MICRODATA ANALYSIS OF PRICE SETTING BEHAVIOUR AND MACRODATA ANALYSIS OF HETEROGENEOUS DSGE MODELS

by

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ABSTRACT

This thesis investigates nominal frictions in price setting behaviour from both microeconometric and macroeconometric perspectives. Chapter I and II use the unpublished retailer-level and producer-level microdata underlying CPI and PPI in the UK statistical authority to study empirical price rigidity and price setting mechanisms. Based on the conventional frequency-based method, little rigidity is found since the implied price duration is less than half a year. However, this method is shown to significantly underestimate the true duration due to oversampling of short price spells. Alternatively, a trajectory-based cross-sectional approach is adopted, giving an unbiased and robust estimate for average duration over 9 months (retailer price) and 15 months (producer price). That is to say, producer price has higher degree of rigidity than retailer price if cross-sectional approach is used. Both time-dependent and state-dependent features exist in price setting. In particular for retailer price, results also suggest conspicuous heterogeneities in price rigidity across sectors and shop types, but weak difference across regions and time. The overall hazard function of price change can be decomposed into a decreasing component from goods sectors and a 4-month cyclical component from services sectors.

The empirical findings in the microdata not only contribute to the microdata literature on price setting behaviour, but also make possible the calibrations of macroeconomic DSGE model with heterogeneous price setting. Hence, based on the microdata findings in Chapter I and II, Chapter III uses Classical maximum likelihood and Bayesian inference to evaluate and estimate DSGE models with various price setting mechanisms. A vital problem with homogeneous price setting models is that they cannot generate enough persistence while keeping calibration of average price rigidity consistent with microdata evidence. In contrast, this “persistence puzzle” is successfully resolved by heterogeneous price setting models, which greatly improve the dynamic performance of macroeconomic models.

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GENERAL INTRODUCTION

Nominal frictions (price rigidity and wage rigidity) lie in the heart of macroeconomic research. In fact, it is the fundamental criterion to distinguish among different schools of thought. Before 1936, the mainstream Classical school of thought treated prices and wages as flexible in perfect competition, leading to the ideal Walrasian equilibrium. The Keynesian revolution initiated by Keynes (1936) argued that nominal variables (prices and wages) are rigid in the short run, which contributed to the prolonged disequilibrium in Great Depression from 1929 to late 1930's. Following that, "Neoclassical Synthesis" framework (IS-LM-Phillips Curve) was developed as the dominant macroeconomics from 1950's to mid-1970's, combining the short run Keynesian theory and long run Classical theory, with backward looking adaptive expectations.

However, rational expectations and Lucas (1976) led to a new "microfounded" modelling paradigm. Real Business Cycle (RBC) by Kydland & Prescott (1982) has established a benchmark model without nominal frictions, which is termed as "New Classical". Almost at the same time, "New Keynesian" incorporated rational expectations and microfoundation from New Classical models with nominal frictions from late 1970's to 1980's, such as Taylor (1979), Calvo (1983), Akerlof & Yellen (1985) and Mankiw (1985). The former two are the most famous "time dependent pricing models", while the latter two are important examples of "state dependent pricing models". Under both types of models, firm's price setting behaviour is not perfectly flexible due to various nominal frictions. Before long, in the 1990's, a combination of the dynamic structure from New Classical theory with nominal frictions from New Keynesian theory leads to the "New Neoclassical Synthesis"[①]. Since then, many popular Dynamic Stochastic General Equilibrium (DSGE) models with nominal frictions are developed, such as Yun (1996), Chari et al. (2000), Smets & Wouters (2003), and Christiano et al. (2005).

However, these models will be all rejected by data if serious macroeconometric approaches are applied. A vital reason for this failure is that these models based on homogeneous price setting behaviour cannot generate enough persistence. Chari, Kehoe & McGrattan (2000) argue 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". They also show that a standard staggered price setting cannot achieve enough persistence, unless five-year exogenous price stickiness is used—which is obviously not plausible from

[①] For a detailed survey of New Neoclassical Synthesis, see **Dixon, H.** 2007. "New Keynesian Macroeconomics: Entry for New Palgrave Dictionary of Economics." *Cardiff Business School Working Paper Series*.

microdata evidence. This dilemma is termed as “persistence problem” or “persistence puzzle”. One of the important contributions of this thesis is that it provides a heterogeneous price setting model solution to this puzzle, consistent with both microdata evidence and macrodata evidence.

Along with the development of theoretical economic models, empirical methodology has evolved from simple calibration in Kydland & Prescott (1982), to partial-feature-based approaches such as Generalised Method of Moments (GMM) in Hansen & Singleton (1982) and indirect inference in Le et al. (2010), to system-based approaches such as maximum likelihood in Sargent (1989) and Bayesian inference in Geweke (1999). In addition to macrodata research, numerous microdata studies are also conducted to estimate the degree of price rigidity directly based on firm-level data in order to facilitate macrodata analysis of DSGE models. Often referenced works include Bils & Klenow (2004) for US, Bunn & Ellis (2009) for UK, Baumgartner et al. (2005) for Austria, Aucremanne & Dhyne (2005) for Belgium, Vilmunen & Laakkonen (2004) for Finland, Baudry et al. (2007) for France, Hoffmann & Kurz-Kim (2006) for Germany, Veronese et al. (2005) for Italy, Lünnemann & Mathä (2005) for Luxembourg, Jonker et al. (2004) for Netherlands, Álvarez & Hernando (2004) for Spain, Dias et al. (2004) for Portugal and Dhyne et al. (2005) for the whole Euro area.

In the light of these theoretical and empirical frameworks established in previous literature discussed above, this PhD thesis attempts to answer two research questions, which are closely correlated but addressed by very different methodologies. The first question is how firms set prices from *microeconometric* perspective, while the second question is the effect of price setting behaviour on performance of DSGE model from *macroeconometric* perspective. The link between the two inquiries is that microdata evidence will be used to calibrate the degree of price rigidity in conducting macrodata analysis of DSGE models.

To answer the first research question, two subtopics are investigated. The first subtopic focuses on the *outcome* of price setting behaviour, and the second focuses on the *mechanism* of price setting behaviour. The former aims to descriptively measure the degree of price rigidity, while the latter tries to identify the covariates or factors that might affect this price rigidity, resulting in a detailed explanation of price setting behaviour. These two subtopics are studied in both retailer price microdata (Chapter I) and producer price microdata (Chapter II). Note that these two chapters are the first systematic attempt in literature to explore microdata-level evidence for price setting behaviour in the UK, based on the confidential microdata underlying price indices in Office for National Statistics.

Regarding the first subtopic (outcome of price setting behaviour), both conventional frequency-based approach (popularly used in current literature for other economies) and cross-sectional trajectory-based approach (proposed by Dixon (2010)) are applied. The conventional approach implies an average price duration less than 6 months or little price rigidity, but it is criticised to be underestimated due to oversampling of short price spells. In contrast, the cross-sectional approach uses “duration across firms” (DAF) treating price trajectory, rather than duration, as the basic unit. Following this, substantial price rigidity (DAF is over 9 months) is found. Moreover, the two approaches also give different implications between retailer and producer price rigidities. Conventional approach suggests that producer price has less rigidity, but cross-sectional approach finds that this is merely an illusion due to high weights in energy goods and oversampling of short price spells.

Turning to the second subtopic (mechanism of price setting behaviour), survival analysis is employed to investigate the factors that might influence the observed price rigidity, or equivalently, the hazard function of price change. The least restricted approach, nonparametric analysis, is applied first, which includes time as the only independent variable to explain the variation in hazard function. Next, semiparametric analysis is used to account for effects of other covariates in time, space, microeconomic and macroeconomic dimensions. After controlling for these factors, the baseline hazard function is obtained, measuring the pure relationship of conditional probability of price change with time. Moreover, parametric analysis is also explored, where the baseline hazard function is explicitly specified in a parametric form. Some stylised facts in price setting behaviour for both retailers and producers are observed and summarised.

Based on the microdata findings in Chapter I and Chapter II, not only the average degree of price setting behaviour, but also the distribution of price rigidity across the economy, can be estimated. As mentioned earlier, the prevailing DSGE models assume homogeneous price setting, i.e. there is a representative firm with the average degree of price rigidity. However, this framework fails to explain the persistence of structural shocks under calibrations consistent with microdata findings. In other words, to get enough persistence, a ridiculously high degree of rigidity is needed. This dilemma results from the inability of homogeneous price setting models to generate dispersion of distribution of price duration. This “persistence puzzle” induces the second research question, which is successfully resolved by heterogeneous price setting behaviour models in Chapter III.

Following the seminal work in Dixon & Le Bihan (2010), heterogeneous price setting models are incorporated into the most popular DSGE framework in Smets & Wouters (2003). In order to conduct model comparison and evaluate whether heterogeneous agent model improves the performance of DSGE models, the price setting behaviour in the benchmark model, which is Calvo with Indexation (ICE), is replaced by Generalised Taylor Economy (GTE), Generalised Calvo Economy (GCE) as well as simple Taylor and simple Calvo. Bayesian model comparison is applied and it turns out that heterogeneous price setting models, especially GCE, performs much better than homogeneous agent models. This relative ranking seems to be robust to different calibration, prior and approach. In particular, indirect inference approach gives exactly the same result as obtained under Bayesian inference. However, if one only cares about dynamics in output, inflation and nominal interest rate, GTE might performs the best. Furthermore, some specific features of DSGE models, such as impulse response functions and variance decomposition, are also investigated. Heterogeneous price setting models can again better capture the stylised facts (based on unrestricted VAR).

Some important findings of this thesis are summarised below in terms of the two research questions.

Research Question 1: Microdata Analysis

Subtopic 1: Degree of Price Rigidity

This thesis is the first attempt in literature to estimate the degree of price rigidity using the cross-sectional approach. The frequency-based approach used in most studies is shown downward biased due to oversampling of short durations. The average price duration for retailer price is 9.3 months in terms of cross-sectional approach, much longer than that (5.5 months) under the frequency-based approach. Meanwhile, it is found that producer price on average lasts longer (15.3 months) than retailer price.

There is little support for rigidity in direction of price change, but the results do show evidence for rigidity in magnitude of price change. In other words, price faces the same friction to rise or fall, but it tends to end with attractive numbers (e.g. £6.99) and change by fixed proportions (e.g. 20% off).

For retailer price, significant cross-sectional heterogeneity in price rigidity is observed by sector and by shop type, while little regional difference or time-series heterogeneity is found. Goods sectors tend to be more flexible than services sectors, while multiple shops change prices more frequently than independent shops. For producer price, heterogeneity is much less between consumption goods and production goods.

Subtopic 2: Mechanism of Price Setting

For retailer price, the hazard function can be decomposed into decreasing component from goods sectors and the cyclical component from services sectors. One remarkable feature is the 12-month major spikes and 4-month minor spikes in hazard functions. January is the calendar month with the highest hazard rate of price change, followed by April and August due to seasonal sales. Also, both backward looking and forward looking expectations are supported by microdata evidence.

A very similar pattern is found in hazard function of producer price, i.e. downward sloping and typical 4-month spikes. Heterogeneity across sectors is also examined and consumption goods sectors have longer implied duration than production goods sectors. After filtering out the effects from seasonality, macroeconomic and microeconomic covariates, the baseline hazard functions of different sectors turn out very similar across sectors. The downward slope and typical spikes features still remain, but the difference between consumption goods sectors and production goods sectors vanishes.

By comparative study between retailer and producer prices, it is implied that the upstream firms (producers) in the supply chain tend to have more nominal frictions in price setting than downstream firms (retailers). As moving more towards the downstream of supply chain, the number of firms grows, and the products are more differentiated. Competition is greater due to more substitutable goods in the market. The structure of the supply chain looks like an "ecological pyramid". This conclusion not only holds in general from producers to retailers, but also holds in particular industry. For example, although some sectors such as energy goods sector might have more flexible prices than retailer prices as a whole, the energy goods producers still have more rigidities than the energy goods retailers.

Research Question 2: Macrodata Analysis

Chapter III proposes a DSGE model with either homogeneous or heterogeneous price setting behaviour. Based on the microdata findings in microdata analysis, calibrations for heterogeneous price setting models (GTE and GCE) become possible. Both Classical maximum likelihood and Bayesian inference are applied to evaluate and estimate the DSGE model. It is shown that, in both general and specific, heterogeneous price setting models (GCE, GTE) outperform homogeneous counterparts (ICE, Calvo, Taylor), because homogeneous agent models can only explain the "first order" properties, such as means and correlations of variables. However, this simplification averages away many important aspects which are essential to explain the "second order" properties, such as dispersion and persistence of variables. Chapter III extends the benchmark DSGE framework in the direction of heterogeneity in price setting behaviour, which successfully improves the performance in dynamic persistence and distribution of price rigidity. This is a novel solution to the “persistent puzzle” in monetary economics literature.

If all the 7 macroeconomic observables are used, GCE then performs the best and GTE follows. In homogeneous price setting models, simple Taylor is the worst, because it generates the least persistence. This model ranking is also robust to different calibrations, priors and approaches. However, GTE could be the best model if one puts more weight on explaining output, inflation and interest rate.

In fact, this is not just a particular solution limited for nominal frictions, but also a general prescription for any scenario when heterogeneous agents might emerge. For example, if the policy maker cares about both per-capita growth in GDP (first order inquiry) and the distribution of wealth across the society (second order inquiry), then representative agent model is not enough for the second issue. It then entails the use of heterogeneous agent models with different endowment, resulting in a distribution or a dispersion of income as in Gorman (1953), Bewley (1986) and Chatterjee (1994). Another example of heterogeneous agent model might be idiosyncratic risks in financial markets as in Aiyagari (1994). Hence, if one only cares about simple relationships of per capita variables, representative agent model might work quite well. However, if one tries to address distributional issue or persistence, heterogeneous agent models are necessary.

CHAPTER I

Heterogeneity and Rigidity of Retailer Firm's Price Setting Behaviour[①]

[①] This work contains statistical data from ONS which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

1. Introduction

The price rigidity has been the fundamental issue of the dispute between Keynesian and Classical schools of thought since macroeconomics was established in the 1930's. In recent theoretical literature, many influential works[①] incorporate price rigidity into the Dynamic Stochastic General Equilibrium (DSGE) models. This trend of combing the New Classical microfoundation and New Keynesian rigidity is often termed as "New Neoclassical Synthesis"[②]. However, this integration in methodology does not resolve the discrepancy in assumption on nominal frictions between the two schools. Usually, to make judgement, macroeconomic models are compared in terms of goodness of fit to macro evidence, such as second moments of output and employment. Little effort was made in terms of micro evidence mainly due to lack of data.

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

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

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

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

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

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

Following this introduction, Section 2 summarizes the methodologies in a consistent and strict terminology system, for both descriptive and inferential sections. Section 3 introduces the data source used in this paper and describes the features of our sample. Section 4 and Section 5 are devoted to the outcome of price setting behaviour, by conventional and cross-sectional methods respectively. Section 6 characterizes the mechanism of price setting behaviour by survival analysis, where nonparametric, semiparametric, and parametric methods are applied to pooled and separate models. To link the five methods presented in this paper, Section 7 develops a uniform measure to contrast the results, and Section 8 concludes.

2. Methodology

There are two issues in price setting behaviour to be addressed. The first question is to summarize the *outcome* of price setting behaviour, i.e. price change. The purpose of the first question is actually to measure the rigidity of price change. The second question, in contrast, is to investigate the *mechanism* of price setting behaviour, i.e. factors affecting the price change. The purpose of the second question is to obtain the risk profile of price change that is influenced by various factors. As a result, different methodologies are needed to deal with the two tasks.

2.1. Cross-Sectional Method

To study the outcome of price setting behaviour, duration is used as a measure of rigidity. The conventional method, as adopted by most authors such as Bils & Klenow (2004) and Bunn & Ellis (2009), is to calculate the frequency of price change for each period, then use its inverse as the average duration. Dixon (2010) points out the oversampling problem for this method, which leads to underestimation of rigidity. The argument is that “price spells across time are linked by the fact that they are set by the same firm”, and “focussing on the distribution of durations is in effect ignoring the *panel structure* and the fact that it is firms which are generating the price spells”. In other words, it is unfair to firms with longer spells, because firms with short spells are considered too many times. For example, if there are two firms, one changes its price every month, while the other changes price every 12 months. The frequency of price change is 50% each month, and the implied duration is 2 months. However, the true mean duration across the two firms is $(1+12)/2=6.5$ months, much higher than the implied duration using conventional method.

To address the oversampling problem, Dixon (2010) proposes a cross-sectional method in terms of duration across firm (DAF). This new method chooses a cross-section of firms at a particular point in time. Each firm’s price belongs to a certain duration, whether it is completed or not at that moment. The essence of this new method is to collapse the panel structure into a cross-sectional structure to remove the oversampling problem. In the previous example, the mean DAF for each period is equal to 6.5 months, exactly the same as the true mean duration. Dixon (2010) also develops a unified framework to transform between distribution of DAF, distribution of age, distribution of duration and “hazard function”. Note that distributions of DAF and age are defined in the cross-sectional sense, while distributions of duration and “hazard function” are defined in the panel sense. Hence, the “hazard function” here is different from that used in this paper, which is defined in the cross-sectional sense.

2.2. Survival Analysis Method

Survival analysis, also termed duration analysis, studies the time to the occurrence of a random event. It originates in statistics, 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 method. Many papers, such as Jonker, Folkertsma & Blijenberg (2004) and Nakamura & Steinsson (2008), apply survival analysis to studying price duration. However, different authors use different terminology systems, and they only use nonparametric and semiparametric analysis to model the price setting behaviour. Standing on their shoulders, this paper tries to unify the definitions under the strict terminology of statistics, and construct a comprehensive econometric model by nonparametric, semiparametric as well as parametric analysis.

2.2.1. Terminology

The object of survival analysis in this paper is price duration, which is a random variable due to the uncertainty of when the price change occurs. T is defined as a nonnegative random variable denoting the time to a price change event for a price duration. It could be either continuous or discrete, depending on whether or not the time line is infinitely divisible.

An important note on discrete time is due here. The time line is discrete because either (i) the time line is *intrinsically* discrete, or (ii) failure event occurs in continuous time but duration is only observed in discrete intervals. The price duration data in our case is actually the second possibility, since the price change could occur any time within a month, but the event is only observed in monthly interval. 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 of the current literature.

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 tradition 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 here means *analy-*

sis time, rather than *calendar time*. A duration could begin at any point in calendar time, but it always starts at 0 in analysis time.

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 a continuous random variable, or the Probability Mass Function (PMF) of T if it is a discrete random variable. $F(t)$ is the Cumulative Distribution Function (CDF) of T, defined as $F(t) \equiv \Pr(T \le t)$. $S(t)$ is the Survivor Function, which is the probability of surviving beyond date t: $S(t) \equiv \Pr(T > t) = 1 - F(t)$.

The most important way of presenting the distribution of T is the Hazard Function, $h(t)$, which returns instantaneous Hazard Rate at any time t. Here, two possible cases for discrete time are distinguished, and the last formula will be used as argued earlier.

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

Accordingly, the Cumulative Hazard Function up to date 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 $(0, t]$.

The hazard function $h(t)$ actually describes a *conditional* probability, as opposed to the *unconditional* probability function $f(t)$. The condition here is that the price successfully survives up to t. There are several well-known function forms to model $h(t)$ in statistics. This paper will bother exponential distribution and Weibull distribution in parametric analysis. If $h(t)$ is subject to exponential distribution, then the hazard rates are constant over the time line. It is just a special case of Weibull distribution, which could be increasing, decreasing or constant. The shape parameter of Weibull is equal to 1 if it reduces to exponential distribution.

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 other forms. $h(t)$ gives a more natural way to interpret the process that generates duration, and regression models for survival data are more easily grasped by observing how covariates affect the hazard rates.

Also, the 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).

2.2.2. Model

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 survivor function from survival time data. A plot of the Kaplan & Meier survivor 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 survivor 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 "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, $t_1 \le t_2 \le \ldots \le t_N$ 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.

[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 survivor function $S(t)$ step by step as follows:

t_i	n_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	n_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:

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

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, on the other end, explicitly uses covariates to model $h(t)$ in a function 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. After the trial and error, Weibull turns out to be the most appropriate choice due to its flexibility. 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 counterpart of PH model in parametric analysis. 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 $\boldsymbol{\beta}$. That is also why it is termed semiparametric analysis, since it is not estimating the full model.

Arguably, nonparametric analysis is too naïve to generate informative results because it does not control for covariates. However, parametric analysis is too restrictive due to its inflexibility in assuming $h_0(t)$. As a result, semiparametric analysis has the advantages of both, and is expected to generate the most reliable conclusions. This section will mainly focus on the interpretations of semiparametric analysis results, while adventuring on nonparametric and parametric analyses at the same time.

2.2.3. Censoring and Truncation

In practice, price change may have not yet occurred by the end of the observation period, or the duration may also have lasted for a while before entering the observation. In these cases, there are *incomplete* observations over time. These complications entail a discussion in censoring and truncation, which are always confusingly defined in different papers. This paper will disambiguate the confusions by strictly following the definitions in statistics.

A *subject* is defined as the process being studied, which is price in our case. 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, meaning price change in our case.

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. There are three types of censoring:

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

(ii) Left Censoring: the failure occurs prior to the subject entering the observation. It is often abused as left truncation.

(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 *completely* ignorance about the subject over a truncated period. The censoring stresses the knowledge of failure time. In contrast, the truncated subjects are not even detectable during the truncation period, and it emphasises a complete ignorance of the subject. There are also three types of truncation:

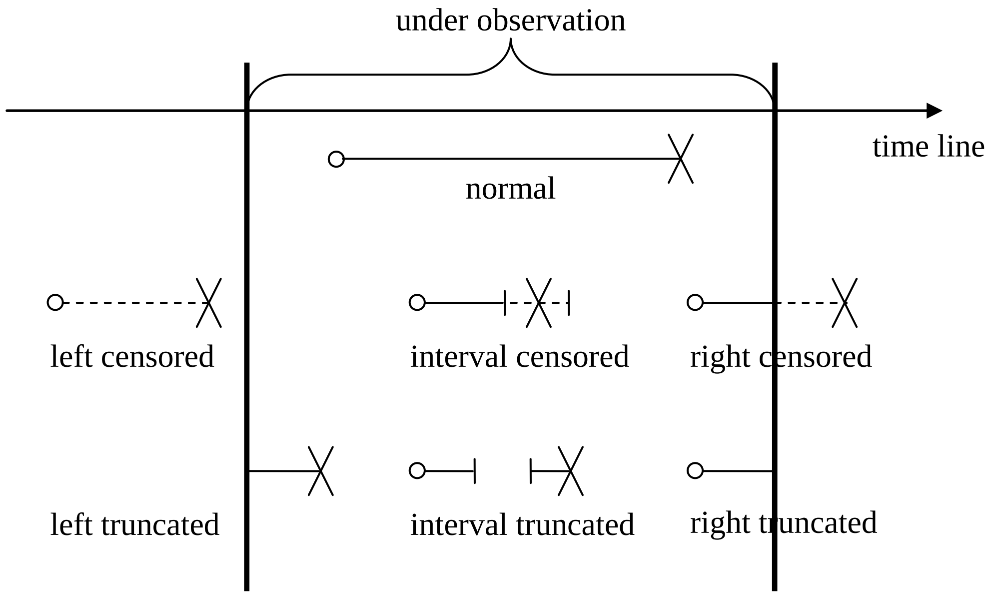
(i) Right Truncation: the subject is under observation for a while, but it leaves the study before it fails. (indistinguishable from right censoring)

(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.

(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, an intuitive graph below is used to present the relationship. The solid line is the duration under observation, with a beginning (circle) and an end (cross). The dashed part means censoring, while the blank part means truncation. As indicated earlier, right censoring and right truncation are indistinguishable.

In practice, the *left censored* and *left truncated* cases are dropped, because the duration information cannot be extracted under these circumstances. This treatment is also followed in other studies. Fortunately, other cases can still be used, since precise information on duration up to the time of censoring or truncation is known. For example, when a duration is right censored, it is known that the price does not change in the previous month before censoring. The information before that period is still usable, and the last observation in estimation is simply ignored. By this means, the estimate is both unbiased and efficient. A detailed statistical presentation for dealing with censoring and truncation can be found in Jenkins (2004).



3. Data

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

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

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

3.1. Data Description

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

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

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

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

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

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

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

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

3.2. Weight System

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

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

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

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

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

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

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

Thus, the big formula now becomes:

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

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

The last problem is then to choose between CPI weights and RPI weights for calculating the grand weight $\omega_{i,j,k,s,t}$. The CPI weights are preferred in this chapter 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 chapter. 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 across the Euro area.

3.3. Descriptive Summary

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

3.3.1. Overall Distribution of Price Trajectory

As in other studies, this panel is unbalanced, because new items enter while old items exit the CPI/RPI baskets frequently. Table 1 provides a summary of trajectory length:

Table 1 Descriptive Summary of Retailer Price Trajectory (Overall)

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

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

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

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

3.3.2. Heterogeneity in Distribution of Price Trajectory

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

Table 2 Descriptive Summary of Retailer Price Trajectory by Division

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

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

Table 3 Descriptive Summary of Retailer Price Trajectory by Sector

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

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

Table 4 Descriptive Summary of Retailer Price Trajectory by Goods/Services

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

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

Table 5 Descriptive Summary of Retailer Price Trajectory by Shop Type

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

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

Table 6 Descriptive Summary of Retailer Price Trajectory by Region

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

4. Conventional Method

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

4.1. Rigidity in Frequency of Price Change

4.1.1. Overall Frequency

In existing literature, both mean[①] and median[②] are used for the measure of frequency of price change. The advantage of median over mean is that it is more robust to outlier observations. As shown later, there is indeed an outlier around 2005m6, so median is preferred. For the interest of comparison with other literatures, both measures are used in this chapter and summarised in Table 7.

