

The Cyclicalities 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 a third the one-year response of real consumption.

Keywords: Price dynamics, Sales, Price index measurement.

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

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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 these facts.

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

¹For 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 economy comprises multiple locations. Each location is composed of ex-ante identical households and a *local shopping mall* populated by monopolistically competitive retailers. A retailer is a firm that sells a unit measure of perfectly homogeneous brands of the same variety. Each retailer chooses 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. Retailers set prices before households make their decisions.

Every household is composed of shoppers, each responsible for purchasing a single variety. The household head is aware of the prices posted by retailers in the location she lives in. In addition, she knows the overall distribution of prices across other locations. Based on this information, she picks a shopper type for each variety: a household member can either be a random shopper, who draws a brand of her assigned variety from a random location; or a bargain hunter, who buys from the local retailer and is more likely to find a discounted brand. Bargain hunters, however, are costly because they spend more time shopping. The household head optimally assigns shopper types according to a cut-off rule: a shopper is designated as bargain hunter if the stochastic shopping cost is below a certain threshold. Even if retailers cannot discriminate between the two types of shoppers, they

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 34% 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 cyclical 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 cyclical of sales across products, much of this cyclical 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 cyclical 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 also 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 in-

complete 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 cyclicity 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

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

brief description of the U.K. dataset, while postponing the details to Data 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 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 [Bunn and Ellis \(2012\)](#) for the United Kingdom.

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.⁴ 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.⁵

Finally, we compute a reference price similar to the 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

⁴To 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.

⁵If 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.

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.⁶

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.⁷ 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.

⁶See, for example, [Klenow and Kryvtsov \(2008\)](#) and [Nakamura and Steinsson \(2008\)](#) for the United States, and [Alvarez et al. \(2006\)](#) for Europe.

⁷Though 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.

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 the cyclical nature of aggregate sales frequency is not due to 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 cyclical nature 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 cyclical pattern 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

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

⁹Our findings are unchanged if we consider sales of all sizes instead of focusing on a 10% threshold for the size of

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 to May 2014, unweighted and weighted using the CPI expenditure weights used by BLS.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.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 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).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”).¹³ While some of the time series exhibit a pronounced upward trend, the sales.

¹⁰We 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.

¹¹Vavra 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.

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

¹³We thank Ben Malin for clarifying how these series were constructed and for sharing the replication materials for

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.¹⁴ This pattern is confirmed if we 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 countercyclicity of price discounts. Nonetheless, AMNSS conclude that time variation in sale prices contributes very little to the variance or cyclicity 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 confirms 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.

Our application is related to the work of [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

[Anderson et al. \(2017\)](#). See Data Appendix A in their paper for further details.

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 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 cyclicity 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.

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 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 Data 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.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) data, using the following empirical specification: $\gamma_t = \alpha + \beta u_t + X_t' \Phi + error$, where γ_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

¹⁵In 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.

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%.

For the United States, this elasticity in the regression without the trend is 0.177 in our sample, and equal to 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 verifying the robustness of our 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 Data 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 Data 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.¹⁶ 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 cyclicity of sales, and the coefficients

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.

on the unemployment rate are even larger in this case than the coefficients reported in Table 3.

Second, we directly investigate the cyclicity 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 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.

Cyclicity of sales across product categories. As a first exercise, we verify that the cyclicity 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 countercyclicity 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.¹⁷

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

¹⁷Figure A.1 in Data Appendix A.5 visualizes time series for selected categories.

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.

Cyclicalities and category characteristics. In addition, we explore how the category-level cyclicity 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 Data 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.

Cyclicalities of sales at the regional level. Next, we verify whether the cyclicity 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 Data 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 cyclical nature 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.¹⁸ 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 cyclical nature of overall temporary discounts does not appear to be driven by clearance sales.

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 γ_{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.¹⁹

¹⁸A price line can end because the product is replaced by another comparable item at a specific store, because the ONS stops collecting its price, or if the store permanently shuts down. Data Appendix A.8 provides additional evidence on the prevalence of sales over the product life cycle. For this exercise, we rely on the ONS sales flag, as the forward-looking nature of the V-shaped or reference price filters makes them inadequate to identify end-of-price-lines discounts.

¹⁹In Table A.8 in Data 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 basic specification is standard and given by

$$\gamma_{ijt} = \alpha_{ij} + \beta u_t + X_t' \Phi + error, \quad (1)$$

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).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

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.

²⁰As a point of reference, the unemployment rate during the 2007–09 recession rose by a magnitude of four standard deviations.

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 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 Data 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

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.

store networks, such as Tesco, Sainsbury’s and Asda, run local price discounts based on centrally determined criteria or as part of national promotional programs.

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 rather than local economic conditions.²² 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.

²²Unfortunately, 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.

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. Before delving into the details of the model, we provide a summary of its main components and features.

5.1 Overview of the model

The economy is composed of a very large number L of locations. In each location l , there lives a measure one of infinitely-lived ex-ante identical households who derive utility from consuming perishable products of countably many differentiated varieties, indexed by $j = 1, 2, \dots, J$, where J is a very large number. Also, in every location, there exists a *local shopping mall* populated by J firms, each selling a unit measure of perfectly substitutable brands of specific variety j .

Every firm chooses three objects in its pricing decision: a regular nominal price p^H , a nominal sale price p^L , and the fraction γ of homogenous brands that it sells at the sale price.²³ The regular nominal price can only be changed every N_P periods. In contrast, the firm can change its sale price in any period for free, but it incurs the cost of $\kappa\gamma$ units of labor for the fraction γ of its goods on sale. Firms make their pricing decisions before the households' shopping decisions.

Each household is composed of a household head and J shoppers, where each shopper is assigned to one and only one variety. Since J is a large number, a shopper can be interpreted as atomistic for the total consumption of the household. Households living in location l^* know the pricing decisions $\{p_{j,l^*}^H, p_{j,l^*}^L, \gamma_{j,l^*}\}$ of every j retailer at the local shopping mall. In addition, they know the *distribution* of $\{p_{j,l}^H, p_{j,l}^L, \gamma_{j,l}\}$ across all the other locations l . For each shopper j , the household head has two options. One is to instruct her to draw a brand from the seller in a random location l , with (unknown) probability $\gamma_{j,l}$ of drawing the sale price $p_{j,l}^L$. Another option is to send the shopper to the local shopping mall, with the instruction of searching for a brand on sale. As a *bargain hunter*, the known probability that she finds a discounted brand is higher and is given by $f\gamma_{j,l^*}$, with $f > 1$. This, however, comes at a cost: the household head commits to paying a random cost z (in units of time) if she sends the shopper as a bargain hunter to the local shopping mall. Under these assumptions, household i 's decision for assigning a type to the shopper of variety j will be in

²³This 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.

the form of a static cut-off rule: the household head chooses a value $z_j^*(i)$ such that member j is designated as bargain hunter for low realizations of the shopping costs, $z \leq z_j^*(i)$, and as *random shopper* when the shopping cost is high, $z > z_j^*(i)$. This implies that from the point of view of a firm, shoppers visiting it as bargain hunters have a higher probability of finding a product on sale than do the random shoppers. The firm cannot, however, discriminate between these two types.

When setting its pricing policy— p_{j,l^*}^H, p_{j,l^*}^L and γ_{j,l^*} —the firm thinks through the reactions of local households who are informed about prices in the local shopping mall l^* , and those who live in other locations. First, it realizes that it can attract a higher fraction of informed local households by lowering their expected price, $f\gamma_{j,l^*}p_{j,l^*}^L$. Even though its regular price p_{j,l^*}^H is sticky, this can be achieved by lowering the flexible sale price p_{j,l^*}^L , or by raising the fraction of brands on sale γ_{j,l^*} , at a cost $\kappa\gamma_{j,l^*}$. In turn, a lower expected price raises the cutoff cost z_j^* that these local households are willing to pay to designate shoppers as bargain hunters. By contrast, the firm cannot influence the mass of shoppers from other locations, who visit it randomly. Second, the firm's pricing policy determines the quantity demanded by each shopper in its store. This quantity is a standard CES function of the specific price she draws. Ultimately, the firm has to trade off the costs and benefits from changing its prices on the profits made from the two types of shoppers.

Because prices are sticky, monetary contractions are associated with high average price markups, making it desirable for retailers to expand their market share by posting more discounts. This, in turn, incentivizes households to send more bargain hunters. In Section 6, we show that our model can account quantitatively for countercyclical fluctuations of the fraction of discounts over the business cycle. But first, we lay out the model's structure and provide its main equilibrium conditions. The presentation of the full framework and a graphical representation of its most important components is relegated to the online Model Appendix.

5.2 Households

Consider a household i who lives in location l^* . As mentioned earlier, the household head knows p_{j,l^*}^H, p_{j,l^*}^L and γ_{j,l^*} on offer for each variety j sold at the local shopping mall. In addition, she knows the overall distribution of $\{p_{j,l}^H, p_{j,l}^L, \gamma_{j,l}\}$ across the other locations, but not which prices are charged in each of those locations.

