The Determinants of Price Rigidity in the UK:

Analysis of the CPI and PPI Microdata and Application to Macrodata Modelling*

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Abstract

This paper systematically investigates price rigidity in UK consumer and producer markets, by estimating the hazard functions of price changes in microdata which are then used in macrodata modelling. We explore the mechanism of price-setting using survival analysis in order to see what factors drive the observed price rigidity. We find significant effects of macroeconomic variables such as inflation and output, which should be purged off before calibrating any macroeconomic models. The microdata findings are then used to estimate and simulate a heterogeneous price-setting model with a generalised Calvo goods sector and a generalised Taylor service sector, which improves the performance in matching macrodata persistence.

Key Words:

Price Rigidity, Price Setting Behaviour, Microdata, Survival Analysis, Heterogeneous Agent Model, Persistence Puzzle

JEL Classification: C41, D21, E31, E32

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The importance and extent of price rigidity has been a fundamental matter of dispute between the Keynesian and Classical schools of thought since the 1930's. Since 2000, there has been a growing literature on price rigidity based on microdata, such as Bils and Klenow (2004) and Nakamura and Steinsson (2008) for the US, the Inflation Persistence Network (IPN) country-level studies for the Euro area[1], and Bunn and Ellis (2009, 2012a, 2012b) for the UK. Other empirical studies on aspects of price setting behaviour have grown out of this, including Alvarez et al (2006), Alvarez and Burriel (2010), Alvarez et al (2013), Alvarez and Lippi (2014), Costain and Nakov (2011), Vavra (2014) and Kara (2015) Berardi et al (2015), and Dixon and Tian (2017).

The major contribution of this paper is to employ survival analysis (nonparametric, semiparametric and parametric models) to understand how prices were set in the UK in the decade preceding the crisis. We use the micro-price data (individual price quotes) used to construct both the CPI (Consumer Price Index) and PPI (Producer Price index) over the period 1996-2007. This period is chosen because it is part of the pre-crisis great moderation and because the PPI data is not currently available after 2007 and neither data series is available prior to this period. The main purpose is to explain the hazard rate, the probability of a price changing conditional on having lasted for a number of periods. Our preferred approach is the semi-parametric approach, a proportional hazard Cox model. The hazard is decomposed into two components: the baseline hazard which is not restricted to any functional form and is common across all products and a second component containing the explanatory factors determining the hazard function. The baseline hazard is simply a function of duration—how long it is since the price was last reset. The second part includes variables for seasonality, location, firm characteristics and macroeconomic variables. Our main interest is in the macroeconomic variables and the extent to which they matter. Many existing studies have found that the main influences on price-setting are microeconomic ones (Klenow and Malin, 2011; Alvarez et al, 2015). However, it still remains to be seen whether we can find macroeconomic effects—they may be less important for individual firms, but they affect all firms and so may still have an important overall effect on the economy.

The main findings of the paper can be summarised as follows:

- Finding 1: For both consumer and producer prices, macroeconomic factors (e.g. inflation, interest rate) have a significant effect on the probability of a price change (the

[1] The IPN working paper series include Baumgartner et al (2005) for Austria, Aucremanne and Dhyne (2005) for Belgium, Vilmunen and Laakkonen (2004) for Finland, Baudry et al (2007) for France, Hoffmann and Kurz-Kim (2006) for Germany, Veronese et al (2005) for Italy, Lünnemann and Mathä (2005) for Luxembourg, Jonker et al (2004) for Netherlands, Dias et al (2008) for Portugal, Álvarez and Hernando (2004) for Spain, and Dhyne et al (2005) for the whole Euro area.

hazard rate). Producer price's hazard rates are more sensitive to shifts in inflation and the interest rate than retail prices.

- Finding 2: Hazard rates have a downward sloping trend (becoming smaller as the price spell gets older), supporting the hypothesis of the "selection effect" (older prices are likely to belong to products with a lower frequency of adjustment). This finding is also documented in Álvarez et al (2005).
- Finding 3: There is also a 4-month cycle of spikes in the hazard rates of both consumer and producer prices, and this pattern is stronger for the goods sector and independent/local shops.
- Finding 4: When we use the microdata evidence in a simple DSGE model, we find that allowing for sectoral heterogeneity in price setting behaviour yields the best results. In particular, we find that best model is one in which the service sector (as defined by the ONS) has Taylor pricing and the goods sector is Calvo.

These empirical results based on microdata provide insights into macrodata modelling in monetary economics. Finding 4 favours heterogeneous pricing models with sectoral differences over homogeneous pricing models. Furthermore, there is evidence for both state-dependent (Finding 1) and time-dependent (Finding 3 and 4) pricing models as well as heterogeneity in hazard rates across products (Finding 2). An important application of these microdata findings is to better calibrate the macroeconomic models. A simple simulation excercise is conducted to illustrate how incorporating the microdata into a DSGE model can improve its performance in matching macrodata. It is shown that the model with multi-sector or heterogeneous price setting behaviour can resolve the famous "persistence puzzle" in the monetary economics literature.

Section 1 outlines in more detail the approaches adopted by this paper, with a brief clarification of different terminology systems. The data is described in the section 2. In section 3, we examine the determinants of price-change using survival analysis models. Finally, we provide a simple application of the microdata findings to a stylised macroeconomic model in section 4 and then conclude.

1 Methodology

Survival analysis (aka "duration analysis" or "reliability analysis") studies the time to the occurrence of a random event. It originates in Biometrics and Engineering, dealing with topics such as death in biological organisms and failure in mechanical systems. If price-change is treated as the random event, then price setting behaviour can be studied using the same approach. Many papers, such as Jonker et al (2004), Nakamura and Steinsson (2008), and Bunn and Ellis (2009, 2012a, 2012b), already apply survival analysis to studying price duration. Our approach is similar to Dias et al (2007), but their specification only includes the current inflation as the measure of the economic state. By contrast, our economic state measure is both wider (including inflation, interest rate and oil price) and dynamic (including lead, lag and current values). However, different authors use different words, causing considerable confusions for the readers. **Appendix I** is devoted to clarifying the related concepts using the terminology conventions in statistics. The definitions of a point in time t, a period of time, a price quote, a price-spell, a price duration T, its probability density/mass function $f(t)$, cumulative distribution function $F(t)$, survival function $S(t)$, hazard function $h(t)$, baseline hazard function $h_0(t)$ and cumulative hazard function $H(t)$ can be found there. As some techniques used in this paper have not been applied to studying price setting behaviour before, the **Appendix II** introduces the survival analysis framework, including nonparametric, semiparametric and parametric models.

One alternative method to survival analysis is logit model[2], the dependent variable of which is a dummy variable—whether or not the price changes—and the independent variables are similar to (or even the same as) those used in the survival analysis models. Logit model is used by Álvarez and Hernando (2004), Aucremanne and Dhyne (2005), Baumgartner et al (2005), Dhyne et al (2005), Hoffmann et al (2006), Baudry et al (2007) and Berardi et al (2015)[3]. Undoubtedly, it is statistically superior to OLS which is used in Baharad and Eden (2004), but the logit model is essentially a cross-sectional econometric model which again ignores the panel structure of the price duration data. The intertemporal link of the price quotes of the same product is not taken into account in the regression. To address this, many papers attempt to use time-series models (such as VAR in Baharad and Eden, 2004) and panel-data models (such as fixed effects model in Lünnemann and Mathä, 2005) to include the time dimension, but these models are estimated at the aggregate levels, so almost all the microdata level information is lost. Another problem lies in the unavoidable censorings and truncations in the price data—there are always missing values during and at the end of the observation period. Omitting these censored or truncated data leads to selection bias due to over-representation of short spells.

Accordingly, survival analysis has two advantages. First, survival models are designed specifically for studying duration data, so they can fully capture the panel structure of price quotes across products and over time. In other words, it can keep and utilise all the microdata information in the analysis. Second, it handles the problems due to censoring and truncation well, which is illustrated with two examples in **Appendix II**.

There are three types of models commonly used in survival analysis. Arguably, nonparametric analysis is too simple to account for all the factors determining the probability of the price-

[2] In fact, the authors have done the logit regressions as well but these are not reported (available on request).
[3] They also used multinomial logit (mlogit), which is an extended version of the logit model.

change, because it ignores all the covariates other than t (the time elapsed since the last price-change). However, parametric analysis is too restrictive due to its assumption of the functional form of the baseline hazard function $h_0(t)$. As a result, semiparametric analysis has the advantages of both, and we believe it generates the most reliable conclusions so it will be one we focus on.

2 The Data

The data used in this paper includes both consumer price quotes (1996m1-2008m1) and producer price quotes (1998m1-2008m2) collected monthly by the Office for National Statistics (ONS)[4] in the UK, underlying the construction of various price indices such as Consumer Price Index (CPI), Retail Price Index (RPI)[5] and Producer Price Index (PPI)[6]. We have not used the data since 2008 for two reasons[7]. First, the PPI data is not available after 2008m2 and we want to compare the two sources. Second, the period 1996-2008 is mostly (except perhaps for the last year) in the Great Moderation period, when we can expect the distributions estimated to be stable. For an analysis of the crisis period using UK CPI data see Dixon et al (2014a) [8].

Compared to Bunn and Ellis (2012a, 2012b), this paper extends the dataset on both ends to include the updated price quotes available before the financial crisis. The findings in this paper are generalisable to "normal" economic conditions which we are believed to be returning to—the main economic indicators[9] such as GDP (£436 billion, 2015Q1) and unemployment (5.5%, 2015Q1) are back to the pre-crisis levels. Since the data used here have substantial overlapping parts with those used in Bunn and Ellis (2012a, 2012b), the description and summary of the data are omitted in this paper[10] and only the information on the price trajectories—the basis for

[4] The 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 the price microdata. The only previous users of this dataset are Bunn and Ellis (2009, 2012a, 2012b) from Bank of England.

[5] Both CPI and RPI measure the changes in the general price level of products 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. CPI becomes the monetary policy target since 2003m12, instead of RPI.

[6] PPI includes both output PPI (the prices of output produced by manufacturers for sale) and input PPI (the prices of input purchased by manufacturers). The output PPI, commonly known as "factory gate" prices, measures the price level at the wholesaler's level, in contrast to CPI/RPI at retailer level. It gives extra information of the price setting behaviour in the early stage of supply chain. The input PPI provides important information about the input markets, which complement the knowledge of output markets.

[7] There is a third more technical reason: the ONS changed the way they collected energy data, and it is not part of the locally collected price data we use from 2008 onwards.

[8] See Dixon et al (2014) for a discussion of the price setting behaviour during the financial crisis. They find a shorter price duration during the crisis period than the sample period of our data (the Great Moderation). One of the difficulties in studying the price setting in the crisis period is that the price trajectories are too short.

[9] Source: ONS website http://www.ons.gov.uk/.

[10] The more detailed descriptive statistics of the dataset can be found in Bunn and Ellis (2012a, 2012b) or in the working paper version of this paper.

estimating the distribution of duration and the survival analysis models—will be detailed, because this is useful for understanding the censoring and truncation issues that survival analysis helps address.

