3.4. Our approach, which follows DellaVigna and Gentzkow (2019) closely, proceeds in two steps. First, we back out an estimate of marginal cost at the product-store-year level assuming that the average price is set optimally. Second, we calculate profits with optimally time-varying prices, with constant prices, and with prices at the observed path.

Recovering marginal costs We assume that the demand for product \( i \) in store \( j \), week \( t \), year \( y \), and month \( m \) is given by \( Q_{ijt} = D_{ijt}P^m_{ijt} + \eta_{im} \), where \( \eta_i + \eta_{im} \) corresponds to the price elasticity of demand for product \( i \) in month \( m \). This specification parallels our empirical approach: the price
elasticity $\eta_i + \eta_{im}$ varies at the product-month level but not more finely; and, $D_{ijt}$ is an arbitrary demand shifter. We further assume that marginal cost for a given product-store-year is constant and given by $c_{ijy}$.

To recover marginal costs, we assume that stores price correctly on average, choosing the average price to maximize variable profits. That is, let $P_{ijy}$ be the average price charged for product $i$, by store $j$, in year $y$. We assume that:

$$P_{ijy} = \arg\max_P \sum_{t \in y} (P - c_{ijy}) D_{ijt} P^{\eta_i + \eta_{im}}.$$  

(D.10)

Rearranging the first-order condition for $P$, we obtain an expression for marginal costs:

$$c_{ijy} = \sum_{t \in y} \frac{\left(1 + \eta_i + \eta_{im}\right) D_{ijt} P^{\eta_i + \eta_{im}}}{\sum_{t \in y} \left(\eta_i + \eta_{im}\right) D_{ijt} P^{\eta_i + \eta_{im} - 1}}.$$  

To back out $c_{ijy}$ and calculate profits, we require estimates of $\eta_i + \eta_{im}$ and $D_{ijt}$, together with each product-store-year’s average price $\bar{P}_{ijy}$. For $\eta_i + \eta_{im}$, we take the monthly elasticity implied by the (shrunken) estimates of Equation 1, (i.e., $\tilde{\eta_i} + \tilde{\eta_{im}}$). Then, our estimate of the demand shifter is given by $\tilde{D}_{ijt} = Q_{ijt}/P_{ijy}^{\eta_i + \eta_{im}}$.

### Profits under alternative pricing rules

We consider profits under optimal prices, as well as under the observed price path and under constant prices. Optimal prices are given by maximizing profits week-by-week, and adjusting prices to accommodate the fluctuations in the price elasticity of demand over the year. We use the average price at the product-store-year level as our measure of constant prices to be consistent with our estimate of marginal costs. To obtain the observed price path, we let prices fluctuate throughout the year around the constant level, with fluctuations given by our estimates of the seasonal fluctuations of prices. Specifically, along the “observed” path, we set the price in week $t$ for product $i$ store $j$ and year $y$ as

$$\bar{P}^{\text{obs}}_{ijt} = \bar{P}_{ijy} \exp\left\{K_{ijy}\right\} \exp\left\{\tilde{\beta}_{im}\right\},$$

where $\tilde{\beta}_{im}$ are the (shrunken) estimated coefficients on the month-of-year effects from Equation 5 (when log price is the dependent variable), and $K_{ijy}$ is a product-store-year specific constant that ensures the average of the seasonally fluctuating price equals $\bar{P}_{ijy}$. This expression takes the average price and moves it up or down during the year according to observed seasonal movements outlined in our previous results.

### Totaling up the lost profit estimates

This gives a product-specific estimate of lost profits (relative to the benchmark optimal price). We aggregate across all products in our sample to obtain an in-sample estimate of total lost profit. We extrapolate to all products by assuming that lost profits are a constant share of revenue. Additionally, to highlight the scope that time varying elasticities can rationalize countercyclical pricing, we also report the profits gained exclusively between peak and trough months between observed prices and uniform prices across those two months. Each of these steps are repeated using the seasonal fluctuations in elasticities across several of our demand specifications.

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42 This means that in store-weeks with zero sales, $\tilde{D}_{ijt} = 0$, and price changes do not affect quantities. We do not believe this is important for our results because these store-weeks would be predicted to have very low quantities, and hence very low profits, under any alternative approach.

43 In what follows, we ignore the issue of pricing around holidays, as our time varying elasticity estimates do not pertain to holiday periods. Furthermore, in this section we limit the analysis to food stores to provide a more consistent means of extrapolating the amount of lost profits for our product categories and their share of yearly revenue for the
Table B.5: How much profit could retailers be losing relative to benchmark prices?

