

On the Importance of Sales for Aggregate Price Flexibility*

Oleksiy Kryvtsov[†] and Nicolas Vincent[‡]

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Abstract

Macroeconomists traditionally ignore temporary price mark-downs (“sales”) under the assumption that they are unrelated to aggregate phenomena. We challenge this view. First, we provide evidence from the U.K. and U.S. CPI micro data that the frequency of sales is strongly countercyclical. Second, we build a general equilibrium model in which sales arise endogenously. In response to a monetary contraction, firms facing rigid regular prices post more sales, and households search more intensively. The resulting fall in the aggregate price level can be significantly larger than if sales were ignored, implying a much smaller response of real consumption to monetary shocks.

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JEL classification: E31, E32, E52, L11, L25, L81, M31.

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[†]Bank of Canada, 234 Laurier Street Ottawa, Ontario K1A 0G9, Canada. Email: okryvtsov@bankofcanada.ca

[‡]HEC Montréal, Department of Applied Economics, 3000 Côte-Sainte-Catherine, Montréal, Quebec H3T 2A7, Canada. Email: nicolas.vincent@hec.ca

1 Introduction

Price discounts, or “sales,” are an essential feature of retail price behavior and an important factor for households’ consumption decisions. A typical sale is associated with a large but temporary price drop that returns close to its pre-sale level. In the past decade or so, macroeconomists extensively employed detailed weekly and monthly price data for a broad variety of retail goods to study implications of retail pricing for aggregate price flexibility. These studies find that although temporary price discounts imply more frequent price changes by retailers,¹ they do not, on the whole, play a significant role for inflation dynamics. More generally, the prevalent view in macroeconomics has been that retail price discounts have little to do with aggregate phenomena and should be ignored by macroeconomists.² In this paper, we challenge this view.

Our contributions are both empirical and theoretical. First, we provide empirical evidence on variations in the incidence of sales over time based on data for both the United Kingdom and the United States. For the U.K., we use the publicly available micro data underlying the consumer price index (CPI) composed by the Office for National Statistics (ONS). The data contain monthly price quotes collected from local retail outlets for a wide range of consumer goods and services over the period from 1996 to 2012. We find that the frequency of sales in the U.K. data is strongly countercyclical: a 1 percentage point (ppt) rise in the unemployment rate is associated with a roughly 0.4 ppt increase in the fraction of products on sale. For example, during the Great Recession the fraction of sales more than doubled from 1.8% to 3.8% of observations. This strong correlation between the business cycle and the use of temporary discounts by firms is extremely robust: it does not depend on how sales are identified; it is observed for more than three-quarter of categories; it is not a product of the exit of low-sale-frequency items; and it survives the use of multiple controls and alternative macroeconomic indicators.

Our finding is not specific to the United Kingdom. An aggregate time series on the incidence of sales obtained from the U.S. Bureau of Labor Statistics shows that temporary discounts are also strongly countercyclical in the United States. This evidence is corroborated by series derived from Vavra (2014) based on the U.S. CPI micro data since 1990.

Unlike the fraction of sales, the average size and duration of sales in the United Kingdom are

¹For example, Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008) find, using U.S. CPI micro data, that, on average, prices adjust every four to seven months, and that excluding sale prices increases price durations by around three to five months. Klenow and Malin (2011) provide an excellent survey of microeconomic evidence on price setting.

²Eichenbaum, Jaimovich and Rebelo (2011) argue that most high-frequency movements in prices have little to do with monetary policy. An important exception is Klenow and Willis (2007), who find that, in the United States, CPI micro data sale-related price changes respond to macro information in a similar way as regular price changes.

acyclical and much less volatile. Nonetheless, the observed fluctuations in the fraction of sales may well be an important source of aggregate price fluctuations due to two factors. First, sale-related price drops are large, on average between 20% and 25% in the U.K. Second, each additional sale generates almost three times more revenue than a regular-price transaction, and the revenue share of goods on sale may increase during economic slumps as households shift their consumption toward sale prices. Our theoretical contribution is to quantify the aggregate price flexibility due to these two factors.

To this end, in the second part of the paper, we develop a general equilibrium business cycle model with consumer search and price discrimination by monopolistically competitive retailers. Households face an independent, identically distributed (i.i.d.) time cost of searching for low prices. Those households who draw sufficiently low cost realizations become bargain hunters and find, on average, lower prices. Retailers, in a desire to attract bargain hunters, keep a positive fraction of brands on sale in the store. The higher is the return to households from bargain hunting, the larger is the fraction of price discounts. Retailers' revenue from posting sales increases with households' willingness to substitute between market work and searching for sales. When the elasticity of substitution is sufficiently high, both the fraction of sales and the fraction of bargain hunters are strongly countercyclical, amplifying procyclical aggregate price dynamics. When matched to key moments of sale-price behavior, the model predicts that in response to, say, an unanticipated monetary contraction, the increases in the fractions of sales and bargain hunters lead to an aggregate price decrease that is twice as large as the one in the standard sticky-price model with a single price per variety. Accordingly, the size of the real effect in response to monetary shocks is twice as small, and it can be even smaller depending on the response of the fraction of bargain hunters.

We show that the main mechanism underlying the importance of sale prices for aggregate price flexibility is based on the interaction between the retailers' price discounting and the households' search for low prices. At the time of the monetary contraction, some prices fail to decrease due to constraints on price adjustment, leading to an increase in retail markup. High profit margins make it desirable for retailers to increase their market share. In our model, they do so through an increase in the fraction of brands on sale. In turn, more aggressive price discounting by retailers increases the return on searching for low prices, leading to a larger number of bargain hunters. The resulting reallocation of the consumption weight toward lower-priced products amplifies the fall in both store-average and aggregate price levels. The model's central feature—countercyclical shopping intensity—is corroborated by evidence from time-use surveys and household panel scanner data sets obtained by Aguiar, Hurst and Karabarbounis (2013), and Kaplan and Menzio (2015),

among others.

A few recent studies have examined the potential role of sales in macroeconomic models. Kehoe and Midrigan (2015), using modified versions of standard sticky-price models, argue that sales are mostly irrelevant for the transmission of monetary shocks, since, due to their temporary nature, sales cannot offset aggregate shocks well. Guimaraes and Sheedy (2011) reach similar conclusions using a sticky-price model with sales stemming from consumer heterogeneity and incomplete information. In their model, strong strategic substitutability of sales at the micro level implies that their frequency and size barely responds to monetary shocks. Both papers, therefore, predict that the sale margin is not useful for retailers' price adjustment in response to changes in macroeconomic conditions. Neither paper, however, tests whether the model predictions are borne out in the data. This is partly due to the fact that the empirical evidence on the cyclical properties of sales is very limited. There are, however, a few recent exceptions.

Coibion, Gorodnichenko and Hong (2014) use a scanner data set from U.S. grocery stores and conclude that sales for grocery products are acyclical and that most adjustment is done through consumers switching from high- to low-end retailers. We exploit additional time series for food products obtained from the BLS to show that our finding of cyclical sales at the aggregate level does not contradict less-than-cyclical behaviour of sales for food found in Coibion, Gorodnichenko and Hong (2014). We show that food is not representative of the aggregate: it exhibits an upward trend in the frequency of sales. As a consequence, the introduction of a time trend in regressions, as in Coibion, Gorodnichenko and Hong (2014), eliminates most of the cyclicalities in sales. Likewise, Anderson *et al.* (2013) do not find evidence that sales respond to wholesale and commodity cost shocks nor to changes in local unemployment rates. Both studies are, however, limited in scope: the sample of Coibion, Gorodnichenko and Hong (2014) focuses mostly on food products, while Anderson *et al.* (2013) have information from a single U.S. retailer. In contrast, our study is based on Consumer Price Index (CPI) micro price data and, therefore, has much broader coverage.

At the aggregate level, Berardi, Gauthier and Le Bihan (2015) find little time variation in sales based on French micro CPI data, a result that may be a reflection of the fact that sales are heavily regulated in France. The closest paper to ours in scope and findings is Sudo *et al.* (2014) that looks at the behavior of sales across a wide range of product categories in Japan since 1988. The authors find a rise in the frequency of sales in Japan during the 1990s and 2000s at the same time as hours worked were declining and the unemployment rate was rising. However, this evidence is dominated by strong trends in all three series during Japan's "lost decades," making it difficult to determine whether the behavior of sales is due to their countercyclical use by retailers or to structural

changes in the Japanese retail industry that are not related to business cycles. Also, while their scanner dataset is quite extensive, ultimately it excludes important categories and covers only 17% of household's expenditure.

The paper is organized as follows. Section 2 presents empirical evidence on the frequency and size of sales from the end of the 1990s to 2012 using product-level price quotes from the U.K. CPI data set; the findings for the United Kingdom are corroborated by evidence for the United States. In Sections 3 to 5 we describe the model with sales and analyze its response to shocks under plausible parameterizations. Section 6 concludes.

2 Empirical evidence on sales

2.1 Data

Throughout the empirical section, we will provide evidence from two sources. Most of it will be from the consumer price index (CPI) micro dataset of the United Kingdom's Office for National Statistics (ONS), which is publicly available. We describe the database in details below. Access to CPI micro data in other countries is very limited. That being said, we also provide aggregate evidence for the United States on the incidence of sales computed for us by the United States' Bureau of Labor Statistics from their CPI-RDB database.³

To construct the consumer price index (CPI), the Office for National Statistics (ONS) surveys the prices for goods and services that are included in the household final monetary consumption expenditure component of the U.K. National Accounts.⁴ The survey includes prices for more than 1,100 individual goods or services a month, collected locally from more than 14,000 retail stores across the United Kingdom. The survey excludes the housing portion of consumer prices, such as mortgage interest payments, house depreciation, insurance and other house purchase fees.⁵ Also, expenditures for purposes other than final consumption are excluded, e.g., those for capital and financial transactions, direct taxes, and cash gifts.⁶

Goods and services in the CPI are classified into 71 classes, according to the international

³U.S. CPI micro data have been extensively studied in the past. Descriptions and the key stylized facts for the U.S. CPI micro data can be found in Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008), among other sources. In many aspects of retail price behavior they obtain very similar results to those documented here and in Bunn and Ellis (2012) for the United Kingdom.

⁴Detailed descriptions of the data underlying the CPI, the statistical methodology used, collection and validation of prices, and calculation of weights, can be found in ONS (2014). The price quote data are available via the ONS website: <http://www.ons.gov.uk/ons/datasets-and-tables/index.html>.

⁵These prices are used to construct the retail prices index (RPI).

⁶CPI inflation was used by the government for its inflation target starting in December 2003. Before then, the index was published in the United Kingdom as the Harmonised Index of Consumer Prices (HICP).

(European) classification of household expenditure, Classification of Individual Consumption by Purpose (COICOP). A CPI class represents a basic group category, such as “Meat,” “Liquid Fuels” or “New Cars.” Each item in a given class is assigned an item weight that reflects its relative importance in households’ consumption expenditures.⁷ Changes in expenditure weights over time reflect changes in the expenditure composition of households’ consumption baskets.

Prices are collected across 13 geographical regions (e.g., London, Wales, East Midlands). There are four levels of sampling for local price collection: locations, outlets within location, items within section and product varieties. For each geographical region, locations and outlets are based on a probability-proportional-to-size systematic sampling with a size measure based on the number of employees in the retail sector (locations) and the net retail floor space (outlets). The data set contains around 150 locations with an average of more than 90 outlets per location.

Representative items are selected based on a number of factors, including expenditure size and product diversity, variability of price movements, and availability for purchase throughout the year (except for certain goods that are seasonal). There are currently over 510 items in the basket. Examples of representative items include: onions, men’s suit, single bed. Finally, for each item-outlet-location, individual products and varieties are chosen by price collectors based on their shelf size and regular stock replenishment.

Most prices are collected monthly, except for some services in household and leisure groups, and seasonal items. For the purpose of this paper, the sample period includes 212 months, from February 1996 till September 2013. The total raw number of observations is over 24.4 million, or about 115,000 per month, though we make some adjustments that are described later in order to make the database amenable to analysis.

In addition to posted prices, the data set also contains information about some characteristics of goods during price collection. Prices for goods that are on special offer (available to all consumers) or on temporary sale comprise 6.4% of observations in the data set (4.4% weighted). It is important to note that these “sales” have to be available to everyone (i.e., coupons and discounts that require a loyalty card are not taken into account) and on a single purchase (e.g., discounts implied by “buy-two-get-one-free” promotions are not recorded). Forced substitutions happen 8.0% (5.5% weighted) of the time, with about a quarter (three-quarters) of them corresponding to substitutions for items that are non-comparable (comparable) to previously priced items. An item can be temporarily out of stock (2.2% or 1.5% weighted) or permanently missing (0.5% or 0.3% weighted). Finally, a small

⁷Weights are calculated based on the Household Final Monetary Consumption Expenditure (HFMCE) and ONS Living Cost and Food Survey (LCF).

subset of goods has distinct seasonal patterns and is treated separately: they include some items of clothing, gardening products, holiday products and air fares. For those seasonal goods for which prices are not available, such as clothing, gardening and food, prices are imputed based on prices observed at the end of the previous season or based on prices observed for in-season goods in the same item category; in addition, weights are adjusted in accordance with the availability of such goods throughout the year.

