The Cyclicality of Sales and Aggregate Price Flexibility*

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Abstract

Macroeconomists traditionally ignore temporary price markdowns ("sales") under the assumption that they are unrelated to aggregate phenomena. We revisit this view. First, we provide robust evidence from the U.K. and U.S. CPI micro data that the frequency of sales is strongly countercyclical, as much as doubling during the Great Recession. Second, we build a general equilibrium model in which cyclical sales arise endogenously as retailers try to attract bargain hunters. The calibrated model fits well the business cycle co-movement of sales with consumption and hours worked, and the strong substitution between market work and shopping time documented in the time-use literature. The model predicts that after a monetary contraction, the heightened use of discounts by firms amplifies the fall in the aggregate price level, attenuating by almost 40% the one-year response of real consumption.

Keywords: Price dynamics, Sales, Price index measurement.


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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 and a half, macroeconomists have extensively employed detailed weekly and monthly price data for a broad variety of retail goods to study the implications of retail pricing for aggregate price flexibility.\(^1\) The prevalent view has emerged that retail price discounts do not play a significant role in inflation and business cycle dynamics, and therefore, should be ignored by macroeconomists.\(^2\) In this paper, we revisit this view by providing new evidence from consumer micro price data for the United Kingdom and the United States and developing a model that can account for this evidence.

In the first part of the paper, we provide empirical evidence on variations in the incidence of sales over time based on data for the United Kingdom and the United States. For the United Kingdom, we use the publicly available micro data underlying the consumer price index (CPI) constructed 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 1996 to 2013. We find that the frequency of sales in the United Kingdom is strongly countercyclical: a 1-percentage-point rise in the unemployment rate is associated with a roughly 0.5-percentage-point increase in the fraction of products on sale. For example, during the Great Recession the fraction of sales more than doubled, from 1.7% to 3.7% of observations for our preferred measure of sales. Unlike the fraction of sales, the average size and duration of sales in the United Kingdom are mostly acyclical and much less volatile. For the United States, we use multiple time series constructed from the U.S. CPI micro data going as far back as 1988 and covering three distinct recessions. The similarities with our results for the United Kingdom are evident: we again document a very clear positive co-movement between the incidence of sales and unemployment.

The strong correlation between the business cycle and the use of temporary discounts by firms is highly robust. First, our conclusions are unaffected when we use alternative empirical specifications to adjust for potential serial correlation in the error term or to account for small sample bias. Second, by exploiting detailed micro data for the United Kingdom, we demonstrate that the correlation

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\(^1\)For example, Klenow and Kryvtsov (2008) and 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 (2010) provide an excellent survey of microeconomic evidence on price setting.

\(^2\)Eichenbaum, 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.
is not sensitive to how sales are identified; it applies to both clearance and non-clearance sales; it is common across goods and services, and across regions; and it survives different empirical specifications using multiple controls and alternative macroeconomic indicators. The relationship is also present at a disaggregate level: namely, the frequency of price discounts co-moves negatively with economic activity measures in most CPI categories and in all U.K. regions.

We exploit the cross-sectional dimension of the U.K. dataset to gain additional insights into the characteristics of temporary sales. There is little evidence that sales co-vary with unemployment across U.K. regions, a finding that we attribute to the well-documented use of uniform national pricing strategies by large retailers, which account for the bulk of sales in our dataset. Looking across consumption sectors, we find that more durable goods and sectors with more concentrated businesses tend to have more countercyclical sales, in favor of theories in which retailers compete for market share or in which intertemporal demand effects are present. Discounts for goods with smaller mean absolute sizes of price changes or those with more volatile frequencies of price changes tend to be more countercyclical, in accordance with models featuring fixed costs of price adjustment.

In the second part of the paper, we demonstrate how the cyclical variation in the incidence of sales can significantly impact aggregate price and quantity dynamics at business cycle frequency. To this end, we develop a general equilibrium business cycle model with endogenously cyclical sales. The environment is populated by households who consume products sold by monopolistically competitive retailers in multiple locations. A retailer is a firm that sells a unit measure of perfectly homogeneous brands of the same variety in a specific location, at two different price points: a portion of the brands are sold at the regular price, while the others are discounted. In line with the literature, we assume that regular prices are sticky (Guimaraes and Sheedy, 2011; Kehoe and Midrigan, 2015). The fraction and size of sales, however, are unconstrained.

Every household is composed of shoppers, each responsible for purchasing a single variety. For each variety, the household head is aware of the overall distribution of prices across retailers, and the exact price menu for one specific retailer. Based on this information, she picks a shopper type: a household member can either be a random shopper, who draws a brand of her variety from a random location; or a bargain hunter, who is more likely to find a discounted brand at the retailer she is informed about, but at the cost of more time spent shopping instead of working. In turn, retailers can use sales to attract bargain hunters and increase their market share. This setup produces two important implications for retailers: (1) the two-price strategy dominates posting a single price, and (2) fluctuations in the value of shoppers incentivize variations in the use of sales.

We calibrate our model based on the U.S. data and show that it successfully matches salient
features of retail discounts and search behavior highlighted in the literature, including the prevalence of large but temporary sales ("V-shapes"); significant fluctuations in the average fraction of discounts, and only little variation in their average size; the high elasticity of substitution between hours worked and shopping time documented in studies of time-use surveys (Aguiar and Hurst, 2007; Aguiar, Hurst, and Karabarbounis, 2013); a sensitivity of price savings to shopping time that matches evidence from Aguiar, Hurst, and Karabarbounis (2013); and relative volatilities and correlations between the frequency of sales and aggregate consumption or hours worked that are close to those found in the U.S. data.

The model predicts that in response to an unanticipated monetary contraction, the increases in the fractions of sales and bargain hunters lead to a 12-month fall in real consumption that is 40% less than if sales were absent or constant over time. The reason behind this large difference is intuitive: firms use sales to offset some of the rigidity of regular prices. More specifically, we show that the importance of sale prices for aggregate price flexibility comes from the interaction between the retailers’ price discounting and the households’ search for low prices. At the time of the monetary contraction, most regular 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 by raising the fraction of brands on sale. In turn, more aggressive price discounting by retailers increases the return on time spent searching for low prices, leading to a larger number of bargain hunters. The resulting reallocation of consumption toward lower-priced products amplifies the fall of the aggregate price level. We also show that our conclusions are robust to departures from the baseline calibration.

We conclude that properly accounting for sales can have important ramifications for our assessment of the cyclical behavior of aggregate price and real variables. Macroeconomists who calibrate their models using micro- or macro-level price data without properly accounting for the dynamics of sales may be led to underestimate the degree of aggregate price flexibility and overestimate the fluctuations of real variables over the cycle.

Our paper is closely related to a number of recent studies analyzing the importance of price discounts. On the empirical front, Coibion, Gorodnichenko, and Hong (2015) use a scanner dataset from U.S. grocery stores and provide evidence of consumers switching their spending from high- to low-price retailers during economic slumps. They find that sales for grocery products are acyclical and do not seem to contribute to the effective grocery prices paid by consumers. We exploit additional time series for food and personal care products obtained from the BLS and show that unlike for the majority of products in the BLS basket, the fraction of price discounts for food
exhibits a distinct upward trend and only a weak cyclicality around the trend. Since about three quarters of the grocery data in Coibion, Gorodnichenko, and Hong (2015) come from food products, our findings are consistent with theirs. Our results therefore emphasize that while there are large differences in the degree of cyclicality of sales across products, much of this cyclicality is preserved at the aggregate level.

Anderson et al. (2017) analyze micro price data from a U.S. retailer selling general merchandise and groceries. For this specific retailer, they conclude that sales do not respond to identified wholesale and commodity cost shocks or to changes in local unemployment rates. Unlike Anderson et al. (2017), we focus on the unconditional correlation of sales with the business cycle, and we use the BLS dataset that is representative of all U.S. retailers. When Anderson et al. (2017) consider additional evidence from the BLS micro data, they too find substantial countercyclical time variation in sales. They conclude, however, that time variation in sale prices contributes very little to the variance or cyclicality of inflation, or the response of inflation to an identified monetary policy shock. Our point is related but distinct: we argue that the macroeconomic impact of changes in the frequency of sales accrues over the entire duration of the business cycle, and therefore works via its effect on cumulative inflation, i.e., the price level. In addition, we show that expenditure switching between products priced regularly and at a discount can amplify the response of the aggregate price level during recessions, while dampening the response of consumption. The application of the role of price-level dispersion to variation of consumption-weighted price level and consumption spending is akin to the line taken in Coibion, Gorodnichenko, and Hong (2015). While they focused on consumer switching between high- and low-price-level outlets, we emphasize the consumer switching within outlets, between regular- and sale-price products. The upshot of our work is that the analysis of the full impact of sale prices should not ignore the behavior of consumption spending associated with temporary discounts.

Our work is closely related to two recent studies that have reached different conclusions. 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, they cannot offset persistent aggregate shocks. Guimaraes and Sheedy (2011) reach similar conclusions using a sticky-price model with sales stemming from consumer heterogeneity and incomplete information. In their model, a strong strategic substitutability of sales at the micro level implies that their frequency and size barely respond to monetary shocks. Both models, therefore, predict that the sale margin is not useful for retailers' price adjustment in response to changes in macroeconomic conditions. Yet, our paper shows that introducing a role for price discounts that is compatible with
the empirical evidence in an otherwise standard macroeconomic model has quantitatively important implications for its dynamic properties.

Finally, there are a few recent studies on the cyclical tendency of sales for other countries. The closest paper to ours in scope and findings is Sudo et al. (2018), which looks at the behavior of sales across a wide range of product categories covering around 17\% of households’ consumption expenditures 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. This evidence, while dominated by strong trends in all three series during Japan’s “lost decades,” is very much in line with our findings. Berardi, Gautier, and Bihan (2015), however, find little time variation in sales based on French CPI micro data, a result that may be a reflection of the fact that heavy price discounting is regulated in many EU member states, including France, Belgium, Germany, Greece, Italy and Spain (Freeman et al., 2008). These regulations may significantly limit the extent to which retailers can adjust their prices in response to economic disturbances and diminish households’ ability to rebalance their spending over the business cycle.

The paper is organized as follows. Section 2 describes the data and basic statistics on sales. Sections 3 and 4 document aggregate and disaggregate evidence on the cyclicity of sales for both the United Kingdom and United States. We develop and study the predictions of a general equilibrium model with sales in sections 5 and 6. Section 7 concludes.

2 Data

2.1 Data sources

Throughout the paper, we provide evidence from two sources. Most of it is from the CPI micro dataset of the United Kingdom’s Office for National Statistics. We focus on the U.K. data because they are publicly available, whereas access to CPI micro data in other countries is very limited. 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.\(^3\) We provide below a brief description of the U.K. dataset, while postponing the details to Appendix A.1.

To construct the CPI, the 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. The

\(^3\)U.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.
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. It excludes the housing portion of consumer prices, such as mortgage interest payments, house depreciation, insurance and other house purchase fees. Goods and services in the CPI are classified into classes that represent basic group categories, such as “Meat,” “Garments” or “New Cars”; and each CPI class is divided into finer categories, “items.” For each item and stratum (given by region and shop type pairing in the U.K. data), the ONS dataset provides sampling weights that reflect products’ relative importance in households’ consumption expenditures. These weights exhibit small variation over time due to annual revisions to capture permanent changes in the expenditure composition of households’ consumption baskets. Unless otherwise noted, all weighted statistics are constructed using the CPI consumption expenditure weights.

The sample period in the ONS dataset includes 212 months, from February 1996 till September 2013. We make some adjustments to make the dataset suitable for our analysis. First, we delete observations that are not used for CPI construction 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 dataset contains a total of 20.7 million observations across about 2.3 million unique products, covering about 57% of the U.K. CPI basket. For our empirical analysis we will mostly focus on items that have at least ten price quotes (17.1 million observations).

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 dataset.

