The Cyclicality of Sales and Aggregate Price Flexibility – Supplementary Material*–

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Oleksiy Kryvtsov[†] and Nicolas Vincent[‡]

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

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

Contents

A U.K. ONS Data **3**

B Additional robustness checks **5**

B.1 Median sales frequency 5
B.2 Probit regressions 5
B.3 Retailer type 5
B.4 Clearance sales 5
B.5 Regional regressions 6
B.6 Cyclicality of sales at the category level 6

C Reconciling our results and Coibion, Gorodnichenko and Hong (2014) **7**

D Detailed model mechanics **7**

D.1 Equilibrium price dispersion 7
D.2 Fraction of sale prices 9
D.3 Size of price discount 10

E Robustness of model predictions **11**

E.1 What do sales tell us about business cycles? 11
E.2 Responses to serially correlated money growth impulses 12

F Equilibrium conditions for sticky-price model with sales **12**

G Alternative approach to measuring the impact of sales **15**

G.1 Measuring discount weights directly in the data 15
G.2 Contribution of sales to the food price index 16

A U.K. ONS Data

Here we provide a more detailed description of the consumer price index (CPI) micro dataset from the United Kingdom's Office for National Statistics (ONS), which is publicly available. We also describe some adjustments we made to the raw data to ensure their suitability for our exercises.

To construct the consumer price index (CPI), the Office for National Statistics (ONS) surveys the prices for goods and services that are included in the household final monetary consumption expenditure component of the U.K. National Accounts.[1] The survey includes prices for more than 1,100 individual goods or services a month, collected locally from more than 14,000 retail stores across the United Kingdom. The survey excludes the housing portion of consumer prices, such as mortgage interest payments, house depreciation, insurance and other house purchase fees.[2] Also, expenditures for purposes other than final consumption are excluded, e.g., those for capital and financial transactions, direct taxes, and cash gifts.[3]

Goods and services in the CPI are classified into 71 classes, according to the international (European) classification of household expenditure, Classification of Individual Consumption by Purpose (COICOP). A CPI class represents a basic group category, such as "Meat," "Liquid Fuels" or "New Cars"; 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), 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.[4]

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

Representative items are selected based on a number of factors, including expenditure size and product diversity, variability of price movements, and availability for purchase throughout

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

[2] These prices are used to construct the retail prices index (RPI).

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

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

the year (except for certain goods that are seasonal). There are currently over 510 items in the basket. Examples of representative items include: onions, men's suit, single bed. Finally, for each item-outlet-location, individual products and varieties are chosen by price collectors based on their shelf size and regular stock replenishment.

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

In addition to posted prices, the data set also contains information about some characteristics of goods during price collection. Prices for goods that are on special offer (available to all consumers) or on temporary sale comprise 6.4% of observations in the data set (4.4% weighted). It is important to note that these "sales" have to be available to everyone (i.e., coupons and discounts that require a loyalty card are not taken into account) and on a single purchase (e.g., discounts implied by "buy-two-get-one-free" promotions are not recorded). Forced substitutions happen 8.0% (5.5% weighted) of the time, with about a quarter (three-quarters) of them corresponding to substitutions for items that are non-comparable (comparable) to previously priced items. An item can be temporarily out of stock (2.2% or 1.5% weighted) or permanently missing (0.5% or 0.3% weighted). Finally, a small subset of goods has distinct seasonal patterns and is treated separately: they include some items of clothing, gardening products, holiday products and air fares. For those seasonal goods for which prices are not available, such as clothing, gardening and food, prices are imputed based on prices observed at the end of the previous season or based on prices observed for in-season goods in the same item category; in addition, weights are adjusted in accordance with the availability of such goods throughout the year.

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

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

2011. We control for these events in our analysis.[5]

B Additional robustness checks

B.1 Median sales frequency

The cyclicality of sales in the aggregate could be driven by a few number of large highly cyclical categories. To make sure that our main result is immune to the effect of outliers, for each month we compute the average sales frequency at the category (COICOP) level and then take the median frequency across all categories. Comparing the median measures of Figure 1 to the time series of Figure 2 in the main paper, it is clear that our finding was not driven by atypical categories.

Furthermore, during the period straddling the Great Recession, between 2005–06 and 2009–10, the number of products that experienced a rise in their sale frequency is almost three times as high as those that saw a drop, another sign that the countercyclicality of sales is broad-based.

B.2 Probit regressions

In addition to the results from the linear probability model of the main text, here we provide robustness checks using probit regressions instead. Estimation results are summarized in the top panel of Table 1, while the bottom panel shows the predicted sales frequencies at various unemployment rate levels.

B.3 Retailer type

In Table 2, we report results from a panel regression in which we estimate the distinct sensitivity of sales to the unemployment rate for independent stores and chains. The UK ONS calls "Independent retailers" those have less than 10 outlets, while "Chains" (or "Multiples") must have at least 10 outlets.

Strikingly, the relationship between unemployment rate and sales frequency is more than 10 times larger for chains than for independent retailers, with coefficients of 0.638 vs 0.061 respectively.

B.4 Clearance sales

As evidenced from Figure 2, temporary sales tend to be more prevalent toward the end of the price quote line, an indication that clearance sales are an important part of retailers' pricing

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

strategies in the U.K. To construct these plots, we computed the probability of observing a sale N months before the end of a quote line.[6] Aggregating across all products, this probability is almost 8% in the last month of a typical quote line, compared to 3.5% three years earlier. There are wide differences in this pattern across product categories, however. For Clothing and Footwear, 22% of the observations in the last month are flagged as sales by the ONS, compared to a frequency of around 8% one year earlier, while the same numbers are 26% and 14% respectively for Audio and Video. Food products, on the other hand, display a very flat hazard function with no evidence of clearance sales. We also find that the average size of discounts tends to increase as the end of a quote line approaches.

B.5 Regional regressions

Table 4 shows the results of panel regressions with region fixed effects, in which the dependent variable is the fraction of sales flag for a given region and month. The first regression yields results very much in line with the benchmark regressions from the main text. The conclusions are little changed once we include a time trend. However, when we include time fixed effects, the unemployment rate becomes non-significant, in line with the Coibion *et al.* (2014) who find little evidence of a relationship between sales and unemployment in the cross-section.

Finally, Table 5 reports the coefficients from region-specific regressions of the frequency of sales on the monthly regional unemployment rate and a time trend. The largest semi-elasticities are recorded for Scotland and East Anglia, and the lowest for London, North and Yorks & Humber. One can also notice that there is very little variation in the unconditional frequency of sales across regions, at around 2.5%. The only exception is London, where the frequency is somewhat lower at 1.9%.

B.6 Cyclicality of sales at the category level

We explore more on composition and differences by sector. Table 6 reports coefficients from two regressions at basic class level. Column (1): Sales frequency on monthly aggregate unemployment rate and a time trend (t-statistics in Column 2); Column (3): Sales frequency on the log of quarterly category-level real consumption and a time trend (t-statistics in Column 4). Sales are identified using the ONS sales flag and must be at least 10% in size.

We merge the results from these regressions with three types of sector-specific information. First, we add the data on life expectancy for durable goods, obtained from Bils and Klenow (1998) for the United States (Column 6 in the Table). Second, we add 5-firm concentration ratios for the United Kingdom in 2004 from Mahajan (2006), see Column (7). Finally, we compute class-specific moments for price-adjustment variables: inflation, frequency of price

[6] A 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.

changes, and absolute size of price changes, their means and standard deviations over time, using posted and regular prices (Columns 8 through 17).

We find that more durable goods and goods with more concentrated businesses tend to have *more countercyclical* sales. These correlations are relatively weak with p-values in regression on unemployment rate of 0.027 and 0.016, respectively; and in regression on real consumption 0.162 and 0.224 respectively, owing to the small number of observations for which we matched the data for durability (12) and concentration ratios (29).

In regressions on price-adjustment moments, only two of them result in significant correlations across basic classes. Goods with smaller mean absolute size of price changes or those with more volatile frequency of price changes (for either poster or regular prices) tend to be *more countercyclical*, with coefficients significant at 1% level or better for regressions on unemployment rate and 5% or better for regressions on real consumption. The number of matched goods in these regressions is 35.

C Reconciling our results and Coibion, Gorodnichenko and Hong (2014)

In the main text, we showed that the Food products that are the focus of the dataset used by CGH exhibited an upward trend in the frequency of sales that could explain why they find little support for cyclical sales in their sample. In Table 3, we present regression results that confirm this conjecture: for the Food category, once we include a time trend, the coefficient on the unemployment rate becomes much smaller and loses in significance.

D Detailed model mechanics

D.1 Equilibrium price dispersion

This section derives a sufficient condition on the expected fixed cost $\Xi(\alpha)$, probability parameter f, the cost of posting sales κ, and demand elasticity θ, for which retailer prefers to post two different prices, instead of a single price for all its brands. We consider the case with fully flexible prices; and we omit indexes for variety and time.

Denote by $\mathit{\Pi}(p) = (p - W)\left(\frac{p}{P_t}\right)^{-\theta} c_t$ the retailer's current-period profit function at price p, and by $R_t(p) = p\left(\frac{p}{P}\right)^{-\theta} c$ the current-period revenue function at p. The retailer's expected profit and revenue from selling to regular shoppers in period t are

$$\Pi^R = \gamma \mathit{\Pi}\left(P^L\right) + (1-\gamma)\,\mathit{\Pi}\left(P^H\right) ,$$

$$R^R = \gamma R\left(P^L\right) + (1-\gamma)\,R\left(P^H\right) .$$

Similarly, the retailer's expected profit and revenue from selling brands to bargain hunters, Π^B and R^B, are the same as above with γ replaced by $f\gamma$.

To gain intuition for why it is optimal for retailers to post different prices, consider the effect of the search constraint (4, main text) on the retailer's pricing behavior. If this constraint were not binding, and the retailer took the number of bargain hunters in its location as given (like they do for the number of regular shoppers), there would be no price dispersion. The retailer would choose—due to concavity of the profit function—to charge the monopoly price for all its brands, $P^L = P^H = P^* \equiv \frac{\theta}{\theta-1}W$, and collect monopoly profits $\Pi^* = \mathit{\Pi}\left(P^*\right)$.