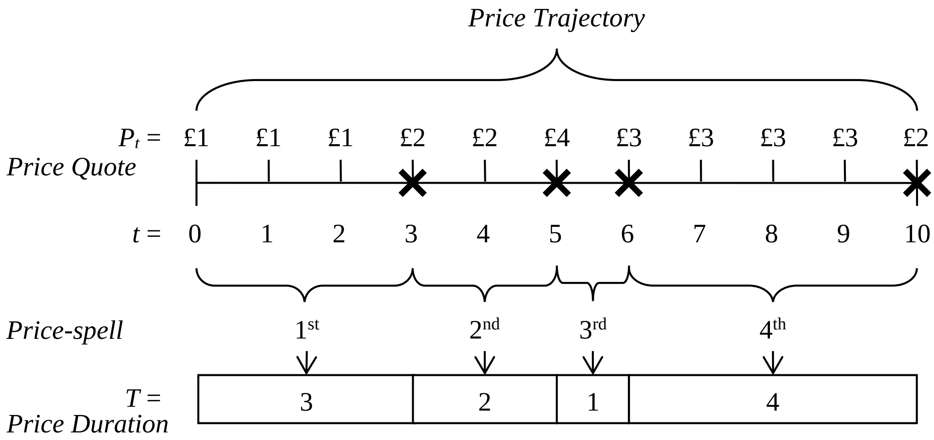

Figure 1 *Illustration of a Typical Price Trajectory*

The data has an unbalanced panel structure. Each firm, a retailer for CPI/RPI and a producer for PPI, has several products, and for each product there is a series of price quotes observed during the sample period, which is termed as a *price trajectory*. Each price trajectory can contain a number of price-spells, and for each *price-spell* there is a series of fixed price quotes. The length the price-spell is the *price duration*. To illustrate, **Figure 1** gives a simple example of the price trajectory of a hypothesised product, which is under observation for 10 periods, from $t = 0$ to $t = 10$. Accordingly, there are 11 price quotes (P_t) for this price trajectory. A price-change defines the end of a price-spell, i.e. at $t = 3, 5, 6, 10$, resulting in 4 price-spells in this trajectory. The corresponding durations (T) of the price-spells are 3, 2, 1 and 4.

After dropping the unreliable observations, there are around 12.8 million price quotes covering 60.69%[11] of the microdata underlying the CPI/RPI (144 months), and 822,579 price quotes covering the entire microdata underlying the PPI of goods sectors (122 months). These price quotes compromise 612,173 consumer price trajectories and 23,781 producer price trajectories. **Table 1** summarises the distribution of the price trajectories.

	Mean	**1%**	**10%**	**25%**	**Median**	**75%**	**90%**	**99%**	**Obs.**
Retailer	20.72	1	3	7	14	30	46	95	612,173
Producer	25.45	3	8	11	23	46	79	116	23,781

Table 1 *Distribution of Price Trajectory Lengths (in months)*

[11] Price quotes are collected either locally or centrally. Our data do not include quotes that are collected centrally. The same is true for many other studies, such as Bils and Klenow (2004), Álvarez and Hernando (2004), Veronese et al. (2005), and Bunn and Ellis (2012a, 2012b). Fortunately, the coverage of the clean data on the aggregate CPI/RPI is adequately large to represent the general price setting behaviour in the whole economy.

The producer price trajectories tend to be longer than the consumer price trajectories. It reflects that the upstream of the supply chain is more stable in product line, and the rotation of the producer-level products is less frequent than that of the retailer/consumer products. The distribution is skewed to the right, and there are some very long price trajectories[12]. The consumer price trajectories are relatively shorter also implies that many spells are censored or truncated, which provides further justification for the use of survival analysis than logit model.

The retailers are classified according to the COICOP classification[13] and can be combined into 9 divisions/sectors: (i) Food and Non-Alcoholic Beverages, (ii) Alcoholic Beverages and Tobacco, (iii) Energy Goods, (iv) Non-Energy Industrial Goods, (v) Housing Services, (vi) Transport and Travel Services, (vii) Communications, (viii) Recreational and Personal Services, and (ix) Miscellaneous Services. The first four are *goods sectors*, and the rest five are *service sectors*. Sectors such as non-energy industrial goods (e.g. clothing) and communications have shorter price trajectories, due to the frequent rotations of product lines. On average, goods sectors tend to have shorter price trajectories. In contrast, the producer price trajectories are grouped into 6 sectors, according to the SIC[14], including: (i) Consumer Food Goods, (ii) Consumer Durable Goods, (iii) Consumer Nonfood Nondurable Goods, (iv) Intermediate Goods, (v) Capital Goods, and (vi) Energy Goods. The first three are *consumption goods* sector, and the rest three are *production goods* sector. Note that there is no service sector in the producer data. The sampling method, weighting system and the descriptive statistics of the price trajectories by sector/region can be found in **Appendix III** and Jenkins and Bailey (2014).

3 Determinants of Price Rigidity

The data show that prices in the British economy do not change frequently (the median duration is 9.5 months for consumer prices and 15.8 months for producer prices), but there are also clear heterogeneities across sectors and shop type. Therefore, the estimated distribution of duration is a result of a very complicated price setting mechanism, which needs to be "purified" before applying to macroeconomic models. To be ideal for calibrating a time-dependent pricing model, the purified distribution of price duration, or equivalently the hazard function, should only depend on time. To achieve this, all the three models in the survival analysis, including nonparametric, semiparametric and parametric models, are employed in this paper.

The nonparametric model only controls for the time since last price-change, resulting in a hazard function $h(t)$ only depending on t without controlling for other factors nor the function form. At the other extreme, the parametric model isolates the baseline hazard function $h_0(t)$,

[12] For example, in the consumer price data, there are 18,767 price trajectories longer than 60 months, while 1,929 price trajectories stay in the dataset for longer than 120 months, and only 49 price trajectories are present in the dataset throughout the entire 144 months (12 years).
[13] The Classification of Individual Consumption by Purpose (COICOP) is used in computing CPI.
[14] The Standard Industrial Classification (SIC) is the used in computing PPI.

which only depends on t and has a functional form, from the component containing various covariates which affect the overall hazard function. As a middle way, the semiparametric model does not impose a functional assumption on $h_0(t)$ but controls for covariates.

In this paper, only the first non-left-truncated price spell of each price trajectory is used to estimate the hazard functions. This is to save computational burden without losing too much efficiency, because we have 612,173 observations for retailer prices and 23,781 for producer prices. This technique is also used by Dias et al (2007). As a robustness check, we also try the full sample in combination with a weighted estimation procedure, with the weight defined as the inverse of the number of non-left-truncated spells of each product. The results remain qualitatively the same.

3.1 The Nonparametric Model

The estimated overall hazard function $h(t)$ for both consumer and producer prices are compared in the upper right of **Figure 2**, along with the other equivalent ways to present the distribution of the price duration T. Since hazard function is the most convenient form for estimation purposes, this paper will focus on the hazard function hereinafter.

Figure 3 decomposes the hazard function $h(t)$, which has a decreasing and periodic shape, and the consumer prices have relatively higher hazard rates. It is not surprising to obtain the similarity because the hazard function describes the *conditional* probability of price-change over time, while the distribution of duration is the *unconditional* probability. Thus, the two functions can be transformed to each other through simple formula (Dixon, 2012). The distribution of duration is handy for calibrating the Generalised Taylor (GT) model, while the hazard/survival function is more appropriate for calibrating the Generalised Calvo (GC) model.

In **Figure 3**, the hazard functions are decomposed by sector. Note that the decreasing consumer prices are derived from the goods sector while periodicity mainly comes from the service sector. In contrast, the hazard function of the producer prices has a similar shape across consumption goods and production goods sectors but with a more volatile tail, and that is consistent with the long tails in the distribution of duration. This decomposition across sector can be used for calibrating the Multiple Calvo (MC) model.

The heterogeneities across the 12 regions in the UK and over the 3 sub-periods are also checked, but the Kolmogorov-Smirnov tests suggest that the regional differences are not significant in the UK, apart from London where the hazard rates are relatively higher due to a higher degree of competition.