First, we apply a V-shaped sales filter on the U.K. data, similar to the one used by Nakamura and Steinsson (2008), among many 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. Under this definition, we do not require the price at the end of the sale to be at or above the price at the beginning of the sale.

Second, for both the United Kingdom and the United States, 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.” 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 some adjustments. For example, there
are a few instances in which the occurrence of a sales flag is accompanied by zero change in the posted price, or even, in some rare instances, by 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.\footnote{To 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. Also, for discounted prices to be recorded by ONS agents, they 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). Hence, our estimates of the incidence of sales using this filter are most likely conservative.} For both the V-shaped and sales-flag filters, the unobserved regular price during a sale is assumed to be equal to the last observed regular price.\footnote{If 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. We 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.}

Finally, we compute a reference price similar to one in Eichenbaum, Jaimovich, and Rebelo (2011), using a seven-month window. 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 or a 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.

### 2.3 Basic statistics

In Table 1 we report some basic statistics on price dynamics in our dataset. Unless otherwise stated, all moments are weighted using the official CPI weights. The fraction of price changes is 15.8% over the sample period, and the average size of a price change is 11.9% in absolute terms. Price increases are more likely than price decreases (9.8% vs 6.0% 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 10.9%, 13.2% and 7.5%, based on the V-shaped, sales flag, 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.\footnote{See, for example, Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) for the United States, and Alvarez et al. (2006) for Europe.}

Table 2 reports several basic statistics for sales. The first row shows that the frequency of sales varies significantly depending on the definition used, from 2.9% for the ONS sales flag to 5.2% for the sales based on the reference price filter.\footnote{Though 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.} Differences are also visible for both the mean and median sale sizes: they are much higher for the sales flag (between 20% and 22%) than the three other filters (between 8% and 14%).

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 dataset. The discount size in a given month is given by (the absolute value of) the difference between log sale price and log regular prices in that month. We set the bound of the histogram at 60%, since larger sales are rare. Reassuringly, there are 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 suggests 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, summary statistics are very similar across filters, as can be seen from the bottom portion of Table 2: the frequency of sales is equal to 2.3% for all three, and the size statistics are much more comparable.

## 3 Aggregate time-series behavior of sales

We now turn our attention to the main objective of our empirical work and study the aggregate behavior of temporary sales over time.

### 3.1 Evidence from the United Kingdom

First, we look at the behavior of the frequency of sales over the 1996:02–2013:09 period in the United Kingdom. For each category and month, we compute the proportion of items with a sale of at least 10% as identified by the V-shaped filter, 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 for
civilians aged 16 and over. Because of the strong seasonal patterns of sales, we also report on the right-hand 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 2.5% at the beginning of the sample in 1997, then declines to a trough of about 1.6% in 2006 before rising back to about 3.7% 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 a time trend that may bias our conclusions; we formally control for this potential issue in our regression analysis.

Figure 3 compares the evidence from the V-shaped sales filter to that of the sales flag and reference-price filters described earlier. First, the top-right panel demonstrates that aggregate sales frequency is not cyclical because of larger weights on sales-heavy items during recessions: using time-invariant CPI weights makes no noticeable difference. Second, overall patterns are very similar across sales filters: all give rise to a highly cyclical sales frequency.

Conceivably, retailers could use different sales-related margins in response to aggregate shocks. First, the cyclicality of the fraction of products on sale could be driven by fluctuations in the incidence of new sales and 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 sale spells remained very stable around 1.6 months over our sample period, with no discernible cyclicality or trend.8

Second, retailers could vary the size of price discounts over the business cycle. Figure 4 shows the evolution over our sample period of the average absolute size of sales, conditioning on sales of at least 10%. Under the three definitions, there is a noticeable increase in the absolute size of sales over the sample period. Nonetheless, in relative terms, the 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 fluctuates between roughly 22% and 25%. But most importantly, there is no clear cyclical pattern for this margin of adjustment: at the height of the Great Recession, sales tended to become a little smaller based on the sales flag filter, but slightly larger according to the other two definitions.9

3.2 Evidence from the United States

We next ask whether the strong countercyclicality of sales is also present in the United States. We have obtained evidence from the U.S. Bureau of Labor Statistics CPI micro data via three sources. First, the BLS provided us with the monthly fraction of items with a sales flag from January 2000

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8 The monthly frequency of our data may hinder identification of changes in the average duration of sales.

9 Our findings are unchanged if we consider sales of all sizes instead of focusing on a 10% threshold for the size of sales.
to May 2014, unweighted and weighted using the CPI expenditure weights used by BLS.\textsuperscript{10} The weighted time series, smoothed out using a 12-month centered moving average, is presented in the top left-hand plot of Figure 5, alongside the U.S. civilian unemployment rate over the same period. 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 frequency of sales in the midst of the 2001 and 2008–09 recessions.

Second, the top right-hand plot in Figure 5 depicts a series derived from Vavra (2014). For his analysis, Vavra filtered out both temporary sales and product substitutions to focus on regular prices.\textsuperscript{11} Despite the fact that the series is somewhat more volatile, possibly due to the behavior of substitutions, the results visually appear to confirm our the findings based on the data provided directly by the BLS. Moreover, Vavra’s series spans 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.

Third, the bottom-left plot in Figure 5 replicates the series from Figure A.2 in the appendix for Anderson et al. (2017) (hereafter, AMNSS).\textsuperscript{12} The underlying micro data is also taken from the BLS CPI database, and the series span the period 1988 to 2014. The figure compares three alternative measures of the aggregate frequency of sales. The series closest to ours is constructed by taking the weighted mean of the frequency of the sales flag, using the weights from the BLS ("BLS weights, Sales flag"). The series used by AMNSS is constructed using fixed category-level weights, using a refined definition of sales, and by dropping observations that are out-of-season, do not have a lagged regular price, or have a discount that is larger than an 80% ("Fixed weights"). The third line provides an intermediate case with variable BLS weights and AMNSS’ preferred sales measure ("BLS weights").\textsuperscript{13} While some of the time series exhibit a pronounced upward trend, the countercyclical pattern is shared by all: for every series, the frequency of sales rises in the wake of recessions and falls during recoveries. The only exception is the fixed-weights series, which seems to “miss” the recovery following the recession in the early 1990s.\textsuperscript{14} This pattern is confirmed if we

\textsuperscript{10}We are grateful to Brendan Williams and the BLS for providing these series to us. BLS computes the weights for each area–item stratum based on Consumer Expenditure Surveys; these weights are updated monthly as price indexes are calculated.

\textsuperscript{11}Vavra uses a joint sales-flag and 3-month V-shaped filter to extract sales. He kindly provided us with the time series for the combined frequency of sales and substitutions.

\textsuperscript{12}AMNSS express the frequency of sales as changes relative to 2001. We do not apply this normalization.

\textsuperscript{13}We thank Ben Malin for clarifying how these series were constructed and for sharing the replication materials for Anderson et al. (2017). See Appendix A in their paper for further details.

\textsuperscript{14}Anderson et al. (2017) focus on fixed weights in an attempt to isolate the use of temporary sales by the seller of the product, leaving aside a possible shift in expenditure shares due to the consumer response to sales. Fixing
focus on the cyclical component of the time series: the last plot (bottom right) of Figure 5 depicts the same sales and unemployment series from AMNSS once they have been detrended using a Hodrick-Prescott filter with the smoothing parameter set at 129,600.

All BLS series unequivocally point toward a strong countercyclicality of price discounts. Nonetheless, AMNSS conclude that time variation in sale prices contributes very little to the variance or cyclicality of inflation, or its response to an identified monetary policy shock. This may be explained by the fact that inflation fluctuations over this period are quite transient, while sales exhibit business-cycle-like persistence. Hence, the macroeconomic impact of changes in the frequency of sales accrues over the entire duration of the business cycle, and therefore works via its effect on the cumulative inflation, i.e., the price level. Our subsequent analysis using a quantitative general equilibrium model with sales in Sections 5 and 6 to confirm this intuition. In addition, we show in Section 6.3 that expenditure switching between products priced regularly and at a discount can amplify the response of prices to recessions while dampening the response of consumption, a margin not accounted for by standard CPI indices.

The application of the role of price-level dispersion to variation of consumption-weighted price level and consumption spending is akin to the line taken in Coibion, Gorodnichenko, and Hong (2015), henceforth CGH. They use the Symphony IRI scanner dataset, which covers multiple grocery stores in 50 U.S. metropolitan areas over the 2001–11 sample period. CGH 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 panel regressions. Instead, CGH document substantial consumer switching from high- to low-price-level outlets during region-specific slumps, amplifying the decline of the consumption-weighted price level.

We reconcile our findings by observing that the U.S. grocery products studied by CGH display a different behavior than most consumption products. We obtained from the Bureau of Labor Statistics the frequency of sales for food from the CPI micro data, both weighted and unweighted. Figure 6 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 the BLS sample and only food—the frequency of sales exhibits rapid increases in the wake of the 2001 and 2008–09 recessions. However, as the U.S. unemployment rate declines in the middle

the weights, however, may create an upward drift in the weighted mean sales frequency if there is a gradual shift of consumption toward sectors with more price discounts and more flexible prices. Moreover, since such sectors tend to be the sectors with more cyclical sales, the cyclicality of the aggregate time series around the trend would also be reduced. Finally, we argue later in the paper that the response of consumers should not be ignored if one is interested in assessing the role of sales for aggregate price and output dynamics.
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 Appendix A.2 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.\textsuperscript{15}

In all, CGH focused on consumer switching between high- and low-price-level outlets, while we emphasize the consumer switching within outlets, between regular- and sale-price products. The upshot from both studies is that the analysis of the full impact of sale prices should not ignore the behavior of consumption spending associated with sales.

3.3 Regression analysis and robustness

In the previous two sections, we have shown that for both the United Kingdom and the United States, and at least since the late 1980s, sales exhibit a clear countercyclical pattern. Next, we turn to a regression analysis to verify that this graphical evidence is statistically significant and robust. As a starting point, we run OLS time-series regressions for the U.K. (all three sales filters) and the U.S. (BLS, Vavra and AMNSS) time series, using the following empirical specification:

\[ \gamma_t = \alpha + \beta u_t + X_t'\Phi + \text{error}, \]

where \( \gamma_t \) is the fraction of sales in month \( t \), \( u_t \) is an aggregate business cycle indicator, usually the unemployment rate, and \( X_t \) is a set of controls, which includes calendar month dummies and also a linear time trend or a lagged sales frequency. For every regression involving sales in Table 3, the coefficient on the unemployment rate is statistically significant at the 1\% level, even if we include a time trend or one lag of the dependent variable. The elasticity of the frequency of sales to fluctuations in the unemployment rate is higher in the United Kingdom than in the United States, varying between 0.358 and 0.544, depending on the measure of mean sales frequency and whether or not the trend is included (Panel A in Table 3). These effects are economically large: for example, a 5-percentage-point (ppt) increase in the unemployment rate is associated with a 2.7-ppt higher probability of observing a V-shaped sale, which is more than double the unconditional sales frequency of 2.3\%. When we use the median instead of mean sales frequency across sectors (last two columns of Panel A), conclusions are unaffected: the coefficients are lower but so are the unconditional frequencies, at about 1.5\%.

\textsuperscript{15}In an earlier version of their paper, CGH report category-level results and find a significant positive relationship between sales frequency and unemployment for personal care products in their dataset. 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.
For the United States, this elasticity in the regression without the trend is 0.177 in our sample, and it is 0.067, 0.151 and 0.219 for the AMNSS series (Panels B and C in Table 3). The elasticities are somewhat higher for the Vavra series, possibly reflecting a cyclical pattern in product substitutions. Including a linear time trend in the set of regression controls increases the estimated elasticity in our sample to 0.233, but reduces it in AMNSS’ longer sample to 0.035, 0.073, and 0.152. Given the high persistence of both the sales frequency and unemployment series, it is worth us checking the results using alternative detrending methods. Panel C in Table 3 provides the results for the series detrended with the Hodrick-Prescott filter. The resulting elasticities are not only higher, but also much more similar in magnitude: 0.177, 0.171, and 0.166. In Appendix A.3, we also document the countercyclicality of sales frequency using other business cycle indicators, such as hours worked and real consumption expenditures.