In contrast, when the retailer can attract bargain hunters, it chooses the number of bargain hunters in its location, facing constraints (4) and (6) in the main text. In this case, posting a single price for all of its brands is no longer optimal. Consider a small price perturbation for a retailer that, instead of posting a single monopoly price P^* for all its brands, posts an arbitrarily lower price $P^L < P^*$ for a small fraction of brands $d\gamma$, attracting a small number of bargain hunters, $d\alpha$, and taking as before the number of regular shoppers as given, $\alpha^R \lessapprox 1$. The variation of the retail firm's profit relative to monopolistic profit $\delta\Pi^* \equiv \Pi - \Pi^*$ is, up to the first order of magnitude, given by

$$\delta\Pi^* \approx \Pi^* d\alpha + d\gamma\left[\mathit{\Pi}\left(P^L\right) - \mathit{\Pi}\left(P^*\right) - \kappa W\right] . \tag{1}$$

The first term on the right-hand side is the gain in profits due to sales to the extra fraction $d\alpha$ of bargain hunters. The second term is the loss in profits due to sales of the fraction $d\gamma$ of brands at a lower price P^L and the total fixed cost of posting sale prices. From the search constraint (6, main text), we can express $d\alpha$, up to the first order of magnitude, as

$$d\alpha \approx (f-1)\, d\gamma \cdot \frac{\frac{1}{\theta-1}\left(R\left(P^L\right) - R\left(P^*\right)\right)}{W\Xi''(0)} . \tag{2}$$

For a household, the increase in the probability of becoming a bargain hunter, $d\alpha$, is proportional to the increase in the probability of finding a low price, $(f-1)\,d\gamma$, and the ratio of the marginal utility of switching consumption from high to low price, $\frac{1}{\theta-1}\left(R\left(P^L\right) - R\left(P^*\right)\right)$, to the marginal cost of becoming a bargain hunter, $W\Xi''(0)$.

Plugging (2) into the expression (1) for profit variation, we obtain

$$\delta\Pi^* \approx d\gamma \cdot \Pi^* \left[-\frac{\mathit{\Pi}\left(P^*\right) - \mathit{\Pi}\left(P^L\right) + \kappa W}{\Pi^*} + \frac{f-1}{\theta-1}\frac{R\left(P^L\right) - R\left(P^*\right)}{W\Xi''(0)}\right] .$$

If the expression in brackets is positive, i.e., if

$$(f-1)\cdot\frac{\frac{1}{\theta-1}\left(R\left(P^L\right) - R\left(P^*\right)\right)}{W\Xi''(0)} > \frac{\mathit{\Pi}\left(P^*\right) - \mathit{\Pi}\left(P^L\right) + \kappa W}{\Pi^*} ,$$

then the benefits stemming from the increase in the market share of the retailer from selling to bargain hunters outweigh the cost of a smaller profit margin from selling at lower prices, and so the retailer can improve upon single-price monopolistic profit by posting two prices.

Also note that as $\gamma \to 0$, $P^H \to P^*$ and $P^L \to \frac{1}{1+\frac{f-1}{\theta-1}\frac{\Pi^*}{W\Xi''(0)}}P^* < P^*$; i.e., price dispersion does not disappear as the fraction of sale prices goes to zero. This means that there is no equilibrium with a single price. The reason why firms find it optimal to deviate from having a single price for all brands is that for any small but positive measure of brands on sale, the return for the household becoming a bargain hunter is strictly positive, given by the right-hand side of the first-order condition (4) for the fraction of bargain hunters α in the main text. So if the marginal expected fixed cost of becoming a bargain hunter is not growing too quickly with the fraction of bargain hunters (e.g., if $\Xi''(0)$ is low enough), then there will always be households with low-enough fixed cost realizations who choose to become bargain hunters, justifying price dispersion by retailers.

D.2 Fraction of sale prices

What is the desirable number of discount prices for a retailer? From the retailer's problem, the first-order condition with respect to the fraction of brands on sale γ_{jt} is

$$\left(\alpha_{jt}^R + f\alpha_{jt}^B\right)\left[\mathit{\Pi}_t(P_{jt}^H) - \mathit{\Pi}_t(P_{jt}^L)\right] + \kappa W_t = \frac{\partial \alpha_{jt}^B}{\partial \gamma_{jt}}\Pi_{jt}^B. \tag{3}$$

The left-hand side is the opportunity cost of increasing the fraction of sales. It consists of two terms: the first term is the marginal loss from selling more goods at a lower price, equal to the product of the loss per brand on sale, $\mathit{\Pi}_t(P_{jt}^H) - \mathit{\Pi}_t(P_{jt}^L)$ and the measure of shoppers who buy on sale, $\alpha_{jt}^R + f\alpha_{jt}^B$. The second term is the marginal increase in the total fixed cost of posting sales, κW_t.

The right-hand side is the marginal return from extra sales: it is the product of the marginal increase in the number of bargain hunters, $\frac{\partial \alpha_{jt}^B}{\partial \gamma_{jt}}$, and the average profits per bargain hunter, Π_{jt}^B. Since $\frac{\partial \alpha_{jt}^B}{\partial \gamma_{jt}} = \frac{\partial \alpha_{jt}}{\partial \gamma_{jt}}$, we can show—by differentiating household's first-order condition for α_{jt} with respect to γ_{jt}—that $\frac{\partial \alpha_{jt}^B}{\partial \gamma_{jt}}$ is decreasing in γ_{jt}, i.e., the inflow of bargain hunters dissipates as sales become more frequent. This is the case because the household's marginal cost of becoming a bargain hunter, $\Xi''(\alpha_{jt})$, is increasing with the number of bargain hunters; and because the utility loss due to price dispersion, given by D_{jt}^B and D_{jt}^R, is growing faster for bargain hunters than for workers.

In turn, the retailer's expected profit per bargain hunter, Π_{jt}^B, is also decreasing with γ_{jt}, since more brands are sold at a lower price. We find that both the cost and the return on extra sales (left- and right-hand sides of (3)) are very flat with respect to the level of γ_{jt}, which implies that their shifts due to aggregate shocks lead to large changes in γ_{jt}—the feature that helps the model match important aspects of the data, as we discuss in the next section.

D.3 Size of price discount

How does the firm pin down the levels of its high and low prices? The corresponding first-order conditions are

$$N_{jt}^{i}\left(MR_t(P_{jt}^{i}) - MC_t(P_{jt}^{i})\right) + \frac{\partial \alpha_{jt}^{B}}{\partial \ln P_{jt}^{i}} \frac{\Pi_{jt}^{B}}{P_{jt}^{i}} = 0\,, \tag{4}$$

where $i = H, L$, and $MR_t(\cdot)$ and $MC_t(\cdot)$ are the period-t marginal revenue and marginal cost functions of a single-price firm: $MR_t(P) = -(\theta-1)\left(\frac{P}{P_t}\right)^{-\theta} c_t$ and $MC_t(P) = -\theta\frac{W_t}{P}\left(\frac{P}{P_t}\right)^{-\theta} c_t$; N_{jt}^{H} and N_{jt}^{L} are the number of transactions at high and low prices: $N_{jt}^{H} = (1-\gamma_{jt})\alpha_{jt}^{R} + (1-f\gamma_{jt})\alpha_{jt}^{B}$ and $N_{jt}^{L} = \gamma_{jt}\left(\alpha_{jt}^{R} + f\alpha_{jt}^{B}\right)$; and $\frac{\partial \alpha_{jt}^{B}}{\partial \ln P_{jt}^{H}}$, $\frac{\partial \alpha_{jt}^{B}}{\partial \ln P_{jt}^{L}}$ are the marginal changes in the number of bargain hunters due to the increase in the high and low log prices, respectively.

Conditions (4) imply that if the retailer could not affect the number of bargain hunters in its store (i.e., if $\frac{\partial \alpha_{jt}^{B}}{\partial \ln P_{jt}^{H}} = \frac{\partial \alpha_{jt}^{B}}{\partial \ln P_{jt}^{L}} = 0$), then the optimal low and high prices would both equate the single-firm marginal revenue and marginal cost, and would be equal to the optimal monopolistic price P_{jt}^{*}, since $MR_t(P_{jt}^{*}) = MC(P_{jt}^{*})$. In contrast, if the retailer can attract bargain hunters, household's first-order condition for α_{jt} implies that $\frac{\partial \alpha_{jt}^{B}}{\partial \ln P_{jt}^{H}} > 0$ and $\frac{\partial \alpha_{jt}^{B}}{\partial \ln P_{jt}^{L}} < 0$; i.e., a higher regular price (sale price) make bargain hunting more (less) attractive. Then from (4) it follows that $MR_t(P_{jt}^{L}) > MC_t(P_{jt}^{L})$ and $MR_t(P_{jt}^{H}) < MC_t(P_{jt}^{H})$; i.e., the retailer's optimal sale (regular) price is below (above) the monopolistic price, $P_{jt}^{L} < P_{jt}^{*} < P_{jt}^{H}$, see Figure 12 in the main text.

First-order conditions (4) yield equations for sale prices

$$P_{jt}^{L} = \frac{\theta}{\theta-1}\frac{W_t}{1 - \frac{\partial \alpha_{jt}}{\partial \ln P_{jt}^{L}} \frac{\Pi_{jt}^{B}}{(\theta-1)N_{jt}^{L}R_{jt}^{L}}}\,, \tag{5}$$

and, taking into account price adjustment constraints, reset regular prices:

$$P_{jt}^{H} = \frac{\theta}{\theta-1}\frac{E_t\sum_{\tau=t}^{t+T-1}\beta^{t-\tau}c_{\tau}^{1-\sigma}P_{\tau}^{\theta-1}N_{j\tau}^{H}W_{\tau}}{E_t\sum_{\tau=t}^{t+T-1}\beta^{t-\tau}c_{\tau}^{1-\sigma}P_{\tau}^{\theta-1}N_{j\tau}^{H}\left(1 - \frac{\partial \alpha_{j\tau}}{\partial \ln P_{j\tau}^{H}}\frac{\Pi_{j\tau}^{B}}{(\theta-1)N_{j\tau}^{H}R_{j\tau}^{H}}\right)}\,. \tag{6}$$

where $R_{jt}^{i} = P_{jt}^{i}\left(\frac{P_{jt}^{i}}{P_t}\right)^{-\theta} c_t$ is the revenue per brand priced at P_{jt}^{i}.

