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An Empirical Study on Price Rigidity

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An Empirical Study on Price Rigidity*

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Abstract:

This paper§ uses unpublished retailer-level microdata underlying UK consumer price indices to investigate price rigidity. Based on the conventional method, little rigidity is found in frequency of price change, since the implied price duration is only 5.5 months. However, it significantly underestimates the true duration (9.3 months) as suggested by cross-sectional method. Results also exhibit conspicuous heterogeneities in rigidity across sectors and shop types but weak difference across regions and time. The overall distribution of duration can be decomposed by sector into a decreasing component and a cyclical component with 4-month cycles. Both time and state dependent features exist in pricing. These findings support New Keynesian theories and enable a better calibration to improve the performances of macroeconomic models.

Key Words: Price Rigidity, Price Duration, Microdata, Cross-Sectional

JEL Classification: C41, D22, E31, L11

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1 Introduction

The price rigidity has been the fundamental issue of the dispute between Keynesian and Classical schools of thought since macroeconomics was established in the 1930's. In recent theoretical literature, many influential works[①] incorporate price rigidity into the Dynamic Stochastic General Equilibrium (DSGE) models. This trend of combing the New Classical microfoundation and New Keynesian rigidity is often termed as "New Neoclassical Synthesis"[②]. However, this integration in methodology by no means resolves the discrepancy in assumption on price rigidity between the two parties. Usually, to make judgement, macroeconomic models are compared in terms of goodness of fit to macro evidence, such as second moments of output and employment. Little effort was made in terms of micro evidence mainly due to lack of data.

Recently, there is a growing literature on price rigidity using unpublished microdata[③], such as Bils & Klenow (2004) and Nakamura & Steinsson (2008) in the US, Inflation Persistence Network (IPN) series in the Euro area, and Bunn & Ellis (2009) in the UK. There are two profound effects of the micro evidence on macroeconomic theory. On the one hand, these works make it possible to justify or falsify the assumption of price rigidity, at least in particular place and period. On the other, many papers[④] start to utilize the results in calibration to improve the performance of macroeconomic models.

There are basically three aspects of price rigidity, namely, the rigidity in *frequency* of price change, the rigidity in *direction* of price change and the rigidity in *magnitude* of price change. The frequency of price change is defined as the proportion of firms that change prices at a particular point in time. The direction of price change investigates whether price increases and price decreases share the same rigidity. The magnitude of price change analyses the frictions in the size of change. A price spell is defined as a period of time during which a price does not change, and price duration is the length of the price spell. Price duration is an important measure of rigidity in frequency of price change, and it is vital for macroeconomic modelling as well as monetary policy.

According to the previous empirical findings, price rigidity is not strong since the implied average price durations are only around 2 quarters for most countries. Unfortunately, the approach used in these studies is criticized by Baharad & Eden (2004) as

[①] For example, Goodfriend & King (1997), Rotemberg & Woodford (1997), Chari, Kehoe & McGrattan (2000), Clarida, Gali & Gertler (1999) and Smets & Wouters (2003).
[②] The "old" neoclassical synthesis is to name the trend of attempting to summarize the Keynesian theory in the form of neoclassical economics in the 1950's and 1960's.
[③] Microdata are usually collected by national authorities to construct macroeconomic statistics, such as price indices, GDP and unemployment.
[④] For example, Dixon & Kara (2010) use US micro evidence, while Dixon & LeBihan (2010) use French and UK micro evidence.

being downward biased due to oversampling of short durations. The results obtained by conventional method are effectively the duration across contracts, rather than the duration across firms. Dixon (2010) pushes this argument further and develops a unified framework to indirectly derive the cross-sectional distribution of duration across firms (DAF) from other estimated distributions.

This paper is the first attempt in literature to estimate this new measure of price rigidity from real microdata. It turns out that the conventional method gives a much lower estimate of duration (5.5 months) than the true duration (9.3 months) according to the cross-sectional method. Moreover, two other important issues of price rigidity are discussed. One is to investigate the cross-sectional and time-series heterogeneity in distribution of DAF. The other is to figure out important factors affecting the price setting behaviour, which generates the distribution of DAF.

Section 2 summarizes the methodologies in a consistent and strict terminology system. Section 3 introduces the data source used in this study and describes the features of our sample. Section 4 applies the conventional method to study the three aspects of price rigidity, to be comparable with other literature. Section 5 employs the cross-sectional methods to re-evaluate the price rigidity, and Section 6 concludes.

2 Methodology

Price rigidity is often measured by price duration, which is a random variable due to the uncertainty of when the price change occurs. T denotes the price duration, i.e. the time to the event of price change. It could be either continuous or discrete, depending on whether or not the time line is infinitely divisible. An important note on discrete time is due here. The time line is discrete because either (i) the time line is *intrinsically* discrete, or (ii) failure event occurs in continuous time but duration is only observed in discrete intervals. The price duration data in our case is actually the second possibility, since the price change could occur any time within a month, but the event is only observed in monthly interval.

The conventional method, as adopted by most authors such as Bils & Klenow (2004) and Bunn & Ellis (2009), is to calculate the frequency of price change for each period, then use its inverse as the average duration. Dixon (2010) points out the oversampling problem for this method, which leads to underestimation of rigidity. The argument is that “price spells across time are linked by the fact that they are set by the same firm”, and “focussing on the distribution of durations is in effect ignoring the *panel structure* and the fact that it is firms which are generating the price spells”. In other words, it is unfair to firms with longer spells, because firms with short spells are considered too many times in calculating average duration.

For example, if there are two firms, one changes its price every month, while the other changes price every 12 months. The frequency of price change is 50% each month, and the implied duration is 2 months. However, the true mean duration across the two firms is $(1+12)/2=6.5$ months, much higher than the implied duration using conventional method.

To address the oversampling problem, Dixon (2010) proposes a cross-sectional method in terms of duration across firms (DAF). This new method chooses a cross-section of firms at a particular point in time. Each firm's price belongs to a certain duration, whether it is completed or not at that moment. The essence of this new method is actually to collapse the panel structure into a cross-sectional structure to remove the oversampling problem. In the previous example, the mean DAF for each period is equal to 6.5 months, exactly the same as the true mean duration.

Apart from the cross-sectional distribution of DAF, we can also define cross-sectional distribution of age. Age is defined as how long the current price has survived since the last change. Therefore, age is less or equal to a duration. Dixon (2010) also develops a unified framework to transform between distribution of DAF, distribution of age, distribution of duration and hazard function. Note that distributions of DAF and age are defined in the cross-sectional sense, while distributions of duration and hazard function are defined in the panel sense.

To summarize, there are two methodologies to price rigidity, the conventional method and the cross-sectional method. This paper will apply both to the same dataset to compare the different results. There is another agenda of interest in this study, namely, to check the validity of formulae in Dixon (2010) using the real data.

3 Data

The data used in this study are retailer-level price quotes collected by the Office for National Statistics (ONS) in the UK. The price microdata are monthly collected from 1996m1 to 2008m1, underlying the construction of various price indices such as Consumer Price Index (CPI) and Retail Price Index (RPI). Both price indices measure the changes in the general price level of products[①] purchased for the purpose of consumption in the UK. However, they have subtle differences in coverage, methodology and purpose. For example, a key difference between CPI and RPI is that housing costs, such as buildings insurance and council tax, are given higher weight in RPI. Also, CPI uses geometric mean to calculate the primary indices, while RPI uses arithmetic mean.

The price microdata collected by ONS are not publicly available due to the confidentiality issues. To assist the researchers to make full and secure use of these microdata, the Virtual Microdata Laboratory (VML) was launched in 2004 to allow for access to these potentially valuable resources including price microdata. This dataset is not updated frequently, and the latest release only includes price microdata from 1996m1 to 2008m1 for CPI/RPI. The only previous users of this price microdata are Bunn & Ellis (2009) from Bank of England.

Each price quote represents the price of a particular product in a particular retailer in a given month. The observations not used by ONS in constructing indices are excluded. The double entries and the zero weighted observations are also omitted. After filtering out the improper observations, there are around 12.8 million price quotes finally been used in the clean data, spanning 144 months from 1996m1 to 2007m12.

3.1 Data Description

Individual price quote is collected either locally or centrally. Local collection is used for most items, where prices are obtained by visiting the retailers in about 150 locations. Central collection is used for central shops or central items, where prices do not vary throughout the country. However, the centrally collected data is not available in VML. The problem of lacking access to the underlying centrally collected microdata also exists for most studies, such as Bils & Klenow (2004) for the US, Álvarez & Hernando (2004) for Spain, Veronsese et al (2005) for Italy, and Bunn & Ellis (2009) for the UK. Fortunately, the coverage of the clean data on the aggregate CPI/RPI is 60.69%, which adequately represents the general price setting behaviour in the whole economy.

[①] In this paper, goods and services are both termed as products.

There are over 650 *representative items* each year to represent price movements in the fixed CPI/RPI basket each year. For each item collected locally, the sampling process could be stratified by region, by shop type[①], or by both. There are in total 12 government office regions and 2 shop types, so there can be 12 strata, 2 strata, or 24 strata, depending on the stratification method. Within each stratum, locations and retailers are then randomly sampled. Finally, price quote of an item in a randomly sampled retailer is collected on a particular Tuesday of each month (Index Day). Once the price quotes are collected, one can calculate indices in 4 steps.