We make some adjustments to the ONS database to make it suitable for our analysis. First, we delete observations that are not coded as valid by the ONS. Second, we deal with product substitutions by splitting the price time series of a given item every time we encounter a substitution flag. The resulting benchmark data set contains a total of 20.7 million observations across about 2.3 million unique items. It should be noted that for our empirical analysis, we will mostly focus on items that have at least ten price quotes (17.1 million observations).

Value-added taxes (VAT) are included in the price quotes. The implication is that any change in the VAT rate will automatically lead to a price change. VAT changes, however, were very few over our sample period. The only exceptions are three major changes to the standard VAT rate in the later part of the sample. First, in response to the Great Recession, the Conservative government announced a widespread reduction in the VAT rate from 17.5% to 15% effective 1 December 2008. Then, the rate was brought back to 17.5% starting 1 January 2010. Finally, the standard VAT rate was raised from 17.5% to 20% on 4 January 2011. We control for these events in our analysis.⁸

2.2 Sales filters

The first challenge when studying temporary sales in micro price data is to identify them. Ideally, we want to discriminate between price drops that are temporary and drops in regular prices. We use three main ways of identifying sales in our data set.

First, for both the U.K. and U.S., we present results using the “sales flag” available in the respective datasets. The ONS indicates that “sale prices are recorded if they are temporary reductions on goods likely to be available again at normal prices or end-of-season reductions.” Once again, it is important to point out that this indicator does not reflect coupons, discounts conditional on the purchase of multiple units or promotions linked to loyalty cards; it therefore arguably represents a lower bound on the actual incidence of sales. Despite the advantage of being made directly available by the statistical agency, there are some issues with the sales flag that require us to make

⁸Moreover, VAT changes are more akin to regular price changes, while our focus is on temporary sales. For this reason, they have little incidence on our results.

some adjustments. For example, there are a few instances in which the occurrence of a sales flag is accompanied by no recent change in the posted price, or even, in some very rare instances, a price increase. One possible explanation is that the retailer uses some advertising features to gain or retain customers despite not actually changing the price; another is misreporting or a coding error. In what follows, we adopt a conservative approach and present results based only on sale flags that correspond to price decreases.⁹

Second, we apply a V-shaped sales filter, similar to the one used by Nakamura and Steinsson (2008), among others. In this instance, a “sale episode” begins with a price drop and ends as soon as a price increase is registered, as long as this price increase occurs within three months.¹⁰ Under this definition, the price increase at the end of the sale need not be as large as the price drop at the beginning of the sale. For the sales-flag and V-shaped filters, the unobserved regular price during a sale is assumed to be equal to the last observed regular price.¹¹

Finally, we compute a reference price similar in spirit to Eichenbaum, Jaimovich and Rebelo (2011) using a seven-month window. More precisely, for a given month t we set the reference price equal to the modal price observed between $t - 3$ and $t + 3$, as long as there are at least four price observations within that window. To avoid identifying spurious sales that arise from a lag/lead in the adjustment of reference prices, we then apply a procedure similar to Kehoe and Midrigan (2015) to ensure that a change in the reference price coincides with an actual price change. A price observation corresponds to a sale price whenever the posted price is below the reference price.

Because the moving window procedure automatically leads to censoring at end points, we drop the first and last three months of each quote line when presenting the results, to make the filters comparable. Combined with our decision to split price time series whenever there is a product substitution, this implies that clearance sales occurring at the end of a product’s life are for the most part filtered out. This is why we also report some of our results using the raw sales flag filter which is computed without any manipulations of the ONS database.¹²

⁹To be precise, a sales flag is deemed valid only if it coincides with a price quote that is lower than the price that was posted right before the start of the spell of sales flags, which we define as the regular price for the duration of the spell.

¹⁰If two price drops occur in a row before the posted price settles to a new regular level, our filter will identify the first price drop as corresponding to a sale. To assume instead that this episode corresponds to either two distinct sales or two consecutive drops in the regular price has no impact on our results.

¹¹We also considered a more-restrictive filter whereby a V-shaped sale is initiated by a price drop that is followed within three months by a return to a price equal to or higher than the initial price level. Results are not presented here because they are very similar, but are available upon request.

¹²According to our calculations, clearance sales (defined as occurring right before a product’s disappearance from the sample) account for less than 10% of overall sales in the U.K. We find them to have cyclical properties very similar to those of the aggregate sales series.

2.3 Preliminary statistics

In Table 1 we report some basic statistics on price dynamics in our data set. Unless otherwise stated, all moments are weighted using the official CPI category weights. The fraction of price changes is 17.2% over the sample period, and the average size of a price change is 11.1% in absolute terms. Price increases are more likely than price decreases (10.7% vs 6.5% of observations, respectively). Not surprisingly, we find lower price change frequencies if we focus on regular prices, i.e., price series that were purged of observations for which the posted price differs from the regular price. The probabilities of observing a price change are 14.6%, 12.1% and 7.3%, based on the sale flag, V-shaped and reference price filters, respectively. Hence, the reference price filter generates significantly stickier price series, largely because it filters out both upward and downward temporary price deviations. Overall, our basic statistics show that prices are stickier in the United Kingdom than in the United States, but more flexible than in Europe.¹³

Table 2 reports several basic statistics for sales, using CPI weights for all calculations. The first row shows that the frequency of sales varies significantly depending on the definition used, from 2.6% for the ONS sales flag to 6.2% for the sales based on the reference price filter.¹⁴ Differences are also visible for both the average and median sale sizes: they are much higher for the sales flag (between 20% and 23%) than the three other filters (between 6% and 12%).

To understand why this is the case, we show in Figure 1 the truncated distribution of the size of sales across all observations in our data set (we drop the alternative V-shaped filter, since it shows no significant difference).¹⁵ We set the bound of the histogram at 60%, since larger sales are rare. Reassuringly, one can immediately notice spikes in the distribution at the familiar discount points: 10% off, 20% off, 25% off, 33% off and 50% off. Second, the three distributions exhibit striking differences between -10% and zero: the mass closer to zero is significant for the V-shaped and reference price filters, while there are very few small sales according to the ONS indicator. This seems to indicate that the sales filters commonly used in the literature have a tendency to pick up small price drops that are not advertised as sales by retailers. On the other hand, the three distributions are much more similar for sales larger than 10%, a sensible threshold. For this reason, we focus on sales of at least 10% in our analysis. Under this condition, sale frequencies and sizes

¹³See, for example, Klenow and Kryvtsov (2008) or Nakamura and Steinsson (2008) for the United States and Alvarez et al. (2006) for Europe.

¹⁴Though direct comparisons can be difficult, the prevalence of sales seems to be much lower than in the United States. For instance, Klenow and Kryvtsov (2008) find that about 11% of price observations have a sales flag, while Nakamura and Steinsson (2008) find that sales account for about 7.4% of observations using a V-shaped filter.

¹⁵The size of a sale corresponds to the difference between the sale and the regular price, and is therefore not limited to the onset of the sale (initial price drop).

become very similar across filters, as can be seen from the bottom portion of Table 2.

Finally, it is important to recall that because the data set does not take into account some popular price-promotion strategies (coupons, loyalty card discounts, “buy-two-get-one-free” deals, etc.), our sale frequencies are likely to be downwardly-biased estimates of the true prevalence of temporary discounts.

2.4 Aggregate time-series behavior of sales in the United Kingdom

We next look at the behavior of the frequency of sales during the past 15 years in the United Kingdom. For each category and month we compute the proportion of items with a sales flag, and then aggregate them using CPI weights. In the left plot of Figure 2 we show the raw constructed series as well as the U.K. unemployment rate. Because of the very strong seasonal patterns of sales, we also report on the right plot the 12-month moving average centered around each month. Clearly, the fraction of items on sale is far from being constant over time: it is around 3.4% at the beginning of the sample in 1997, then declines to a trough of about 1.8% in 2006 before rising back to more than 3.6% by 2011. Also, it is strongly countercyclical: the fraction of sales moves very closely with the unemployment rate, rising as the economy is slowing down. Neither series seems to exhibit any time trend that may bias our conclusions; we formally control for this potential issue later on.

The countercyclicity of sales is not an artifact of the specific choice of sales filters. Figure 3 compares the series from the previous figure to the raw sales flag filter, as well as the V-shaped sales filters and reference-price filters we described earlier. Except for the raw sales flag filter, all series focus on sales of at least 10%. While there are some differences at the beginning of the sample (a potential artifact of left-censoring for the reference price filter), the patterns tell a very similar story: there are large swings in the incidence of sales over the sample period, and the prevalence of sales tends to be higher when the economy exhibits significant slack.

Arguably, retailers could use different sales-related margins in response to aggregate shocks. First, the cyclicity of the fraction of products on sale could either be driven by fluctuations in the incidence of new sales or by changes in the average length of existing sales over time. We find no evidence of the latter in the data: the average duration of sales spells remained very stable around 1.6 months over our sample period, with no discernible cyclicity or trend.¹⁶

Second, retailers could vary the size of price discounts over the business cycle. Figure 4 shows the evolution of the average absolute size of sales over our sample period. Under the three definitions of sales, there is a slight rise in the absolute size of sales over the sample period. Still, while the average

¹⁶Monthly frequency of our data may hinder identification of changes in the average duration of sales.

size of discounts is not perfectly constant, its variation is largely contained, unlike fluctuations in the frequency of sales. For example, using the V-shaped filter, we find that the average size of sales goes from about 21% in 1997 to 26% by the end of 2012; and there is no noticeable cyclical behavior for this margin of adjustment by any definition of sales.¹⁷

2.5 Aggregate time-series behavior of sales in the United States

Before analyzing further the robustness of this result for the United Kingdom, we turn our attention to the United States to see whether the strong countercyclicality of sales is also present in the U.S. Bureau of Labor Statistics (BLS) CPI micro data. Despite not having direct access to the data, we were able to obtain aggregate evidence from two sources. First, the BLS provided us with the monthly fraction of items with a sales flag since January 2000, aggregated using CPI expenditure weights.¹⁸ The time series is represented in the left-hand plot of Figure 7, alongside the U.S. civilian unemployment rate over the same period.¹⁹ The similarities with our results for the United Kingdom are striking. There is a very clear positive co-movement between the incidence of sales and unemployment, with a correlation coefficient of 0.88. The turning points in the two series coincide very closely, with two clear spikes in the sales' fraction in the midst of the 2001 and 2008–09 recessions. Our finding of countercyclical sales in the United States appears to contradict Coibion, Gorodnichenko and Hong (2014) who report acyclical sales in a U.S. scanner dataset of grocery items, mostly food products. We show in Section 2.7 that our results align with Coibion, Gorodnichenko and Hong's if we limit the analysis to food items, a categories which exhibits atypical sales behavior.

Second, the right-hand plot in Figure 7 depicts a series derived from Vavra (2014). For his analysis, Vavra filtered out both temporary sales and product substitutions to focus on regular prices.²⁰ Vavra kindly provided us with the time series for the combined frequency of sales and substitutions. Despite the fact that the series is somewhat more volatile, possibly due to the behavior of substitutions, the results visually appear to confirm our findings based on the data provided directly by the BLS. Moreover, the series span an additional 12 years of data from 1988 to 1999, showing a clear rise in the fraction of sales and substitutions during the 1990–91 recession, similar to those in two subsequent downturns.

To confirm the graphical evidence, we run regressions for the U.K, ONS (all three sales filters),

¹⁷Our findings are unchanged if we consider sales of all sizes instead of focusing on a 10% threshold for the size of sales.

¹⁸We are grateful to Brendan Williams at the BLS for producing these series for us.

¹⁹To smooth out the strong seasonality in sales, we present the 12-month centered moving average.

²⁰Vavra uses a joint sales-flag and 3-month-V-shaped filter to extract sales.

BLS and Vavra time series. Results are presented in Table 3. In every regression, the coefficient on the unemployment rate is statistically significant at the 1% level, a finding that holds even if we include a time trend or one lag of the dependent variable. Alongside Figures 2 and 7, these results indicate that the countercyclicality of the aggregate sales frequency is robust for both the United Kingdom and the United States.

2.6 Category- and product-level results

To show that our aggregate findings apply at an economy-wide scale and are not merely driven by a few large categories, we study sales behaviour at a disaggregate level using U.K. data.