Since the sales and unemployment series are quite persistent and the sample periods include a limited number of complete business cycles, we compute alternative standard errors that are robust to potential misspecifications of the base OLS empirical model. In addition to robust, Cochrane-Orcutt, and Newey-West standard errors, we conduct a non-parametric bootstrap exercise to correct for any potential small sample bias in addition to serial correlation of the residuals. In Appendix A.4, we provide details of the implementation of the bootstrap procedure and report the alternative standard errors alongside the point estimates and OLS standard errors that were provided in Table 3. All alternative specifications yield highly significant results, except for one case with statistical significance at the 10% level.

We complete the aggregate analysis by investigating regular price changes. First, we explore whether the frequency of sales correlates with the frequency of changes in regular prices: retailers may use sales in conjunction with other margins of price adjustments, for example, to offset customers’ response to longer-lived regular price increases. The results in Table 4 indicate that the coefficient on the unemployment rate remains mostly unaffected by the inclusion of the frequency of regular price changes. Only for Vavra’s U.S. time series do we find a significant relationship between the frequencies of regular price changes and sales, beyond the impact of the unemployment rate. Nonetheless, this does not alter our finding about the cyclicality of sales, and the coefficients on the unemployment rate are even larger in this case than the coefficients reported in Table 3.

Second, we directly investigate the cyclicality of regular price changes. We find that a 5-ppt increase in the unemployment rate is associated with a 3-ppt higher probability of observing a change 16.

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16The results shown Table 4 are based on the sales flag filter; they hold for the other two definitions of sales or if we use lagged values.
in the regular price based on the V-shaped filter, compared to an unconditional frequency of 10.9% (see bottom panel of Table 4). The corresponding effect for reference prices is 1.5 ppt (unconditional frequency of 7.5%). When we use the sales flag, the effects of unemployment on regular or reference prices are not statistically significant. The variation of regular price changes, while not negligible, is smaller than for sales frequency: we found earlier that a similar unemployment rate hike about doubled the incidence of sales. The empirical fit is also lower based on the $R^2$. Conclusions are similar for the United States and in line with the findings of Vavra (2014).

4 Disaggregate evidence

Next, we investigate the robustness of our findings at a more disaggregated level. In the process, we document some other salient features of temporary sales in the data.

4.1 Category- and region-level results

We start by verifying that the aggregate relationship we found earlier is present at the category and regional level.

Cyclicality of sales across product categories. As a first exercise, we verify that the cyclicality of aggregated V-shaped sales is not merely driven by a few large categories and is in fact widespread across product types. We run separate regressions of sales frequency on the unemployment rate and a time trend for the 36 U.K. CPI categories with data for the whole sample and an average frequency of sales of at least 0.5%. The top row of Figure 7 shows histograms of the regression coefficients on the unemployment rate at the category level, for both the V-shaped (left column) and sales flag (right column) filters. They confirm that the countercyclicality of sales is reasonably broad based: out of 36 categories, only two have a negative coefficient for both filters, and neither is statistically significant based on Newey-West standard errors. Of the 34 for which the coefficient on unemployment is positive, 26 are significant at the 5% level for the V-shaped sales filter, with a mean and median of 0.81 and 0.71 respectively.\footnote{Figure A.1 in Appendix A.5 visualizes time series for selected categories.}

We also use real consumption at the category level instead of aggregate unemployment. Because the data is only available at the quarterly frequency, we aggregate the fraction of items on sale accordingly. We then run regressions of category-specific sales frequency on the category-specific log of real consumption and a linear trend. The distribution of coefficients on consumption is
reported in the bottom panel of Figure 7. Once again, sales are countercyclical for most sectors (29 out of 36 for V-shaped sales), with a mean and median of –0.004 and –0.003 respectively.

**Cyclicality and category characteristics.** In addition, we explore how the category-level cyclicality of sales changes with observed category characteristics and pricing behavior, including the data on life expectancy for durable goods, obtained from Bils and Klenow (1998) for the United States; 5-firm concentration ratios for the United Kingdom in 2004 from Mahajan (2006); and category-specific moments for price-adjustment variables (inflation, frequency of price changes, and absolute size of price changes; their means and standard deviations over time, using posted and regular prices); see Appendix A.6 for more details.

We find that more durable goods and goods with more concentrated businesses tend to have more countercyclical sales, although these correlations are relatively weak due to the small number of observations for which we matched the data for durability (12) and concentration ratios (29). Theories in which retailers compete for market share or in which intertemporal demand effects are present would be favored by such evidence (e.g., Hendel and Nevo, 2006).

In regressions on price-adjustment moments, two of them result in significant correlations across categories. Discounts for goods with smaller mean absolute sizes of price changes or those with more volatile frequencies of price changes (for either posted or regular prices) tend to be more countercyclical. This evidence is consistent with predictions of models with fixed costs of price adjustment, in which goods with smaller fixed costs and more flexible price adjustment, and in particular, more frequent sales, would need smaller price changes on average.

**Cyclicality of sales at the regional level.** Next, we verify whether the cyclicality of sales is present across U.K. regions. To do so, we regress the frequency of V-shaped sales on the monthly regional unemployment rate and a time trend. The coefficients from these regressions are plotted in Figure 8. The frequency of temporary discounts is significantly countercyclical for all 11 regions. The strongest relationship is for East Anglia: a 5-ppt increase in the unemployment rate is associated with a 2.8-ppt increase in the sales frequency, or more than double its unconditional mean. The weakest, on the other hand, is the North, at about 40% of the size. These differences in estimates are directly related to the fact that while the frequency of sales is very similar across regions, unemployment rates vary much more. Additional region-level results can be found in Appendix A.7. In Section 4.3, we discuss how uniform national pricing strategies by large retailers can rationalize this finding.

**The role of clearance sales.** Finally, we investigate whether the cyclicality of temporary discounts
is driven by the higher occurrence of clearance sales during recessions relative to booms, possibly as firms are left with unsold inventories. To this end, we compute the probability of observing a sales flag within the last two months of a quote line.\footnote{We find that in a typical month, clearance sales are much rarer (average probability of 0.7\%) than non-clearance sales (3.5\%). This is mainly due to the fact that clearance sales can only occur at the end of a quote line; clearance sales in fact account for about 8.2\% of price observations within the last two months of a quote line. In other words, while markdowns are particularly frequent towards the end of the life of a typical product, these clearance sales account for only about one sixth of all sales in the sample.} We find that in a typical month, clearance sales are much rarer (average probability of 0.7\%) than non-clearance sales (3.5\%). This is mainly due to the fact that clearance sales can only occur at the end of a quote line; clearance sales in fact account for about 8.2\% of price observations within the last two months of a quote line. In other words, while markdowns are particularly frequent towards the end of the life of a typical product, these clearance sales account for only about one sixth of all sales in the sample.

Figure 9 plots the time series of both clearance and non-clearance sales for the aggregate as well as three broad categories. There are wide differences in the prevalence of sales across product categories. For Clothing and Footwear, 18\% of the observations in the last two months are flagged as sales by the ONS, compared to a frequency of around 8\% for other periods, while the same numbers are 25\% and 13\% respectively for Audio and Video. Food products, on the other hand, do not display more sales towards the end of quote lines. Second, for the aggregate as well as the three broad categories, Figure 9 indicates that the frequency of both clearance and non-clearance sales follow the same countercyclical pattern that we documented earlier. In sum, the cyclicality of overall temporary discounts does not appear to be driven by clearance sales.

\subsection*{4.2 Product-level results}

To control for composition bias as well as additional factors that may affect our conclusions, we supplement our analysis with a panel regression analysis at the product-store level. The dependent variable is the sale indicator $\gamma_{ijt}$, which is equal to 1 if product $i$ at store $j$ is on sale at time $t$, and 0 otherwise. We run linear probability models (LPM) in order to exploit the panel structure of our dataset and include product-store fixed effects; including a large number of fixed effects with a nonlinear method such as probit would expose us to bias caused by the incidental parameters problem.\footnote{In Table A.8 in Appendix A.9, we compare the predictions from our benchmark LPM with product-store fixed effects (first column) to LPM, probit and logit regressions with category and region dummies only. We find that the predicted sales frequencies are very comparable across specifications for a plausible range of unemployment rates (between 4\% and 10\%), indicating that the estimated marginal effects are close to linear. This comforts us in our use of linear probability models.}
The basic specification is standard and given by

$$\gamma_{ijt} = \alpha_{ij} + \beta u_t + X_t' \Phi + error,$$

where $u_t$ 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. Table 5 summarizes our results. The unemployment rate is a statistically significant predictor of the occurrence of a temporary sale: a 5-ppt increase in the unemployment rate raises the likelihood of observing a sale by about 2.2 ppt. Adding a time trend or one lag of the dependent variable has little effect on the economic or statistical significance of this relationship. The results are also robust to the use of the two other definitions of sales.

We also verify that our findings are robust to the use of alternative business cycle indicators in equation 1 instead of $u_t$. 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 faced by 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 5 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 ppt in the frequency of sales, and that increase is around 0.5 ppt for a one-standard deviation increase (decrease) in the unemployment rate (retail sales volume).\(^\text{20}\)

### 4.3 Sales across stores and space

Finally, we discuss the characteristics of sales in the cross-section, focusing on retailer type and regions.

**Retailer type.** For each price quote, the ONS provides both a store identifier and a flag indicating whether the store belongs to an independent retailer (less than 10 locations) or a chain (10 locations or more), a category labeled “Multiples” by the ONS. Chains account for about 64% of

\(^{20}\)As a point of reference, the unemployment rate during the 2007–09 recession rose by a magnitude of four standard deviations.
observations and 55% of CPI weights. We find striking differences between the incidence of discounts for both types of stores: sales are much more prevalent and volatile for larger retailers than for smaller retailers, for both the V-shaped and sales flag filters (see Appendix A.10). For example, using V-shaped sales and CPI weights, the average frequencies are 3.4% for multiples and 1% for independents (4.5% and 1.5% unweighted), while the time series standard deviations are 1.3% and 0.5% respectively. Moreover, there is some evidence that sales are more cyclical for larger retailers.

Our finding that sales are much more prevalent at large chains could be an indication that there are non-trivial costs and scale effects associated with store discounts. Some of these costs may be monetary, such as the production of displays and flyers or the adoption of specific sales-optimization technologies, but they could also be managerial. For example, it is well known that in some sectors, temporary sales are often negotiated between the retailer and the manufacturer; Anderson et al. (2017), for example, highlight the role of “trade deal budgets” and “trade promotion calendars”. If this coordination is costly, smaller retailers may limit their use, and suppliers may be less inclined to design and finance promotions with independent stores than large retailers. Alternatively, there may be economies of scale in the benefits from temporary sales. For example, consider that retailers use discounted products as loss leaders, in the hope that consumers will also buy other products at higher prices. The benefits from such a strategy are likely to be more limited at smaller stores with less product variety.

**Sales and local economic conditions.** Despite our very robust time-series evidence, we did not find any significant relationship between sales and economic conditions across U.K. regions. In fact, as we discussed in Section 4.1, there is very little regional variation in the frequency of sales. This is in line with the evidence from Anderson et al. (2017) and Coibion, Gorodnichenko, and Hong (2015), who do not find evidence of economic variation in sales in the U.S. cross-section data.21

Combined with our finding that larger chains account for a disproportionate fraction of discounts, the documented widespread use of uniform pricing may rationalize these findings. Dobson and Waterson (2008) document that since the early 2000s, “the major retailers [...] have eschewed the opportunity to customize prices on a store-by-store basis in favor of national pricing.” In addition, Freeman et al. (2008) provide evidence that the largest UK chains with the most widespread store network, such as Tesco, Sainsbury’s and Asda, run local price discounts based on centrally determined criteria or as part of national promotional programs.