Step 1: **Elementary Index** ($I^E_{j,k,s,t}$) is obtained for each item within a stratum by either geometric mean (CPI) or arithmetic mean (RPI), taking into account the shop weight $w^P_{i,j,k,s,t}$ for each price quote $p_{i,j,k,s,t}$. Here, the subscripts i, j, k, s, t uniquely identify the retailer, stratum, item, division/group[②], and time of any price quote. Accordingly, N_j is the total number of price quotes (i.e. retailers) in stratum j for item k, N_k is the total number of strata for item k, N_s is the total number of items for division/group s, and N_t is the total number of divisions/groups for period t.

Step 2: **Item Index** ($I^I_{k,s,t}$) is obtained across the strata within an item based on elementary indices $I^E_{j,k,s,t}$ and strata weights $w^E_{k,s,t}$.

Step 3: **Division/Group Index** ($I^S_{s,t}$) is obtained across items within a division/group based on item indices $I^I_{k,s,t}$ and item weights $w^I_{k,s,t}$.

Step 4: **Aggregate Index** (I^A_t) for a month is obtained across divisions/groups based on division/group indices $I^S_{s,t}$ and division/group weights $w^S_{s,t}$.

$$\underbrace{I^E_{j,k,s,t} = \frac{\sum_{i=1}^{N_j} w^P_{i,j,k,s,t} p_{i,j,k,s,t}}{\sum_{i=1}^{N_j} w^P_{i,j,k,s,t}}}_{\text{step 1}} \Rightarrow \underbrace{I^I_{k,s,t} = \frac{\sum_{j=1}^{N_k} w^E_{j,k,s,t} I^E_{j,k,s,t}}{\sum_{j=1}^{N_k} w^E_{j,k,s,t}}}_{\text{step 2}} \Rightarrow \underbrace{I^S_{s,t} = \frac{\sum_{k=1}^{N_s} w^I_{k,s,t} I^I_{k,s,t}}{\sum_{k=1}^{N_s} w^I_{k,s,t}}}_{\text{step 3}} \Rightarrow \underbrace{I^A_t = \frac{\sum_{s=1}^{N_t} w^S_{s,t} I^S_{s,t}}{\sum_{s=1}^{N_t} w^S_{s,t}}}_{\text{step 4}}$$

3.2 Weight System

The weights in calculating price indices reflect the expenditure or market share. The 4 steps above need 4 weights corresponding to each step, i.e. the shop weight $w^P_{i,j,k,s,t}$, stratum weight $w^E_{k,s,t}$, item weight $w^I_{k,s,t}$, and division/group weight $w^S_{s,t}$. If one ig-

[①] There are 2 shop types: independent shop, defined as retailer with fewer than 10 outlets; and multiple shop, defined as retailer with 10 or more outlets.
[②] Between item level and the aggregate level of CPI/RPI, there is an intermediate level. For CPI, it is called "division" based on COICOP (classification of individual consumption by purpose); while for RPI, it is called "group". For details, please refer to Consumer Price Indices Technical Manual (2010).

nores the centrally collected price quotes, then the process for the aggregate indices can be summarized into one big formula:

$$I_t^A = \frac{\sum_{s=1}^{N_t} w_{s,t}^S \times \frac{\sum_{k=1}^{N_s} w_{k,s,t}^I \times \frac{\sum_{j=1}^{N_k} w_{j,k,s,t}^E \times \frac{\sum_{i=1}^{N_j} w_{i,j,k,s,t}^P p_{i,j,k,s,t}}{\sum_{i=1}^{N_k} w_{i,j,k,s,t}^P}}{\sum_{j=1}^{N_k} w_{j,k,s,t}^E}}{\sum_{k=1}^{N_s} w_{k,s,t}^I}}{\sum_{s=1}^{N_t} w_{s,t}^S}$$

$$= \sum_{s=1}^{N_t}\sum_{k=1}^{N_s}\sum_{j=1}^{N_k}\sum_{i=1}^{N_j}\left(\frac{w_{s,t}^S \times w_{k,s,t}^I \times w_{j,k,s,t}^E \times w_{i,j,k,s,t}^P}{\sum_{s=1}^{N_t} w_{s,t}^S \times \sum_{k=1}^{N_s} w_{k,s,t}^I \times \sum_{j=1}^{N_k} w_{j,k,s,t}^E \times \sum_{i=1}^{N_k} w_{i,j,k,s,t}^P} \cdot p_{i,j,k,s,t}\right)$$

The aggregate indices can be interpreted as a weighted average of price quotes, with a "grand weight" $\omega_{i,j,k,s,t}$ specific to each observation:

$$\omega_{i,j,k,s,t} \equiv \frac{w_{s,t}^S \times w_{k,s,t}^I \times w_{j,k,s,t}^E \times w_{i,j,k,s,t}^P}{\sum_{s=1}^{N_t} w_{s,t}^S \times \sum_{k=1}^{N_s} w_{k,s,t}^I \times \sum_{j=1}^{N_k} w_{j,k,s,t}^E \times \sum_{i=1}^{N_k} w_{i,j,k,s,t}^P}, \text{ where } \sum_{s=1}^{N_t}\sum_{k=1}^{N_s}\sum_{j=1}^{N_k}\sum_{i=1}^{N_j} \omega_{i,j,k,s,t} = 1$$

Thus, the big formula now becomes:

$$I_t^A = \sum_{s=1}^{N_t}\sum_{k=1}^{N_s}\sum_{j=1}^{N_k}\sum_{i=1}^{N_j}\left(\omega_{i,j,k,s,t} \cdot p_{i,j,k,s,t}\right)$$

Similarly, to study price rigidity, this cross-sectional "grand weight" $\omega_{i,j,k,s,t}$ will be used to calculate the weighted measures. One thing to be noted here is that the grand weight $\omega_{i,j,k,s,t}$ is different from the official weight used in calculating price indices, because the centrally collected data is not available in VML. Hence, the grand weight is recalculated among the weights of locally collected observations. It could be higher or lower than the official weight, since some divisions are more or less likely to be locally collected. Luckily, the difference between the grand weight and official weight is tiny. This treatment of weight is similar to other studies.

The last problem is then to choose between CPI weights and RPI weights for calculating the grand weight $\omega_{i,j,k,s,t}$. The CPI weights are preferred in this study due to three reasons. Firstly, the published CPI weights are largely calculated from Household Final Consumption Expenditure (HHFCE) data, since they cover the relevant population and range of goods and services and, in addition, are classified by CPI divisions. This is supplemented by data from the EFS and the International Passenger Survey, which are used to calculate the weights of package holidays and airfares respectively. By contrast, the RPI weights are mainly based on data from the EFS and relate to expenditure by private households only, excluding the highest income households and pensioner households mainly dependent on state benefits. Secondly, when the Bank of England was announced independent in May 1997, the inflation target was originally set at 2.5% in terms of the RPI excluding mortgage interest payments (RPIX). However, since December 2003, the inflation target has changed to 2% in terms of CPI, previously known as Harmonised Index of Consumer Prices (HCIP). The importance of CPI in monetary policy justifies the use of CPI weight in this study. The comparability is the third advantage of using CPI weights, because HICP is also used by the European Central Bank (ECB) as the measure of price stability across the Euro area.

3.3 Descriptive Summary

As mentioned earlier, there are over 650 representative items each year, and a number of products across strata are sampled for each representative item. Each product has a price trajectory[①] made up of several "price spells" or "durations", while each duration is made up of several price quotes. Thus, the dataset has a panel structure, because there are 612,173 products (cross-sectional variation) over 12 years (time-series variation). The panel of price trajectories are described by the distributions.

3.3.1 Overall Distribution of Price Trajectory

As in other studies, this panel is unbalanced, because new items enter while old items exit the CPI/RPI baskets frequently. Here is the summary of price trajectory length (in month) in the panel.

Mean	1%	10%	25%	Median	75%	90%	95%	Obs.
20.72	1	3	7	14	30	46	56	612,173

Source: Office for National Statistics, UK.

As shown in the table, the mean length of price trajectory is higher than the median, so the distribution is positively skewed. This means that the right tail of the distribution is longer, and it has relatively few long price trajectories. There are 18,767 price trajectories longer than 60 months, while 1,929 price trajectories stay in the dataset

[①] A "price trajectory" is defined as the entire series of price quotes for a particular product.

for longer than 120 months, and only 49 price trajectories are present in the dataset throughout the entire 144 months (12 years).

3.3.2 Heterogeneity in Distribution of Price Trajectory

The first criterion of classifying price trajectories is by category. Given that CPI division is quite similar to RPI group, we will just use CPI division categories, which are classified according to COICOP (classification of individual consumption by purpose). The distribution of price trajectory across CPI division is summarized as follows:

Division	**Median**	**Mean**	**Obs.**
Food and Non-Alcoholic Beverages	17	22.70	135,201
Alcoholic Beverages and Tobacco	20	26.75	19,439
Clothing and Footwear	9	13.35	136,910
Housing and Utilities	19	23.57	25,567
Furniture and Home Maintenance	16	21.62	79,352
Health	23	28.27	7,741
Transport	23	25.64	27,501
Communications	12	16.03	1,600
Recreation and Culture	13	19.32	60,037
Education	–	–	–
Restaurants and Hotels	21	24.26	76,651
Miscellaneous Goods and Services	18	23.26	42,174
Total	**14**	**20.72**	**612,173**

Source: Office for National Statistics, UK.

The price trajectories for divisions like clothing and communications are relatively shorter, because there are more frequent rotations in these industries. Note that there are few observations for education division, because it is centrally collected and not available. To make the divisions more balanced, the 12 divisions are re-categorized into 9 sectors, following Bunn & Ellis (2009).