As a first exercise, we compute the time series correlation between sales frequency and unemployment rate for each U.K. CPI category. Once we condition on price series with at least 150 months of data, we are left with 59 categories. Figure 6 shows a histogram of category-level correlation coefficients between the sales frequency and unemployment. The histogram confirms that the countercyclicality of sales is broad-based: out of 59 categories, 50 show a positive correlation, of which 46 are statistically significant at the 5% level. Furthermore, during the period straddling the Great Recession, between 2005–06 and 2009–10, the number of products that experienced a rise in their sale frequency is almost three times as high as those that saw a drop, another sign that the countercyclicality of sales is broad-based. While category-level correlations point to countercyclical sales across most goods and services in the CPI basket, some heterogeneity across categories suggests that the cyclicalities of sales is unlikely to be generated mechanically, for example, because of some changes in data collection or the definition of sales over time.

To control for various factors that may affect our conclusions, we supplement our graphical analysis with a panel regression analysis at a product level. The basic specification is standard and given by

$$s_{it} = \alpha_i + \beta u_t + X_t' \Phi + e_{it}, \quad (1)$$

where s_{it} is an indicator equal to 1 if product i is on sale at time t , and 0 otherwise; u_t is the unemployment rate, and X_t is a matrix of controls such as calendar month dummies or a time trend. All regressions include dummies for the months in which VAT rate changes occurred, as described in Section 2.1.²¹

Table 4 summarizes our results. The unemployment rate is a statistically significant predictor of

²¹To allow for the inclusion of item fixed effects, we run linear regressions despite the fact that we have a binary 0/1 dependent variable. The results are very similar, and in fact generally slightly stronger, if we use probits instead, supporting the view by Wooldridge (2010) that the use of linear probability models is appropriate for the majority of applications. Results from probit regressions are reported in the Supplementary Material.

the occurrence of a temporary sale: a 5 ppt increase in the unemployment rate raises the likelihood of observing a sale by about 2 percentage points. Adding a time trend or one lag of the dependent variable has little effect on economic or statistical significance of this relationship. The results are also robust to the use of the two other definitions of sales, with the strongest effects found for the benchmark V-shaped filter.

So far, our analysis has been carried out using the unemployment rate as our measure of the aggregate cycle. While this is a sensible indicator of the financial and economic situation of households, it is hardly the only one. In the last panel of Table 4, we report results for our benchmark specification, but with alternative business cycle indicators on the right-hand side. First, we replace the unemployment rate with monthly retail sales volume, linearly detrended. This is a measure that is arguably a particularly relevant indicator of aggregate economic conditions for retailers. Second, to capture the economic outlook of households, we also use consumer confidence indicators for the United Kingdom as compiled by the company GfK on behalf of the European Commission. In these monthly surveys, various questions are asked to a sample of households. We focus on the aggregate consumer confidence index as well as the question about the personal financial situation over the next 12 months. To facilitate comparisons, we normalize all indicators by dividing them by their respective time-series standard deviations over the sample. The results in Table 4 show responses in the same order of magnitude across all four indicators: a one-standard-deviation decrease in either measure of consumer confidence leads to a statistically significant increase of around 0.3 percentage points in the frequency of sales, and that increase is around 0.5 ppt for one-standard deviation increase (decrease) in the unemployment rate (retail sales volume).²²

2.7 Evidence in Coibion, Gorodnichenko and Hong (2014)

Our main finding is clear: there is robust evidence that the incidence of temporary sales in both the United Kingdom and the United States varied significantly with the business cycle over the past 15 years. At first glance, our U.S. results seem to be at odds with those of Coibion, Gorodnichenko and Hong (2014), henceforth CGH. Their findings are based on the Symphony IRI scanner dataset which covers multiple grocery stores in 50 U.S. metropolitan areas over the 2001-2011 sample period. The database covers mostly food products as well as some personal care categories. In the first part of their paper, they find that the relationship between unemployment and the frequency of sales becomes small or non-significant once they include a linear time trend or time fixed effects in their

²²As a point of reference, the unemployment rate during the 2007–09 recession rose by a magnitude of four standard deviations.

panel regressions.

One reason behind CGH results could be that their categories, comprised mostly of food products, display a different behavior than what we find at the aggregate level. To explore this possibility, we obtained from the Bureau of Labor Statistics the frequency of sales for food CPI micro data, both weighted and unweighted. Figure 7 demonstrates that the behavior of sales frequency for food products is indeed markedly different from that at the economy-wide level that we documented in Figure 2.

For both groups—all products in BLS sample and only food—the frequency of sales exhibits rapid increases in the wake of the 2001 and 2008–2009 recessions. However, as the U.S. unemployment rate declines in the middle of the 2000s, sales become less prevalent at the aggregate level, while the weighted (unweighted) sales frequency for food products is instead rising (flat). Hence, the cyclical fluctuations in the time series for sales in the food category are difficult to distinguish from an upward trend. Indeed, we show in Supplementary Material that controlling for a linear time trend in the regression of sales frequency on unemployment, as it is done in CGH, yields only a weak relationship for food products, but does not alter the strong positive correlation at the aggregate level.²³

Finally, our results for the United Kingdom corroborate the results in CGH for the United States along another dimension: we find no evidence of a relationship between sales and the unemployment rate in the cross-section. For example, U.K. regions with higher unemployment rates do not exhibit more frequent sales.²⁴ In light of our strong time-series evidence this lack of correlation in the cross section may seem puzzling. Our theory developed in the next section explains that sales are important because they increase retailers’ ability to adjust their average price in the face of price-adjustment constraints. Such constraints are binding over the short run as retailers respond to unexpected disturbances to their market conditions. By contrast, price adjustment constraints are typically less of a factor across markets or regions.²⁵

²³In an earlier version their paper, CGH report category-level results and find a significant positive relationship between sales frequency and unemployment for personal care products in their data set. We find that the sales flag time series for the CPI category “Personal care products”—also provided to us by the BLS—indeed exhibits a strong cyclical pattern. In a regression that includes a time trend, we find that the coefficient on the unemployment rate is strongly significant at 0.29, compared to 0.23 for the aggregate but only 0.10 for food products.

²⁴Anderson et al. (2013) study the effect of supply-contract arrangements on sales behavior for a national chain retailer in the United States; they also find no relationship between sales and regional unemployment rates.

²⁵We also find that in the U.K. data chain retailers tend to have more cyclical sales than independent stores, suggesting that chain retailers may tailor their pricing policies to the national level, instead of regional or local markets. See Supplementary Material for regression results.

3 A general equilibrium model with sales

To understand the variation of sales and its importance for aggregate fluctuations, we cannot rely on the general equilibrium models of Guimaraes and Sheedy (2011) or Kehoe and Midrigan (2015). Both models predict that the fraction of sales is very stable following aggregate shocks, which is at odds with our empirical findings from the U.K. and U.S. We therefore develop in this section a general equilibrium model in which sales arise due to price discrimination by retailers and search for low prices by consumers. In the model, firms will respond to aggregate conditions by adjusting the frequency of sales, in line with our empirical evidence.²⁶

3.1 The economic environment

At its core the model is a standard macroeconomic model with monopolistic competition and constant elasticity of substitution (CES) preferences; we add to this core several features that are sufficient to generate sales.

A model economy is composed of a large number of isolated “locations”. Each location is populated by a unit measure of infinitely-lived, ex-ante identical households who derive utility from consuming a continuum of differentiated-good varieties, indexed by j . Every household is itself comprised of a continuum of members, each of whom is responsible of purchasing a specific variety.

Varieties in each location are produced by an industry of monopolistically competitive retail firms. Each retail firm sells a continuum of perfectly substitutable brands of a given variety. For simplicity, we assume that each retailer can choose at most two price points for each brand it sells: a high (regular) price and a low (sale) price.²⁷ A retailer j in a particular location l posts a fraction $\gamma(j, l)$ of its prices at level $P^L(j, l)$ and the remaining fraction, $1 - \gamma(j, l)$, at level $P^H(j, l)$, where $P^H(j, l) \geq P^L(j, l)$. Hence, for a given variety, a household potentially faces a non-degenerate distribution of prices—across brands in a given location and across locations.

A household can exploit this variation in prices by choosing which of its members will be bargain hunters and which will be workers. A worker earns labor income and, on the way back from work, randomly picks a brand of her designated variety from a random location. Conversely, a bargain hunter pays a search cost in terms of lost labor income and visits the local store selling her designated variety. Unlike workers, who shop at a random location l' and find low price with probability $\gamma(j, l')$,

²⁶There is a vast economic and marketing literature that studies the dispersion of prices in markets with monopolistic sellers and consumers who face costs of searching for low prices. See, for example, Butters (1977), Salop and Stiglitz (1977), and Varian (1980).

²⁷See Burdett and Judd (1983) for analysis of equilibrium price dispersions with many price points.

bargain hunters face a higher probability of finding a low price $f\gamma(j, l)$, where $f > 1$. The search costs are realized at the beginning of the period and are i.i.d. across household members.

In this setup, there is no ex-ante heterogeneity of buyers (households) or sellers (retailers). Households know the distribution of prices for each variety across all locations, and they are cognizant of the distributions of prices at the retailers in their location. Retailers know consumer matching behavior. Price dispersion will arise from ex-post differences between bargain hunters and workers: retailers will find it optimal to set a lower price for a subset of the brands they sell in order to ensure that local households shop at their store instead of going elsewhere.^{28,29}

Another feature of our setup is that it makes the individual decisions in the model amenable to aggregation. Aggregate fluctuations in the model stem from shocks to the money supply. We assume that the supply of money follows a random-walk process of the form

$$\ln M_t = \ln M_{t-1} + \mu_t,$$

where μ_t is log money growth, a normally distributed i.i.d. random variable with mean 0 and standard deviation σ_μ . We show in the next section that, because the number of bargain hunters is endogenous and time varying, firms use the sales margin as a means to adjust to aggregate shocks. This is in contrast to Guimaraes and Sheedy (2011), where the fraction of bargain hunters is fixed.

3.2 Household's problem

Denote the search cost by z and let its distribution be given by a twice continuously differentiable distribution $G(z)$, with $0 \leq z \leq z_{\max}$. Since the fixed search cost is i.i.d., the household's search-and-matching decision for variety j in period t can be characterized by a cut-off fixed cost, $z_t^*(j)$, for which it is indifferent between assigning bargain-hunter and worker types to its members. If the realized fixed cost is low, $z \leq z_t^*(j)$, the household member responsible for purchasing that variety will be a bargain hunter; otherwise, if the fixed cost is high, $z > z_t^*(j)$, the household member will be a worker. Denote by $\alpha_t(j)$ the probability of drawing a search cost smaller than the threshold level $z_t^*(j)$, i.e., $\alpha_t(j) = G(z_t^*(j))$. Under our assumptions, $\alpha_t(j)$ is equal to the probability that

²⁸These outcomes can be interpreted as stemming from ex-post heterogeneity in consumer information; Burdett and Judd (1983) study equilibrium price dispersion of this type. Our setup is akin to one studied by Lester (2011). In his consumer search model buyers are heterogeneous with respect to ex-ante information about sellers. A fraction of buyers have perfect information about both the prices and locations of all sellers. These buyers will choose the seller (or mix between sellers) promising the maximum expected utility. The remaining fraction of buyers cannot observe the prices posted by any particular seller. Since all sellers appear ex-ante identical to an uninformed buyer, he picks a seller to visit at random.

²⁹Our model can be interpreted in the spirit of loss-leader models of retail competition, which are supported by evidence on retailer behavior (Chevalier, Kashyap and Rossi, 2003).

a household member for variety j will be a bargain hunter in period t . The decision of choosing the search-and-matching type for variety j boils down to choosing the cutoff fixed cost $z_t^*(j)$, or equivalently, the probability $\alpha_t(j)$. Note that because there is complete symmetry across locations, we drop the location indicator to ease the exposition of the model.

We assume that workers and bargain-hunters cannot communicate the prices they find to the household head. Therefore, the household has no opportunities to arbitrage price differences ex-post, and has to decide consumption demand conditional on the price for each variety prior to sending its members to shop. This implies that consumption demand will depend on the price drawn, but not on the member type. Denote by $c_t^L(j)$ consumption demand if a household member finds a brand on sale, $P_t^L(j)$, and by $c_t^H(j)$ consumption demand at a regular price, $P_t^H(j)$.³⁰

In addition to searching and consuming, households supply working hours in a competitive labor market, and trade money and nominal bonds. Let B_t denote holdings of nominal bonds paying the household a gross return R_t in period $t + 1$. In each period the timing of events is as follows. First, the aggregate money shock and household-specific fixed costs are realized. Retail firms post their prices. For each variety, households observe the distributions of posted prices as explained above and choose their member types. Workers earn their income, while bargain hunters pay the fixed cost of searching. The household combines unspent money holdings from the previous period with labor income, return on bonds, dividends, and transfers, and splits them into current-period cash and bond holdings to be carried over to the next period. The household then decides how much to consume and provides its members with consumption demand schedules. Household members are then matched with particular brands according to their types for their designated varieties and use current-period cash to make their consumption purchases according to their consumption demand schedules.