21An additional explanation is provided in Gagnon, López-Salido, and Sockin (2017), who point out that the methodology in Coibion, Gorodnichenko, and Hong (2015) relies on aggressive censoring of price adjustments and a treatment for missing observations that can leave out some of the price variation, and that their results are highly sensitive to alternative measurement approaches.
Uniform pricing is also ubiquitous in the United States. DellaVigna and Gentzkow (2019), for example, find that for a typical U.S. product in a given week, retail chains post almost uniform prices across all their stores, irrespective of local differences in household income. Looking at evidence from a representative chain in the Nielsen dataset, they “[...] see variation across products in the depth and timing of sales, but again no systematic variation in prices across stores [within the chain].” This is in line with the evidence in Hitsch, Hortacsu, and Lin (2019), who find that “the incidence of price promotions is strongly coordinated within retail chains, both at the local market level and nationally”. Nakamura, Nakamura, and Nakamura (2011) study the Symphony IRI scanner dataset and conclude that a large portion of the variation in the use of sales across stores is due to chain-level heterogeneity. In the context of home improvement stores, Adams and Williams (2019) document a lot of heterogeneity across products, with a mix of uniform and zone pricing.

All in all, in a market dominated by large national chains with uniform pricing strategies, we should therefore not be surprised to find that sales are more reflective of aggregate than local economic conditions.\footnote{Unfortunately, data limitations do not allow us to test rigorously for the presence of uniform pricing the same way as in DellaVigna and Gentzkow (2019): the U.K. CPI dataset does not include chain identifiers that would allow us to link stores.} Possible reasons behind such pricing strategy are numerous, even if direct evidence is relatively scarce in the literature. Based on empirical estimates, Hitsch, Hortacsu, and Lin (2019) suggest that “demand similarity and the inability to distinguish demand across the stores in a local market are likely the primary reason for the similarity in prices and promotions”, which would explain why managers view local pricing as difficult to implement in practice. Similarly, DellaVigna and Gentzkow (2019) “suspect that managerial inertia may be the most important explanation for uniform pricing.” Responses indicate that this inertia may arise from the limited sophistication of pricing teams and organizational barriers at the store level, or rational inattention: faced with limited resources and scarce attention, chains decide to optimize along other dimensions (such as overall sales patterns and price levels). They also highlight brand image concerns: if consumers see different prices across stores as unfair, this may hurt profits in the long run. Faced with these constraints, it may seem that a natural alternative would be for the chain to defer all pricing decisions, including promotions, to store managers. As Adams and Williams (2019) show, however, this can give rise to large losses as individual stores fail to internalize the impact of their pricing decisions on other stores from the same chain.
5 A general equilibrium model with sales

To understand the dynamics of temporary sales and their importance for aggregate fluctuations, we build a general equilibrium business cycle model in which discounts arise endogenously. In order to simplify the exposition, we focus in this section on the key non-standard features of the model, relegating the presentation of the full framework to Appendix B. In addition, we provide in Figure 10 a graphical representation of the most important components of the model. We encourage the reader to refer to it while going through the textual exposition.

5.1 Static shopping-time problem

The economy is populated with a measure $L$ of infinitely-lived ex-ante identical households who shop for and consume products of $J$ differentiated varieties; work in a monopolistically competitive labor market; and trade money, state-contingent securities and nominal bonds. We assume that the household’s disutility from shopping time is additively separable from the utility derived from consumption and hours worked, which allows us to solve the household’s shopping time problem in a static setting. Each household is composed of a household head, who is the decision maker, as well as shoppers. Each shopper is in charge of shopping for a specific variety and is indexed accordingly by $j$. At the beginning of each period, the household head deposits its cash $M$ in a checking account and gives each shopper a debit card to pay for their purchases. In this section, we abstract from the household subscript.

**Products and prices.** The product space is defined by three dimensions: locations, varieties and brands. There are $L$ shopping locations, and all varieties can be found in every location. For a specific variety $j$ in location $l$, there is a continuum of perfectly substitutable brands, all produced by a single retail firm. These dimensions, as well as many of the model features that are discussed next, are represented in the diagram of Figure 10.

The retail firm selling variety $j$ in location $l$ is not able to differentiate among shoppers. For simplicity, we assume that it can choose only two price points for its brands: a fraction $\gamma_{j,l}$ of brands are at the discounted price $P_{j,l}^L$, while the remaining fraction, $1 - \gamma_{j,l}$, are priced at $P_{j,l}^H$, where $P_{j,l}^H \geq P_{j,l}^L$.\(^{23}\)

\(^{23}\)This assumption is in line with Klenow and Malin (2010) and Stevens (2019), who show that individual prices often follow pricing regimes with only a few price points. There is an extensive 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) or Varian (1980). Burdett and Judd (1983) analyze equilibrium price dispersion with many price points. Alvarez and Lippi (2019) argue that when firms can choose a 2-point “price plan” that allows them to deviate temporarily from the sticky reference price, the flexibility of the aggregate price increases significantly.
**Price information.** For each variety, the household head knows the distribution of prices across locations. In addition, for one random location, denoted by \( l^* \), she learns about the price “menu” it offers: \( P_{j,l^*}^H \), \( P_{j,l^*}^L \) and \( \gamma_{j,l^*} \). How she learns about this specific location is unimportant: it could be the result of an internet search, the arrival of a flyer, word of mouth, or even specific knowledge about pricing at the neighborhood store.\(^{24}\) What is important is that for each variety, she is informed about a single location, and that this information is dispersed uniformly across varieties and households. This feature will allow firms to attract shoppers while keeping the model tractable.

**Matching shoppers and retailers.** A shopper for a specific variety can be one of two types: *bargain hunter* or *random shopper*. These two types differ in their ability to find low prices:

- A random shopper \( j \) does not observe the specific prices posted by retailers, so she randomly visits a location \( l \), goes to the store selling variety \( j \) and picks a brand at random, i.e., she draws a brand priced at \( P_{j,l}^L \) with probability \( \gamma_{j,l} \) or at \( P_{j,l}^H \) with probability \( 1 - \gamma_{j,l} \).

- A bargain hunter visits the location for which information was obtained, \( l^* \). Equipped with this information, she generates a higher probability of drawing a brand with a low price \( P_{j,l^*}^L \), \( f \gamma_{j,l^*} \), where by assumption \( f > 1 \). She then has a lower probability of finding \( P_{j,l^*}^H \), \( 1 - f \gamma_{j,l^*} \).

Bargain hunters yield higher returns from shopping because they are more likely to find a low-priced brand from a given retailer. They, however, cost the household \( z \) in units of time, where \( z \) is i.i.d. across shoppers and time.

**Consumption outcomes.** Given two possible types of shoppers and two price points, there are four possible consumption outcomes for each variety: the bargain hunters who find a brand for a low (high) price purchase \( c_{j,l^*}^L \) (\( c_{j,l^*}^H \)) units of that brand, while random shoppers buy \( c_{j,l}^L \) (\( c_{j,l}^H \)) units.\(^{25}\) Let \( I [X] \) be the indicator for four mutually exclusive consumption outcomes: \( X = \{ BL, BH, RL, RH \} \), where the first letter indicates the shopper type and the second the price drawn. The *ex post* consumption of variety \( j \) is therefore

\[
    c_j = I [BL] c_{j,l^*}^L + I [BH] c_{j,l^*}^H + I [RL] c_{j,l}^L + I [RH] c_{j,l}^H.
\]

**Decision rule for shopper type.** Upon receiving information about the overall distribution

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\(^{24}\) Kaplan and Menzio (2015) document that households concentrate their shopping on only a small number of stores per quarter.

\(^{25}\) Since consumption goods are perishable, bargain hunters cannot stock up on discounted goods. Therefore, our model does not incorporate strategic discounts by firms nor large cross-brand substitutions by consumers. Chevalier and Kashyap (2019) provide a model in which price-sensitive consumers have only infrequent shopping opportunities but can stockpile purchased goods to smooth consumption over time.
of prices for variety $j$ as well as specific prices at location $l^*$, the household head decides the shopper’s type. This decision takes a form of a cut-off rule: the household head chooses a value $z^*_j$ such that member $j$ is designated as bargain hunter for low realizations of the shopping costs, $z_j \leq z^*_j$, and as random shopper when the shopping cost is too high, $z_j > z^*_j$. The choice of $z^*_j$ determines the probability that variety $j$ will be purchased by a bargain hunter, which we denote by $\alpha_j(z^*_j)$. This probability function depends on the distribution of the fixed cost $z$, $G(z)$. The associated expected shopping cost in terms of forgone hours worked for variety $j$ can be expressed as $\Xi(\alpha_j) = \int_0^{G^{-1}(\alpha_j)} z dG(z)$.

**Aggregate consumption.** Aggregate ex post consumption is the CES aggregate $c = \left[ \sum_j c_j^{1-\theta} \right]^{\frac{\theta}{\theta-1}}$, where $\theta$ is the elasticity of substitution across varieties. Since the realizations of the search costs are independent across varieties, and shoppers are matched independently with retailers, then by the law of large numbers ex post consumption is equal to ex ante consumption

$$c = \left\{ \sum_j \left[ \alpha_j \left( \gamma_j \left( c_{L,j}^{1-\frac{1}{\theta}} + (1-\gamma_j) c_{H,j}^{1-\frac{1}{\theta}} \right) \right) \right] + (1-\alpha_j) L^{-1} \sum_l \left( \gamma_{j,l} \left( c_{L,j,l}^{1-\frac{1}{\theta}} + (1-\gamma_{j,l}) c_{H,j,l}^{1-\frac{1}{\theta}} \right) \right) \right\}^{\frac{\theta}{\theta-1}},$$

(3)

where each of the four possible consumption outcomes for variety $j$ contributes with its respective probability, and $L^{-1} \sum_l$ denotes the mean across locations.\footnote{A similar aggregation result is also derived in Guimaraes and Sheedy (2011).}

Similarly, denoting by $P$ the price of the consumption bundle $c$; by $X^B_j$ the expected consumption spending by a bargain hunter, $X^B_j = f_{\gamma_j, l^*} P_{L,j}^{L_{j,l^*}} c_{L,j,l^*} + (1-f_{\gamma_j, l^*}) P_{H,j}^{H_{j,l^*}} c_{H,j,l^*}$; and by $X^R_j$ the expected spending of a random shopper, $X^R_j = L^{-1} \sum_l \left( \gamma_{j,l} P_{L,j,l}^{L_{j,l}} c_{L,j,l} + (1-\gamma_{j,l}) P_{H,j,l}^{H_{j,l}} c_{H,j,l} \right)$, total consumption spending can be written as

$$Pc = \sum_j \left\{ \alpha_j X^B_j + (1-\alpha_j) X^R_j \right\}.$$

(4)

**Household optimality conditions.** The households’ search problem in each period is to minimize expected spending on consumption as well as the cost of bargain hunting, where the price of shopping time is the market wage:

$$\min_{\{\alpha_j, c_{L,j}^L, c_{L,j}^H, c_{H,j}^L, c_{H,j}^H\}} \{Pc + W \sum_j \Xi(\alpha_j)\},$$

subject to standard budget and cash-in-advance constraints.
The first-order conditions for consumption varieties yield standard CES demand schedules,

\[ c_{j,l}^k = \left( \frac{P_{j,l}^k}{P} \right)^{-\theta} c, \quad \text{and} \quad c_{j,l}^* = \left( \frac{P_{j,l}^*}{P} \right)^{-\theta} c, \quad k = \{L, H\}. \tag{6} \]

Note that demand does not depend on the type of shopper or the location of the retailer: a bargain hunter and a random shopper who draw the same price will purchase the same quantity.

