# 6 Online Appendix (Not for publication in OBES)

## 6.1 Appendix 1: Data.

There are two basic price collection methods utilized by the ONS: local and central. The CPI research data in this study are the locally collected price quotes, covering two-thirds of total CPI. Local collection covers about 150 locations around country, and generates around 110,000 quotations each month. Centrally collected data cover about one-third of CPI, and are not available to our research.[27]The price quotes are usually for a single cash transaction, inclusive of Value Added Tax (VAT) and any compulsory service charge. The period covered in the data goes from March 1996 to June 2013.

### 6.1.1 Sales

As pointed out by Nakamura and Steinsson (2008), sale price changes display markedly different empirical features than do regular price changes. Sale price changes are more transient that yield much less aggregate price adjustment than that of regular price changes (Kehoe and Midrigan 2015). Guimaraes and Sheedy (2011) build a macroeconomic model with rationale for sales based on firms facing consumers with different price sensitivities.[28] They find that the flexibility of prices at the micro level due to sales does not translate into flexibility at the macro level. Nakamura and Steinsson (2008) also suggest that some types of sales may be orthogonal to macroeconomic conditions. The idea that sales may not respond to changes in macroeconomic conditions is suggestive of information costs, sticky information or rational inattention (Mankiw and Reis, 2002; Burstein, 2006; Woodford, 2009; Sims, 2011). Furthermore, sales may be more responsive to idiosyncratic shocks than aggregate shocks. Anderson et al. (2012) analyze unique dataset from a large U.S. retailer that explicitly identifies sales and regular prices. They show that regular prices react strongly to wholesale price movements and wholesale prices respond strongly to underlying costs, but the frequency and depth of sales is largely unresponsive to these shocks. Coibion, Gorodnichenko, and Hong (2012) show that the frequency and size of sales falls when unemployment rates

[27]The centrally collected data set include price quotes for education, some of the energy goods, and some communication services.

[28]Sobel (1984) originally introduced the idea that sales might be due to price discrimination between customers with different price elasticities. Other important papers on sales in the industrial organizations (IO) literature include Varian (1980), Salop and Stiglitz (1982), Lazear(1986), Agguirregabiria (1999), Hendel and Nevo (2006), and Chevalier and Kashyap (2011). Hosken and Reiffen (2004) use BLS CPI data to evaluate the empirical implications of IO models of sales.

rise (i.e., changes in the behavior of sales raise rather than reduce prices in a recession). In contrast, Klenow and Willis (2007) show that in the BLS CPI data, the size of sales price changes is related to recent inflation in much the same way as the size of regular price changes. Klenow and Malin (2010) present evidence that sales do not fully wash out with cross-sectional aggregation in the BLS CPI data, but do substantially cancel out with quarterly time aggregation. More research is needed to assess the extent to which sales respond to macro conditions.

The ONS gathers consumer price data on whether a product was "on sale" or "recovering from sale" when its price was sampled in a particular month. Sales prices are recorded if they are temporary reductions on goods likely to be available again at normal prices or end of season reductions. Prices in closing down sales and for special purchase of end of range, damaged, shop soiled or defective goods are not recorded as they are deemed not to be the same quality as, or comparable with, goods previously priced or those likely to be available in future. Sale prices are only recorded if it is available to anyone with no conditions. In the paper, we follow Bunn and Ellis (2009, 2012) and identify temporary "sales" with the flag provided by ONS.

However, alternative "sales" filters are proposed by other researchers. There are three mainly used price filters:

1. The AC Neilsen filter, which is used by Kehoe and Midrigan (2015) (KM hereafter), indicates a sale if "price decrease is followed by *any* price increase thereafter".

2. Nakamura and Steisson (2008) (NK hereafter) suggest a sale filter that flag a sale only when a price decrease is followed by a return to the price in effect just before the decrease.

3. Eichenbaum, Jaimovich and Rebelo (2011) (EJR hereafter) identify the most frequently observed price in a given quarter as "reference price", which means that it excludes an even larger portion of price changes than sale filters, yielding "more persistent series and suggesting a stronger role for nominal rigidities."[29]

The EJR filter restricts regular prices to change only on certain dates, and therefore greatly increases estimates of price persistence. The KM filter is much more likely to records a sale even if it is a reversion in regular price, and therefore it may identify spurious sales.

[29] Chahrour (2010) proposes a new price filter similar to th EJR (2010) and show that implications for price duration depend on the choice of filter.