Households choose sequences of consumption varieties $c_t^L(j)$, $c_t^H(j)$, total consumption c_t , hours worked l_t , probabilities of bargain hunting $\alpha_t(j)$, cash holdings, M_t , and bond holdings B_t to maximize lifetime expected utility:

$$E_0 \sum_t \beta^t \left[\frac{c_t^{\sigma-1}}{1-\sigma} - l_t \right].$$

³⁰Since all households and all stores of type j are ex-ante identical, we focus our analysis on decision rules that are invariant to a store's location, omitting location index from now on.

Utility is derived from expected consumption of good varieties according to a CES aggregator

$$c_t = \left\{ \int_j \left(\alpha_t(j) (f\gamma_t(j) c_t^L(j) + (1 - f\gamma_t(j)) c_t^H(j))^{1-\frac{1}{\theta}} \right) dj + \int_j \left((1 - \alpha_t(j)) (\gamma_t(j) c_t^L(j) + (1 - \gamma_t(j)) c_t^H(j))^{1-\frac{1}{\theta}} \right) dj \right\}^{\frac{\theta}{\theta-1}}, \quad (2)$$

where θ is the elasticity of substitution across varieties. Utility maximization is subject to the budget constraint

$$\begin{aligned} M_t + B_t &\leq M_{t-1} - \int_j [\alpha_t(j) (f\gamma_t(j) P_t^L(j) c_t^L(j) + (1 - f\gamma_t(j)) P_t^H(j) c_t^H(j))] dj \\ &\quad - \int_j [(1 - \alpha_t(j)) (\gamma_t(j) P_t^L(j) c_t^L(j) + (1 - \gamma_t(j)) P_t^H(j) c_t^H(j))] dj \\ &\quad + W_t \left[l_t - \int_j \Xi(\alpha_j(s^t)) dj \right] + R_{t-1} B_{t-1} + \Pi_t + T_t, \end{aligned} \quad (3)$$

and a cash-in-advance constraint

$$P_t c_t \leq M_t,$$

where P_t is the price of consumption c_t . Since consumption decisions are made ex-ante, then by the law of large numbers expected consumption c_t is equal across households, even though they encounter different prices for different varieties.

In the budget constraint, W_t is the nominal wage, Π_t are dividends paid, and T_t are lump-sum government transfers; $\Xi(\alpha_t(j)) = \int_0^{G^{-1}(\alpha_t(j))} z dG(z)$ denotes the expected cost of becoming a bargain hunter for variety j , expressed in terms of forgone hours worked.

The first-order conditions for consumption varieties, conditional on price $P_t^k(j)$, $k = L, H$, yield standard CES demand schedules:

$$c_t^k(j) = \left(\frac{P_t^k(j)}{P_t} \right)^{-\theta} c_t, \quad (4)$$

and P_t is

$$\begin{aligned} P_t &= \left\{ \int_j \left[\alpha_t(j) \left(f\gamma_t(j) (P_t^L(j))^{1-\theta} + (1 - f\gamma_t(j)) (P_t^H(j))^{1-\theta} \right) \right] dj + \int_j \left[(1 - \alpha_t(j)) \left(\gamma_t(j) (P_t^L(j))^{1-\theta} + (1 - \gamma_t(j)) (P_t^H(j))^{1-\theta} \right) \right] dj \right\}^{\frac{1}{1-\theta}}. \end{aligned} \quad (5)$$

The difference between the bargain hunters and the workers stems entirely from the price distributions they face, with bargain hunters encountering, on average, lower prices. Because household

members who decide to search actively do so at their local store, retailers will have an incentive to lower some of their prices to capture this market share and avoid having too many local workers purchase the same variety in another random location.

The first-order condition for the probability of bargain hunting for variety j , $\alpha_t(j)$ is

$$\begin{aligned} W_t \Xi'(\alpha_t(j)) = & \left(\frac{\theta}{\theta-1} D_t^B(j) - 1 \right) (f\gamma_t(j)P_t^L(j)c_t^L(j) + (1-f\gamma_t(j))P_t^H(j)c_t^H(j)) \\ & - \left(\frac{\theta}{\theta-1} D_t^W(j) - 1 \right) (\gamma_t(j)P_t^L(j)c_t^L(j) + (1-\gamma_t(j))P_t^H(j)c_t^H(j)) , \end{aligned} \quad (6)$$

where $D_t^B(j)$ and $D_t^W(j)$ are factors stemming from price dispersion faced by bargain hunters and workers, and $D_t^B(j) > D_t^W(j) > 1$, if $P_t^L(j) < P_t^H(j)$, as explained in Appendix E in Supplementary Material. Combined with the fact that bargain hunters buy more consumption on average, this implies that the right-hand side of (6) is positive.

Condition (6) equates the marginal utility flow from bargain hunting for variety j (on the right-hand side) with its marginal expected fixed cost (left-hand side). Since for a given j the right-hand side is positive, and the distribution of the fixed search cost is continuous over $0 \leq z \leq z_{\max}$, the measure of households that draw a sufficiently low fixed cost for a particular variety is always positive, i.e., $\alpha_t(j) > 0$.

This time-varying split of household types is the key difference from Guimaraes and Sheedy (2011), who assume a constant fraction of bargain hunters. In our model, the fraction of bargain hunters is determined endogenously by the value of search for lower prices through equation (6). We demonstrate below that the importance of sale prices for aggregate price flexibility crucially depends on the interaction of households' search for lower prices and retailers' decisions for setting those prices.

The remaining optimality conditions are standard: the first-order condition for hours worked implies

$$P_t c_t^\sigma = W_t ,$$

while the first-order conditions for nominal bonds yield

$$1 = \beta R_t E_t \left(\frac{c_{t+1}^{-\sigma}}{c_t^{-\sigma}} \frac{P_t}{P_{t+1}} \right) ,$$

where $E_t(\cdot)$ denotes the expected value with respect to information available through period t .

3.3 Retailer's problem

A retailer selling brands of variety j in a given location is endowed with a linear production technology that converts hours worked $n_t(j)$ into output of brands of variety j , $y_t(j)$:

$$y_t(j) = n_t(j) . \quad (7)$$

where once again we drop the location indicator for expositional purposes.

Let $\alpha_t^B(j)$ and $\alpha_t^W(j)$ denote the fractions of bargain hunters and workers buying variety j in a particular location. Due to the random and uniform allocation of workers across stores selling the same variety, any retailer selling that variety takes the number of workers as given. By contrast, the retailer can affect the measure of bargain hunters in its location, since bargain-hunting members of local households have to shop at the local shops to look for low prices. In the symmetric case, retailers across all locations post the same prices, and each location receives the same measure of bargain hunters for that variety, i.e.,

$$\alpha_t^B(j) = \alpha_t(j) , \quad (8)$$

where $\alpha_t(j)$ is the average measure of bargain hunters in a particular location given by (6). The relationship between prices posted by a retailer selling variety j and the measure of bargain hunters visiting its location applies equally in any location.

In each period, upon realization of the aggregate shock, the retailer posts price $P_t^L(j)$ for a fraction $\gamma_t(j)$ of its brands and price $P_t^H(j)$ for the remaining fraction $1 - \gamma_t(j)$. The brands with a price discount are chosen at random (among brands that are not subject to price adjustment constraints below) and independently across periods. Posting a price discount requires a fixed cost κ , expressed in labor units; total fixed cost for a retailer, therefore, is $\kappa W_t \gamma_t(j)$. Households of either type who are matched with the retailer in a particular location draw their respective prices and purchase according to the demand schedules (4). The retailer produces using technology (7) to fully satisfy the demand at posted prices. Finally, retailers face constraints on price adjustment, which we explicitly specify in Section 4.2.

The problem of a retail store selling variety j in location l is to choose the sequences of its two price points $P_t^H(j)$ and $P_t^L(j)$, fraction of price discounts $\gamma_t(j)$, the expected fraction of bargain hunters in retailer's location $\alpha_t^B(j)$, total labor inputs $n_t(j)$, and total outputs $y_t(j)$, to maximize

the present discounted value of its profits :

$$\begin{aligned}
E_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{-\sigma}}{P_t} \cdot \{ & \alpha_t^B(j) [f\gamma_t(j) (P_t^L(j) - W_t) c_t^L(j) + (1 - f\gamma_t(j)) (P_t^H(j) - W_t) c_t^H(j)] \\
& + \alpha_t^W(j) [\gamma_t(j) (P_t^L(j) - W_t) c_t^L(j) + (1 - \gamma_t(j)) (P_t^H(j) - W_t) c_t^H(j)] \\
& - \kappa W_t \gamma_t(j) \} ,
\end{aligned} \tag{9}$$

subject to

$$\begin{aligned}
y_t(j) \leq & \alpha_t^B(j) [f\gamma_t(j) c_t^L(j) + (1 - f\gamma_t(j)) c_t^H(j)] \\
& + \alpha_t^W(j) [\gamma_t(j) c_t^L(j) + (1 - \gamma_t(j)) c_t^H(j)] ,
\end{aligned} \tag{10}$$

and the demand constraints (4), the technology constraints (7), the constraints for the number of bargain hunters in retailer's location (6) and (8), and price adjustment constraints.

3.4 Equilibrium

The market clearing condition for labor implies that the hours supplied by households in the labor market are equal to the total hours demanded by the retail firms across all locations:

$$\sum_l \left(l_t - \int_j \Xi(\alpha_t(j)) dj \right) = \sum_l \int_0^1 [n_t(j) + \kappa \gamma_t(j)] dj .$$

The market clearing condition for each good variety j states that the total consumption of that variety is equal to the total amount of that variety produced:

$$\sum_l [\alpha_t(j) c_t^B(j) + (1 - \alpha_t(j)) c_t^W(j)] = \sum_l \int_0^1 y_t(j) dj .$$

The equilibrium search flow condition states that the total number of households who choose to become workers for variety j is equal to the total number of workers buying variety j across all locations:

$$\sum_l \int_0^1 (1 - \alpha_t(j)) dj = \sum_l \int_0^1 \alpha_t^W(j) dj .$$

Finally, money and bond markets also clear.

A *symmetric equilibrium* for this economy is a collection of allocations for households: c_t , l_t , $c_t^H(j)$, $c_t^L(j)$, M_t , B_t , $\alpha_t(j)$; prices and allocations for firms: $y_t(j)$, $n_t(j)$, $P_t^H(j)$, $P_t^L(j)$, $\gamma_t(j)$, $\alpha_t^B(j)$, $\alpha_t^W(j)$; and aggregate prices P_t , W_t , R_t that satisfy household and retailer maximization, and market clearing conditions.

4 Model mechanics

4.1 Model with flexible prices

We first study an environment with fully flexible prices: firms face no constraints to change either $P_t^L(j)$ or $P_t^H(j)$.

4.1.1 Equilibrium price dispersion

Under certain conditions, there is an equilibrium with price dispersion. Appendix F in Supplementary Material derives a sufficient condition for the expected fixed cost $\Xi(\alpha)$, probability parameter f , cost of posting sales κ , and demand elasticity θ , for which retailer prefers to post two different prices, instead of a single price for all its brands. This condition states that the benefits to retailer from generating extra inflow of bargain hunters from posting a fraction of brands on sale must outweigh the cost of decreasing the average profit margin. For example, the sufficient condition is satisfied if the expected fixed cost of searching is not very steep (e.g., if $\Xi''(\alpha)$ is low enough). In that case, there are always varieties for which the search cost realizations are low-enough so that households choose the members responsible for that variety to be bargain hunters. The presence of bargain hunters validates retailers' incentive to post sales.

4.1.2 Fraction of sale prices

Denote by $\Pi_t(P) = (P - W_t) \left(\frac{P}{P_t}\right)^{-\theta} c_t$ the period- t retailer's profit function at price P . The retailer's expected profit from selling to bargain hunters in period t is

$$\Pi_t^B(j) = f\gamma_t(j) \Pi_t(P_t^L(j)) + (1 - f\gamma_t(j)) \Pi_t(P_t^H(j)) .$$

What is the desirable number of discount prices for a retailer? From the retailer's problem (9), for the case with non-trivial price dispersion, the first-order condition with respect to the fraction of brands on sale $\gamma_t(j)$ is

$$(\alpha_t^W(j) + f\alpha_t^B(j)) [\Pi_t(P_t^H(j)) - \Pi_t(P_t^L(j))] + \kappa W_t = \frac{\partial \alpha_t^B(j)}{\partial \gamma_t(j)} \Pi_t^B(j) . \quad (11)$$

The left-hand side is the marginal loss from increasing the fraction of sales. It consists of two terms: the first term is the marginal loss from selling more goods at a lower price, equal to the product of the marginal increase in the measure of transactions at a low price, $\alpha_t^W(j) + f\alpha_t^B(j)$, and the absolute value of the profit loss per each brand on sale, $\Pi_t(P_t^H(j)) - \Pi_t(P_t^L(j))$. The

second term is the marginal increase in the total fixed cost of posting sales, κW_t .