The first-order condition for the probability of bargain hunting for variety \( j \), \( \alpha_j \), is given by

\[ \frac{\Delta x_j}{z_j} = \frac{W}{P}, \tag{7} \]

where \( \Delta x_j = \frac{1}{\theta - 1} \left( X_j^B - L^{-1} \sum_l X_{j,l}^R \right) / P \) is the return on shopping in consumption units, which is increasing in the fraction and size of discounts. According to condition \( (7) \), households choose their shopping time to equate the marginal rate of transformation of time for consumption, \( \frac{\Delta x_j}{z_j} \), to the price of time, \( \frac{W}{P} \). Therefore, condition \( (7) \) implies that the household’s optimal choice of shopping time is increasing with the use and magnitude of sales. The endogeneity of the shopping effort is the crucial difference from Guimaraes and Sheedy (2011), who assume a constant fraction of bargain hunters. We demonstrate below that the interaction of households’ search for lower prices and retailers’ decisions for setting those prices can account for the behavior of sales documented in the empirical part of the paper.

### 5.2 Production and pricing of consumption brands

There are two types of firms in our model: intermediate good producers and retailers. A continuum of competitive intermediate good firms own and invest in capital stock, hire labor and produce a homogeneous good using a Cobb-Douglas technology. The homogeneous good is sold to other intermediate good firms in order to augment their capital stock, and to retail firms for producing consumption varieties. Each retail firm converts the homogeneous good into a continuum of perfectly substitutable brands of specific variety \( j \). All varieties are sold to households in a monopolistically competitive market in each of \( L \) locations.

Let \( \alpha_{j,l,t}^B \) and \( \alpha_{j,l,t}^R \) denote the fractions of bargain hunters and random shoppers buying from the retailer selling variety \( j \) in location \( l \). The mass of bargain hunters visiting the retailer is derived from the set of households who know about its prices, which we denote by \( \Psi_{j,l,t} \), and is given by

\[ \alpha_{j,l,t}^B = \int_{i \in \Psi_{j,l,t}} \alpha_{i,j,t} di = \alpha_{j,l,t}, \tag{8} \]
where we introduced a household identifier $i$ to clarify the exposition. The last equality stems from two features of the model. First, since there is a measure $L$ of households and $L$ retailers for a specific variety, and because households are matched uniformly across locations, $\Psi_{j,l,t}$ is measure 1. Second, all bargain hunters visiting the same retailer have the same information and therefore choose the same cut-off rule for their shopper $j$, defined earlier as the probability $\alpha_{j,l,t}$. By the law of large numbers, this \textit{ex ante} probability $\alpha_{j,l,t}$ is equal to the realized mass of bargain hunters for the firm $j$ in location $l$.

Since equation (7) implies that the probability $\alpha_{j,l,t}$ is increasing in $\gamma_{j,l,t}$ and decreasing in $P_{j,l,t}^L$, retailers can attract informed shoppers by increasing the incidence and magnitude of price discounts. By contrast, random shoppers are matched randomly across retailers, and therefore each retailer takes the mass of random shoppers $\alpha_{j,l,t}^R$ coming to its location as given. Hence, retailers can directly influence their market share at the margin by attracting more shoppers from those households who are informed about its prices, while maintaining their share of random shoppers because it is insensitive to a given retailer’s pricing.\footnote{Note that the pools of potential bargain hunters are completely segmented across retailers, and that the measure of bargain hunters cannot exceed 1 for each store. This rules out the motive for a retailer to undercut prices of other retailers selling the same variety to divert their bargain hunters.}

**Pricing decision.** In each period, upon realization of the aggregate shock, the retailer posts price $P_{j,l,t}^L$ for a fraction $\gamma_{j,l,t}$ of its brands and price $P_{j,l,t}^H$ for the remaining fraction $1 - \gamma_{j,l,t}$. The use of discounts entails a cost expressed in labor units, equal to $\kappa W_t \gamma_{j,l,t}$. The brands with a price discount are chosen randomly (among brands that are not subject to the price adjustment constraints below) and independently across periods.

Retailers face Taylor (1980) price adjustment constraints for the high price $P_{j,l,t}^H$: retailer $j$ in location $l$ sets a new high price in period $t$ and keeps that price fixed for $T$ periods. Such price contracts are evenly staggered across varieties 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 $j$. The full optimization problem for retailers and intermediate good producers are provided in Appendix B. Low prices $P_{j,l,t}^L$ are assumed to be flexible, although this has virtually no effect on our results.

## 6 Model simulations

After calibrating the model’s key parameters, we demonstrate in this section that fluctuations in retailers’ sales behavior can have sizable implications for the economy’s response to aggregate
nominal shocks.

6.1 Parameterization

Table 6 summarizes the calibration that we use in our quantitative simulations. Our calibration is based on U.S. data, since many parameter values and targeted moments are only available for the United States. In a later section, we explore the sensitivity of our main conclusions to deviations from our baseline.

The parameters that determine the household’s shopping time and the firm’s discounts are the elasticity of substitution across good varieties $\theta$, the bargain-hunting technology parameter $f$, the fixed cost of posting price discounts $\kappa$, and the parameters of the fixed cost distribution. The latter govern the relationship between the fraction of bargain hunters, $\alpha_{jt}$, and the shopping time for a marginal bargain hunter, $z^*_j$. Since we are focusing on small fluctuations around the steady state, we can approximate this relationship up to a second order by

$$\alpha_{jt} - \alpha \approx \xi \ln \left( \frac{z^*_{jt}}{z^*} \right), \quad (9)$$

where $z^*$, $\alpha$ are steady-state values of $z^*_{jt}$, $\alpha_{jt}$. The parameter $\xi$ is the semi-elasticity of the fraction of bargain hunters with respect to the shopping time of the marginal bargain hunter in the steady state. With this approximation, the parameterization of the fixed-cost distribution is reduced to the choice of two parameters: the fraction of bargain hunters $\alpha$ and the semi-elasticity $\xi$.\(^{28}\)

We jointly calibrate five parameters ($\theta$, $f$, $\kappa$, $\alpha$, and $\xi$) using five moments; see Panels A and B in Table (6). First, the steady-state price markup in the model is 1.25. This value is standard and lies between the high disaggregate markup estimates consistent with the industrial organization literature and the low macro aggregate markup estimates. The steady-state fraction of sales, $\gamma = 0.058$, matches the average fraction of products on sale for the weighted BLS sample described in Section 3.2. It is in the range found in other studies of micro price data.\(^{29}\) The average size of price discounts $P_L/P_H$ is 0.749, based on Table III in Klenow and Kryvtsov (2008).

To calibrate the steady-state fraction of bargain hunters $\alpha$, we match the ratio of the consumption

\(^{28}\)A log-linear approximation allows us to calibrate parameters in equation (9) without specifying the fixed-cost distribution. An equivalent but more involved calibration is to choose the fixed cost distribution and map its parameters into $\alpha$ and $\xi$. To this end, the log-linear approximation of the expected cost of shopping $\Xi(\alpha_{jt}) = \int_{0}^{z^*_j} z dG(z)$ yields equation (9), where $\xi = \frac{z^*}{\alpha'}$ and $\alpha = G(z^*)$.

\(^{29}\)For the United States, sales frequencies found by Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008) are between 0.066 and 0.11. The fraction of sales reported in the European CPI data studies includes between 0.03 and 0.05 in Austrian CPI data (Baumgartner et al., 2005); 0.03 in Norwegian CPI data (Wulfsberg, 2016), and 0.02 in French CPI data (Sevestre et al., 2004; Berardi, Gautier, and Bihan, 2015).
revenue share of discounted products over the fraction of products on sale. Glandon (2018) estimates this spending share to be 2.7.

The last calibration target is the price saving by bargain hunters relative to an average price for an identical basket of goods. The literature has relied on age or employment status to proxy for household’s propensity for additional shopping. For example, Kaplan and Menzio (2015) 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. Aguiar and Hurst (2007) study ACNielsen’s Homescan Panel and find that households in their 40s pay on average 4% more for identical goods than households in their 60s. Aguiar and Hurst (2007) show that these price savings largely stem from higher shopping frequency and higher usage of discounts by older shoppers. In line with this evidence, we target the unit price paid by bargain hunters in steady state to be 4% lower than the average unit price for an identical basket of goods.

Regular prices change once every 12 months, 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, Jaimovich, and Rebelo (2011) and Kehoe and Midrigan (2015). Stickiness of sale prices is less consequential; we assume they are fully flexible in the baseline model, and show later that firms do not exploit this margin in the model. Nominal wage contracts are also 12 months long, on the short end of the range of estimates in the literature, reported in Table 12 in Grigsby, Hurst, and Yildirmaz (2019).

Finally, for the standard portions of the dynamic model, we choose parameter values that are common in the business cycle literature. The period is a month, so the discount factor is $\beta = 0.96^{1/12}$. Period utility is $u(c) - v(l) = \frac{c^{1-\sigma}}{1-\sigma} - \psi l^{1+1/\eta}$. We set $\sigma = 2$ and a Frisch elasticity of labor supply $\eta = 1$, in line with research on fluctuations of consumption, employment and hours over the business cycle (Hall, 2009; Bils, Klenow, and Malin, 2018). We set the elasticity of substitution across labor varieties at 5, in the middle of the estimates in the literature (Kryvtsov and Midrigan, 2013). The share of capital in production is $1/3$, and the monthly rate of capital depreciation is 0.01. We assume that the growth rate of the money supply in the benchmark model is serially uncorrelated with a standard deviation of 0.0023 (Nakamura and Steinsson, 2010; Kryvtsov and Midrigan, 2013). We also include a TFP shock with a serial correlation of 0.983 and a standard deviation of its innovations of 0.0026, derived from quarterly values estimated in Smets and Wouters (2007).
6.2 Steady-state and dynamic properties

Despite its tractability, the model is consistent with several salient features of retail discounts and time use that are found in the data and the related literature: 1) discounts are associated with large and short-lived price decreases; 2) the elasticity of shopping time with respect to the real wage is in line with empirical estimates; 3) an increase in shopping time yields a sizable reduction in the price of consumption; and 4) the business-cycle volatility and cyclicality of sales are empirically plausible. In the text we focus on the results, and we refer the reader to Appendices B.7 and B.8 for details.

Discounts are short-lived. In the model, when the retailer chooses a fraction $\gamma$ of brands to go on sale, it is immaterial which brands are discounted. To keep the model tractable, we assume the retailer picks discounted brands randomly. This implies little persistence in sales: for example, under our benchmark calibration, discounted price quotes have an average duration of 1.1 months. In the data, sales tend to be weakly serially correlated: for example, Nakamura and Steinsson (2008) find average duration across four broad product categories to be between 1.8 and 2.3 months. We conjecture that one could generate serially correlated sales by adding a fixed cost of implementing a sale (Kehoe and Midrigan, 2015) or by introducing strategic motives for retailers (Chevalier and Kashyap, 2019). While incorporating such mechanisms could be an interesting extension that would allow us to match the serial correlation of sales, the fact that sales are only weakly correlated to begin with makes it unlikely that our conclusions would materially change.

Discounts as loss leaders. The retailer’s first-order conditions for $P^L$ and $P^H$ are such that if bargain hunters are insensitive to discounts, the retailer sets both prices equal to the optimal monopoly price. If bargain hunters are price sensitive, the firm has an incentive to deviate from setting the single monopoly price: by setting $P^L$ below $P^H$ it can attract informed shoppers, while keeping its market share of random shoppers unchanged. In our baseline calibration, the firm can increase its market share by varying its low price at a rate that is 3.9 times higher than if it were to vary its high price. This, however, comes at a cost: because the average sale price is 0.3% below marginal cost, transactions at the discounted price are much costlier for the firm than transactions at the regular price, with a markup of 30%. The firm accepts to sell discounted items at a loss because it needs to offer large discounts to generate a large expected return on shopping for households, and because it knows that 77% of bargain hunters will buy at the regular price, while only 5.8% of regular shoppers will find a discount. Our framework, therefore, is akin to loss-leader models of imperfect competition (Lal and Matutes, 1994). Thomassen et al. (2017) estimate a model of retail competition with two shopper types using data from the U.K. supermarket industry. They find
that when supermarkets raise their price marginally, they lose profits earned on one-stop shoppers and gain profits from bargain hunters.