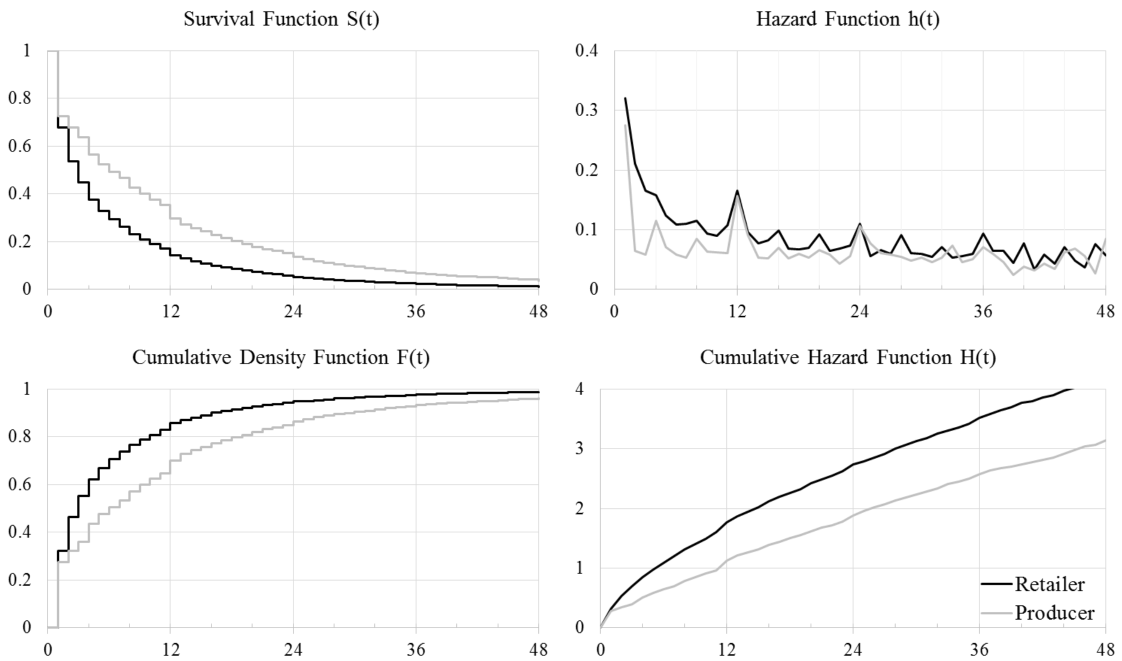

Figure 2 *The Estimated Distributions of the Nonparametric Model (in months)*

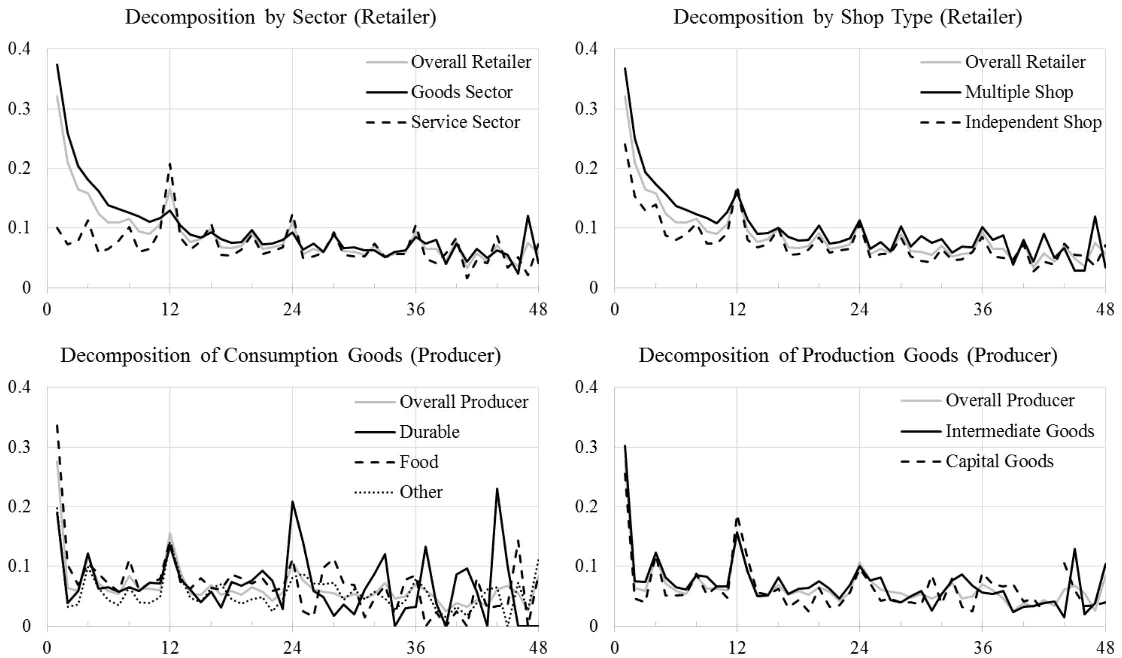

Figure 3 *The Decomposition of the Nonparametric Hazard Functions (in months)*

3.2 The Semiparametric Model

In the light of the previous findings, the hazard function varies across sectors and other dimensions. These can be explicitly incorporated into a pooled[15] proportional hazard Cox model:

[15] The separate estimation results by sector and by sub-period can be found in the working paper version, in which little difference in the coefficients is found.

$$h(t) \equiv h_0(t) \cdot g(\boldsymbol{\beta}'\mathbf{x}) = h_0(t) \cdot \exp(\boldsymbol{\beta}_i'\mathbf{x}_i + \boldsymbol{\beta}_{ii}'\mathbf{x}_{ii} + \boldsymbol{\beta}_{iii}'\mathbf{x}_{iii} + \boldsymbol{\beta}_{iv}'\mathbf{x}_{iv}) \qquad ...(1)$$

There are two components in the semiparametric model. The first component $h_0(t)$ is the baseline hazard function with no restriction on the function form. The second component $g(\boldsymbol{\beta}'\mathbf{x})$ contains all the factors affecting the hazard function $h(t)$ in a generalised linear fashion (usually exponential), including:

(i) The covariates in the Time Dimension ($\mathbf{x}_i$): Although $h_0(t)$ already captures the common pattern of variation over time in $h(t)$, the time t refers to the analysis time, rather than calendar time. To characterise the seasonality, the 11 calendar month dummies are included in the first group of covariate vector, where January is the reference group.

(ii) The covariates in the Space Dimension ($\mathbf{x}_{ii}$): To see if regional difference is significant as found in the nonparametric analysis, the 11 region dummies are also included, where London is the reference group.

(iii) The covariates in the Macroeconomic Dimension ($\mathbf{x}_{iii}$): To control for the macroeconomic state, inflation, interest rate, wage and oil price are included in $\mathbf{x}_{iii}$. Moreover, both lags and leads of these variables are included, allowing for dynamics and expectations. The reaction of retailers to these covariates can be used to check the validity of state-dependent models, such as Mankiw (1985) and Rotemberg (2005). This set of covariates are also included to remove the endogeneity of the hazard rates to be used for calibrating the macroeconomic models.

(iv) The covariates in the Microeconomic Dimension ($\mathbf{x}_{iv}$): Firm-level characteristics are included to control for the cross-sectional heterogeneities, such as sector, shop type, market share[16], as well as some features of the prices per se—the level of prices and the size of price-changes are believed to be positively correlated with the probability of price-change (Bunn and Ellis, 2009).

Table 2 lists the estimated coefficients of the second component of the proportional hazard Cox model. Note that some covariates are only available to consumer prices while others are specific to producer prices.

Firstly, in the time dimension ($\mathbf{x}_i$), January, the reference group for calendar months, has the highest probability of price-change, because the biggest sales season in the UK, i.e. the Christ-

[16] The market share for the consumer prices is the "grand weight" ($\omega_{i,j,k,s,t}$) as described in **Appendix II**, because it measures how important the product is in the whole economy. For the producer prices, there is also an extra measure of the industry-wide weight of the producer to measure the market share of a product within the industry.

mas sales, usually lasts until the beginning of January after which new prices are set. The calendar months with the next highest hazard rates are respectively April for consumer prices and March for producer prices, probably due to the beginning of a new tax year in April which is also the month of the spring sales. The producer prices seem to change prior to the consumer prices because of its upstream position in the supply chain. Secondly, in the space dimension ($\mathbf{x}_{ii}$), consistent with the previous findings in nonparametric analysis, there is little evidence for heterogeneity across regions since most of the regional dummies are not significant.

The third set of covariates in the macroeconomic dimension ($\mathbf{x}_{iii}$), the costs of capital, labour and energy, are shown to play a significant role, and both forward-looking and backward-looking effects exist in the price setting behaviour.

- Inflation: The retailers only react to past and expected future inflation but not to the current inflation, maybe because the announcement of inflation by the ONS is one-month behind. The producers are reacting to the inflation in the past, present and the future but mostly to the lagged information as in the consumer prices.
- Interest Rate: The firms are more likely to change their prices if the interest rates has changed in recent months, but less likely if the current or expected future interest rates are to change. It implies that the monetary policies have a lagged effect, since firms tend to react after policies are announced rather than in anticipation.
- Wages: The producer prices are more sensitive to the wage changes than the consumer prices, because the labour costs are critical for managerial decisions at the producer level. The price-change tends to occur immediately after or even in advance to a change in the labour market, supporting the forward-looking rational expectation hypothesis.
- Oil Price: The oil price is a proxy for the costs of energy and resources, which significantly affect the hazard rates in both consumer and producer prices. Similar to the reaction to the changes in wage, the current and expected future oil price is more influential to the price resetting probability, i.e. more forward looking.

Lastly, in the microeconomic dimension ($\mathbf{x}_{iv}$), the firm-level and product-level characteristics can explain much of the observed cross-sectional heterogeneities.

- Sector: The retailer-level energy goods and alcoholic/beverage sectors have the most flexible prices in the consumer prices, and the producer-level energy goods and consumer food sectors are the counterparts in the producer prices. It is partly due to the high degree of competition in the international energy market and partly due to the non-storability nature of the food/drink products. Overall, the goods sector has higher hazard rates than the service sector, consistent with the nonparametric findings.
- Price: A higher level of price (due to indivisibility) is positively associated with a higher hazard rate, in line with the previous findings in the IPN literature. For example, if the

price of a product is £100, then the probability of price-change is higher than that of a cheap product worth £1. However, the size of price-change has little influence on the hazard rate, which is at odds with Bunn and Ellis (2009), but their simple regression between the hazard rates and sizes of price-changes does not control for other covariates. Additionally, prices labelled as sales have very high chances to change again.

- Market Share: The hazard rates of both consumer and producer prices are higher as the market share of the product in the whole economy is higher. However, the industry-wide market share indicates the market power, which is negatively related to the degree of competition, so it has a negative effect on the hazard rates.

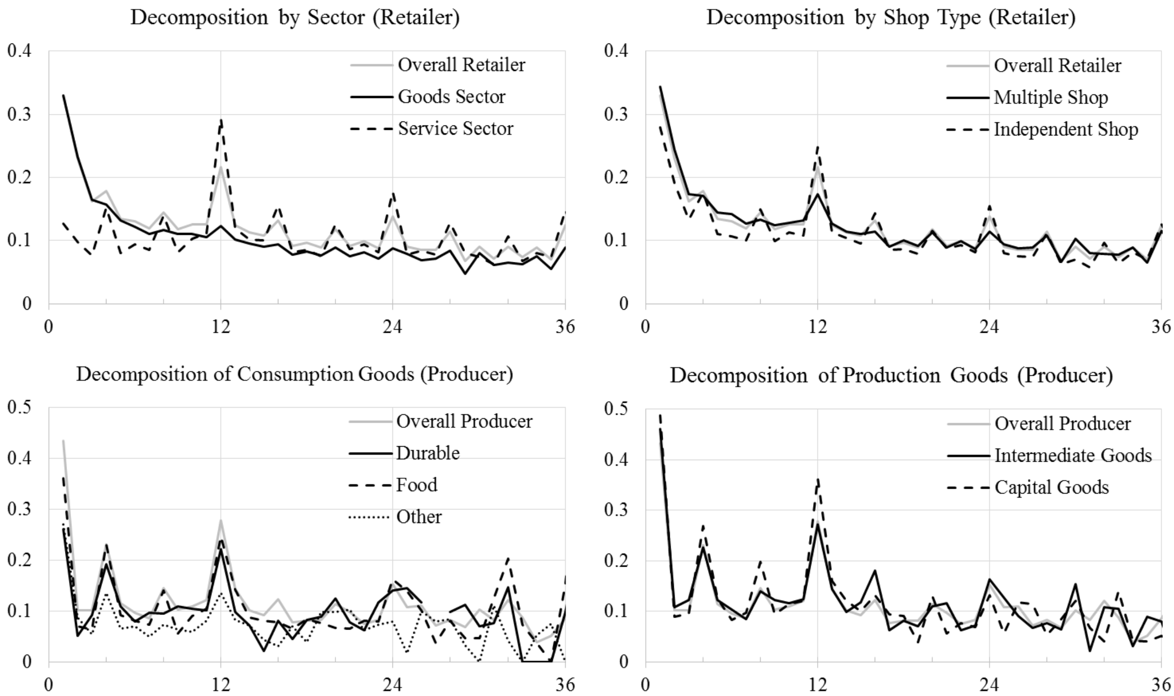

Figure 4 *The Decomposition of the Semiparametric Baseline Hazard Functions (in months)*

The resulting baseline hazard function $h_0(t)$ after controlling for various covariates are shown in **Figure 4** with decomposition by sector and shop type. The features identified in the previous analysis are maintained but the periodic feature is even more conspicuous, because $h_0(t)$ focuses on the variation pattern over time only. As argued later, the estimated baseline hazard function and the implied distribution of duration in the semiparametric model are the most suitable results for calibrating the macroeconomic models.