Under the assumption that households are distributed uniformly across locations l^* , and given that there is a large number of households and varieties, households and firms are symmetric. Therefore, we will focus on a symmetric equilibrium in which in any given period t , each household i sends the same fraction of bargain hunters, and all firms receive the same fraction of bargain

hunters, and hence, make the same pricing decisions. Going forward, we will drop variety index j and use capital letters to identify aggregate variables to simplify notation. We will also drop location indices, and distinguish variables pertaining to locations $l \neq l^*(i)$ by a tilde. The sets of varieties and locations are denoted by \mathcal{J} and \mathcal{L} respectively. Aggregate events in this economy up to and including period t are recorded in the vector $s^t = (s_0, \dots, s_t)$, and $\pi(s^t)$ denotes the probability of a particular history s^t . We will use subscript t to annotate functions of state history s^t . Below we will use the operator $E_t(X_\tau)$ to denote expected values of function $X(s^\tau)$ conditional on history s^t , i.e., $E_t(X_\tau) \equiv \sum_{s^\tau | s^t} \pi(s^\tau | s^t) X(s^\tau)$.

Shopper types. A shopper for a specific variety can be one of two types: bargain hunter or random shopper. These two types differ in how they convert available price information into a probability of being matched with a low price.

A random shopper j does not observe the specific prices posted by retailers, so she randomly visits a location $l \neq l^*$, goes to the store selling variety j in that location and picks a brand at random, i.e. she draws a brand priced at \tilde{p}^L with probability $\tilde{\gamma}$ or at \tilde{p}^H with probability $1 - \tilde{\gamma}$.

A bargain hunter visits the local shopping mall in l^* , for which she knows the retailers' prices. Equipped with price information, she generates a higher probability of drawing a brand with a low price p^L , given by $f\gamma$, where by assumption $f > 1$. Accordingly, she has a lower probability of finding a regular price p^H , equal to $1 - f\gamma$. Bargain hunters yield to the household higher returns from shopping because they are more likely to be matched with a low-priced brand. They are also, as we see next, costlier.

Cost of shopping. Each bargain hunter costs the household z units of time, where z is i.i.d. across shoppers and time, and distributed according to a smooth c.d.f. $G(z)$, $0 \leq z \leq z_{max}$. Under these assumptions, household i 's decision for assigning a type to the shopper of variety j will be in the form of a static cut-off rule: the household head chooses a value $z^*(i)$ such that member j is designated as bargain hunter for low realizations of the shopping costs, $z \leq z^*(i)$, and as random shopper when the shopping cost is high, $z > z^*(i)$. The choice of $z^*(i)$ determines the probability that variety j will be purchased by a bargain hunter, which we denote by $\alpha(i) \equiv G(z^*(i))$. The expected shopping cost for variety j is $\int_0^{z^*(i)} z dG(z)$.

Recall that this household knows the exact price menu $\{p_j^H, p_j^L, \gamma_j\}$ in a given location l^* , and the distribution of prices everywhere else. Hence, the key decision of the household head is whether to pay the fixed cost z and have a higher probability of finding a discounted brand in the local shopping mall, or forego the cost and just shop randomly. Since households pick the shopper type after obtaining information about prices, firms know that their pricing decision will influence the

fraction of bargain hunters that visit them.

Consumption outcomes. For each variety j , and for any cut-off value $z^*(i)$, household i faces four random and *mutually exclusive* consumption outcomes:²⁴

- the shopper will be a bargain hunter and visit the local shopping mall in her location l^* , matched with a discounted brand with probability $\alpha(i)f\gamma$, or with a regularly-priced brand with probability $\alpha(i)(1 - f\gamma)$;
- the shopper will be a random shopper in a random location l , matched with a discounted brand with probability $(1 - \alpha(i))\tilde{\gamma}$, or with a regularly-priced brand with probability $(1 - \alpha(i))(1 - \tilde{\gamma})$.

Let $x_t(i)$ denote the realization of one of these four consumption outcomes, and let $\pi^x(x_t(i))$ be its respective probability, as specified above. Also, let $c_t(x_t(i))$ denote a *consumption plan*—units of consumption of variety j purchased by shopper j and conditional on the realization of one of the four consumption outcomes $x_t(i)$.

Total consumption. Household i 's *ex post* consumption—i.e., consumption conditional on realizations of $x_t(i)$ —is the CES aggregate

$$C_t(i) = \left[\sum_{\mathcal{J}} c_t(x_t(i))^{1 - \frac{1}{\theta}} \right]^{\frac{\theta}{\theta - 1}}, \quad (2)$$

where θ is the elasticity of substitution across varieties. Since draws of $x_t(i)$ are identically and independently distributed across households and varieties, by the law of large numbers, the summation in (2) does not depend on *which* outcomes $x_t(i)$ are realized across specific households and varieties. This implies two convenient aggregation properties.²⁵

First, since households are *ex ante* identical, total consumption $C_t(i)$ and the price aggregate $P_t(i)$ are equal for all households, i.e., $C_t(i) = C_t$, $P_t(i) = P_t$, $\forall i$. This also implies that a household's *ex post* consumption, $C_t(i)$, is equal to its *ex ante* consumption, $\sum_{x_t(i)} \pi^x(x_t)C_t(i)$. Second, since realizations $x_t(i)$ are independent across varieties, we can take probabilities $\pi^x(x_t)$ inside the

²⁴Since 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. Household also cannot transfer goods across locations upon realizing their matches.

²⁵Similar aggregation results are also derived in [Guimaraes and Sheedy \(2011\)](#).

summation in (2) and write

$$C_t(i) = \left\{ \sum_J \left[G(z_t^*(i)) \left(f\gamma_t (c_t^L(i))^{1-\frac{1}{\theta}} + (1-f\gamma_t) (c_t^H(i))^{1-\frac{1}{\theta}} \right) + (1-G(z_t^*(i))) \sum_{\mathcal{L} \setminus l^*} \left(\tilde{\gamma}_t (\tilde{c}_t^L(i))^{1-\frac{1}{\theta}} + (1-\tilde{\gamma}_t) (\tilde{c}_t^H(i))^{1-\frac{1}{\theta}} \right) \right] \right\}^{\frac{\theta}{\theta-1}}. \quad (3)$$

where $c_t^L(i)$, $c_t^H(i)$, $\tilde{c}_t^L(i)$, $\tilde{c}_t^H(i)$ denote the four possible consumption outcomes for variety j in period t , and $\sum_{\mathcal{L} \setminus l^*}$ denotes the average over $L-1$ locations the random shopper is uninformed about. From now on, we will omit the household index i , unless necessary.

Dynamic optimization problem of the household. Households are organized in labor unions over countably many differentiated labor services indexed by $u = 1, 2, \dots, U$. Each union consists of all households with labor type u , and supplies labor services of that type in a monopolistically competitive labor market. A household head who is a member of union u supplies all labor services L_t demanded by the union and receives wage W_t set by the union. For the remaining decisions, the household head chooses the sequences of total consumption C_t , cash holdings M_t , security holdings \mathbf{A}_{t+1} , bond holdings B_t , the cut-off search cost for each variety z_t^* , and consumption plans for each variety $c_t^L, c_t^H, \tilde{c}_t^L, \tilde{c}_t^H$ to maximize:

$$E_0 \sum_t \beta^t [u(C_t) - v(L_t)], \quad (4)$$

subject to the definition of aggregate consumption (3), the sequence of budget constraints

$$\begin{aligned} M_t + B_t + \sum_{t+1|t} \mathbf{Q}_{t+1|t} \mathbf{A}_{t+1} &\leq W_t L_t + R_{t-1} B_{t-1} + A_t + \Pi_t + T_t \\ + M_{t-1} - W_{t-1}^F \sum_j \int_0^{z_{t-1}^*} z dG(z) & \\ - \sum_{\mathcal{J}} [G(z_{t-1}^*) (f\gamma_{t-1} p_{t-1}^L c_{t-1}^L + (1-f\gamma_{t-1}) p_{t-1}^H c_{t-1}^H) & \\ + (1-G(z_{t-1}^*)) \sum_{\mathcal{L} \setminus l^*} (\tilde{\gamma}_{t-1} \tilde{p}_{t-1}^L \tilde{c}_{t-1}^L + (1-\tilde{\gamma}_{t-1}) \tilde{p}_{t-1}^H \tilde{c}_{t-1}^H)] & \end{aligned} \quad (5)$$

where the last three rows represent unspent cash carried over from period $t-1$ to t , W_t^F is aggregate wage, Π_t are dividends paid and T_t are lump-sum government transfers; and the sequence of cash-

in-advance constraints for total consumption and shopping expenses²⁶

$$M_t \geq W_t^F \sum_j \int_0^{z_t^*} z dG(z) + \sum_{\mathcal{J}} [G(z_t^*) (f\gamma_t p_t^L c_t^L + (1-f\gamma_t) p_t^H c_t^H) + (1-G(z_t^*)) \sum_{\mathcal{L} \setminus l^*} (\tilde{\gamma}_t \tilde{p}_t^L \tilde{c}_t^L + (1-\tilde{\gamma}_t) \tilde{p}_t^H \tilde{c}_t^H)] . \quad (6)$$