The right-hand side is the marginal profit from increasing the fraction of sales: it is the product of the marginal increase in the number of bargain hunters, $\frac{\partial \alpha_t^B(j)}{\partial \gamma_j(s^t)}$, and the average profits per bargain hunter, $\Pi_t^B(j)$. Since $\frac{\partial \alpha_t^B(j)}{\partial \gamma_j(s^t)} = \frac{\partial \alpha_t(j)}{\partial \gamma_j(s^t)}$, we can show—by differentiating (6) with respect to $\gamma_t(j)$ —that $\frac{\partial \alpha_t^B(j)}{\partial \gamma_j(s^t)}$ is decreasing in $\gamma_t(j)$, i.e., the inflow of bargain hunters from an extra 1 percentage point of sales diminishes with the fraction of sales. This is the case because the household's marginal cost of becoming a bargain hunter, $\Xi''(\alpha_t(j))$, is increasing with the number of bargain hunters; and because the utility loss due to price dispersion, given by $D_t^B(j)$ and $D_t^W(j)$, is growing faster for bargain hunters than for workers. In turn, the retailer's expected profit per bargain hunter, $\Pi_t^B(j)$, is also decreasing with $\gamma_t(j)$, since more brands are sold at a lower price. Figure 8 plots the retailer's marginal gain (right-hand side of (11)) and marginal loss (left-hand side of (11)) stemming from an extra 1 percentage point of sales as functions of the fraction of sales. Both lines are very flat with respect to the level of $\gamma_t(j)$, which implies that their shifts due to aggregate shocks will lead to large changes in $\gamma_t(j)$ —the feature that helps the model match some important aspects of the data, as we discuss in the next section.

4.1.3 Size of price discount

How does the firm pin down the levels of its high and low prices? For the case with non-trivial price dispersion, the corresponding first-order conditions are

$$N_t^i(j) (MR_t(P_t^i(j)) - MC_t(P_t^i(j))) + \frac{\partial \alpha_t^B(j)}{\partial \ln P_t^i(j)} \Pi_t^B(j) = 0, \quad (12)$$

where $i = H, L$, and $MR_t(\cdot)$ and $MC_t(\cdot)$ are the marginal revenue and marginal cost period- t functions of a single-price firm, respectively:

$$\begin{aligned} MR_t(P) &= -(\theta - 1) \left(\frac{P}{P_t} \right)^{-\theta} c_t, \\ MC_t(P) &= -\theta \frac{W_t}{P} \left(\frac{P}{P(s^t)} \right)^{-\theta} c_t. \end{aligned}$$

$N_t^H(j)$ and $N_t^L(j)$ are the number of transactions at high and low prices:

$$N_t^H(j) = (1 - \gamma_t(j)) \alpha_t^W(j) + \alpha_t^B(j) (1 - f \gamma_t(j)),$$

$$N_t^L(j) = \gamma_t(j) (\alpha_t^W(j) + \alpha_t^B(j) f),$$

and $\frac{\partial \alpha_t^B(j)}{\partial \ln P_t^H(j)}$, $\frac{\partial \alpha_t^B(j)}{\partial \ln P_t^L(j)}$ are the marginal changes in the number of bargain hunters due to the increase in the high and low log prices, respectively.

Conditions (12) imply that if the retailer could not affect the number of bargain hunters in its store (i.e., if $\frac{\partial \alpha_t^B(j)}{\partial \ln P_t^H(j)} = \frac{\partial \alpha_t^B(j)}{\partial \ln P_t^L(j)} = 0$), then the optimal low and high prices would both equate the single-firm marginal revenue and marginal cost, and would be equal to the optimal monopolistic price $P_t^*(j)$, since $MR_t(P_t^*(j)) = MC(P_t^*(j))$. In contrast, if the retailer can indeed attract bargain hunters, search condition (6) implies that $\frac{\partial \alpha_t^B(j)}{\partial \ln P_t^H(j)} > 0$ and $\frac{\partial \alpha_t^B(j)}{\partial \ln P_t^L(j)} < 0$; i.e., a higher high price and a lower low price make bargain hunting more attractive. Then from (12) it follows that $MR_t(P_t^L(j)) > MC_t(P_t^L(j))$ and $MR_t(P_t^H(j)) < MC_t(P_t^H(j))$; i.e., the retailer's optimal low (high) price is below (above) the monopolistic price, $P_t^L(j) < P_t^* < P_t^H(j)$, see Figure 9.

4.2 Model with sticky prices

Next, we turn to our benchmark version with sticky prices: we assume that retailers face Taylor (1980) price adjustment constraints for high prices. Low prices are assumed to be flexible, although this has virtually no effect on our results, as we show below. Retailer j sets a new high price in period t and keeps that price fixed for T periods, facing the following pricing constraints:

$$P_t^H(j) = P_{t+1}^H(j) = \dots = P_{t+T-1}^H(j) . \quad (13)$$

Such price contracts are evenly staggered across varieties j , so that in every period a measure $1/T$ of retailers resets their prices. To keep the model tractable, we assume that all price changes are perfectly synchronized for all retailers selling the same variety j .

Retailer j 's problem, then, is to choose prices $P_\tau^L(j)$, $P_\tau^H(j)$, the number of prices on sale $\gamma_\tau(j)$, and the number of bargain hunters in their location $\alpha_\tau^B(j)$ to solve

$$\max E_t \sum_{\tau=t}^{t+T-1} \left\{ \beta^{t-\tau} \frac{c_\tau^{-\sigma}}{P_\tau} \cdot [\alpha_\tau^B(j) \Pi_\tau^B(j) + \alpha_\tau^W(j) \Pi_\tau^W(j) - \kappa W_\tau \gamma_\tau(j)] \right\} ,$$

subject to the same constraints as in the flexible-price case, and pricing constraints (13).

The first-order conditions yield equations for low prices

$$P_\tau^L(j) = \frac{\theta}{\theta - 1} \frac{W_t}{1 - \frac{\partial \alpha_t(j)}{\partial \ln P_t^L(j)} \frac{\Pi_t^B(j)}{(\theta - 1) N_t^L(j) R_t^L(j)}} , \quad (14)$$

and reset high prices:

$$P_{\tau}^H(j) = \frac{\theta}{\theta - 1} \frac{E_t \sum_{\tau=t}^{t+T-1} \beta^{t-\tau} c_{\tau}^{1-\sigma} P_{\tau}^{\theta-1} N_{\tau}^H(j) W_{\tau}}{E_t \sum_{\tau=t}^{t+T-1} \beta^{t-\tau} c_{\tau}^{1-\sigma} P_{\tau}^{\theta-1} N_{\tau}^H(j) \left(1 - \frac{\partial \alpha_{\tau}(j)}{\partial \ln P_{\tau}^H(j)} \frac{\Pi_{\tau}^B(j)}{(\theta-1) N_{\tau}^H(j) R_{\tau}^H(j)} \right)}. \quad (15)$$

Appendix J in Supplementary Material contains the full system of equilibrium conditions in the model with sticky prices. The model is solved by applying the Blanchard-Khan (1980) local solution method to the log-linearized system of stochastic equilibrium equations around the deterministic steady state.

5 Results of Model Simulations

In this Section we use model simulations to analyze the importance of countercyclical sales behavior for macroeconomists. After properly calibrating the model's key parameters, we demonstrate that fluctuations in retailers' sales behavior can have sizeable implications for the economy's response to aggregate shocks and the measurement of aggregate price changes.

5.1 Parameterization

Table 5 provides the parameter values that we use in our quantitative simulations. The period is a month, so the discount factor is $\beta = 0.96^{1/12}$. We set $\sigma = 1$, a standard value in business cycle literature, which implies that nominal wages track the money supply, $W_t = M_t$. Following Kryvtsov and Midrigan (2013), we assume that the growth rate of the money supply in the benchmark model is serially uncorrelated; we also report the results for serially correlated money growth to facilitate comparisons with findings in Guimaraes and Sheedy (2011).

We set the elasticity of substitution across good varieties equal to $\theta = 5$, implying a 25% markup, which is between the high disaggregate markup estimates consistent with the industrial organization literature and the low macro aggregate markup estimates (e.g., see Basu and Fernald, 1997). Aggregate fluctuations in our model are not sensitive to the level of θ .

We assume that regular prices change once every 12 months ($T = 12$), consistent with our data and existing studies. Although this degree of price stickiness is somewhat higher than reported in Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008), it is consistent with the findings of Eichenbaum et al. (2011) and Kehoe and Midrigan (2015). We assume that sale prices are fully flexible. As we show below, this assumption has little effect on the aggregate price flexibility, since firms prefer to keep the size of the price discount roughly constant. The latter result is consistent

with our findings that the size of the average price discount is very acyclical. It is also consistent with Klenow and Kryvtsov (2008), who find that sale prices are roughly as sticky as regular prices.

Parameters that are specific to our price-discrimination model are the bargain hunting technology parameter f , the fixed cost of posting price discounts κ , and parameters of the distribution of the fixed cost of searching $G(z)$. In our model, since the parameter κ determines the average fraction of sales γ , we set κ to 0.08 to match the average fraction of sale prices $\gamma = 0.05$. This number is midway between the unconditional sales frequencies we found for the U.K. and the U.S. (see Figures 2 and 5). In addition, while it is in the upper range of values in other European CPI data studies,³¹ it is somewhat lower than the 0.07 and 0.11 frequencies found for the United States by Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008) respectively.³²

The parameters of $G(z)$ imply a specific level and slope of the marginal expected cost function $\Xi'(\alpha)$, and jointly determine the fraction of bargain hunters α and the size of the price discount P^L/P^H . Indeed α depends on the level of the marginal expected fixed cost $\Xi'(\alpha)$ in equation (6); and the price discount depends on its slope, $\Xi''(\alpha)$, which in turn affects the derivatives $\frac{\partial \alpha_\tau(j)}{\partial \ln P_\tau^H(j)}$ and $\frac{\partial \alpha_\tau(j)}{\partial \ln P_\tau^L(j)}$ in pricing equations (14) and (15). To calibrate the average fraction of bargain hunters, we match the relative share of consumption at low prices. Gandon (2011) reports that for groceries in the United States, sales account for 17% of price quotes but 40% of revenue. In other words, one percentage point of price discounts accounts for 2.7 percentage points of revenue share; this ratio is our calibration target. The other calibration target is the average size of price discounts, which is $P^L/P^H = 0.78$ in our data. We find that if $G(z)$ is a uniform distribution that assigns equal probabilities of any fixed cost between 0 and $z_{\max} = 0.31$, the model matches both of these calibration targets.

Finally, given our definition of bargain hunting technology and the uniform fixed cost of access to that technology, the parameter f has little effect on our calibration targets. We therefore fix f at 2, which means that bargain hunting allows households to double the probability of finding the low price.

The calibrated model predicts that the average consumption-weighted (unweighted) price paid by bargain hunters is 2% (1.2%) lower than the price expected to be paid by workers. This prediction is in line with some evidence on time use by households. For example, Kaplan and Menzio (2015)

³¹The fraction of sales is between 0.03 and 0.05 in Austrian CPI data (Baumgartner et al. 2005); 0.03 in Norwegian CPI data (Wulfsberg 2009), 0.02 in French CPI data (Baudry et al. 2004; Berardi et al. 2013).

³²Since sale prices are chosen at random out of those prices that are not subject to pricing constraints, the measure of prices that experience a V-shaped regular-sale-regular path is $(1 - \gamma) \frac{1}{T} \cdot \frac{\gamma(1-\gamma)^{\frac{1}{T}}}{[(1-\gamma)^{\frac{1}{T}} + \gamma]^2}$. For $\gamma = 0.05$ and $T = 12$, the average fraction of V-shapes in any period is 0.019, or 38% of all sale observations. See Appendix H in Supplementary Material.

use the Kilts-Nielsen Consumer Panel Dataset to show that households with more non-employed members face prices that are, on average, 1% to 4.5% lower than prices faced by households whose members are all employed.