	Covariates	Retailer	Producer	Covariates specific to Producer
Covariates from Time Dimension (x_i)	February	-0.3030**	-0.6378**	
	March	-0.2230**	-0.0564**	
	April	-0.1257**	-0.3086**	
	May	-0.1826**	-0.4010**	
	June	-0.2438**	-0.2885**	
	July	-0.1790**	-0.1421**	
	August	-0.3614**	-0.2524**	
	September	-0.3704**	-0.4321**	
	October	-0.2534**	-0.2525**	
	November	-0.2828**	-0.1735**	
	December	-0.3020**	-0.4108**	
Covariates from Space Dimension (x_{ii})	South East	-0.0003		
	South West	-0.0097		
	East Anglia	-0.0276**		
	East Midlands	0.0195*		
	West Midlands	0.0234**		
	Yorks & Humber	0.0014		
	North West	0.0203**		
	North	0.0176		
	Wales	-0.0071		
	Scotland	0.0102		
	Northern Ireland	-0.0032		
Covariates from Macroeconomic Dimension (x_{iii})	Inflation t	-0.0022	0.1134**	
	Inflation t-1	0.0507**	0.4840**	
	Inflation t+1	-0.1164**	0.0158**	
	Interest Rate (Δ) t	-0.0723**	-0.0060**	
	Interest Rate (Δ) t-1	0.1318**	0.2359**	
	Interest Rate (Δ) t+1	-0.1558**	-0.1377**	
	Wage (%Δ) t	0.0271	0.2174**	
	Wage (%Δ) t-1	0.0100	-0.4946**	
	Wage (%Δ) t+1	0.1019**	0.0225**	
	Oil Price (%Δ) t	-0.0050**	0.0022**	
	Oil Price (%Δ) t-1	-0.0029**	-0.0072**	
	Oil Price (%Δ) t+1	0.0076**	0.0035**	
Covariates from Microeconomic Dimension (x_{iv})	Alcoholic/Beverage	0.0134	0.0781**	Consumer Food
	Non-Energy Industrial	-0.3227**	-0.1913**	Consumer Durable
	Housing	-0.6547**	-0.3427**	Consumer Nonfood Nondurable
	Transport/Travel	-0.6938**	0.0058**	Intermediate Goods
	Communications	-0.2599**	-0.1452**	Capital Goods
	Recreation/Personal	-0.5863**		
	Miscellaneous	-0.6465**		
	Independent Shop	-0.0823**		
	Price	0.0002**	0.0000*	
	Price (%Δ)	0.0000**	0.0000*	
	Sales	0.9909**		
			-0.0010**	Market Share (Industry-Wide)
	Market Share	2.6790**	1.5069**	Market Share (Economy-Wide)

Table 2 *Estimated Proportional Hazard Cox Models*

Notes: * denotes 5% significance level. ** denotes 1% significance level. The base group is January for calendar months, London for regions, and energy goods for sectors (the only common sector for both prices). There is a constant term included in the regression, so the estimated $h_0(t)$ is the average baseline hazard function for the whole economy.

Covariates	Retailer	Producer
Inflation t	-0.22%	12.01%
Inflation t-1	5.20%	62.26%
Inflation t+1	-10.99%	1.59%
Interest Rate (Δ) t	-6.97%	-0.60%
Interest Rate (Δ) t-1	14.09%	26.60%
Interest Rate (Δ) t+1	-14.43%	-12.86%
Wage (%Δ) t	2.75%	24.28%
Wage (%Δ) t-1	1.01%	-39.02%
Wage (%Δ) t+1	10.73%	2.28%
Oil Price (%Δ) t	-0.50%	0.22%
Oil Price (%Δ) t-1	-0.29%	-0.72%
Oil Price (%Δ) t+1	0.76%	0.35%

***Table 3** Elasticities of $h(t)$ with respect to Macroeconomic Covariates*

Table 3 shows the elasticities of $h(t)$ after one percentage changes in macroeconomic covariates, implied from the estimated coefficients in **Table 2**. For example, if inflation in the current period rises by one percentage point, the retailer price's hazard rate will be 0.22% lower. For example, falling from $h_0(1) = 33\%$ in the first month to $33\% \times (1 - 0.22\%) = 32.93\%$ in the first month. Note that the elasticities have significantly different reactions to the timing of the shocks. **Figure 5** illustrate this difference and the resulting dynamics using inflation and interest rate shocks.

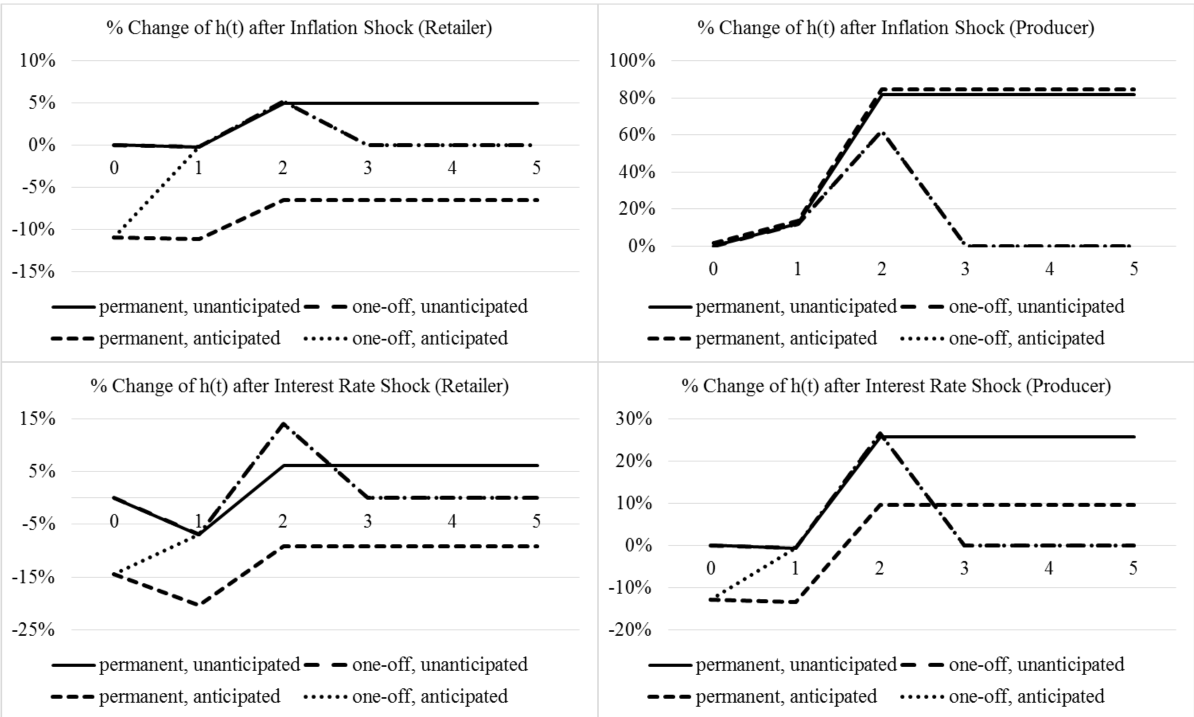

***Figure 5** The Percentage Changes of $h(t)$ after Simulated Shocks*

Notes: The two panels on top show responses after inflation shocks, and the two panels on bottom show responses after interest rate shocks. The left two panels are $h(t)$ of retailer prices, and the right two panels are those of producer prices. Each panel shows four possible shocks, distinguished in terms of permanent/one-off and anticipated/unanticipated. A permanent shock means 1 percentage point higher from period 1 onwards, and a one-off shock means 1 percentage point higher only in period 1 and 0% in other periods. An anticipated shock means the price-setter knows the shock one period in advance, and an unanticipated shock means the price-setter does not know the shock until it occurs.

For unanticipated shocks, the hazard rates do not change until the shocks are realised and observed by the price setters at period t, while the anticipated shocks will have a leading effect in period $t-1$. For permanent shocks, the hazard rates will be permanently different from the original level (similar to a random walk), while the effect of one-off shocks will quickly die away. It can be seen that the effects of inflation and interest rate are both qualitatively and quantitatively similar, and the producer price's hazard rates tend to be more sensitive to macroeconomic shocks than the retailer price's.

3.3 The Parametric Model

For completeness and robustness, we will also estimate a fully parametric model using the Weibull distribution. The estimated $h_0(t)$ in the previous sections do exhibit a very stereotypical shape—decreasing in a convex shape with periodic spikes. Note that the periodicity feature can be easily separated from $h_0(t)$ by adding time/age dummies in the covariates **x** when spikes occur, i.e. $t = 1, 4, 8, 12, \ldots$. Then, the resulting $h_0(t)$ will be smoothly decreasing, and that can be well modelled by the Weibull distribution in a full parametric form in addition to the specification in equation (1):

$$h_0(t) = pt^{p-1} \cdot \exp(\beta_0) \quad \text{...(2)}$$

The parameter p is to be estimated along with $\boldsymbol{\beta}$, and it determines the shape of $h_0(t)$. In the parametric model, an intercept term β_0 will also be estimated within the second component $\exp(\boldsymbol{\beta}'\mathbf{x})$. Since the intercept term is just a constant, it is usually combined into $h_0(t)$ and serves to scale $h_0(t)$. **Figure 6** compares the estimated hazard functions in nonparametric, semiparametric and parametric models, and decomposes them by sectors for both consumer and producer prices. The estimation results of the parametric model are similar in both signs and magnitudes to the semi-parametric model, so they are omitted here[17].

The estimated parameter p is less than 1 (consumer prices, 0.71; producer prices, 0.68), so the Weibull distributions are both decreasing exponentially with time t. Within the consumer prices, the goods sector is more flexible than the service sector, and within the producer prices, the consumption goods sector is more flexible than the production goods sector. Overall, the consumer prices have a slightly higher hazard rates than the producer prices, which is qualitatively consistent with the previous findings.

[17] The estimation results of the parametric model are available on request.

The main purpose of the parametric analysis in this section is to show the robustness of the estimation results. However, if the three estimates are placed together (**Figure 6**), it seems that the overall effects of the covariates on the hazard function is negative, i.e. $g(\boldsymbol{\beta}'\mathbf{x}) < 1$ and $h(t) < h_0(t)$. It means that if we use the nonparametric estimates to calibrate a macroeconomic model, the hazard rates of the Calvo-type model would be too low, and the durations of the Taylor-type model would be too high. It is reverse if we use the parametric estimates. According to Carvalho and Schwartzman (2015), a decreasing hazard function is a feature that reduces selection and favours non-neutrality.