Consumption decisions. The first-order conditions for consumption varieties yield the consumption plan

$$\tilde{c}_t^k = \left(\frac{\tilde{p}_t^k}{P_t} \right)^{-\theta} C_t, \text{ and } c_t^k = \left(\frac{p_t^k}{P_t} \right)^{-\theta} C_t, \quad k = \{L, H\}. \quad (7)$$

where the aggregate price index is

$$P_t \equiv \left\{ \sum_{\mathcal{J}} \left[G(z_t^*) \left(f\gamma_t (p_{jt}^L)^{1-\theta} + (1-f\gamma_t) (p_t^H)^{1-\theta} \right) + (1-G(z_t^*)) \sum_{\mathcal{L} \setminus l^*} \left(\tilde{\gamma}_t (\tilde{p}_t^L)^{1-\theta} + (1-\tilde{\gamma}_t) (\tilde{p}_t^H)^{1-\theta} \right) \right] \right\}^{\frac{1}{1-\theta}} .$$

Since there is a single shopper per variety and no means of transferring consumption across shoppers or across time, a household cannot improve on these allocations after the realization of its consumption outcome x_t . Note that the optimal consumption plan for purchasing variety j is represented by a CES demand function which is invariant to the type of shopper or the match with a specific retailer/location; the number of consumption units purchased by the shopper will depend only on the price draw (high or low). Finally, total consumption is characterized by the standard Euler equation $1 = \beta R_t E_t \left(\frac{u'(c_{t+1})}{u'(c_t)} \frac{P_t}{P_{t+1}} \right)$.

Shopping-time decision. The first-order condition for the cut-off z_t^* is:

$$0 = u'(C_t) \frac{\theta}{\theta-1} G'(z_t^*) (C_t)^{\frac{1}{\theta}} \left[f\gamma_t (c_t^L)^{1-\frac{1}{\theta}} + (1-f\gamma_t) (c_t^H)^{1-\frac{1}{\theta}} - \sum_{\mathcal{L} \setminus l^*} \left(\tilde{\gamma}_t (\tilde{c}_t^L)^{1-\frac{1}{\theta}} + (1-\tilde{\gamma}_t) (\tilde{c}_t^H)^{1-\frac{1}{\theta}} \right) \right] - \frac{u'(C_t)}{P_t} \left\{ W_t^F z_t^* G'(z_t^*) + G'(z_t^*) \left[f\gamma_t p_t^L c_t^L + (1-f\gamma_t) p_t^H c_t^H - \sum_{\mathcal{L} \setminus l^*} (\tilde{\gamma}_t \tilde{p}_t^L \tilde{c}_t^L + (1-\tilde{\gamma}_t) \tilde{p}_t^H \tilde{c}_t^H) \right] \right\} \quad (8)$$

The first row gives the additional utility of consumption from marginally increasing the cut-off z_t^* : a higher cut-off increases the probability that the shopper of variety j will be a bargain hunter and

²⁶Including shopping expenses in the cash-in-advance constraint does not alter the results in the paper. It does help to obtain simpler first-order conditions for consumption and shopping time, as we show in detail in the online Model Appendix.

become matched with a lower priced brand. On the other hand, a lower expected price implies higher nominal expenditures under standard values of the elasticity of substitution, and a higher cut-off implies higher expected costs from bargain hunting. These terms are captured by the second row of (8). We can simplify (8) by dividing it through by $u'(c_t)G'(z_t^*)$, and applying demand equations (7); this simplified condition is

$$\frac{\Delta x_t}{z_t^*} = \frac{W_t^F}{P_t}, \quad (9)$$

where the real return on shopping is denoted by $\Delta x_t \equiv \frac{1}{\theta-1} [(f\gamma_t p_t^L c_t^L + (1-f\gamma_t)p_t^H c_t^H) - \sum_{L \setminus l^*} (\tilde{\gamma}_t \tilde{p}_t^L \tilde{c}_t^L + (1-\tilde{\gamma}_t)\tilde{p}_t^H \tilde{c}_t^H)] / P_t$. According to condition (9), households choose their shopping time to equate the marginal rate of transformation of time for real consumption, $\frac{\Delta x_t}{z_t^*}$, to the price of time, $\frac{W_t^F}{P_t}$. The household's optimal shopping time increases with real return on shopping, which depends on the use and magnitude of sales, and decreases with the real price of time.²⁷

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 underpins the mechanism that helps account for the behavior of sales documented in the empirical part of the paper.

Union's labor supply and wage-setting decisions. Each union consists of all households with labor type u . It supplies labor services L_t in a monopolistically competitive labor market.²⁸ Labor services can be aggregated over the set of union types \mathcal{U} into a final labor service L_t^F , according to $L_t^F = \left\{ \sum_{\mathcal{U}} L_t^{1-\frac{1}{\vartheta}} \right\}^{\frac{\vartheta}{\vartheta-1}}$, where ϑ is the elasticity of substitution across labor services. Each union sets wages W_t for its services, and accordingly faces the demand $L_t = \left(\frac{W_t}{W_t^F} \right)^{-\vartheta} N_t$ from firms, where N_t is the demand for final labor service and $W_t^F = \left\{ \sum_{\mathcal{U}} W_t^{1-\vartheta} \right\}^{\frac{1}{1-\vartheta}}$ is the aggregate wage. We assume unions set wages according to Taylor contracts, with wages fixed for N_W periods. Contracts are perfectly staggered across unions, i.e., in every period a fraction $1/N_W$ of unions reset their wages. Union u supplies all services demanded at wage W_t . The first-order condition for the union's reset wage gives a standard expression elaborated in the Model Appendix.

²⁷The problem of choosing shopping time and composition of consumption across varieties can also be formulated as a static expenditure minimization problem. See the Model Appendix for details.

²⁸For an example of the setup with unions supplying differentiated labor services in monopolistically competitive labor markets, see [Chari, Kehoe, and McGrattan \(2002\)](#).

5.3 Production and pricing

There are two types of firms: intermediate good producers and retailers.

Intermediate input producers. A continuum of competitive intermediate good firms own and invest in capital K_t , acquire final labor service N_t and produce homogeneous good Y_t using a Cobb-Douglas technology

$$Y_t = a_t N_t^{1-\chi} K_t^\chi, \quad (10)$$

where a_t is total factor productivity in period t , following an AR(1) process in logs, $\ln a_t = \rho_a \ln a_{t-1} + \epsilon_{at}$, with normal i.i.d. innovations ϵ_{at} with mean 0 and standard deviation σ_a .

The homogeneous good is sold at the competitive price P_t^I to other intermediate good firms as investment good, and to retail firms as the sole input in their production of consumption varieties.

Retailers. The retail firm selling brands of variety j in location l^* is endowed with a linear production technology that converts Y_t units of homogeneous intermediate input into y_t units of perfectly substitutable brands of variety j : $y_t = Y_t$. This technology implies that the retailer's marginal cost of production is equal to the price of the intermediate input, P_t^I .

Let us denote by α_t^B the mass of bargain hunters visiting their local shopping mall in location l^* . They belong to local households who are informed about the prices posted and draw a shopping cost below the cut-off level. Specifically, α_t^B is defined as

$$\alpha_t^B = \int_0^1 G(z_t^*(i)) di. \quad (11)$$

We can substitute for the cut-off $z_t^*(i)$ using the household's first-order condition (9) and then plugging $c_t^L(i)$ and $c_t^H(i)$ from demand equations (7). This yields an expression for α_t^B as a function of the prices posted by the retailer of the relevant variety in location l^* (p_t^L , p_t^H , and γ_t):

$$\begin{aligned} \alpha_t^B &= \int G \left(\frac{(W_t^f)^{-1}}{\theta - 1} \left[\left(f \gamma_t p_t^L \left(\frac{p_t^L}{P_t} \right)^{-\theta} C_t + (1 - f \gamma_t) p_t^H \left(\frac{p_t^H}{P_t} \right)^{-\theta} C_t \right) \right. \right. \\ &\quad \left. \left. - \sum_{\mathcal{L} \setminus l^*} (\tilde{\gamma}_t \tilde{p}_t^L \tilde{c}_t^L(i) + (1 - \tilde{\gamma}_t) \tilde{p}_t^H \tilde{c}_t^H(i)) \right] \right) di. \\ &\equiv \alpha^B(p_t^L, p_t^H, \gamma_t) \end{aligned} \quad (12)$$

where the function $\alpha^B(p_t^L, p_t^H, \gamma_t)$ denotes the right-hand side of (12).

Equation (12) implies that the mass of bargain hunters visiting the retailer of a specific variety in location l^* is increasing in γ_t and decreasing in p_t^L and p_t^H . Through its pricing decision, the firm

can attract local shoppers who are informed about its prices. All other shoppers are by definition random shoppers for whom l^* is the randomly assigned location. As a result, the retailer takes the mass of random shoppers coming to its location as given. We denote this mass by α_t^R .