E Robustness of model predictions

E.1 What do sales tell us about business cycles?

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

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

$$W_t = W_{t-1}^{11/12} M_t^{1/12}\,, \tag{7}$$

so that it takes around a year for nominal wages to converge to their pre-shock level. We will assume that the retailers' marginal cost is still flexible and equal to the money supply, as in the baseline model. Second, we assume that household wages are flexible, and it is the nominal marginal cost that is sticky, obeying the same law of motion as in (7).[7]

Table 7 provides responses at the time of the same shock (1% negative impulse to money growth) in the baseline model (column A) and its two variants (columns B and C). Our model predicts that the quick fall of household wages after the shock matters relatively little for incentivizing households to look harder for price discounts (column B). When nominal wages are sticky, they fall by only about 0.1% after the shock, as opposed to 1% in the baseline model. Since the marginal time cost of searching, in dollars, is equal to $W_t\alpha_t$, a 0.9% smaller fall in wages implies a smaller rise in the fraction of bargain hunters by only 0.1 ppt ($= 0.9\alpha$). In addition, retailers post sales less aggressively, amplifying the effect on the fraction of bargain hunters by 0.26 ppt, (i.e., the increase in the fraction is 1.36 ppt vs 1.62 ppt in the baseline model)—still a relatively small difference.

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

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

retailers to make more-intensive use of sales during slumps.

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

E.2 Responses to serially correlated money growth impulses

To show that impulse responses in Section 7 do not depend on the persistence of the monetary shock, we repeat the impulse-response function simulations assuming that the money-growth proces is serially correlated with persistence parameter equal to 0.536, as in Guimaraes and Sheedy (2011). Figure 3 shows that indeed all the insights from Section 7 carry over to the case with the persistent shock.

F Equilibrium conditions for sticky-price model with sales

Denote the following auxilliary variables:

$$
\begin{aligned}
\Pi^L_{jt} &= \left(P^L_{jt} - W_t\right)\left(\frac{P^L_{jt}}{P_t}\right)^{-\theta} c_t, \quad \Pi^H_{jt} = \left(P^H_{jt} - W_t\right)\left(\frac{P^H_{jt}}{P_t}\right)^{-\theta} c_t\,, \\
\Pi^R_{jt} &= \gamma_{jt}\Pi^L_{jt} + \left(1-\gamma_{jt}\right)\mathit{\Pi}^L_{jt}, \quad \Pi^B_{jt} = f\gamma_{jt}\Pi^L_{jt} + \left(1-f\gamma_{jt}\right)\Pi^L_{jt}\,,
\end{aligned}
$$

$$
\begin{aligned}
R^L_{jt} &= P^L_{jt}\left(\frac{P^L_{jt}}{P_t}\right)^{-\theta} c_t, \quad R^H_{jt} = P^H_{jt}\left(\frac{P^H_{jt}}{P_t}\right)^{-\theta} c_t\,, \\
R^R_{jt} &= \gamma_{jt}R^L_{jt} + \left(1-\gamma_{jt}\right)R^L_{jt}, \quad R^B_{jt} = f\gamma_{jt}R^L_{jt} + \left(1-f\gamma_{jt}\right)R^L_{jt}\,,
\end{aligned}
$$

$$
D^R_{jt} = \frac{\left(\gamma_{jt}\left(\frac{P^L_{jt}}{P^H_{jt}}\right)^{-\theta} + 1 - \gamma_{jt}\right)^{1-1/\theta}}{\gamma_{jt}\left(\frac{P^L_{jt}}{P^H_{jt}}\right)^{1-\theta} + 1 - \gamma_{jt}}\,,
$$

$$D_{jt}^{B}=\frac{\left(f\gamma_{jt}\left(\frac{P_{jt}^{L}}{P_{jt}^{H}}\right)^{-\theta}+1-f\gamma_{jt}\right)^{1-1/\theta}}{f\gamma_{jt}\left(\frac{P_{jt}^{L}}{P_{jt}^{H}}\right)^{1-\theta}+1-f\gamma_{jt}},$$

where D_{1jt}^{B} and D_{1jt}^{R} are derivatives of D_{jt}^{B} and D_{jt}^{R} with respect to $\frac{P_{jt}^{L}}{P_{jt}^{H}}$; and D_{2jt}^{B} and D_{2jt}^{R} are derivatives of D_{jt}^{B} and D_{jt}^{R} with respect to γ_{jt}.

Equilibrium consists of $5N+5$ equations for $5N+5$ variables P_{jt}^{L}, P_{jt}^{H}, γ_{jt}, α_{jt}^{R}, α_{jt}, P_t, c_t, W_t, R_t, M_t including:

- equation for $P_{t,0}^{H}$

$$P_{t,0}^{H}=\frac{\theta}{\theta-1}\frac{E_t\sum_{\tau=t}^{t+N-1}\beta^{\tau}c_{\tau}^{1-\sigma}P_{\tau}^{\theta-1}\cdot N_{\tau,\tau-t}^{H}W_{\tau}}{E_t\sum_{\tau=t}^{t+N-1}\beta^{\tau}c_{\tau}^{1-\sigma}P_{\tau}^{\theta-1}\cdot N_{\tau,\tau-t}^{H}\left(1-\Delta_{\tau,\tau-t}^{H}\right)},$$

- $N-1$ equations for $P_{t,1}^{H}$, ..., $P_{t,N-1}^{H}$

$$P_{t,0}^{H}=P_{t+1,1}^{H}=...=P_{t+N-1,N-1}^{H},$$

- N equations for $P_{t,0}^{L}$, ..., $P_{t,N-1}^{H}$

$$P_{jt}^{L}=\frac{\theta}{\theta-1}\frac{1}{1+\Delta_{jt}^{L}}W_t,$$

where

$$N_{jt}^{H}=\left(1-\gamma_{jt}\right)\alpha_{jt}^{R}+\alpha_{jt}\left(1-f\gamma_{jt}\right),$$

$$N_{jt}^{L}=\gamma_{jt}\left(\alpha_{jt}^{R}+\alpha_{jt}f\right),$$

$$\Delta_{jt}^{H}=\frac{\partial\alpha_{jt}}{\partial\, lnP_{jt}^{H}}\frac{\Pi_{jt}^{B}}{\left(\theta-1\right)N_{jt}^{H}R_{jt}^{H}},$$

$$\Delta_{jt}^{L}=-\frac{\partial\alpha_{jt}}{\partial\, lnP_{jt}^{L}}\frac{\Pi_{jt}^{B}}{\left(\theta-1\right)N_{jt}^{L}R_{jt}^{L}},$$

$$\begin{aligned}\frac{\partial\alpha_{jt}}{\partial\, lnP_{jt}^{H}} \quad = \quad & \frac{D_{jt}^{B}R_{jt}^{B}}{W_t\Xi''\left(\alpha_{jt}\right)}\frac{1}{\theta-1}\left[-\frac{D_{1jt}^{B}\frac{P_{jt}^{L}}{P_{jt}^{H}}}{D_{jt}^{B}}-\left(\theta-1\right)\frac{\left(1-f\gamma_{jt}\right)R_{jt}^{H}}{R_{jt}^{B}}\right]\\ & -\frac{D_{jt}^{R}R_{jt}^{R}}{W_t\Xi''\left(\alpha_{jt}\right)}\frac{1}{\theta-1}\left[-\frac{D_{1jt}^{R}\frac{P_{jt}^{L}}{P_{jt}^{H}}}{D_{jt}^{R}}-\left(\theta-1\right)\frac{\left(1-f\gamma_{jt}\right)R_{jt}^{H}}{R_{jt}^{R}}\right],\end{aligned}$$

$$\frac{\partial \alpha_{jt}}{\partial \ln P^L_{jt}} = \frac{D^B_{jt} R^B_{jt}}{W_t \Xi''(\alpha_{jt})} \frac{1}{\theta - 1} \left[-\frac{D^B_{1jt} \frac{P^L_{jt}}{P^H_{jt}}}{D^B_{jt}} - (\theta - 1) \frac{f \gamma_{jt} R^L_{jt}}{R^B_{jt}} \right]$$
$$- \frac{D^R_{jt} R^R_{jt}}{W_t \Xi''(\alpha_{jt})} \frac{1}{\theta - 1} \left[-\frac{D^R_{1jt} \frac{P^L_{jt}}{P^H_{jt}}}{D^R_{jt}} - (\theta - 1) \frac{f \gamma R^L_{jt}}{R^R_{jt}} \right],$$

- N equations for the fraction of bargain hunters α_{jt}

$$W_t \Xi'(\alpha_{jt}) = \left(\frac{\theta}{\theta - 1} D^B_{jt} - 1 \right) R^B_{jt} - \left(\frac{\theta}{\theta - 1} D^R_{jt} - 1 \right) R^R_{jt},$$

- N equations for the fraction of low prices γ_{jt}

$$\left(\alpha^R_{jt} + f \alpha_{jt} \right) \left[\Pi^H_{jt} - \Pi^L_{jt} \right] + \kappa W_t = \frac{\partial \alpha_{jt}}{\partial \gamma_{jt}} \Pi^B_{jt},$$

where

$$\frac{\partial \alpha_{jt}}{\partial \gamma_{jt}} = \frac{1}{W_t \Xi''(\alpha_{jt})} \frac{f}{\theta - 1} \left[D^B_{2jt} R^B_{jt} + D^B_{jt} \left(R^L_{jt} - R^H_{jt} \right) \right]$$
$$- \frac{1}{W_t \Xi''(\alpha_{jt})} \frac{1}{\theta - 1} \left[D^R_{2jt} R^R_{jt} + D^R_{jt} \left(R^L_{jt} - R^H_{jt} \right) \right],$$