Sector	**Median**	**Mean**	**Obs.**
Food and Non-Alcoholic Beverages	17	22.70	135,201
Alcoholic Beverages and Tobacco	20	26.75	19,439
Energy Goods	23	25.71	11,272
Non-Energy Industrial Goods	12	17.84	314,346
Housing Services	20	23.44	17,210
Transport and Travel Services	23	25.67	10,892
Communications	12	16.03	1,600
Recreational and Personal Services	22	24.52	92,150
Miscellaneous Services	21	22.64	10,063
Total	**14**	**20.72**	**612,173**

Source: Office for National Statistics, UK.

Similarly, sectors such as non-energy industrial goods (e.g. clothing) and communications have shorter price trajectories, due to the frequent rotations of product lines. The first 4 categories are put together as "goods sectors" and the rest 5 categories are put together as "services sectors". For the same reason of rotation frequency, goods sectors tend to have shorter price trajectories.

Sector	**Median**	**Mean**	**Obs.**
Goods	13	19.76	480,258
Services	21	24.23	131,915
Total	**14**	**20.72**	**612,173**

Source: Office for National Statistics, UK.

The second criterion of classifying price trajectories is by shop type. This distinction is important because the price setting behaviour differs significantly between big and small firms. According to the convention in CPI/RPI, the "independent shop" is basically defined as small retailer, while the "multiple shop" is defined as big retailer. The price trajectories for multiple shops tend to be longer, since new products are mostly sold there and the rotation frequency is higher.

Shop Type	**Median**	**Mean**	**Obs.**
Multiple	13	20.70	372,940
Independent	17	20.76	239,180
Unknown	-	-	53
Total	**14**	**20.72**	**612,173**

Source: Office for National Statistics, UK.

The third criterion of classifying price trajectories is by region. It turns out that the heterogeneity in price setting behaviour across region in the UK is not significant, though London has shorter price trajectories because high frequency of rotations.

Region	**Median**	**Mean**	**Obs.**
London	13	19.69	71,978
South East	15	20.51	99,512
South West	16	20.78	52,272
East Anglia	15	20.84	44,335
East Midlands	16	22.15	42,295
West Midlands	15	21.09	53,260
Yorkshire & Humber	14	20.50	51,582
North West	13	19.73	63,928
North	12	20.12	32,078
Wales	16	23.45	28,183
Scotland	15	20.89	46,905
Northern Ireland	15	20.45	22,536
Unknown	-	-	3,309
Total	**14**	**20.72**	**612,173**

Source: Office for National Statistics, UK.

4 Conventional Method

The primary results reported in this section follow the conventional method and provide a comprehensive descriptive statistics of the three aspects of rigidity, including the *frequency*, *direction* and *magnitude* of price change. These results are in line with Bunn & Ellis (2009) and other IPN literature. If these naïve empirical results are used to describe price setting behaviour in the UK, not much rigidity is found. However, next section will show that this conclusion is biased.

4.1 Rigidity in Frequency of Price Change

4.1.1 Overall Frequency

In existing literature, both mean[1] and median[2] are used for the measure of frequency of price change. The advantage of median over mean is that it is more robust to outlier observations. As shown later, there is indeed an outlier around 2005m6, so median is preferred. For the interest of comparison with other literatures, both measures are used in this study and summarized in Table 1.

Table 1 Overall Frequency of Price Change

	Mean	**Median**	**S.D.**	**Skewness**	**Period**
Unweighted	17.89%	17.54%	0.02904	3.311818	1996m1-2007m12
Weighted	18.63%	18.34%	0.03525	2.936525	
		Literature			
UK	18.80%	Bunn & Ellis (2009)			1996m1-2006m12
Euro Area	15%	Dhyne et al (2005)			
Australia	15%	Baumgartner et al (2005)			1996m1-2003m12
Belgium	17%	Aucremanne & Dhyne (2004)			1989m1-2001m12
Finland	20%	Vilmunen & Laakkonen (2005)			1997m1-2003m12
France	19%	Baudry et al (2004)			1994m7-2003m2
Germany	10%	Hoffmann & Kurz-Kim (2005)			1998m1-2004m1
Italy	9%	Veronese et al (2005)			1996m1-2003m12
Luxembourg	17%	Lünnemann & Mathä (2005)			1999m1-2004m12
Netherlands	17%	Jonker et al (2004)			1998m11-2003m4
Portugal	22%	Dias et al (2004)			1992m1-2001m1
Spain	15%	Álvarez & Hernando (2004)			1993m1-2001m12
US	26%	Bils & Klenow (2004)			1995m1-1997m12
	27%	Nakamura & Steinsson (2008)			1998m1-2005m12

Source: Office for National Statistics, UK.

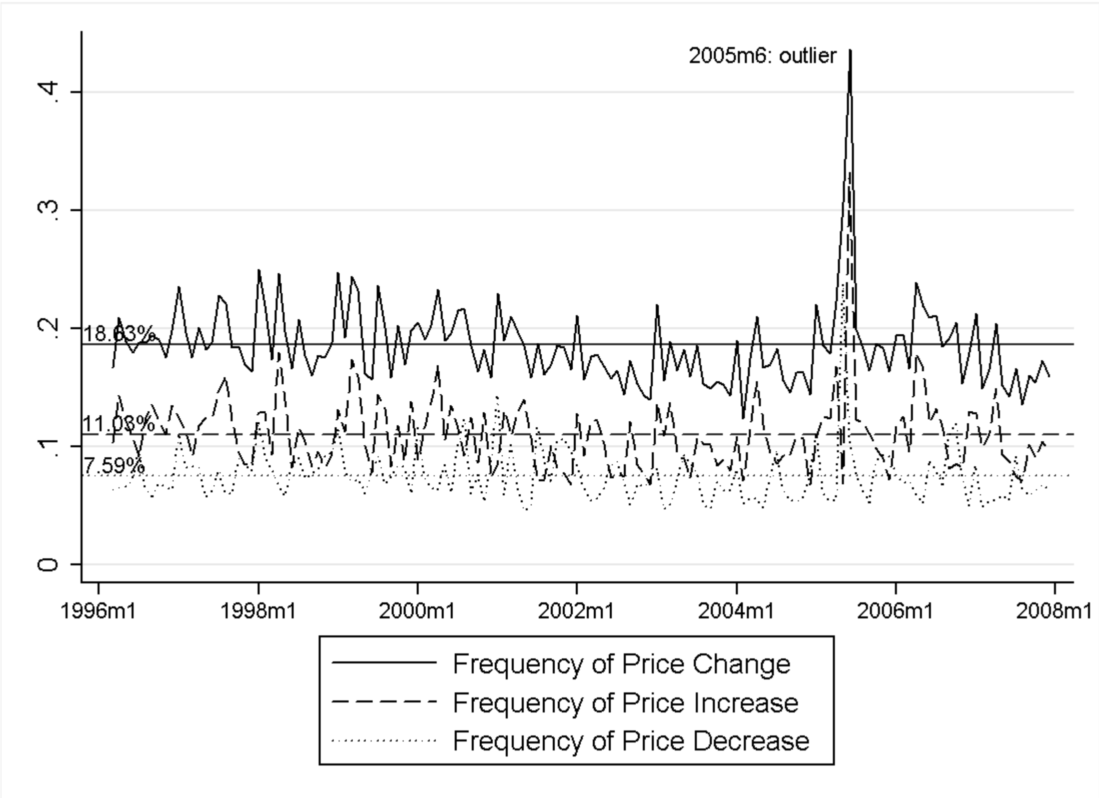
[1] Mean is popular in IPN literature, such as Dhyne et al (2005).
[2] Median is used in Bils & Klenow (2004) and Nakamura & Steinsson (2008).

The result presented here is almost the same as that found in Bunn & Ellis (2009) except that the mean frequency is slightly lower. That is because the mean frequency in 2007 is relatively lower (16.46%), which is not included in their study, dragging the overall mean a bit downward. This tiny difference does not affect the conclusion they find, i.e. the mean frequency of price change in the UK is higher than that in the Euro area, but lower than that in the US. Furthermore, according to the conventional method, the "duration" can be calculated by the inverse of frequency, which describes how long for all the prices to turnover once. Therefore, the implied mean duration based on this conventional method, 5.5 months, also lies between the Euro area and the US, and so does the degree of price rigidity in the UK.

4.1.2 Time-Series Heterogeneity in Frequency of Price Change

The frequency of price change varies across time, and this time-series heterogeneity can be seen from Figure 1. Two features are found: (i) some months (January and April have mean frequency higher than 20%) tend to have higher frequency, compared to the other months; and (ii) there is an outlier around 2005m6, where the frequency is extraordinarily high, over 40%. This outlier will be explained in details later by oil price shocks.