Pricing decision. Retailers face Taylor (1980) price adjustment constraints for the high price: each keeps its price fixed for N_P periods. Such price contracts are evenly staggered across varieties so that in every period a measure $1/N_P$ of retailers resets their prices. Since firm's price choices will vary with price duration, $k = 0, \dots, N_P$, we will let $p_{t-k,t}^L, p_{t-k,t}^H, \gamma_{t-k,t}$ denote prices and the fraction of discounts in period t for the retailer that reset its regular prices in period $t - k$. Discounted prices are flexible, and posting γ discounts entails a period cost of $\kappa\gamma$ units of final labor service. We denote the measure of transactions at the sale price as $n_{t-k,t}^L \equiv (\alpha_{t-k,t}^R + \alpha_{t-k,t}^B f) \gamma_{t-k,t}$, and the mass of transactions at the regular price as $n_{t-k,t}^H \equiv \alpha_{t-k,t}^R (1 - \gamma_{t-k,t}) + \alpha_{t-k,t}^B (1 - f \gamma_{t-k,t})$.

A retail firm resetting its regular price in period t chooses the sequences of its two consumption price points $p_{t,t+k}^H$ and $p_{t,t+k}^L$; the fraction of price discounts $\gamma_{t,t+k}$; the fraction of bargain hunters visiting its location, $\alpha_{t,t+k}^B$; intermediate inputs $Y_{t,t+k}$; and output levels $y_{t,t+k}$ to maximize the discounted flow of profits over the duration of its regular price:

$$E_t \sum_{\tau=t}^{t+N_P-1} \left\{ \beta^\tau \frac{u'(C_\tau)}{P_\tau} \cdot \left[n_{t,\tau}^H p_{t,\tau}^H c_{t,\tau}^H + n_{t,\tau}^L p_{t,\tau}^L c_{t,\tau}^L - P_\tau^I Y_{t,\tau} - \kappa W_\tau^f \gamma_{t,\tau} \right] \right\}$$

subject to the demand constraints (7), the constraint on the measure of bargain hunters in location l^* (12), the production technology

$$n_{t,\tau}^H c_{t,\tau}^H + n_{t,\tau}^L c_{t,\tau}^L \leq Y_{t,\tau},$$

and constraints on regular price adjustments, $p_{t,t}^H = p_{t,t+1}^H = \dots = p_{t,t+N_P-1}^H$.

First-order conditions. The retailer's first-order conditions for prices in period t , $p_{t-k,t}^H$, $p_{t-k,t}^L$ and $\gamma_{t-k,t}$, will include partial derivatives of the function $\alpha^B(p_{t-k,t}^L, p_{t-k,t}^H, \gamma_{t-k,t})$ to reflect the influence of the retailer's pricing on its fraction of bargain hunters. For the firm in period t that set its regular price k periods ago, where $k = 0, \dots, N_P - 1$, denote the semi-elasticity of the fraction of bargain hunters with respect to the discounted price by $\varepsilon_{t-k,t}^{B,L} \equiv \frac{\partial \alpha^B(p_{t-k,t}^L, p_{t-k,t}^H, \gamma_{t-k,t})}{\partial \ln p_{t-k,t}^L}$. The first-order condition for the discounted price can then be written as follows

$$p_{t-k,t}^L = \frac{\theta}{\theta - 1} P_t^I \left(\frac{1}{1 + |\varepsilon_{t-k,t}^{B,L}| \Delta_{t-k,t}^L} \right), \quad (13)$$

where the factor $\Delta_{t-k,t}^L > 0$ depends on the measure of transactions at a discounted price $n_{t-k,t}^L$

and the profits from sales per bargain hunter. Intuitively, a lower (higher) discount price makes it more (less) worthwhile for households to pay the cost z and send more bargain hunters to this retailer, effectively making demand more elastic. A more elastic demand is captured by the term in parentheses in condition (13), and it implies that the discounted price is below the single-good monopoly price $p_{t-k,t}^L < \frac{\theta}{\theta-1} P_t^I$. Note that the retailer's cost may depend on the number of periods until the next regular price reset, which will have an effect on both $p_{t-k,t}^L$ and $\gamma_{t-k,t}$, while $p_{t-k,t}^H$ is constrained. Hence, discounts provide retailers with an additional margin of price adjustment that they can use to partially offset sticky regular prices.

The first-order condition for the reset regular price $p_{t,t}^H$ is different from (13) in two respects. First, it reflects the effects of price-adjustment constraints by including the summations over periods t to $t + N_P - 1$:

$$p_{t,t}^H = \frac{\theta}{\theta-1} \frac{E_t \sum_{\tau=t}^{t+N_P-1} \beta^\tau (u'(C_\tau) / P_\tau) P_\tau^\theta C_\tau \cdot n_{t,\tau}^H P_\tau^I}{E_t \sum_{\tau=t}^{t+N_P-1} \beta^\tau (u'(C_\tau) / P_\tau) P_\tau^\theta C_\tau \cdot n_{t,\tau}^H \left(1 + |\varepsilon_{t,\tau}^{B,H}| \Delta_{t,\tau}^H\right)}, \quad (14)$$

where $\varepsilon_{t,\tau}^{B,H} \equiv \frac{\partial \alpha^B(p_{t,\tau}^L, p_{t,\tau}^H, \gamma_{t,\tau})}{\partial \ln p_{t,\tau}^H}$ is the semi-elasticity of the fraction of bargain hunters with respect to the regular price, and the factor $\Delta_{t,\tau}^H > 0$ depends on the measure of transactions at the regular price $n_{t,\tau}^H$. Second, like the discounted price, the regular price also attracts bargain hunters and increases demand elasticity, but to a smaller degree: a 1\$ lower discounted price is worth more to households than a 1\$ lower regular price, since a bargain hunter is f times more likely to draw a discounted price than a random shopper. We can show that the resulting regular price is above the discount price, but below the single-good monopoly price: $p_{t-k,t}^L < p_{t-k,t}^H < \frac{\theta}{\theta-1} P_t^I$.

Finally, the first-order condition for the fraction of discounts equates the benefits and costs to the retailer from marginally increasing the proportion of its brands that are discounted:

$$\varepsilon_{t-k,t}^{B,\gamma} \Pi_{t-k,t}^B = \frac{n_{t-k,t}^L}{\gamma_{t-k,t}} \left[(p_{t-k,t}^H - P_t^I) \left(\frac{p_{t-k,t}^H}{P_t} \right)^{-\theta} C_t - (p_{t-k,t}^L - P_t^I) \left(\frac{p_{t-k,t}^L}{P_t} \right)^{-\theta} C_t \right] + \kappa W_t^F \quad (15)$$

The benefits on the left-hand side depend on two factors. First, they rise with the expected profits per each bargain hunter, $\Pi_{t-k,t}^B$. Note that even though each discounted unit is sold at a loss, the expected profit from attracting more bargain hunters is still positive: many of them will still end up drawing a regular price. Second, the benefit of discounting more brands is higher when the sensitivity of the fraction of bargain hunters with respect to the proportion of discounts, $\varepsilon_{t-k,t}^{B,\gamma} \equiv \frac{\partial \alpha^B(p_{t-k,t}^L, p_{t-k,t}^H, \gamma_{t-k,t})}{\partial \gamma_{t-k,t}}$, is higher. The costs of raising $\gamma_{t-k,t}$ are represented on the right-hand side of (15). They comprise the profit losses per each discount and the costs of posting an extra discount.

5.4 Monetary policy and budget balance

Monetary policy is conducted such that the quantity of money M_t follows a random-walk process of the form $\ln M_t = \ln M_{t-1} + \mu_t$, where μ_t is log money growth, a normally distributed i.i.d. random variable with mean 0 and standard deviation σ_μ . In addition, the government balances its budget in every period, $T_t = M_t - M_{t-1}$.

The timing of events, market clearing conditions and the definition of equilibrium in our model are standard and are presented in detail in the Model Appendix.

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 θ , the bargain-hunting technology parameter f , the fixed cost of posting price discounts κ , and the parameters of the fixed cost distribution. The latter govern the relationship between the fraction of bargain hunters, α_t , and the shopping time for a marginal bargain hunter, z_t^* . Since we are focusing on small fluctuations around the steady state, we can approximate this relationship up to a second order by

$$\alpha_t - \alpha \approx \xi \ln(z_t^*/z^*), \quad (16)$$

where z^* , α are steady-state values of z_t^* , α_t . The parameter ξ 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 α and the semi-elasticity ξ .²⁹

²⁹A log-linear approximation allows us to calibrate parameters in equation (16) without specifying the fixed-cost distribution. An equivalent but more involved calibration is to choose the fixed cost distribution and map its param-

We jointly calibrate five parameters (θ , f , κ , α , and ξ) 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.³⁰ 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 α , we match the ratio of the consumption revenue share of discounted products over the fraction of products on sale. Gandon (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 flexibility 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

eters into α and ξ . To this end, the log-linear approximation of the expected cost of shopping $\Xi(\alpha_t) = \int_0^{z^*} z dG(z)$ yields equation (16), where $\xi = \frac{z^*}{\Xi(\alpha)}$ and $\alpha = G(z^*)$.

³⁰For 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).

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 $u(C) - v(L) = \frac{C^{1-\sigma}}{1-\sigma} - \psi \frac{L^{1+1/\eta}}{1+1/\eta}$. 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 cyclical nature of sales are empirically plausible. In the text we focus on the results, and we refer the reader to the Model Appendix for details.