The fixed costs of bargain hunting are uniformly distributed between 0 and 0.31 units of time. Assuming that households work on average 26 hours a week, as reported by Cociuba, Prescott and Prescott (2009), this amounts to a range between 0 and 10 hours a week. Given this cost, the calibrated model predicts that only one out of 10 households decides to become a bargain hunter, i.e., $\alpha = 0.10$. The break-even fixed cost that makes a marginal household indifferent between bargain hunting and working is 0.03 units of time, or 1 hour a week. Hence, the average cost per household is around 10 minutes per week. This feature of the model is qualitatively consistent with evidence on search and shopping activity across households derived from time-use surveys. For example, Aguiar and Hurst (2007) document important fluctuations in the shopping margin over the household's life cycle; Krueger and Mueller (2010) find that unemployed individuals devote 15% to 30% more time to shopping than the employed.

5.2 Responses to monetary shocks

Our baseline experiment is a negative 1% innovation to the growth rate of the money supply. Figure 10 compares the responses of output and the aggregate price level in the model with sales to the model without sales, i.e., the standard Taylor model with a single retail price.

The figure demonstrates a stark difference in the output and price responses in two models. The aggregate price level (top-right panel) in the Taylor model falls steadily to -1% within one year, as additional sticky-price cohorts of retailers get a chance to lower their prices after the shock. Accordingly, the fall in output (top-left panel) is immediate, down to around -0.9% at the time of the shock, dissipating to zero after one year. By contrast, in the model with sales the real effect on output is about half as large, with output falling by about 0.5% on impact and going back to its pre-shock level within a year or so. Such a response in output is due to a faster fall in the aggregate price level, which, unlike in the standard single-price Taylor model, immediately drops by 0.5% at the time of the shock.

The marked difference in the degree of the aggregate price flexibility between the two models is due to the combined effect of price discounting by retailers and bargain hunting by households. To understand this mechanism, let us review the factors that determine the size of the decline in the aggregate price level immediately after the shock.

First, we log-linearize the expression for the aggregate price level (5) around the steady state

assuming that both γ and α are, on average, close to zero, and P^H is close to P . Denoting the average price discount by $\delta = P^L/P^H$, we obtain that the log deviation of the aggregate price level from its steady-state value is, approximately,

$$\hat{P}_t \approx -\frac{P}{\theta - 1} \left(\delta^{1-\theta} - 1 \right) \tilde{\gamma}_t, \quad (16)$$

where a hat (tilde) denotes the log-linearized (difference-) deviation from the steady state, and steady-state values have no subscripts. Expression (16) indicates that the response of the average fraction of sales γ_t affects the aggregate price response by shifting the weight from high to low prices. The impact of this shift depends on both the size of the response of the fraction of sales itself and on the size of the shift in consumption, given by the factor $\delta^{-\theta}$. The response of the fraction of sales is $\tilde{\gamma}_t = 1.1$ percentage points (bottom-left panel in Figure 10), while $\delta = 0.78$, $\theta = 5$ by calibration. Plugging these values into (16) gives a price level response of -0.5% at the time of the shock, as shown in the figure. Hence, both the average discount and the size of the response of the fraction of sales contribute to the fivefold difference of price responses in the model with and without sales.

We next explain how the magnitudes of the average discount δ and the response in the fraction of discounts $\tilde{\gamma}_t$ stem from bargain hunting by households. First, use pricing equations (12) to approximate the average size of price discount:

$$\delta \approx \left(1 + \frac{f-1}{\theta(\theta-1)} \frac{1}{\Xi''(\alpha)} \right)^{-1}. \quad (17)$$

As we already established in Section 4.1, a larger search elasticity (lower $\Xi''(\alpha)$) and a larger search efficiency f imply a larger discount. Keeping $f = 2$, and using the steady-state value for $\Xi''(\alpha) = 0.3$, we obtain from (17) that the average discount is, approximately, 0.85, close to the accurate steady-state value of 0.78.

Second, to understand the response in the fraction of sales, $\tilde{\gamma}_t$, note that due to sticky regular prices the fall in wages after the shock drives up the average markup at the store, increasing the expected profit per each buyer. According to the first-order condition (11), the marginal benefit of an extra sale rises relative to its marginal cost. To equate the marginal benefit of sales to the marginal cost, retailer must increase the number and the size of price discounts.³³ It turns out that in our model retailers mostly prefer to vary the fraction of price discounts, and not their size. This arises because the retailer's value is nearly linear in the fraction of sales: when that fraction is small,

³³Since the impact of a given shock on the marginal benefit is proportional to the sensitivity of the fraction of bargain hunters to extra sales, given by the derivative $\frac{\partial \alpha_t(j)}{\partial \gamma_t(j)}$, the magnitude of the response of the fraction and size of sales increases with the sensitivity of bargain hunting.

on average, both retailer's marginal gains and losses are very inelastic with respect to changes in the fraction, see Figure 8. Overall, given our calibration, the response of the fraction of sales is $\tilde{\gamma}_t = 1.1$ percentage points, while the average size of price discounts (not shown on the figure) is virtually unchanged, increasing by only 0.07 percentage points.³⁴

From (6) the response in the fraction of bargain hunters is approximately

$$\tilde{\alpha}_t \approx \tilde{\gamma}_t \frac{1}{\theta - 1} \frac{f - 1}{W\Xi''(\alpha)} \left(\delta^{1-\theta} - 1 \right),$$

which, given our calibrated parameter values, yields $\tilde{\alpha}_t = 1.6$ percentage points (lower-right panel in Figure 10). The prediction of the model that households increase their search for low prices during economic downturns is corroborated by ample evidence from time-use surveys on search and shopping activity over the business cycle. For example, Aguiar, Hurst and Karabarbounis (2013) find a significant increase in time spent shopping for a typical household during the 2008–09 recession based on the American Time Use Survey. They document that about 7% of forgone market hours are allocated to increased shopping time. Using a similar data set, Nevo and Wong (2014) estimate that household consumption declined by 60% less than market expenditures due to the reallocation of time from market work to home production and shopping.³⁵

Finally, we mentioned in Section 2 that while the time-series correlation between the frequency of price discounts and unemployment is strongly positive, both in the United Kingdom and the United states, there appears to be little or no correlation between sales frequency and unemployment across U.K. regions or U.S. markets (as reported in Coibion, Gorodnichenko and Hong, 2014). We show in Supplementary Material (Appendix I) that such a disconnect is also present in our model. We show that varying the steady state fraction of bargain hunters between 0.05 and 0.20 has only small impact on the impulse responses of the fraction of bargain hunters and the fraction of sales to the monetary shock. Since these effects are small, the interaction between the steady state fraction of bargain hunters and the cyclicalities of sales is not very strong, as suggested by cross-section evidence.

5.3 Measuring the aggregate price level

Flexibility of the aggregate price response is due to the increase in the fraction of sale prices and a shift of consumption weights toward discounted items. Because the shift in consumption

³⁴We repeated these simulations for the case when low prices P^L are also sticky and can be adjusted every 12 months together with high prices. The results are very close to the benchmark case with flexible sale prices.

³⁵Additional evidence of countercyclical search behaviour using online activity measures is presented in Supplementary Material.

weights is generally not observed by statistical agencies,³⁶ fluctuations in sale prices may have important implications for aggregate price measurement. Figure 11 compares the response of the true price index in our benchmark experiment, denoted by “ P ,” equal to -0.56% on impact, to two counterfactual responses. The price index that ignores the variations in consumption weights, “ P_{CPI} ,” is the model’s counterpart to a standard fixed-weight CPI index: it decreases by 0.37% after the shock. Ignoring sales altogether, as in the standard Taylor model, brings the impulse response to a mere -0.07% on impact, shown by the graph denoted by “ $P_{CPI}(regular)$ ”. Hence, fluctuations in price discounts (keeping consumption weights constant) account for about two-thirds of the additional variance of the true aggregate price level relative to the price level ignoring sales; and the unmeasured variation in consumption weights accounts for the remaining one-third.³⁷

These findings build on the insights from Chevalier and Kashyap (2012), who emphasize the importance of accounting for the shift in consumption weights toward sale prices for the degree of aggregate price flexibility. We quantify that such a shift can add about half of the variance implied by the constant-weight price index. Our contribution is to show that—even for a fixed-weight index such as the CPI—fluctuations in the number of temporary discounts can be important for aggregate price dynamics.³⁸

5.4 What do sales tell us about business cycles?

Our impulse-response results demonstrate the importance of accounting for the interaction between retailers’ price-discounting behavior and households’ search for low prices. This feature of the model allows us to provide important insights for the sources of households’ time use and the cyclicity of markups over the business cycle.

We conduct two alternative simulations of the model. First, we assume that nominal wages are sticky. While in the benchmark model nominal wages and retailers’ marginal cost track the money stock, in this case we assume that nominal wages are given by equation

$$W_t = W_{t-1}^{11/12} M_t^{1/12}, \quad (18)$$

so that it takes around a year for nominal wages to converge to their pre-shock level. We will assume that the retailers’ marginal cost is still flexible and equal to the money supply, as in the baseline

³⁶Consumption expenditure weights used by ONS and BLS to construct the U.K. and U.S. CPI are updated annually; and they are produced at a stratum level (e.g., by region and shop type in the U.K. data).

³⁷Most of the shift in consumption weights toward lower prices after the shock is due to the increase in consumption per household, while the increase in the number of households buying at low prices has a smaller impact.

³⁸If in addition consumers tend to migrate towards lower-prices products or retailers during recessions, as argued by Coibion, Gorodnichenko and Hong (2014), then the importance of sales would be heightened even more.

model. Second, we assume that household wages are flexible, and it is the nominal marginal cost that is sticky, obeying the same law of motion as in (18).³⁹

Table 6 provides responses at the time of the same shock (1% negative impulse to money growth) in the baseline model (column A) and its two variants (columns B and C). Our model predicts that the quick fall of household wages after the shock matters relatively little for incentivizing households to look harder for price discounts (column B). When nominal wages are sticky, they fall by only about 0.1% after the shock, as opposed to 1% in the baseline model. Since the marginal time cost of searching, in dollars, is equal to $W_t\alpha_t$, a 0.9% smaller fall in wages implies a smaller rise in the fraction of bargain hunters by only 0.1 ppt ($= 0.9\alpha$). In addition, retailers post sales less aggressively, amplifying the effect on the fraction of bargain hunters by 0.26 ppt, (i.e., the increase in the fraction is 1.36 ppt vs 1.62 ppt in the baseline model)—still a relatively small difference.

In the variants of the model considered so far (columns A and B), markups rise by roughly half of a percentage point after the monetary contraction, making it a good time for retailers to increase their market share. In the third simulation, we limit the rise in the markup on impact by assuming sticky marginal cost (column C). In this case, retailers barely change their prices after the shock. The fraction of bargain hunters increases by only 0.1 ppt due to the 1% fall in household wages, implying only a small effect on the aggregate price and, therefore, a large consumption response at -0.94%, very close to the Taylor model with no sales. Hence, in our model, countercyclical markups represent the central impetus that leads retailers to make more-intensive use of sales during slumps.

In the model, therefore, changes in households' shopping activity are associated, to a large extent, with retailers' pricing over the cycle, and less with changes in the opportunity cost of time. Coibion, Gorodnichenko and Hong (2014) and Nevo and Wong (2014) emphasize the role of the decline in the opportunity cost of time in explaining the increased shopping activity during slumps. Our paper shows that the rise in return to shopping due to more frequent sales in recessions can also be a powerful driving mechanism behind fluctuations in households' shopping time. Ultimately, it would be interesting to disentangle between these two transmission channels.

Finally, a growing consensus in macroeconomic literature is that nominal cost rigidities, rather than countercyclical markups, account for most of the monetary non-neutrality, see Christiano, Eichenbaum and Evans (2005). In contrast, our theory explains how countercyclical fluctuations in the number of sales in response to monetary shocks are associated with countercyclical retail

³⁹It is straightforward to extend our benchmark model to include capital, sticky nominal wages and nominal cost rigidities to explicitly account for reduced forms for sticky wages and marginal cost. Such an extension would not change the point we make here.

markups and their importance of the responses after monetary shocks.⁴⁰

6 Conclusions

Temporary price discounts (“sales”) are an important feature of the pricing behavior of retailers. The recent literature argues that sales are mostly irrelevant for macroeconomists, under the assumption that they are not significantly affected by business cycles and represent high-frequency phenomena that have little impact on the predictions of macro models. We revisit this debate and argue that the dynamics of the observed sales behavior can indeed be important for aggregate price flexibility. First, using the U.K. CPI micro data covering the period from 1996 to 2012, we demonstrate that sales (which normally would be filtered out by macroeconomists) are correlated with the business cycle: in particular, the frequency of sales is strongly countercyclical and doubled during the last recession. Analyzing aggregate time series obtained from the Bureau of Labor Statistics, we find that countercyclical sales are also a feature of price dynamics in the United States.