Table 7 Overall Frequency of Retailer Price Change

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

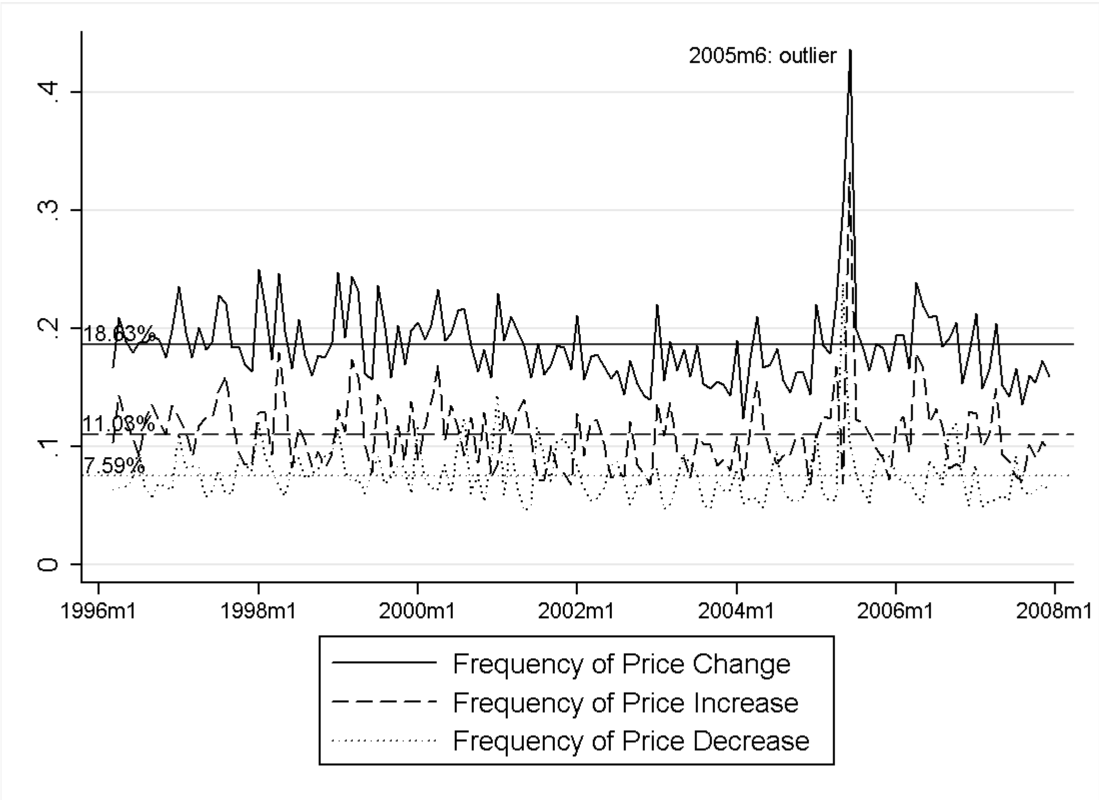
① Mean is popular in IPN literature, such as Dhyne et al (2005).
② Median is used in Bils & Klenow (2004) and Nakamura & Steinsson (2008).

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

4.1.2. Time-Series Heterogeneity in Frequency of Price Change

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

Figure 1 Time-Series Heterogeneity in Frequency of Retailer Price

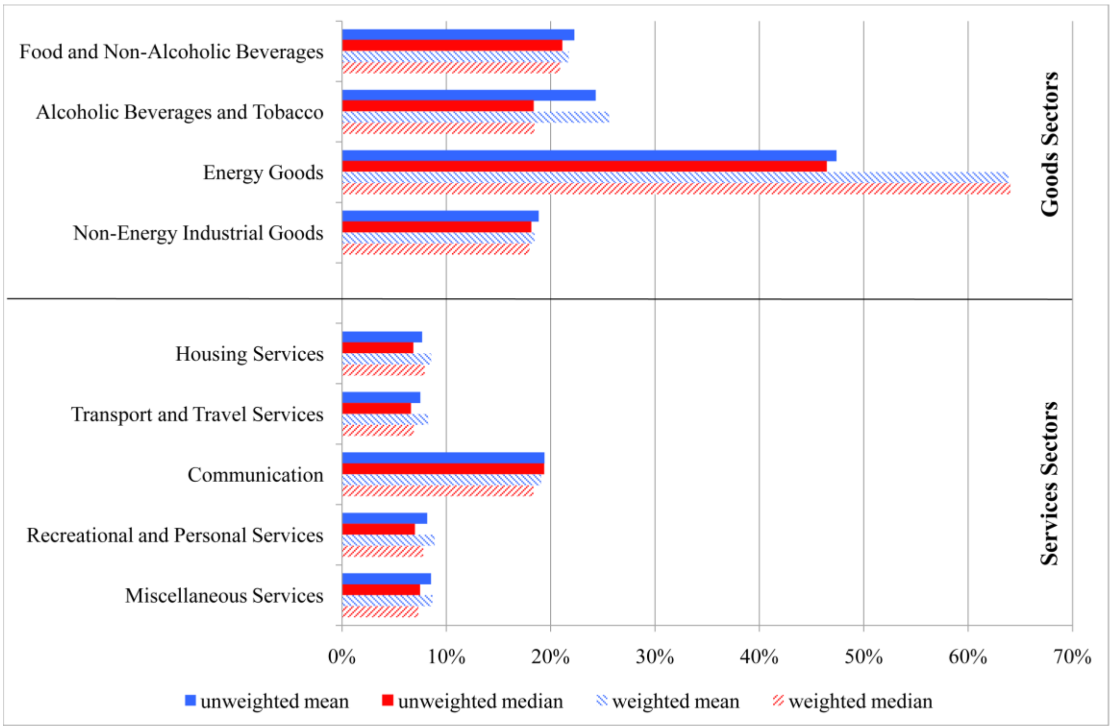


4.1.3. Cross-Sectional Heterogeneity in Frequency of Price Change

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

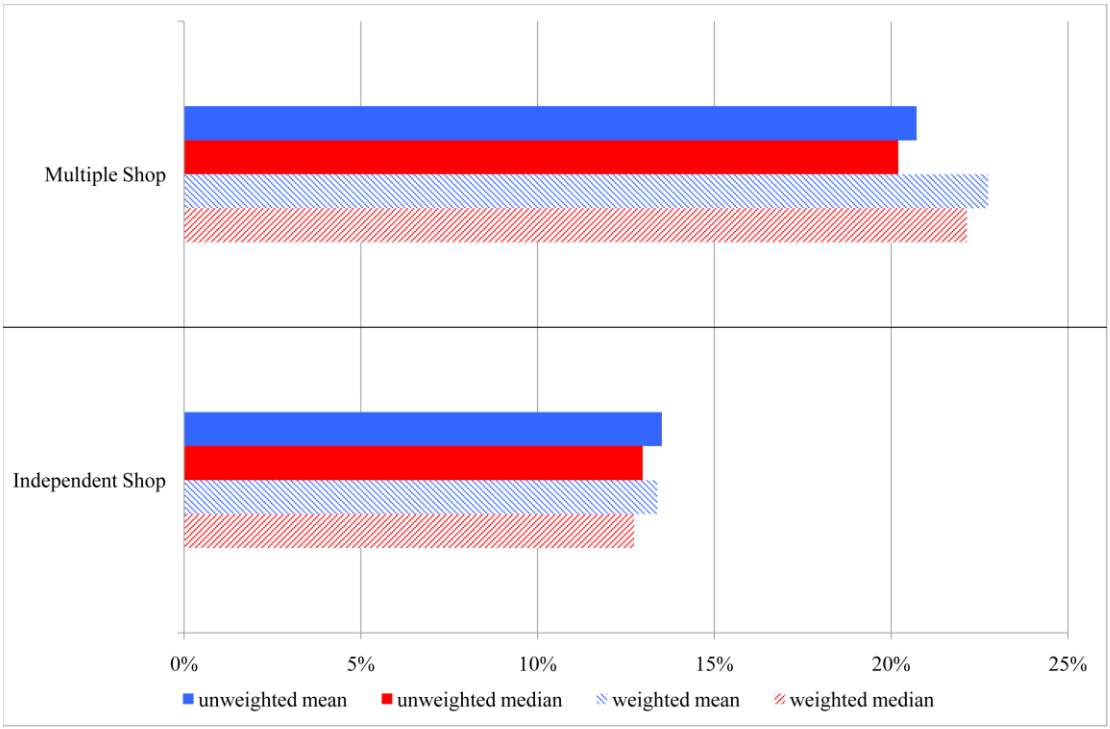
Firstly, the cross-sectional heterogeneity is significant between goods sectors and services sectors. The goods sectors tend to have higher frequency, compared to services sectors. In general, goods markets are more competitive than service markets, resulting in a higher frequency in goods sectors. By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

Figure 2 Cross-Sectional Heterogeneity in Frequency by Sector (Retailer)



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

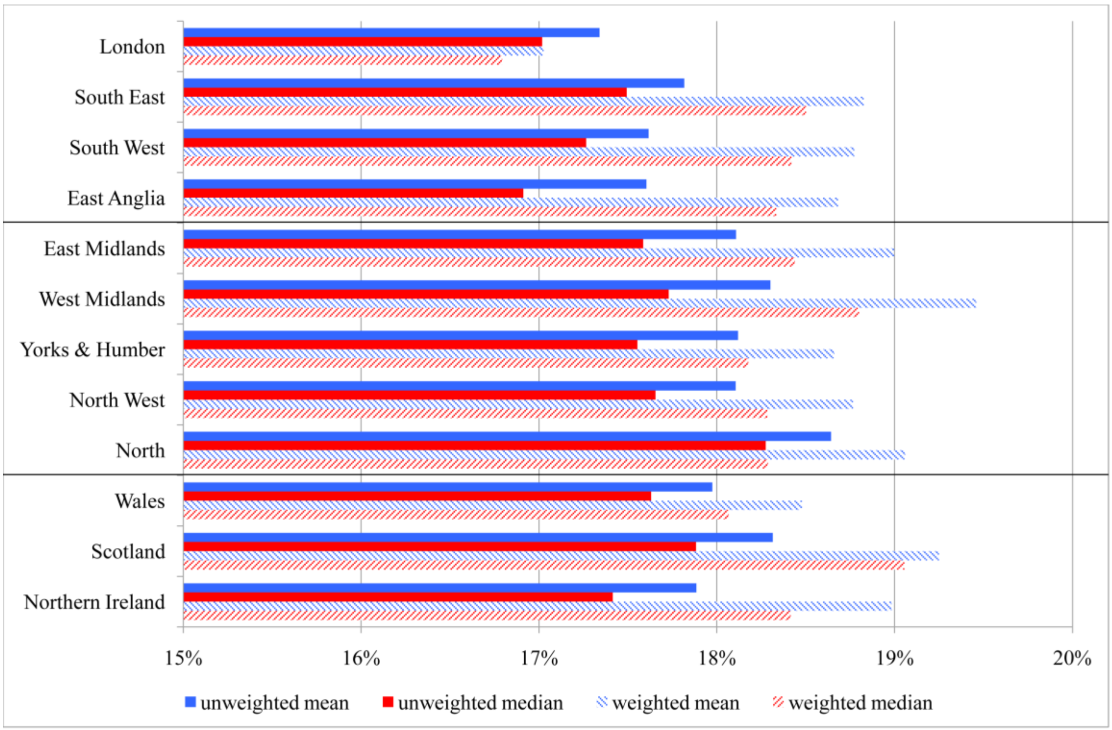
Figure 3 Cross-Sectional Heterogeneity in Frequency by Shop Type (Retailer)



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

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

Figure 4 Cross-Sectional Heterogeneity in Frequency by Region (Retailer)



4.2. Rigidity in Direction of Price Change

Another conclusion drawn from the frequency of price change is that price increases (11.03%) are more frequent than price decreases (7.59%), as shown in Figure 1. This finding is also consistent with other literatures in the US, UK and Euro area. The higher proportion of increase results from the persistent inflation over time. Hence, it should not be regarded as an evidence for the so-called "downward rigidity", which asserts that price is more difficult to adjust downward. Moreover, as shown in Figure 5, the symmetry of the distribution of price change reinforces the conclusion that there is no downward or upward rigidity. The summary of increase versus decrease of price changes is presented in Table 8.

Table 8 Direction of Retailer Price Change

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

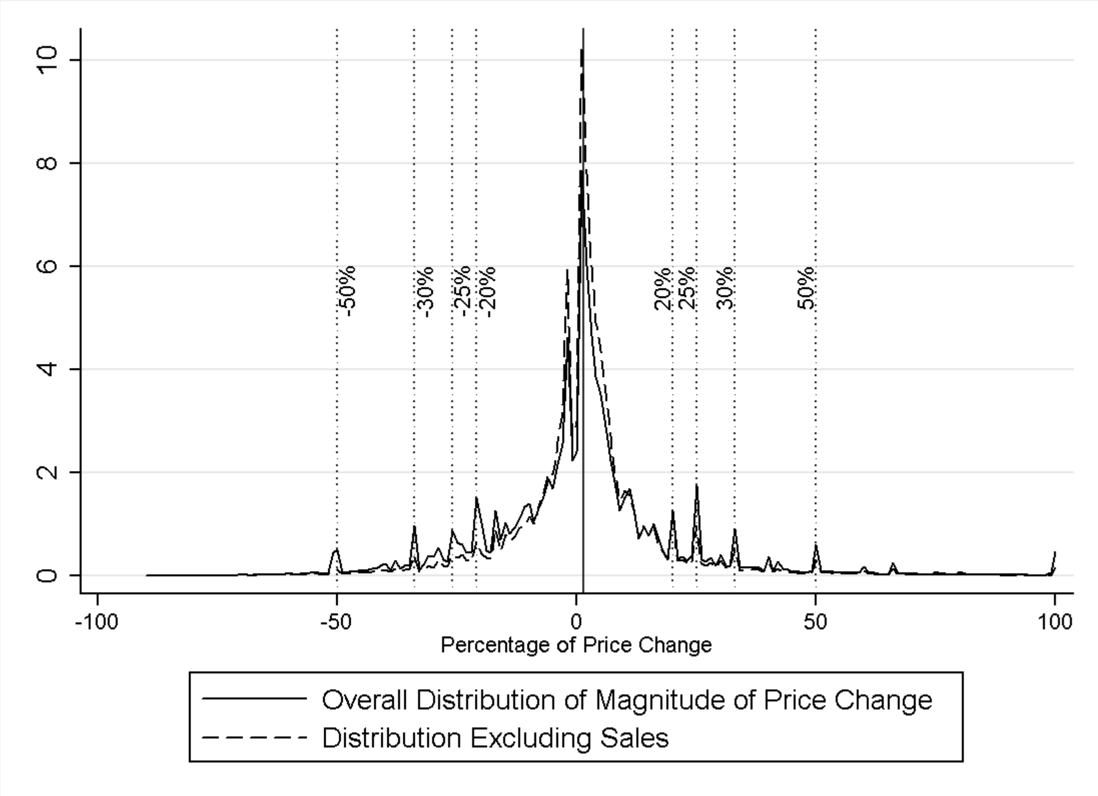
4.3. Rigidity in Magnitude of Price Change

There are two seemingly contradictory opinions on the rigidity in magnitude. On the one hand, Mankiw (1985) menu cost model provides an influential explanation on the “fixed adjustment costs” of price resetting. Similarly, Akerlof & Yellen (1985) suggest that the firm has an interval of optimal prices, rather than a point estimate of a single optimal price. It results in a so-called “band of inertia”, within which a firm will not reset its price. Only when there are big changes in the fundamentals, the firm will review its price and conduct the costly marketing research. Hence, the magnitude of price change cannot be too precise due to this “fixed adjustment costs”. If this is true, then one expects to see two interesting phenomena: (i) price levels tend to end with some particular numbers, like £X.X0, £X.X5, or £X.X9, which is referred to as “attractive pricing”; (ii) price changes tend to be integers, like 20% or 50%, rather than fractional percentage changes, like 3.1415926%. On the other hand, Rotemberg (2005) argues that the magnitude of price change cannot be too large, because it will upset the customers, and firms are reluctant to invoke this “customer anger”. If this is true, then one expects to see more small changes than large changes.

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

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

Figure 5 Distribution of Magnitude of Retailer Price Change



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

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

Table 9 Distribution of Last Decimal of Retailer Price

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

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

5. Cross-Sectional Method

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

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

5.1. Cross-Sectional Distribution of DAF

5.1.1. Overall DAF

Table 10 summarises this new method of calculating duration, in contrast with the duration implied by conventional method. The detailed distribution of DAF can be used to calibrate macroeconomic models.

Table 10 Cross-Sectional Method versus Conventional Method (Retailer)

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

Not surprisingly, DAF is much higher than duration implied by frequency. This is because the frequency is based on the oversampled short durations, as argued in Section 1. As a result, the inverse of frequency is a downward biased estimate of duration. By contrast, DAF does not have this problem. At any point in time, each product's price quote corresponds to a duration, i.e. the length of lifespan of the current price. The cross-sectional distribution of durations, or DAF, can then be obtained. The estimated mean and median of DAF are both over 9 months, much longer than the implied duration. This measure of duration strongly supports the price rigidity in frequency.

5.1.2. Time-Series Heterogeneity in DAF

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

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

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

[①] RPIX is RPI excluding mortgage interest payments.

Figure 6 Time-Series Heterogeneity in Mean DAF of Retailer Price

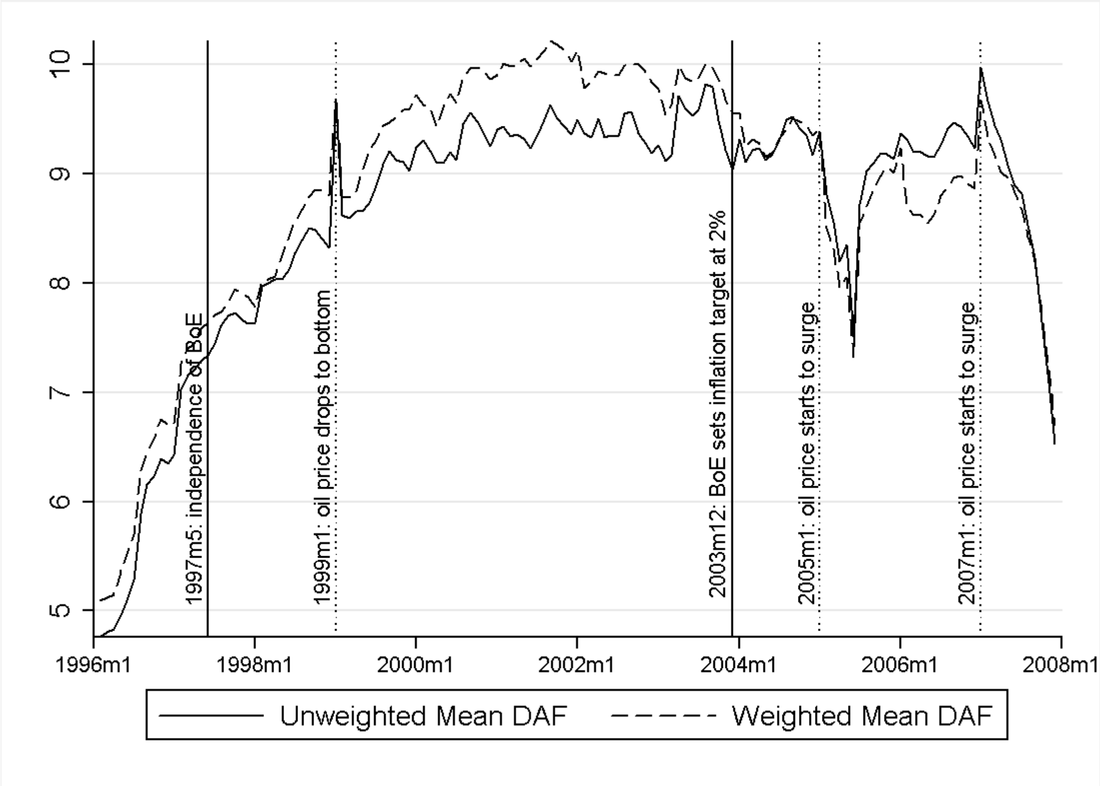


Figure 7 Time-Series Heterogeneity in Distribution of DAF of Retailer Price

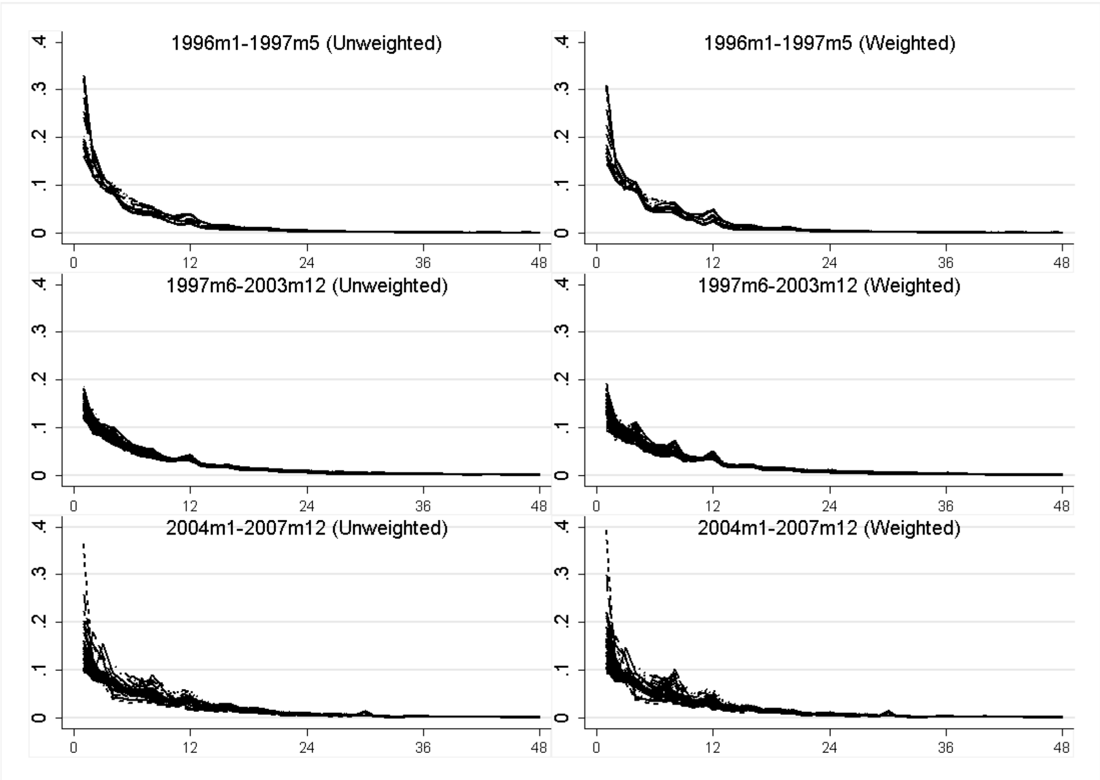
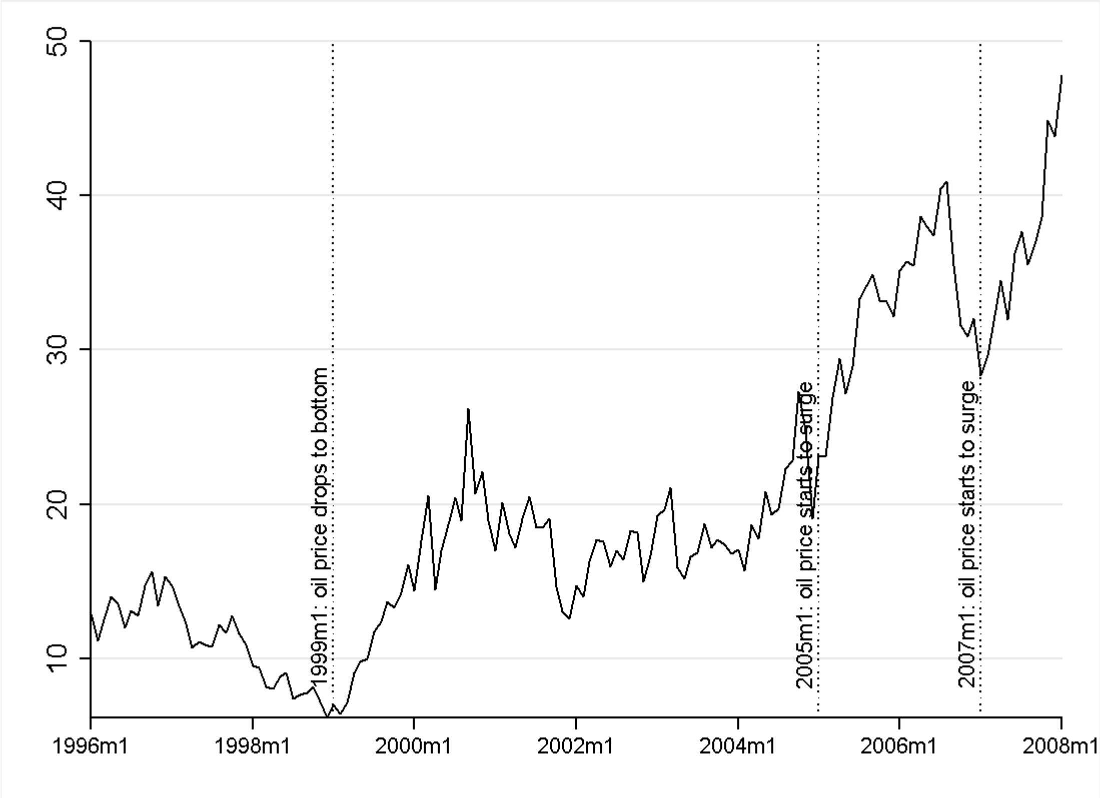


Figure 8 Crude Oil Price in Pounds



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

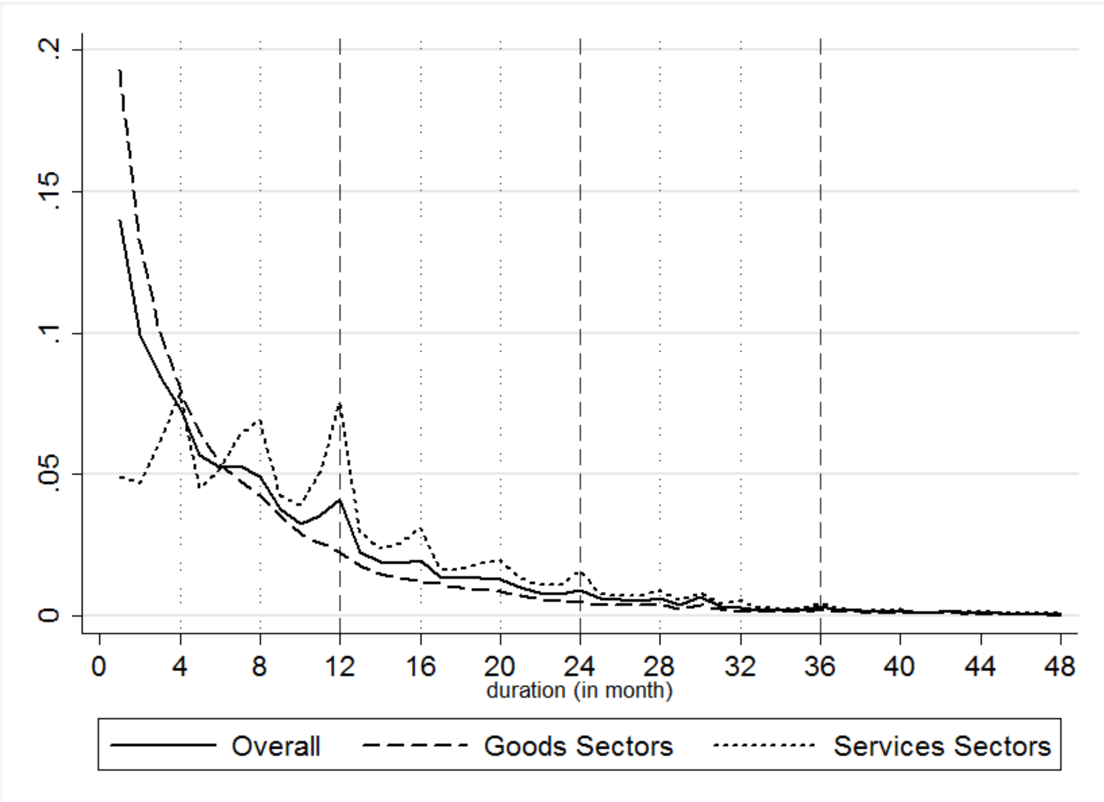
The third feature observed in the results above is that the distribution of DAF is decreasing, with typical spikes around 4 months, 8 months, and 12 months. This stylised fact indicates that at least some firms tend to reset prices at fixed time intervals, and this overall feature will be explained in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

5.1.3. Cross-Sectional Heterogeneity in DAF

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

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

Figure 9 Decomposition of Distribution of DAF of Retailer Price



5.2. Cross-Sectional Distribution of Age

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

The result of distribution of age is presented in Table 11, compared with the distribution of DAF. As expected, both the mean and median of age are less than DAF, but quite close to the duration implied by frequency in Table 10.