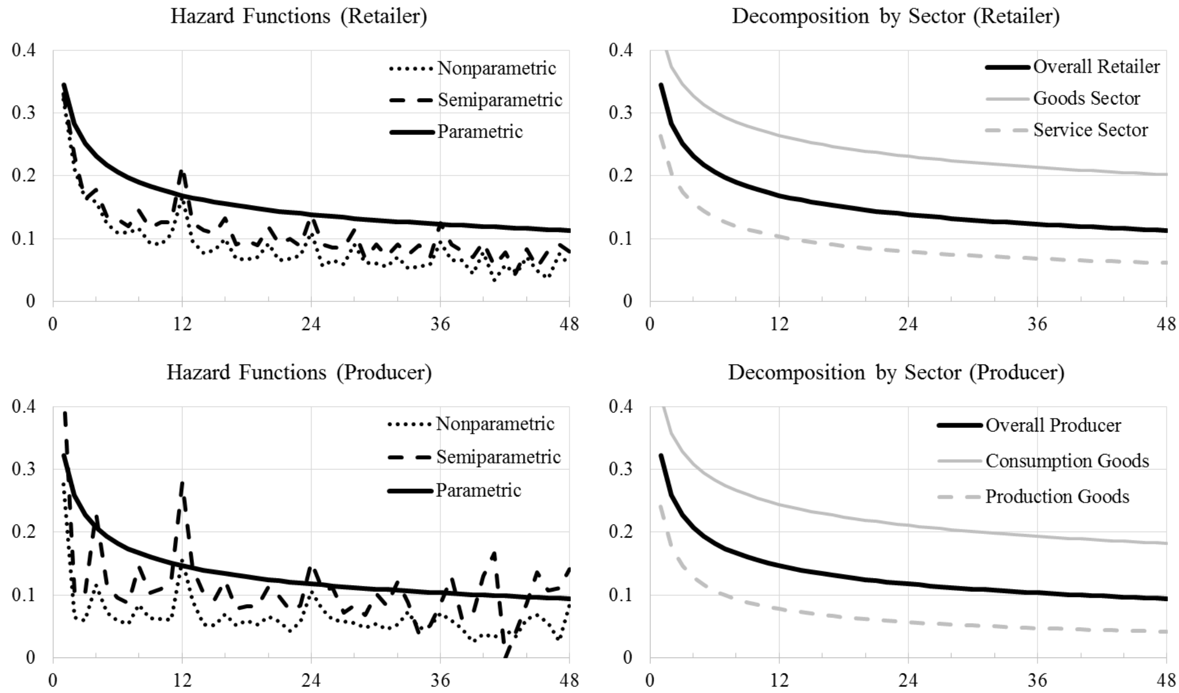

Figure 6 *The Decomposition of the Parametric Baseline Hazard Functions (in months)*[18]

4 Application to a Simple Macroeconomic Model

In this section we illustrate how the microdata of the distribution of durations can be used in a macroeconomic context. We employ a simple macroeconomic model, in which all sources of persistence other than nominal rigidity have been eliminated, except for autocorrelation in monetary growth. In larger models developed for monetary policy simulation, such as Smets and Wouters (2003) there are many other sources of dynamics. Our focus here is on alternative

[18] If the long price durations beyond 48 months are included, then the hazard rate will finally go to 1 because all prices will eventually change. However, the proportion of these very long durations is quite small (less than 1%), so the estimated hazard rates have very high standard errors. Thus, we only focus on the hazard rates up to 48 months.

approaches to modelling nominal rigidity, so we leave out features such as habit formation, investment and Taylor rules which would also have important effects[19].

We consider the "persistence puzzle": Chari et al (2000) point out that "monetary economists have long searched for a mechanism that has a multiplier effect in the sense that small frictions lead to long periods of endogenous price rigidity and, hence, persistent output movements". In other words, the standard New Keynesian models cannot simultaneously achieve both persistence observed in the macrodata and the price rigidity consistent with the microdata. The current new Keynesian orthodoxy is to largely ignore the microdata and focus on matching the macrodata: most approaches assume that prices change every period as with the very common assumption of indexation (Smets and Wouters, 2003, 2007), Eichenbaum et al (2005), and other approaches such as sticky information (Mankiw and Reis, 2002) and rational inattention (Mackowiak and Wiederholt, 2009).

This section will make use of the results of the semiparametric model of consumer prices to calibrate a simple "Quantity Theory" model (see Ascari, 2003)[20]. We employ several sticky price models. As reference points, the two "simple" Taylor (ST) and Calvo (SC) models (without indexation) are used. We then consider the two generalized variants which exactly reflect the distribution of durations found in the UK microdata:

- The generalized Taylor (GT) model, in which there are several sectors each with a different length of price-spell, which is calibrated by the estimated cross-sectional distribution of duration across products (Dixon and Kara 2011, Taylor 2016).
- The generalized Calvo (GC) model, which allows for a duration dependent Calvo-reset probability, which is calibrated by the estimated hazard function $h_0(t)$ (Wolman 1999, Sheedy 2010).

Whilst the GT and GC models both reflect exactly the price microdata, they differ significantly in pricing behaviour. In the GT model, you know exactly how long the price you set is going to last when you set it: whether your price will last for one period or 40, we follow Taylor (1979, 1980) in assuming that this duration is known beforehand. By contrast, in the GC model, when a firm sets a price it has a distribution of probabilities over all possible durations, as represented by the hazard function. As shown in Dixon (2012), when firms know the duration beforehand as in the GT, they are collectively more myopic than in the corresponding GC

[19] Dixon and Le Bihan (2012) use French CPI and wage data to calibrate the Smets-Wouters model. Zhou (2012) uses UK data.

[20] We believe that the most reliable estimates come from the semiparametric model, because the nonparametric model does not control for any covariates apart from t while the semiparametric model imposes a too restrictive assumption on the function form of $h_0(t)$.

model. This myopia means that GT firms pay less attention to more distant events when they set prices than their GC counterparts.

The assumption that the whole economy is either GT or GC may be too extreme. Perhaps in some parts of the economy the duration of price-spells is fairly predictable and Taylor-like, whilst in other parts it is less predictable and more Calvo like. Perhaps there is a systematic difference: the evidence in Section 3 suggests that the service sector is more Taylor-like and the goods sector more Calvo like. In order to explore these possibilities, we develop three "hybrid" models.

- HY1. We take the estimated aggregate distribution as given. However, we assume that there is a share of firms who are GT and the rest who are GC. The share is then estimated using Bayesian methods. Since the distribution within GT and GC are exactly the same as the aggregate, the variation in the share simply reflects the differences in pricing behaviour. HY1 is a generalization of GT and GC.
- HY2. Here we assume that the service sector is GT and the goods sector GC. The weights of the sector weights are calibrated by the ONS data, and the sector-specific microdata estimates are used in calibration, rather than the pooled estimates as in HY1.
- HY3. We apply HY1 separately to both the service and the goods sectors. We take the distribution of durations in the service sector as given, and estimate the share of GC firms in that sector (the rest are GT). We do the same for the goods sector. HY3 is more general than HY1, in which both sectors were effectively required to have the same share of GC firms. HY3 is also more general than HY2, in which each sector had only one type of firm, not a mixture.

Theoretically, the typology of the three hybrid models is $HY1 \subset HY3$, $HY2 \subset HY3$ and $HY1 \not\equiv HY2$, i.e. HY3 is the most general model and the data matching performance of HY3 should be the best. However, note that this proposition only holds when the sector weights and the distribution of durations are all free to adjust. In our example, these parameters are fixed to the microdata estimates, and additionally the distributions used in HY1 (based on the whole economy) are different from those used in HY2 and HY3 (based on each sector separately).

4.1 The Models

There are three sets of equations in the (linearized) Quantity Theory model:

- The Aggregate Demand equation[21], modelled by the Quantity Theory linking the real output (y_t) with the money demand (m_t) and overall price level (p_t) (with a constant velocity assumed to be 1):

$$y_t = m_t - p_t \qquad ...(3)$$

- The Pricing Equations, derived from the dynamic optimisation problem of the firms with sticky prices[22] where the optimal flexible price (p_t^*), optimal reset price (x_t), overall price (p_t) and inflation (π_t) are determined. There are seven variants including SC, ST, GC, GT, HY1, HY2 and HY3. These models have different ways of determining the reset price x_t, but share the same optimal flexible price (p_t^*), where γ is the key parameter capturing the sensitivity of p_t^* to output:

$$p_t^* = p_t + \gamma y_t \qquad ...(4)$$

- The Monetary Policy equation[23], following a random walk process (m_t) with an AR(1) monetary shock ε_t:

$$m_t = m_{t-1} + \varepsilon_t, \text{ where } \varepsilon_t = \rho\varepsilon_{t-1} + \xi_t \qquad ...(5)$$

To calibrate the parameters in the price setting models, we need to transform the monthly estimates to the quarterly ones, because most macroeconomic data and models are quarterly. Relative to other ways of summarizing price behaviour, survival function is the only way that no calculation is required to transform from monthly to quarterly statistics, since the quarterly survival rate at the end of each quarter is just the monthly survival rate at the end of the corresponding month. Hence the estimated monthly $h_0(t)$ is expressed in the equivalent form of monthly $S_0(t)$, which is then transformed into the quarterly $S_0(t)$. Following that, the quarterly $h_0(t)$ and quarterly cross-sectional distribution of duration can be derived. Other model parameters are calibrated following Dixon and Kara (2012): $\beta = 0.99$, $\rho = 0.8$ and $\gamma = 0.2$. The values of these model parameters also lie within the most accepted theoretical ranges in the literature.

4.2 Estimating the Models

We estimated all seven models following standard Bayesian procedures. In the case of ST, SC, GC, GT and HY2, the parameters are calibrated using the microdata estimates: we estimated the standard deviation of the monetary shock (σ_m) and the measurement errors of output (σ_y) and inflation (σ_π). In the case of HY1 and HY3 we also estimate the share of GC firms in the

[21] In a full microfounded DSGE model such as Smets and Wouters (2003, 2007), this block is derived from the household's dynamic optimisation problem, resulting in an Euler equation or IS curve.
[22] The detailed model equations of GC and GT can be found in Dixon and Le Bihan (2012).
[23] The Taylor rule (1993) is usually used instead of a monetary base rule in the DSGE literature.

whole economy (GCW) and the shares of GC firms in the service sector and goods sector (GCG and GCS). The two macroeconomic time series data are used as observables in the estimation process are output and inflation in the UK covering the Great Moderation period (1987Q1-2007Q4). The priors for the GC shares are beta distributions, while uniform distributions are used for the standard deviations of the shocks. The detailed information on the priors and posteriors can be found in **Table 4**.

The estimated and implied sector shares of different models are summarised and compared in the last three columns of **Table 4**. It confirms the hypothesis that the goods sector is closer to GC and the service sector is closer to GT (under HY3 the share GCG is 40% in the goods sector and GCS is only 30% in the service sector). In the model where GC weights are restricted to be the same in both sectors, HY1, the estimated share GCW is 25%.

	σ_m	σ_y	σ_π	GCW	GCG	GCS
Prior	unif	unif	unif	beta	beta	beta
Prior Mean	1	1	1	0.5	0.5	0.5
Prior SD	0.6	0.6	0.6	0.2	0.2	0.2
Lower Bound	0	0	0	0	0	0
Upper Bound	2	2	2	1	1	1
		Posterior Estimates[24]				
SC	0.770	0.123	0.997			
	(0.085)	(0.029)	(0.079)			
GC	0.664	0.159	0.957	1	1	1
	(0.080)	(0.024)	(0.078)	(fixed)	(fixed)	(fixed)
ST	0.492	0.000	1.030			
	(0.038)	(0.000)	(0.080)			
GT	0.554	0.060	0.929	0	0	0
	(0.060)	(0.059)	(0.072)	(fixed)	(fixed)	(fixed)
HY1	0.627	0.094	0.928	0.246		
	(0.074)	(0.040)	(0.072)	(0.132)		
HY2	0.483	0.107	0.879		1	0
	(0.055)	(0.031)	(0.068)		(fixed)	(fixed)
HY3	0.498	0.100	0.880		0.402	0.295
	(0.063)	(0.034)	(0.068)		(0.253)	(0.194)

Table 4 *The Prior and Posterior Distributions of the Bayesian Estimation (standard errors in parentheses)*

NB: SC – simple Calvo; GC – generalised Calvo; ST – simple Taylor; GT – generalised Taylor; HY1 – hybrid model with GC and GT; HY2 – hybrid model with GT service sector and GC goods sector; HY3 – hybrid model with GC and GT in both goods and service sectors; GCW – share of GC in the whole economy; GCG – share of GC in the goods sector; GCS – share of GC in the service sector.