Figure 1 Time-Series Heterogeneity in Frequency



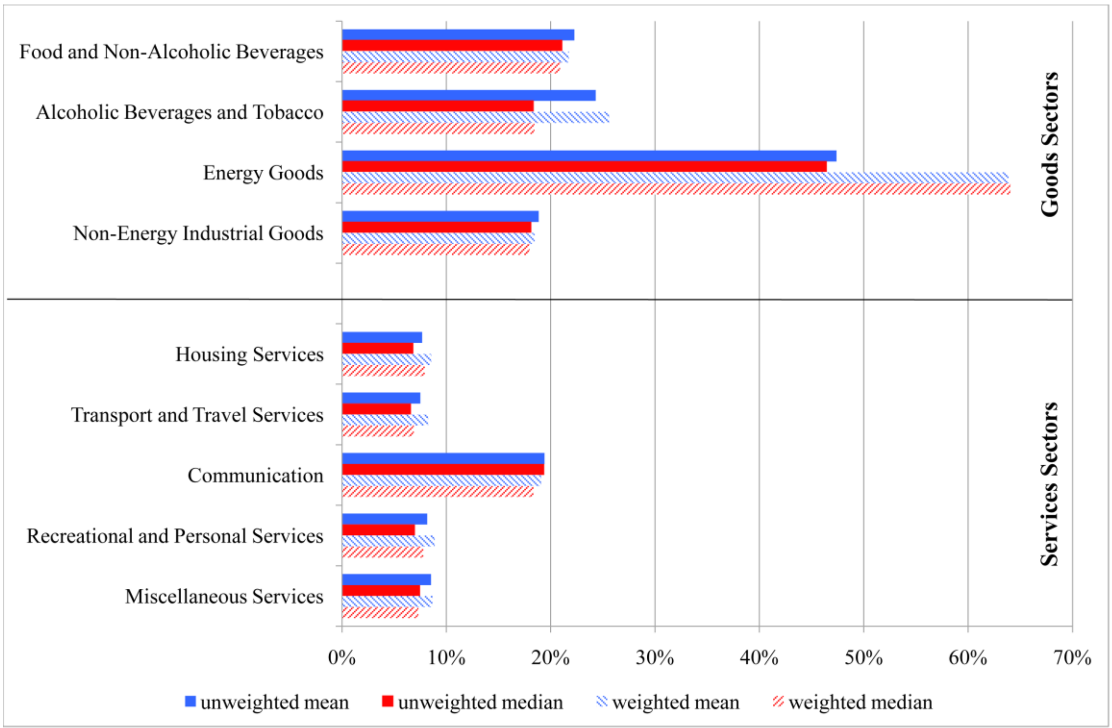
Source: Office for National Statistics, UK.

4.1.3 Cross-Sectional Heterogeneity in Frequency of Price Change

There are also significant cross-sectional heterogeneities in terms of sector, shop type, and region. A key factor affecting the frequency is *degree of competition*. The higher is competition, the less is price rigidity, and the higher is frequency of price change.

Firstly, the cross-sectional heterogeneity is significant between goods sectors and services sectors. The goods sectors tend to have higher frequency, compared to services sectors. In general, goods markets are more competitive than service markets, resulting in a higher frequency in goods sectors. By contrast, the services sectors are more rigid, because the services markets are more close to monopolistic competition. Also, service prices often involve long term contracts, which cannot be flexibly changed.

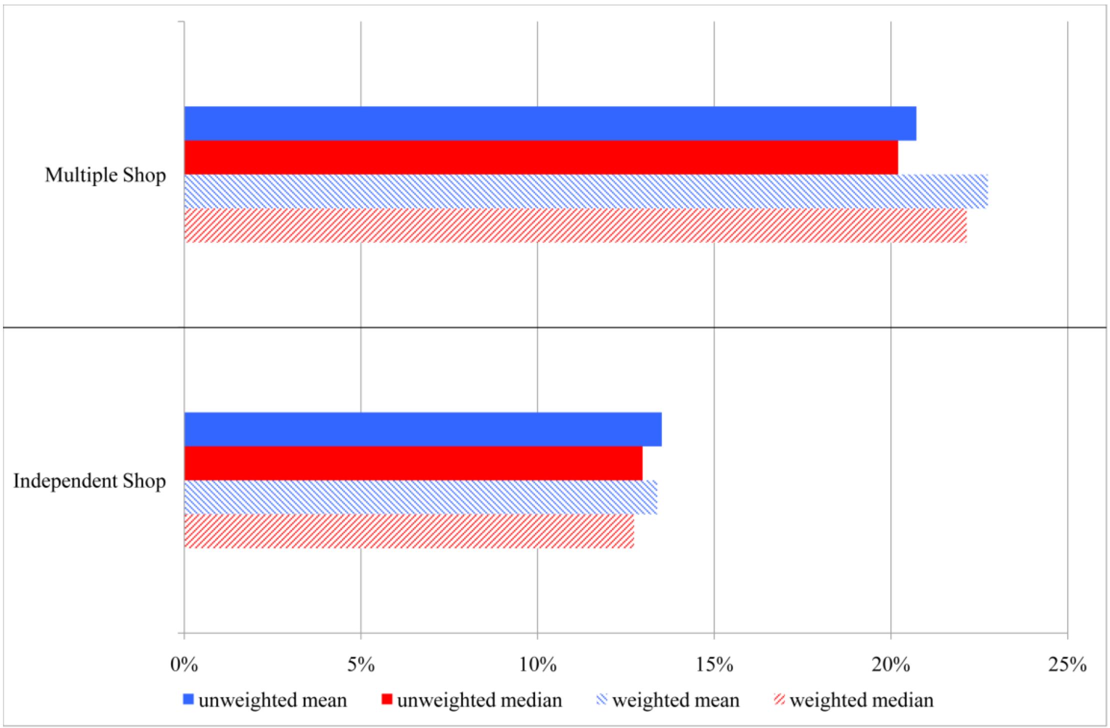
Figure 2 Cross-Sectional Heterogeneity in Frequency by Sector



Source: Office for National Statistics, UK.

Secondly, the cross-sectional heterogeneity across shop types is also significant. Arguably, multiple shops actually face much more competition than independent shops. For example, a local grocery may not care about the price change in TESCO, because its customers are quite fixed within the neighborhood. However, ASDA cannot ignore this change, because it will lose a lot of customers if it does not change the price accordingly. Hence, the multiple shops are more likely to be state dependent in pricing strategy, while the independent shops tend to use time dependent pricing strategy.

Figure 3 Cross-Sectional Heterogeneity in Frequency by Shop Type

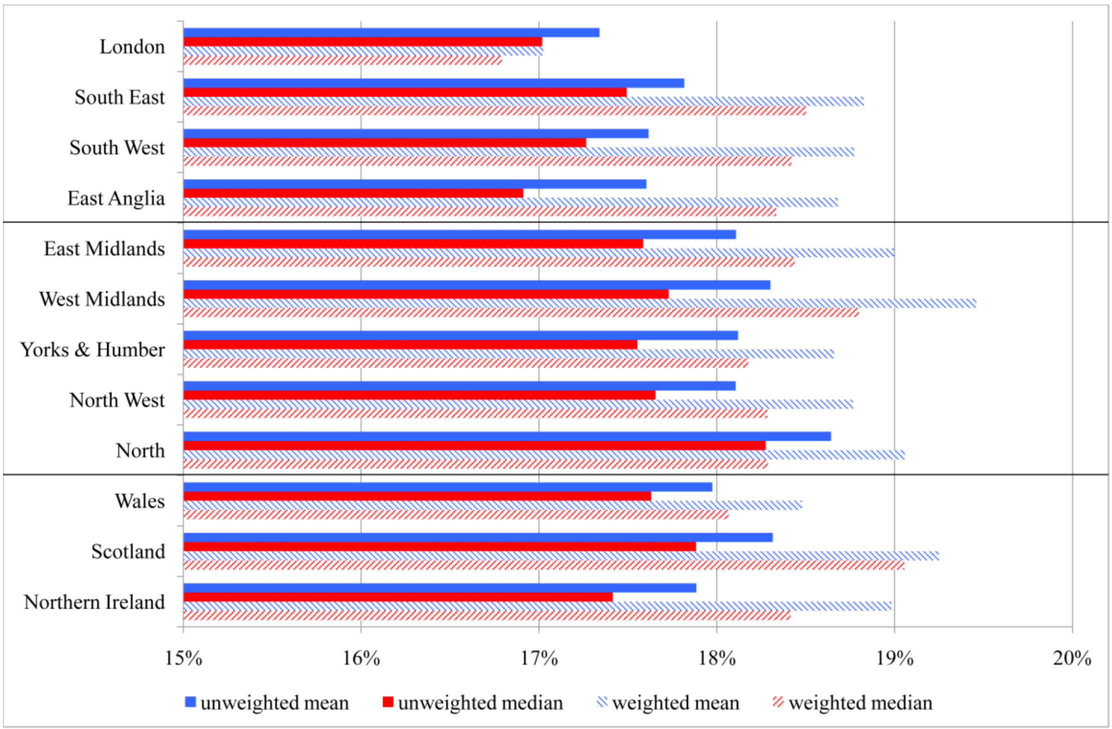


Source: Office for National Statistics, UK.

The third cross-sectional heterogeneity lies across region, which turns out to be quite small as shown in Figure 4. It is not surprising for the UK, whose economy is quite balanced across regions. There is indeed a remarkable exception in London, given that London is the economic and political centre of the whole UK. The frequency of price change in London is relatively lower, because service industries account for a high proportion in the London's economy. Moreover, there is another interesting regional difference, i.e. the "South England" (including London, South East, South West, and East Anglia) has frequencies less than 18%, while the "North England" (including East Midlands, West Midlands, Yorks & Humber, North West, and North) has frequencies more than 18%. Meanwhile, Wales and Northern Ireland seem to be closer to the south England, and Scotland is closer to the north England. Though small, this heterogeneity between the south and the north is still detectable.

To summarize, the cross-sectional heterogeneity in frequency between goods and services is the most significant stylized fact, given that the most frequent sector (energy goods) has a weighted median over 60%, while the least frequent sector (transport and travel services) only has a counterpart less than 7%. The heterogeneity across shop types is also significant and stable. Though little, regional differences are observable between London and non-London, as well as between south and north.

Figure 4 Cross-Sectional Heterogeneity in Frequency by Region



Source: Office for National Statistics, UK.