Discounts are short-lived. In the model, when the retailer chooses a fraction γ 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, marked up at 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 11.1%, compares favorably to their empirical estimate.

Unconditional volatilities and correlations. In the 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 Model Appendix). 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 0.28 in the model, compared to 0.27 in the data. If we use hours worked instead, the relative volatility goes down to 0.21 in our simulations versus 0.14 empirically. The cyclical frequency of sales in the model is also well aligned with the data: the correlations with consumption and hours are respectively -0.54 and -0.49 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.³¹

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.³²
- “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 γ_t and p_t^L/p_t^H from their steady-state values.³³
- “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

³¹[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.

³²The parameter θ is recalibrated in order to match the same markup of 1.25.

³³Specifically, we introduce a convex cost of adjusting the number of discounts by the firm: $\kappa W_t^F (\gamma_{jt} + \frac{\epsilon_\gamma}{2} (\gamma_{jt} - \gamma)^2)$. For the size of discounts, we add a convex adjustment cost term in the decision of adjusting the discount price: $\frac{\epsilon_\delta}{2} (p_t^L/p_t^H - p^L/p^H)^2$.

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 -0.33% below its steady-state value, which is 34% 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 10](#), which respectively compare the responses of the aggregate price level P_t and real consumption C_t under the “Constant discounts” and “Cyclical discounts” 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 total nominal spending falls by the same magnitude as the money supply (1%), the fall in real consumption is large: around -0.97% on impact, dissipating to -0.09% after one year. By contrast, the price level in the baseline model goes down by 0.72% at the time of the shock. As a result, the 0.48% 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, since most firms are not able to adjust their regular prices. This reaction is illustrated in [Panel C of Figure 10](#), where the fraction of price discounts rises by 0.80 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. Once a firm gets to reset its regular price, that price goes down by about the size of the impulse, i.e., 1% . Sale prices, despite being completely flexible, nonetheless follow closely the level of respective regular price: they remain stable while the regular

price is constrained, and they fall down when the regular price is reset. Instead of moving their sale price, retailers increase the fraction of discounts (Panel C), this increase brings extra mass of bargain hunters to their store (Panel D). This prediction of the model that firms move the fraction of discounts rather than their magnitude 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 of these margins 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. The variation in discounts that achieves both of these outcomes is either an increase of the fraction of discounts by 0.45 ppt, or an increase of the size of discounts by 1.36 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 2.17%, 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 2.05%. This is because lowering γ means firms need to satisfy a swing in demand ($c^L - c^H$) 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 efficiently.

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 0.52% 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 −0.72% 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 2.³⁴

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 1.7% following the rise in bargain hunters (Panel D in Figure 10). At the same time, hours worked decline by 3.7%. The corresponding elasticity of shopping time with respect to hours worked is -0.40 . 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 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^F/P (see equation 5). Since prices adjust somewhat faster than wages, real market wages slightly *increase* during a monetary contraction, by 0.22% 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 (2.1 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, $\psi C_t^\sigma L_t^{1/\eta}$. This measure declines after the contractionary shock, leading to an increase in shopping time. The total response of the shopping

³⁴In Data Appendix B, we quantify empirically the wedge between the standard (CPI) aggregate price index and the effective price index using the U.K. micro price data.

time on impact is 2.1%, versus 1.7% in the baseline, leading to a more flexible price response: -0.73% , versus -0.72% in the model. The elasticity of shopping time to hours worked is equal to -0.77 , compared to -0.40 in the baseline model.³⁵

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 [Aguilar, Hurst, and Karabarbounis \(2013\)](#). More 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 the Model Appendix. 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 weaker than in the baseline model (-0.25% versus -0.33%). 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 24.2% smaller than in a version with constant or no discounts, while this difference was 34.0% in the baseline.

Increased wage stickiness. Making wages stickier, in line with some of the higher estimates

³⁵We 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.

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 (−0.31% versus −0.33% 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 between 2% and 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 −0.33% 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 a third, 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.

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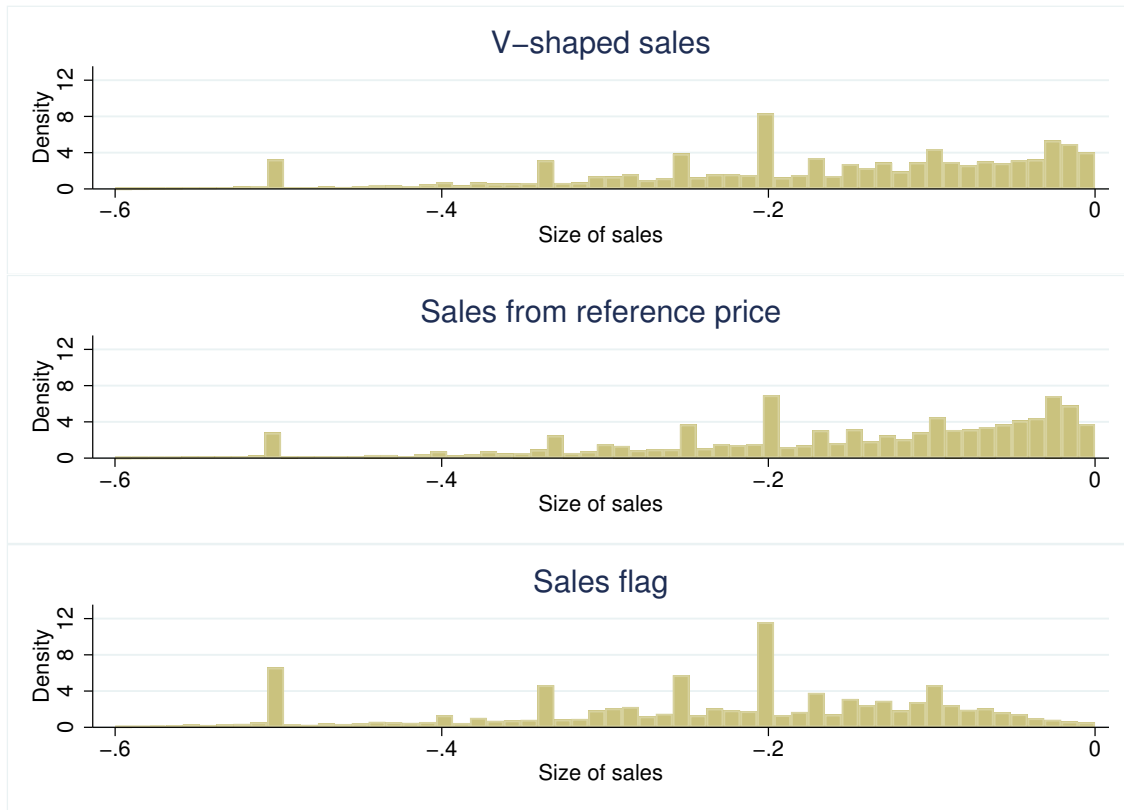
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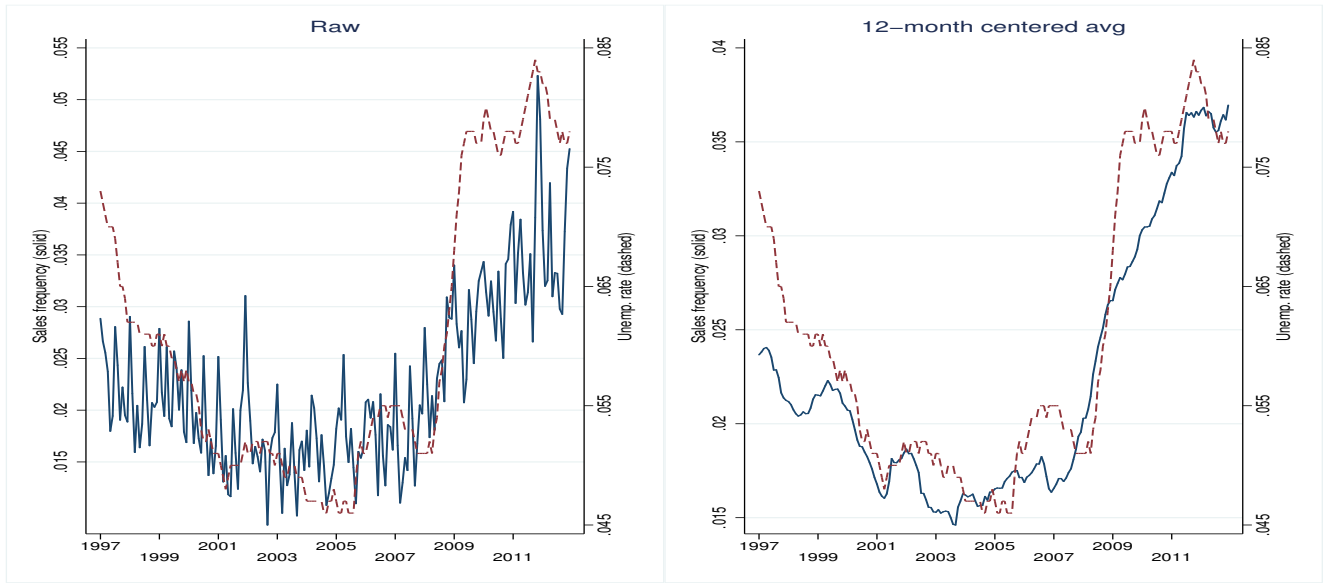
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Figure 1: Distribution of the size of sales for the three main filters