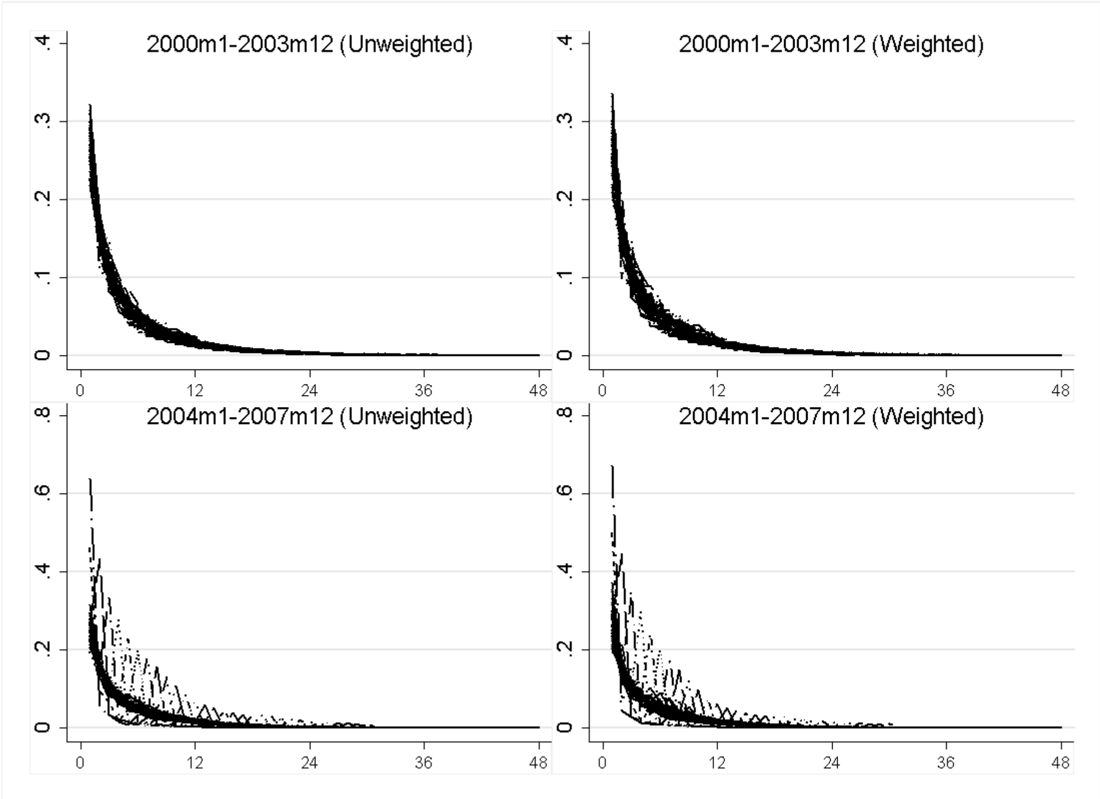
Table 11 Distribution of DAF versus Age (Retailer)

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

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

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

Figure 10 Time-Series Heterogeneity in Distribution of Age of Retailer Price



5.3. Relationship between DAF and Age

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

$$\alpha_i^A = \sum_{j=i}^{N} \frac{\alpha_j}{j}, \text{ where } i = 1, \dots, N$$

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

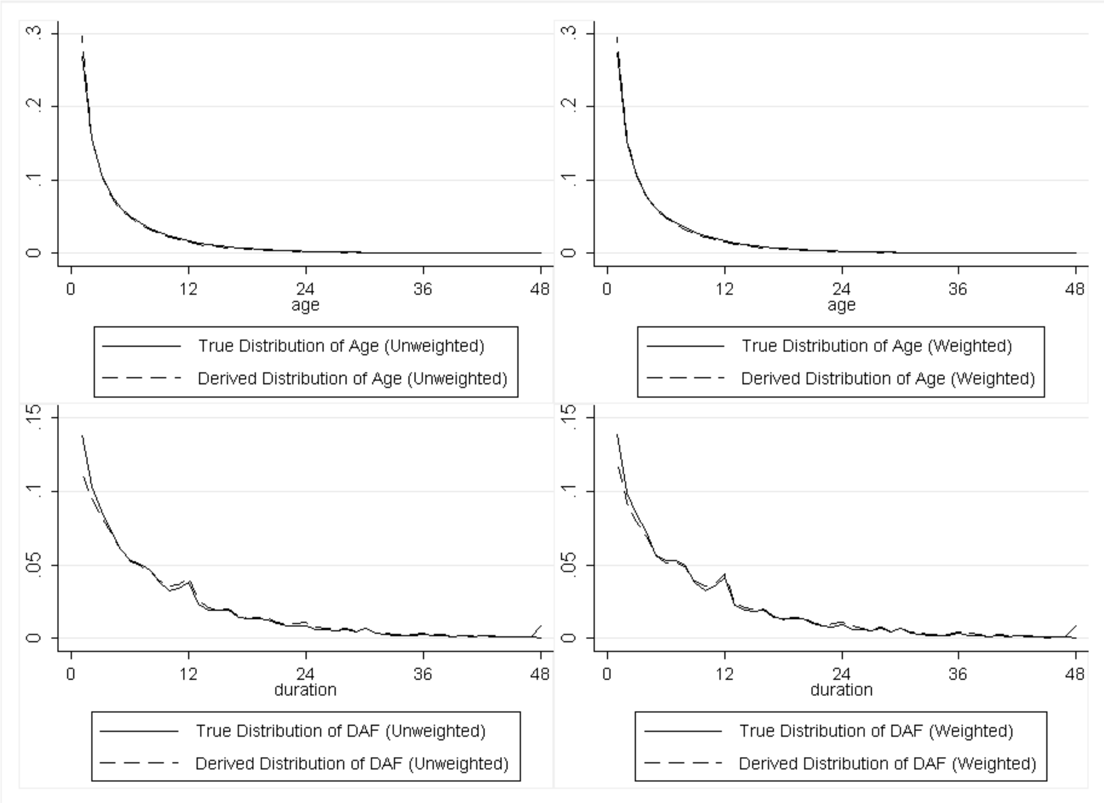
$$\begin{aligned}
&\alpha_1 = \alpha_1^A - \alpha_2^A \\
&\alpha_i = i\left(\alpha_i^A - \alpha_{i+1}^A\right), \text{ where } i = 2, \dots, N-1 \\
&\alpha_N = N\alpha_N^A
\end{aligned}$$

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

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

rived distribution of age. This simple practice successfully justifies this important theoretical contribution of Dixon (2010).

Figure 11 True and Derived Distribution of DAF and Age of Retailer Price



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

6. Survival Analysis

To describe the price setting behaviour, different methods are employed for different purposes. Two classes of measures have been covered in the previous sections for the purpose of studying price rigidity. They both focus on the *outcome* of price setting behaviour, saying little about how retailers set prices. This section diverts the perspective to hazard function $h(t)$ (and other equivalent forms) of price duration. The insight provided by the survival analysis is useful to investigate the *mechanism* of price setting behaviour, in addition to the resulting distribution of durations.

6.1. Nonparametric Analysis

This paper starts with nonparametric analysis as a connecting link with the previous sections, since nonparametric analysis does not impose any assumptions about the data generating process, except that $h(t)$ depends on time t. Hence, $h(t)$ presented in this section is closely correlated to the rigidity measures in previous sections, because time is the only extra factor considered.

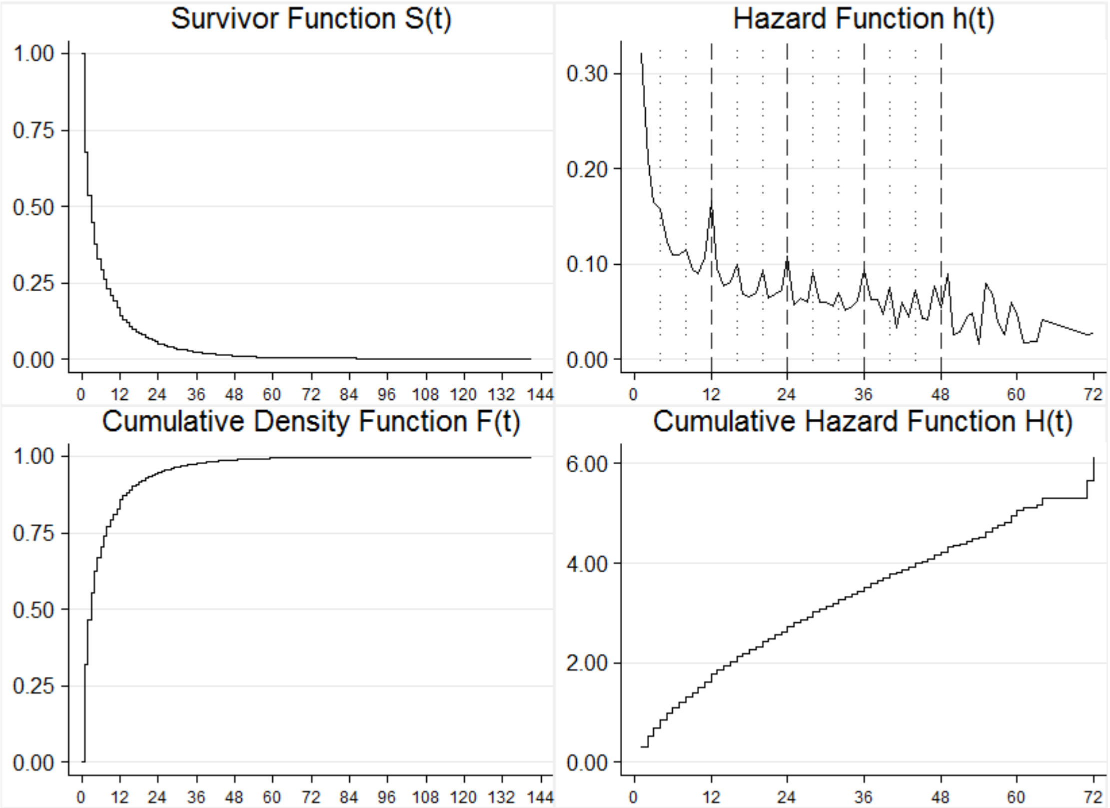
6.1.1. Pooled Hazard Function

As shown in Section 1, there are four equivalent forms of presenting the distribution of duration. It is easy to derive one from another among hazard function $h(t)$, cumulative hazard function $H(t)$, survivor function $S(t)$, and cumulative density function $F(t)$. Figure 12 shows the four equivalent forms of presenting the distribution of duration T. Since $h(t)$ is the most popular form, this paper will only focus on the features of $h(t)$. Also, the weighted and unweighted distributions do not differ qualitatively, therefore only the weighted results are reported hereinafter.

The first feature is that $h(t)$ has a downward slope in the first 72 months, starting with a quite high hazard rate, over 0.25 in our chart. This feature is also found by Bunn & Ellis (2009) and other IPN literature. $h(t)$ is omitted beyond 72 months because the standard error of the estimate is quite high. However, $h(t)$ will finally rise and reach 1, since all prices will change some day.

The second conspicuous feature of $h(t)$ is that there are regular big spikes every 12 months (major cycle) and small spikes every 4 months (minor cycle) up to 48 months. The spikes imply high risk of changing prices, so retailers tend to change prices at fixed time intervals. This is a support to time dependent models, such as Generalised Taylor Economy (GTE). In GTE model, there are many sectors with different duration lengths, and there is a Taylor process within each sector. The minor cycle in 4 months is mainly due to the periodic sales, while major cycle in 12 months may result from the annual change in contracts such as wage. Note that it is consistent with the spike pattern of the distribution of DAF.

Figure 12 Distribution Functions of Retailer Price



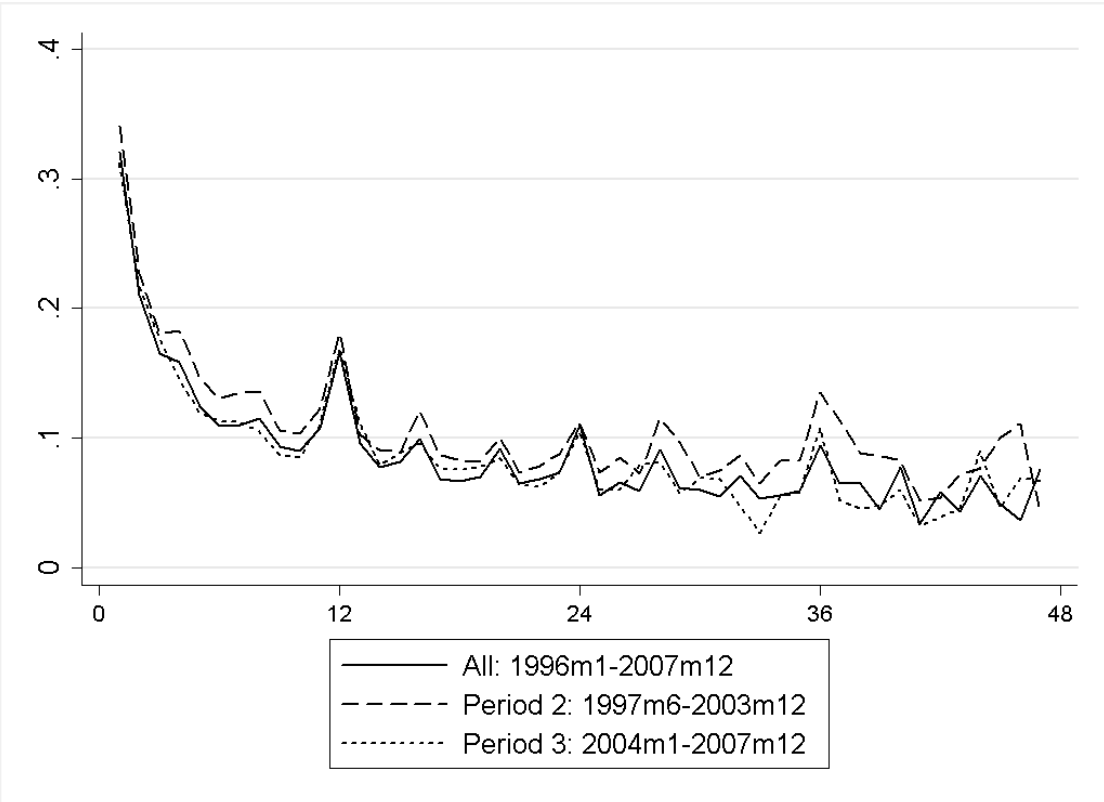
In nonparametric analysis, the object is the average price setting behaviour across the whole economy in a cross-sectional sense. One important issue of this method is that only the first non-left-truncated duration of each product is used. Once a price is reset, the duration is completed and the product leaves the analysis. One reason for this choice is that the panel is not balanced, because the price trajectories are of different lengths. Thus, if all the durations in a price trajectory are used, those with longer price trajectories will be considered more than those with shorter trajectories. Moreover, the whole dataset is too large to be utilised anyway. There are totally 12.8 million price quotes and 612,173 price trajectories. Due to the memory limit of STATA in VML, even if the panel is balanced, it is impossible to use all the data in practice. This is also the way that other studies, such as Jonker, Folkertsma & Blijenberg (2004) and Bunn & Ellis (2009), have used in survival analysis. Fortunately, thanks to a large enough sample, the estimate is still unbiased, without losing much efficiency. Furthermore, the omitted information here will be still used in studying time-series heterogeneity anyway.

6.1.2. Time-Series Heterogeneity in Hazard Function

Note that in the nonparametric analysis, $h(t)$ only varies with analysis time, not calendar time. Hence, a duration may start at any time during the whole sample period. The validity of the overall $h(t)$ depends on the stability of the price setting behavior during the sample period. Only when the true $h(t)$ does not vary significantly over the 144 months, the estimated overall $h(t)$ is meaningful.

This entitles an inspection of time-series heterogeneity in $h(t)$. This section follows the division of subperiods earlier in terms of structural breaks of monetary policy, resulting in 3 subperiods. Figure 13 shows the comparison between all periods, period 2 and period 3. Period 1 (1996m1-1997m5) is not used, because it is too short. They seem to be quite close, and share the stylised features.

Figure 13 Time-Series Heterogeneity in Hazard Function of Retailer Price



To strictly test the equality of the distributions between subperiods, the two-sample Kolmogorov-Smirnov (KS) test is employed, which is a form of minimum distance estimation used to compare two distributions. The KS statistic quantifies a distance between the empirical distribution functions of two samples. The null hypothesis of KS test is that the samples are drawn from the same distribution.

There are three distributions on hand, so all possible combinations are tested: all periods versus period 2, period 2 versus period 3, and all periods versus period 3. Table 12 summarises the results of KS tests.

Table 12 KS Test of Time-Series Heterogeneity in Hazard Function (Retailer)

	Distribution	D	P-Value	Corrected
Test 1	All	0.3611	0.0090	
	Period 2	0.0000	1.0000	
	Combined KS	0.3611	0.0180	0.0100
Test 2	Period 2	0.0000	1.0000	
	Period 3	-0.3056	0.0350	
	Combined KS	0.3056	0.0690	0.0430
Test 3	All	0.1389	0.4990	
	Period 3	-0.1111	0.6410	
	Combined KS	0.1389	0.8780	0.8250

The null hypothesis of equal distribution cannot be rejected for any of the three tests at 1% significance level. In particular, period 3 is very similar to the whole sample period with a high probability of 82.5%, which means the price setting behavior does not change much after the monetary policy reform. Hence, the time-series heterogeneity in $h(t)$ is not strong, if any.

6.1.3. Cross-Sectional Heterogeneity in Hazard Function

Apart from time-series dimension, cross-sectional heterogeneity is of interest as well. Similar to previous analysis, the retailers are classified in terms of sector, shop type, and region, to investigate the cross-sectional heterogeneity.

Firstly, the heterogeneity by sector is significant, because retailers in different sectors do follow different price setting strategy. Figure 14 graphs the $h(t)$ for different sectors, divided into goods sectors and services sectors. The key to explaining the difference across sectors is again the competitiveness of market structure.

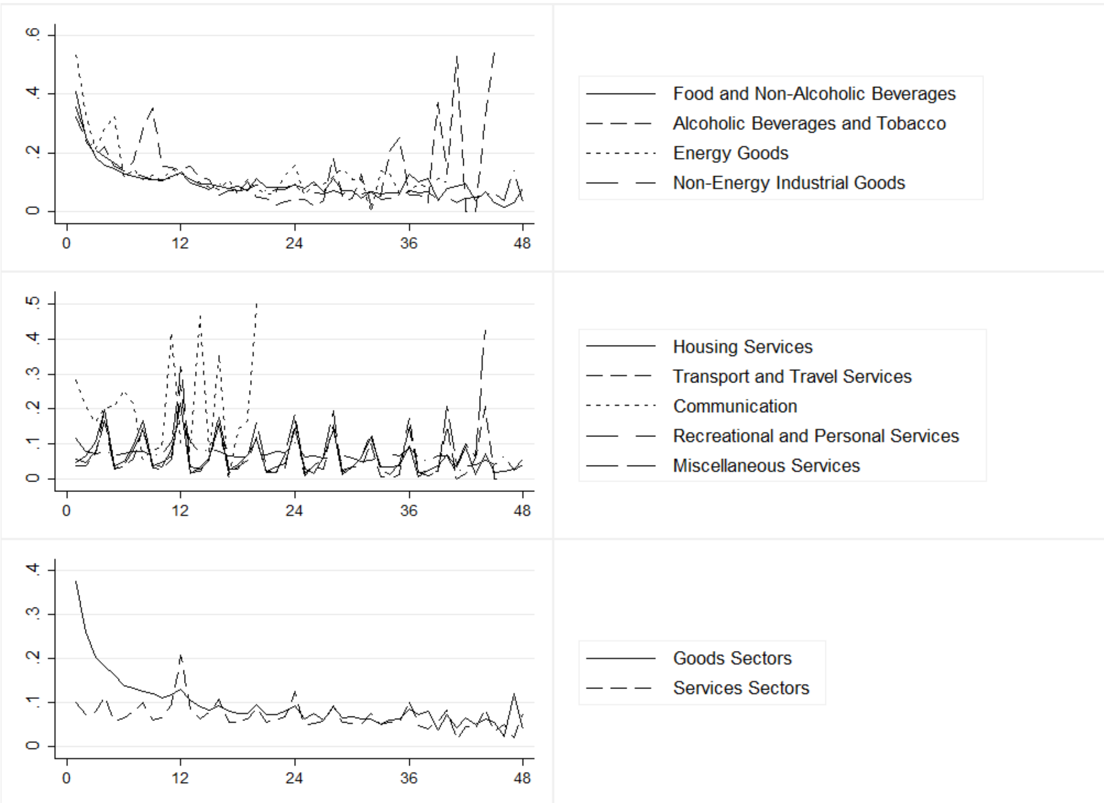
The goods sectors share a *decreasing* and *smooth* $h(t)$, with energy goods as an exception. Since goods are mostly homogeneous, the goods sectors are regarded as more competitive markets and flexible prices. As a result, a high hazard rate is observed in the short run, leading to the decreasing feature. Also, it is not necessary to follow time dependent pricing strategy, as retailers can change price at any time.

By contrast, the services sectors share a *horizontal* and *cyclical* $h(t)$, with communication as an exception. Since services are differentiated between retailers, so the market structure for services sectors is more like a monopolistic competition. The lack of competition makes the hazard rates lower in the short run and flat over a long period. Moreover, services are likely to involve contract, so the contracted price cannot change flexibly during a fixed period.

Among others, communication sector has the shortest duration, which ends within 2 years. It is because the contracts subscribed for mobile or internet services usually last 12 months or 18 months. The short duration of contracts reflects the short product life cycle and fast evolution in communication industries, but it still has a cyclical feature as other services sectors.

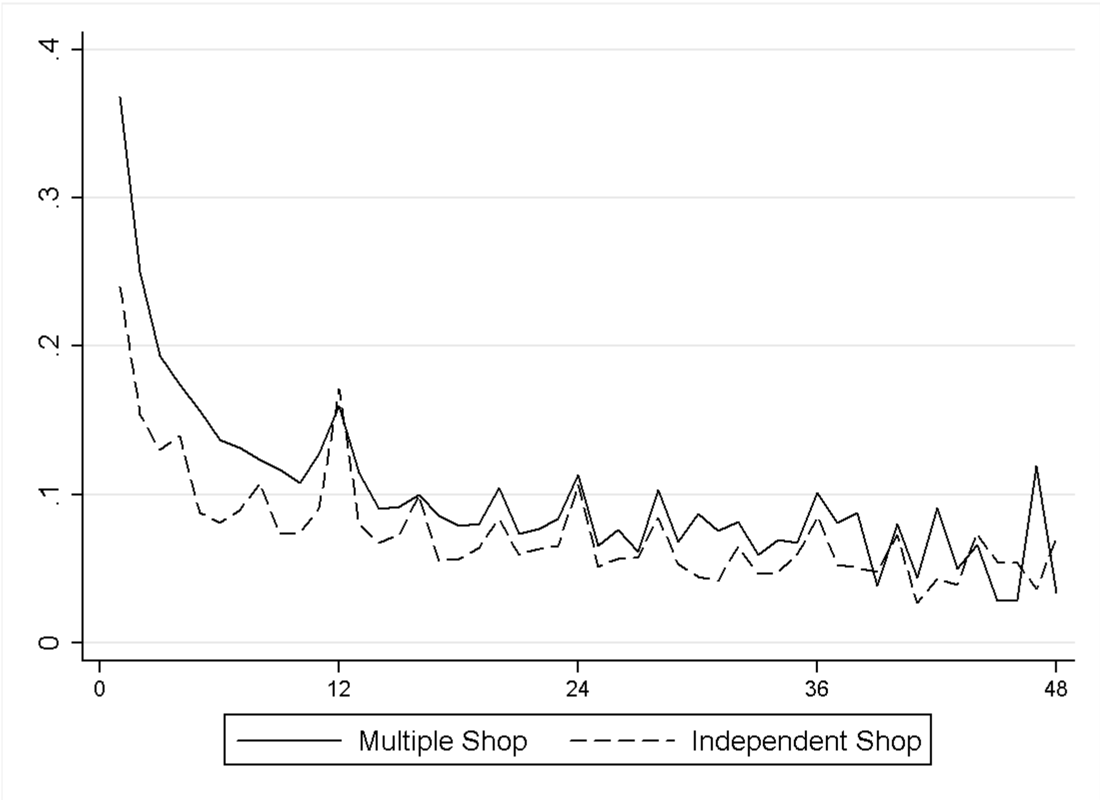
As a result, the two features of overall $h(t)$ in Figure 12 can actually be decomposed into a *decreasing* feature from goods sectors and a *cyclical* feature from services sectors. This finding can also be linked to the results in Section 1, where goods sectors reset the prices more frequently on average.

Figure 14 Cross-Sectional Heterogeneity in Hazard Function by Sector



The second cross-sectional heterogeneity in $h(t)$ exists between shop types, as shown in Figure 15. Consistent with earlier argument, multiple shops face fiercer competition from their opponents, so they have to react to changes in the market quicker and have relatively higher hazard rates than independent shops. For the same reason, their cyclical feature is weaker than the independent shops, because they have more flexible pricing strategy. The result here is consistent with the findings in frequency of price change by conventional method.

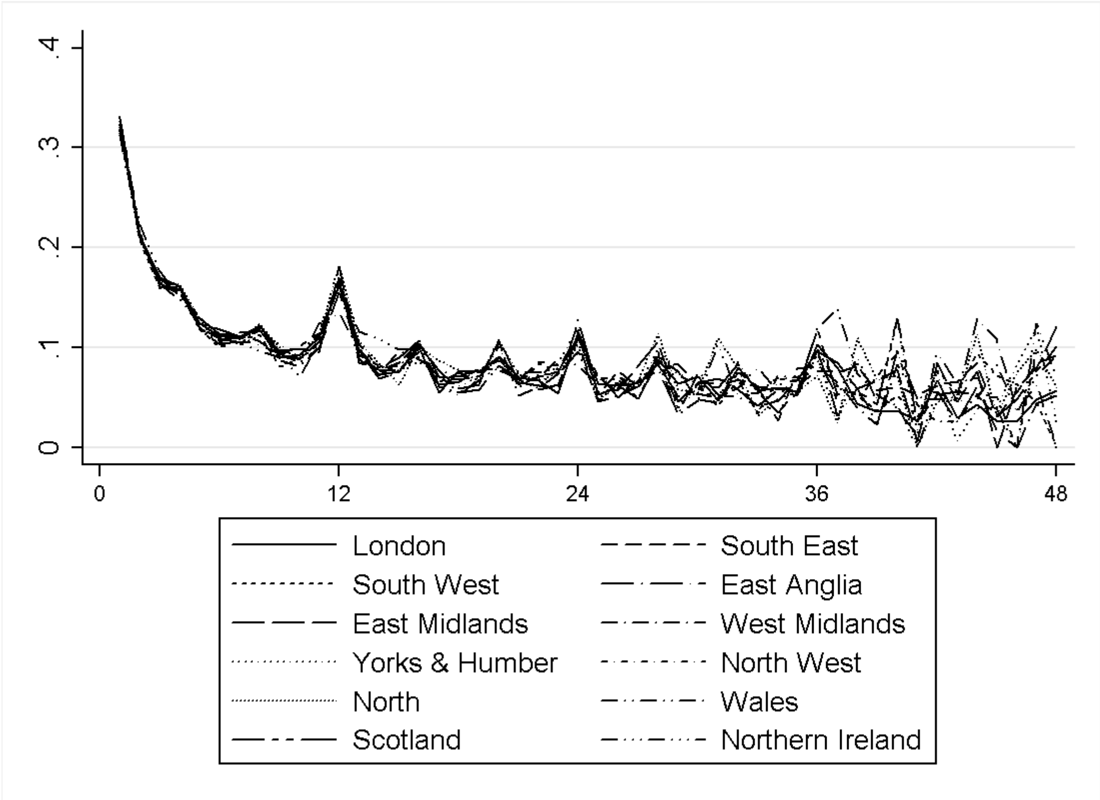
Figure 15 Cross-Sectional Heterogeneity in Hazard Function by Shop Type



The last cross-sectional heterogeneity considered is across regions, and it turns out to be little. As shown in Figure 16, $h(t)$ of the 12 government office regions are almost identical in the first 36 months. The discrepancies after 36 months are again mainly due to the decreasing sample size and increasing standard errors.