- N equations for the fraction of regular shoppers of variety j

$$\alpha^R_{jt} = 1 - \alpha_{jt},$$

- equation for the price of aggregate consumption P_t

$$P_t = \left[\begin{array}{c} \frac{1}{N} \sum_{j=0}^{N-1} \alpha_{jt} \left[f \gamma_{jt} \left(P^L_{jt} \right)^{1-\theta} + (1 - f \gamma_{jt}) \left(P^H_{jt} \right)^{1-\theta} \right] \\ + \frac{1}{N} \sum_{j=0}^{N-1} \alpha^R_{jt} \left[\gamma_{jt} \left(P^L_{jt} \right)^{1-\theta} + (1 - \gamma_{jt}) \left(P^H_{jt} \right)^{1-\theta} \right] \end{array} \right]^{\frac{1}{1-\theta}},$$

- the cash-in-advance constraint

$$M_t = P_t c_t,$$

- a labor-market condition

$$\frac{W_t}{P_t} = c_t^{\sigma},$$

- equation for the risk-free rate

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

- and an exogenous AR(1) process (in logs) for money growth $\mu_t = \frac{M_t}{M_{t-1}}$:

$$\ln \mu_{t+1} = (1 - \rho_\mu) \ln \mu + \rho_\mu \ln \mu_t + \varepsilon_{\mu t} ,$$

where i.i.d. innovations $\varepsilon_{\mu t}$ drawn from $N\left(0, \sigma_\mu^2\right)$.

G Alternative approach to measuring the impact of sales

The challenge in estimating the contribution of sales is to construct the discount weight factors $h_{i,t}^{\Delta}$ since this requires information on quantities purchased, in addition to prices. In the main text (Section 8), we assumed that these weight factors are given by a constant-elasticity-of-substitution function of the product's price discount. In this Appendix, we explore an alternative approach where, instead of assuming CES demand, we measure the weight factors $h_{i,t}^{\Delta}$ directly in the data. Because such data are not broadly available, we focus on food products and complement the CPI data with weights derived from a scanner dataset.

G.1 Measuring discount weights directly in the data

Let $h(\Delta)$ denote the increase in units purchased on sale with log discount Δ relative to units purchased at regular price for a food product. For example, if a 1L carton of skim milk is on sale from 1.99 pounds to 1.49 pounds (25% discount) and the number of units sold increases by a factor of 2, then the implied discount weight is $h(\Delta)$=2. To estimate $h(\Delta)$, we use data from Symphony IRI scanner dataset. It provides information on quantities sold and revenues generated for a large number of food products across 50 U.S. markets between January 2001 and December 2011.[8] We first obtain the unit price by dividing weekly revenue by quantity, and then we apply the V-shaped filter described in Section 4 in the main text to identify sales in the price series.

Next, we discretize the size of price discounts in twelve 5% bins: $0\% \leq |\Delta_1| \leq 5\%$, $5\% < |\Delta_2| \leq 10\%$, ..., $55\% \leq |\Delta_{12}|$. For each metropolitan market (m), good category (c) and discount size bin $d = 1, ..., 12$ we then compute the weight factor $h_{m,c,d}$ as the ratio of the total units purchased on sale across all stores and months for that market-category-bin to total units purchased at regular price across all stores and months for that market-category-

[8]See Bronnenberg, Kruger and Mela (2008) for a description of this database.

bin.[9] We then compute the average discount weight h_d for discount bin d as the weighted mean of weights $h_{m,c,d}$ for that bin size across all markets and good categories, using relative revenue shares as weights.

Figure 4 plots the discount weights h_d for food in IRI data. Unit spending strongly increases with the discount size: from a factor of 2 for sales below 15% (48% of all V-shaped sales in ONS data, 44% in IRI data), to upward of 7 for sales larger than 45% (around 6% of all sales in ONS data and 7% in IRI data). The distributions of discounts for food are very similar in ONS and IRI data, with the average implied discount weight equal to 3.0 and 3.2 respectively. These estimates are in line with other studies. For example, Glandon (2011) reports that for groceries in the United States, sales account for 17% of price quotes but 40% of revenue, i.e., one percentage point of price discounts accounts for 2.7 percentage points of revenue share. Assuming a 20% discount, Glandon's results imply a discount weight of 4.1, which is even larger than what we find. We also compared our discount weight estimates with those implied by a constant-elasticity-of-substitution price index and found an elasticity of around 4 to be a good approximation. Using IRI data, Chevalier and Kashyap found those elasticities for peanut butter to be above 4.5 across metropolitan markets, and between 2 and 10 for coffee. In sum, the amount of extra consumption generated by sales is substantial.

By construction, the discount weights h_d used in computing the price gaps do not vary over time. Therefore, time variation in the sale-price contribution to the price of food will almost entirely be due to time variation in the fraction and size of price discounts.[10] However, as we discuss in Section 6, there is ample evidence from time-use surveys on search and shopping activity showing that households increase their search for low prices during economic downturns. In light of this evidence, the degree to which price discounts amplify consumption spending is likely to be countercyclical. The upshot is that our estimates of the impact of sales on the effective price level are likely to be on the conservative end.

G.2 Contribution of sales to the food price index

To compute the sale-price term for food in the United Kingdom, we assign the IRI discount weights h_d reported in Figure 4 to price observations within each stratum for food products in the ONS CPI micro data. We then compute for each month the weighted mean sale-price term Δ_t for each food class in the ONS dataset as defined in Section 8 in the main text.[11]

[9] The weight factor for market m, category c, and discount size d is computed as $h_{m,c,d} = \frac{Rev(m,c,d)}{Rev(m,c,Regular)} \cdot \frac{\#obs(m,c,Regular)}{\#obs(m,c,d)} \cdot \frac{1}{exp(\Delta(m,c,d))}$, where $\frac{Rev(m,c,d)}{Rev(m,c,Regular)}$ is the ratio of total expenditures on sales of size d to total expenditures on regular-priced products, $\frac{\#obs(m,c,Regular)}{\#obs(m,c,d)}$ is the ratio of the number of regular price observations to the number of price discounts, and $\frac{1}{exp(\Delta(m,c,d))}$ is the inverse of the average price discount for that discount size.

[10] Variation in CPI consumption weights from year to year is unimportant for time variation in the price gap.

[11] Food group includes 11 basic classes: Bread and Cereals; Meat; Fish; Milk, cheese and eggs; Oils and fats; Fruit; Vegetables; Sugar and sweet products; Other food n.e.c.; Coffee, tea and cocoa; Mineral water and soft

The weights are given by combining quote-level weights $\omega_{i,t}$ within each stratum and ONS sampling weights across strata. The combined weights are normalized to add up to 1 in each month. To obtain the sale-price component for all food, we take the weighted mean across food classes. In light of the discussion in Section 2, we use V-shaped sales of 10% or more in our computations.

The mean sale-price term for food is reported in Figure 5 (blue lines). Price discounts have a significant impact on the effective price level that is especially pronounced from 2007 to 2010 when the fraction of sales experienced its largest increase in the United Kingdom, from 2.7 to 6.1%. During this period, the mean sale-price term decreased from 3.7 to 7.2%, i.e., by almost 1 percentage points per year. Table 8 reports coefficients of regressions of sale-price terms on the fraction of price discounts. For all food, a one percentage point increase in the fraction of sales decreases the effective price level by 1.0% (1.2%) if the linear time trend is included (not included).

Although official price indices do incorporate sales, they underestimate their effect on the aggregate price level by ignoring the increase in consumption spending associated with discounts. We show this by computing the sale-price term assuming that weights are the same for discounts and regular prices ($h_d = 1$). This sale-price term provides the contribution of sales to the conventionally-measured price index.[12] The bottom left panel in Figure 5 plots the mean sale-price terms with CPI quote weights (green dash-dotted line). When the shift in consumption spending toward sales is ignored, the effect of sales on the food price level is significantly smaller. The elasticity of the sale-price term with respect to the fraction of sales in this case is only –0.3. These findings are consistent with Anderson et al. (2016) who document a small contribution of sales to U.S. inflation measured using the BLS methodology.

We also consider an intermediate case, where the discount weights affect relative weights within strata (given by region-shop type pairings for each category) but not across strata. The resulting sale-price terms (red dashed line in the bottom left panel in Figure 5) show the contribution of sales at the disaggregated (stratum) level but not across strata. The split between within and across stratum sale-price terms is roughly two-thirds and one-third, indicating that a substantial portion of the impact of sales on the price level occurs at a disaggregated (category and store) level.

We explored the robustness of the results along a number of dimensions in the data. Measuring the sale-price term for all food as the weighted median across basic classes (instead of weighted mean) yields similar results: for example, the median sale-price term falls from 3.3 to 6.5% during 2007–10 (top left panel in Figure 5). Adding small discounts (less than 10%) has virtually no impact (top right panel in Figure 5). By contrast, larger sales, though fewer in

drinks.

[12]Fox and Sayed (2016) use the IRI scanner dataset to document the average bias in traditionally-measured price level due to under-weigthing sale prices.

number, have a much larger impact on the effective price: for example, removing sales larger than 45% reduces the fall in sale-price term by about a half. Looking at the contribution of sales across shop types, larger chains (with 10 or more retail outlets) drive most of the action (bottom right panel), in line with our findings for chain effects reported in Section B.3. While the sale-price term for retailers with less than 10 outlets also falls during the Great Recession, this drop is about twice as small and short-lived, fully recovering by 2014. The differences in sales contributions between chains and independent stores were smaller in the first half of our sample, indicating the increased role of retail chains in consumption sector.