4.2 Rigidity in Direction of Price Change

Another conclusion drawn from the frequency of price change is that price increases (11.03%) are more frequent than price decreases (7.59%), as shown in Figure 1. This finding is also consistent with other literatures in the US, UK and Euro area. The higher proportion of increase results from the persistent inflation over time. Hence, it should not be regarded as an evidence for the so-called "downward rigidity", which asserts that price is more difficult to adjust downward. Moreover, as shown in Figure 5, the symmetry of the distribution of price change reinforces the conclusion that there is no downward or upward rigidity. The summary of increase versus decrease of price changes is presented in Table 2.

Table 2 Direction of Price Change

	Unweighted				**Weighted**			
	Mean	**Median**	**S.D.**	**Skewness**	**Mean**	**Median**	**S.D.**	**Skewness**
Overall	17.89%	17.54%	0.0290	3.3118	18.63%	18.34%	0.0352	2.9365
Increase	10.08%	9.92%	0.0200	4.8750	11.05%	10.81%	0.0320	2.5707
Decrease	7.82%	7.29%	0.0198	2.1103	7.58%	7.08%	0.0234	2.8011

Source: Office for National Statistics, UK.

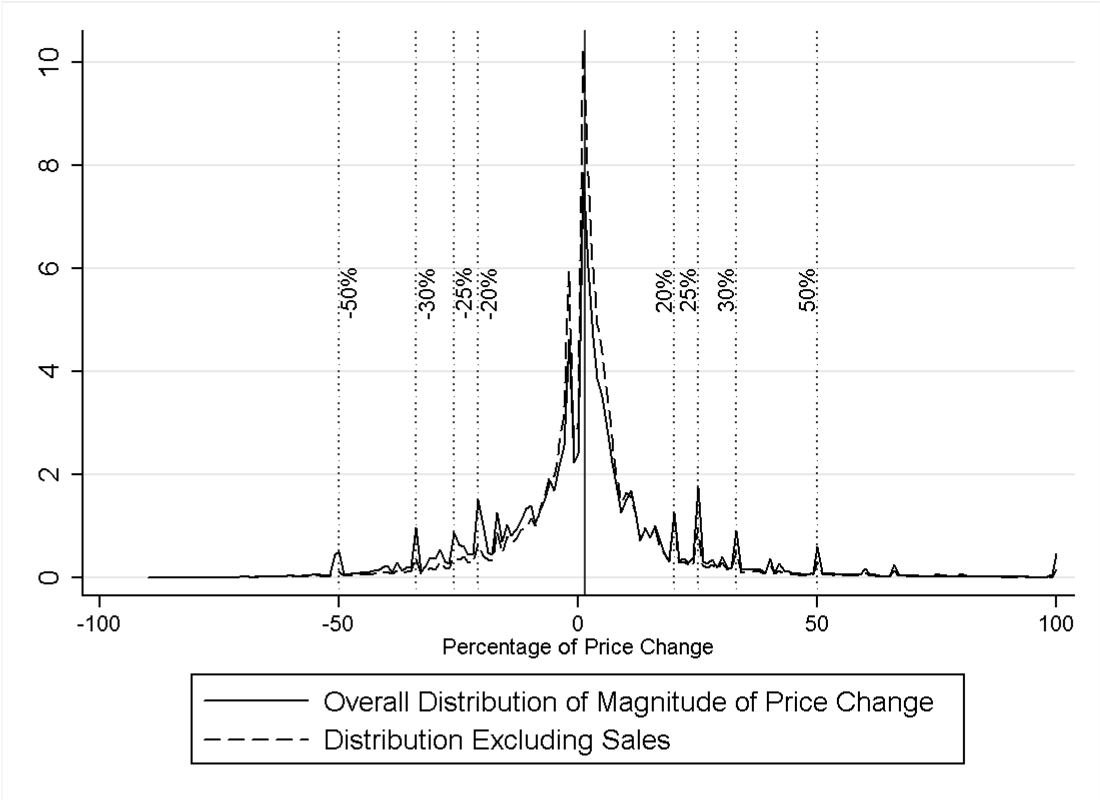
4.3 Rigidity in Magnitude of Price Change

There are two seemingly contradictory opinions on the rigidity in magnitude. On the one hand, Mankiw (1985) menu cost model provides an influential explanation on the “fixed adjustment costs” of price resetting. Similarly, Akerlof & Yellen (1985) suggest that the firm has an interval of optimal prices, rather than a point estimate of a single optimal price. It results in a so-called “band of inertia”, within which a firm will not reset its price. Only when there are big changes in the fundamentals, the firm will review its price and conduct the costly marketing research. Hence, the magnitude of price change cannot be too precise due to this “fixed adjustment costs”. If this is true, then one expects to see two interesting phenomena: (i) price levels tend to end with some particular numbers, like £X.X0, £X.X5, or £X.X9, which is referred to as “attractive pricing”; (ii) price changes tend to be integers, like 20% or 50%, rather than fractional percentage changes, like 3.1415926%. On the other hand, Rotemberg (1982) argues that the magnitude of price change cannot be too large, because it will upset the customers, and firms are reluctant to invoke this “customer anger”. If this is true, then one expects to see more small changes than large changes.

Many authors, including Bunn & Ellis (2009), misunderstand that these two strands of models are competing against each other. However, imprecise change does not necessarily lead to more large changes, and more small changes do not either imply that all changes are precisely set. The two models focus on different aspects of price change, i.e. the precision of magnitude and the range of the magnitude. Two empirical results are used to check the two models: the distribution of magnitude of price changes and the distribution of the last decimal of price level.

The first feature from Figure 5 is that most price changes are around zero. In other words, the “customer anger” models are supported. This finding is similar to Bunn & Ellis (2009) in the UK, but different from the IPN literatures. For example, Álvarez and Hernando (2004) find that most price changes in Spain are quite large, not around zero. The second feature is that the distribution of magnitude is almost symmetric, with several stylized spikes around ±20%, ±25%, ±30%, and ±50%. When sales are excluded, this stylized pattern is weaker but still significant. This suggests that firms tend to change their prices by a fixed proportion, rather than tiny fractions. Thus, it supports the “fixed adjustment costs” models, in the sense that firms prefer to follow “rule of thumb”, because carrying out marketing research is too costly. For firms with bounded rationality, it is better for them to change imprecisely than doing nothing. Hence, the two opinions are not actually contradictory. Rather, they can perfectly coexist under our empirical result.

Figure 5 Distribution of Magnitude of Price Change



Source: Office for National Statistics, UK.

Another interesting evidence for "fixed adjustment costs" models is the distribution of the last decimal of prices. It is termed "attractive pricing" in Dhyne et al (2005) and other literatures. If there are no adjustment costs, the distribution of the last decimal should be close to uniform. However, as shown in Table 3, the prices ending in "0" have the highest proportion up to 32.73%, followed by "8", "9" and "5". The other numbers do not have balanced proportions. This result is confirmed by our everyday experience that these numbers are more attractive. Bergen et al (2003) find that over 65% of the prices in the US food industry end in "9". Álvarez & Hernando (2004) also study the last two decimals of prices, detailing the distribution.

Similar to the frequency of price change, there are also time-series and cross-sectional heterogeneities in magnitude of price change. In particular, the goods sectors tend to have higher proportion around zero, compared to services sectors. Also, the multiple shops change their prices in smaller steps, compared to independent shops. This result is consistent with the relationship between frequency and magnitude of price change, as suggested in Bunn & Ellis (2009). The more frequent is price change, the smaller is the magnitude. Since the goods sectors and multiple shops have higher frequencies compared to services sectors and independent shops, their prices have smaller change in magnitude.

Table 3 Distribution of Last Decimal of Price

Last Decimal	Example	Percentage
0	£9.5**0**	32.73%
1	£8.3**1**	2.11%
2	£7.6**2**	2.02%
3	£6.2**3**	2.45%
4	£5.0**4**	7.01%
5	£4.7**5**	10.01%
6	£3.8**6**	2.20%
7	£2.1**7**	3.37%
8	£1.4**8**	21.22%
9	£0.9**9**	16.87%

Source: Office for National Statistics, UK.

To summarize the findings by conventional method, little rigidity is found in frequency of price change (implying a mean duration of 5.5 months), featured with both time-series and cross-sectional heterogeneity. There is no evidence for rigidity of direction of price change. However, rigidity in magnitude is supported in the data.

5 Cross-Sectional Method

Based on the conventional method, one cannot say there is much rigidity in price setting behavior, since the frequency is quite high (around 18.63%) and the implied duration is less than half a year. However, there are several drawbacks of this method of measuring duration and rigidity. On the one hand, this naïve method, which computes the duration by the inverse of frequency, has the problem of oversampling. On the other hand, the data available is designed for price indices rather than duration, so the basket is changing each year, resulting in many censoring and truncation cases.

Dixon (2010) argues that the duration implied by the inverse of frequency is downward biased due to oversampling of short durations. He also suggests that the cross-sectional distribution of duration across firm (DAF) is an unbiased measure of duration and robust to censorings. The DAF here is defined as the length of the lifespan of the current price. In reality, it is difficult to know the duration of a current price, because one does not know *ex ante* when this price will change in the future. However, the duration for each price can be easily worked out *ex post* in the historical data.

5.1 Cross-Sectional Distribution of DAF

5.1.1 Overall DAF

Table 4 summarizes this new method of calculating duration, in contrast with the duration implied by conventional method. The detailed distribution of DAF can be used to calibrate macroeconomic models.