[24] The "posterior Estimates" are the posterior modes and the standard errors of the posterior distributions, obtained using Nelder-Mead simplex based optimization routine.

4.3 Solving the Persistence Puzzle

To address the persistence puzzle, two objectives need to be achieved. On the one hand, the calibration of the price setting behaviour must be in line with the microdata evidence. On the other hand, the simulated impulse response functions, in particular the responses of output and inflation following the monetary shock, needs to be in line with the macrodata evidence. Similar to the US data based on which the original "persistence puzzle" was raised, we find a similar pattern in the UK macrodata (1987Q1-2007Q4 to be in line with the microdata). A VAR(4) model is estimated using output, inflation and M2 to be comparable with the micro-founded macroeconomic model estimated in this section. The impulse response functions (IRFs) to Cholesky one standard deviation of the monetary shock are shown in **Figure 7**. The half-lives of output and inflation are respectively 25 and 15, indicating a very persistent feature.

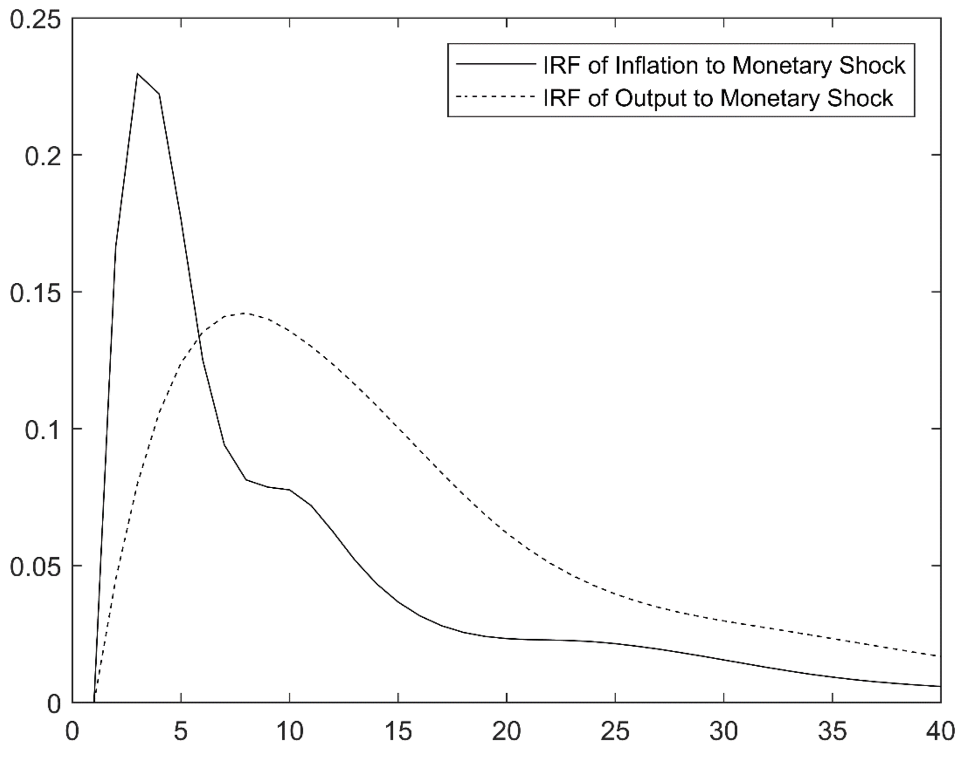

Figure 7 *The IRFs of Output and Inflation of the VAR Model*

As pointed out in Chari et al (2000), the IRFs of empirical VARs in the macroeconometric literature usually have a hump shape and a sluggish convergence. From the UK microdata, the simple versions of both Calvo and Taylor models are at odds with the empirical estimates: the SC implies a constant hazard rate and ST implies a degenerate cross-sectional distribution of duration with only one duration, while the estimation results imply a duration dependent hazard and heterogeneous durations. In contrast, GT and GC are consistent with any distribution and can be directly calibrated on the microdata estimates. The left two graphs of **Figure 8** compare the responses of inflation and output to the monetary shock among the four models. For inflation (the upper left), only Taylor-type models (ST and GT) exhibit the desired hump shape, while Calvo-type models (SC and GC) get to the maximum effect immediately after the shock[25]. However, the Calvo-type models tend to have higher persistence, especially in the impulse responses of output (the lower left). Based on the above analysis, the conclusion is that the simple models (SC and ST) cannot match the microdata evidence, but GC cannot generate hump shape and GT cannot generate enough persistence in the macrodata evidence.

It seems that again there is no model can achieve all desirable features. However, remember that, from the microdata analysis of the consumer prices, the baseline hazard function can be decomposed into two components—a smooth but decreasing component from the goods sector, and a periodic but flat component from the service sector. It implies that the whole economy may not follow the same price setting behaviour, neither Taylor-type only nor Calvo-type only. In particular, the goods sector tends to be more competitive and more likely to face high uncertainty of price-change, which can be better modelled as GC. The service sector, on the contrary, may normally reset prices with fixed term contracts and so may suit GT better. This gives rise to hybrid model HY2. The ONS updates the COICOP sector weights every year (Jenkins and Bailey, 2014), according to which the average goods sector weight (1997-2007) is 30% and the service sector weight is 70%. Furthermore, since both GT and GC are consistent with the microdata, we can allow for a proportion of firms to be GT and the rest GC: this can either be done at the aggregate level (HY1) or at the level of service and goods sectors (HY3).

As shown on the right half of **Figure 8**, the HY models now have both hump shape and persistence as observed in the macrodata in addition to matching the microdata evidence—the "persistence puzzle" can be resolved! The purpose of this application section is only to illustrate a way of using the microdata results in macroeconomic models, rather than to develop a serious macroeconomic model. However, even in such a simple model setting, a great potential of application can be developed.

The implied IRFs of the seven estimated macroeconomic models are compared in the graph below. All the hybrid models show desirable features—a hump and persistence—as shown in the VAR model above. In contrast, the Calvo-type models (both GC and SC) do not have hump, while Taylor-type models lack persistence. However, in terms of half-lives, all the models are still less persistent than the VAR(4) model. For example, the longest half-lives are found in HY2 and HY3 (11 quarters for inflation and 13 quarters for output) while the counterparts in the VAR(4) model are 15 quarters and 25 quarters. This is because our macroeconomic model is extremely simple apart from nominal friction. A typical DSGE model, like the one in Smets

[25] As shown in Dixon (2012), the Multiple Calvo (MC) also has similar pattern as SC and GC. See Kara (2015) for an application of the MC model to US data.

and Wouters (2003, 2007), should have richer shock propagation mechanisms. Our purpose in this section is not to match the data empirically, but to show the effect of heterogenous price rigidity and to illustrate how to make use of microdata evidence in macrodata modelling.

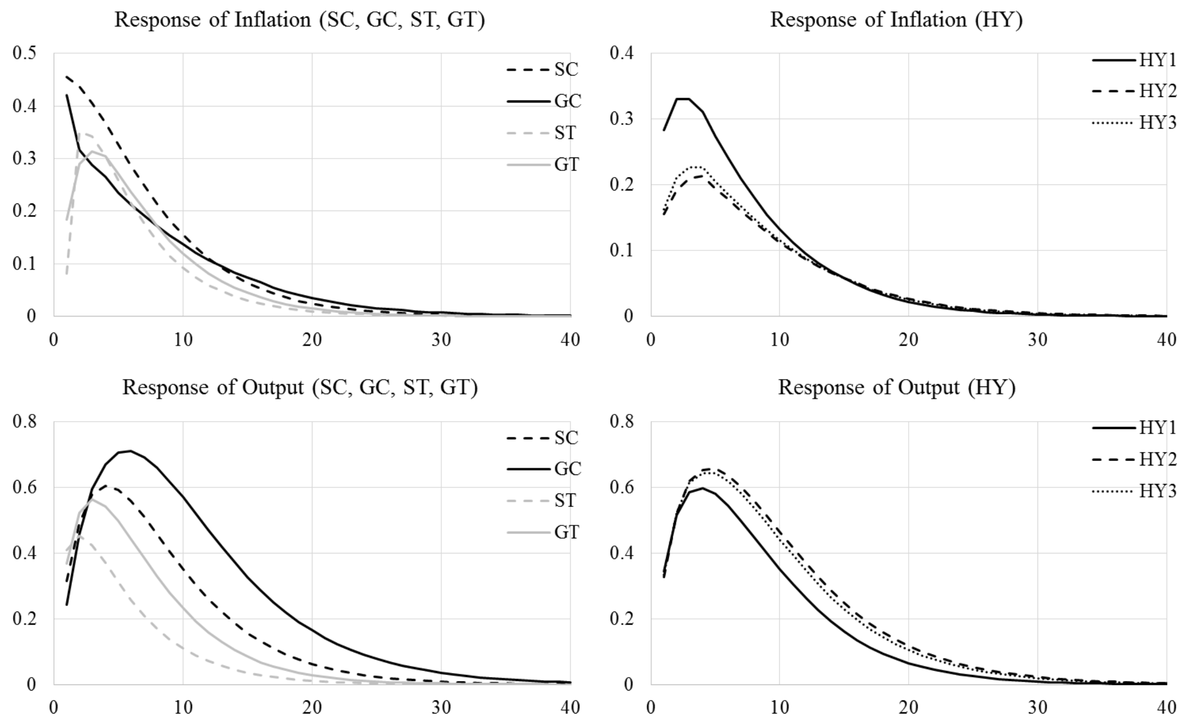

***Figure 8** The IRFs of Output and Inflation of the Calibrated Model*

NB: SC – simple Calvo; GC – generalised Calvo; ST – simple Taylor; GT – generalised Taylor; HY1 – hybrid model with GC and GT; HY2 – hybrid model with GT service sector and GC goods sector; HY3 – hybrid model with GC and GT in both goods and service sectors.

One important advantage of Bayesian estimation is that we can conduct post-estimation model comparison in a more systematic and quantitative way, in addition to using the IRF qualitative features as a basis for comparison. The marginal densities after integrating out the parameters from the posterior distribution are usually used to measure the goodness of fit and are presented in **Table 5** in terms of Bayes Factors. The last two columns take HY2 as the base model (lowest marginal density) and then apply the significance criteria as put forward originally by Jefferys and later updated by Kass and Raftery.

As we would expect, the simple ST and SC do not do well. Amongst the two generalised models, the GT outperforms the GC, almost certainly reflecting the lack of a hump in the GC inflation IRF. When we turn to the hybrid models, we see that the GT is slightly better than HY1 ($e^{1.44} = 4.22$), albeit "barely worth mentioning" on the Jefferys (1961) scale. Both HY2 and HY3 perform best of all. The bottom line is that the "strength of evidence" for HY3 and HY2 against all of the other models is "decisive", whilst the better performance of HY3 over HY2 being "hardly worth mentioning".