<table>
<thead>
<tr>
<th></th>
<th>(1) Constant Price</th>
<th>(2) Observed Price</th>
<th>(3) Peak-Trough Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Median Chain Year–Sample Products</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>$264,784 (0.005)</td>
<td>$262,617 (0.005)</td>
<td>$973 (0.001)</td>
</tr>
<tr>
<td>DMA competition</td>
<td>$263,754 (0.005)</td>
<td>$265,695 (0.005)</td>
<td>$855 (0.001)</td>
</tr>
<tr>
<td>Other product competition - avg</td>
<td>$243,596 (0.005)</td>
<td>$245,591 (0.005)</td>
<td>$11 (0.000)</td>
</tr>
<tr>
<td>Other product competition - min</td>
<td>$261,221 (0.005)</td>
<td>$260,496 (0.005)</td>
<td>$964 (0.001)</td>
</tr>
</tbody>
</table>

| **Panel B: Median Chain Year–All Products** |                    |                    |                      |
| Baseline         | $3,287,698 (0.005) | $3,304,234 (0.005) | .                    |
| DMA competition  | $3,364,634 (0.005) | $3,392,337 (0.005) | .                    |
| Other product competition - avg | $3,025,780 (0.005) | $3,100,350 (0.005) | .                    |
| Other product competition - min | $3,250,099 (0.005) | $3,282,576 (0.005) | .                    |

Notes: This table reports the results of the lost profit calculations described in Appendix Section D, in annual dollars and as a share of revenue in parentheses, for the median chain-year under constant prices and observed prices in our sample of food stores. Additionally, profit gains from observed prices relative to constant prices exclusively for peak and trough months of demand is also reported. In the top panel, the lost profits are reported for our set of sample products. In the bottom panel, the revenue shares of our sample products are used to construct an estimate of the aggregate lost profits across all the products within a chain. Within each panel, the lost profits are reported using our baseline (shrunken) estimates of the price elasticity of demand as well as each of our alternative specifications. See notes to Table A.3 for an explanation of the different specifications.

Each chain offers many more products than those found in our sample. To provide a sense of the overall magnitude our lost profit estimates might have on chain level decisions, we scale up our product-level estimates to the aggregate chain level. To scale up our estimates, we assume that the profit lost from seasonal miss-pricing is a constant share of revenue across all products within a chain, and use the share of revenue coming from our sample of products as the basis for the scaling up our lost profit estimates. Although this procedure is crude, we believe that it provides a conservative upper bound on profits lost from failing to more accurately time price deviations with seasonal fluctuations in the price elasticity of demand, because our sample of products represent a diverse and wide set products that span both ex-ante highly seasonal demand products as well as products that turned out not to be, as well as the most widely available products.

Table B.5 reports the lost profits from constant (column 1) and observed (column 2) pricing, relative to our benchmark of optimal pricing, for the median chain-year. First, aggregating across all the products in our sample (Panel A), the estimated lost profits for the median chain-year are just about $250,000, or about 0.5 percent of revenue. Scaling up to the aggregate chain level (Panel B), the median chain loses about $3 million. Additionally, these lost profit estimates are robust to the multi-product and competitive considerations we explored in our alternative demand specifications.

The lost profits arising from both the observed seasonal price paths of retailers as well as a perfectly constant price path are remarkably similar. This partly reflects the fact that broadly speaking elasticities vary little over the year. To shed further light on how this relates to the pattern chains in our sample.
of countercyclical pricing, we also calculate the profits (gained) of the observed relative to constant path, specifically over the peak and trough months of demand (column 3). Focusing exclusively on the pricing behavior between peak and trough demand months, the median retailer increases profits by about 0.1 percent of revenue with the observed price changes relative to uniform pricing. This calculation of course confirms the product category level results discussed in the previous section.

The overall magnitude of lost profits for both the observed and constant is small in multiple senses. First, it is small relative to revenue, which totals about $1 billion per year for the typical chain in our data. Second, it works out to about more than $190 per product (i.e. $250,000/1321), meaning any product-level costs of reoptimizing would likely swamp the gains. Even this per product number is likely an overestimate given that our sample of products focuses on widely available products. Finally, it is small relative to lost profit from other forms of apparent mispricing. For example, DellaVigna and Gentzkow (2019) argue that the median chain loses about $16 million from charging uniform prices across stores. On the other hand, retail profit margins tend to be quite small, because of large fixed costs. On a profit margin of just a few percent, an increase of 0.5 percent of revenue could be large. Overall, although observed prices do not perfectly coincide with optimal prices in our simple benchmark model, for the median chain the returns to addressing this issue are likely low, and are not in conflict with the countercyclical pricing we observe.

While admittedly stylized, the lost profit estimates are generally supportive of approximate profit maximization in the context of seasonal demand fluctuations—and that countercyclical price elasticities can partially rationalize the observed countercyclical pricing patterns in retail. The approach used to evaluate this claim is in contrast with the standard approach, especially in industrial organization, which typically assumes profit maximization and works out its implications (e.g., implied marginal costs or merger effects). Interestingly, our results indicate only modest departures from this common assumption, which has been questioned with the emerging literature that has documented departures from it (Hortacşu and Puller (2008); Goldfarb and Xiao (2011); Cho and Rust (2010); Goldfarb and Xiao (2018); Ellison et al. (2018); DellaVigna and Gentzkow (2019)).

We caution, however, that this conclusion, comes at the cost of several strong assumptions including constant marginal costs, and largely abstracting from multi-product and/or competitive effect considerations. We have discussed the credibility and robustness of our estimates associated with each of these assumptions above, and broadly view them as unlikely to strongly alter the results reported here. An assumption unique to the lost profit calculation is that average prices over the year are set optimally. This assumption is of course weaker than what is commonly made in the literature. We have no way to verify the optimal average price assumption and we view it as the most critical and perhaps the most suspect. Testing this assumption would likely require, at a minimum, data on marginal cost, although such data might be difficult to obtain given that the marginal cost to a retailer includes the opportunity cost of retail space. Evidence on the optimality of the average level of prices would be an important question for future research.