Table 4 Cross-sectional Method versus Conventional Method

	Cross-Sectional Method		Conventional Method	
	Unweighted	**Weighted**	**Unweighted**	**Weighted**
Mean	9.1847	9.3460	5.7007	5.5165
Median	9.3145	9.5493	5.7027	5.4531
S.D.	0.5194	0.7094	0.7364	0.8489
Skewness	-2.8158	-1.2760	-0.5532	-0.2191
1%	6.5289	6.7016	3.6598	3.2552
5%	8.1957	7.9567	4.5075	4.2309
10%	8.7173	8.5054	4.7611	4.5223
25%	9.1443	8.9375	5.3522	4.9836
75%	9.4350	9.9120	6.2047	6.1083
90%	9.5571	10.0024	6.5755	6.5076
95%	9.6654	10.1311	6.8573	6.9420
99%	9.9782	10.2182	7.2006	7.3768

Source: Office for National Statistics, UK.

Not surprisingly, DAF is much higher than duration implied by frequency. This is because the frequency is based on the oversampled short durations, as argued in Section 2. As a result, the inverse of frequency is a downward biased estimate of duration. By contrast, DAF does not have this problem. At any point in time, each product's price quote corresponds to a duration, i.e. the length of lifespan of the current price. The cross-sectional distribution of durations, or DAF, can then be obtained. The estimated mean and median of DAF are both over 9 months, much longer than the implied duration. This measure of duration strongly supports the price rigidity in frequency.

5.1.2 Time-Series Heterogeneity in DAF

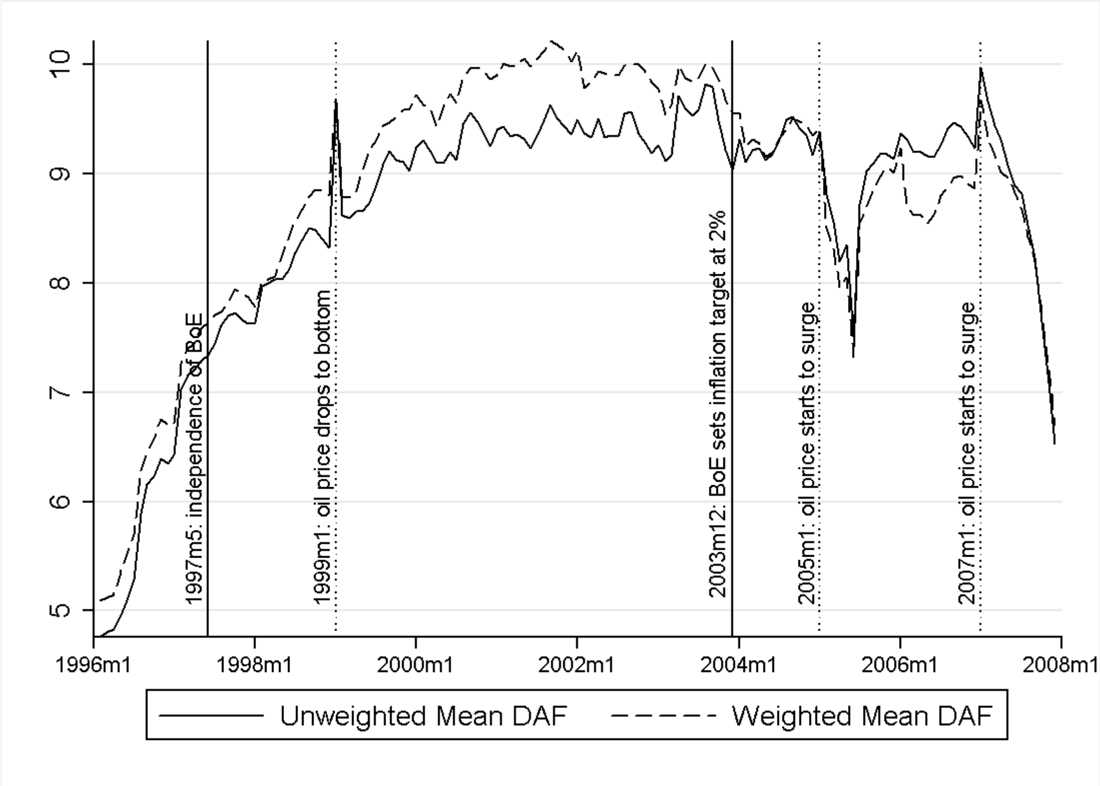
Similar to the frequency of price change, DAF is also heterogeneous in two dimensions, time-series and cross-section. The mean DAF fluctuated over the sample period from 1996m1 to 2007m12, which can be divided into three subperiods in terms of the historical changes in monetary policy. The first subperiod is from 1996m1 to 1997m5, due to the independence of Band of England in 1997m5. The second subperiod is from 1997m6 to 2003m12, when Bank of England changed its inflation target from 2.5% based on RPIX[①] to 2% based on CPI. The third subperiod runs from 2004m1 to 2007m12, until the end of the microdata sample period. The UK economy was close to but not always in steady state during the 12 years, since there are several important events and shocks occurred. Figure 6 shows the evolution of mean DAF over time, and Figure 7 shows the difference in distribution of DAF over the three subperiods, where each curve represents the distribution of DAF in a particular month.

The first feature is the importance of monetary policy on pricing behaviour. In the second subperiod after the independence of Bank of England, mean DAF steadily increases, with a special spike in 1999m1. This overall trend reflects that independence of monetary policy did stabilize the price levels and the expectation of inflation of the public. The mean DAF does not change much in the third subperiod after the change in inflation target, except for the two low spikes in 2005m1 and 2007m1. This is because the change in measure of inflation target does not actually change the effective inflation target much, since RPIX *per se* tends to be lower than CPI.

The second feature is the importance of macroeconomic state on pricing behaviour. In particular, the oil price shocks seem to have a co-movement with mean DAF. If Figure 6 and Figure 8 are contrasted, it is clear that the oil price has a conspicuous negative effect on mean DAF. This finding shows support to state dependent models, and also suggests including oil price in econometric models.

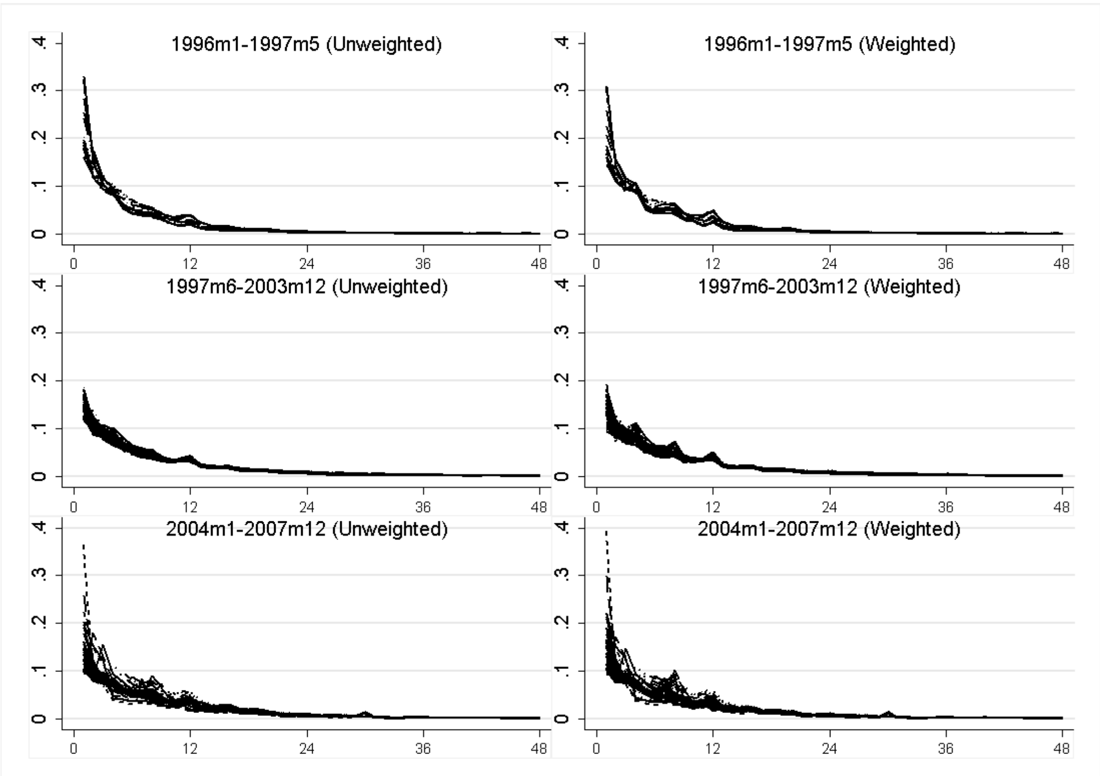
[①] RPIX is RPI excluding mortgage interest payments.