This finding seems a bit different from that in Section 1, but they are not contradictory. $h(t)$ describes the risk profile of price change in terms of time, while frequency is just a simple measure of rigidity without reference to any covariate. Some regions may have higher frequency, but it does not mean they have different pattern of risk of changing price. The pairwise KS tests also suggest that there is no difference in $h(t)$ by region at 5% significance level. With high confidence, one can conclude that $h(t)$ of the 12 regions share the same decreasing and cyclical features as the overall $h(t)$.

Figure 16 Cross-Sectional Heterogeneity in Hazard Function by Region



To summarise the nonparametric analysis, the cross-sectional heterogeneity in $h(t)$ is significant across sectors and shop types, but little across regions or periods. Decomposition of the overall $h(t)$ between *decreasing* feature (goods sectors) and *cyclical* feature (services sectors) provides detailed information of the price setting behaviour. It implies a strong need to model the economy by heterogeneous agents in theoretical model, and also a strong need to estimate $h(t)$ separately in empirical model.

6.2. Semiparametric Analysis

As shown in Section 1, the advantage of semiparametric analysis is that it controls for covariates that differ across observations, leaving the baseline hazard function $h_0(t)$ unspecified. Thus, it is more flexible and reliable in obtaining both qualitative and quantitative effects of various covariates on hazard function $h(t)$.

6.2.1. Model Specification

Based on the previous findings, there are cross-sectional and time-series heterogeneities in $h(t)$. Coupled with controls for other possible distinctions, four sets of covariates are classified in the pooled semiparametric model. There are several candidate semiparametric models, but the most popular one, the proportional hazard (PH) Cox model, is adopted.

(i) Covariates from Time Dimension: $\mathbf{x}_i$

Indeed, semiparametric analysis already uses the $h_0(t)$ to capture the common features of variation over time in $h(t)$. However, it depends on analysis time, rather than calendar time. Thus, to characterise the seasonality of $h(t)$, it is advisable to put the 11 calendar month dummies into the Cox model, where January is the reference group. Based on the significance of these dummies, the validity of time-dependent models could be checked.

(ii) Covariates from Space Dimension: $\mathbf{x}_{ii}$

To investigate the cross-sectional heterogeneity in space, 11 region dummies are also included in the model, where London is the reference group. In the nonparametric analysis, not much regional difference is found, and now this conclusion can also be checked by the significance of region dummies.

(iii) Covariates from Macroeconomic Dimension: $\mathbf{x}_{iii}$

To control for the state of the macroeconomy, both the revenue side and the cost side are considered. The revenue side of a retailer is influenced by the inflation, since the real revenue will be lower if inflation is high. The cost side is influenced by three factors: interest rate (capital costs), wage (labour costs), and oil price (resources costs). The percentage changes are used in these covariates to consider the sensitivity of price change to the volatilities. Also, both lags and leads 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.

(iv) Covariates from Microeconomic Dimension: $\mathbf{x}_{iv}$

There are several characteristics to distinguish a retailer from another, such as sector, shop type, level of price, percentage change of price and demand. The price here is the price of the specific product (good/service), and the demand is measured by the share of expenditure on a particular product of a particular retailer within the whole CPI basket, i.e. the grand weight $\omega_{i,j,k,s,t}$ as defined in Section 1. It can also be understood as the relative market share of the product across the whole economy.

The Cox model can be expressed as: $h(t) = h_0(t) \cdot \exp(\boldsymbol{\beta}_i' \mathbf{x}_i + \boldsymbol{\beta}_{ii}' \mathbf{x}_{ii} + \boldsymbol{\beta}_{iii}' \mathbf{x}_{iii} + \boldsymbol{\beta}_{iv}' \mathbf{x}_{iv})$, where $\mathbf{x}_i, \mathbf{x}_{ii}, \mathbf{x}_{iii}, \mathbf{x}_{iv}$ are the four sets of covariates, and $\boldsymbol{\beta}_i, \boldsymbol{\beta}_{ii}, \boldsymbol{\beta}_{iii}, \boldsymbol{\beta}_{iv}$ are the corresponding coefficient vectors. Two notes for $\mathbf{x}_{iii}$ are due. Firstly, the absolute values of percentage changes[①] for the covariates are used, because this section focuses on the price change without specifying increase or decrease, on the ground that there is little rigidity in direction of price change as shown in Section 1. The second issue is that, many papers[②] also consider other macroeconomic covariates, such as Euro changeover and VAT change. However, there were no such changes during our sample period (1996m1-2007m12) in the UK. Hence, it is not necessary to consider these covariates.

Firstly, a pooled Cox model is estimated for all sectors and all years. Based on the nonparametric analysis results, there is a significant cross-sectional heterogeneity in $h(t)$ across sectors. In particular, goods sectors tend to have decreasing and smooth $h(t)$, while services sectors share a horizontal and cyclical $h(t)$. Also, energy sector and communication sector are quite special, entailing separate estimation. Thus, the Cox models for goods sectors excluding energy, services sectors excluding communication, energy sector and communication sector are estimated separately. The estimation results of pooled and separate Cox models are reported in Table 13 and Table 14.

To check whether there is time-series heterogeneity in $h(t)$ across periods, the Cox models for period 2 (1997m6-2003m12) and for period 3 (2004m1-2007m12) are also estimated separately. The estimation for period 1 (1996m1-1997m5) is not used, because the sub-sample period is not long enough and observations are too few to generate meaningful estimates. The results are summarised in Table 15 and Table 16.

① Note that inflation itself is the percentage change, so we just use the absolute values of inflation directly. Interest rate itself is a percentage, so the absolute values of changes in interest rate are used.
② For example, Jonker et al (2004) use VAT in the Cox model, while Aucremanne and Dhyne (20005) use VAT in the logit model. Almost all the IPN literatures consider the Euro change in 2002m1.

Table 13 Estimation Results of Pooled and Separate Cox Model by Sector (Part A)

		Pooled		Goods sectors excluding Energy		Services sectors excluding Communication		Energy		Communication	
		H. R.	**Coeff.**	**H. R.**	**Coeff.**	**H. R.**	**Coeff.**	**H. R.**	**Coeff.**	**H. R.**	**Coeff.**
Covariates from Time Dimension	**February**	0.7386**	-0.3030**	0.8219**	-0.1961**	0.5216**	-0.6509**	0.7525*	-0.2844*	0.6684	-0.4029
	March	0.8001**	-0.2230**	0.8397**	-0.1747**	0.6999**	-0.3568**	1.2306	0.2075	0.9112	-0.0929
	April	0.8819**	-0.1257**	0.8952**	-0.1107**	0.7516**	-0.2856**	1.7705**	0.5712**	0.9649	-0.0358
	May	0.8331**	-0.1826**	0.8019**	-0.2208**	0.9215**	-0.0817**	2.0940**	0.7391**	0.7840	-0.2433
	June	0.7836**	-0.2438**	0.8028**	-0.2196**	0.7358**	-0.3067**	1.3441**	0.2957**	0.8863	-0.1207
	July	0.8361**	-0.1790**	0.9174**	-0.0862**	0.5718**	-0.5590**	1.5283**	0.4242**	0.9741	-0.0263
	August	0.6967**	-0.3614**	0.7683**	-0.2636**	0.4703**	-0.7543**	1.1068	0.1015	1.0789	0.0759
	September	0.6904**	-0.3704**	0.7300**	-0.3148**	0.5220**	-0.6501**	1.5495**	0.4379**	0.5197*	-0.6545*
	October	0.7762**	-0.2534**	0.8106**	-0.2100**	0.6135**	-0.4886**	2.1013**	0.7425**	1.1778	0.1637
	November	0.7537**	-0.2828**	0.7916**	-0.2337**	0.5853**	-0.5357**	1.7168**	0.5405**	0.8203	-0.1980
	December	0.7393**	-0.3020**	0.8104**	-0.2102**	0.4826**	-0.7285**	1.3210**	0.2784**	1.2570	0.2287
Covariates from Space Dimension	**South East**	0.9997	-0.0003	1.0025	0.0025	1.0026	0.0026	0.9529	-0.0482	0.7414*	-0.2992*
	South West	0.9903	-0.0097	1.0001	0.0001	0.9627*	-0.0380*	0.8944*	-0.1116*	0.8160	-0.2034
	East Anglia	0.9728**	-0.0276**	0.9808*	-0.0194*	0.9276**	-0.0752**	0.8972*	-0.1085*	0.8522	-0.1600
	East Midlands	1.0197*	0.0195*	1.0250**	0.0247**	1.0181	0.0179	0.9151	-0.0887	0.9360	-0.0662
	West Midlands	1.0236**	0.0234**	1.0259**	0.0255**	1.0108	0.0107	0.9800	-0.0202	0.8648	-0.1453
	Yorks & Humber	1.0014	0.0014	1.0033	0.0033	0.9930	-0.0070	0.9838	-0.0163	0.8928	-0.1133
	North West	1.0205**	0.0203**	1.0180*	0.0179*	1.0343	0.0337	0.9729	-0.0274	0.8504	-0.1620
	North	1.0178	0.0176	1.0238*	0.0235*	1.0068	0.0068	0.9022	-0.1029	0.8843	-0.1230
	Wales	0.9929	-0.0071	0.9982	-0.0018	0.9928	-0.0072	0.8300**	-0.1863**	0.9384	-0.0636
	Scotland	1.0102	0.0102	1.0121	0.0120	1.0151	0.0150	0.9228	-0.0803	0.7950	-0.2294
	Northern Ireland	0.9968	-0.0032	0.9997	-0.0003	0.9826	-0.0176	0.8266	-0.1905	0.9573	-0.0436

Notes: * denotes 5% significance level. ** denotes 1% significance level. H. R. denotes hazard ratio, which is equal to $\exp(coeff)$.

Table 14 Estimation Results of Pooled and Separate Cox Model by Sector (Part B)

		Pooled		Goods sectors excluding Energy		Services sectors excluding Communication		Energy		Communication	
		H. R.	**Coeff.**	**H. R.**	**Coeff.**	**H. R.**	**Coeff.**	**H. R.**	**Coeff.**	**H. R.**	**Coeff.**
Covariates from Macroeconomic Dimension	**Inflation t**	0.9978	-0.0022	0.9990	-0.0010	0.8849**	-0.1223**	1.3050**	0.2662**	1.3806	0.3225
	Inflation t-1	1.0520**	0.0507**	1.0532**	0.0518**	1.0132**	0.0131**	1.9294**	0.6572**	1.8299	0.6043
	Inflation t+1	0.8901**	-0.1164**	0.8918**	-0.1145**	0.9054**	-0.0994**	0.8546	-0.1571	0.8547	-0.1570
	Interest Rate (Δ) t	0.9303**	-0.0723**	0.9314**	-0.0710**	0.8563**	-0.1551**	1.1891	0.1732	0.8384	-0.1763
	Interest Rate (Δ) t-1	1.1409**	0.1318**	1.0853**	0.0819**	1.3396**	0.2923**	1.3960**	0.3336**	0.6903	-0.3707
	Interest Rate (Δ) t+1	0.8558**	-0.1558**	0.8731**	-0.1357**	0.8776**	-0.1306**	0.7882*	-0.2380*	0.6980	-0.3596
	Wage (%Δ) t	1.0275	0.0271	0.9827	-0.0174	1.2003**	0.1826**	0.8915	-0.1149	2.0309**	0.7085**
	Wage (%Δ) t-1	1.0101	0.0100	1.0494**	0.0482**	0.8892**	-0.1174**	0.9711	-0.0293	1.0966	0.0922
	Wage (%Δ) t+1	1.1072**	0.1019**	1.1220**	0.1151**	1.1442**	0.1347**	0.8679	-0.1417	0.9853	-0.0148
	Oil Price (%Δ) t	0.9950**	-0.0050**	1.0001	0.0001	0.9751**	-0.0253**	1.4981**	0.4042**	0.9610	-0.0397
	Oil Price (%Δ) t-1	0.9971**	-0.0029**	0.9927**	-0.0074**	1.0209**	0.0207**	1.1423**	0.1331**	1.0406	0.0398
	Oil Price (%Δ) t+1	1.0077**	0.0076**	1.0065**	0.0065**	1.0087**	0.0086**	1.5375**	0.4302**	0.9899	-0.0102
Covariates from Microeconomic Dimension	**Alcoholic/Beverage**	1.0135	0.0134	1.0401**	0.0393**	–	–	–	–	–	–
	Energy	1.7440**	0.5562**	–	–	–	–	–	–	–	–
	Non-Energy	0.7242**	-0.3227**	0.7269**	-0.3189**	–	–	–	–	–	–
	Housing	0.5196**	-0.6547**	–	–	–	–	–	–	–	–
	Transport/Travel	0.4997**	-0.6938**	–	–	1.0134	0.0133	–	–	–	–
	Communication	0.7711**	-0.2599**	–	–	–	–	–	–	–	–
	Recreation/Personal	0.5564**	-0.5863**	–	–	1.1548**	0.1439**	–	–	–	–
	Miscellaneous	0.5239**	-0.6465**	–	–	1.0351	0.0345	–	–	–	–
	Independent Shop	0.9210**	-0.0823**	0.9473**	-0.0541**	0.8330**	-0.1827**	0.9241**	-0.0789**	0.7566**	-0.2789**
	Price	1.0002**	0.0002**	1.0002**	0.0002**	1.0006**	0.0006**	1.0035**	0.0035**	1.0034*	0.0034*
	Price (%Δ)	1.0000**	0.0000**	1.0000**	0.0000**	1.0006**	0.0006**	1.0128**	0.0128**	1.0012	0.0012
	Sales	2.6936**	0.9909**	2.6267**	0.9657**	3.6455**	1.2935**	1.3450**	0.2964**	2.8898**	1.0612**
	Market Share	14.5700**	2.6790**	1.5093*	0.4116*	24.735**	3.2082**	3.9447**	1.3724**	9.3169	2.2318

Notes: * denotes 5% significance level. ** denotes 1% significance level. H. R. denotes hazard ratio, which is equal to $\exp(coeff)$.

Table 15 Estimation Results of Separate Cox Model by Period (Part A)

		Goods sectors excluding Energy			Services sectors excluding Communication			Energy		
		All	**Period 2**	**Period 3**	**All**	**Period 2**	**Period 3**	**All**	**Period 2**	**Period 3**
Covariates from Time Dimension	**February**	-0.1961**	-0.1113**	-0.1328**	-0.6509**	-0.5050**	-0.6542**	-0.2844*	-0.1818	0.1092
	March	-0.1747**	-0.0951**	-0.2730**	-0.3568**	-0.2805**	-0.3832**	0.2075	0.2593	0.7480*
	April	-0.1107**	-0.1709**	-0.1464**	-0.2856**	-0.3582**	-0.2652**	0.5712**	0.7092**	1.2945**
	May	-0.2208**	-0.2457**	0.0376	-0.0817**	-0.1268**	-0.2023**	0.7391**	0.9686**	0.7516**
	June	-0.2196**	-0.2430**	0.0504	-0.3067**	-0.3791**	-0.0881	0.2957**	0.2455	0.7054*
	July	-0.0862**	-0.0276	-0.0506	-0.5590**	-0.5395**	-0.4934**	0.4242**	0.7525**	0.7487*
	August	-0.2636**	-0.2016**	-0.0304	-0.7543**	-0.4807**	-0.7838**	0.1015	0.3367*	0.2881
	September	-0.3148**	-0.1586**	-0.0904**	-0.6501**	-0.5693**	-0.2998**	0.4379**	0.6269**	0.3369
	October	-0.2100**	-0.1749**	-0.2401**	-0.4886**	-0.4099**	-0.3451**	0.7425**	0.8250**	1.1255**
	November	-0.2337**	-0.1605**	0.0843**	-0.5357**	-0.4839**	-0.1392*	0.5405**	0.3779*	0.7259*
	December	-0.2102**	-0.2889**	-0.0134	-0.7285**	-0.8752**	-0.2963**	0.2784**	-0.2160	-0.0470
Covariates from Space Dimension	**South East**	0.0025	-0.0238*	-0.0027	0.0026	-0.0446*	0.0381	-0.0482	-0.0768	0.0559
	South West	0.0001	-0.0298**	0.0317*	-0.0380*	-0.1058**	0.0601*	-0.1116*	-0.1380*	0.0044
	East Anglia	-0.0194*	-0.0262*	0.0348*	-0.0752**	-0.0512	-0.0558	-0.1085*	-0.1520*	0.0508
	East Midlands	0.0247**	0.0141	0.0421**	0.0179	0.0133	0.0221	-0.0887	-0.1125	-0.0700
	West Midlands	0.0255**	0.0041	0.0809**	0.0107	0.0001	0.0233	-0.0202	-0.0481	0.0722
	Yorks & Humber	0.0033	-0.0100	0.0602**	-0.0070	-0.0439	0.0098	-0.0163	-0.0327	-0.0887
	North West	0.0179*	0.0039	0.0622**	0.0337	0.0542*	0.0402	-0.0274	-0.0878	0.0916
	North	0.0235*	0.0191	0.0826**	0.0068	-0.0147	0.0433	-0.1029	-0.1405*	0.0384
	Wales	-0.0018	0.0009	0.0593**	-0.0072	-0.0669*	0.1584**	-0.1863**	-0.1164	-0.1220
	Scotland	0.0120	0.0008	0.0618**	0.0150	0.0269	0.0334	-0.0803	-0.1130	0.0588
	Northern Ireland	-0.0003	-0.0049	0.0539**	-0.0176	-0.1183**	0.0728	-0.1905	-0.1894**	-0.1405

Notes: * denotes 5% significance level. ** denotes 1% significance level. Period 2: 1997m6-2003m12. Period 3: 2004m1-2007m12.

Table 16 Estimation Results of Separate Cox Model by Period (Part B)

		Goods sectors excluding Energy			Services sectors excluding Communication			Energy		
		All	Period 2	Period 3	All	Period 2	Period 3	All	Period 2	Period 3
Covariates from Macroeconomic Dimension	**Inflation t**	-0.0010	-0.0892**	-0.0824*	-0.1223**	0.2861**	-0.2916**	0.2662**	-0.0970	0.6199
	Inflation t-1	0.0518**	0.0606**	-0.0432	0.0131**	-0.2648**	0.2060**	0.6572**	0.3498**	-0.1105
	Inflation t+1	-0.1145**	-0.0778**	-0.2654**	-0.0994**	0.2099**	-0.6314**	-0.1571	0.2504	-0.8754*
	Interest Rate (Δ) t	-0.0710**	-0.0875**	-0.7063**	-0.1551**	-0.2337**	-0.8313**	0.1732	0.2686	-0.5542
	Interest Rate (Δ) t-1	0.0819**	0.0710**	-0.1302*	0.2923**	0.1157	0.4527**	0.3336**	1.0576**	0.4771
	Interest Rate (Δ) t+1	-0.1357**	-0.0188	-0.5975**	-0.1306**	-0.2242**	-1.0383**	-0.2380*	-0.2161	-0.2939
	Wage (%Δ) t	-0.0174	-0.0479*	0.2098**	0.1826**	0.0998	0.2303*	-0.1149	0.1719	-1.8409**
	Wage (%Δ) t-1	0.0482**	0.0436**	0.0496**	-0.1174**	0.0065	-1.1555**	-0.0293	-0.0445	-0.6744
	Wage (%Δ) t+1	0.1151**	0.0425**	0.1982**	0.1347**	0.2084**	0.7923**	-0.1417	-0.1812	0.8985*
	Oil Price (%Δ) t	0.0001	-0.0017	-0.0110**	-0.0253**	0.0003	-0.0831**	0.4042**	0.1262**	0.5197**
	Oil Price (%Δ) t-1	-0.0074**	-0.0057**	-0.0075**	0.0207**	0.0243**	0.0504**	0.1331**	0.0808**	0.3497**
	Oil Price (%Δ) t+1	0.0065**	0.0049**	0.0206**	0.0086**	-0.0480**	0.0354**	0.4302**	0.2891**	0.4907**
Covariates from Microeconomic Dimension	**Alcoholic/Beverage**	0.0393**	0.0820**	0.1687**	–	–	–	–	–	–
	Energy	–	–	–	–	–	–	–	–	–
	Non-Energy	-0.3189**	-0.3393**	-0.2681**	–	–	–	–	–	–
	Housing	–	–	–	–	–	–	–	–	–
	Transport/Travel	–	–	–	0.0133	-0.0429	0.0967**	–	–	–
	Communication	–	–	–	–	–	–	–	–	–
	Recreation/Personal	–	–	–	0.1439**	0.0880**	0.2226**	–	–	–
	Miscellaneous	–	–	–	0.0345	-0.0024	0.0778**	–	–	–
	Independent Shop	-0.0541**	-0.0463**	-0.0896**	-0.1827**	-0.1739**	-0.2167**	-0.0789**	-0.1179**	-0.0669
	Price	0.0002**	0.0001**	0.0001**	0.0006**	0.0007**	0.0005**	0.0035**	0.0044**	0.0031**
	Price (%Δ)	0.0000**	0.0000**	0.0022**	0.0006**	0.0005**	0.0018**	0.0128**	0.0179**	0.0120**
	Sales	0.9657**	0.9762**	0.9873**	1.2935**	1.3339**	1.1397**	0.2964**	0.4227**	0.3441**
	Market Share	0.4116*	2.4819**	2.4705**	3.2082**	2.6115**	4.1390**	1.3724**	1.8564**	2.7682**

Notes: * denotes 5% significance level. ** denotes 1% significance level. Period 2: 1997m6-2003m12. Period 3: 2004m1-2007m12.

6.2.2. Pooled Cox Model

The estimation results of pooled Cox model is reported in the first two columns of Table 13 and Table 14. It is to model the overall price setting behaviour, assuming there is no significant cross-sectional and time-series heterogeneity in $h_0(t)$. This assumption will be examined later, but some conclusions, which are robust to this assumption, can still be drawn.

Firstly, January, the reference group for calendar months, has the highest probability of price change, because all the other calendar month dummies have negative signs. A direct reason is that Christmas sales typically last until January. This result is consistent with our earlier finding for rigidity in frequency. April, the beginning of each tax year, seems to have the highest hazard rate among the other months. In addition, all the 11 calendar month dummies are significant, which strongly supports the time-dependent models.

Secondly, as expected, there is little evidence for heterogeneity by region, since only 4 region dummies are significant. However, a familiar feature is still recognisable, i.e. the north (including Scotland) tends to have higher $h(t)$ than the south. This finding is again consistent with the corresponding result for rigidity in frequency.

The third conclusion is that the retailer is sensitive to changes in macroeconomic state. In particular, the reaction to the four sets of macroeconomic state variables is studied, and the retailer seems to respond to information using both backward looking expectations and forward looking expectations.

(i) Inflation:

The retailer is not significantly sensitive to the current inflation, but it positively reacts to the absolute value of inflation last period (0.0507) and negatively to that next period (-0.1164). It may result from lack of information on inflation, so the retailer prefers to change the price after the precise information is available.

(ii) Interest Rate:

This feature of price setting behaviour is also found when the retailer faces interest rate changes. The only difference is that the retailer does have precise information on the current interest rate, leading to a significant coefficient on current changes in interest rate too. Furthermore, the negative coefficients on the current (-0.0723) and future (-0.1558) changes in interest rate are coherent in logic with the positive coefficient on the current (0.1318) change in interest rate. Obviously, if a change in interest rate is only reacted after one period, the probability of price change is then relatively lower when the change in interest rate actually occurs or expected to occur.

(iii) Wage:

By contrast, the response to changes in wage is only significant for the future values. It shows that the retailer has quite reliable information and bargaining power on wage, and it adjusts price based on *forward* looking expectations. Hence, the past and current changes in wage hardly affect the price setting.

(iv) Oil Price:

The last factor introduced by this chapter is the volatility of resource price, proxied by oil price, which seems to play an essential role in price setting when studying the distribution of DAF. Indeed, all the related coefficients are highly significant. The past (-0.0029) and current (-0.0050) changes in oil price both have negative effect, while the effect of future (0.0076) change is positive. This pattern is similar to wage, but different from inflation and interest rate. It may be attributed to the developed commodity markets based on financial derivatives, which reduced the uncertainty of oil price in the future.

The last but not least conclusion is that microeconomic covariates play important role in price setting behaviour. As expected, the coefficients of sector and shop type dummies are significant. In particular, goods sectors have higher $h(t)$ than the services sectors. The highest is energy good, which must be treated as an exception in goods sectors. Also, communication service is the highest among all the services sectors, and it should be treated as an exception in the services sectors and estimated separately. Moreover, independent shops have lower $h(t)$, compared to multiple shops. In addition, the level of price and the (absolute) percentage change of price have little but positive effect on $h(t)$. The two positive coefficients suggest that higher price levels give more space of price change, and that there is a positive relationship between frequency and the magnitude of price change. Items on sales have much higher probability to change price. Next, the elasticity of the hazard rate on the demand (described by the market share) is as high as 14.57. It means that if the "grand" market share of a particular item of a particular retailer grows 1% (which is very huge), then the hazard rate of price change will be 14.57 times higher than before. It actually reflects the difference between independent shops and multiple shops from another perspective, since an independent shop would become a multiple shop if its market share increases by 1%.

6.2.3. Separate Cox Model by Sector

Since remarkable differences in $h(t)$ are observed between goods sectors and services sectors, there is no such a common $h_0(t)$ underlying both sectors. However, there is indeed a similarity within goods sectors except for energy and within services sectors except for communication. Thus, it is advisable to run at least four separate Cox models for goods sectors excluding energy, services sectors excluding communication, energy sector itself and communication sector itself. The results are listed in the rest columns of Table 13 and Table 14. Note that a key principle to explain the effect of macroeconomic covariates is the *input intensity*.

