Cardiff Economics Working Papers

Working Paper No. E2018/18

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Peng Zhou and Huw Dixon

June 2018

ISSN 1749-6010

Cardiff Business School
Cardiff University
Colum Drive
Cardiff CF10 3EU
United Kingdom
t: +44 (0)29 2087 4000
f: +44 (0)29 2087 4419
business.cardiff.ac.uk

The Determinants of Price Rigidity in the UK:

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

Peng Zhou† Huw Dixon‡

Abstract

This paper systematically integrates microdata and macrodata analysis of price rigidity in monetary economics. We explore the mechanism of price-setting using survival based approaches 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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† Corresponding Author: D47, Aberconway Building, Cardiff Business School, Cardiff University, CF10 3EU. Email: zhoup1@cardiff.ac.uk. Telephone: +44-(0)2920688778.

‡ Cardiff Business School, Cardiff University, Cardiff, UK, CF10 3EU. Email: dixonh@cardiff.ac.uk.

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. In the last decade, where 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 and Burriel (2010), Alvarez et al (2013), Alvarez and Lippi (2014), Costain and Nakov (2011), Vavra (2014) and Kara (2015), and Dixon and Tian (2017).

The major contribution of this paper is to employ the survival analysis (nonparametric, semi-parametric 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 hazard rate). Producer price's hazard rates are more sensitive to shifts in inflation and the interest rate than retail prices.

[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.

- 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).
- 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 5 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 models with heterogeneous agents (Finding 2). An important application of these microdata findings is to better calibrate the macroeconomic models. A simple simulation practice is conducted to illustrate how incorporating the microdata evidence into the DSGE model can improve its performance in matching the macrodata evidence. 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 of 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) and Baudry et al (2007)[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, which is a similar problem to the drawback of the frequency-based approach of measuring the price rigidity. To some extent, the logit modelling approach is the counterpart of the frequency-based approach in studying the mechanism of price setting behaviour, while the survival analysis is the counterpart of the cross-sectional approach.

Accordingly, the survival analysis has two advantages. First, the models are designed specifically for studying duration data, so it 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 the **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 is believed to generate the most reliable conclusions and 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).

Compared to Bunn and Ellis (2012a, 2012b), this paper extends the dataset on both ends to include all price quotes available before the financial crisis[8]. 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. 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 across products and the survival analysis models—will be detailed, because it is unique to this paper.

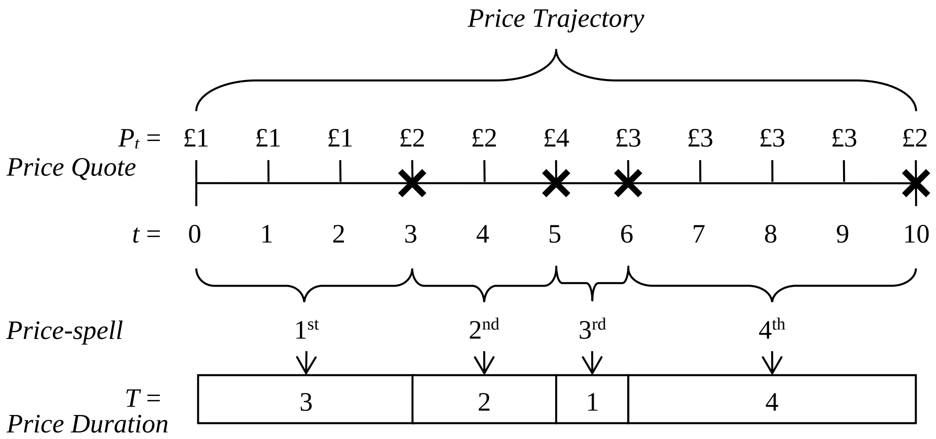

Figure 1 *Illustration of a Typical Price Trajectory*

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 *Descriptive Statistics of Price Trajectories (in months)*

[11] Individual price quote is collected either locally or centrally. The problem of lacking access to the centrally collected microdata also exists for most 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 retailers are classified according to the COICOP[13] and can be combined into 9 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 the Price Rigidity

Previous section have shown that the overall price rigidity is substantial in the British economy, 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. Ideally, 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[15], 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

[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.