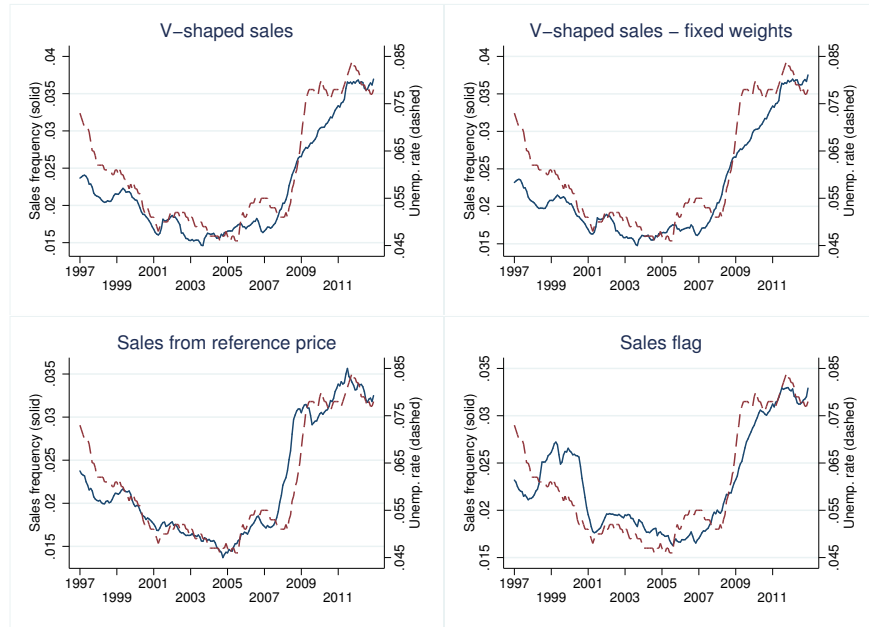
Notes: Histograms of the size of discounts for the sales flag, V-shaped sales and sales from reference price. Sample period is 1996:02–2013:09. U.K. Office for National Statistics data.

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



Notes: Monthly proportion of products at discounted price based on the V-shape filter. Aggregation is done using CPI quote weights. Sample period is 1996:02–2013:09. U.K. Office for National Statistics data.

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



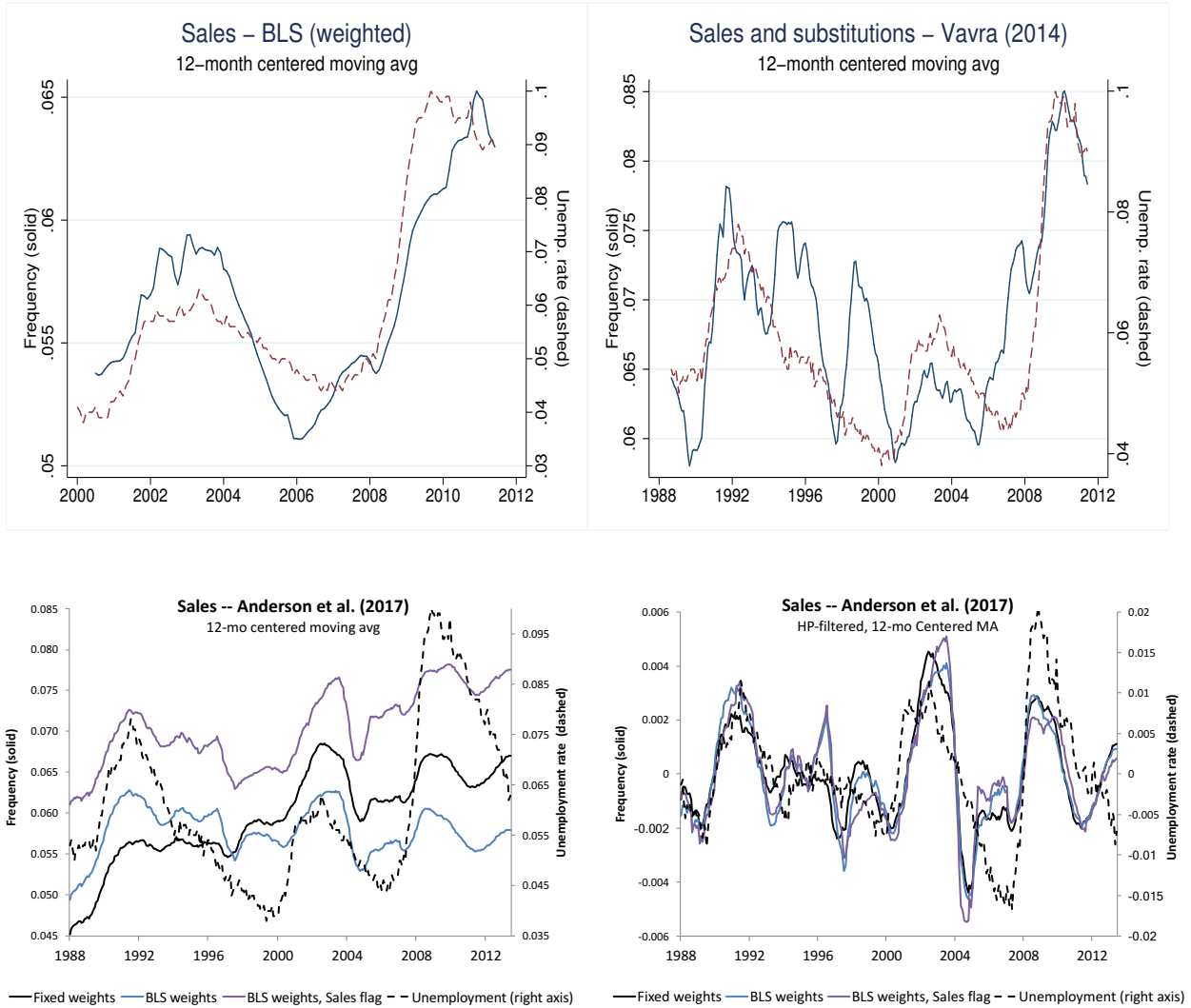
Notes: Monthly proportion of products on sale using the three types of filters. Aggregation is done using CPI quote weights. For the top right plots, the product-level weights are time invariant and correspond to their time-series average. Sample period is 1996:02–2013:09. U.K. Office for National Statistics data.

Figure 4: The evolution of the size of sales



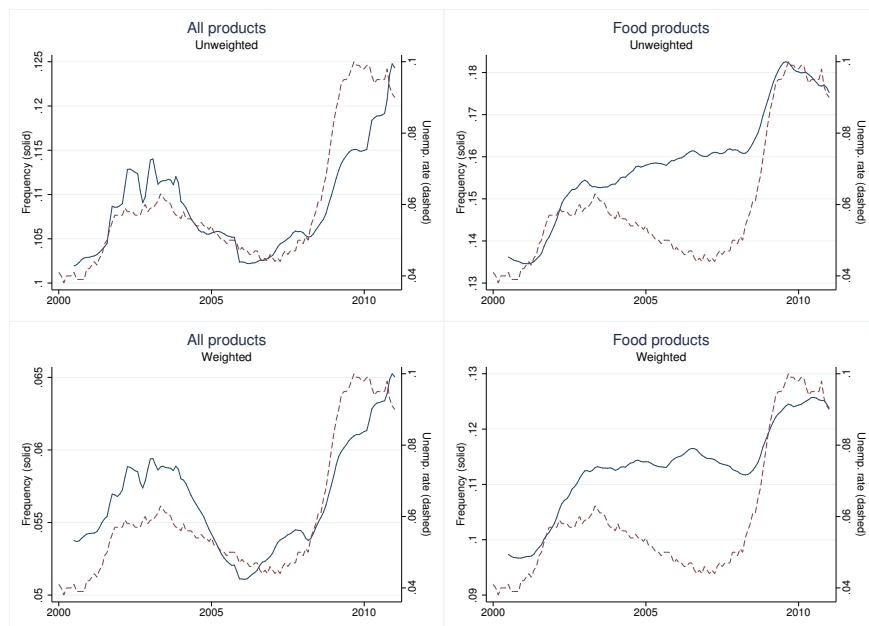
Notes: Weighted average of the size of discounts using the three types of filters. Aggregation is done using CPI quote weights. Data is monthly and the sample period is 1996:02–2013:09. U.K. Office for National Statistics data.