The results for goods sectors are almost the same as the pooled model, but some new features emerge. The calendar month with the second highest hazard rate is not April but July now, because the summer sales are usually in July, which is the second biggest shopping season next to Christmas sales in January. It shows one of the special features in seasonality of goods sectors. The difference across regions is little. The effects of state variables are quite similar to pooled Cox model, except for slight differences in magnitude and significance. One exception is that the effect of shop type is greater for goods sectors than services sectors. That is to say, being a multiple shop is more important for a retailer in goods sectors than that in services sectors. Another exception is that the effect of past change in wage is now positive, implying that goods sectors have lagged response to labour costs. It may be because goods sectors in the UK are mainly *capital intensive*, so retailers are relatively insensitive to the changes in labour market.

The separate Cox model for services sectors excluding communication is a bit more different in several aspects. The foremost difference is still in seasonality. Compared to April for the pooled model and July for the goods sectors, May is the month with the second highest hazard rate. The gap between January and May is just 4 months, which may be related with the minor cycle observed in services sectors. Regarding the state variables, an important difference is the effect of past change in wage, which is negative. With the same argument, services sectors are mainly *labour intensive*, so changes in wage are quickly reacted to, and the effect of past changes in wage has less effect.

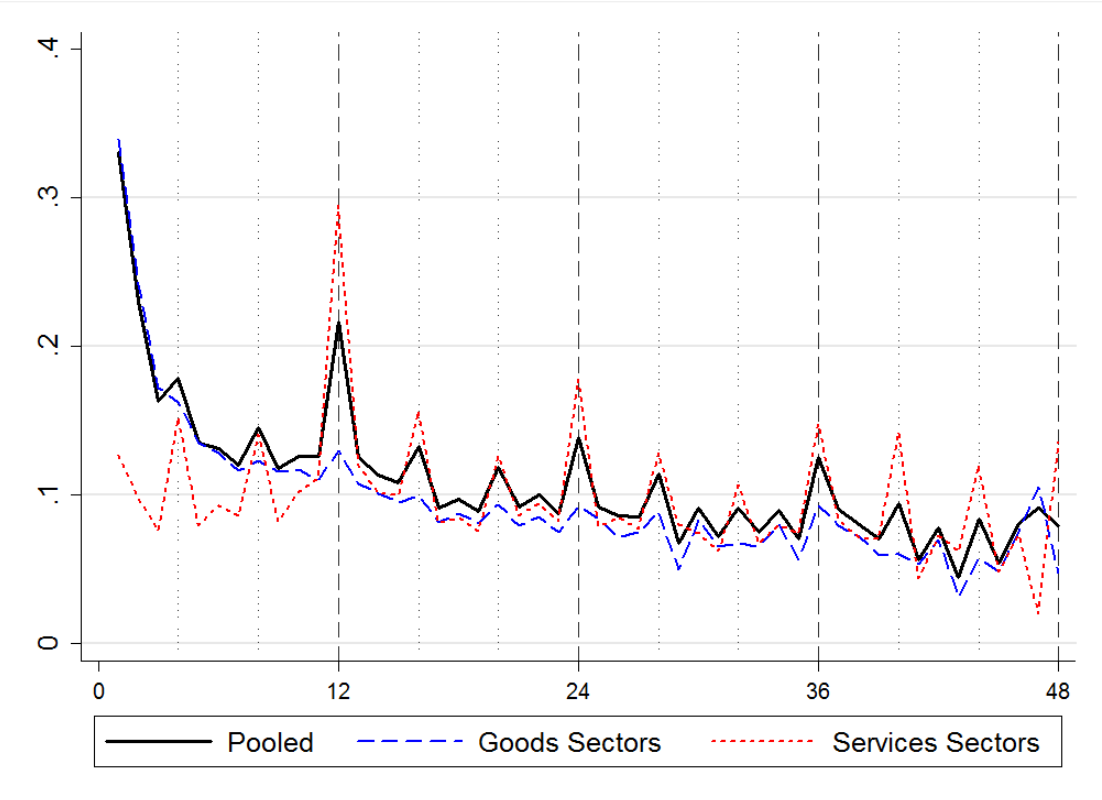
For energy sector, the results are quite different and unique. Firstly, January now does not have the highest hazard rate. Instead, October stands out and becomes the highest.

Secondly, even less heterogeneity across regions are presented. Thirdly, no coefficients related to wage are significant, but, by contrast, all the coefficients related to oil price are positive and significant. This apparent results from the fact that energy sector is *resource intensive*.

For communication sector, very few coefficients are significant. It may be due to lack of enough observations, or it may imply weak state-dependent features. However, the effect of current change in wage is quite noticeable, which again can be explained by the *labour intensity* of communication service.

After controlling for all the four sets of covariates, the heterogeneities in the hazard function $h(t)$ are purified away. The resulting $h_0(t)$ is more reliable to represent the common features of $h(t)$, which is only dependent of the analysis time t. Figure 17 presents $h_0(t)$ for the Cox models of pooled, goods sectors and services sectors. Similar to but more precise than nonparametric analysis, the pooled $h_0(t)$ can be decomposed into a decreasing part (goods sectors) and a cyclical part (services sectors).

Figure 17 Baseline Hazard Functions for Cox Models of Retailer Price



6.2.4. Separate Cox Model by Period

To investigate the time-series heterogeneity in price setting behaviour by means of semiparametric analysis, the sample is splitted into three sub-samples, as defined earlier. The results for all the periods (1997m1-2007m12), period 2 (1997m6-2003m12) and period 3 (2004m1-2007m12) are compared in Table 15 and Table 16, where only coefficients of separate models for goods sectors, services sectors and energy are reported. The formula $\exp(coeff)$ can be used to obtain the hazard ratios. The signs of coefficients do not change much over time, but the magnitude of the effects is volatile.

For the goods sectors excluding energy, January is still the calendar month with highest hazard rate for period 2, but November takes over its place for period 3. May and June are not significantly different from January in hazard rate for period 3, implying that the summer sales seem to be prolonged and very similar to the Christmas sales in latest years. There is little difference across regions for period 2, and the distinction between south and north is preserved over time, as in the pooled estimation. However, for period 3, the difference across regions is more significant. As for macroeconomic covariates, similar results are found in the backward looking feature and forward looking feature. Regarding microeconomic covariates, alcoholic/beverage and non-energy goods sectors have much higher hazard rates for period 3. In addition, similar effects are found in shop type (negative), level of price (positive), percentage change of price (positive), sales (positive) and market share (positive). For most state variables in the model, the magnitude of effects always tends to be lower for period 2 relative to period 3. One possible reason could be the uncertainty right after the independence of Bank of England, resulting in a weaker state dependent feature in price setting behaviour for period 2. By contrast, period 3 is more familiar with the new government system, so is more active to react to the changes in economic state.

In services sectors excluding communication, other calendar months are systematically lower in hazard rates than January throughout the 12 years, despite a bit difference in magnitude. Heterogeneity across regions is still little for both periods. The backward and forward looking feature becomes stronger and more significant in period 3, compared to period 2. The cross-sectional difference by sector is also more conspicuous in period 3, which reflects the speciality in services sectors. Also, there are higher effects for services sectors than those for goods sectors, in level of price, percentage change of price, sales and market share. This phenomenon implies that services sectors are less competitive than goods sectors, given that the services sectors have stronger state dependent price setting feature and higher pricing power.

Energy is a special sector in goods sectors, and it has a different $h(t)$. Instead of January, energy price is more likely to be reset in October and May, which may reflect the seasonality of demand in energy. As shown in Table 15, all the region dummies are insignificant for period 3, which implies that the price setting behaviour in energy market is more and more integrated across the UK. However, energy price of period 3 is no longer significantly affected by interest rate, but it now negatively reacts to the current wage change. The effect of oil price is still strong and significant. The only change in microeconomic covariates is the shop type which is insignificant, because a smaller retailer can just follow the price change in other retailers.

To summarise the findings in semiparametric analysis, there are three key features. Firstly, both time dependent and state dependent features are found in price setting behaviour. Goods sectors are more state dependent, while services sectors are more time dependent. Second, both backward looking and forward looking are used in state dependent feature. Third, there is evidence of cross-sectional but little time-series heterogeneities in $h(t)$, since the changes over time are mainly in the magnitude of coefficients rather than in direction.

6.3. Parametric Analysis

In fact, semiparametric analysis is the most reliable approach in analysing price setting behaviour, because of its flexibility in $h_0(t)$. However, if the shape of $h_0(t)$ is known to some extent, an adventure can be done on specifying $h_0(t)$ by a certain distribution, as in parametric analysis.

There are two equivalent ways of parametric analysis, namely, proportional hazard (PH) model and accelerated failure time (AFT) model. The key difference is the dependent variable on the left hand side of the model. The PH model uses hazard rate as dependent variable, so it is very similar to Cox model. By contrast, the AFT model puts failure time on the left hand side. In fact, the two models generate exactly the same conclusions for Weibull distribution, so only PH model estimations are reported. The results can be easily compare with the semiparametric analysis.

6.3.1. Model Specification

There are two important differences in model specification between parametric analysis and semiparametric analysis. On the one hand, the semiparametric analysis leaves $h_0(t)$ unspecified, while in semiparametric analysis a specific distribution for $h_0(t)$ has to be assumed *ex ante*. Two popular candidates are exponential distribution and Weibull distribution. In fact, the former is just a special case of the later, because exponential distribution implies a horizontal $h_0(t)$, while $h_0(t)$ implied by Weibull distribution could be increasing, decreasing or constant.

On the other hand, some cycle dummies have to be added to the parametric model. It is obviously biased if the spikes in $h_0(t)$, as found in nonparametric and semiparametric analysis, are ignored. To capture the spiky feature, the model includes cycle dummies measured in analysis time, from 4-month to 60-month by 4 months. It also includes a 1-month dummy to reflect the high hazard rate in the first month. Now, the covariates from time dimensions $\mathbf{x}_i$ also include these extra cycle dummies, while keeping the rest three sets of covariates $\mathbf{x}_{ii}, \mathbf{x}_{iii}, \mathbf{x}_{iv}$ unchanged.

Like semiparametric analysis, a pooled PH model is conducted for all the sectors and all the years first, and then the separate PH models by sector and by period are estimated to take into account the cross-sectional and time-series heterogeneities. Since Weibull distribution is more general, exponential distribution results are only reported in pooled model. All the other separate models use Weibull specification.

Table 17 Estimation Results of Pooled and Separate PH Model by Sector (Part A)

			Pooled		Goods sectors excl. Energy	Services sectors excl. Comm.	Energy	Communication
			Exponential	Weibull				
Covariates from Time Dimension	Calendar Month	**February**	-0.3194**	-0.3547**	-0.2631**	-0.6543**	-0.4754**	-0.4432
		March	-0.2283**	-0.2692**	-0.2322**	-0.3543**	0.0131	0.0743
		April	-0.1343**	-0.1531**	-0.1345**	-0.2981**	0.6072**	0.2659
		May	-0.1464**	-0.1188**	-0.1552**	-0.0468*	0.9750**	-0.1167
		June	-0.2088**	-0.1666**	-0.1358**	-0.2697**	0.3993**	0.0167
		July	-0.1420**	-0.0936**	0.0028	-0.5154**	0.7915**	0.2429
		August	-0.3366**	-0.3028**	-0.2058**	-0.7181**	0.3442**	0.1320
		September	-0.3316**	-0.2810**	-0.2202**	-0.6114**	0.6360**	-0.4764
		October	-0.2445**	-0.2249**	-0.1844**	-0.4672**	0.9258**	0.2427
		November	-0.2806**	-0.2683**	-0.2176**	-0.5269**	0.5567**	-0.0499
		December	-0.3010**	-0.2945**	-0.1942**	-0.7383**	0.2361*	0.5180
	Cycle Dummies	**1-month**	0.5931**	2.0112**	2.0279**	1.5295**	2.7890**	1.9298**
		4-month	0.2151**	0.5825**	0.4763**	0.8592**	0.6888**	0.4138**
		8-month	0.0197	-0.0125	-0.2063**	0.4651**	-0.6233**	-0.8658**
		12-month	0.3698**	0.1111**	-0.4777**	1.0503**	-1.0035**	-0.9151*
		16-month	-0.0772**	-0.5205**	-0.8575**	0.2832**	-1.5053**	-2.2151*
		20-month	-0.1986**	-0.7607**	-1.0442**	-0.0513	-1.5788**	-1.1524
		24-month	-0.0789**	-0.7434**	-1.2208**	0.2283**	-1.8549**	–
		28-month	-0.2326**	-0.9926**	-1.2978**	-0.1705**	-1.9636**	–
		32-month	-0.4413**	-1.2731**	-1.6025**	-0.4438**	-2.2028**	–
		36-month	-0.1697**	-1.0679**	-1.4272**	-0.1398	-2.1252**	–
		40-month	-0.4558**	-1.4210**	-1.9398**	-0.2018	-2.6930**	–
		44-month	-0.4855**	-1.4966**	-1.9103**	-0.4252**	–	–
		48-month	-0.6784**	-1.7450**	-2.3532**	-0.3016	–	–
		52-month	-0.3775*	-1.4712**	-1.6271**	-0.7695*	–	–
		56-month	-0.9674**	-2.1198**	-3.2415**	-0.2770	–	–
		60-month	-1.6140**	-2.7661**	-2.9717**	-1.3773	–	–

Table 18 Estimation Results of Pooled and Separate PH Model by Sector (Part B)

		Pooled		Goods sectors	Services sectors	Energy	Communication
		Exponential	Weibull	excl. Energy	excl. Comm.		
Covariates from Macroeconomic Dimension	**Inflation t**	0.0035	0.0102	0.0106	-0.1206**	0.2956**	0.2117
	Inflation t-1	0.0598**	0.0899**	0.0994**	0.1274**	0.7857**	1.0227**
	Inflation t+1	-0.0997**	-0.0801**	-0.0819**	-0.0705*	-0.1003	-0.4622
	Interest Rate (Δ) t	-0.0778**	-0.0929**	-0.0911**	-0.1584**	0.1657	-0.0959
	Interest Rate (Δ) t-1	0.1232**	0.1035**	0.0564**	0.2732**	0.0850	-0.0616
	Interest Rate (Δ) t+1	-0.1635**	-0.1906**	-0.1716**	-0.1540**	-0.6182**	-0.1439
	Wage (%Δ) t	0.0066	-0.0519**	-0.1005**	0.1407**	-0.3842**	0.7144*
	Wage (%Δ) t-1	0.0097	0.0027	0.0454**	-0.1248**	-0.0985	-0.3070
	Wage (%Δ) t+1	0.0729**	0.0144	0.0172	0.1187**	-0.2577**	-0.1980
	Oil Price (%Δ) t	-0.0050**	-0.0052**	-0.0001	-0.0252**	0.0083**	-0.0333
	Oil Price (%Δ) t-1	-0.0020*	-0.0011**	-0.0061**	0.0222**	0.0120**	0.0238
	Oil Price (%Δ) t+1	0.0050**	0.0002**	0.0013	0.0040	0.0057**	-0.0115
Covariates from Microeconomic Dimension	**Alcoholic/Beverage**	0.0338**	0.0936**	0.1440**	–	–	–
	Energy	0.5854**	0.6557**	–	–	–	–
	Non-Energy	-0.3188**	-0.3205**	-0.3178**	–	–	–
	Housing	-0.6793**	-0.7376**	–	–	–	–
	Transport/Travel	-0.7123**	-0.7529**	–	0.0268	–	–
	Communication	-0.2257**	-0.1450**	–	–	–	–
	Recreation/Personal	-0.6063**	-0.6436**	–	0.1594**	–	–
	Miscellaneous	-0.6531**	-0.6526**	–	0.0756**	–	–
	Independent Shop	-0.0879**	-0.1014**	-0.0713**	-0.2027**	-0.0399	-0.3259**
	Price	0.0002**	0.0003**	0.0003**	0.0006**	0.0044**	0.0043**
	Price (%Δ)	0.0000**	0.0000**	0.0000**	0.0006**	0.0079**	0.0020
	Sales	1.0216**	1.1026**	1.0993**	1.3488**	0.4539**	1.1861**
	Market Share	2.7265**	2.7881**	0.5325**	3.4474**	1.9090**	2.2431*
Shape Parameter (Weibull)		–	1.5622**	1.5806**	1.4221**	1.8979**	1.9055**

Table 19 Estimation Results of Separate PH Model by Period (Part A)

			Goods sectors excluding Energy			Services sectors excluding Communication			Energy		
			All	**Period 2**	**Period 3**	**All**	**Period 2**	**Period 3**	**All**	**Period 2**	**Period 3**
Covariates from Time Dimension	**Calendar Month**	**February**	-0.2631**	-0.2159**	-0.2571**	-0.6543**	-0.5222**	-0.7181**	-0.4754**	-0.3344	-0.0799
		March	-0.2322**	-0.1878**	-0.2253**	-0.3543**	-0.2913**	-0.3391**	0.0131	0.1698	1.0416**
		April	-0.1345**	-0.2579**	-0.0440	-0.2981**	-0.3897**	-0.2543**	0.6072**	0.6972**	1.9140**
		May	-0.1552**	-0.2730**	0.1487**	-0.0468*	-0.1178**	-0.1675**	0.9750**	1.1322**	1.4980**
		June	-0.1358**	-0.1992**	0.0618*	-0.2697**	-0.3577**	-0.1261*	0.3993**	0.3659*	1.3788**
		July	0.0028	0.0155	0.0754*	-0.5154**	-0.5198**	-0.4232**	0.7915**	0.9614**	1.8619**
		August	-0.2058**	-0.1246**	0.1497**	-0.7181**	-0.4322**	-0.7133**	0.3442**	0.5202**	1.3933**
		September	-0.2202**	-0.0440*	-0.0871**	-0.6114**	-0.5157**	-0.3340**	0.6360**	1.0611**	0.8692**
		October	-0.1844**	-0.1002**	-0.1128**	-0.4672**	-0.3632**	-0.2682**	0.9258**	1.0020**	1.4791**
		November	-0.2176**	-0.0357	0.1830**	-0.5269**	-0.4361**	-0.1489*	0.5567**	0.4522**	0.8182*
		December	-0.1942**	-0.2280**	-0.0619*	-0.7383**	-0.8757**	-0.3648**	0.2361*	-0.2114	-0.2943
	Cycle Dummies	**1-month**	2.0279**	2.0653**	2.1481**	1.5295**	1.3990**	1.9616**	2.7890**	3.8131**	2.9210**
		4-month	0.4763**	0.4604**	0.3283**	0.8592**	0.9272**	0.6391**	0.6888**	0.8265**	0.2203
		8-month	-0.2063**	-0.3308**	-0.3838**	0.4651**	0.5375**	0.2595**	-0.6233**	-0.3514**	-0.9519**
		12-month	-0.4777**	-0.5717**	-0.5711**	1.0503**	1.0104**	0.8959**	-1.0035**	-0.9908**	-0.6322**
		16-month	-0.8575**	-0.9338**	-0.9338**	0.2832**	0.3117**	0.0869	-1.5053**	-1.2959**	-2.0951**
		20-month	-1.0442**	-1.2359**	-1.3729**	-0.0513	-0.1618**	-0.1986**	-1.5788**	-1.6834**	-1.3487**
		24-month	-1.2208**	-1.2002**	-1.4467**	0.2283**	0.0576	0.2334**	-1.8549**	-2.0820**	-2.3448**
		28-month	-1.2978**	-1.3477**	-1.3526**	-0.1705**	-0.1163	-0.4561**	-1.9636**	-2.4717	-1.7714*
		32-month	-1.6025**	-1.7901**	-1.9087**	-0.4438**	-0.5492**	-0.3159*	-2.2028**	-2.3295**	-14.7168
		36-month	-1.4272**	-1.3698**	-1.6007**	-0.1398	-0.3324*	0.0740	-2.1252**	-1.8527**	-14.4069
		40-month	-1.9398**	-2.3287**	-1.3706**	-0.2018	-0.4692*	-0.6803*	-2.6930**	-2.4551*	–
		44-month	-1.9103**	-2.2903**	-1.0820**	-0.4252**	-0.9531**	-0.4478	–	–	–
		48-month	-2.3532**	-2.2425**	–	-0.3016	-0.4681	–	–	–	–
		52-month	-1.6271**	-2.2142**	–	-0.7695*	-1.2622	–	–	–	–
		56-month	-3.2415**	-4.0450**	–	-0.2770	-1.1309	–	–	–	–
		60-month	-2.9717**	-3.7135**	–	-1.3773	-13.2547	–	–	–	–

Table 20 Estimation Results of Separate PH Model by Period (Part B)

		Goods sectors excluding Energy			Services sectors excluding Communication			Energy		
		All	Period 2	Period 3	All	Period 2	Period 3	All	Period 2	Period 3
Covariates from Macroeconomic Dimension	**Inflation t**	0.0106	0.1709**	0.1325**	-0.1206**	-0.3564**	-0.3399**	0.2956**	-0.1811	1.5011**
	Inflation t-1	0.0994**	0.2108**	0.0846*	0.1274**	0.2449**	0.1829*	0.7857**	0.3415**	-0.2531
	Inflation t+1	-0.0819**	-0.0795**	-0.1889**	-0.0705*	-0.2649**	-0.5371**	-0.1003	0.4214	-0.0294
	Interest Rate (Δ) t	-0.0911**	-0.2332**	-0.8069**	-0.1584**	-0.2998**	-0.8059**	0.1657	0.0377**	-1.6884**
	Interest Rate (Δ) t-1	0.0564**	0.0058	-0.0123	0.2732**	0.1592*	0.3708**	0.0850	0.9907**	-0.6045
	Interest Rate (Δ) t+1	-0.1716**	-0.1804**	-0.5811**	-0.1540**	-0.3391**	-0.9236**	-0.6182**	-0.6612	-1.4259**
	Wage (%Δ) t	-0.1005**	-0.1122**	0.0018	0.1407**	0.0316	0.4178**	-0.3842**	0.0985	-2.4761**
	Wage (%Δ) t-1	0.0454**	0.0300	0.6389**	-0.1248**	-0.0093	-1.1258**	-0.0985	0.1470	-0.4525
	Wage (%Δ) t+1	0.0172	0.1289**	0.1619**	0.1187**	0.1672**	0.4309**	-0.2577**	-0.3522*	1.6205**
	Oil Price (%Δ) t	-0.0001	-0.0104**	-0.0016	-0.0252**	-0.0043	-0.0769**	0.0083**	0.0104	0.0210
	Oil Price (%Δ) t-1	-0.0061**	-0.0056**	-0.0231**	0.0222**	0.0258**	0.0453**	0.0120**	0.0109	0.0718**
	Oil Price (%Δ) t+1	0.0013	0.0254**	0.0065**	0.0040	-0.0602**	0.0221**	0.0057**	0.0356**	0.0327
Covariates from Microeconomic Dimension	**Alcoholic/Beverage**	0.1440**	0.1599**	0.1907**	–	–	–	–	–	–
	Energy	–	–	–	–	–	–	–	–	–
	Non-Energy	-0.3178**	-0.3502**	-0.2439**	–	–	–	–	–	–
	Housing	–	–	–	–	–	–	–	–	–
	Transport/Travel	–	–	–	0.0268	-0.0470	0.1280**	–	–	–
	Communication	–	–	–	–	–	–	–	–	–
	Recreation/Personal	–	–	–	0.1594**	0.0778**	0.2692**	–	–	–
	Miscellaneous	–	–	–	0.0756**	0.0484	0.1138**	–	–	–
	Independent Shop	-0.0713**	-0.0482**	-0.0808**	-0.2027**	-0.1898**	-0.2441**	-0.0399	-0.0752**	-0.0215
	Price	0.0003**	0.0002**	0.0002**	0.0006**	0.0007**	0.0006**	0.0044**	0.0053**	0.0039**
	Price (%Δ)	0.0000**	0.0000**	0.0027**	0.0006**	0.0005**	0.0021**	0.0079**	0.0246**	0.0068**
	Sales	1.0993**	1.1183**	1.1021**	1.3488**	1.3890**	1.1769**	0.4539**	0.6216**	0.4584**
	Market Share	0.5325**	3.9004**	2.9668**	3.4474**	2.7473**	4.8835**	1.9090**	8.7467**	12.332**
Shape Parameter (Weibull)		1.5806**	1.6398**	1.6369**	1.4221**	1.4750**	1.5213**	1.8979**	2.2195**	2.1772**

6.3.2. Pooled PH Model

The pooled regression is to summarise the overall feature of price setting behaviour in the whole economy. The resulting $h_0(t)$ is the pure relationship between price resetting probability and time, after controlling other factors. To model $h_0(t)$, both exponential and Weibull distribution are tried. The latter is more general and flexible, since the former has an extra restriction on the shape parameter. If exponential distribution is correct, then the estimated shape parameter in Weibull distribution should be close to 1. However, it turns out to be significantly different from 1. Thus, Weibull distribution is preferred to model $h_0(t)$, and it is used for estimating the separate PH models.

As shown in Table 17 and Table 18, the estimated coefficients are close to semiparametric analysis in Table 13 and Table 14, both in direction and in quantity. Though it does not mean these results are true, it still suggests that inclusion of the cycle dummies in parametric analysis does make the model comparable with semiparametric analysis. This section will only focus on the cycle dummies added to the PH model. Note that the covariates from space dimension, i.e. region dummies, are omitted in the reported estimation results, because most of them turn out to be insignificant.

Not surprisingly, the cycle dummy for 1-month has the highest effect on $h(t)$, similar to the previously observed feature that there is a sharp decline in the first period $h(t)$. There is an overall declining trend of cyclical effect, and it even goes negative after 12-month cycle. It does not mean that $h(t)$ is lower in these periods. Rather, this is because the discrepancy between actual $h(t)$ and estimated $h_0(t)$. As shown earlier, the actual $h(t)$ is downward sloping. However, the estimated shape of Weibull $h_0(t)$ turns out to be upward sloping, since the shape parameter is greater than 1. Even for exponential $h_0(t)$, the slope is horizontal. The cyclical dummies for longer periods have to compensate for the increasing gap between the estimated $h_0(t)$ and the actual $h(t)$. As a result, the cyclical effects are more and more negative. Nevertheless, compared to the neighbourhood, 4-month, 12-month, 24-month, 36-month and 52-month cycles tend to have relatively higher effect. This is consistent with the spiky features observed earlier.

There are several drawbacks of parametric analysis. Apart from the inflexible shape of $h_0(t)$, it assumes that all the sectors share a common $h_0(t)$ throughout the sample period. The problem of inflexibility is common to all parametric PH models, but the second issue can be addressed by running separate estimations.

6.3.3. Separate PH Model by Sector

Based on the previous findings, the whole economy is disaggregated into goods sectors excluding energy, services sectors excluding communication, energy sector and communication sector. PH models for the 4 sectors are run separately, and reported with the pooled model in Table 17 and Table 18.

For the covariates from time dimension, January is still the calendar month with the highest probability to reset prices for both goods sectors and services sectors. Consistent to the semiparametric analysis, July is next to January for goods sectors, and April is ranked as the second highest for services sectors. This finding reinforces the explanations that summer sales and the beginning of a tax year have substantial effect on the price setting behaviour in goods sectors and services sectors respectively. Similarly, October and May are still the two calendar months when energy sector is most likely to adjust the prices, though the rankings of the two months are reversed. Also, there is no significant seasonality for communication sector, suggesting a very fast change and short product life cycle in this market.

The estimated coefficients of cycle dummies for goods sectors do not exhibit a clear cyclical manner, since the estimated coefficients decrease in a monotonic way. In contrast, those for services sectors jump around every 12 months. (Figure 18) This corresponds to the previous conclusion that goods sectors contribute to the decreasing component of $h(t)$, and services sectors account for the cyclical component.