We also revisited our earlier conjecture that fluctuations in the average size of discounts are not an important margin for retailers' price adjustment. We re-compute the sale-price term, keeping all price discounts fixed at their across-time means at a basic class level. The difference between such sale-price term and the benchmark sale-price term will quantify the contribution of time variation in the size of price discounts to the effective price level. Figure 8 shows that the difference is small, and that the large variation in contribution of sales to the effective price level remains, especially around the timr of the Great Recession

Finally, we examine the evolution of the sale-price terms for food classes and regions. Figures 6 and 7 show that although the sale-term series vary in level and volatility across goods and across regions, they typically fall around the Great Recession period. Table 8 reports the results for panel regressions of category- and region-specific sale-price terms on respective frequencies of sales. Depending on specification, the elasticity of the sale-price term with respect to the fraction of sales is between –0.97 and –1.09 for food classes, and between –0.95 and –1.54 for U.K. regions; and it is therefore in line with the elasticity for all food observations.

This evidence suggests that the impact of time-variation in sale frequencies on the price level can be significant by macroeconomic standards. For example, during the period around Great Recession, sales contributed to a more than 1%-per-year fall in food prices, of which around 0.8% per year we estimate to be due to the shift in consumption spending from regular to sale prices, not measured by official methods. By comparison, the official consumption deflator and CPI for food in the United Kingdom grew by an average of 5.2% and 5.5% per year over this period. Adjusting these price measures by –0.8% per year of unmeasured contribution from sales would reduce their annual change to 4.4% and 4.7%, respectively; and it would reduce the implied fall in real food consumption in 2007–10 from 2% per year to 1.2% per year, or by about 40%.

References

[1] Bils, M. and P. Klenow. 1998. "Using Consumer Theory to Test Competing Business Cycle Models," *Journal of Political Economy*, University of Chicago Press, vol. 106(2), pages 233-261, April.

[2] Bronnenberg, B. J., Kruger, M. W. and C. F. Mela. 2008. "Database paper: The IRI Marketing Data Set,", *Marketing Science* 27(4):745-748.

[3] Mahajan, S. 2006. "Concentration ratios for businesses by industry in 2004," *Economic Trends,* Office for National Statistics, 635, October 2006.

Table 1: Probit regressions at the product level

	(1)	(2)	(3)
u_t	5.89***	6.839***	5.922***
Calendar month dummies	Y	Y	N
Categories dummies	N	Y	Y
Region dummies	N	Y	Y
Linear time trend	N	N	Y
	Predicted sales frequencies		
$u_t = 0.04$	0.025	0.025	0.026
$u_t = 0.06$	0.033	0.033	0.033
$u_t = 0.08$	0.043	0.043	0.042
$u_t = 0.10$	0.054	0.055	0.052

Notes: Probit regressions. *** indicate statistical significance at the 1% level.

Table 2: Panel regressions - Retailer type

	(1)	(2)
u_t - Chain	0.639***	0.543***
u_t - Independent	0.061***	-0.041
Calendar month dummies	Y	N
Linear time trend	N	Y
F-stat	6.66	7.52

Notes: Panel regressions with product fixed effects.The coefficient on 'u_t - Chain' corresponds to the response of the frequency of sales of retailer chains to a 1 percent point increase in the unemployment rate. *** indicate statistical significance at the 1% level.

Table 3: Regressions at the aggregate level

	Aggregate				**Food**			
	W	*W*	*UW*	*UW*	*W*	*W*	*UW*	*UW*
u_t	0.179***	0.233***	0.286***	0.328***	0.341***	0.110**	0.574***	0.207***
Linear time trend	N	Y	N	Y	N	Y	N	Y
R^2	0.42	0.45	0.26	0.26	0.40	0.55	0.55	0.72

Notes: OLS regressions. The dependent variable is the fraction of sales flag in a given month. 'W' indicates that the series is weighted using CPI weights, 'UW' is unweighted. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

Table 4: Panel regressions with regional unemployment rate

	(1)	(2)	(3)
u_{rt} - Regional	0.300***	0.258***	0.017
Calendar month dummies	Y	N	N
Linear time trend	N	Y	N
Time fixed effects	N	N	Y
R^2	0.34	0.47	0.77

Notes: Panel regressions with region fixed effects. Each observation is a region/month. The dependent variable is the fraction of sales flag in a given region/month. u_{rt} is the unemployment rate in region r at time t. *** indicates statistical significance at the 1% level based on robust standard errors.

Table 5: Region-specific regressions

	Scotland	*East Anglia*	*East Midlands*	*South West*	*Wales*	*West Midlands*
u_{rt}	0.415 (0.042)	0.415 (0.074)	0.397 (0.059)	0.369 (0.050)	0.366 (0.047)	0.316 (0.055)
R^2	0.56	0.35	0.56	0.44	0.56	0.45
Sales freq.	2.4%	2.4%	2.3%	2.5%	2.6%	2.4%
	South East	*North West*	*London*	*North*	*Yorks & Humber*	
u_{rt}	0.307 (0.060)	0.306 (0.045)	0.219 (0.024)	0.211 (0.032)	0.193 (0.031)	
R^2	0.463	0.55	0.45	0.46	0.62	
Sales freq.	2.4%	2.4%	1.9%	2.5%	2.4%	

Notes: Linear regressions of the frequency of sales on the regional unemployment rate (u_{rt}) and a time trend, ran separately for each region. Newey-West standard errors allowing for a maximum autocorrelation of 4 lags are indicated in parentheses.

Table 6: Cyclicality of sales by basic class, United Kingdom

coicop_id	Basic class	Class weight	Unemployment rate		Real consumption		Frequency of sales	Durability	5-firm concentration ratio	mean(π_t)	mean(fr_t)	mean (|DP_t|)	mean(π_t)	mean(fr_t)	mean (|DP_t|)	std(π_t)	std(π_t)	std(fr_t)	std(fr_t)
			(1) coeff	(2) t-stat	(3) coeff	(4) tstat	(5)	(6)	(7)	(8)	(9) posted prices	(10)	(11)	(12) regular prices	(13)	(14) posted	(15) regular	(16) posted	(17) regular
10101	BREAD & CEREALS	4.98	1.05	11.20	-1.10	-6.92	0.031		31	0.23	0.20	17.1	0.27	0.16	12.3	0.74	0.57	0.08	0.07
10104	MILK, CHEESE & EGGS	4.12	0.75	10.07	-0.45	-2.82	0.022		32	0.23	0.17	15.7	0.26	0.14	11.3	0.92	0.81	0.09	0.08
10109	FOOD PRODUCTS	1.00	0.98	7.87	-0.06	-0.40	0.032		39	0.19	0.18	18.5	0.23	0.14	13.1	0.97	0.71	0.09	0.07
10107	VEGETABLES INCLUDING POTATOES AND OTHER TUBERS	4.50	0.84	7.51	-0.47	-3.03	0.030			0.06	0.34	19.6	0.08	0.30	17.9	2.57	2.37	0.06	0.06
10202	MINERAL WATERS, SOFT DRINKS AND JUICES	2.74	1.41	7.03	-1.47	-7.58	0.034		75	0.18	0.20	17.1	0.21	0.16	11.7	0.93	0.66	0.11	0.10
50601	NON-DURABLE HOUSEHOLD GOODS	1.69	1.57	6.94	-1.93	-6.86	0.043			0.13	0.21	17.7	0.19	0.16	12.7	1.23	0.75	0.12	0.10
20102	WINE (INC PERRY)	2.90	1.16	6.31	-1.41	-4.78	0.067		50	0.19	0.26	17.6	0.30	0.17	12.8	1.27	0.75	0.13	0.10
120301	JEWELLERY CLOCKS AND WATCHES	1.78	0.89	6.18	-0.71	-2.76	0.031	7.8	16	0.32	0.12	24.6	0.41	0.09	22.1	0.88	0.60	0.07	0.06
10105	OILS & FATS	0.62	1.60	5.74	-0.76	-1.63	0.038		88	0.28	0.21	16.0	0.33	0.16	10.8	1.89	1.39	0.12	0.11
120102	APPLIANCES, ARTICLES & PRODUCTS FOR PERSONAL CARE	5.79	0.68	5.47	-0.59	-3.71	0.037		40	0.13	0.17	21.3	0.23	0.13	16.6	0.74	0.58	0.08	0.06
50400	GLASSWARE, TABLEWARE AND HOUSEHOLD UTENSILS	1.94	0.85	4.42	-0.69	-3.42	0.050	17.7	26	0.01	0.16	28.7	0.16	0.11	27.8	1.54	0.89	0.08	0.07
10108	SUGAR, JAM, HONEY, SYRUPS, CHOCOLATE AND CONFECTIONERY	3.42	0.46	4.16	-0.20	-2.13	0.018		81	0.30	0.14	14.4	0.34	0.12	10.6	0.76	0.47	0.08	0.07
120302	OTHER PERSONAL EFFECTS	0.97	1.19	3.71	-0.07	-0.17	0.057	17.5	26	0.14	0.19	24.4	0.31	0.13	23.2	1.66	1.06	0.08	0.06
20101	SPIRITS	1.68	1.39	3.64	-0.97	-1.74	0.092		50	0.15	0.34	11.3	0.23	0.20	8.1	2.35	1.03	0.17	0.13
40301	PRODUCTS FOR THE REGULAR MAINTENANCE AND REPAIR OF DWELLING	2.80	0.44	3.41	-0.39	-2.79	0.020			0.24	0.11	18.8	0.27	0.10	17.0	0.89	0.79	0.08	0.08
10102	MEAT	6.73	0.67	3.39	-0.83	-4.39	0.050		17	0.28	0.25	18.3	0.34	0.19	14.2	0.93	0.77	0.06	0.06
90503	MISC. PRINTED MATTER AND STATIONERY AND DRAWING MATERIALS	1.77	0.35	3.35	-0.14	-1.30	0.011		12	0.16	0.09	23.5	0.20	0.09	22.3	0.70	0.65	0.06	0.06
90304	PETS AND RELATED PRODUCTS INCLUDING VETERINARY AND OTHER SERVICES FOR PETS	2.41	0.26	3.31	-0.29	-3.74	0.011		36	0.23	0.13	13.1	0.25	0.12	10.5	0.65	0.48	0.07	0.07
10201	COFFEE, TEA, COCOA	0.97	0.56	3.08	-0.46	-2.17	0.038			0.20	0.24	15.1	0.22	0.19	10.3	1.46	0.94	0.13	0.12
90101	EQUIPMENT FOR THE RECEPTION & REPRODUCTION OF SOUND & PICTURE	1.76	1.55	2.89	-1.23	-1.81	0.103	11.9	27	-0.70	0.31	15.9	-0.46	0.22	16.9	1.96	1.92	0.11	0.08
70201	SPARE PARTS & ACCESSORIES	1.83	0.26	2.81	-0.14	-1.43	0.012	3.0	34	0.17	0.11	13.3	0.19	0.10	12.4	0.63	0.57	0.08	0.08
20103	BEER	1.60	0.87	2.69	-1.48	-3.10	0.065		50	0.11	0.30	14.5	0.18	0.22	11.6	1.55	1.15	0.13	0.12
60102	OTHER MEDICAL PRODUCTS THERAPEUTIC APPLIANCES AND EQUIPMENT	1.36	0.17	2.53	0.11	1.39	0.009	2.9	14	0.08	0.06	21.6	0.08	0.05	19.5	0.67	0.56	0.04	0.04
10103	FISH	1.30	0.94	2.35	-0.09	-0.15	0.054		36	0.42	0.26	18.7	0.53	0.19	13.3	1.33	0.78	0.07	0.06