Figure 6 Time-Series Heterogeneity in Mean DAF



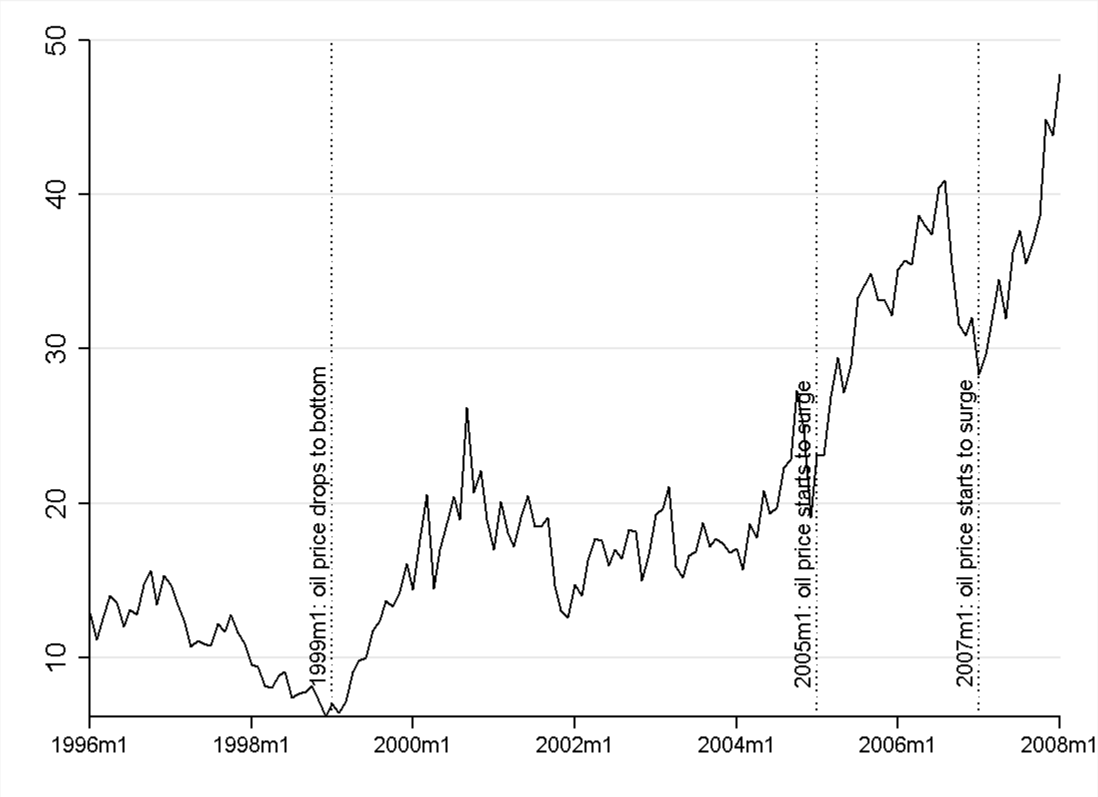
Source: Office for National Statistics, UK.

Figure 7 Time-Series Heterogeneity in Distribution of DAF



Source: Office for National Statistics, UK.

Figure 8 Crude Oil Price in Pounds



Source: Office for National Statistics, UK.

The first outlier in 1999m1 can be explained by the level of oil price, which drops to bottom in 1999m1. Arguably, when the oil price level is low, the pressure of changing prices on the whole economy is much relieved. Similarly, the outliers in 2005m1 and 2007m1 can also be attributed to the high oil price. As the oil price starts to surge, the firms are more sensitive to macroeconomic shocks. Due to the drastic fluctuations of oil price in the third subperiod, the distribution of DAF is quite volatile, compared to the stable distributions in the first and second subperiods. There is a process for the effect of oil shocks to pass throughout the whole economy, because different sectors, shops, and regions react to oil shocks differently. From Figure 6, after about 2 quarters, the shocks die away and DAF converges back to its normal level.

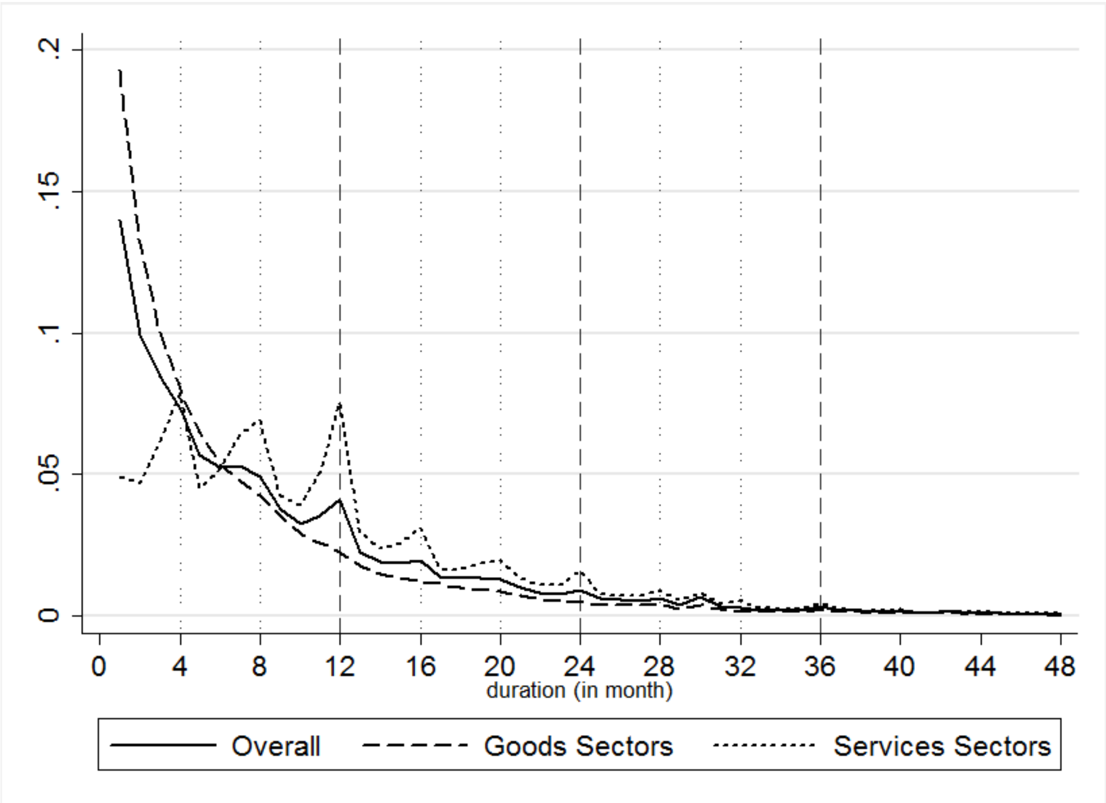
The third feature observed in the results above is that the distribution of DAF is decreasing, with typical spikes around 4 months, 8 months, and 12 months. This stylized fact indicates that at least some firms tend to reset prices at fixed time intervals, and this overall feature will be explained in details later by decomposition of distribution of DAF. The length of cycles is a bit different from the empirical findings in the Euro area, where firms are more likely to reset prices every 3 months, not every 4 months. The existence of cycles also supports the time dependent models.

5.1.3 Cross-Sectional Heterogeneity in DAF

In addition to time dimension, DAF is also heterogeneous across sectors, shop types, and regions. Similar to the conclusion obtained in conventional method, services sectors (11.38 months) have longer DAF than goods sectors (7.43 months), while independent shops (10.06 months) have longer DAF than multiple shops (7.60 months). The heterogeneity across regions is still small. Thus, the new measure of rigidity does not change the cross-sectional rankings in rigidity, but the degree of rigidity. The detailed distributions of DAF by sector and by shop type can also be used for future use in calibrating macroeconomic models.

In particular, Figure 9 shows the heterogeneity in distribution of DAF across sectors, in comparison to the overall distribution of DAF. A key finding is that the decreasing feature of the overall distribution of DAF is mainly due to the goods sectors, while the cyclical feature is mainly due to the services sectors. It is because the services sectors involve contracts to be signed over a certain period, which is found 4 months in UK case. Thus, services sectors are more time dependent. By contrast, the goods sectors are more competitive and flexible, resulting in a decreasing and smooth distribution. This decomposition provides deeper insight into the firms' pricing strategy by sector.

Figure 9 Decomposition of Distribution of DAF



Source: Office for National Statistics, UK.

5.2 Cross-Sectional Distribution of Age

The age of price is another cross-sectional measure of rigidity, which is closely correlated with DAF. Age is defined as how long the current price has survived since the last change. Instead of using complete duration, the current age of each firm's price, i.e. how many months have passed since the last change, is used. In fact, age is an incomplete duration, so the mean/median age must be less than mean/median DAF.

The result of distribution of age is presented in Table 5, compared with the distribution of DAF. As expected, both the mean and median of age are less than DAF, but quite close to the duration implied by frequency in Table 4.