**Shopping time.** In the model, a higher return on shopping or a lower opportunity cost of time raises the cut-off search cost $z^*$, leading to an increase in the mass of bargain hunters and shopping time. Aguiar and Hurst (2007) estimate that the elasticity of (log) shopping time with respect to (log) wages is about –0.12: for each 10% decrease in wages, households increase their shopping time by 1.2%, all else equal. They argue that this suggests a high elasticity of substitution between hours worked and shopping time. In the baseline model, the steady-state elasticity of shopping time to the real wage is –0.14, in line with the evidence.

**Returns on shopping.** Aguiar and Hurst (2007) document that doubling the shopping intensity lowers the price of consumption by 7 to 10%. For our baseline calibration, we find that the corresponding elasticity in the model, at 11.9%, compares favorably to their empirical estimate.

**Unconditional volatilities and correlations.** In the first two columns of Panel A in Table 7, we report the joint variation of sales and business cycle variables in our baseline model as well as in the U.S. data (details are in Appendix B). In general, the model does very well, despite the fact that these moments are not targeted. For example, the ratio of the time-series standard deviation of the fraction of sales to that of real consumption is 0.24 in the model, compared to 0.27 in the data. If we use hours worked instead, the relative volatility goes down to 0.20 in our simulations versus 0.14 empirically. The frequency of sales tends to be slightly less cyclical in the model: the correlations with consumption and hours are respectively –0.53 and –0.35 in the simulations, compared to –0.64 and –0.44 in the data.

### 6.3 Response to a monetary shock

Next, we turn our attention to one of our main objectives: assessing the importance of the endogenous cyclical variation of sales in shaping the response of the economy to aggregate shocks. Following Guimaraes and Sheedy (2011) and Kehoe and Midrigan (2015), we focus on the response of the model economy to nominal demand disturbances (monetary shocks): our baseline experiment is a negative 1% innovation to the growth rate of the money supply. This shock is of particular interest because the sluggishness in the dynamics of the aggregate price level determines the response of real variables. Unlike Guimaraes and Sheedy (2011) and Kehoe and Midrigan (2015), where the size and frequency of sales are insensitive to shocks, in our model the frequency of sales is strongly countercyclical, in line with the empirical evidence in Section 3. This feature allows us to assess the
role of sales dynamics for macroeconomic fluctuations.\textsuperscript{30}

In what follows, we will compare responses to the monetary shock in three versions of the model:

- “No discounts” version: There are no discounts and firms can only post a single price. There is no incentive for bargain hunting, and therefore, all household members are random shoppers. In a nutshell, this model is a standard business cycle framework with sticky prices and wages.\textsuperscript{31}

- “Constant discounts” version: Firms post two prices in steady state, but cannot vary the frequency or size of sales over time. In order to make sales time-invariant, we impose large quadratic adjustments costs that punish deviations of $\gamma_t$ and $P_t^H - P_t^L$ from their steady-state values.\textsuperscript{32}

- “Cyclical discounts” version: Our baseline model.

The response of aggregate consumption and prices. Panel B in Table 7 describes the average 12-month response of real consumption to the monetary shock. In the standard, one-price version of our model, the 1% negative impulse to money supply growth generates an average consumption response of -0.48% over one year. This is due to the fact that prices are sticky, adjusting only slowly to the shock. The second line of Panel B shows that introducing time-invariant sales is not enough to influence meaningfully the consumption response: firms do not adjust the frequency or depth of discounts, and bargain hunting is little changed following the shock. As a result, aggregate dynamics remain very similar to those in a model without sales altogether. This is essentially the insight from Guimaraes and Sheedy (2011): their model generates very little time variation in sales and no significant impact on impulse responses.

The third line of Panel B indicates that making sales cyclical to a degree that is in line with our empirical evidence alters significantly the aggregate dynamics of the model. Over the first 12 months following the shock, real consumption is on average -0.29% below its steady-state value, which is almost 40% less than if sales are absent or constant over time. The reason behind this difference is intuitive: firms use sales as a means to offset some of the rigidity of regular prices. This margin is evident in Panels A and B of Figure 11, which respectively compare the responses of the aggregate price level $P_t$ and real consumption $C_t$ under the “Constant discounts” and “Cyclical discounts”

\textsuperscript{30}Sudo et al. (2018) extend the model of Guimaraes and Sheedy (2011) to include time-varying consumption weights and use it for understanding trends in sales behavior in Japan.

\textsuperscript{31}The parameter $\theta$ is recalibrated in order to match the same markup of 1.25.

\textsuperscript{32}Specifically, we introduce a convex cost of adjusting the number of discounts by the firm: $\kappa W_t (\gamma_t + \frac{\epsilon}{2} (\gamma_t - \gamma)^2)$. For the size of discounts, we add a convex adjustment cost term in the decision of adjusting the discount price: $\frac{\epsilon}{2} \left( P_{jt}^L / P_{jt}^H - P_t^L / P_t^H \right)^2$. 

29
versions of the model. The differences are stark. The price level in the version with constant sales falls by only 0.09% on impact and gradually reaches −0.91% within one year, as additional sticky-price cohorts of retailers get a chance to lower their prices after the shock. Since nominal spending falls by the same magnitude as the money supply (1%), the fall in real consumption is large: around −0.91% on impact, dissipating to −0.09% after one year. By contrast, the price level in the baseline model goes down by 0.60% at the time of the shock. As a result, the 0.40% response of real consumption on impact is only about half that when sales are time-invariant (or not present at all).

**Mechanism: countercyclicality of sales.** By definition, the differences in the aggregate dynamics of the “Constant discounts” and “Cyclical discounts” versions of the model are due to the response of sales to the shock. Following the negative aggregate shock, the fall in marginal cost drives up the price markup, raising the expected return from each additional shopper. In order to attract valuable bargain hunters, the firm needs to offer a more attractive price menu; in the model, this happens through the sales margin, given the firm’s inability to adjust its regular price. This reaction is illustrated in Panel C of Figure 11, where the fraction of price discounts rises by 0.66 ppt in the wake of the shock. As households expect to find lower prices, they in turn search more intensively through additional bargain hunting.

**Mechanism: fraction versus size of discounts.** The household is indifferent to whether the firm increases the number or size of price discounts; what matters is the price she expects to pay for a given variety. Yet, an important prediction of the model is that the firm chooses to keep the size of its discounts stable and vary their number. This prediction is consistent with our empirical findings that the average size of price discounts is acyclical, while their average fraction fluctuates over the cycle.

To better understand why the firm favors varying the fraction of sales instead of their size, we compare impulse responses when we shut down one margin at a time. For this exercise, we choose combinations of the convex adjustment costs such that (i) only one discount margin varies—the fraction or the size, and (ii) the response of the mass of bargain hunters is the same in both simulations. Variation in discounts is achieved by either increasing the fraction of discounts by 0.39 ppt, or raising the size of discounts by 1.18 ppt.

In both cases, the firm faces the same average inflow of bargain hunters and charges the same average price. The different combinations of the fraction and size of discounts imply, however, different responses of the production cost. When firms increase the fraction of discounts, their total cost falls by 1.89%, reflecting the overall decline in demand following the shock, counterbalanced
by a slightly higher cost of posting sales. If instead retailers only adjust the size of price discounts, we find a smaller fall in costs, at only 1.79%. This is because lowering $\gamma$ means firms need to satisfy extra demand $(e^L - e^H)$ for only a small fraction of transactions; by contrast, when they raise the discount size, demand is higher for all transactions at the low price. Hence, in our model, firms choose to keep the size of their discounts stable because it allows them to scale down their production cost more effectively.

The role of expenditure switching. In our model, the flexibility of the aggregate price response is due to two factors. First, an increase in the fraction of sale prices mechanically increases the frequency weight on $P^L$ relative to $P^H$. Second, each additional 1 ppt of discounts is associated with a disproportionate shift of consumption share toward discounted goods (by 2.7 ppt in our calibration).

To quantify the role of the disproportionate shift in consumption weights, we construct a geometric mean price index which incorporates frequency weights but keeps relative consumption weights constant. This is the model’s counterpart to a standard CPI index. We find that the geomean index falls by 0.43% on impact following the monetary shock. This response is larger than in a model with constant sales (–0.09%), reflecting the higher frequency of discounted prices, but significantly lower than the –0.60% decline of the actual price index $P$ in our baseline version. Hence, the variation in consumption weights accounts for about one-third of the response of the aggregate price level relative to a model ignoring sales; fluctuations in price discounts (keeping consumption weights constant) account for the remaining two thirds. This is reminiscent of a standard criticism of the traditional consumer price index: variations in expenditure switching between low- and high-price items are not systematically taken into account by statistical agencies (Boskin et al., 1996, Nakamura, 1998, Chevalier and Kashyap, 2019). Our analysis highlights that this limitation can have important consequences for aggregate price measurement when discounts are cyclical, as we have documented in Section 2.\textsuperscript{33}

Elasticity of shopping time to hours worked. The increase in the number of price discounts raises the return on shopping for households, which leads to an increase in shopping time by 1.4% following the rise in bargain hunters (Panel D in Figure 11). At the same time, hours worked decline by 3.0%. The corresponding elasticity of shopping time with respect to hours worked is –0.39. To assess how sensible this estimate is, we turn our attention to Aguiar, Hurst, and Karabarbounis (2013): using ATUS evidence around the Great Recession, they estimate the same elasticity to be

\textsuperscript{33}In Appendix C, we quantify empirically the wedge between the standard (CPI) aggregate price index and the effective price index using the U.K. micro price data.
between –0.69 to –0.37, a range that includes the value from our baseline model.

**Returns to shopping and the price of time.** One interpretation of the reallocation of market work towards shopping that is documented by Aguiar, Hurst, and Karabarbounis (2013) is that it reflects a fall in the opportunity cost of time during downturns. Alternatively, it can be driven by a rise in the returns to shopping as discounts become more frequent, as we showed in Section 2. While Aguiar, Hurst, and Karabarbounis (2013) do not test which of these two channels is more relevant empirically, we can gauge their relative importance in our calibrated model.

In the baseline version, the price of shopping time is assumed to be the real market wage $W/P$ (see equation 5). Since prices adjust somewhat faster than wages, real market wages slightly *increase* during a monetary contraction, by 0.19% on average over the first year. This small increase in the price of shopping time lowers the household’s incentive to shop. Consequently, the rise in the shopping time after the shock must be driven entirely by the increase in the return to shopping (1.9 ppt over the first year).

Real market wage may be an imperfect measure of the price of shopping time, due to labor market frictions and sticky wages. We consider a plausible alternative, whereby the household head bases her decision of shopper type on the cost of supplying time, equal here to the marginal rate of substitution between consumption and hours worked, $\sigma c_t + \eta^{-1} t_t$.34 This measure declines after the contractionary shock, leading to an increase in shopping time. This increase is amplified by the higher returns to shopping as firms post more sales. The total response of the shopping time on impact is 2.2%, versus 1.4% in the baseline, leading to an even more flexible price response: –0.76%, versus –0.60% in the model. To assess the relative contributions of the price of time and returns on shopping, we repeat this simulation, but this time adjusting the convex adjustment costs on sales to keep the response of the return to shopping identical to the one in the baseline model. We find that the increase in the opportunity cost of time now accounts for roughly three quarters of the shopping time response. The elasticity of shopping time to hours worked is equal to –0.77, compared to –0.39 in the baseline model.

In sum, in our baseline framework most of the variation in shopping time is driven by fluctuations in the return to shopping, rather than the price of time. Modifying the model to give a more important role to the latter only amplifies the role of sales as a price flexibility mechanism. While the two versions imply somewhat different elasticities of shopping time to hours worked, both lie around the –0.69 to –0.37 range estimated by Aguiar, Hurst, and Karabarbounis (2013). More

34We also used the non-sticky real wages of new hires, but found smaller effects. Bils, Klenow, and Malin (2018) discuss measurement of the cyclical price of labor in the context of business cycle co-movement of work, productivity and consumption.
precise empirical estimates would allow us to better discriminate between these alternate forces.