Second, we study the propagation of monetary shocks in an environment where sales respond to macroeconomic conditions in line with the empirical evidence. We build a general equilibrium business cycle model with consumer search and price discrimination by retailers. Our model, calibrated to price-discounting behavior in the data, predicts that sale prices represent a significant source of price flexibility. In response to an unanticipated monetary contraction, the increase in consumer search activity and more-aggressive discounts by retailers lead to a much faster decrease in the aggregate price level and a substantially smaller response of real output.

Our conclusion is that focusing on posted regular or reference prices may lead macroeconomists to miss important aspects of pricing over the business cycle. More generally, we believe that future research should be aimed at investigating the cyclical properties and aggregate implications of the numerous price-discrimination strategies used by firms. Furthermore, evidence on retailers’ price-discounting behavior, combined with evidence on households’ search for low prices, can provide useful insights for the debate on the driving forces of business cycles.

⁴⁰Kryvtsov and Midrigan (2013) arrive at a similar conclusion, based on the study of the observed behavior of inventories.

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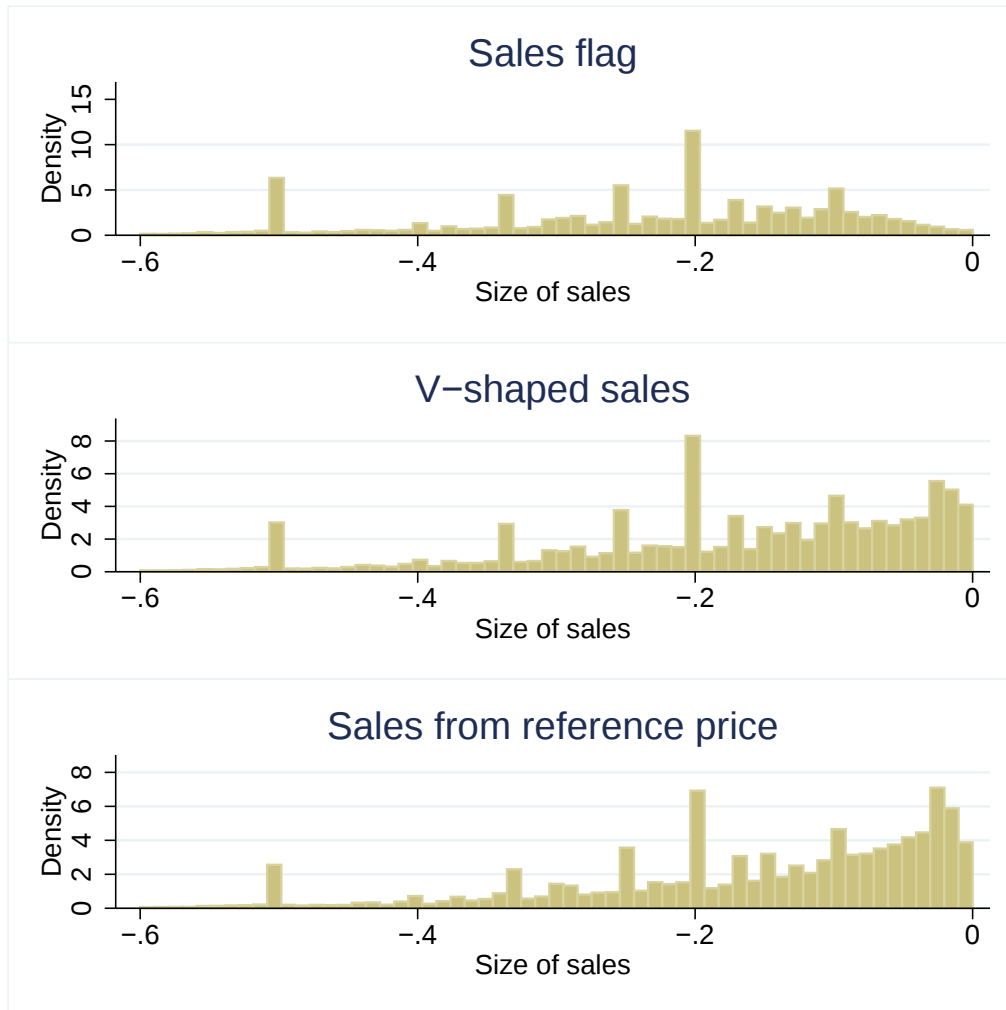


Figure 1: Distribution of the size of sales for the three main filters

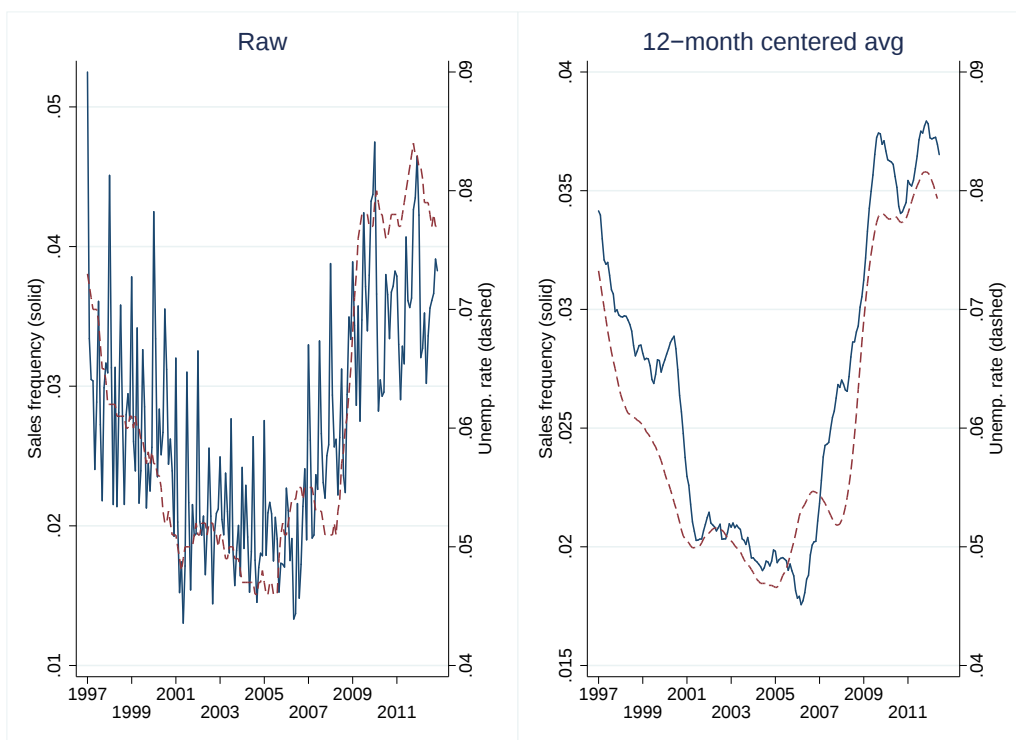


Figure 2: Frequency of sales flags (raw and 12-month moving average) and unemployment rate



Figure 3: The evolution of the frequency of sales (alternative filters)

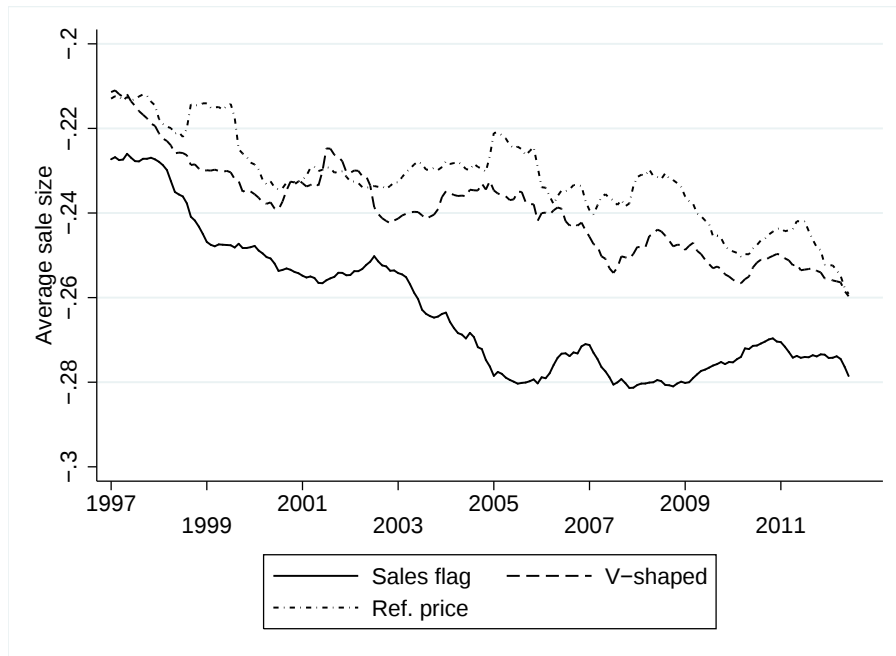


Figure 4: The evolution of the size of sales

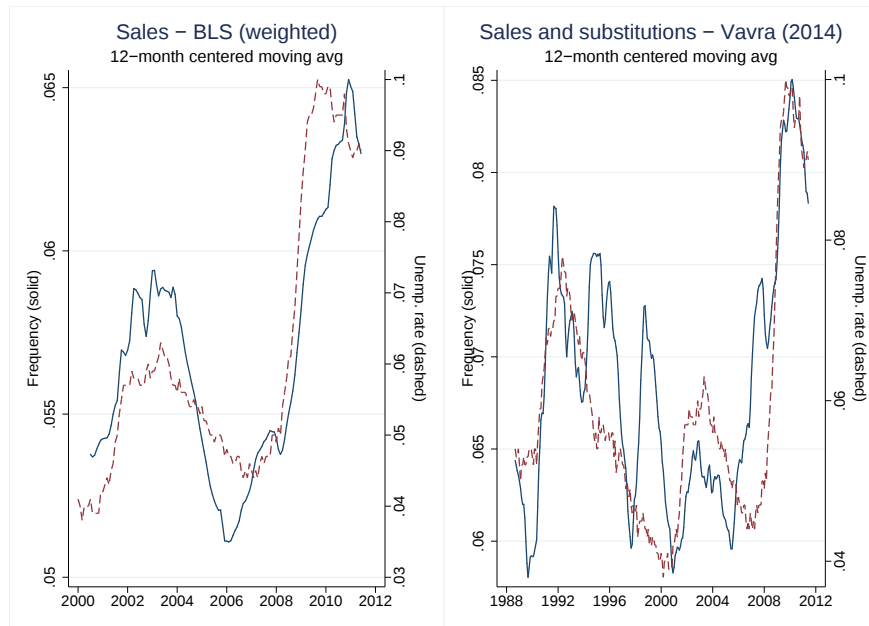


Figure 5: Frequency of sales in the U.S. CPI data and unemployment rate

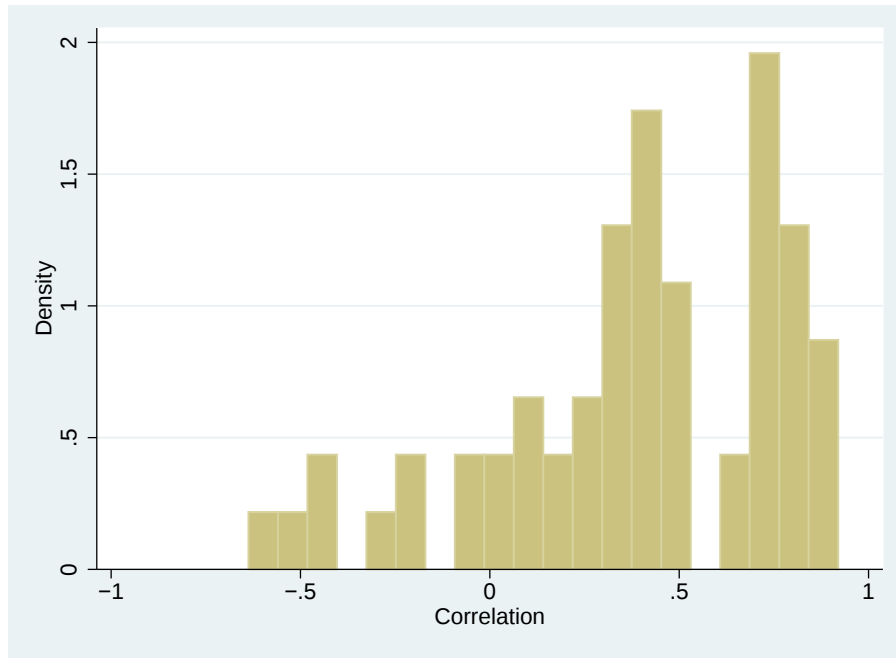


Figure 6: Correlation between sales frequency and unemployment rate - Distribution across categories