The NS filter is more strict, which will typically identify fewer sales and more frequent price changes.

The sales price quotes account for about 8% of whole sample. Furthermore, price changes that result from sale account for 22.3% of all the price changes. Alvarez et al. (2013) report that sales account for approximately 17% of all the price changes in French CPI data. While Nakamura and Steinsson (2008) document that the share of price change due to sales is 21.5%.

We find seasonality with sales, as shown in Figure A1. Generally, sales are more likely to happen in January, reflecting post-Christmas sales. Sales also peak at July and August, reflecting end of season sales, especially in Clothes and Footwear division.

We also find that the share of sales has increased since crisis happened in January 2008. And the upward trend in share of sale keeps on after crisis period.

Figure A1: Sales in Calendar Month.

### 6.1.2 Substitution

As a measure of price change alone, the CPI should reflect the cost of buying a fixed basket of goods and services of constant quality. However, products often disappear or are replaced with new versions of a different quality or specification, and brand new products also become available. When such a situation arises, direct comparison is adopted. If there is another product which is directly comparable (that is, it is so similar to the old one that it can be assumed to have the same base price), for example a garment identical except that it is a different colour, then the new one directly replaces the old one and its base price remains the same. This is described as "obtaining a replacement which may be treated as essentially identical" (CPI Technical Manual,2007), and is equivalent to saying that any difference in price level between the new and the old product is entirely due to price change and not quality differences. In CPI data, such "comparable" substitution flagged by ONS is not uncommon. It accounts for about 5 percent of our total CPI research dataset . The substitution happens more likely in the January, August, and September.[30] This partially reflects the fact that

[30] Nakamura and Steinsson (2010) document very pronounced seasonality in product turnover for both apparel and transportation goods. They argue that this suggests that the timing of product turnover is likely to be motivated primarily by factors such as development cycles and changes in consumer tastes (for example, the fall and spring clothing seasons in apparel), that are largely orthogonal to a firm's desire to change its price. While the introduction of the new spring clothing line may be a good opportunity for a rm to adjust its price, this type of new product introduction does not occur because of the rm's desire to adjust its price. That is, while price changes are likely to occur when new products are introduced, new products

ONS adjust the basket of CPI in the beginning of the year. Beside, the clothing and footwear are more likely to change the style when summer ends. We can show the substitutions as percentage in whole price quotes in each calendar month as Figure A2:

Figure A2: Substitution in Calendar Month.

The raw data set has passed a series of validity checks conducted by ONS (see CPI Tech Manual for details). However, as argued by Alvarez et al. (2013) and Eichenbaum et al. (2013), the majority of small changes and large changes are due to measurement error. In line with Alvarez et al. (2013), we exclude price changes smaller than 0.1 percent, or larger than ln(10/3) (both in absolute value). The share of outliers in total data set is less than 0.3 percent.

There was a change in methodology of collecting data. Energy prices collected centrally since January 2007. We construct a consistent series based on excluding these energy prices for the whole period 1996-2013. As table A1 shows, the division Food and non-alcoholic beverages accounts for about 13.9% of the CPI weight in the subsample available in the dataset. Whereas the education division is excluded from our research due to lack of observation.

Table A1: Sample weights comparison

# 7 Appendix 2: Replication of Vavra methodology for UK data.

In this appendix, we replicate the empirical method used by Joe Vavra in his (2014) paper, applying it to UK data. Vavra does not use the raw data, but instead bases his analysis on the seasonally adjusted data smoothed by a 6 month moving average, which we will denote by $IQRsama$ and $SDsama$ respectively, or smoothed using bandpass filters (these are depicted in Figures A3 and A4). In Table A2, we present results comparable to Vavra, showing correlations between our smoothed dependant variables and smoothed independent

are not introduced because the old products were mispriced. If the timing of product substitutions are less "selected," it may be appropriate to model product substitutions not as optimally timed price changes such as those that arise in a pure menu cost model but rather as price changes without any selection effect such as those that arise in the Calvo or Taylor models.

variables with monthly data.

Figure A2: Bandpassed regular price changes over business cycle

Figure A3: Smoothed regular price changes over time

Table A2: Correlations at Business cycle frequencies

As we can see, the results are similar to the regression analysis with the raw data. Inflation has a negative effect on the IQR and SD of price growth (regressions 3, 4, 6) which is very significant for annual inflation (3). Output variables always have a positive sign (regressions 1, 2, 5) which is significant for the bandpass filter (5) and annual growth (2). There is no evidence for the signs found by Vavra when we use exactly the same methodology: as in the time-series regressions, we find only evidence for the opposite signs.