6.4 Sensitivity analysis

We conducted a number of simulations to check the robustness of the model predictions to various deviations from the baseline framework. The main results are presented in columns 3 to 6 of Table (7), and additional results are in Appendix B.9. We perform two types of exercises. First, we focus on changes that do not impact the steady state of the model.

No TFP shocks. In a version of the model with only monetary shocks, sales are relatively more volatile and countercyclical (column 3). This is because the TFP and monetary shocks have opposite implications for the response of discounts. After a negative TFP shock, the firms’ inability to raise prices leads to low markups, incentivizing them to reduce the number of discounts. The high cost of production decreases demand for labor input, and as prices gradually catch up with cost, consumption falls. Hence, TFP shocks generate procyclical price discounts, unlike demand shocks.

Reduced price stickiness. Column (4) of Table (7) shows the results when $P^H$ is assumed to be sticky for 6 instead of 12 months, closer to the estimates in Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008). Weaker nominal rigidities imply, not surprisingly, that the response of real consumption to the monetary shock is lower than in the baseline model (−0.22% versus −0.29%). More importantly, when equipped with more flexible regular prices, the firm does not need to rely so heavily on sales in its response to aggregate shocks: the consumption response with cyclical sales is only 29.5% smaller than in a version with constant or no discounts, while this difference was 39.7% in the baseline.

Increased wage stickiness. Making wages stickier, in line with some of the higher estimates in the literature (see Table 12 in Grigsby, Hurst, and Yildirmaz, 2019), adds sluggishness to the firm’s marginal cost, reducing the volatility of its markup. While present, the effect on sales is quantitatively small: column (6) of Table (7) shows that assuming that nominal wage contracts last 18 months instead of 12 only slightly decreases the relative volatility and the countercyclicality of sales, as well as the size of the consumption response to the monetary shock.

Next, we turn our attention to deviations from the targeted moments described in Section 6.1. In all cases, we recalibrate the model parameters to match the new calibration targets.

More frequent sales. We calibrated the model to a higher average fraction of discounts, 0.074, which is the value documented by Nakamura and Steinsson (2008) in the U.S. CPI micro data for 1998–2005. A higher average fraction of sales implies that firms need to adjust this fraction
more (in ppt) in order to generate the same variations in shopping activity as in the baseline. As a result, firms make discounts more responsive to shocks, leading to a marginally smaller response of real consumption (−0.27% versus −0.29% in the baseline). The impact on the volatilities and correlations is also quantitatively limited, as indicated in column (5).

**Additional exercises.** In addition to the scenarios above, we have also performed sensitivity analysis along other dimensions. First, we found that increasing the persistence parameter of the money-growth process closer to the values used by Guimaraes and Sheedy (2011), 0.536, and Kehoe and Midrigan (2015), 0.61, had no noticeable impact on our findings. The same is true if we re-calibrate the model to a wider range of price savings by bargain hunters from 2% to 8%, which nests the estimates reported in Kaplan and Menzio (2015) and Aguiar and Hurst (2007). The quantitative results are somewhat more sensitive to the average revenue share, even though our conclusions remain broadly unchanged. For example, lowering the share from the 2.7 value of Glandon (2018) to a value of 2.0 produces only a small change in the 12-month consumption response (−0.31% versus −0.29% in our baseline). A lower share leads to lower returns on shopping, generating a smaller steady-state fraction of bargain hunters and a less elastic response of shopping time in the model. The latter, in turn, decreases the reallocation of consumption weights to low prices during recessions.

7 Discussion and conclusions

A large body of literature in industrial organization has analyzed the motives behind the use of temporary discounts in the retail sector, such as price discrimination (Varian, 1980), discounts as loss leaders (Lal and Matutes, 1994), consumer stockpiling behavior (Pesendorfer, 2002) or inventory management under uncertainty (Aguirregabiria, 1999). Yet, despite their ubiquity in many micro-price datasets, macroeconomists have traditionally paid little attention to the role of sales, instead focusing on regular price moments to calibrate their models. We provide evidence from CPI micro data that the frequency of sales is strongly countercyclical in the United Kingdom and United States, and that it rose significantly in both countries during the Great Recession as well as past downturns. We then build a general equilibrium model with sales that is calibrated to match our novel empirical facts. We find that incorporating cyclical price discounts in an otherwise standard framework lowers the 12-month response of real consumption by about 40%, due to the additional aggregate price flexibility arising from sales. Our conclusion is that focusing on regular or reference prices may lead macroeconomists to miss economically relevant aspects of pricing over the business
cycle.

Our findings offer some guidance as to which modeling features may be most appropriate. For example, the much higher use of sales by larger retailers in our data may be evidence that posting temporary discounts comes with significant fixed marketing costs, such as in-store displays or the distribution of promotional flyers. It could also be a sign that wholesalers are more likely to put in place trade promotion agreements of the type studied by Anderson et al. (2017) with larger, more visible retailers. Paying particular attention to large retail chains also appears increasingly justified not only because of the prevalence of national pricing strategies, but also because of a trend toward higher concentration in the retail industry, as evidenced, for example, in Hong and Li (2017).

Moreover, even if we observe that sales are more likely to occur toward the end of a product life, the similar cyclical behavior of clearance and non-clearance sales seems to indicate that inventory decisions are not likely to be the main cause behind the more prevalent use of discounts during recessions. Instead, our findings appear to favor mechanisms in which the time-varying use of sales by retailers is driven by variations in the price sensitivity of consumers over the cycle. Further exploration of the factors behind cyclical shopping activity and its link to retailers’ price discrimination behavior appears promising.

References


Alvarez, Luis J., Emmanuel Dhyne, Marco Hoeberichts, Claudia Kwapił, Hervé Le Bihan, Patrick Lünnemann, Fernando Martins, Roberto Sabbatini, Harald Stahl, Philip Vermeulen, and Jouko


Kehoe, Patrick and Virgiliu Midrigan. 2015. “Prices are sticky after all.” *Journal of Monetary Economics* 75 (C):35–53.


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

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


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

Notes: Monthly proportion of products on sale using the three types of filters. Aggregation is done using CPI quote weights. For the top right plots, the product-level weights are time invariant and correspond to their time-series average. Sample period is 1996:02–2013:09. U.K. Office for National Statistics data.
Notes: Weighted average of the size of discounts using the three types of filters. Aggregation is done using CPI quote weights. Data is monthly and the sample period is 1996:02–2013:09. U.K. Office for National Statistics data.
Figure 5: Frequency of sales in the U.S. CPI data and unemployment rate

Notes: Data from the U.S. Bureau of Labor Statistics, Vavra (2014) and Anderson et al. (2017). All sales frequency series are 12-month moving averages. Monthly weighted fraction of products with a sales flag (top left) and sales flag or substitution (top right), using BLS expenditure weights. Series in bottom plots: “BLS weights, Sales flag” (purple line) is constructed by taking the weighted mean of the frequency of the sales flag and using the weights from the BLS; “Fixed weights” (black line) is constructed using fixed category-level weights, with alternative definition of sales, and restricting their sample; “BLS weights” (blue line) provides an intermediate case with variable BLS weights and Anderson et al.’s sales measure. Series in the bottom-right plot are HP filtered. Sample periods are 2000:01–2011:12 (top left), 1988:01–2011:12 (top right), 1988:07–2014:11 (bottom).
Figure 6: Frequency of sales for food products, U.S. CPI


Figure 7: Cyclicality of sales at the category level, U.K. CPI data

Notes: Distribution of coefficients from two regressions at the category level. Top row: Sales frequency on monthly aggregate unemployment rate and a time trend. Bottom row: Sales frequency on the log of quarterly category-level real consumption and a time trend. Sales are identified using the V-shape (left column) or sales flag (right column) filter and must be at least 10% in size. U.K. Office for National Statistics data.
Figure 8: Cyclicality of sales at the regional level, U.K. CPI data

![Sensitivity to unemployment graph]

Notes: Distribution of coefficients from regional regressions of sales frequency on the monthly regional unemployment rate and a time trend. Sales are identified using the V-shape filter and must be at least 10% in size. U.K. Office for National Statistics data.

Figure 9: Frequency of clearance and non-clearance sales

![Frequency graphs for all products, food products, clothing & footwear, audio & video]

Notes: Clearance sales are defined as sales flags occurring within the last two months of a quote line. CPI quote weights are used for aggregation. U.K. Office for National Statistics data.
Notes: The environment consists of a measure $L$ of households, each comprised of many shoppers (one per each variety), indexed by $j$. Retail firms are dispersed over $L$ locations. Each location is populated by $J$ retailers, each selling one variety. A retailer sells a measure one of perfectly substitutable brands of specific variety $j$. In each period, the timing of events is as follows: First, the aggregate shocks are realized, the household head deposits all of its cash in the checking account, retail firms post their prices and send their price menus to households. Then the search costs are realized, the household head chooses the shopping types, consumption plans, and pays search costs $z$. She also provides debit cards to shoppers and sends them off to shop. All shoppers are matched with locations, retail firms and consumption brands; they bring the purchased consumption goods back to the household.
Figure 11: Responses to a negative 1% i.i.d. impulse to money growth

A. Price

B. Consumption

C. Discounts

D. Time
### Table 1: Summary statistics for posted and regular price changes

<table>
<thead>
<tr>
<th></th>
<th>Frequency of price changes</th>
<th>Frequency of price increases</th>
<th>Frequency of price decreases</th>
<th>Abs. size of price changes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All prices</strong></td>
<td>15.8%</td>
<td>9.8%</td>
<td>6.0%</td>
<td>11.9%</td>
</tr>
<tr>
<td><strong>Regular prices</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>V-shaped</td>
<td>10.9%</td>
<td>7.6%</td>
<td>3.3%</td>
<td>8.6%</td>
</tr>
<tr>
<td>Sales flag</td>
<td>13.2%</td>
<td>8.6%</td>
<td>4.6%</td>
<td>8.5%</td>
</tr>
<tr>
<td>Reference price</td>
<td>7.5%</td>
<td>5.4%</td>
<td>2.1%</td>
<td>9.4%</td>
</tr>
</tbody>
</table>

Notes: CPI data are from the U.K. Office for National Statistics; sample period is from February 1996 to September 2013. “V-shaped”, “Sales Flag” and “Ref.” refer to the sales filters described in the main text.