[15] In the previous section, the full data is used to estimate the price rigidity using either frequency-based or cross-sectional approach. In this section, by contrast, 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).

form. At the other end, the parametric model isolates the baseline hazard function $h_0(t)$, 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 the functional assumption on $h_0(t)$ but control for the covariates.

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 purpose, this paper will focusing on reporting and analysing the hazard function hereinafter.

Similar to the distribution of duration across products, the $h(t)$ also 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 better for calibrating the Generalised Calvo (GC) model.

In **Figure 3**, the hazard functions are decomposed by sector. It is again confirmed that the decreasing feature of the consumer prices is derived from the goods sector while the periodic feature 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.

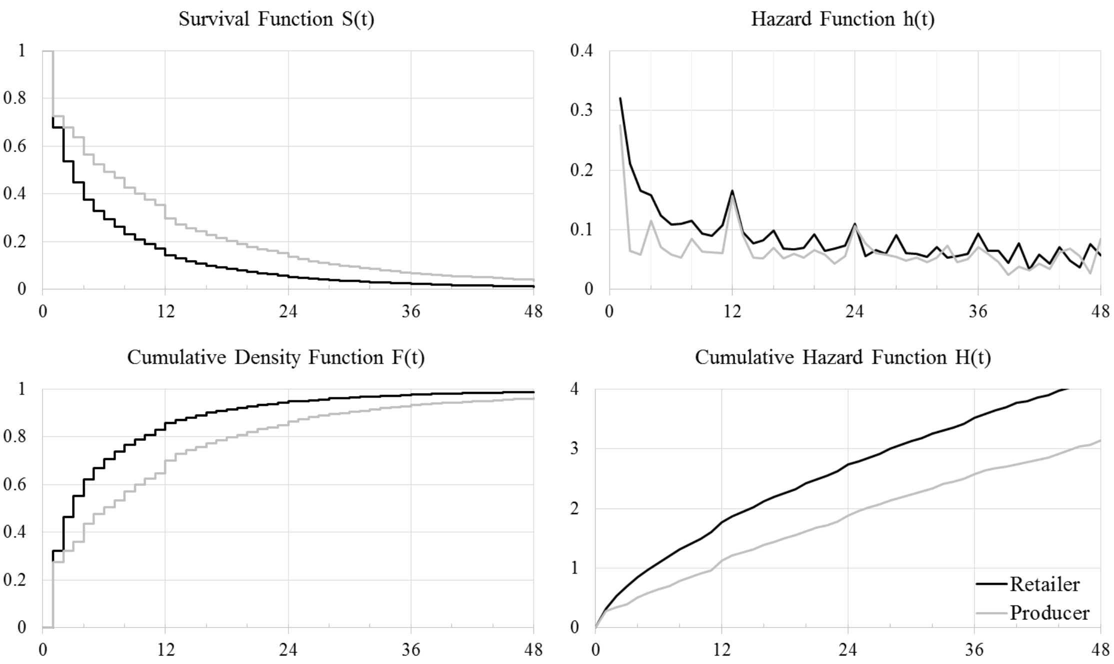

Figure 2 *The Estimated Distributions of the Nonparametric Model (in months)*

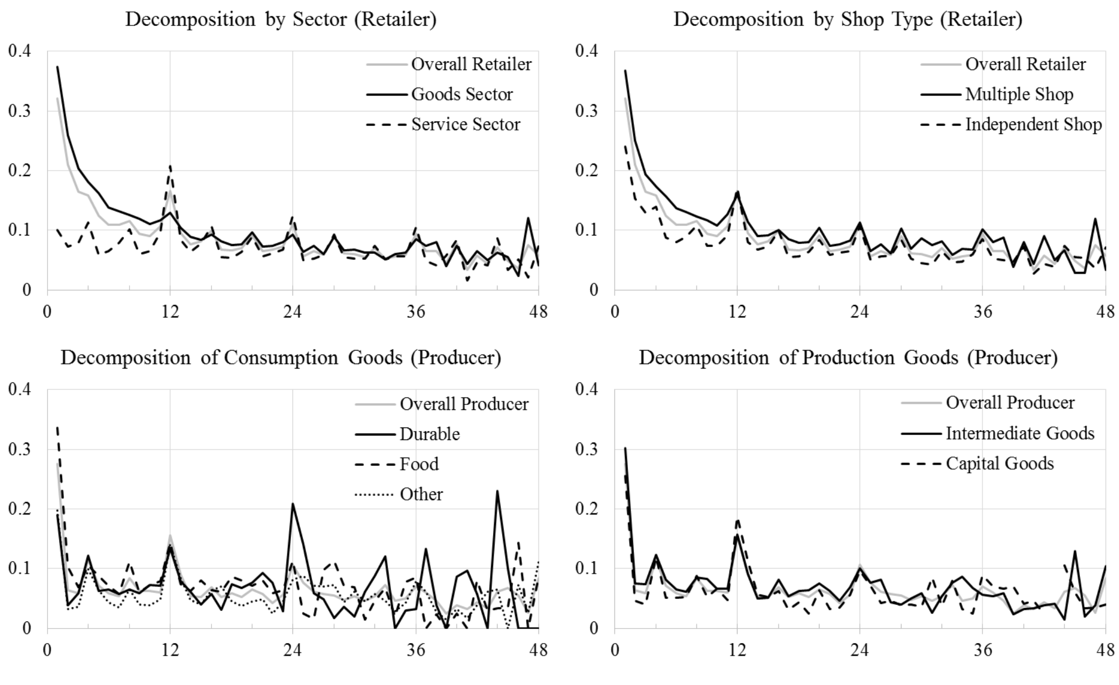

Figure 3 *The Decomposition of the Nonparametric Hazard Functions (in months)*

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[16] proportional hazard Cox model:

[16] 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 ("the third drawback").

(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[17], 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-

[17] 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 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.

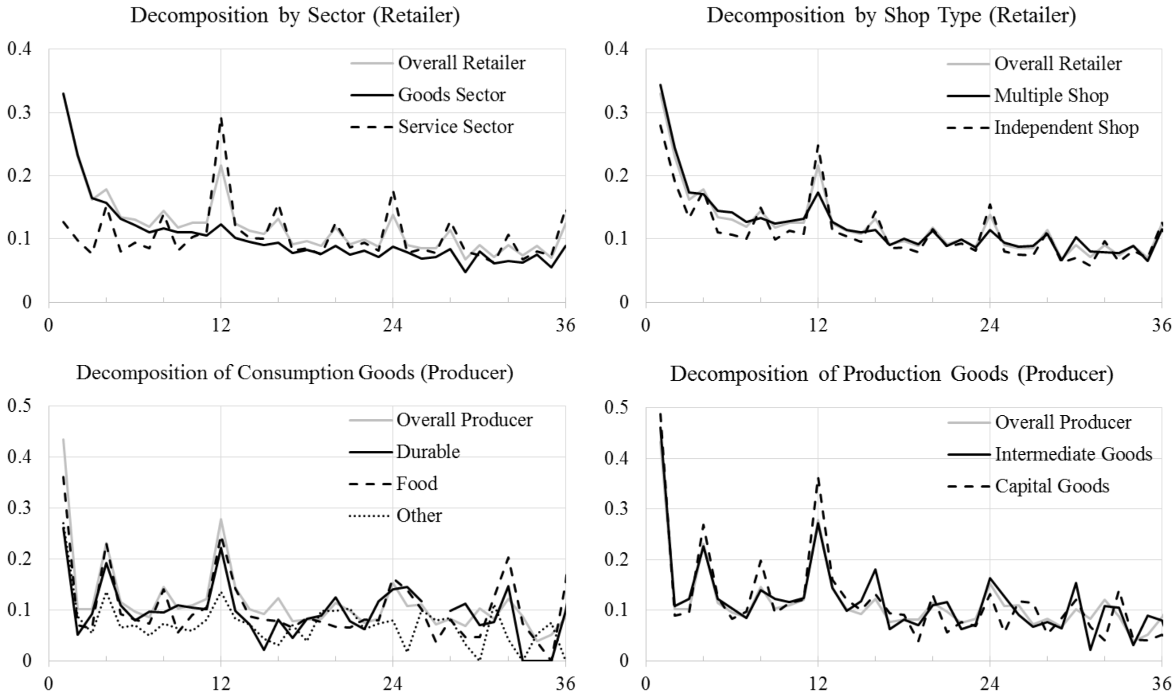

Figure 4 *The Decomposition of the Semiparametric Baseline Hazard Functions (in months)*

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).