Vavra also links together the frequency of price-change with the standard deviation of price growth. We performed the same exercise for the UK data, which we present in Table A3. Newey-West standard errors are in parentheses, all data are seasonally adjusted using 12 monthly dummies. Regressions in first two columns include a quadratic time-trend. All data for regressions in the last two columns are bandpass-filtered using a Baxter King (18, 96, 33) filter.

Table A3: Correlations between frequency and price-growth dispersion

The results are highly consistent: we find that the seasonally adjusted and the filtered data both display negative correlations between price-growth dispersion and the frequency of price-change. The results in Tables A2 and A3 tell the same story as the time-series results reported in the main paper: we find the opposite relationships to those found by Vavra (2014), even when we use the same estimation methodology.

## 7.1 Appendix 3. Kurtosis in UK.

Looking at all price changes Alvarez et al. (2016, Table 1) find kurtosis of 20.8 when sales are excluded: this is not dissimilar to the magnitude found in US studies (Nakamura and Steinsson 2008). A large part of the explanation for this high value is the presence of a large mass of small price changes. Alvarez and Lippi (2014) have developed the (S,s) dynamic menu cost model to the multiproduct monopolist. This assumes that when the firm pays the menu cost, it can change all of its prices at the same time at no additional cost. This will result in small price changes as well as larger ones (if a firm is ready to change at least one price, the marginal cost of changing additional prices is zero, so even small adjustments will increase profits). If we look across the whole period 1996-2013 we also find high kurtosis in the UK data. We adopt two methods: one is to look at the distribution of price growth across all prices and all periods; the second is to look at each item and type of outlet and calculate the kurtosis, then aggregating over all products. We also calculate this both including all observations and excluding outliers as in Alvarez at al. (2013). Whilst these estimates for the UK are smaller than found in France and the US, they still show considerable kurtosis. The results are presented in Table A4:

Table A4: Selected moments from the distribution of price changes

## 7.2 Appendix Bibliography. (additional items cited only in the appendix).


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Figure A1: Sales in Calendar Month