As indicated earlier, the other covariates have almost the same estimated coefficients as those in semiparametric analysis. Due to the inflexible and unrealistic restriction of $h_0(t)$, the coefficients are less credible than those obtained in semiparametric analysis. However, one interesting result of running parametric models is the estimated shape parameter of Weibull distribution. This shape parameter determines what $h_0(t)$ looks like, after controlling for all the covariates. If it is equal to 1, then there is a flat $h_0(t)$, which is in fact an exponential distribution. If the shape parameter is less than 1, $h_0(t)$ is decreasing. If it is greater than 1, then there is an upward sloping $h_0(t)$. In our case, all the sectors, including the pooled model, have upward sloping $h_0(t)$, which are graphed in Figure 19. Goods sectors are quite close to the pooled model, while services sectors have a very flat (close to 1) $h_0(t)$. Communication sector seems to have the highest slope, and the hazard rate is almost equal to 1 at 18 months' time. This is consistent with the results obtained in previous sections.

Figure 18 Estimated Coefficients of Cycle Dummies of Retailer Price

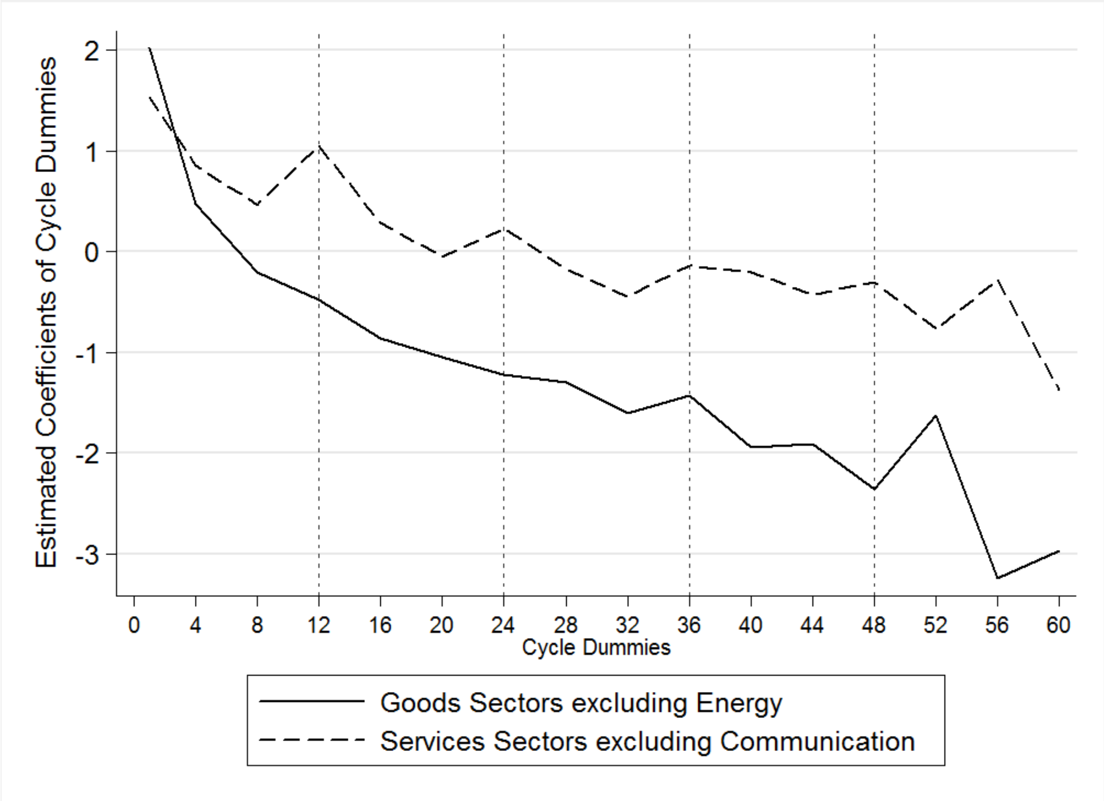
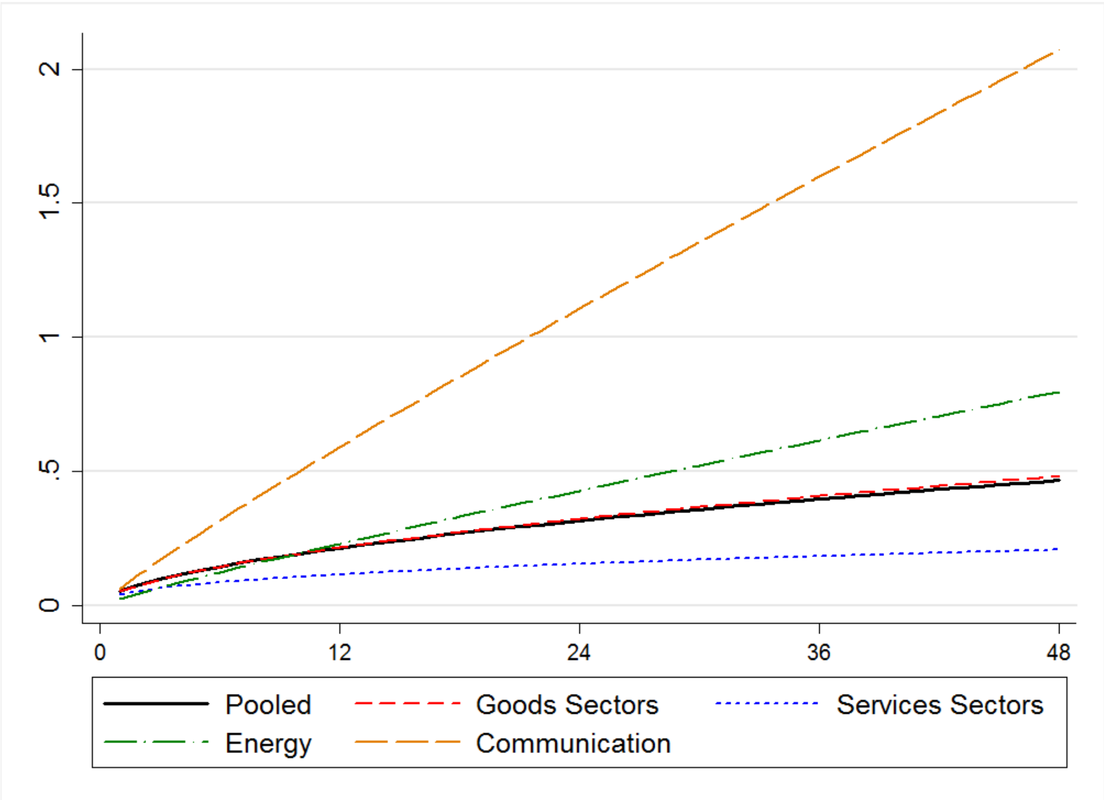


Figure 19 Estimated Weibull Baseline Hazard Functions by Sector (Retailer)



The upward sloping $h_0(t)$ found in parametric analysis seems to be contradictory to the semiparametric analysis, where all $h_0(t)$ are found downward sloping. However, this might be an illusionary discrepancy, because the graphs only show the first 72 months for nonparametric analysis and 48 months for semiparametric analysis. If the complete time horizon is shown, $h(t)$ in any cases will eventually increase to 1, since all prices will finally change. Only the first 72 months are graphed because the survived prices become less as time gets longer, and the standard errors of the estimated hazard rates get greater. Moreover, it is a general consensus in the literature to show $h(t)$ only in the first several years, cutting the wild end out. For example, Álvarez & Hernando (2004) and Aucremanne & Dhyne (2005) keep 36 months, while Bunn & Ellis (2009) only keep 24 months. Though all $h(t)$ tend to grow in the end, the parametric analysis still fails to capture the declining feature at the beginning.

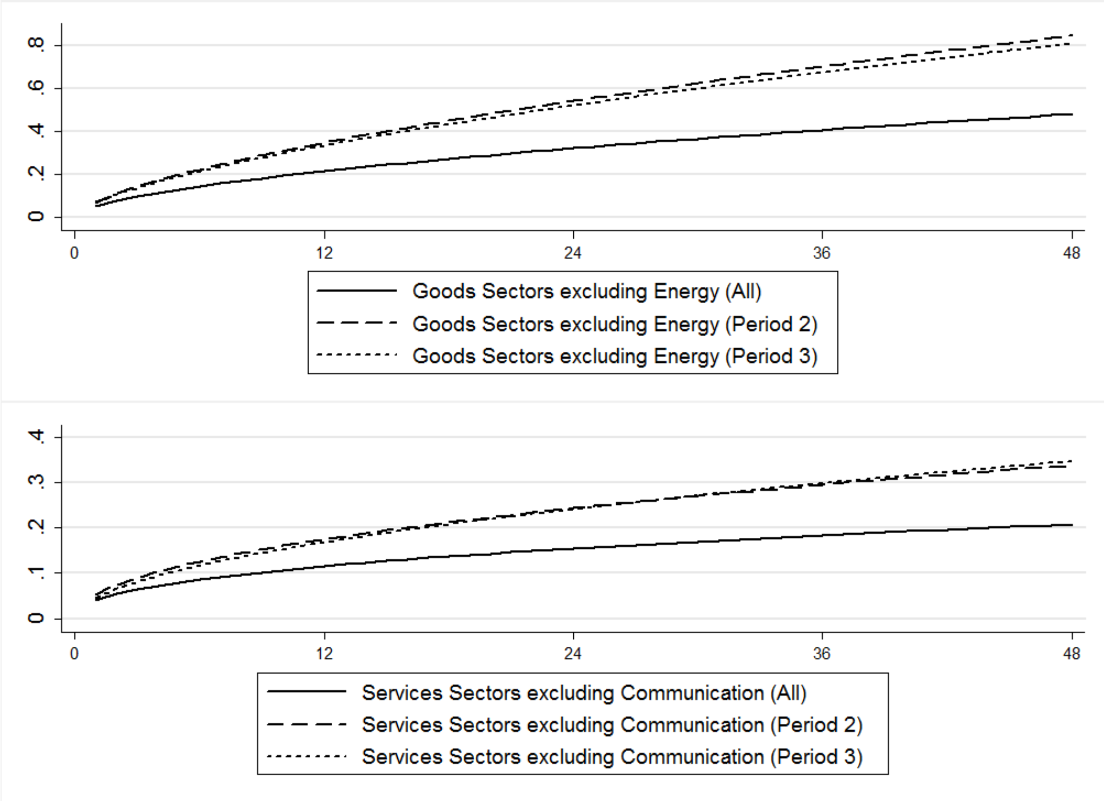
6.3.4. Separate PH Model by Period

The estimated results of separate PH model by period are presented in Table 19 and Table 20, omitting the results of covariates from space dimension, i.e. region dummies $\mathbf{x}_{ii}$. The estimated coefficients are again qualitatively consistent with the Cox model but quantitatively different. This section will only focus on the implied $h_0(t)$ of the two subperiods, which reveal additional information about heterogeneity.

The first thing noticed in Figure 20 is that both sectors in the two subperiods have $h_0(t)$ significantly higher than that estimated for all periods. This is mainly due to the shorter length of the two periods. For the whole sample, there are 144 months, but there are only 79 months for period 2 and 48 months for period 3. More price spells will be right censored in the two subperiods, and the average length of duration will be shorter. That implies the estimated $h_0(t)$ will accordingly be higher, due to oversampling of short price spells.

Though the estimation by period is biased in the absolute sense, it is still sensible to conclude that there is little time-series heterogeneity based on the relative position between $h_0(t)$ for the two subperiods. Also similar to previous results, goods sectors (excluding energy) have consistently higher hazard rates than services sectors (excluding communication), after controlling for other covariates.

Figure 20 Estimated Weibull Baseline Hazard Functions by Period (Retailer)



7. Comparison between Methods

Two important issues are studied in price setting behaviour, based on microdata for retailers in the UK. The first is the measure of rigidity focusing on the *outcome* of price setting behaviour. Both conventional and cross-sectional methods are used, but the new method (DAF) is preferred due to its unbiasedness. The second issue is $h(t)$ focusing on the *mechanism* of price setting behaviour, which generates the price duration. All the three types of models in nonparametric, semiparametric, and parametric analyses are covered, but semiparametric analysis is preferred due to its efficiency and flexibility.

Note that one can always derive the predicted duration for each product after estimation of survival analysis models. To make different methods comparable, duration is appropriate as a unified connecting link between different methods. The five methods employed across this paper are compared in terms of duration in Table 21.

Table 21 Comparison between Methods to Measure Retailer Price Rigidity

Method	Overall	Goods sectors	Services sectors
Conventional Method (derived from frequency)	5.5165	4.1374	11.3826
Cross-Sectional Method (directly estimated DAF)	**9.3460**	**7.4287**	**11.3803**
Nonparametric Analysis (predicted from model)	6.9063	5.2155	12.1521
Semiparametric Analysis (predicted from model)	**9.6181**	**7.4664**	**11.1098**
Parametric Analysis (predicted from model)	10.4289	8.8361	14.7224

As indicated earlier, conventional method results in underestimation of duration, due to the oversampling of short spells. The new measure DAF is a cross-sectional method of duration, estimated directly from data, so it is the most reliable estimate of duration, among all the five methods. Thus, DAF is used as the true estimate of duration.

In nonparametric analysis, the expected duration can be derived using standard definition of expectation, based on estimated $h(t)$. The result should be close to mean DAF, since they are both unbiased estimates of the same thing. However, it turns out to be 6.9063 months, lower than the mean DAF 9.3460 months, but higher than the conventional method 5.5165 months. This is because nonparametric analysis only uses one spell out of the whole trajectory for each product. The problem of inefficiency may lead to the difference between true and estimated durations, though it is still unbiased.

In semiparametric analysis, the mean duration can also be obtained based on the predicted hazard rates from the estimated Cox models. As shown in Table 21, the resulting durations are very close to those of DAF, implying a strong support for semiparametric analysis. Indeed, it is the most appropriate method in survival analysis, and two advantages make it outperform nonparametric and parametric analyses. Namely, it is both more efficient in using data (efficiency), and more flexible in model specification (unbiasedness).

In parametric analysis, the derived durations are a bit longer, compared to DAF. That is because the restricted assumption on $h_0(t)$ leads to biasedness in predicted durations. As seen from nonparametric or semiparametric analyses, $h(t)$ has a complicated shape, which is difficult to be characterised by any known function form. Though only two candidates, exponential and Weibull distributions, are reported in this paper, the problem exists for all functions with analytical closed form in parametric analysis.

To summarise, nonparametric analysis is unbiased but inefficient, parametric analysis is efficient but biased, while semiparametric analysis is both unbiased and efficient. It also gives very close estimate of durations to the true value, as suggested by DAF. If one only focuses on the outcome of price setting behaviour, DAF is the best choice. If one wants to study the mechanism of price setting behaviour, then semiparametric analysis is the most appropriate method.

8. Conclusion

This paper addresses two aspects, i.e. outcome and mechanism, of price setting behaviour for the retailers in the UK. The cross-sectional DAF methodology is applied for the first issue and survival analysis methodology for the second.

There are three important stylised facts on the first issue, which is actually to measure the rigidity of price change.

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

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

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

Apart from the stylised facts on rigidity, another important conclusion is drawn in the descriptive statistics. That is, the distribution of DAF directly estimated from data is very close to that indirectly derived from distribution of age according to the formula proposed by Dixon (2010).

There are also three important findings on the second issue, which is actually to identify the factors that influence retailers' price setting behaviour.

(i) The hazard function can be decomposed into decreasing component from goods sectors and the cyclical component from services sectors. Moreover, there are major cycles of 12 months and minor cycles of 4 months.

(ii) January is the calendar month with the highest hazard rate of price change, followed by April and August for different sectors. This is consistent with time dependent models with Taylor feature.

(iii) Both backward looking and forward looking expectations are used in evaluating the effects of macroeconomic state. Retailers are also sensitive to changes in microeconomic state. This supports state dependent models.

The findings on heterogeneities overlap those in descriptive statistics, but with more detailed explanations. For example, input intensity is introduced to interpret the different coefficients for different sectors. Regional difference is still insignificant after controlling for other covariates, suggesting a uniform pricing strategy across UK. In adventuring on parametric models, a monotonically increasing $h_0(t)$ is found, which is decreasing initially in other analyses. One cannot make too much out of this result because the restriction of parametric analysis is liable to bias the estimation.

A comparison is made in terms of mean duration among the five methods. The conclusion is that DAF, as the best estimate of duration, is preferred in studying the outcome of price setting behaviour, while semiparametric analysis, as the unbiased and efficient estimate of hazard function, is preferred in studying the mechanism of price setting behaviour. The two methods give similar results in mean duration, so either could be used to calibrate or confront with the macroeconomic models.

CHAPTER II

Heterogeneity and Rigidity of Producer Firm's Price Setting Behaviour[①]

[①] This work contains statistical data from ONS which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

1. Introduction

The retailers are closely interacting with producers in price setting. This chapter will focus on the producer price setting behaviour to paint a complete picture of how firms set prices in the whole economy, because the producers play an indispensible role in price rigidity and shock persistence in macroeconomic models.

On the one hand, as being in the earlier stage (upstream) in the supply chain, some producers (e.g. energy goods firms) are facing more volatile input prices, so the producer prices tend to be more flexible for these sectors, as in Nakamura & Steinsson (2008) for US, Vermeulen et al. (2007) for EU and Bunn & Ellis (2009) for UK. The producer price change absorbs some effects from structural shocks. In this sense, the producers act as a "buffer" for the retailers against the fluctuations in resource prices. Hence, the producers make the retailer price rigidity even greater.

On the other hand, the effect of macroeconomic shocks will have more persistent effect, if producers provide an additional channel of propagating the shocks. The producers then act as a "container" for the retailers to prolong the effect of shocks. Thus, the producers make the response of the economy to shocks more persistent. There is another possible scope to use producer prices, given that there is a subtle link between price and wage setting behaviour. Since producers are mainly manufacturers, labour is an important input. A change in wage is usually accompanied by a change in producer price to reflect the production costs. There are no wage microdata ready for use, so the producer prices are useful to draw informative inference on wage setting behaviour. It can then be used to calibrate macroeconomic models.

This chapter does not differ from the previous chapter in structure. Both conventional and cross-sectional methods are used to study the *outcome* of price setting behaviour, while survival analysis is employed to investigate the *mechanism* of price setting behaviour, taking various factors into account, especially the degree of competition and friction. Systematic comparisons between retailers and producers are made.

This chapter is organised as follows. Section 2 summarises the methodologies, with emphasis on the difference from the previous chapter. Section 3 describes and compares the microdata of retailer and producer prices. Price rigidity is measured by both conventional and cross-sectional methods in Section 4 and Section 5, while Section 6 applies survival analysis to model the producer price setting behaviour. Section 7 concludes.

2. Methodology

This chapter follows the same methodology and terminology established in the previous chapter to study the producer price data. Since this chapter only focuses on the producer or wholesaler firm's price setting behaviour, the terms "firm" and "producer" are interchangeably used in this chapter.

2.1. Cross-Sectional Method

Firstly, to descriptively summarise the *outcome* of the producer's price setting behaviour, i.e. the price change, both traditional and cross-sectional methods are used. The results give different implications to the rigidity of the economy in the early stage of supply chain. Again, cross-sectional method is preferred due to its robustness to oversampling in short price spells.

There is a complicated panel structure for producer price dataset. Each producer has several products, and the entire series of price quotes over the sample period for each product is termed as a "price trajectory". Each price trajectory is then made of several price spells, and each price spell contains several consecutively constant price quotes over the price duration of that price spell.

To study the economy-wide price setting behaviour, essentially it is to study how the cross-section of products behaves over time. Thus, it is the price trajectory, rather than price spell, that should be the basic unit. It is because one price trajectory corresponds to only one product, but there may be many price spells belonging to one product. If price spell is regarded as the basic unit, products with short duration of spells will be oversampled, and it is obviously unfair to products with longer duration of price spells.

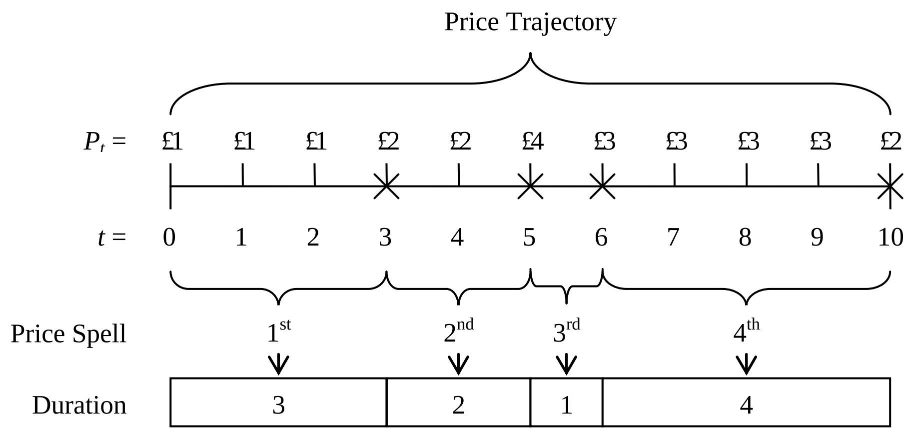
2.2. Survival Analysis Method

The second question, in contrast, is to investigate the *mechanism* of the producer's price setting behaviour, i.e. factors affecting the price change. Survival analysis approaches (nonparametric and semiparametric) are applied and compared. One difference from the previous chapter lies in the econometric models specified in semiparametric analysis. Since producers tend to have higher market power in price setting, they are more responsive to the change in their demand curves, which can be reflected in the firms' market shares. Based on this feature, the models include both market share within industry and market share across economy to capture the detailed mechanism.

3. Data

The microdata used in this chapter are individual price quotes of goods bought and sold by UK manufacturers, underlying the construction of Producer Price Indices (PPI) including both output PPI (the prices of output produced by manufacturers for sale) and input PPI (the prices of input purchased by manufacturers)[1]. On the one hand, 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. On the other hand, input PPI provides important information about the input markets, which complement the knowledge of output markets. It enables econometricians to draw a complete implication of price setting behaviour in the entire economy, and also enables macroeconomists to calibrate DSGE models with nominal rigidities in both markets.

The producer data has a panel structure. Each producer firm has several products, and for each product the entire series of price quotes over the sample period is termed as a “price trajectory”. Each price trajectory is then made of several price spells, and each price spell consists of several price quotes constant over that duration. To illustrate, the following graph 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 of the spells are respectively 3, 2, 1 and 4.



To study the economy-wide price setting behaviour, it is essentially to study how the cross-section of products behaves over time. Thus, the price trajectory, rather than price spell, is the basic unit in this paper. It is because one product only has one price

[1] **Richardson, I.** 2000. "Producer Price Indices: Principles and Procedures," In *Government Statistical Service Methodology Series*. ONS.

trajectory, while there may be many price spells belonging to one product. It will result in oversampling of short spells if price spell is treated as the basic unit.

Each price quote in the data represents the price of a particular product for a particular producer in a given month. Monthly price movements outside the range -25% to 25% are regarded as "incredible" by ONS and are not used if the contributing firms fail to confirm. This paper follows this treatment. After filtering out the improper observations, there are 822,579 price quotes finally being used in the clean data, spanning 122 months from 1998m1 to 2008m2.

3.1. Data Collection

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[①].

Here, a 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.

Step 1: **6-Digit**[②] **Product Index** ($I^E_{j,k,s,t}$) is obtained for each product j by weighted ($w^P_{i,j,k,s,t}$) mean of price relatives, where the price relative is the current price of a product divided by its price in the base year: $p_{i,j,k,s,t} = P_{i,j,k,s,t} / P_{i,j,k,s,b}$.

Step 2: **4-Digit Industry Index** ($I^I_{k,s,t}$) is obtained across the products within an industry based on 6-digit product indices $I^E_{j,k,s,t}$ and product weights $w^E_{k,s,t}$.

Step 3: **2-Digit Division Index** ($I^S_{s,t}$) is obtained across industries within a division based on 4-digit industry indices $I^I_{k,s,t}$ and industry weights $w^I_{k,s,t}$.

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

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① **Morris, L. and T. Birch.** 2001. "Introducing a New Estimator for the Producer Price Index." *Economic Trends*, 573, pp. 63-71.
② 6-digit product group is defined by the European "Classification of Products by Activity" (CPA).

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

3.2. Weight

The 4 steps above to obtain the aggregate indices need 4 weights[①] corresponding to each step, i.e. the producer weight $w^P_{i,j,k,s,t}$, product weight $w^E_{k,s,t}$, industry weight $w^I_{k,s,t}$ and division weight $w^S_{s,t}$. In particular, the producer weight $w^P_{i,j,k,s,t}$ is the value of the reporting producer's sales of products within the 6-digit product relative to the sales of products within the product of other reporting producers included in the sample. Information on the value of a reporting producer's sales of products is based on the PRODCOM[②] survey by Eurostat. The process for the aggregate indices can then be summarised into one big formula:

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

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

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:

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

[①] **Morris, L. and J. Gough.** 2003. "Introducing a New Method to Calculate Index Weights for the Producer Price Indices." *Economic Trends*, 598, pp. 71-76.
[②] PRODCOM is an acronym for "Products of the European Community".

Thus, the big formula now becomes:

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

Accordingly, to study price duration, this cross-sectional "grand weight" $\omega_{i,j,k,s,t}$ will be used to calculate the weighted distribution of durations.

Note that, for each product, in addition to this "weight across economy" ($\omega_{i,j,k,s,t}$), we can also define its "weight within industry" ($\omega^I_{i,j,k,s,t}$). Both will be used in semiparametric model specifications.

$$\omega^I_{i,j,k,s,t} = \frac{w^E_{j,k,s,t} \times w^P_{i,j,k,s,t}}{\sum_{j=1}^{N_k} w^E_{j,k,s,t} \times \sum_{i=1}^{N_j} w^P_{i,j,k,s,t}}$$

3.3. Data Summary

The clean data contains 23,781 price trajectories (products) containing 822,579 price quotes collected from 11,562 producers. Note that there is only manufacturing goods in the producer data. There is no services counterpart as in retailer data. This difference contributes to the observed higher flexibility in producer price later on, since goods prices are more flexible than services prices. The panel of price trajectories can be characterised in two dimensions: the variation in length and the variation by sector.

On the one hand, the variation in length results from the unbalanced panel structure. As in retailer data, new products enter while old products exit the PPI baskets, so the lengths of price trajectories are different for each product. The table below gives the summary of price trajectory length (in month) in the producer price panel.

Table 22 Descriptive Summary of Price Trajectory (Retailer V.S. Producer)

	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

The producer price trajectories tend to be much longer than the retailer price trajectories. It reflects that the early stage of the supply chain is more stable in product line, and the rotation of products is less frequent than that of retailer products.

On average, the producer's products are under observation longer than 2 years. Similar to the retailer price trajectories, the mean length of producer price trajectories is also higher than the median, so the distribution is slightly positively skewed. Thus, the right tail of the distribution is longer, and it has some very long price trajectories.

On the other hand, the variation by sector is straightforward. The producers can be grouped into 6 main sectors, according to the Standard Industrial Classification (SIC). A more general distinction between "consumption goods" and "production goods" can also be drawn. Note that there are no services sectors in producer data.

Table 23 Descriptive Summary of Producer Price Trajectory by Sector

Sector	Median	Mean	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**

Note that 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.