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



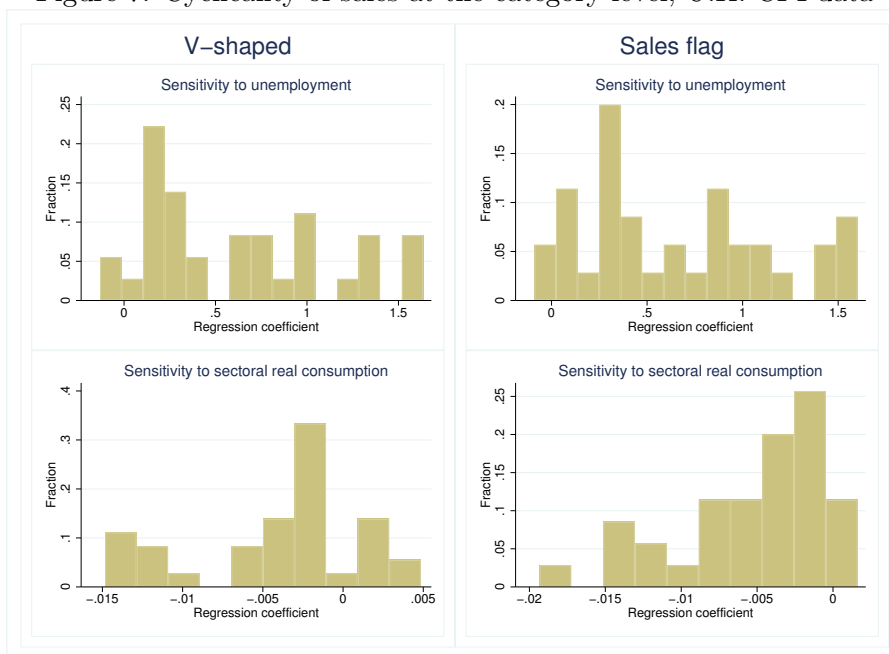
Notes: Data from the U.S. Bureau of Labor Statistics, [Vavra \(2014\)](#) and [Anderson et al. \(2017\)](#). All sales frequency series are 12-month moving averages. Monthly weighted fraction of products with a sales flag (top left) and sales flag or substitution (top right), using BLS expenditure weights. 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



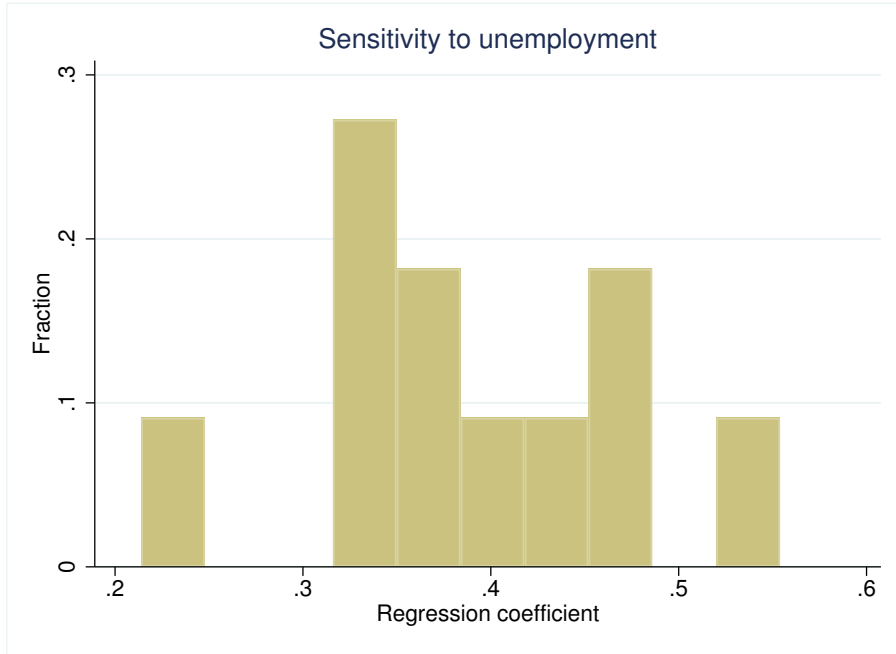
Notes: Monthly proportion of products with a sales flag. For the plots in the left column, aggregation is done using CPI quote weights. Sample period is 2000:01–2011:12. U.S. Bureau of Labor Statistics data.

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



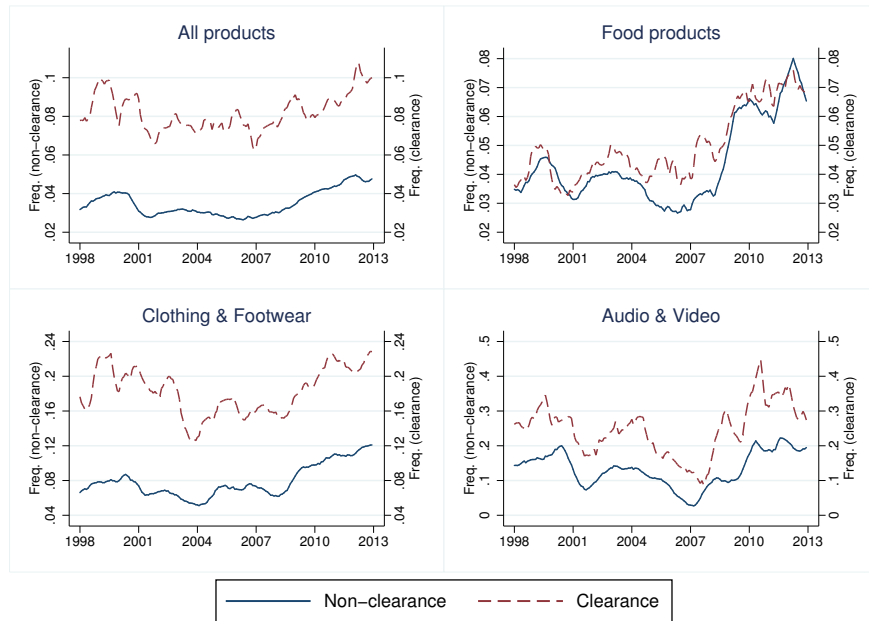
Notes: Distribution of coefficients from two regressions at the category level. Top row: Sales frequency on monthly aggregate unemployment rate and a time trend. Bottom row: Sales frequency on the log of quarterly category-level real consumption and a time trend. Sales are identified using the V-shape (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: Cyclicity of sales at the regional level, U.K. CPI data



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



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.

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

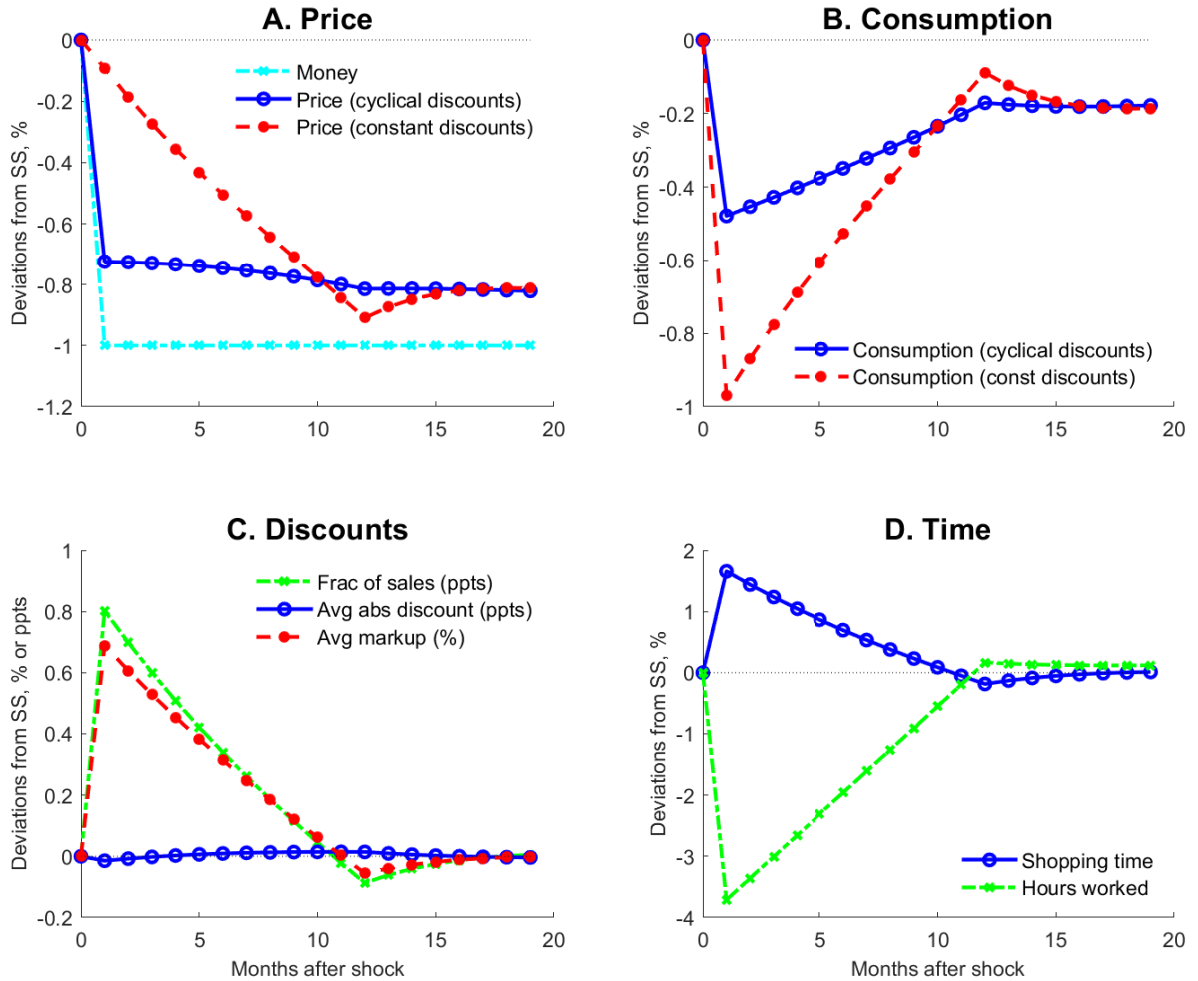


Table 1: Summary statistics for posted and regular price changes

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

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

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

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

| | | United Kingdom | | | | | | |
|---------|-------------------|---------------------|---------------------|---------------------|---------------------|---------------------|--------------------------|----------------------|
| Panel A | | <i>V-shaped</i> | <i>V-shaped</i> | <i>V-shaped</i> | <i>Flag</i> | <i>Ref.</i> | <i>V-shaped - median</i> | <i>Flag - median</i> |
| | u_t | 0.544*** (0.024) | 0.194*** (0.036) | 0.464*** (0.023) | 0.358*** (0.025) | 0.424*** (0.024) | 0.267*** (0.028) | 0.328*** (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 |