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 1% changes in macroeconomic covariates, implied from the estimated coefficients in **Table 2**. For example, if inflation in the current period rises by 1%, then the retailer price's hazard rate will be 0.22% lower. 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.

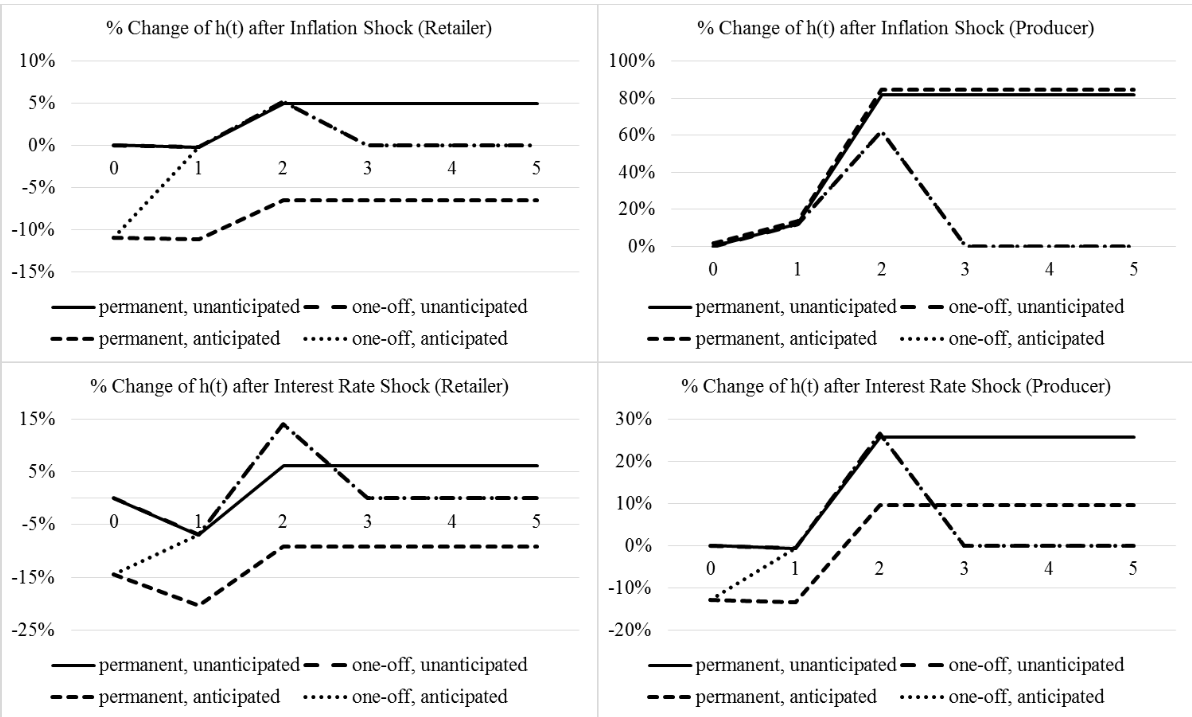

Figure 5 *The Percentage Changes of $h(t)$ after Simulated Shocks*

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% higher from period 1 onwards, and a one-off shock means 1% 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 $\mathbf{x}$ 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:

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

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[18].

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.

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

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

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.