Model	Marginal Density	Bayes Factor	Jefferys (1961)	Kass and Raftery (1995)
SC	-168.19	$e^{10.91}$	*"decisive"*	*"very strong"*
GC	-166.85	$e^{9.57}$	*"decisive"*	*"very strong"*
ST	-189.43	$e^{32.15}$	*"decisive"*	*"very strong"*
GT	-161.08	$e^{3.8}$	*"decisive"*	*"strong"*
HY1	-162.52	$e^{5.24}$	*"decisive"*	*"very strong"*
HY2	-157.28	base	—	—
HY3	-157.73	$e^{0.45}$	*"barely worth mentioning"*	*"not worth more than a bare mention"*

Table 5 *Marginal Densities of the Models*

NB: SC – simple Calvo; GC – generalised Calvo; ST – simple Taylor; GT – generalised Taylor; HY1 – hybrid model with GC and GT; HY2 – hybrid model with GT service sector and GC goods sector; HY3 – hybrid model with GC and GT in both goods and service sectors.

What is perhaps most interesting is that with this simple model, the pricing model with micro-calibrated pricing behaviour (HY2) does better than both of the other hybrid models in which the share of GC and GT firms is estimated. The best model is the one in which only the variances of the error terms are estimated. Of course, this estimation exercise is primarily illustrative, showing how we can use the micro evidence from the earlier sections in a macroeconomic context with macrodata.

5 Conclusion

We have studied the price setting behaviour underlying the price rigidity using all the three models in survival analysis, which are arguably superior to the logit regression model, adopted by many papers in the IPN literature, mainly due to its robustness to the censoring/truncation issues. This paper also estimates a parametric model of the baseline hazard function, although the main purpose is to provide a robustness check for the results obtained under the nonparametric and semiparametric models.

The microdata findings above are applied to calibrate and estimate a set of simple macroeconomic models using Bayesian methods. It shows that the simple Calvo and Taylor models cannot match the microdata evidence, while neither generalised Calvo model nor generalised Taylor model can match all the macrodata evidence. The persistence puzzle is then solved by respecting the heterogeneity in price setting between the goods sector and service sector discovered in the microdata. A hybrid model with GC and GT in different sectors is shown to be able to match both hump shaped and persistent features of the impulse responses. Using Bayes Factors, we show that the best model is the hybrid one in which the service sector is generalized Taylor and the goods sector Generalized Calvo. A future research agenda is to apply this approach to examine the role of state-dependent price setting in macrodata models.

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Appendix I: Terminology System of Survival Analysis

In the microeconometric literature on price setting behaviour, different papers seem to use different terminology systems, because they may come across the survival analysis originating in different disciplines, such as Biometrics and Engineering. This appendix aims to resolve the confusion caused by different conventions and standardise the terminology system based on the definitions in statistics.

This paper defines t as any given date in the time line, with $t \in [0, +\infty)$. In discrete time, the time line is divided into several periods of the same length. In continuous time, the time line is infinitely divisible. In fact, continuous time is the limiting version of discrete time, in which the period length is infinitesimal. The time line in our case is discrete with an equal size of one month. Following the convention in statistics, the first observation of a duration is recorded at $t = 0$. A period is nominated by the date at the end of that period. For example, the 1st period means $(0,1]$, the 2nd period means $(1,2]$, and the n^{th} period means $(n-1, n]$. Note that the time t here means *analysis time*, rather than *calendar time*. A price duration could begin at any point in calendar time, but it always starts at 0 in analysis time.

In the context of price setting behaviour, the subject under study is price duration—the length of a complete price-spell—which is regarded as a random variable due to the uncertainty of when the price changes. A price-spell is a certain period within which a series of the same price quotes are observed on a particular product. The price duration, T, is defined as a non-negative random variable denoting the time to a price-change event for a price-spell. 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) price-change event occurs in continuous time but duration is only observed in discrete intervals. The price duration data is actually the second case, since the price-change could occur any time within a month, but the data is only collected in monthly interval. This distinction leads to different formulae for calculating distributions and relevant properties, because the second case actually assumes interval censoring. Unfortunately, this important issue is ignored by most papers.

Like other random variables, there are several equivalent ways of presenting the distribution of T. $f(t)$ is the Probability Density Function (PDF) of T if it is continuous, or the Probability Mass Function (PMF) if it is discrete. $F(t)$ is the Cumulative Distribution Function (CDF) of T, defined as $F(t) \equiv \Pr(T \leq t)$. $S(t)$ is the Survival Function, which is the probability of surviving beyond date t: $S(t) \equiv 1 - F(t)$. The most useful way of presenting the distribution of T is the Hazard Function, $h(t)$, which returns the instantaneous hazard rate at any time t.

$$h(t) \equiv \begin{cases} \lim_{\Delta t \to 0} \frac{\Pr\left(t \le T < t + \Delta t \middle| t\right)}{\Delta t} = \frac{f(t)}{S(t)} & \text{for continuous time;} \\ \frac{f(t)}{S(t-1)} & \text{for intrinsic discrete time;} \\ \frac{S(t-1) - S(t)}{S(t-1)} & \text{for non-intrinsic discrete time.} \end{cases}$$

Accordingly, the Cumulative Hazard Function up to t can also be defined: $H(t) \equiv \int_0^t h(\tau)d\tau$, which measures the accumulated risk for a price to change during the period $(0, t]$.

By definition, it is easy to transform from one to another among $f(t)$, $F(t)$, $S(t)$, $h(t)$ and $H(t)$. However, there are several advantages to think in terms of $h(t)$, rather than the other forms—$h(t)$ gives a more natural way to interpret the process that generates price duration, and the survival data are more easily modelled by the hazard rates with no upper bound.

Also, the statistical properties of the distribution of T can be derived, such as expectation, median and variance. The detailed formulae can be found in any standard statistics textbook, such as Jenkins (2004) or Cleves et al (2008).

In practice, price-change may have not yet occurred by the end of the observation period, or the price-spell may have already lasted for a while before entering the observation. In these cases, there are incomplete observations over time, accounting for around one quarter of all the price trajectories in our sample. These complications justify a discussion in censoring and truncation, which are always confusingly defined in different papers in the literature. This paper will disambiguate the confusions by strictly following the definitions in statistics.

A *subject* is defined as the process being studied, which is the price duration in our context. The subject is said to be in *observation period* after it enters and before it leaves the study. A *failure* is referred to as an event to end the duration, i.e. a price-change. *Censoring* is the case where the subject is not under observation when failure occurs. It is like a veil preventing you from seeing the exact time of the failure that does occur. This is a *partial* ignorance about the duration, because you do know when it does not happen. There are three types of censoring:

(i) Right Censoring: the price is under observation for a while, but it is not under observation when the price-change occurs.

(ii) Left Censoring: the price-change occurs prior to the product entering the observation. It is often confused with left truncation in the literature.

(iii) Interval Censoring: rather than observing the exact time of failure, all one knows is that failure occurs within a given interval.

Truncation, on the other hand, is the case where there is complete ignorance about the subject over a truncated period. The censoring emphasises the uncertainty of failure time, while truncation refers to the complete ignorance of the subject. That is to say, you do not even know if the price-change occurs and how many times it occurs. There are also three types of truncation:

(i) Right Truncation: the subject is under observation for a while, but it leaves the study before it fails (indistinguishable from right censoring).

(ii) Left Truncation: the subject has been under risk before it is under observation. It is a case of late entry, often confused with left censoring in the literature.

(iii) Interval Truncation: the subject is observed at first, but it is not under observation for a while, and is then back after the truncation period.

To show the comparison between censoring and truncation, **Figure 9** is used to illustrate the six cases. The solid line indicates the price-spell under observation, with a beginning (circle) and an end (cross). The dashed part means censoring, while the blank part means truncation.

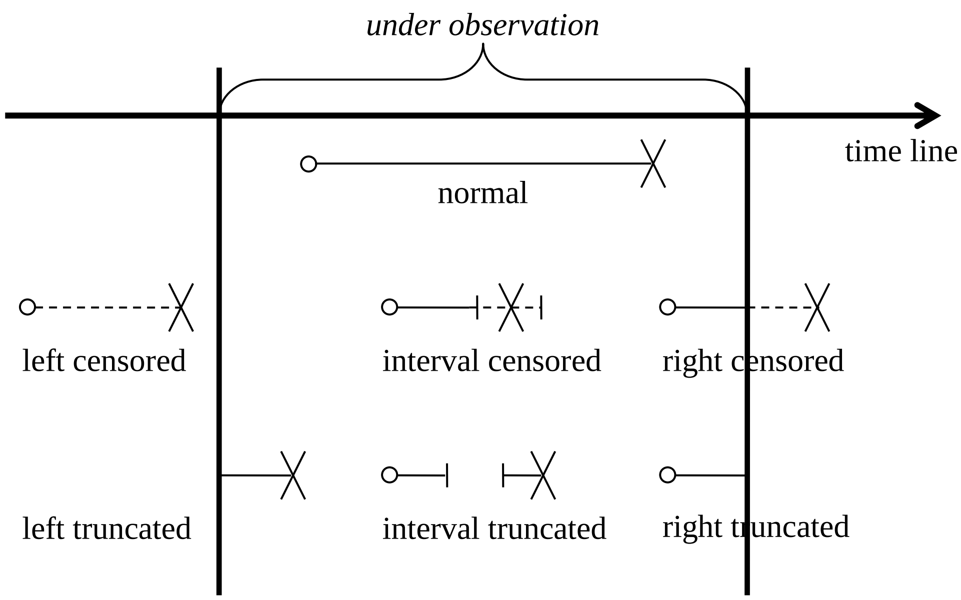

Figure 9 *Illustration of Censoring and Truncation*

The left censored and left truncated cases are not included in our analysis, because the information on the price duration cannot be extracted in these circumstances. Other cases can still be used, since the information on the duration up to the time of censoring or truncation is known. For example, when a price-spell is right censored, it is known that the price does not change in the previous months before censoring, and it can still be included in the survival analysis.

Appendix II: Models of Survival Analysis

The survival analysis is widely used in labour economics to study unemployment duration and in finance to study trading duration, but it is relatively new to price setting literature, especially the semiparametric and parametric models. This appendix is written for the readers unfamiliar with the analysis framework.

Nonparametric Analysis follows the philosophy of letting the data speak for itself and makes no assumption about the function form of the distribution. Hence, the effects of covariates are ignored. The most popular nonparametric methods are Kaplan-Meier estimator of $S(t)$ and Nelson-Aalen estimator of $H(t)$. As indicated previously, $h(t)$ can always be derived easily according to the relationship between them.

In particular, the Kaplan-Meier estimator (also known as the "product limit estimator") estimates the survival function from survival time data. A plot of the Kaplan-Meier survival function is a series of horizontal steps of declining magnitude which, when a large enough sample is taken, approaches the true survival function for that population. The value of the survival function between successive distinct sampled observations is assumed to be constant.

An important feature of the Kaplan-Meier estimator is that the method takes into account the "censored" data, namely, the losses from the sample before the final outcome is observed. It assumes that all the censored subjects do not fail when censoring occurs. The Kaplan-Meier estimation of survival function is given by:

$$\hat{S}(t) = \prod_{t=t_1}^{t_i} \left(\frac{n_i - d_i}{n_i} \right) = \frac{n_1 - d_1}{n_1} \times \frac{n_2 - d_2}{n_2} \times \ldots \times \frac{n_N - d_N}{n_N}$$

Here, $t_1 \leq t_2 \leq \cdots \leq t_N$ is the analysis time when either failure or censoring occurs. n_i is the number of subjects which survive in the beginning of period t_i, d_i is the number of observed failures during the subsequent period, and l_i is the number of losses due to censoring or truncation. Two examples are used below to illustrate the workings of Kaplan-Meier method.