| | | United States - BLS | | | United States - Vavra (2014) | | |
|---------|-------------------|---------------------|---------------------|---------------------|------------------------------|---------------------|---------------------|
| Panel B | | <i>Mean</i> | <i>Mean</i> | <i>Mean</i> | <i>Mean</i> | <i>Mean</i> | <i>Median</i> |
| | u_t | 0.177*** (0.017) | 0.152*** (0.023) | 0.233*** (0.025) | 0.338*** (0.032) | 0.320*** (0.033) | 0.440*** (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 |

| | | United States - Anderson et al. (2017) | | | | | | | | |
|---------|-------------------|--|---------------------|--------------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Panel C | | <i>Fixed weights</i> | <i>BLS weights</i> | <i>BLS weights, Sales flag</i> | | | | | | |
| | u_t | 0.151*** (0.021) | 0.035*** (0.013) | 0.177*** (0.017) | 0.067*** (0.013) | 0.073*** (0.014) | 0.171*** (0.020) | 0.219*** (0.016) | 0.152*** (0.014) | 0.166*** (0.023) |
| | Linear time trend | N | Y | N | N | Y | N | N | Y | N |
| | HP-detrended | N | N | Y | N | N | Y | N | N | Y |
| | Observations | 317 | 317 | 317 | 317 | 317 | 317 | 317 | 317 | 317 |
| | R^2 | 0.29 | 0.75 | 0.68 | 0.42 | 0.43 | 0.61 | 0.54 | 0.71 | 0.57 |

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 | | | | | |
|-------------------|--|---------------------|---------------------|---------------------|---------------------|----------------------|
| | UK | | | US - BLS | US - Vavra (2014) | |
| | <i>V-shaped</i> | <i>V-shaped</i> | <i>Flag</i> | <i>Mean</i> | <i>Mean</i> | <i>Median</i> |
| u_t | 0.459*** (0.033) | 0.457*** (0.032) | 0.363*** (0.041) | 0.208*** (0.033) | 0.357*** (0.057) | 0.483*** (0.058) |
| $freq_t$ | -0.008 (0.008) | | -0.008 (0.005) | | -0.11*** (0.042) | -0.458*** (0.059) |
| $freq_{post}$ | | -0.004 (0.008) | | -0.062* (0.032) | | |
| $freq_{neg_t}$ | | -0.033 (0.022) | | -0.029 (0.037) | | |
| 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 | | | | | |
|-------------------|--|------------------|---------------------|------------------|---------------------|--------------------|
| | UK | | | US - BLS | US - Vavra (2014) | |
| | <i>V-shaped</i> | <i>Flag</i> | <i>Ref. price</i> | <i>Mean</i> | <i>Mean</i> | <i>Median</i> |
| u_t | 0.602*** (0.212) | 0.536 (0.365) | 0.305*** (0.084) | 0.160 (0.219) | 0.335*** (0.089) | 0.195** (0.078) |
| 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 ($freq_t$), increases ($freq_{post}$) and decreases ($freq_{neg_t}$). “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

| | V-shaped | | | Sales flag | Ref. price |
|---|-----------------|------------|------------|-------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) |
| u_t | 0.444*** | 0.364*** | 0.409 *** | 0.402*** | 0.351 *** |
| $s_{i,t-1}$ | | | 0.105*** | | |
| Month dummies | Y | Y | Y | Y | Y |
| Time trend | N | Y | N | N | N |
| Fixed effects | Y | Y | Y | Y | Y |
| Observations | 11,950,985 | 11,950,985 | 10,977,476 | 11,859,985 | 11,892,464 |
| F-stat | 11.48 | 13.02 | 46.35 | 3.77 | 16.26 |
| Alt. macro indicators (normalized) | | | | | |
| | (6) | (7) | (8) | (9) | |
| u_t (normalized) | 0.0052*** | | | | |
| Retail sales vol. | | -0.0046*** | | | |
| Consumer confidence | | | -0.0028*** | | |
| Fin. situation next year | | | | -0.0037*** | |
| Month dummies | | Y | Y | Y | Y |
| Time trend | | N | N | N | N |
| Fixed effects | | Y | Y | Y | Y |
| Observations | | 11,673,020 | 11,673,020 | 11,673,020 | 11,673,020 |
| F-stat | | 13.75 | 14.60 | 12.31 | 14.09 |

Notes: Panel regressions at the item level: $\gamma_{it} = \alpha_i + \beta u_t + X_t' \Phi + e_{it}$, where γ_{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 | | | B. Calibration Targets (steady state) | | |
|--------------------------|--|---------------|---|----------------|------------|
| | | | Data | Model | |
| θ | Elast. subst. goods | 2.49 | Markup | 1.25 | 1.25 |
| f | Search efficiency | 4.00 | Price discount | 0.749 | 0.749 |
| κ | Fixed cost of posting discounts | 0.056 | Fraction of discounts | 0.058 | 0.058 |
| α | Fraction of bargain hunters | 0.285 | Sales expenditure multiplier | 2.7 | 2.7 |
| ξ | Semi-elasticity of α w.r.t. shopping time z^* | 0.188 | Unit price paid by bargain hunters relative to average unit price | 0.96 | 0.96 |
| C. Assigned Parameters | | | D. Additional steady state moments | | |
| | | | Data | Model | |
| | period | 1 month | Elas. of shopping time w.r.t. real wages | -0.12 | -0.14 |
| β | discount factor | $0.96^{1/12}$ | Elas. of price to shopping time | -0.07 to -0.10 | -0.11 |
| σ | risk aversion | 2 | Shopping time, hrs/week | | |
| η | Frisch elasticity | 1 | Random shoppers | | 3.1 |
| θ | Elast. subst. labor | 5 | Bargain hunters | | 3.1 to 6.2 |
| χ | Cost share of capital | 1/3 | | | |
| δ | Capital depreciation rate | 0.01 | | | |
| $1/N_p$ | frequency of price changes | 1/12 | | | |
| $1/N_w$ | frequency of wage changes | 1/12 | | | |
| ρ_μ | serr corr of money shock | 0 | | | |
| σ_μ | std of money shock impulse | 0.23 | | | |
| ρ_a | serr corr of tfp shock | 0.98 | | | |
| σ_a | std of tfp shock impulse | 0.26 | | | |
| L | average hours worked, hrs/week | 37.1 | | | |
| S | average shopping time, hrs/week | 4.0 | | | |

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

| | U.S. Data | Baseline model | Model Robustness | | | |
|--|--------------|----------------|-------------------|-----------------------------|---------------------------------|-----------------------------|
| | | | Money shocks only | Less sticky prices, $N_p=6$ | Higher fraction of sales, 0.074 | More sticky wages, $N_w=18$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>A. Time-series statistics</i> | | | | | | |
| $\text{std}(\gamma_t)/\text{std}(C_t)$ | 0.27 | 0.28 | 0.58 | 0.20 | 0.29 | 0.25 |
| $\text{std}(\gamma_t)/\text{std}(L_t)$ | 0.14 | 0.21 | 0.20 | 0.16 | 0.22 | 0.18 |
| $\text{corr}(\gamma_t, C_t)$ | -0.64 | -0.54 | -0.88 | -0.58 | -0.55 | -0.51 |
| $\text{corr}(\gamma_t, L_t)$ | -0.44 | -0.49 | -0.98 | -0.27 | -0.47 | -0.38 |
| <i>B. Consumption response to a -1% impulse to money supply (average % for 12 months after shock)</i> | | | | | | |
| No discounts | | -0.48 | -0.48 | -0.28 | -0.48 | -0.51 |
| Constant discounts | | -0.50 | -0.50 | -0.33 | -0.51 | -0.56 |
| Cyclical discounts | | -0.33 | -0.33 | -0.25 | -0.31 | -0.39 |
| % difference in responses | | 34.0 | 34.0 | 24.2 | 39.2 | 30.4 |

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 Data Appendix A), (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.