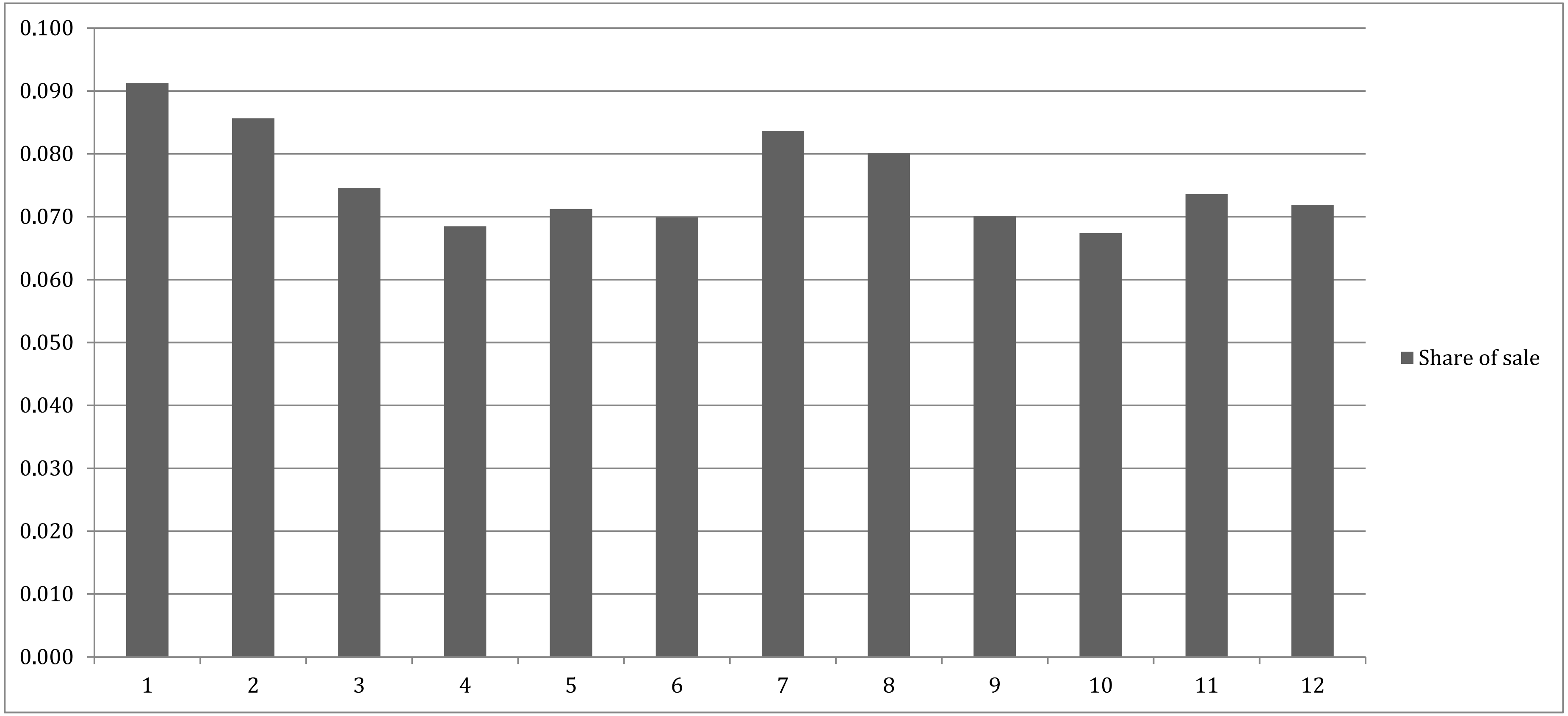
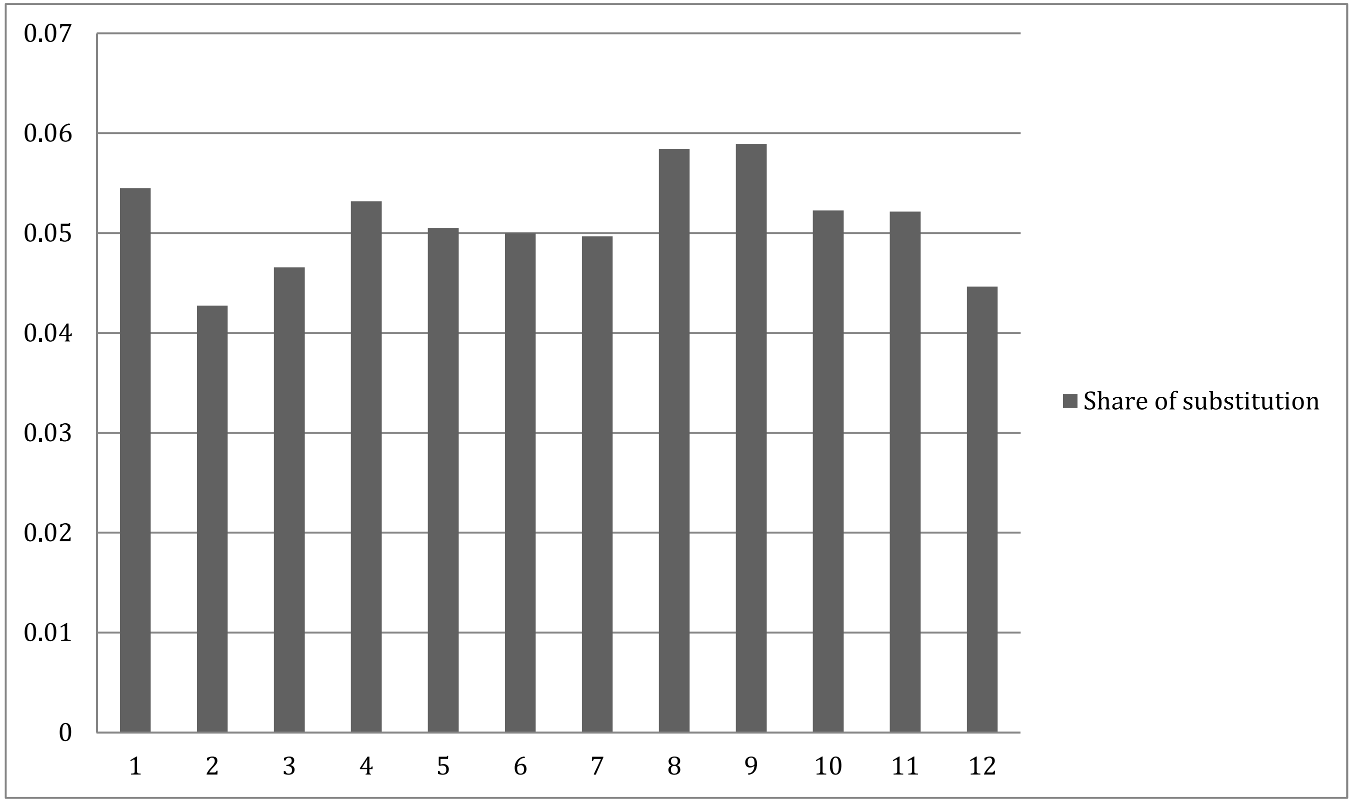