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
50500	TOOLS AND EQUIPMENT FOR HOUSE AND GARDEN	1.79	0.26	2.03	-0.54	-2.06	0.020	7.5	11	0.18	0.11	21.7	0.23	0.09	20.7	1.29	1.22	0.07	0.07
30102	GARMENTS	14.16	0.37	2.03	-0.46	-2.40	0.069	3.1	14	-0.25	0.24	32.7	0.19	0.16	28.0	2.95	0.95	0.07	0.06
90301	GAMES TOYS AND HOBBIES	4.77	0.35	1.89	-0.43	-1.91	0.040	5.0	23	-0.05	0.16	27.1	0.11	0.12	25.5	1.30	1.01	0.09	0.08
30103	OTHER ARTICLES OF CLOTHING & CLOTHING ACCESSORIES	0.88	0.26	1.83	-0.40	-3.06	0.029			0.04	0.14	34.5	0.17	0.10	30.4	2.04	1.03	0.07	0.06
50101	FURNITURE, FURNISHINGS	6.49	0.31	1.29	-0.53	-1.40	0.152	9.6	5	0.17	0.27	23.5	0.38	0.13	22.0	3.51	1.06	0.08	0.05
60101	PHARMACEUTICAL PRODUCTS	1.41	0.05	0.56	0.04	0.46	0.019		57	0.11	0.13	19.6	0.14	0.10	17.2	0.99	0.68	0.08	0.07
90302	EQUIPMENT FOR SPORT CAMPING AND OPEN-AIR RECREATION	1.06	0.06	0.27	-0.15	-0.57	0.054		23	-0.06	0.14	27.4	0.14	0.09	25.4	1.38	0.76	0.08	0.05
50200	HOUSEHOLD TEXTILES	2.13	0.06	0.22	-0.12	-0.37	0.103	6.2	15	-0.01	0.21	25.3	0.20	0.10	23.6	2.22	0.58	0.07	0.05
10106	FRUIT	2.51	0.04	0.17	0.08	0.33	0.031		36	0.02	0.37	23.8	0.08	0.33	22.8	3.14	2.61	0.09	0.08
30200	FOOTWEAR INCLUDING REPAIRS	2.62	-0.03	-0.17	-0.16	-0.70	0.060	2.6	25	-0.14	0.18	28.2	0.20	0.12	22.9	1.84	0.67	0.07	0.05
90303	GARDEN PLANTS AND FLOWERS	1.53	-0.09	-0.35	0.16	0.61	0.023			0.07	0.15	29.0	0.12	0.13	28.1	1.75	1.60	0.07	0.06
	weighted mean		0.60		-0.56		0.05	2.6	26	0.08	0.21	22.0	0.22	0.15	18.8	1.67	0.95	0.08	0.07
	median		0.56		-0.45		0.04	6.8	31	0.15	0.18	19.6	0.21	0.13	17.0	1.30	0.78	0.08	0.07
	(A) regression coeff on (1)						**-0.546**	**0.051**	**0.009**	**0.354**	**1.488**	**-0.034**	**-0.188**	**1.966**	**-0.036**	**-0.123**	**-0.006**	**10.497**	**12.489**
	p-value						0.792	0.027	0.016	0.310	0.150	0.002	0.736	0.123	0.000	0.099	0.965	0.001	0.001
	(B) regression coeff on (3)						**-1.866**	**-0.025**	**-0.005**	**-0.175**	**-1.672**	**0.023**	**0.003**	**-1.412**	**0.028**	**0.076**	**0.110**	**-11.144**	**-11.966**
	p-value						0.387	0.162	0.224	0.632	0.121	0.049	0.996	0.294	0.015	0.338	0.474	0.001	0.002

Notes: Columns (1) and (3) report coefficients from two regressions at the category level. (1): Sales frequency on monthly aggregate unemployment rate and a time trend. (3): Sales frequency on the log of quarterly category-level real consumption and a time trend. Sales are identified using the ONS sales flag and must be at least 10% in size. U.K. Office for National Statistics data. Rows (A) and (B) report coefficients of regressing cyclicality coefficients in columns (1) and (3) on column-variable values across basic classes.

(1)	Unemployment rate	coeff	coefficient in regression of sales frequency on unemployment rate
(2)		t-stat	corresponding t-statistic
(3)	Real consumption	coeff	coefficient in regression of freqS on real consumption (quarterly)
(4)		tstat	corresponding t-statistic
(5)	Frequency of sales		frequency of sales (V-shaped discounts over 10%)
(6)	Durability		expected life (in years), United States, Tables 1-3 from "Using Consumer Theory to Test Competing Business Cycle Models" (Bils and Klenow, JPE 1998)
(7)	5-firm concentration ratio		top 5 businesses as a percentage of total output, United Kingdom, 2004
(8)	mean(π_t)	posted prices	average monthly weighted mean price change, posted prices
(9)	mean(fr_t)		average monthly weighted mean fraction of price changes, posted prices
(10)	mean($\lvert DP_t \rvert$)		average monthly weighted mean absolute size of price change (cond. on change), posted prices
(11)	mean(π_t)	regular prices	average monthly weighted mean price change, regular prices
(12)	mean(fr_t)		average monthly weighted mean fraction of price changes, regular prices
(13)	mean($\lvert DP_t \rvert$)		average monthly weighted mean absolute size of price change (cond. on change), regular prices
(14)	std(π_t)	posted	standard deviation of the weighted mean price change, posted prices
(15)	std(π_t)	regular	standard deviation of the weighted mean fraction of price changes, posted prices
(16)	std(fr_t)	posted	standard deviation of the weighted mean price change, regular prices
(17)	std(fr_t)	regular	standard deviation of the weighted mean fraction of price changes, regular prices

Table 7: Responses to a negative 1% impulse to money growth (on impact)

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

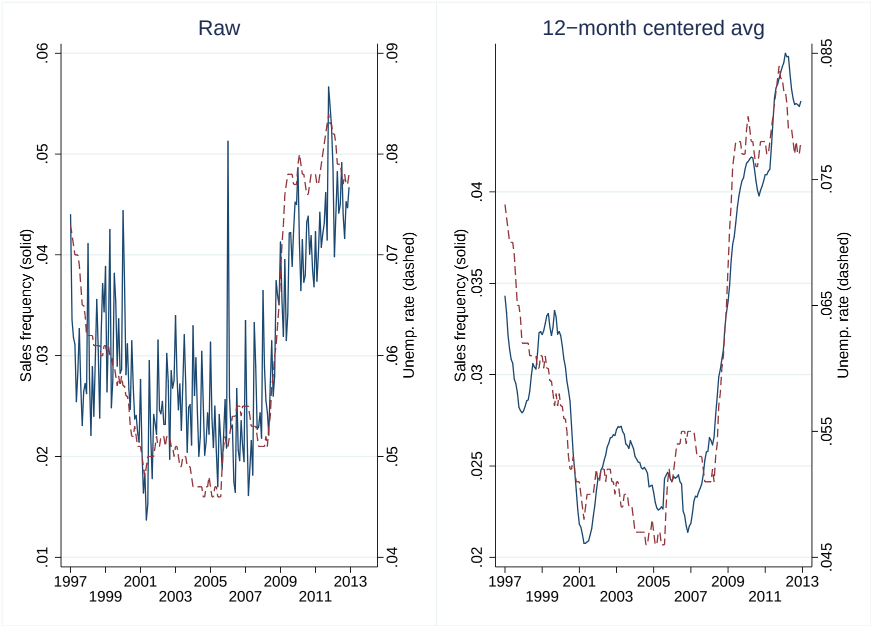
Note: Responses are given in the month of the impulse

Table 8: Contribution of sales to the price of food in the United Kingdom

	Contribution of sales, all food			**Contribution of sales, by basic class**			**Contribution of sales, by region**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fraction of sales	γ_t	γ_t	γ_t	γ_{it} (class)	γ_{it} (class)	γ_{it} (class)	γ_{it} (region)	γ_{it} (region)	γ_{it} (region)
	–1.15	**–1.20**	**–1.04**	**–1.03**	**–0.97**	**–1.09**	**–1.05**	**–0.95**	**–1.54**
Fixed effects				Y (class)	Y (class)	N	Y (region)	Y (region)	N
Month dummies	N	Y	Y	Y (class)	Y (class)	N	Y (region)	Y (region)	N
Linear time trend	N	N	Y	N	Y (class)	N	N	Y (region)	N
Month fixed effects	N	N	N	N	N	Y (class)	N	N	Y (region)
R^2	0.71	0.74	0.82	0.58	0.62	0.92	0.62	0.66	0.57
# obs	216	216	216	2373	2373	11	2592	2592	12