Again, 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.

4. Conventional Method

This section first presents the results following the conventional method and provides a comprehensive descriptive statistics of the three aspects of rigidity, including the *frequency*, *direction* and *magnitude* of price change. It will be shown that the producer price seems more flexible than the retailer price if conventional method is used. This is due to two reasons: the oversampling of short price spells, and the heavy PPI weight given to energy goods which have a high frequency of price change.

4.1. Rigidity in Frequency of Price Change

4.1.1. Overall Frequency

The descriptive statistics of the frequency of producer price change are summarised in Table 24, both unweighted and weighted.

Table 24 Overall Frequency of Producer Price Change

		Mean	**Median**	**S.D.**	**Skewness**
Unweighted	Overall	17.70%	17.52%	0.01994	1.07070
	Increase	10.61%	10.50%	0.02048	0.75566
	Decrease	7.09%	7.15%	0.01096	-0.03169
Weighted	Overall	25.21%	25.01%	0.02376	0.03088
	Increase	15.26%	15.65%	0.03149	-0.24712
	Decrease	9.95%	9.84%	0.02637	0.26188

The first striking feature is that the weighted frequencies are much higher than the unweighted frequencies. This is mainly due to the greater PPI weight[①] given to energy goods (4.4%), compared to the unweighted trajectory percentage (28/23781=0.1%). As shown soon, the energy goods have a very high frequency of price change (mean 84.2% and median 87.14%), pushing the overall frequency from 18% to 25%.

A related feature is that the unweighted frequency is a bit lower than that of retailer price (mean 17.89% and median 17.54%). The weighted frequency, however, is much higher, compared to the retailer price (mean 18.63% and median 18.34%). The CPI weight[②] assigned to energy goods (3.1%), while the unweighted trajectory percentage of energy goods is 11272/612173=1.8%. The high frequency of energy goods price (mean 47.38% and median 46.46%) does push the overall frequency of retailer price change up but relatively less.

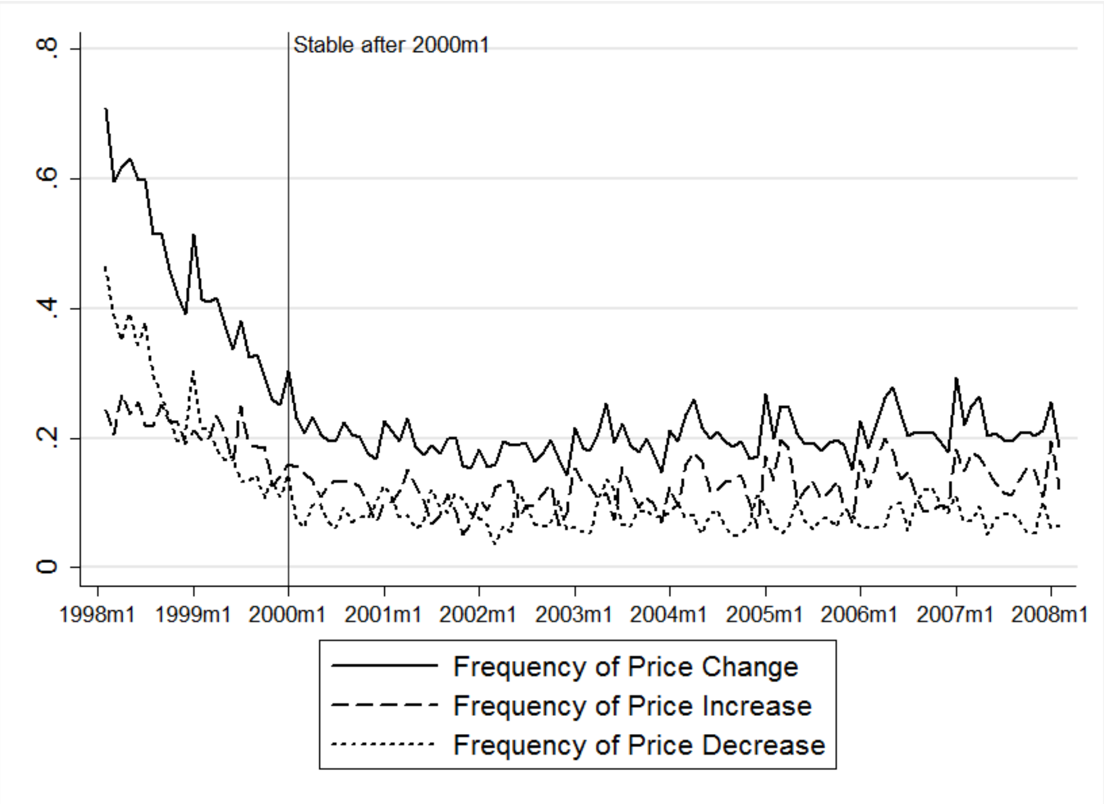
① PPI division weight is based on Annual Business Inquiry (ABI).
② CPI division weight is based on Household Final Consumption Expenditure (HHFCE).

Hence, the perceived difference between unweighted and weighted frequency can be explained by the relative difference between PPI weight and sample structure. Hence, the conclusions are quite different under weighted and unweighted treatment. In this chapter, the weighted results are preferred because (i) there is no doubt to consider the importance of energy goods in the economy; (ii) there are very few energy goods in the sample; and (iii) it is popular in related studies to use weighted frequency. Based on the conventional method, the producer price seems more flexible than retailer price. However, it is known from previous chapter that this is just an illusion due to the oversampling of short price spells.

4.1.2. Time-Series Heterogeneity in Frequency of Price Change

The frequency of price change varies across time, and this time-series heterogeneity can be seen from Figure 21. Two features are found: (i) some months (January and April have mean frequency higher than 20%) tend to have higher frequency, compared to the other months; and (ii) the frequency is very volatile before 2001m1, but becomes relatively stable after that. It can again be explained by the fluctuations in the weights of energy goods and crude oil price, which is even more important for producer price setting behaviour. However, this subtle relation can only be specified in the semiparametric analysis.

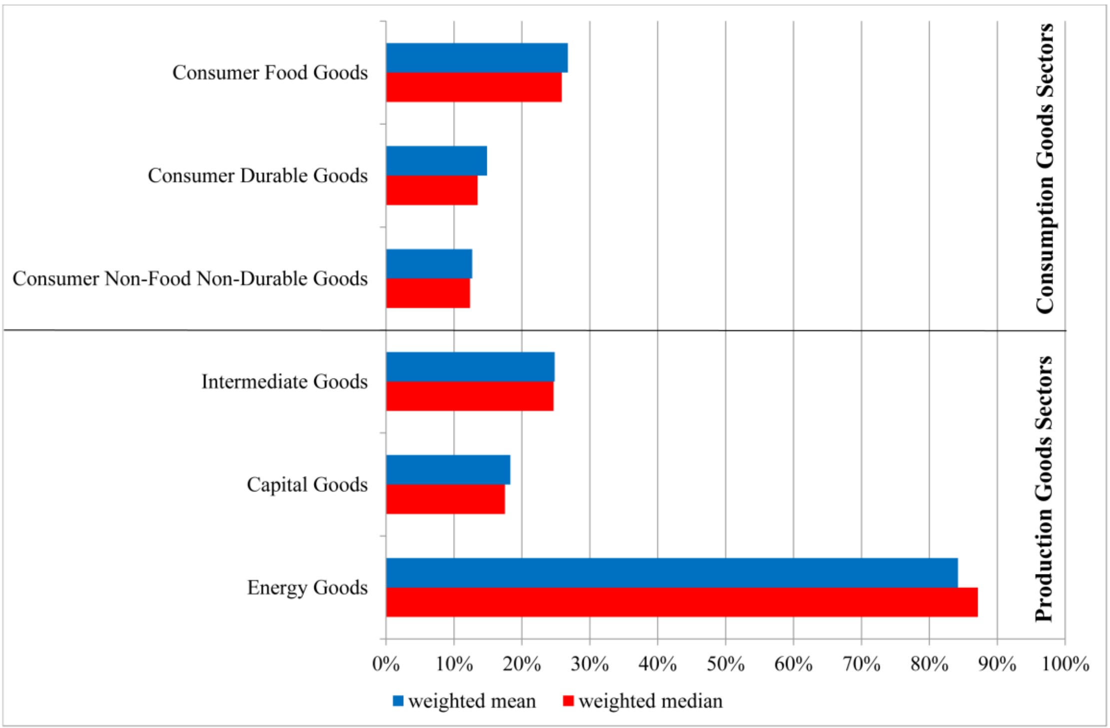
Figure 21 Time-Series Heterogeneity in Frequency of Producer Price



4.1.3. Cross-Sectional Heterogeneity in Frequency of Price Change

There are also significant cross-sectional heterogeneities by sector. Similar to retailer's behaviour, a key cause for the different frequencies across sectors is *degree of competition*. The higher is competition, the less is rigidity and the higher is frequency of price change. Following the convention, the producers can be classified as consumption goods sectors and production goods sectors.

Figure 22 Cross-Sectional Heterogeneity in Frequency by Sector (Producer)



Within the consumption goods sectors, the food goods are more frequent (mean 26.77% and median 25.86%) than durable and other consumption goods (both under 15%). This result corresponds to the findings in retailer's behaviour, where the frequency of the goods sectors is around 20%. This suggests that the retailers and producers have synchronised price setting behaviour. As the link between retailing markets and wholesaling markets, the consumption goods retailers tend to change prices more frequently.

Compared to the consumption goods sectors, production goods sectors are on average more frequent in price change, where intermediate goods are similar to food goods and capital goods are similar to durable goods.

Again, there is a remarkable exception, i.e. energy goods, with an extremely high frequency (mean 84.21% and median 87.14%). Almost all energy goods prices are expected to change within 1 month. Given the high importance of energy goods in supply chain, this outlier plays a significant role in determining the aggregate producer price setting behaviour. As illustrated earlier, inclusion of energy goods will make a huge difference in overall frequency of price change in producer price. If energy goods are left out, the overall frequency will decrease from 25.21% to 19.47%, which would be a bit higher than but close to that of retailer price (18.63%).

Another interesting comparison is that the frequency of retailer energy goods (mean 63.86% and median 64.06%) is lower than that of producer energy goods (mean 84.21% and median 87.14%). It is different from other goods, where retailing markets tend to have higher frequency than wholesaling markets. It could be due to the high volume of transactions and higher degree of competition in energy goods market, given its vital role in modern production. To see the importance of energy goods, it pushes the frequency of producer price from below to above the frequency of retailer price. Both supply side and demand side of the energy goods market are large enough to compete against each other, with influences from international market. However, the retailing markets of energy goods are actually less competitive, and the energy goods retailers have more monopolistic market power.

4.2. Rigidity in Direction of Price Change

Another conclusion drawn from the frequency of price change is that price increases (15.26%) are more frequent than price decreases (9.95%), as shown in Figure 21. The higher proportion of increase results from the persistent inflation over time. Hence, it should not be regarded as an evidence for the so-called "downward rigidity", which asserts that price is more difficult to adjust downward. The summary of increase versus decrease of price changes is presented in Table 25. Moreover, as shown in Figure 23, the symmetry of the distribution of price change reinforces the conclusion that there is no downward or upward rigidity.

Table 25 Direction of Producer Price Change

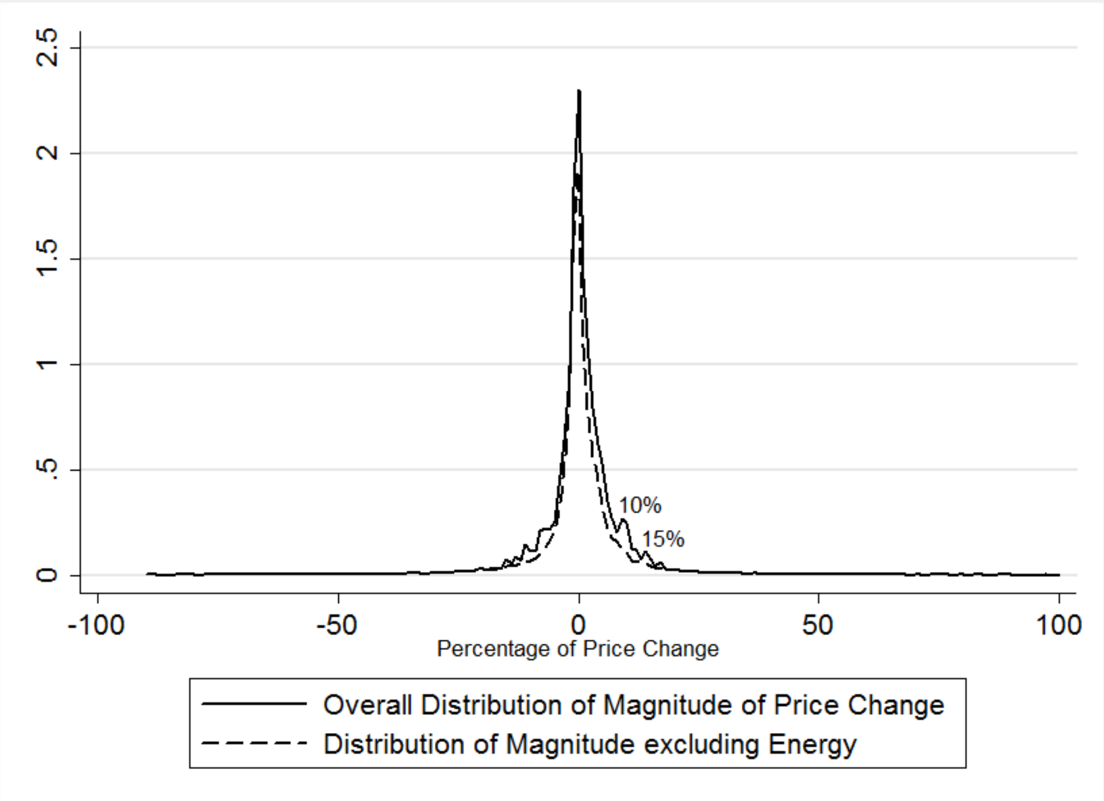
		Mean	Median	S.D.	Skewness
Unweighted	**Overall**	17.70%	17.52%	0.0199	1.0707
	Increase	10.61%	10.50%	0.0205	0.7556
	Decrease	7.09%	7.15%	0.0110	-0.0316
Weighted	**Overall**	25.21%	25.01%	0.0238	0.0309
	Increase	15.26%	15.65%	0.0315	-0.2471
	Decrease	9.95%	9.84%	0.0264	0.2619

4.3. Rigidity in Magnitude of Price Change

Similar to the retailer's price setting behaviour, there is little rigidity in magnitude of price change. As shown in Figure 5, most price changes are around zero, and this feature does not change if energy goods are excluded. This supports the state dependent models. Among others, Rotemberg (2005) "customer anger" model is quite appropriate to explain this feature in the producer's scenario, since big price fluctuations tend to induce more customer loss.

A remarkable difference of this distribution from retailer price change is that there are few percentage spikes. The distribution of magnitude of producer price change is smoother. Arguably, it makes sense for retailers to cut price by percentage, such as 30% or 50%, during sales to attract customers. However, it seems not a popular strategy for producers, especially when energy goods are excluded. As a result, the magnitude of producer price change is more precise and flexible.

Figure 23 Distribution of Magnitude of Producer Price Change



An immediate implication from Figure 23 is that the last decimal of producer prices must be less concentrated, compared to retailer prices. It is justified by Table 26, with "0" being the most likely last decimal, leaving the other decimals close to uniform distribution. Hence, "attractive pricing" is less important for producers.

Table 26 Distribution of Last Decimal of Producer Price

Last Decimal	Example	Percentage
0	£9.5**0**	39.67%
1	£8.3**1**	5.91%
2	£7.6**2**	5.67%
3	£6.2**3**	5.96%
4	£5.0**4**	6.83%
5	£4.7**5**	9.50%
6	£3.8**6**	5.68%
7	£2.1**7**	6.19%
8	£1.4**8**	6.37%
9	£0.9**9**	8.22%

To summarise the findings by conventional methods, there seems to be less rigidity in frequency and magnitude of producer price change, compared to retailer price change. Little rigidity in neither direction nor magnitude of price change is found in both retailer and producer prices.

5. Cross-Sectional Method

Based on the conventional method, the producer prices are even more flexible than the retailer prices, and the implied duration is only 4 months. However, this method is under the same problem of oversampling in short spells. Consistent to the previous chapter, cross-sectional duration across firm (DAF) proposed by Dixon (2010) is employed to provide an unbiased and robust measure of duration, and thus rigidity.

5.1. Distribution of DAF

5.1.1. Overall Distribution of DAF

The overall distribution of DAF during the sample period is illustrated in two forms. Table 27 summarises the estimated price duration following the cross-sectional method (DAF), while the average distribution of DAF is shown in Figure 24, with comparison between retailer and producer prices.

Table 27 Distribution of DAF (Retailer V.S. Producer)

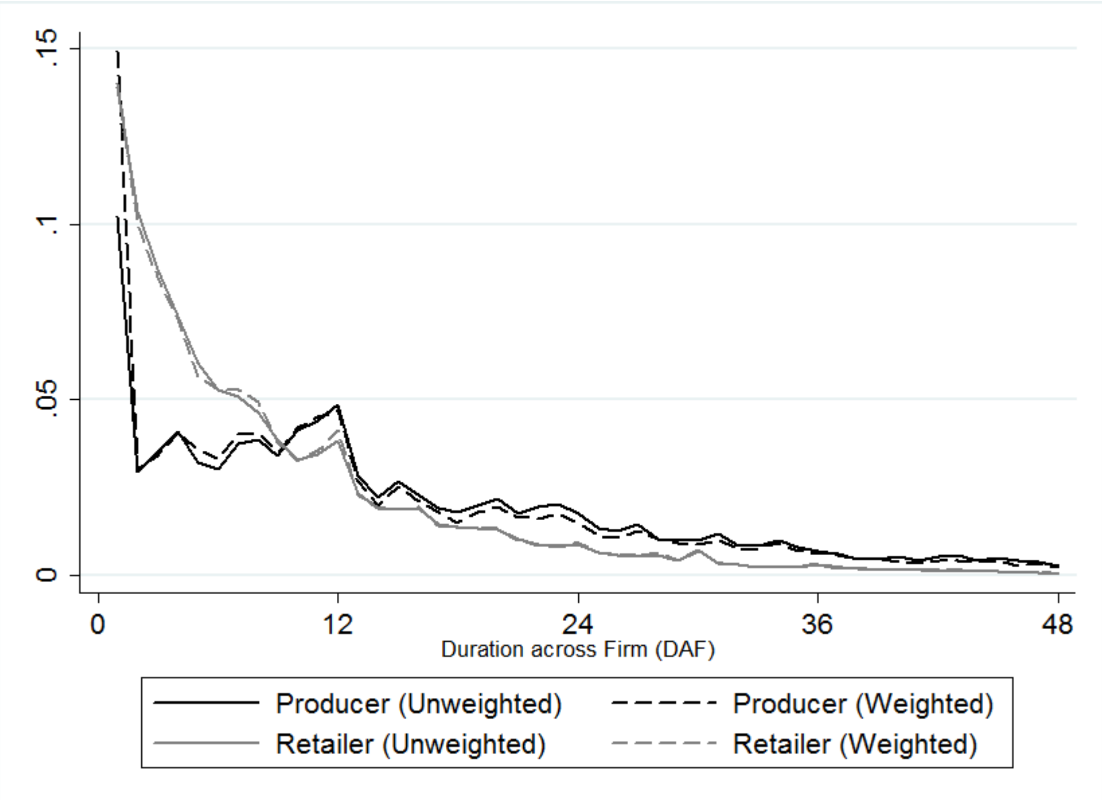
	Retailer Price		**Producer Price**	
	Unweighted	**Weighted**	**Unweighted**	**Weighted**
Mean	9.1847	9.3460	16.9902	15.2838
Median	9.3145	9.5493	17.6946	15.8402
S.D.	0.5194	0.7094	2.6495	2.2965
Skewness	-2.8158	-1.2760	-0.9998	-0.9794
1%	6.5289	6.7016	8.9881	8.4438
5%	8.1957	7.9567	11.7101	10.7961
10%	8.7173	8.5054	13.4574	12.1128
25%	9.1443	8.9375	15.6544	14.1386
75%	9.4350	9.9120	18.9333	16.8416
90%	9.5571	10.0024	19.8711	17.7937
95%	9.6654	10.1311	20.2280	18.2217
99%	9.9782	10.2182	20.8495	18.6982

The first feature is that the average DAF is much longer than the frequency implied duration, which is shared by both retailer and producer prices. Not surprisingly, the cross-sectional method is robust to the oversampling problem. Surprisingly, the weighted mean DAF (15.2838 months) is more than 3 times longer than frequency implied duration (about 4 months). It suggests that the producer prices have a higher proportion of long durations than the retailer prices. This is confirmed by the distribution of DAF in Figure 24, where the producer prices have a fatter tail. This results in a more severe underestimation of duration if conventional method is used.

The second feature is that the weighted DAF is lower than the unweighted DAF for producer prices, but the case is reversed for retailer prices. To see the reason, note that the importance of energy goods in the sample is much higher than the proportion of observations. In addition, the energy goods prices have very short durations, resulting in a significant downward impact on the overall DAF.

Another feature seen in Figure 24 is quite typical in this chapter, i.e. the 4-month minor cycle and 12-month major cycles in the distribution of DAF. This common feature implies that the producers and retailers are synchronised in resetting prices and reinforced by each other. It is again an evidence of time dependent pricing models, such as Taylor (1979) and Calvo (1983).

Figure 24 Distribution of DAF (Producer V.S. Retailer)



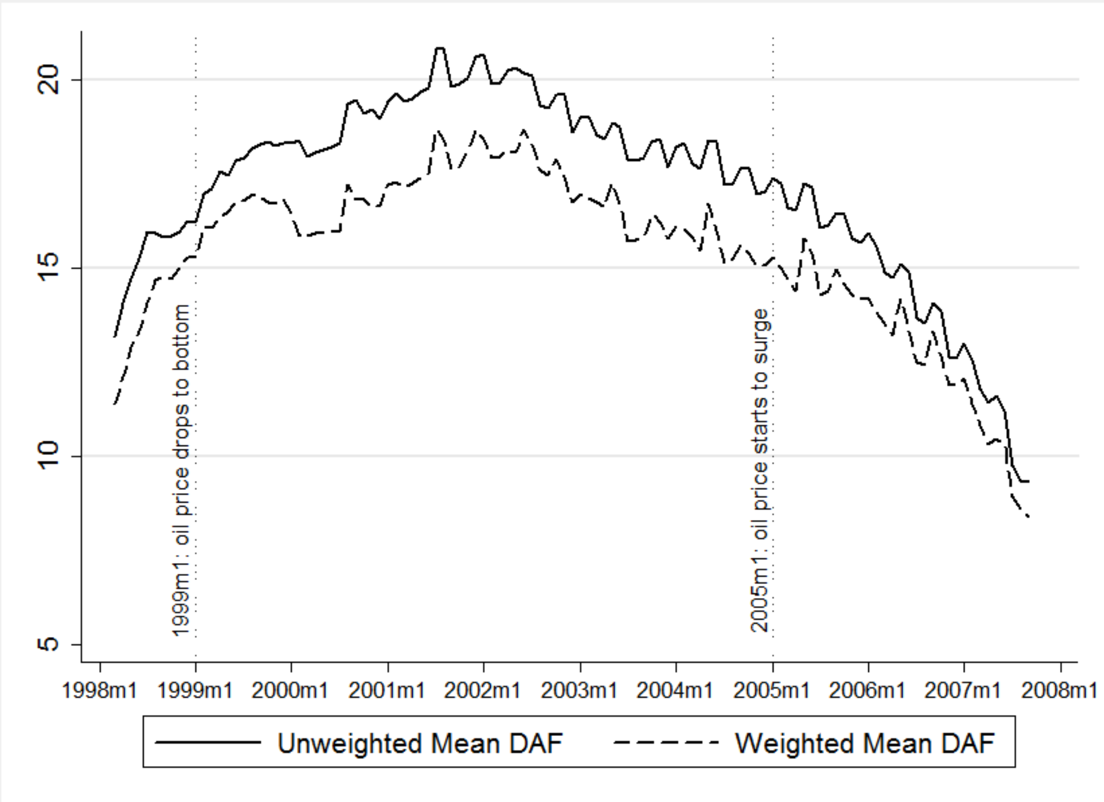
5.1.2. Time-Series Heterogeneity in DAF

The UK enjoyed a quite stable economy during the sample period, just before the outbreak of the late-2000s financial crisis. Figure 25 shows the evolution of mean DAF over time.

Similar to that of retailer price, the mean DAF of producer price is also sensitive to the oil price shocks. Given the importance of oil, the two remarkable dates again divide the sample period into three eras. When the oil price is low and stable after

1999m1, the mean DAF stays high and flat. In contrast, when the oil price is high and volatile after 2005m1, the mean DAF drops considerably. That is to say, the oil price has a negative effect on the mean duration, or equivalently, the producers are more flexible when oil price is fluctuating. This is a strong support for the state dependent pricing models, such as Mankiw (1985) and Rotemberg (2005).

Figure 25 Time-Series Heterogeneity in Mean DAF of Producer Price



5.1.3. Cross-Sectional Heterogeneity in DAF

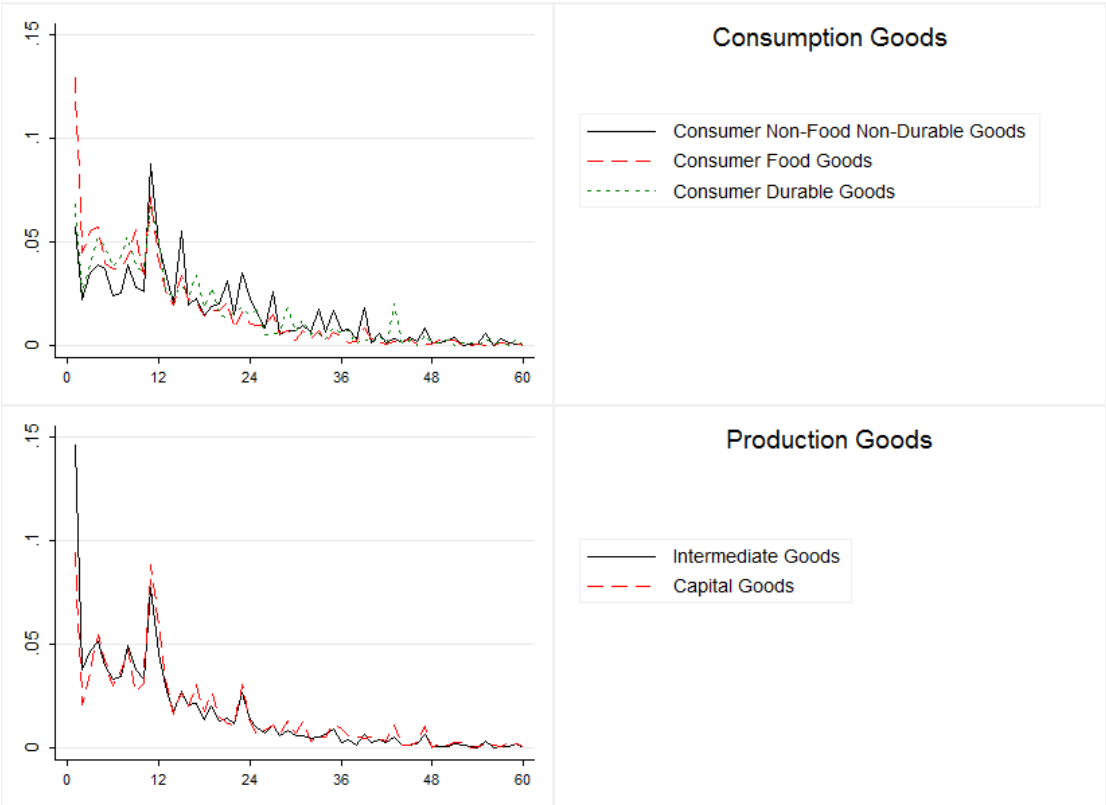
The average DAF also differ across sectors, but not as significant as in retailer price. As shown in Table 28, it is difficult to say whether consumption goods or production goods have higher mean DAF. The food and durable consumption goods are quite flexible, compared to intermediate and capital production goods. However, the non-food non-durable goods have the longest mean DAF (17 months). At the other extreme, the energy goods have the shortest mean DAF (4 months).