Figure A2: Substitution in Calendar Month



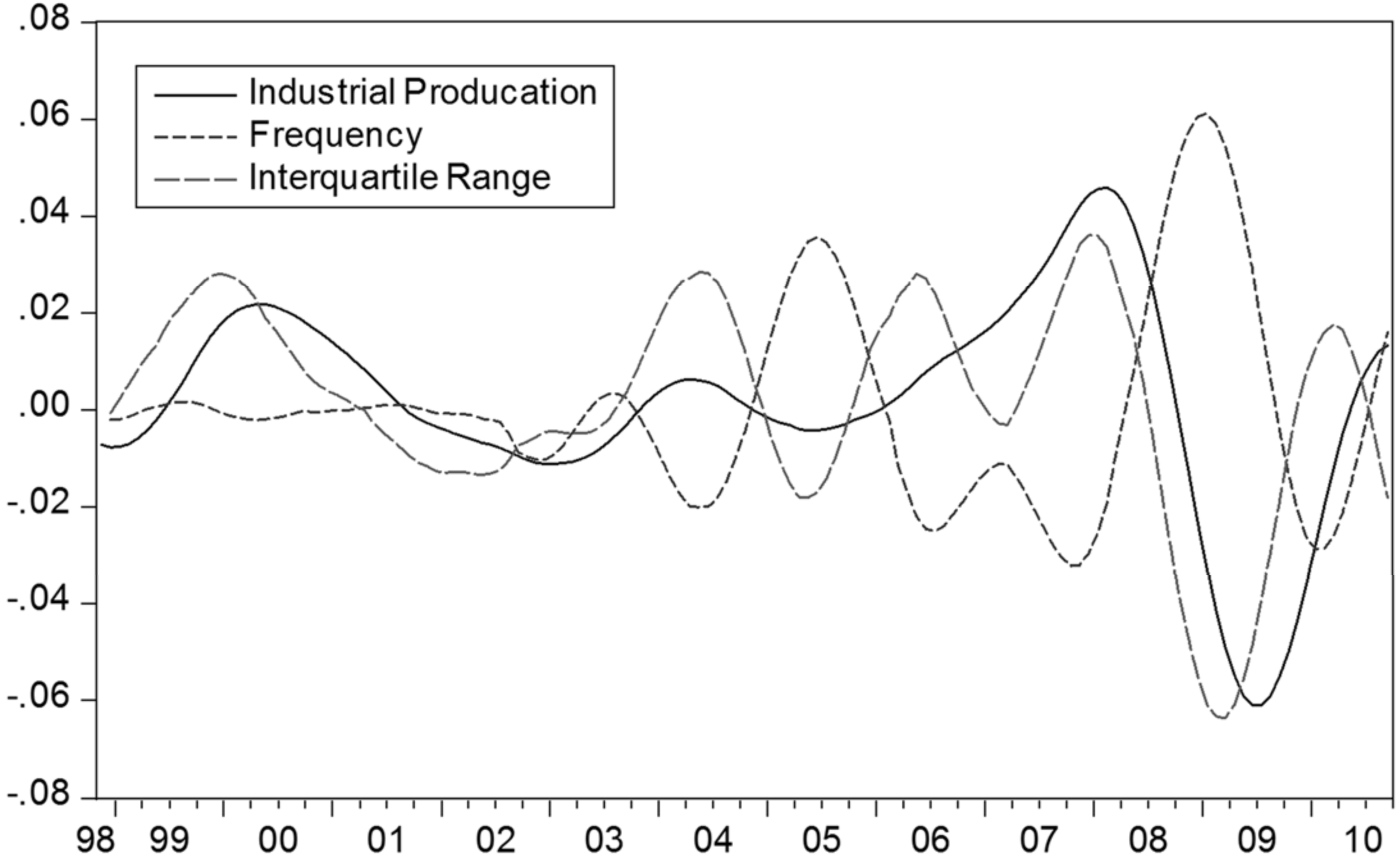


Figure A3: Bandpass filtered regular price changes over business cycle

Note: All series are seasonally adjusted using monthly dummies. All series are bandpass filtered with a Baxter-King (18,96,33) filter. Frequency is the median frequency of price changes. Sales and substitutions are excluded. Interquartile Range is the interquartile range of price changes excluding all zeros.