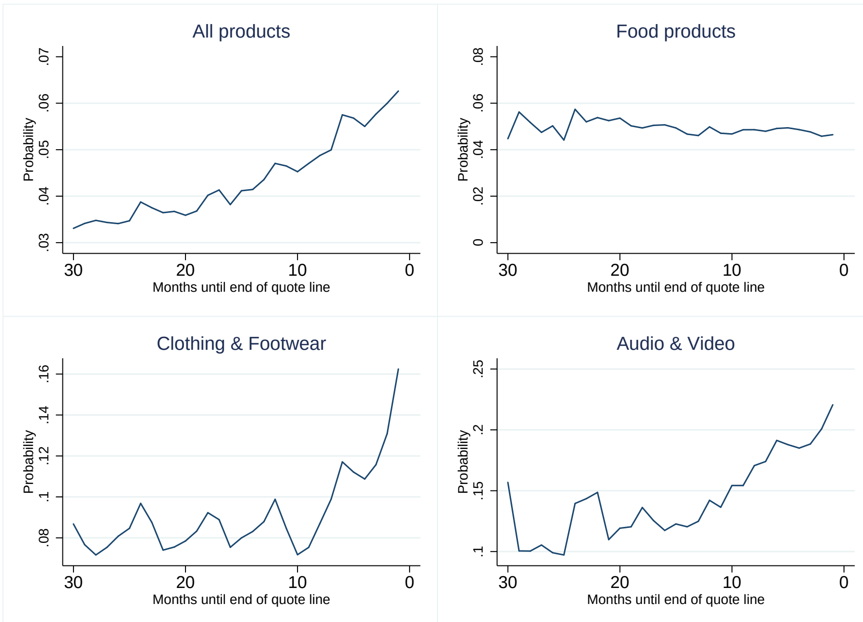
Notes: Sales are defined as V-shaped discounts of 10% or more. Regression types are indicated in columns. Aggregate regression (columns 1-3) is $p_t = c + \beta\gamma_t + X_t'\Phi + e_t$, where p_t is the mean sale-price term for all food, and γ_t is the fraction of sales in month t, and X_t are month dummies and linear trend. Panel regressions are $p_{it} = \alpha_i + \beta\gamma_{it} + X_{it}'\Phi_i + e_{it}$, where p_{it} are the mean price gap for food basic class i (columns 4-6) or for region i (columns 7-9) in period t and γ_{it} is the fraction of sales for that class or region in month t, and X_{it} are month dummies, category-specific linear trend, and fixed effects. Panel regressions are weighted by CPI sample weights. All coefficients are statistically significant at 1% level.

Figure 1: Median frequency of sales



Notes: The time series correspond to the frequency of sales of the median category.

Figure 2: Lifecycle frequency of sales



Notes: Probability of observing a sale flag N months before the end of a quote line. CPI quote weights are used.

Figure 3: Responses to a negative 1% impulse to persistent money growth

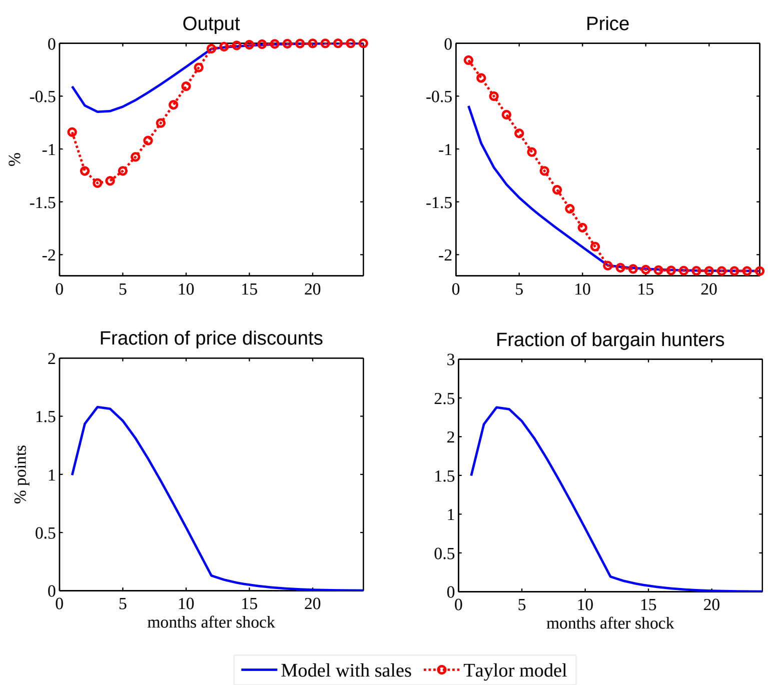
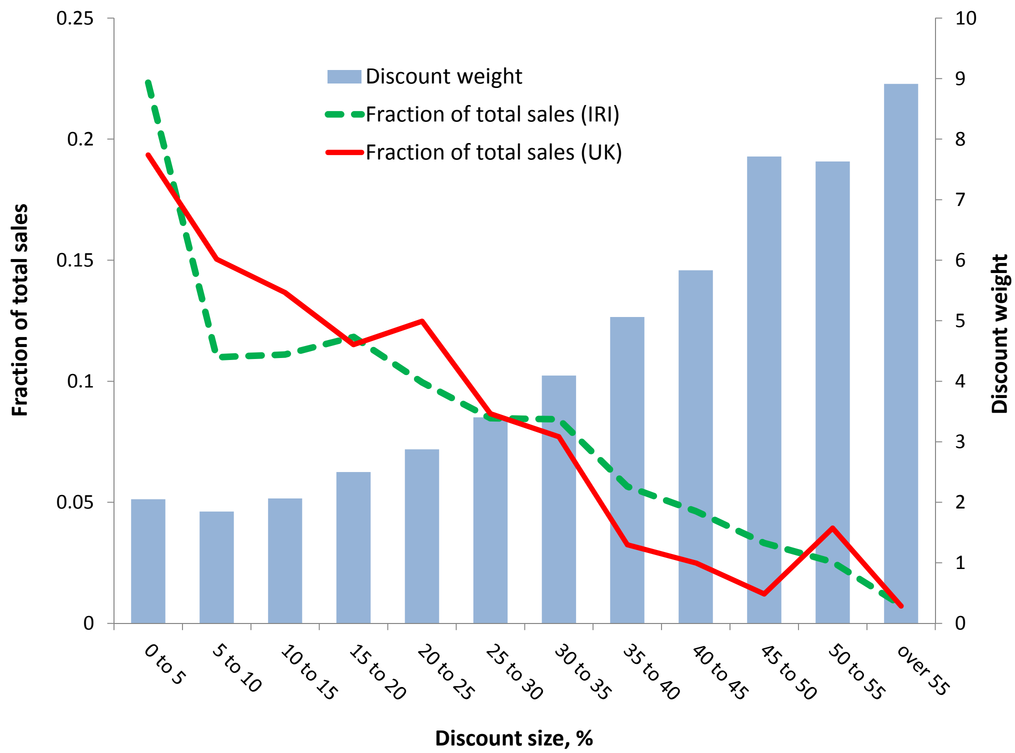
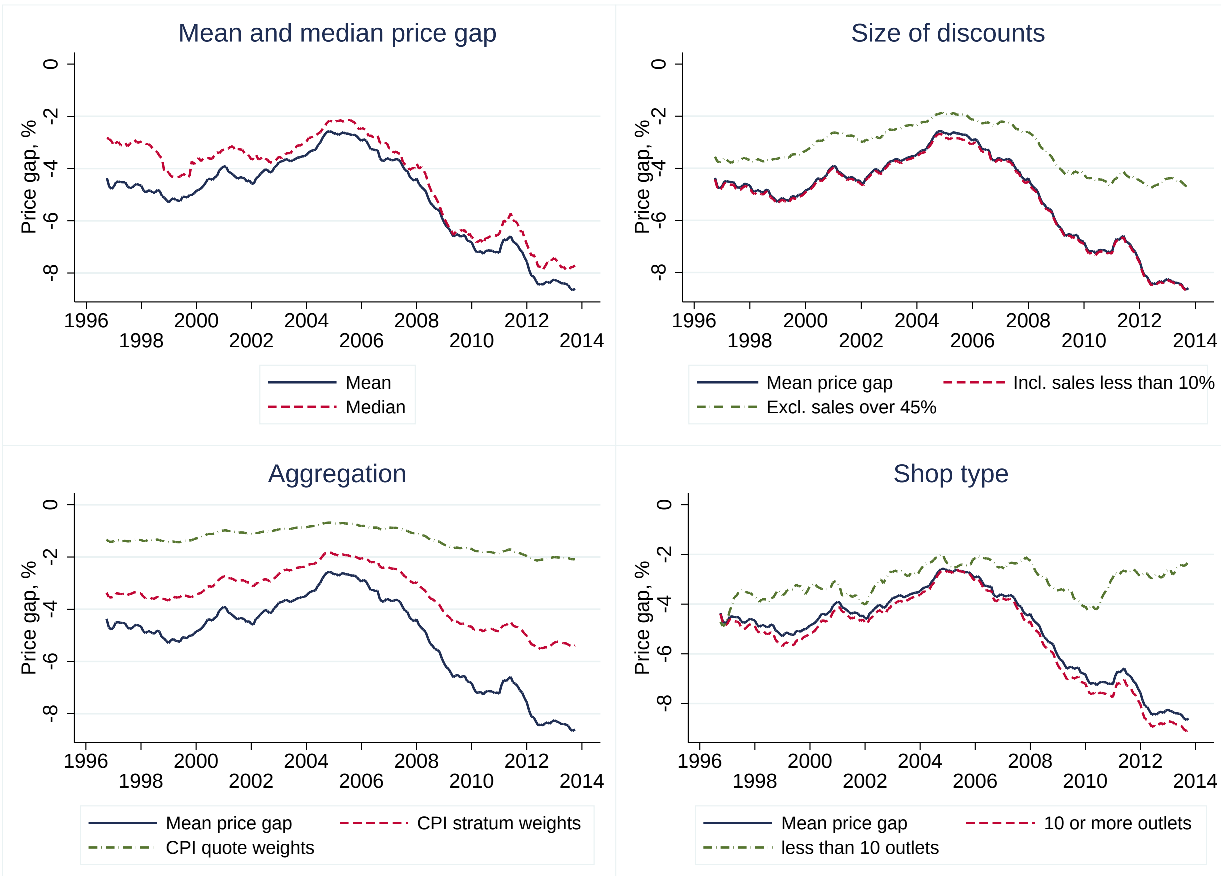


Figure 4: Average increase in unit spending during a sale for food products.