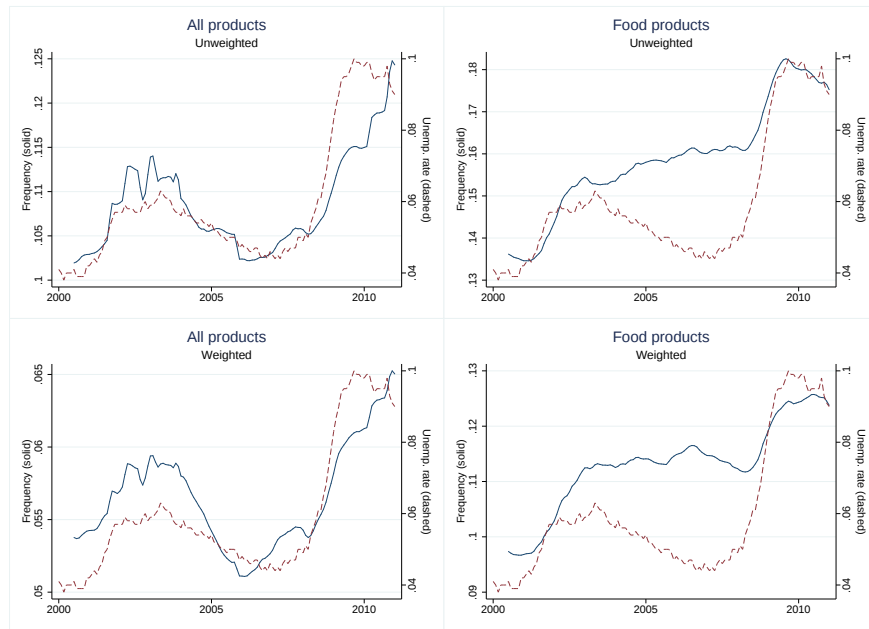


Figure 7: Frequency of sales for food products (U.S. CPI)

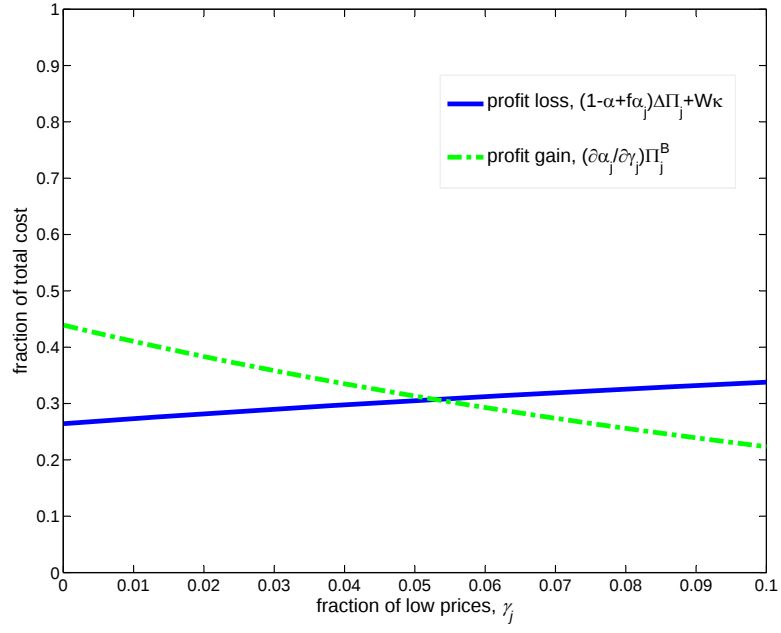


Figure 8: Profit loss and gain from 1 ppt increase in the fraction of low prices

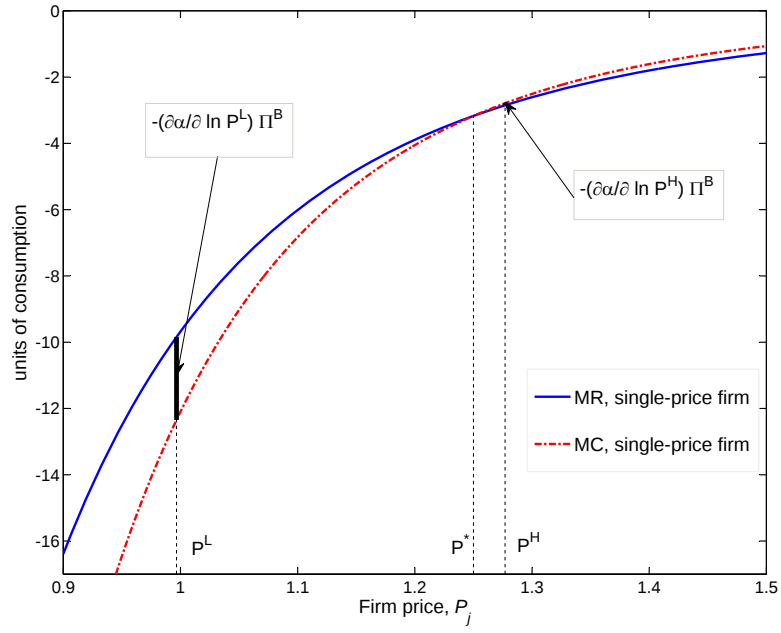


Figure 9: Decision for high and low price levels

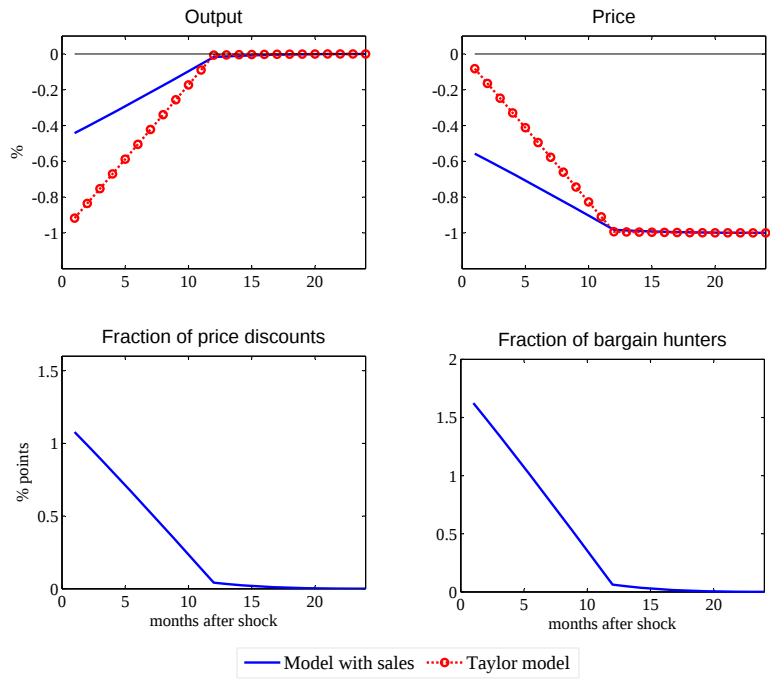


Figure 10: Responses to a negative 1% impulse to money growth

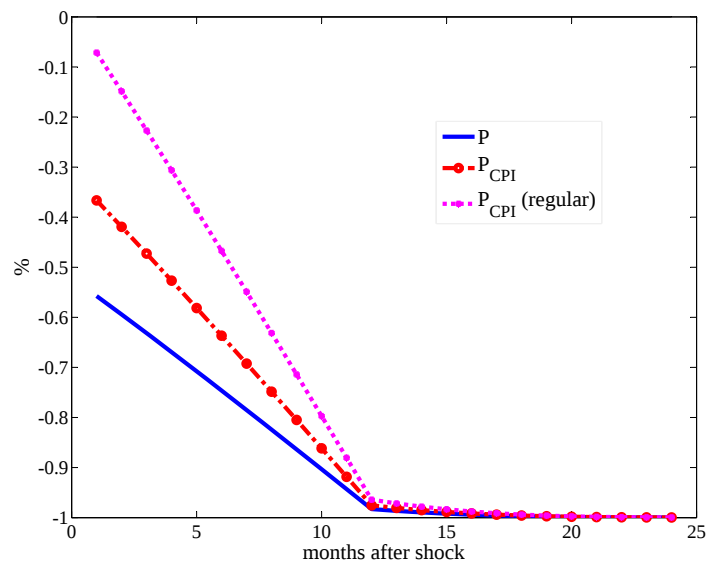


Figure 11: Decomposition of aggregate price response to a negative 1% impulse to money growth

Table 1: Summary statistics for posted and regular price changes

	Frequency of price changes	Frequency of price increases	Frequency of price decreases	Abs. size of price changes
<i>All prices</i>				
	0.172	0.107	0.065	0.111
<i>Regular prices</i>				
Sales flag	0.146	0.095	0.050	0.080
V-shaped	0.121	0.084	0.037	0.087
Reference price	0.073	0.053	0.020	0.095

Table 2: Summary statistics for temporary sales

	Sales flag	Sales flag (raw)	V-shaped	Reference price
<i>All sales</i>				
Frequency	2.6%	4.4%	5.0%	6.2%
Mean size	-22.4%	-20.3%	-11.9%	-10.4%
Median size	-20.0%	-20.0%	-7.0%	-5.6%
<i>Sales of at least 10%</i>				
Frequency	2.1%	2.7%	2.0%	2.5%
Mean size	-26.1%	-27.7%	-23.9%	-23.0%
Median size	-22.2%	-24.9%	-20.1%	-20.0%

Table 3: Regressions at the aggregate level

	UK					US - BLS			US - Vavra		
	Flag	Flag	Flag	V-shaped	Ref.	Mean	Mean	Mean	Mean	Mean	Median
u_t	0.423	0.363	0.369	0.427	0.256	0.179	0.161	0.233	0.571	0.655	0.637
$sales_{t-1}$		0.276					0.104				
Linear time trend	N	N	Y	Y	Y	N	N	Y	N	Y	Y
R^2	0.54	0.60	0.69	0.69	0.54	0.42	0.43	0.45	0.12	0.14	0.24

Notes: Linear regressions of the frequency of sales on the unemployment rate. 'Flag', 'V-shaped' and 'Ref.' refer to the sales filters described in the main text. 'Mean' and 'median' indicate mean and median frequencies respectively. All coefficients are statistically significant at the 1% level using robust standard errors, except for the lag of the dependent variable in the 'US - BLS' panel which is not significant.

Table 4: Panel regression results at the product level

	Sales flag			V-shaped	Ref. price	Alt. macro indicators (normalized)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
u_t	0.407	0.311	0.339	0.427	0.278				
$s_{i,t-1}$			0.203						
u_t (normalized)						0.0050			
Retail sales vol.							-0.0047		
Consumer confidence								-0.0026	
Fin. situation next year									-0.0032
Month dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time trend	N	Y	N	N	N	N	N	N	N
Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-stat	4.67	4.41	47.52	13.73	15.16	4.67	4.91	4.67	4.78

Notes: Panel regressions at the item level: $s_{it} = \alpha_i + \beta u_t + X'_i \Phi + e_{it}$, where s_{it} is a 0/1 sale indicator and u_t is an aggregate business cycle indicator, usually the unemployment rate. For the last panel of the table, the macroeconomic indicators are normalized by their standard deviation to facilitate comparisons. For all regressions, standard errors are clustered at the product category level. All coefficients are statistically significant at the 1% level.

Table 5: Parameterization (benchmark model)

A. Calibrated Parameters			B. Targets (steady state)		
				Data	Model
θ	elast. subst. goods	5	Markup	0.25	0.25
ε_{Ξ}	search cost elasticity	1	Price discount	0.78	0.78
κ	fixed cost of posting discounts *	0.08	Fraction of discounts	0.05	0.05
z_{max}	max fixed search cost *	0.31	Δ Revenue share of sales from $\Delta\gamma=1\text{ppt}$	2.7	2.7
* - in units of time					
C. Assigned Parameters					
	period	1			
β	discount factor	$0.96^{1/12}$			
σ	risk aversion	1			
f	search efficiency	2			
$1/N$	frequency of price changes	1/12			
ρ_{μ}	ser corr of money shock	0			
σ_{μ}	stdev of money shock impulse	0.23			

Table 6: Responses to a negative 1% impulse to money growth (on impact)

	A. Baseline	B. Sticky wages (household)	C. Sticky marginal cost
Avg frac of sales, ppt	1.08	0.93	0.06
Avg discount, ppt	-0.06	0.00	0.00
Wage (households), %	-1.00	-0.08	-1.00
Marginal cost, %	-1.00	-1.00	-0.08
Consumption, %	-0.44	-0.50	-0.94
Frac of bargain hunters, ppt	1.62	1.36	0.09
Avg markup, ppt	0.44	0.50	0.03

Note: Responses are given in the month of the impulse