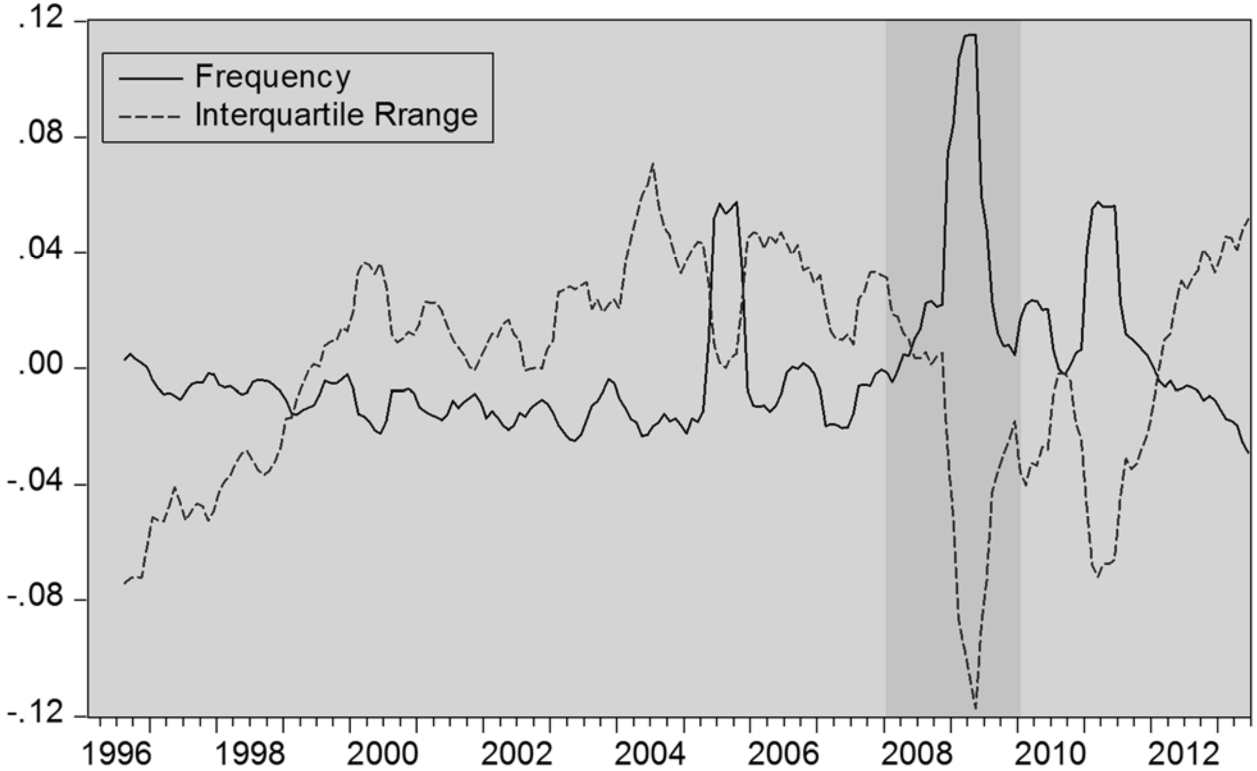



Figure A4: Smoothed regular price changes over time.

Note: The shade area shows the crisis period. Data is seasonally adjusted using 12 monthly dummies and smoothed with a 6 month moving average. Interquartile Range is the interquartile range of price changes excluding all zeros. Frequency is the median frequency of price changes. Both data series exclude price quotes belonging to sales and product substitutions.