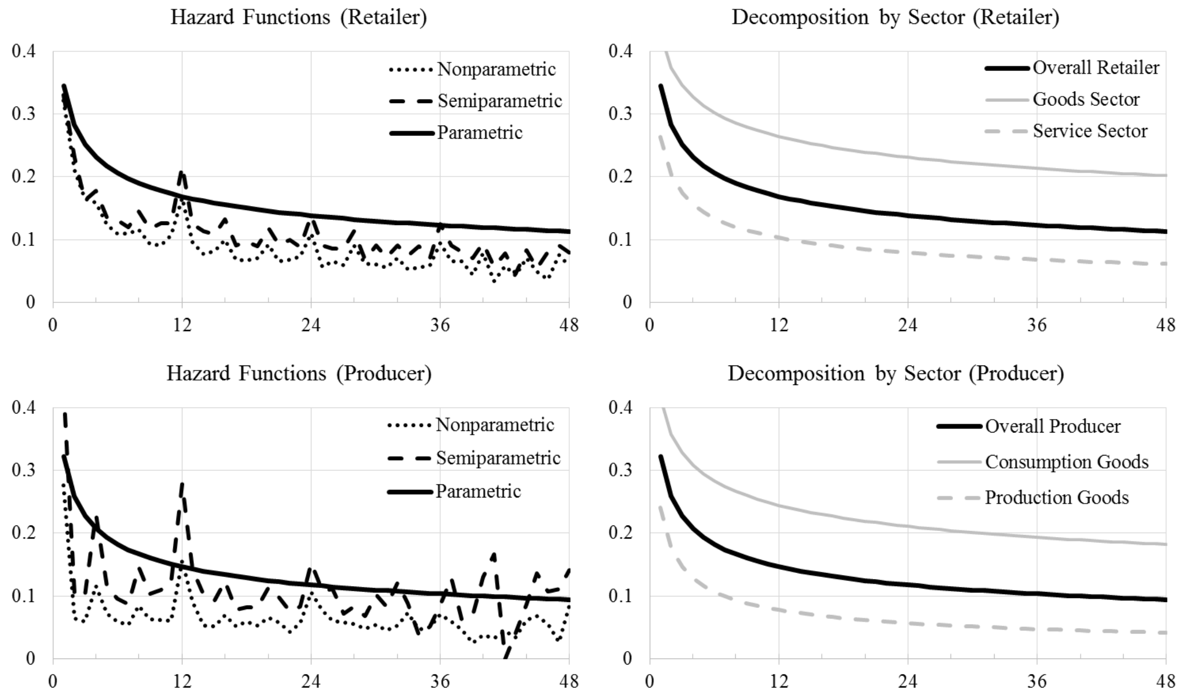

Figure 6 *The Decomposition of the Parametric Baseline Hazard Functions (in months)*[19]

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 dynamics other than those generated by 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 approaches to modelling nominal rigidity, so we leave out features such as habit formation, investment and Taylor rules which would also have important effects[20].

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 persis-

[19] If the long price durations beyond 48 months are included, then the hazard rate will finally go to 100% because all prices will 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.
[20] Dixon and Le Bihan (2012) use French CPI and wage data to calibrate the Smets-Wouters model. Zhou (2012) uses UK data.

tence 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)[21]. 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 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: maybe 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. We consider three different hybrid models:

[21] 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 $h_0(t)$.

- 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[22], 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[23] 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 way of determining the

[22] 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.
[23] The detailed model equations of GC and GT can be found in Dixon and Le Bihan (2012).

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:

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

- The Monetary Policy equation[24], following a random walk process (m_t) with an AR(1) monetary shock ε_t:

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

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. Among all forms of presenting the distribution, survival function is the only way that no calculation is involved in transforming from monthly to quarterly, noting that 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 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 **Table 5**. 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

[24] The Taylor rule (1993) is usually used instead of a monetary base rule in the DSGE literature.