Table 5 Distribution of DAF versus Age

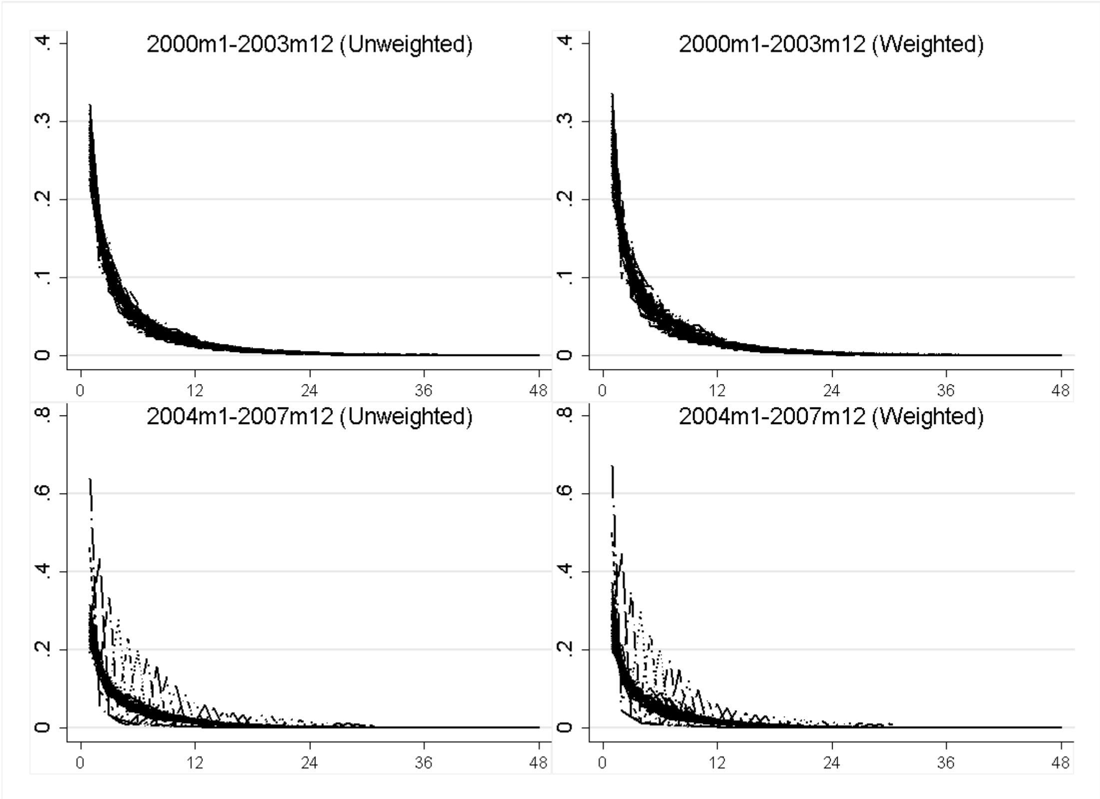
	DAF		Age	
	Unweighted	**Weighted**	**Unweighted**	**Weighted**
Mean	9.1847	9.3460	5.5663	5.6044
Median	9.3145	9.5493	5.5405	5.6459
S.D.	0.5194	0.7094	0.4110	0.4689
Skewness	-2.8158	-1.2760	-0.1492	-0.6205
1%	6.5289	6.7016	4.1205	3.9284
5%	8.1957	7.9567	4.9946	4.8069
10%	8.7173	8.5054	5.1511	4.9801
25%	9.1443	8.9375	5.3588	5.3373
75%	9.4350	9.9120	5.7408	5.8709
90%	9.5571	10.0024	6.1389	6.1696
95%	9.6654	10.1311	6.3450	6.3445
99%	9.9782	10.2182	6.5316	6.7028

Source: Office for National Statistics, UK.

Indeed, the distribution of age is just another perspective of looking at the same process, so it also has time-series and cross-sectional heterogeneities, similar to the distribution of DAF. As shown in Figure 10, the distribution of age is also stable during the second subperiod, since the oil price is relatively low and stable. However, in the third subperiod, when oil price is volatile, the distribution of age becomes wild.

Hence, the stabilization effects of monetary policy and destabilization effects of oil price shocks are found in the distribution of age, reinforcing the earlier conclusions in Section 5.1 that firms have state dependent feature in pricing strategy.

Figure 10 Time-Series Heterogeneity in Distribution of Age



Source: Office for National Statistics, UK.

5.3 Relationship between DAF and Age

Dixon (2010) develops a unified framework to switch between DAF and age in steady state. On the one hand, given the distribution of DAF, $\boldsymbol{\alpha} = \{\alpha_i\}_{i=1}^{N} \in \Delta^{N-1}$[①] where N is the longest DAF, then the distribution of age, $\boldsymbol{\alpha}^A = \{\alpha_i^A\}_{i=1}^{N} \in \Delta^{N-1}$, can be derived by:

$$\alpha_i^A = \sum\nolimits_{j=i}^{N} \frac{\alpha_j}{j}, \text{ where } i = 1, \ldots, N$$

On the other hand, given the distribution of age, $\boldsymbol{\alpha}^A = \{\alpha_i^A\}_{i=1}^{N} \in \Delta^{N-1}$, then the distribution of DAF, $\boldsymbol{\alpha} = \{\alpha_i\}_{i=1}^{N} \in \Delta^{N-1}$, can also be derived by:

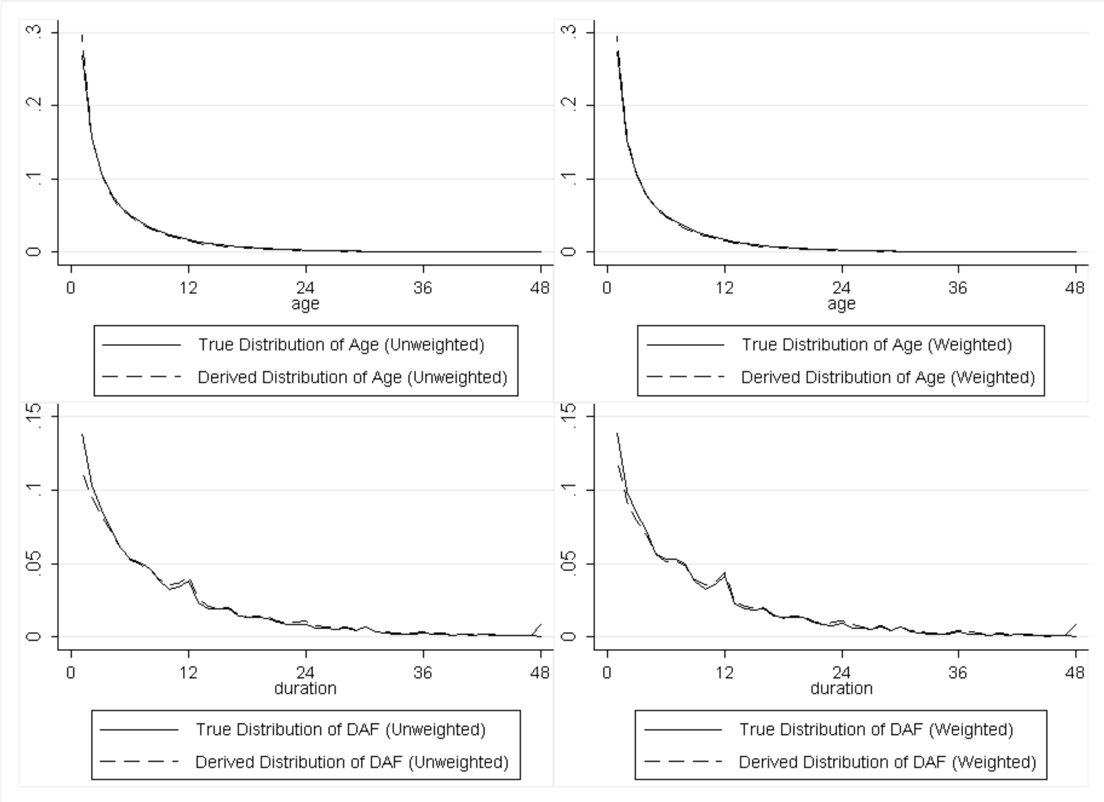
$$\begin{aligned} &\alpha_1 = \alpha_1^A - \alpha_2^A \\ &\alpha_i = i\left(\alpha_i^A - \alpha_{i+1}^A\right), \text{ where } i = 2, \ldots, N-1 \\ &\alpha_N = N\alpha_N^A \end{aligned}$$

This method is only valid in the steady state, so the average distribution of DAF and age in the most stable subperiod (2000m1-2003m12) are used to check the two formulae. The true and derived distributions of DAF and age are compared in Figure 11. It

[①] Here, Δ denotes the simplex as defined in Dixon (2010).

is obvious that the true and derived distributions are quite close, especially for the derived distribution of age. This simple practice successfully justifies this important theoretical contribution of Dixon (2010).

Figure 11 True and Derived Distribution of DAF and Age



Source: Office for National Statistics, UK.

That is to say, once the distribution of age or other distributions are already obtained, the distribution of DAF can also be easily derived using the formula in Dixon (2010). Further work is to be done based on the empirical findings. This unbiased distribution of duration is essential for macroeconomic modelling, because the micro evidence can be applied to calibrating and simulating New Keynesian heterogeneous agent models, or testing theoretical models.

6 Conclusion

This paper studies the price setting behaviour for the retailers in the UK during the latest 12 years. Both conventional and cross-sectional methods are applied to the unpublished microdata, resulting in different conclusions on price rigidity. There are five important stylized facts:

(i) The overall mean duration is 9.3 months in terms of DAF, much longer than 5.5 months as implied from the frequency by the conventional method. This is a strong evidence for rigidity in retailers' price setting behaviour, different from other studies based on the conventional method.

(ii) There is little support for rigidity in direction of price change, but we do find evidence for rigidity in magnitude of price change regarding precision and range. In other words, price faces the same rigidity to rise or fall, but it tends to end with attractive numbers and change by fixed proportion.

(iii) Significant cross-sectional heterogeneity is observed by sector and by shop type, while little regional difference or time-series heterogeneity is found. Goods sectors tend to be more flexible than services sectors, while multiple shops change prices more frequently than independent shops.

(iv) The distribution of DAF has two stable features over the sample period, i.e. the decreasing feature due to goods sectors and the cyclical feature due to services sectors. The length of cycles is around 4 months. This cyclical feature supports the time dependent models.

(v) Macroeconomic factors have considerable effects on the rigidity of price change. The independent monetary policy has a stabilization effect, while oil price shocks have a destabilization effect on the mean DAF. This finding supports state dependent models.

Apart from the stylized facts on rigidity, another important conclusion is drawn in this paper. The distribution of DAF directly estimated from data is very close to that indirectly derived from the distribution of age according to the formula in Dixon (2010). On the one hand, the descriptive results in this paper give insight into econometric modelling of pricing mechanism or strategy. On the other hand, the micro findings of the distributions can be used to calibrate macroeconomic models in order to better mimic the macro evidence, such as the second moments of output and inflation.

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