Table A1: Sample weights comparison

| COICOP division | all included unweighted | all included weighted | excl.sub weighted | excl.sub & sale weighted | excl.fuel.sub weighted | excl.fuel.sub.sale weighted | excl.fuel weighted |
|---|---|---|---|---|---|---|---|
| Food and Non-Alcoholic Beverages | 24.0 | 13.9 | 13.9 | 13.9 | 15.0 | 15.0 | 14.9 |
| Alcoholic Beverages and Tobacco | 3.9 | 5.5 | 5.7 | 5.6 | 6.1 | 6.1 | 5.9 |
| Clothing and Footwear | 18.0 | 9.9 | 8.3 | 7.5 | 9.0 | 8.1 | 10.6 |
| Housing and Utilties | 3.7 | 6.4 | 6.5 | 6.8 | 6.7 | 7.1 | 6.6 |
| Furniture and Home Maintenance | 13.4 | 10.1 | 10.2 | 8.2 | 10.9 | 8.9 | 10.9 |
| Health | 1.6 | 1.3 | 1.4 | 1.4 | 1.5 | 1.6 | 1.4 |
| Transport | 4.4 | 11.3 | 11.9 | 12.6 | 5.4 | 5.7 | 5.2 |
| Communications | 0.3 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 |
| Recreation and Culture | 10.1 | 6.9 | 6.4 | 6.3 | 6.9 | 6.8 | 7.4 |
| Education | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Restaurants and Hotels | 12.9 | 27.5 | 28.5 | 30.3 | 30.7 | 32.8 | 29.5 |
| Miscellaneous Goods and Services | 7.8 | 7.1 | 7.2 | 7.3 | 7.8 | 7.9 | 7.6 |
| Total | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

Note: “all included” means that all price quotes are included. “weighted” means that CPI weights are used for calculation. “excl.sub” means that substitutions are excluded. “excl. fuel. sub” means energy goods’ price quotes and substitutions are excluded. “excl.fuel.sub.sale” means that energy goods’ price quotes, substitutions and sales are excluded. “excl.fuel” means that energy goods’ price quotes are excluded.

Table A2: Correlation at business cycle frequencies

| Dependent Variable | S.D. | IQR | Freq | Med | Skew | Kurt | IQR/Med |
|---|---|---|---|---|---|---|---|
| (1) IP growth(monthly change) | 0.361* | 0.571 | -0.436 | -0.459 | -10.710** | 113.868 | 11.065* |
| | (0.208)) | (0.367)) | (0.337) | (0.300) | (4.936) | (122.252) | (5.670) |
| (2) IP growth(annually change) | 0.292* | 0.485* | -0.282 | -0.296 | -2.567** | 46.368 | 6.383* |
| | (0.154) | (0.280) | (0.246) | (0.250) | (1.097) | (52.562) | (3.684) |
| (3) CPI monthly inflation | -0.988 | -3.005 | 1.032 | -0.157 | -1.856 | -531.793 | -40.091 |
| | (1.572) | (2.564) | (3.406) | (3.194) | (25.829) | (857.571) | (42.404) |
| (4) CPI annually inflation | -1.248*** | -2.435*** | 1.710*** | 1.568*** | -0.903 | -93.258 | -44.904*** |
| | (0.379) | (0.698) | (0.430) | (0.421) | (4.615) | (164.815) | (9.676) |
| (5) IP (Bandpass) | 0.004*** | 0.007*** | -0.003** | -0.004** | -0.002 | -0.052 | 0.073*** |
| | (0.001)) | (0.001) | (0.002) | (0.002) | (0.015) | (0.509) | (0.019) |
| (6) CPI (Bandpass) | -0.005 | -0.009 | 0.014* | 0.014* | -0.122 | 5.702** | -0.182 |
| | (0.005) | (0.009)) | (0.008) | (0.008) | (0.101) | (2.777) | (0.120) |
| (7) Crisis | -0.334*** | -0.061*** | 0.047** | 0.041** | 0.071 | 2.148 | -1.052*** |
| | (0.012) | (0.020) | (0.018) | (0.019) | (0.091) | (3.006) | (0.226) |
| Mean of Dep. Var. Non-Crisis: | 0.300 | 0.289 | 0.143 | 0.110 | -0.095 | 22.767 | 2.782 |
| Mean of Dep. Var. Crisis: | 0.281 | 0.246 | 0.193 | 0.155 | 0.081 | 24.008 | 1.906 |
| Mean of Dep. Var.: | 0.298 | 0.284 | 0.149 | 0.115 | -0.074 | 22.916 | 2.677 |
| Coefficient of Variation | 0.147 | 0.266 | 0.413 | 0.516 | 7.836 | 0.335 | 0.399 |