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[25]						
SC	0.770	0.123	0.997			
	(0.085)	(0.029)	(0.079)			
GC	0.664	0.159	0.957			
	(0.080)	(0.024)	(0.078)			
ST	0.492	0.000	1.030			
	(0.038)	(0.000)	(0.080)			
GT	0.554	0.060	0.929			
	(0.060)	(0.059)	(0.072)			
HY1	0.627	0.094	0.928	0.246		
	(0.074)	(0.040)	(0.072)	(0.132)		
HY2	0.483	0.107	0.879			
	(0.055)	(0.031)	(0.068)			
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)*

Model	**GCW**	**GCG Goods Sector**	**GCS Service Sector**
GC	100%	100%	100%
GT	0%	0%	0%
HY1	24.61%	-	-
HY2	-	100%	0%
HY3	-	40.17%	29.53%

Table 5 *Estimated Posterior Modes of Sector Shares*

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.

[25] 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.

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. From the macroeconomic perspective, the impulse response functions indicated by empirical VAR in the macroeconometric literature have a hump shape and a sluggish convergence (Chari et al, 2000). The left two graphs of **Figure 7** 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[26]. 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 micro-data 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 component—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).

[26] 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.

As shown on the right half of **Figure 7**, 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 impulse response functions (IRFs) of the seven estimated models are compared in the graph below. All the hybrid models show desirable features—a hump and persistence. In contrast, the Calvo-type models (both GC and SC) do not have hump, while Taylor-type models lack persistence.

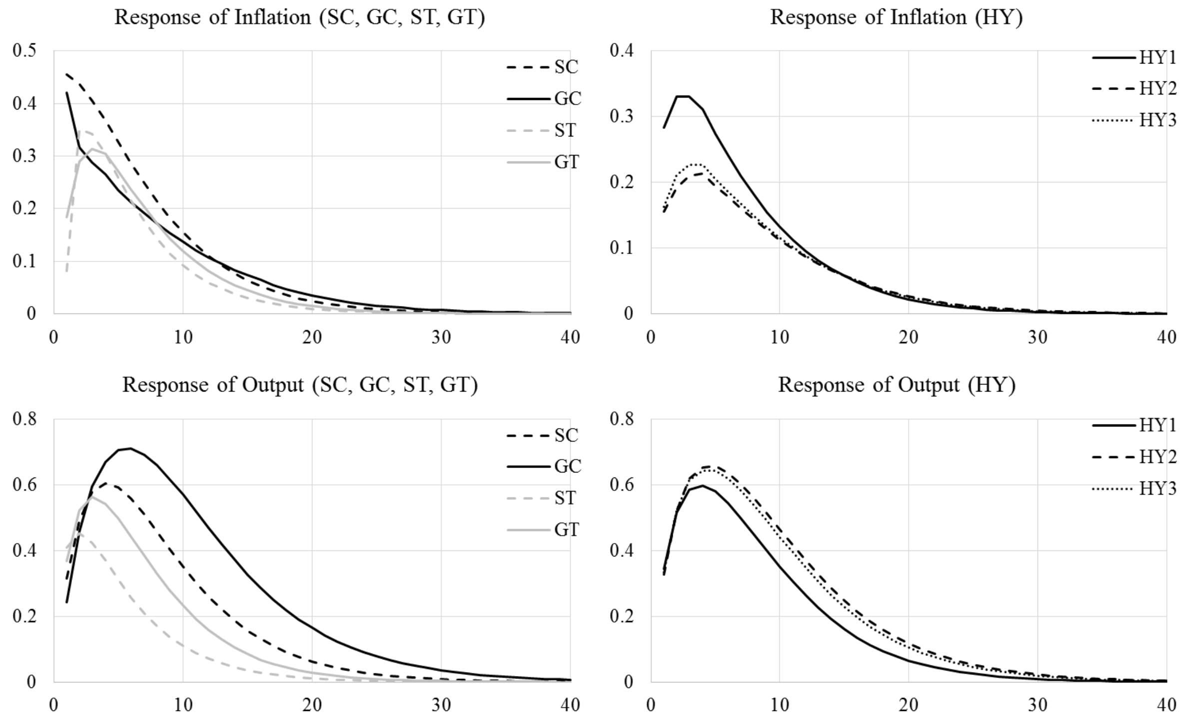

***Figure 7** The IRFs of Output and Inflation following a one-SD Monetary Shock*

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 6** 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 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 6 *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 is also the first attempt to apply parametric model to estimate 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.

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