### Table 2: Summary statistics for temporary sales

<table>
<thead>
<tr>
<th></th>
<th>V-shaped</th>
<th>Sales flag</th>
<th>Reference price</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All sales</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>4.6%</td>
<td>2.9%</td>
<td>5.2%</td>
</tr>
<tr>
<td>Mean size</td>
<td>-13.9%</td>
<td>-22.0%</td>
<td>-12.4%</td>
</tr>
<tr>
<td>Median size</td>
<td>-10.0%</td>
<td>-20.0%</td>
<td>-8.0%</td>
</tr>
<tr>
<td><strong>Sales of at least 10%</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>2.3%</td>
<td>2.3%</td>
<td>2.3%</td>
</tr>
<tr>
<td>Mean size</td>
<td>-23.6%</td>
<td>-25.6%</td>
<td>-23.1%</td>
</tr>
<tr>
<td>Median size</td>
<td>-20.1%</td>
<td>-21.9%</td>
<td>-20.0%</td>
</tr>
<tr>
<td>Observations</td>
<td>12,002,135</td>
<td>11,928,745</td>
<td>11,943,528</td>
</tr>
</tbody>
</table>

Notes: CPI data are from the U.K. Office for National Statistics, sample period is from February 1996 to September 2013. “V-shaped”, “Sales Flag” and “Ref.” refer to the sales filters described in the main text.
Table 3: Regressions at the aggregate level

| Panel A | United Kingdom | | | V-shaped | V-shaped | V-shaped | Flag | Ref. | V-shaped - median | Flag - median |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | |
| \(u_t\) | 0.544*** | 0.194*** | 0.464*** | 0.358*** | 0.424*** | 0.267*** | 0.328*** |
| | (0.024) | (0.036) | (0.023) | (0.025) | (0.024) | (0.028) | (0.029) |
| \(sales_{t-1}\) | 0.647*** | | | | | | |
| | (0.055) | | | | | | |
| Linear time trend | N | N | Y | Y | Y | Y | Y |
| Observations | 210 | 209 | 210 | 210 | 210 | 210 | 210 |
| \(R^2\) | 0.73 | 0.84 | 0.80 | 0.67 | 0.77 | 0.62 | 0.50 |

| Panel B | United States - BLS | | | Mean | Mean | Mean | United States - Vavra (2014) | | | Mean | Mean | Median |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | | |
| \(u_t\) | 0.177*** | 0.152*** | 0.233*** | 0.338*** | 0.320*** | 0.440*** |
| | (0.017) | (0.023) | (0.025) | (0.032) | (0.033) | (0.060) |
| \(sales_{t-1}\) | 0.148 | | | | | |
| | (0.092) | | | | | |
| Linear time trend | N | N | Y | N | Y | Y |
| Observations | 144 | 143 | 144 | 288 | 288 | 288 |
| \(R^2\) | 0.51 | 0.52 | 0.54 | 0.54 | 0.55 | 0.32 |

<table>
<thead>
<tr>
<th>Panel C</th>
<th>United States - Anderson et al. (2017)</th>
<th></th>
<th></th>
<th>Fixed weights</th>
<th>BLS weights</th>
<th>BLS weights, Sales flag</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(u_t)</td>
<td>0.151***</td>
<td>0.035**</td>
<td>0.177***</td>
<td>0.067***</td>
<td>0.073***</td>
<td>0.171***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.013)</td>
<td>(0.017)</td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Linear time trend</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>HP-detrended</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.29</td>
<td>0.75</td>
<td>0.68</td>
<td>0.42</td>
<td>0.43</td>
<td>0.61</td>
</tr>
</tbody>
</table>

Notes: Linear regressions of the fraction of products on sale on the unemployment rate \(u_t\). "Flag", "V-shaped" and "Ref." refer to the sales filters described in the main text. "Mean" and "Median" indicate mean and median frequencies respectively. "HP-detrended" indicates that a Hodrick-Prescott filter has been applied to both the sales frequency and unemployment series beforehand. All regressions include calendar month dummies. *** p<0.01, ** p<0.05, * p<0.1. The sample periods are February 1996 to September 2013 for the U.K.; January 2000 to December 2011 for “U.S. - BLS”; January 1988 to December 2011 for “U.S. - Vavra (2014)”; and July 1988 to November 2014 for “US - Anderson et al. (2017)”.
Table 4: Sales and regular price changes

### Dependent variable: Frequency of sales

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>V-shaped</td>
<td>V-shaped</td>
<td>Flag</td>
</tr>
<tr>
<td>$u_t$</td>
<td>0.459*** (0.033)</td>
<td>0.457*** (0.032)</td>
<td>0.363*** (0.041)</td>
</tr>
<tr>
<td>$f_{reg_t}$</td>
<td>-0.008 (0.008)</td>
<td>-0.008 (0.005)</td>
<td>-0.11*** (0.042)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>freg$^{+}_t$</th>
<th>freg$^{-}_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.004 (0.008)</td>
<td>-0.008 (0.005)</td>
</tr>
<tr>
<td></td>
<td>-0.033 (0.022)</td>
<td>-0.029 (0.037)</td>
</tr>
</tbody>
</table>

Linear time trend | Y | Y | Y | Y | Y | Y |
Observations | 210 | 210 | 210 | 144 | 288 | 288 |
$R^2$ | 0.81 | 0.81 | 0.67 | 0.63 | 0.57 | 0.46 |

### Dependent variable: Frequency of regular price changes

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>V-shaped</td>
<td>V-shaped</td>
<td>Ref.</td>
</tr>
<tr>
<td>$u_t$</td>
<td>0.602*** (0.212)</td>
<td>0.536 (0.365)</td>
<td>0.305*** (0.084)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>freg$^{+}_t$</th>
<th>freg$^{-}_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.004 (0.008)</td>
<td>-0.008 (0.005)</td>
</tr>
<tr>
<td></td>
<td>-0.033 (0.022)</td>
<td>-0.029 (0.037)</td>
</tr>
</tbody>
</table>

Linear time trend | Y | Y | Y | Y | Y | Y |
Observations | 210 | 210 | 210 | 144 | 288 | 288 |
$R^2$ | 0.32 | 0.19 | 0.38 | 0.61 | 0.57 | 0.46 |

Notes: Linear regressions of the fraction of products on sale on the unemployment rate ($u_t$) as well as the frequency of regular price changes ($f_{reg_t}$), increases ($f_{reg^{+}_t}$) and decreases ($f_{reg^{-}_t}$). “Mean” and “Median” indicate mean and median frequencies respectively. All regressions include calendar month dummies. Newey-West standard errors allowing for a maximum autocorrelation of 4 lags are indicated in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Sample periods are described in Table 3.
Table 5: Panel regression results at the product level - U.K. data

<table>
<thead>
<tr>
<th></th>
<th>V-shaped</th>
<th>Sales flag</th>
<th>Ref. price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$u_t$</td>
<td>0.444</td>
<td>0.364</td>
<td>0.409</td>
</tr>
<tr>
<td>$s_{i,t-1}$</td>
<td></td>
<td></td>
<td>0.105</td>
</tr>
<tr>
<td>Month dummies</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Time trend</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>11,950,985</td>
<td>11,950,985</td>
<td>10,977,476</td>
</tr>
<tr>
<td>F-stat</td>
<td>11.48</td>
<td>13.02</td>
<td>46.35</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Alt. macro indicators (normalized)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_t$ (normalized)</td>
<td>0.0052***</td>
</tr>
<tr>
<td>Retail sales vol.</td>
<td>-0.0046***</td>
</tr>
<tr>
<td>Consumer confidence</td>
<td>-0.0028***</td>
</tr>
<tr>
<td>Fin. situation next year</td>
<td>-0.0037****</td>
</tr>
<tr>
<td>Month dummies</td>
<td>Y</td>
</tr>
<tr>
<td>Time trend</td>
<td>N</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>11,673,020</td>
</tr>
<tr>
<td>F-stat</td>
<td>13.75</td>
</tr>
</tbody>
</table>

Notes: Panel regressions at the item level; $\gamma_{it} = \alpha_i + \beta u_t + X_t\Phi + e_{it}$, where $\gamma_{it}$ 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. *** p<0.01, ** p<0.05, * p<0.1. The sample period is February 1996 to September 2013.
Table 6: Parameterization (baseline model)

A. Calibrated Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta ) Elast. subst. goods</td>
<td>2.49</td>
<td></td>
</tr>
<tr>
<td>( \beta ) Search efficiency</td>
<td>4.00</td>
<td></td>
</tr>
<tr>
<td>( \kappa ) Fixed cost of posting discounts</td>
<td>0.060</td>
<td></td>
</tr>
<tr>
<td>( \alpha ) Fraction of bargain hunters</td>
<td>0.285</td>
<td></td>
</tr>
<tr>
<td>( \xi ) Semi-elasticity of sales expenditure multiplier w.r.t. shopping time</td>
<td>0.188</td>
<td></td>
</tr>
</tbody>
</table>

B. Calibration Targets (steady state)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Markup</td>
<td>1.25</td>
<td>1.25</td>
</tr>
<tr>
<td>Price discount</td>
<td>0.749</td>
<td>0.749</td>
</tr>
<tr>
<td>Fraction of discounts</td>
<td>0.058</td>
<td>0.058</td>
</tr>
<tr>
<td>Sales expenditure multiplier</td>
<td>2.7</td>
<td>2.7</td>
</tr>
<tr>
<td>Unit price paid by bargain hunters</td>
<td>0.96</td>
<td>0.96</td>
</tr>
<tr>
<td>Semi-elasticity of sales expenditure multiplier w.r.t. shopping time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unit price paid by bargain hunters relative to average unit price</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

C. Assigned Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
<td>1 month</td>
<td></td>
</tr>
<tr>
<td>( \beta ) discount factor</td>
<td>0.96^{1/12}</td>
<td></td>
</tr>
<tr>
<td>( \sigma ) risk aversion</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>( \eta ) Frisch elasticity</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>( \theta ) Elast. subst. labor</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>( \chi ) Cost share of capital</td>
<td>1/3</td>
<td></td>
</tr>
<tr>
<td>( \delta ) Capital depreciation rate</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>( 1/N_p ) frequency of price changes</td>
<td>1/12</td>
<td></td>
</tr>
<tr>
<td>( 1/N_W ) frequency of wage changes</td>
<td>1/12</td>
<td></td>
</tr>
<tr>
<td>( \rho_\mu ) std corr of money shock</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>( \sigma_\mu ) std of money shock impulse</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>( \rho_\eta ) std corr of tfp shock</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>( \sigma_\eta ) std of tfp shock impulse</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>L average hours worked, hrs/week</td>
<td>37.1</td>
<td></td>
</tr>
<tr>
<td>S average shopping time, hrs/week</td>
<td>4.0</td>
<td></td>
</tr>
</tbody>
</table>

D. Additional steady state moments

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elas. of shopping time w.r.t. real wages</td>
<td>-0.12</td>
<td>-0.14</td>
</tr>
<tr>
<td>Elas. of price to shopping time</td>
<td>-0.07 to -0.10</td>
<td>-0.12</td>
</tr>
<tr>
<td>Shopping time, hrs/week</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regular shoppers</td>
<td>3.1</td>
<td></td>
</tr>
<tr>
<td>Bargain hunters</td>
<td>3.1 to 6.2</td>
<td></td>
</tr>
</tbody>
</table>

Notes: In Panel B, sales expenditure multiplier is the ratio of the consumption revenue share of discounted products over the fraction of products on sale.
Table 7: Model simulations

<table>
<thead>
<tr>
<th></th>
<th>U.S. Data</th>
<th>Baseline model</th>
<th>Model Robustness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Money shocks only</td>
</tr>
<tr>
<td>A. <strong>Time-series statistics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\text{std}(\gamma_t)/\text{std}(C_t))</td>
<td>0.27</td>
<td>0.24</td>
<td>0.56</td>
</tr>
<tr>
<td>(\text{std}(\gamma_t)/\text{std}(L_t))</td>
<td>0.14</td>
<td>0.20</td>
<td>0.19</td>
</tr>
<tr>
<td>(\text{corr}(\gamma_t, C_t))</td>
<td>–0.64</td>
<td>–0.53</td>
<td>–0.88</td>
</tr>
<tr>
<td>(\text{corr}(\gamma_t, L_t))</td>
<td>–0.44</td>
<td>–0.35</td>
<td>–0.98</td>
</tr>
<tr>
<td>B. <strong>Consumption response to a –1% impulse to money supply (average % for 12 months after shock)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No discounts</td>
<td>–0.48</td>
<td>–0.48</td>
<td>–0.28</td>
</tr>
<tr>
<td>Constant discounts</td>
<td>–0.48</td>
<td>–0.48</td>
<td>–0.31</td>
</tr>
<tr>
<td>Cyclical discounts</td>
<td>–0.29</td>
<td>–0.29</td>
<td>–0.22</td>
</tr>
<tr>
<td>% difference in responses</td>
<td>39.7</td>
<td>39.7</td>
<td>29.5</td>
</tr>
</tbody>
</table>

Notes: Panel A provides time-series statistics for the U.S. data and the model. Panel B provides average consumption responses to a –1% impulse to money supply over the first 12 months after the shock. Column (1): U.S. data (details in Appendix C), (2): Baseline model, (3): no TFP shocks, (4): reduce duration of regular price contracts to 6 months, (5): recalibrate to match a higher average fraction of price discounts to 0.074, keeping other calibration targets, (6): increase duration of wage contracts to 18 months.