Each column reports a time-series correlation of a price dispersion statistics with a measure of the business cycle. Mean of Dep. Var. shows the means of the overall mean of these variables as well as their average values during and outside crisis. Zeros are excluded when computing dispersion. All data is seasonally adjusted using 12 monthly. Regression in rows (1) – (4) and (7) include linear and quadratic time-trends. All data for regressions in row (5) and (6) are bandpass filtered using a **Baxter-King** (18,96, 33) filter. IP in (1), (2) and (5)=Industrial Production; Crisis in (3)=1 during 2008m1 and 2010m1, otherwise=0; IQR=Interquatile Range; SD=Standard Deviation; Freq=mean Frequency of price changes; Med=Median Frequency of price changes; Skew=Skewness; Kurt=Kurtosis. Number of observation $n$=209 for (1)-(3) and (7), $n$=142 for (5) and (6). ***=at least 1% significance,**=5% significance, *=10% significance. (Newey-West standard errors in parentheses, which are used to account for autocorrelation)

Table A3: Correlation between Frequency and Price-growth Dispersion

| Dependent Variable | 1. S.D | 2. IQR | 3. S.D.(Bandpass) | 4. IQR(Bandpass) |
|---|---|---|---|---|
| Freq | -0.439*** | -0.746*** | -0.760*** | -0.451*** |
| | (0.049) | (0.097) | (0.122) | (0.081) |
| Med | -0.467*** | -0.824*** | -0.824*** | -0.493*** |
| | (0.049) | (0.107) | (0.104) | (0.069) |

This table reports correlations between measures of frequency and price change dispersion. Newey-West standard errors are in parentheses, which are used to account for autocorrelation. Zeros are excluded when computing dispersion. All data is seasonally adjusted using 12 monthly. Regressions in first two columns include a quadratic time-trend. All data for regressions in the last two columns are bandpass filtered using a **Baxter King**(18,96, 33) filter. IQR=Interquartile range, Freq=Mean frequency of price changes, Med=Median frequency of price changes, S.D.=Standard deviation, IQR= Interquartile range. Number of observation $n$=208 for the first two columns. $n$=142 for the last two columns. ***=at least 1% significance,**=5% significance, *=10% significance.

Table A4: Selected moments from the distribution of price changes

| | Data(Outliers excluded) Method(Aggregated from all price changes) | | Data(Outliers included) Method(Aggregated from all price changes | | Data(Outliers excluded) Method(Aggregated from each product) | | Data(Outliers included) Method(Aggregated from each product) | |
|---|---|---|---|---|---|---|---|---|
| | All records | Exl.sales | All records | Exl.sales | All records | Exl.sales | All records | Exl.sales |
| Frequency of price changes | 18.48 | 14.89 | 18.73 | 15.13 | 18.40 | 14.82 | 18.65 | 15.06 |
| Fraction of price changes that are decreases | 41.98 | 35.03 | 42.11 | 35.28 | 41.94 | 34.95 | 42.08 | 35.21 |
| Moments for the size of price changes | | | | | | | | |
| Average | -0.21 | 2.52 | -0.13 | 2.65 | -0.17 | 0.90 | -0.10 | 0.93 |
| Standard deviation | 28.14 | 25 | 33.74 | 31.82 | 25.53 | 23.73 | 29.40 | 26.97 |
| Kurtosis | 5.66 | 7.80 | 16.73 | 23.60 | 9.31 | 11.92 | 11.04 | 12.22 |
| Moments of standardized price changes | | | | | | | | |
| Kurtosis | 9.98 | 13.78 | 11.70 | 15.06 | 9.31 | 11.92 | 11.04 | 12.22 |
| Moments for the absolute value of standardized price changes | | | | | | | | |
| Average | 0.69 | 0.66 | 0.67 | 0.64 | 0.69 | 0.66 | 0.67 | 0.64 |
| Fraction of observations<0.25*E(\|z\|) | 20.5 | 24.8 | 21.5 | 25.4 | 20.4 | 24.0 | 21.4 | 25.4 |
| Fraction of observations<0.5*E(\|z\|) | 36.7 | 42.5 | 38.5 | 42.4 | 36.6 | 40.8 | 38.5 | 42.4 |
| Fraction of observations>2*E(\|z\|) | 14.6 | 13.7 | 14.4 | 15.0 | 14.6 | 15.2 | 14.4 | 15.0 |
| Fraction of observations>4*E(\|z\|) | 1.7 | 2.2 | 2.3 | 3.0 | 1.7 | 2.6 | 2.3 | 3.0 |
| Number of obs. With $\Delta p \neq 0$ | 3,481,459 | 2,344,945 | 3,549,565 | 2,400,432 | 3,481,459 | 2,344,945 | 3,549,565 | 2,400,432 |