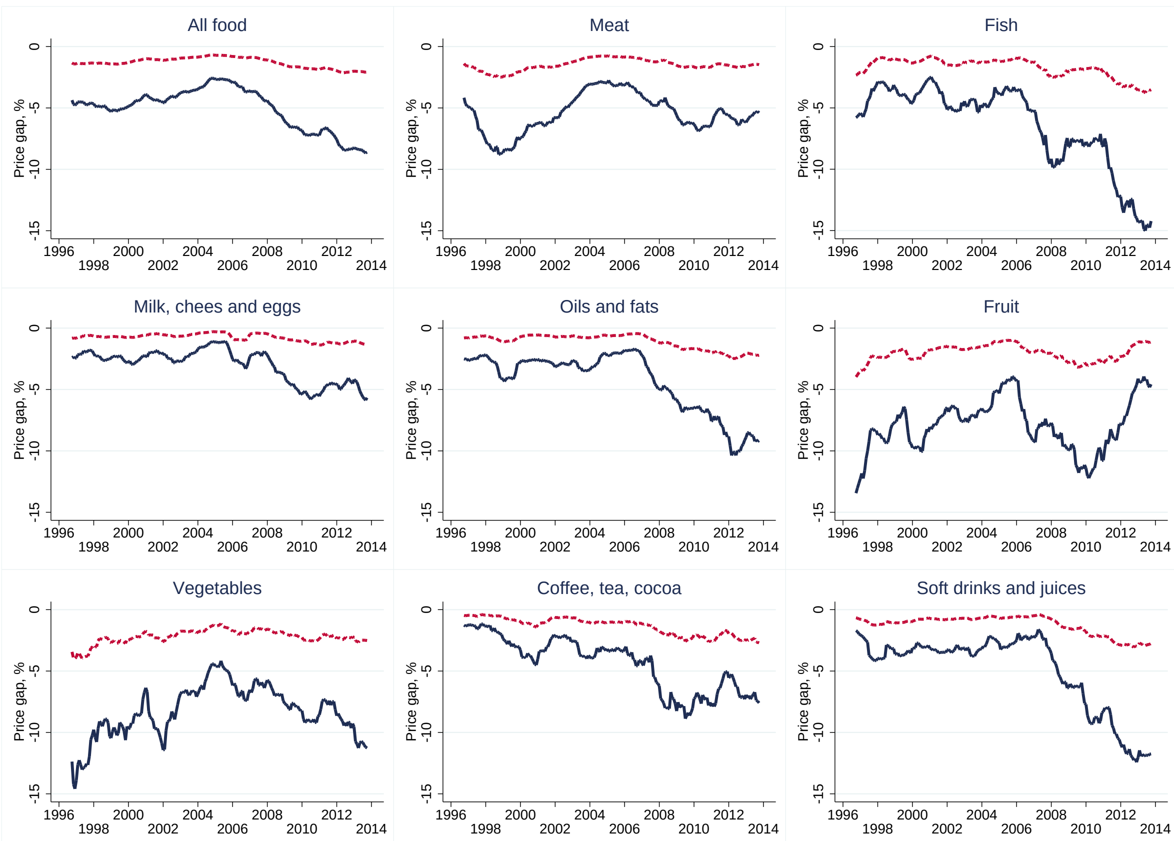
Notes: Discount weights denote the increase in units purchased on sale with a given discount size relative to units purchased at regular price for a food product. Data is from Symphony IRI scanner dataset, 2001:01–2011:12. V-shaped discounts of 10% or more. For each metropolitan market, good category and discount size bin we compute the average discount weight as the ratio of the total units purchased on sale across all stores and months for that market-category-bin to total units purchased at regular price across all stores and months for that market-category-bin. We then compute the average discount weight for discount bin as the weighted mean of discount weights for that bin size across all markets and good categories, using relative revenue shares as weights. Fraction of total sales for a given discount size is the ratio of the weighted number of observations with sales of that size to the total number of sales. The data for the United Kingdom is from the U.K. Office of National Statistics, 1996:02–2013:09.

Figure 5: Contributions of sales to effective price level in the United Kingdom.



Notes: The time series are the 12-month centered moving averages of the sale-price terms defined in (**??**) in Section 5. The benchmark sale-price term is based on V-shaped discounts of 10% or more, and it is the weighted mean across sale-price terms for food basic classes. "Median" sale-price term is computed as the weighted median across food basic classes. "CPI stratum weights" removes the effects of discount weights across strata, and "CPI quote weights" removes them althogether. "Multiples" (retailers with at least 10 outlets) and "Independents" (retailers with less than 10 outlets). Sample period is 1996:02–2013:09, U.K. Office of National Statistics data.

Figure 6: Sale-price terms for selected food products in the United Kingdom

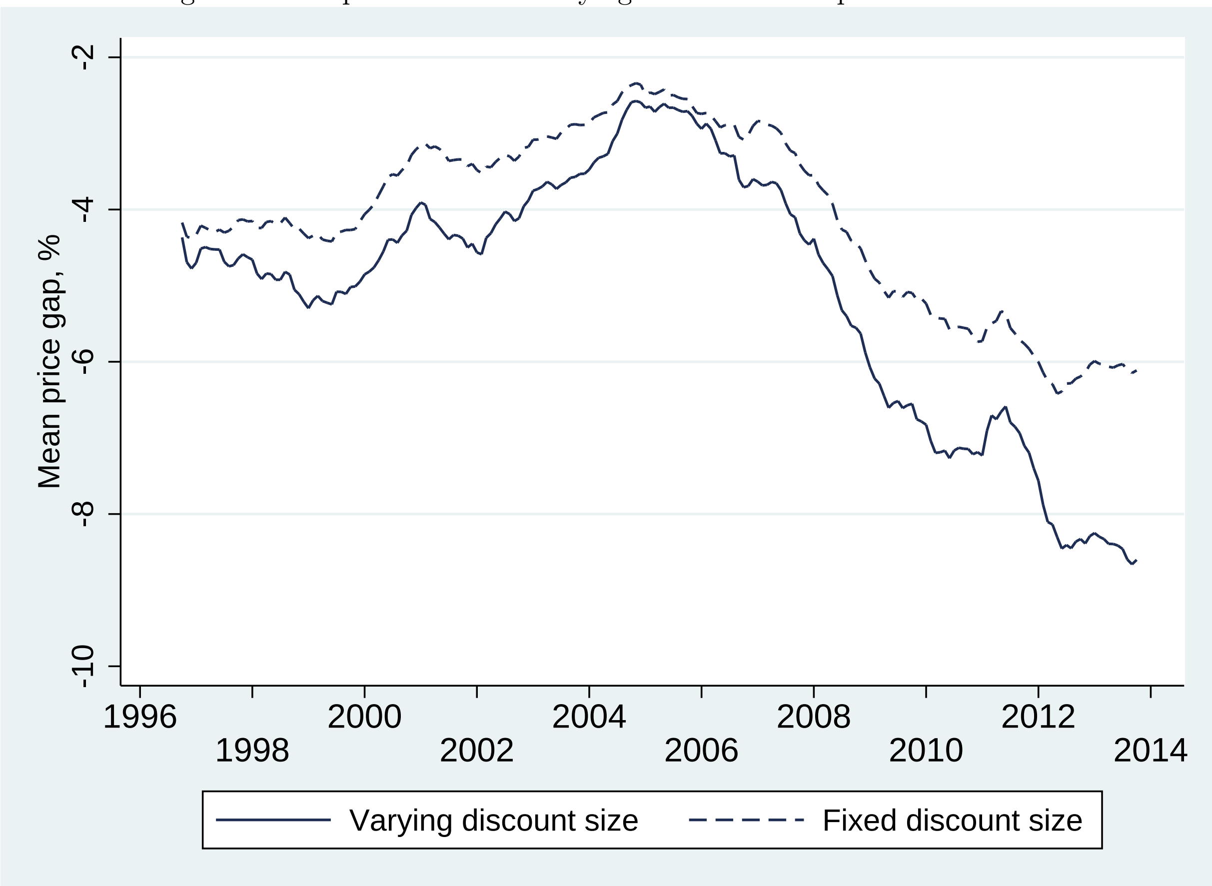


Notes: The time series are the 12-month centered moving averages of the sale-price terms defined in Section 5 in the main text. The benchmark sale-price term (solid blue lines) is based on V-shaped discounts of 10% or more. "CPI quote weights" (red dashed lines) removes the effects of discount weights. Sample period is 1996:02–2013:09, U.K. Office of National Statistics data.

Figure 7: Sale-price terms for selected regions in the United Kingdom

Notes: The time series are the 12-month centered moving averages of the sale-price terms defined in Section 5 in the main text. The benchmark sale-price term (solid blue lines) is based on V-shaped discounts of 10% or more. "CPI quote weights" (red dashed lines) removes the effects of discount weights. Sample period is 1996:02–2013:09, U.K. Office of National Statistics data.

Figure 8: Sale-price terms for varying vs fixed size of price discounts



Notes: The time series are the 12-month centered moving averages of the sale-price terms defined in Section 5 in the main text. "Varying discount size": the benchmark sale-price term (solid blue line) is based on V-shaped discounts of 10% or more. "Fixed discount size": re-compute the sale-price term, keeping all price discounts fixed at their across-time means at a basic class level (blue dashed lines). Sample period is 1996:02–2013:09, U.K. Office of National Statistics data.