[Example 1] Kaplan-Meier estimate of $S(t)$ without censoring

Assume that there are 10 products at the beginning of the analysis time, or at date 0. Note that there is no censoring at any time, so the l_i column is always zero. We can order the failure time in the table and calculate the Kaplan-Meier survival function $S(t)$ step by step:

t_i	m_i	d_i	l_i	calculation	$S(t)$
0	10	0	0	**(10 – 0)/10** = 1	1
1	10	2	0	**((10 – 2)/10)***1= 8/10	0.8
2	8	3	0	**(5/8)***(8/10)	0.5
3	5	4	0	**(1/5)***(5/8)*(8/10)	0.1
4	1	0	0	**1***(1/5)*(5/8)*(8/10)	0.1
5	1	1	0	**0***1*(1/5)*(5/8)*(8/10)	0

[Example 2] Kaplan-Meier estimate of $S(t)$ with censoring

Now assume that there are censored observations at time 2, 4 and 5, when some subjects do not fail but are no longer under observation. Here, we follow a convention in survival analysis that censoring occurs after the failures of other uncensored subjects.

t_i	m_i	d_i	l_i	calculation	$S(t)$
0	10	0	0	**(10 – 0)/10** = 1	1
1	10	2	0	**((10 – 2)/10)***1= 8/10	0.8
2	8	3	1	**(5/8)***(8/10)	0.5
3	4	1	0	**(3/4)***(5/8)*(8/10)	0.375
4	3	1	1	**(2/3)***(3/4)*(5/8)*(8/10)	0.25
5	1	0	1	**1***(2/3)*(3/4)*(5/8)*(8/10)	0.25

Since Kaplan-Meier estimator is estimated from a random sample, it is also a random statistic with standard error. A popular estimator is Greenwood's (1926) formula:

$$\hat{V}ar\left[\hat{S}(t)\right] = \hat{S}^2(t) \cdot \sum_{t=1}^{t_i} \frac{d_i}{n_i(n_i - d_i)}$$

To obtain the confidence intervals, the following asymptotic variance is usually used instead of Greenwood formula:

$$\hat{\sigma}^2(t) = \left[\sum_{t=1}^{t_i} \ln\left(\frac{n_i - d_i}{d_i}\right)\right]^{-2} \sum_{t=1}^{t_i} \frac{d_i}{n_i(n_i - d_i)}$$

Hence, the confidence intervals at significant level of α are calculated as:

$$\left[\hat{S}(t)^{\exp[-z_{\alpha/2}\hat{\sigma}(t)]}, \hat{S}(t)^{\exp[z_{\alpha/2}\hat{\sigma}(t)]}\right]$$

Parametric Analysis, at the other end, explicitly uses covariates to model $h(t)$ in a specific functional form. The most popular model assumes proportional hazard (PH):

$$h(t) = h_0(t)\exp(\boldsymbol{\beta}'\mathbf{x})$$

The name "proportional hazard" comes from the feature that the hazard function $h(t)$ is proportional to $\exp(\boldsymbol{\beta}'\mathbf{x})$, with the Baseline Hazard Function $h_0(t)$ common to all observations. In parametric analysis, a specific function form has to be assumed for $h_0(t)$, which could be exponential, Weibull, log-logistic, lognormal, Gompertz or others. Weibull turns out to be the most appropriate choice for our purpose due to its flexibility in shape. The vector of covariates $\mathbf{x}$ is sometimes called regressor, explanatory variable, control variables or independent variable by other authors, but they mean the same thing, i.e. the factors that affect the hazard rate. Besides, $\boldsymbol{\beta}$ is the coefficient vector for $\mathbf{x}$, but occasionally Hazard Ratio $\exp(\beta_i)$ for each coefficient is used instead. The hazard ratio can be interpreted as the multiplier effect of the coefficient on $h_0(t)$. It is greater than 1 if the coefficient is negative, and it is less than 1 if the coefficient is positive.

Semiparametric Analysis lies in the middle of the two ends. Cox (1972) model is the most popular PH model. Instead of imposing a specific function form for $h_0(t)$, it is left unspecified in Cox model, while covariates are still explicitly specified. One property of Cox model is that the baseline hazard function $h_0(t)$ does not affect the estimate of $\boldsymbol{\beta}$.

Appendix III: The Data Collection and Weight System

The Consumer Price Microdata

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, 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 Tuesday of each month (Index Day). Once the price quotes are collected, one can compute 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[1], 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 $w^E_{j,k,s,t}$.

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 $w^S_{s,t}$.

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

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 $w^P_{i,j,k,s,t}$, the stratum

[1] 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.

weight $w^E_{j,k,s,t}$, the item weight $w^I_{k,s,t}$, and the division/group weight $w^S_{s,t}$. If we ignore the centrally collected price quotes, then the process for the aggregate indices can be summarised into one big formula:

$$I_t^A = \frac{\sum_{s=1}^{N_t} w^S_{s,t} \times \dfrac{\sum_{k=1}^{N_s} w^I_{k,s,t} \times \dfrac{\sum_{j=1}^{N_k} w^E_{j,k,s,t} \times \dfrac{\sum_{i=1}^{N_j} w^P_{i,j,k,s,t}\, p_{i,j,k,s,t}}{\sum_{i=1}^{N_k} w^P_{i,j,k,s,t}}}{\sum_{j=1}^{N_k} w^E_{j,k,s,t}}}{\sum_{k=1}^{N_s} w^I_{k,s,t}}}{\sum_{s=1}^{N_t} w^S_{s,t}}$$

$$= \sum_{s=1}^{N_t}\sum_{k=1}^{N_s}\sum_{j=1}^{N_k}\sum_{i=1}^{N_j}\left(\frac{w^S_{s,t} \times w^I_{k,s,t} \times w^E_{j,k,s,t} \times w^P_{i,j,k,s,t}}{\sum_{s=1}^{N_t} w^S_{s,t} \times \sum_{k=1}^{N_s} w^I_{k,s,t} \times \sum_{j=1}^{N_k} w^E_{j,k,s,t} \times \sum_{i=1}^{N_k} w^P_{i,j,k,s,t}} \cdot p_{i,j,k,s,t}\right)$$

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:

$$\omega_{i,j,k,s,t} \equiv \frac{w^S_{s,t} \times w^I_{k,s,t} \times w^E_{j,k,s,t} \times w^P_{i,j,k,s,t}}{\sum_{s=1}^{N_t} w^S_{s,t} \times \sum_{k=1}^{N_s} w^I_{k,s,t} \times \sum_{j=1}^{N_k} w^E_{j,k,s,t} \times \sum_{i=1}^{N_k} w^P_{i,j,k,s,t}}, \text{ where } \sum_{s=1}^{N_t}\sum_{k=1}^{N_s}\sum_{j=1}^{N_k}\sum_{i=1}^{N_j} \omega_{i,j,k,s,t} = 1$$

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 in the IPN literature.

The last issue 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 paper 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 paper. The comparability is the third advantage of using CPI weights, since HICP is also used by European Central Bank as the measure of price stability.

Table 6, **Table 7** and **Table 8** summarise the average lengths of consumer price trajectories by division, by detailed sector and by grouped sector. It is to show that cross-sectional heterogeneities are remarkable.

Division	**Median Lengths (in months)**	**Mean Lengths (in months)**	**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**

Table 6 *Descriptive Summary of Consumer Price Trajectory Lengths by Division*

Sector	Median Lengths (in months)	Mean Lengths (in months)	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**

Table 7 *Descriptive Summary of Consumer Price Trajectory Lengths by Sector*

Sectors	Median Lengths (in months)	Mean Lengths (in months)	Obs.
Goods	13	19.76	480,258
Services	21	24.23	131,915
Total	**14**	**20.72**	**612,173**

Table 8 *Descriptive Summary of Consumer Price Trajectory Lengths by Goods/Services*

The second criterion of classifying consumer price trajectories is by shop type (**Table 9**). 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. The third criterion of classifying consumer price trajectories is by region (**Table 10**). It turns out that the heterogeneity in price setting behaviour across region in the UK is not significant, though London has a bit shorter price trajectory because of high frequency of rotations and fierce competition.

Shop Type	Median Lengths (in months)	Mean Lengths (in months)	Obs.
Multiple	13	20.70	372,940
Independent	17	20.76	239,180
Unknown	–	–	53
Total	**14**	**20.72**	**612,173**

Table 9 *Descriptive Summary of Consumer Price Trajectory Lengths by Shop Type*

Region	Median Lengths (in months)	Mean Lengths (in months)	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**

Table 10 *Descriptive Summary of Consumer Price Trajectory Lengths by Region*

The Producer Price Microdata

As for the producer price microdata, around 9,000 price quotes are collected monthly by statutory survey from some 4,000 firms. In addition, some prices are obtained from administrative sources, such as other government departments and trade publications. There is no direct price collection of input prices from firms. Output PPI is used as proxy to calculate the input PPI (Morris and Birch, 2001).

Similar to the sampling of consumer price microdata, a producer price quote can be denoted by $P_{i,j,k,s,t}$, where the subscripts i, j, k, s, t uniquely identify the producer, product, industry, division and time of any price quote. Accordingly, N_j is the total number of price quotes (i.e. producers) in product j for industry k, N_k is the total number of products for industry k, N_s is the total number of industries for division s, and N_t is the total number of divisions for period t. For example, $P_{i,j,k,s,t}$ could be the price of frozen potato (j) produced by producer (i), which belongs to potato industry (k) and food division (s) in 2000m1 (t). Given these price quotes, there are 4 steps to calculate PPI, similar to CPI/RPI. The weight system is also similar to consumer price indices which can be found in Morris and Gough (2003).

According to the SIC categories, the intermediate goods sector is the largest group, since it includes all the gross products sold to the next stage in the supply chain. At the other end, the energy goods sector contains only 28 price trajectories, but their importance is considered by industry weights. The price trajectories for producer data are longer than those for retailer data, whose median length is 14 months and mean length is 20.72 months. It suggests that most producers' products have a lifecycle around 2 years, describing the lifetime of a technology generation. An outlier is energy goods sector with a price trajectory around 4 years. This is not a surprise, because energy goods are mainly homogenous raw materials such as oil and coal, of which the product lines do not rotate frequently. The average lengths of producer price trajectory are summarised in **Table 11**.

Sector	**Median Lengths (in months)**	**Mean Lengths (in months)**	**Obs.**
Consumption Goods			
Consumer Food Goods	22	25.24	3,815
Consumer Durable Goods	20	26.67	1,493
Consumer Non-Food Non-Durable Goods	20	24.84	3,909
Production Goods			
Intermediate Goods	20	25.73	10,001
Capital Goods	20	25.02	4,535
Energy Goods	62	55.13	28
Total	**20**	**25.45**	**23,781**

Table 11 *Descriptive Summary of Producer Price Trajectory Lengths by Sector*