The full distributions of DAF are also reported by sector in Figure 26, omitting the energy goods due to its short duration. There is as much difference within groups as between groups. Despite the differences, there are several stylised facts consistent to previous results. Firstly, typical 4-month minor cycles and 12-month major cycles are again observed in the distribution of DAF, echoing the findings in retailer prices. Secondly, a high proportion of producers reset their prices within 1 year, but there is a fat tail in the distribution.

Table 28 Cross-Sectional Heterogeneity in Mean DAF

Sector	DAF
Consumption Goods	
Consumer Food Goods	11.2551
Consumer Durable Goods	11.6582
Consumer Non-Food Non-Durable Goods	17.1228
Production Goods	
Intermediate Goods	12.2292
Capital Goods	14.2833
Energy Goods	3.9619

Figure 26 Cross-Sectional Heterogeneity in Distribution of DAF



5.2. Distribution of Age

The distribution of age is another cross-sectional measure of price rigidity, in the sense that longer average age of the prices in the economy implies higher price rigidity. It is similar to demography, where the age profile of a country gives information of how long people live on average. The advantage of distribution of age over DAF is that it is robust to right censoring, since the definition of age does not require the knowledge of when current price ends.

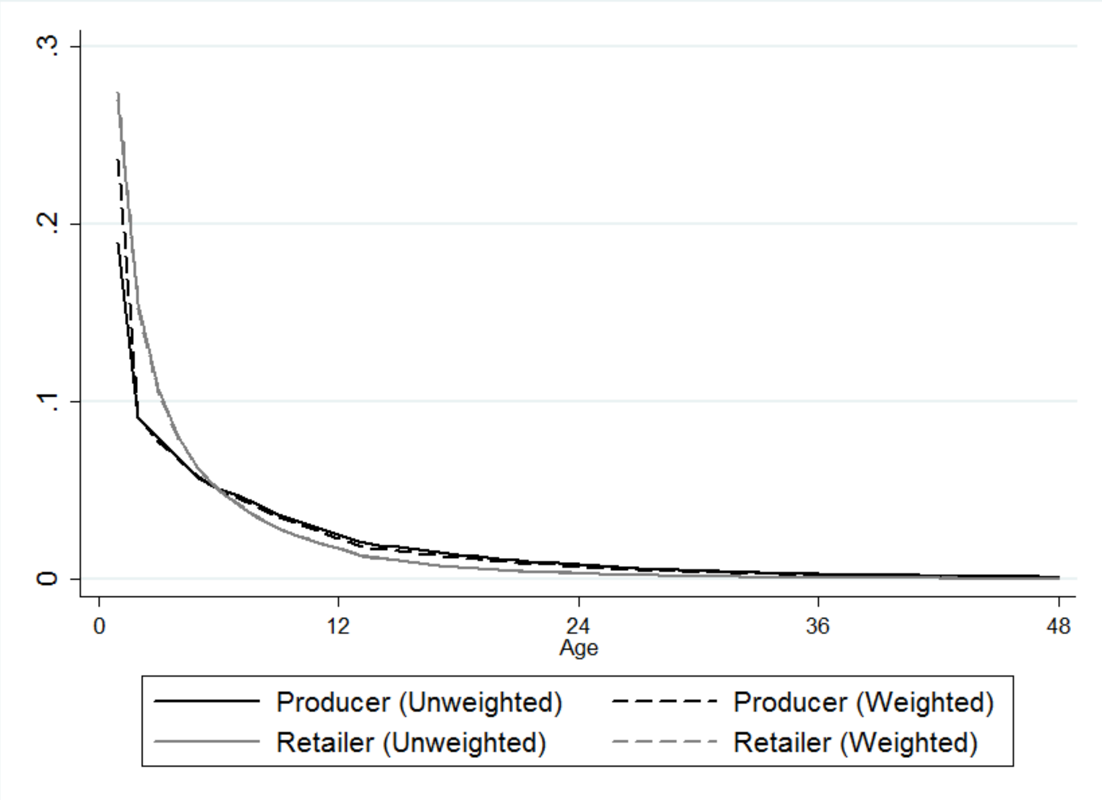
As shown in the previous chapter, the distribution of age is just an equivalent way of looking at the same thing as the distribution of DAF. Therefore, it is not surprising to see some similar features in age, compared to DAF. For example, producer price has a higher average age (8.6007 months) than that of retailer price (5.6044 months), because the former has a fatter tail in the distribution. On the other hand, age (8.6007 months) is shorter than DAF (15.2838 months), since age is incomplete duration.

The distribution of age is summarised in Table 29 and visualised in Figure 27, with comparison between retailer and producer prices. Note that the difference between unweighted and weighted distributions is more significant in producer price than in retailer price. Again, it is due to the extraordinary importance of energy goods, which reduces the rigidity of producer price.

Table 29 Distribution of Age (Retailer V.S. Producer)

	Retailer Price		**Producer Price**	
	Unweighted	**Weighted**	**Unweighted**	**Weighted**
Mean	5.5663	5.6044	9.5988	8.6007
Median	5.5405	5.6459	9.6517	8.6891
S.D.	0.4110	0.4689	0.7518	0.6795
Skewness	-0.1492	-0.6205	-0.3072	-0.1676
1%	4.1205	3.9284	7.7049	7.0395
5%	4.9946	4.8069	8.3459	7.4523
10%	5.1511	4.9801	8.5490	7.7250
25%	5.3588	5.3373	9.0415	8.0346
75%	5.7408	5.8709	10.0424	9.1533
90%	6.1389	6.1696	10.4868	9.4015
95%	6.3450	6.3445	10.7418	9.6249
99%	6.5316	6.7028	11.2720	10.0529

Figure 27 Distribution of Age (Producer V.S. Retailer)

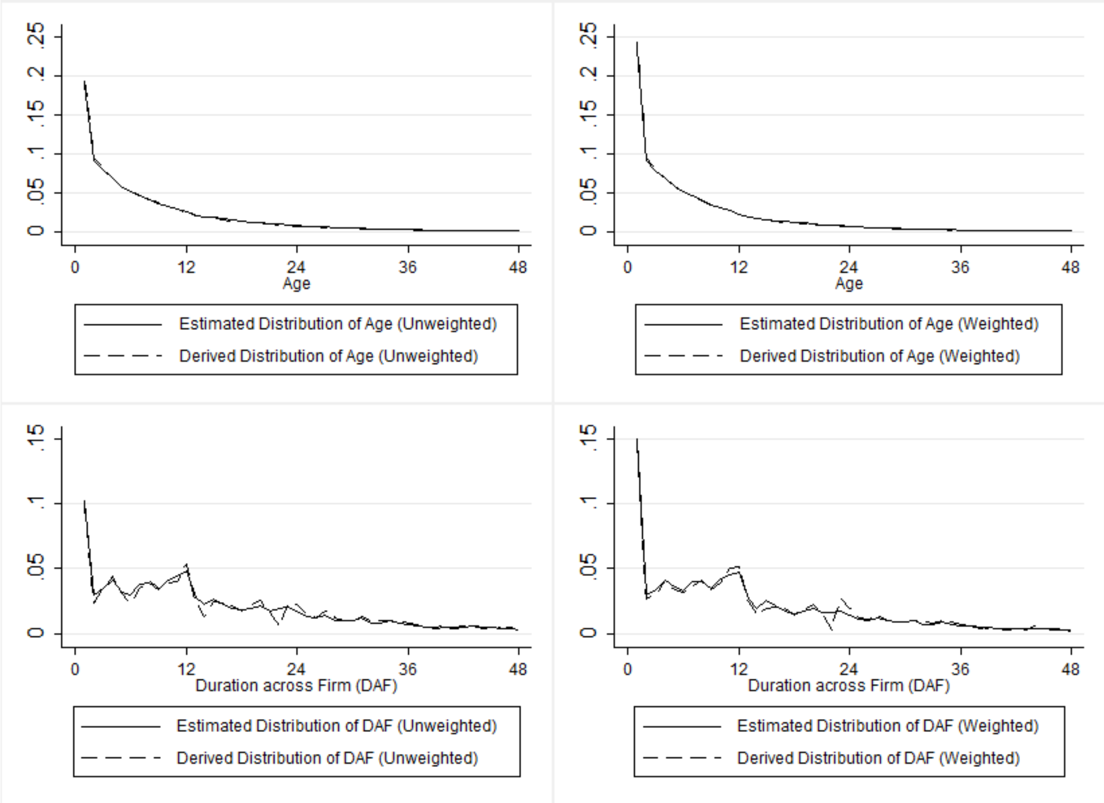


5.3. Relationship between DAF and Age

The formula proposed by Dixon (2010) give analytical relationships between distributions of DAF and age. The estimated and derived distributions turn out to be very close under retailer price. The same job is done under producer price, and they are again proven to hold. This can be seen by Figure 28, where the estimated distributions are almost the same as the derived ones.

In principle, the formulae are theoretically correct, but there are two sources resulting in the tiny discrepancies between the estimated and derived distributions. First, the economy is not always in steady state due to various shocks. Second, the right censoring cases tend to bias the estimated distribution of DAF downward. In contrast, the distribution of age is robust to right censoring, so the derived distribution of DAF is actually more reliable than the estimated one.

Figure 28 True and Derived Distribution of DAF and Age of Producer Price



6. Survival Analysis

The difference in price rigidity between conventional and cross-sectional methods addresses the outcome of price setting behaviour. This section will turn to how this outcome is generated by producers, i.e. factors that influencing firm's price setting behaviour, or the mechanism of price setting.

In the light of survival analysis, hazard function is the key to understand the mechanism of price setting behaviour, since it characterises the *conditional* probability of price change. It is easy to see the link between hazard function $h(t)$ and price duration T, i.e. any factor that positively affects $h(t)$ tend to negatively affecting T. In terms of degree of reliance on assumption, survival analysis can be classified into nonparametric, semiparametric and parametric. Since parametric analysis is proven in last chapter to be too restrictive to be plausible, this chapter will only focus on nonparametric and semiparametric analysis.

6.1. Nonparametric Analysis

Nonparametric analysis assumes the least on data generating process, since the estimated $h(t)$ only depends on time t. Therefore, $h(t)$ presented in this section is closely correlated to the rigidity measures in previous sections, because time is the only extra factor considered to describe the hazard function. In other words, the instantaneous risk of price change only varies with the age of the current price.

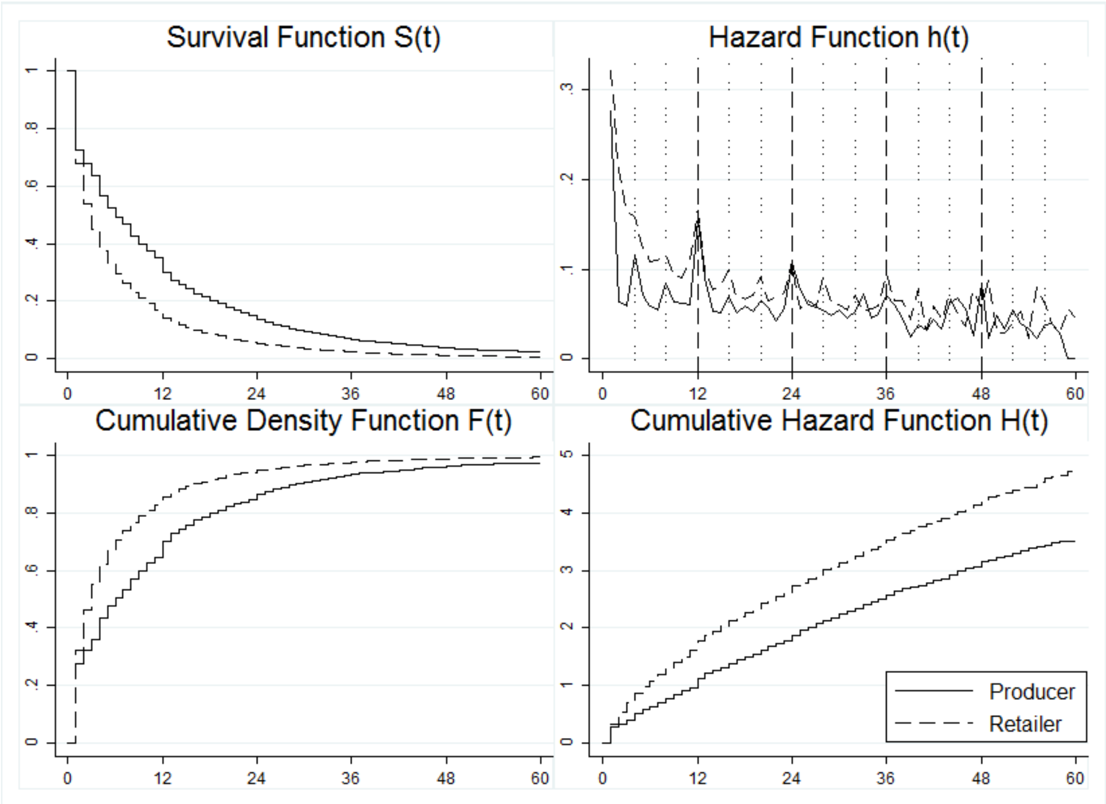
6.1.1. Pooled Hazard Function

As shown in previous chapter, there are four equivalent forms of presenting the distribution of duration. It is easy to derive one from another among hazard function $h(t)$, cumulative hazard function $H(t)$, survivor function $S(t)$, and cumulative density function $F(t)$. Figure 29 shows the four equivalent forms of presenting the distribution of duration. The distribution functions of producers (solid) are contrasted with those of retailers (dashed). Since $h(t)$ is the most popular form, this paper will only focus on the features of $h(t)$. Also, the weighted and unweighted distributions do not differ qualitatively, therefore only the weighted results are reported hereinafter.

There is a high probability (27.57%) of price change in the first month, mainly due to the energy price. However, the producer's $h(t)$ has a relatively flatter shape than the retailer's. The stylised "downward" slope observed in retailer price is not found in producer price. The hazard rates are consistently lower in the first 36 months, suggesting that the producer price is less likely to change, or equivalently, more rigid. This feature is consistent with that drawn from cross-sectional method, but different from the conventional method, which is biased due to oversampling.

Another feature of $h(t)$ is that there are regular big spikes every 12 months (major cycle) and small spikes every 4 months (minor cycle). This is a support to time dependent models, such as Generalised Taylor Economy (GTE). The spikes have a very similar pattern to retailer price, especially at the major cycles. In fact, the two hazard functions in comparison have almost constant differences at the minor cycles. It suggests that the producers and retailers are closely interacting with each other, so the price setting behaviour is much synchronised.

Figure 29 Distribution Functions (Producer V.S. Retailer)



6.1.2. Heterogeneity in Hazard Function

The producers are different in various aspects across sectors. Following the previous classification, distinction between consumption goods and production goods are made.

On average, the production goods have higher hazard functions than the consumption goods. However, similar to the findings in distribution of DAF, there is as much heterogeneity within sector as between sectors, as graphed in Figure 30. This difference is tiny, except for energy goods, which have an extremely high hazard function (not shown). This heterogeneity can be again explained by different degrees of competition in the specific market.

The production goods sectors are usually more competitive, given numerous firms and homogenous products. These sectors are mostly related to raw materials and energy goods, on which the whole economy is based. High degree of competition in these markets results in higher hazard functions. In particular, energy goods have the highest probability of price change, since this sector faces both national and international competition. The energy goods markets could be regarded as perfectly competition and the fluctuations are quite volatile.

In contrast, the consumption goods sectors face lower competition because products tend to be differentiated across firms. Given that consumption goods are final goods, there are more procedures involved in production, so products are more likely to be different across firms. This feature makes the consumption goods markets more close to monopolistic competition.

Figure 30 Heterogeneity in Hazard Function of Producer Price

To summarise, the hazard function of producer price is on average lower than that of retailer price, implying a higher rigidity for producer price. This conclusion is consistent with the cross-sectional method. Moreover, the heterogeneity by sector is not much. The production goods have slightly higher hazard functions than the consumption goods, which can be explained by the degree of competition.

6.2. Semiparametric Analysis

As argued in last chapter, semiparametric analysis controls for covariates that differ across observations, leaving the baseline hazard function $h_0(t)$ nonparametric. Hence, it lies between nonparametric and parametric analysis. It is therefore more flexible and reliable in obtaining both hazard function and effects of various covariates. The proportional hazard Cox model is again used:

$$h(t) = h_0(t) \cdot \exp\left(\boldsymbol{\beta}_i'\mathbf{x}_i + \cancel{\boldsymbol{\beta}_{ii}'\mathbf{x}_{ii}} + \boldsymbol{\beta}_{iii}'\mathbf{x}_{iii} + \boldsymbol{\beta}_{iv}'\mathbf{x}_{iv}\right)$$

Firstly, since $h_0(t)$ only depends on the analytical time t, the monthly seasonality due to calendar time needs to be controlled in the covariates. Thus, similar to the retailer model, January is treated as the base, and the rest 11 calendar month dummies are used to capture the covariates from time dimension ($\mathbf{x}_i$). The estimated coefficients are listed in Table 30.

Secondly, note that the region information is not available in producer price microdata. Also, last chapter shows that there is little regional difference in retailer's price setting in the UK, and it is arguable that the producer's price setting is even less dependent of location since producers are facing wider markets. Thus, the covariates from space dimension ($\mathbf{x}_{ii}$) are omitted.

Thirdly, covariates from macroeconomic dimension ($\mathbf{x}_{iii}$) are the same as those used in retailer model. Inflation is included to capture the impacts of macroeconomic environments on producer's real revenue, while interest rate, wage and oil price are used to capture the macroeconomic effects on producer's capital costs, labour costs and resources costs. Both lags and leads of these variables are used to account for backward looking expectation and forward looking expectation, which might be involved in price setting. The estimates are shown in Table 31.

Lastly, important covariates from microeconomic dimension ($\mathbf{x}_{iv}$) related to each individual firm are considered in the model, including sector dummies, level of price, magnitude of price change, market shares of the producer firms. In particular, both within-industry and economy-wide market shares are available in producer price data, in contrast to retailer model where only economy-wide market share is included. This detailed distinction gives deeper insight into the effect of competitiveness on the price rigidity. Table 32 summarises the estimation results.

Table 30 Estimations of Pooled and Separate Cox Models by PPI Sector (Part A)

	Covariates	Pooled	Consumption Goods			Production Goods	
			Non-Food Non-Durable	Food Goods	Durable Goods	Intermediate Goods	Capital Goods
Covariates from Time Dimension	**February**	-0.6378**	-0.5490**	-0.2970**	-0.7735**	-0.6339**	-0.8120**
	March	-0.0564**	-0.3852**	0.5459**	0.0658**	-0.0024**	-0.5163**
	April	-0.3086**	-0.3456**	0.2775**	0.0613**	-0.3774**	-0.7897**
	May	-0.4010**	-0.4256**	0.1132**	-0.3859**	-0.4652**	-0.6584**
	June	-0.2885**	-0.3172**	0.4053**	-0.2357**	-0.4224**	-0.5804**
	July	-0.1421**	-0.0493**	0.4869**	0.1123**	-0.2756**	-0.5918**
	August	-0.2524**	-0.3161**	0.5273**	0.0108**	-0.4942**	-0.5924**
	September	-0.4321**	-0.3710**	-0.0253**	-0.8381**	-0.4855**	-0.5712**
	October	-0.2525**	-0.5165**	0.3042**	0.1126**	-0.2612**	-0.5792**
	November	-0.1735**	-0.5082**	0.3594**	0.3596**	-0.3742**	-0.1920**
	December	-0.4108**	-0.3865**	0.2362**	-0.4494**	-0.5017**	-0.7085**

Notes: * denotes 5% significance level. ** denotes 1% significance level.

Table 31 Estimations of Pooled and Separate Cox Model by PPI Sector (Part B)

	Covariates	Pooled	Consumption Goods			Production Goods	
			Non-Food Non-Durable	Food Goods	Durable Goods	Intermediate Goods	Capital Goods
Covariates from Macroeconomic Dimension	**Inflation t**	0.1134**	0.1260**	-0.1798**	0.3214**	0.0982**	0.2551**
	Inflation t-1	0.4840**	0.4642**	0.7861**	1.1192**	0.3412**	0.2830**
	Inflation t+1	0.0158**	-0.3361**	0.0149**	0.5873**	0.0623**	0.2986**
	Interest Rate (Δ) t	-0.0060**	-0.6066**	0.6187**	-0.9865**	0.0522**	0.2370**
	Interest Rate (Δ) t-1	0.2359**	0.1451**	-0.2270**	1.0710**	-0.4069**	-0.2128**
	Interest Rate (Δ) t+1	-0.1377**	-0.1369**	-0.2540**	-0.8429**	-0.1885**	0.4805**
	Wage (%Δ) t	0.2174**	0.1706**	-0.2763**	-0.2996**	-0.2627**	-0.5868**
	Wage (%Δ) t-1	-0.4946**	-0.2333**	-1.1784**	-0.3555**	0.4834**	-0.2421**
	Wage (%Δ) t+1	0.0225**	-0.0403**	0.1889**	0.4468**	-0.0752**	0.0482**
	Oil Price (%Δ) t	0.0022**	0.0371**	-0.0183**	-0.0379**	-0.0043**	-0.0052**
	Oil Price (%Δ) t-1	-0.0072**	0.0301**	-0.0234**	-0.0184**	0.0126**	-0.0134**
	Oil Price (%Δ) t+1	0.0035**	0.0287**	0.0243**	0.0480**	0.0173**	0.0060**

Notes: * denotes 5% significance level. ** denotes 1% significance level.

Table 32 Estimations of Pooled and Separate Cox Model by PPI Sector (Part C)

	Covariates	Pooled	Consumption Goods			Production Goods	
			Non-Food Non-Durable	Food Goods	Durable Goods	Intermediate Goods	Capital Goods
Covariates from Microeconomic Dimension	Consumer Food	0.0781**	–	–	–	–	–
	Consumer Durable	-0.1913**	–	–	–	–	–
	Consumer NFND	-0.3427**	–	–	–	–	–
	Intermediate Goods	0.0058**	–	–	–	–	–
	Capital Goods	-0.1452**	–	–	–	–	–
	Price	0.0000*	0.0000*	0.0003*	0.0000**	0.0000**	0.0000*
	Price (%Δ)	0.0000*	0.0003*	0.0003**	0.0043*	0.0000*	0.0000**
	Market Share (Industry-Wide)	-0.0010**	-0.0008**	-0.0017**	-0.0010**	-0.0011**	-0.0029**
	Market Share (Economy-Wide)	1.5069**	1.2996**	2.8108**	1.3910**	1.5867**	1.0643**

Notes: * denotes 5% significance level. ** denotes 1% significance level.

6.2.1. Pooled Cox Model

The estimated coefficients ($\boldsymbol{\beta}_i, \boldsymbol{\beta}_{iii}, \boldsymbol{\beta}_{iv}$) for pooled Cox model are listed in the first columns of Table 30, Table 31 and Table 32, which aim to paint an overall picture of the average producer's price setting behaviour.

From the estimated coefficients of calendar month dummies ($\boldsymbol{\beta}_i$), it is no surprising that January is again the month with highest likelihood that producers change their prices, due to Christmas sales. This finding is consistent with that in retailer microdata. It suggests that this typical seasonality makes price much more flexible than usual, which is a strong evidence for time dependent pricing models. The second highest hazard rates is March, which is one month earlier than that in retailer. Remember that April is the starting month of a new tax year, implying that producers tend to adjust prices a bit in advance, while retailers only react when new tax policy is out. In addition, July is the third highest month, very likely due to summer sales.

Turning to the macroeconomic covariates ($\boldsymbol{\beta}_{iii}$), all the estimates turn out to be highly significant. Both backward looking and forward looking expectations are important in producer's price setting behaviour. The positive estimates for all the three coefficients of inflation show that producer's reaction to inflation is both sensitive and persistent. In contrast, retailers only respond to lagged inflation. Arguably, producers are mainly wholesalers, so a small change in inflation will have massive effects on the real revenue. It motivates the producers to react quicker to the change in general price level. Similar argument holds for explaining the significance of costs covariates. In particular, oil price is very influential in producer's costs. A rise in energy price will bring up the transportation costs of both raw materials and processed products. Moreover, this effect will spread to every corner of the economy. The income effect reinforces the substitution effect, leading to even worse economic environments and even recession. The significant effects are directly tangible for producers, so the change in costs will be immediately reflected in their prices. Furthermore, even the expected change in oil price will be taken into account, which is also found in retailer price. This is because developed commodity markets reveal informative signal of future resources prices, based on which firms could adjust their price in advance.

The microeconomic covariates ($\boldsymbol{\beta}_{iv}$) related to each individual producer firm indicate that hazard function differs significantly among sectors. Treating energy goods as base group, only consumer food sector and intermediate goods sector have higher hazard rates. This is mainly due to the nature of these two sectors, since both food and intermediate goods are not storable. In particular, some food prices might change several times even within one day. The level of price and the change of price are still very close to zero, similar to the findings in retailer price.

Regarding the effects of market shares, it is interesting to observe opposite signs on industry-wide and economy-wide weights. The implied competitiveness of the market is the key to provide a consistent explanation for this seemingly contradictory phenomenon. On the one hand, a higher industry-wide market share implies a higher pricing power of the firm, or equivalently, a lower competitiveness of the industry. It is natural to have a lower frequency of price change in less competitive market. On the other hand, a higher economy-wide market share implies a higher importance of the goods, while most such goods are produced in well-established traditional industries. The competitiveness of these mature industries is usually higher than those which are still growing, so the price change of producer firms with higher economy-wide market share should be more frequent. Hence, the seemingly contradictory phenomenon is actually coherent in mechanism of price setting behaviour.

6.2.2. Separate Cox Model by Sector

Significant estimated coefficients of sector dummies imply remarkable heterogeneity in hazard function across sectors. Therefore, in addition to use pooled model to describe producer's average price setting behaviour. Cox models for each PPI sector are estimated separately and shown in the other columns of Table 30, Table 31 and Table 32.

Firstly on calendar month dummies, non-food-non-durable goods and both production goods exhibit similar seasonal pattern to pooled results. However, January is no longer the month with highest hazard rate for food goods and durable goods sectors. Instead, summer (June, July and August) is the season with most frequent price change for food products, due to the temperature and storability.

Regarding macroeconomic and microeconomic covariates, there are no clear regularities found across different sectors, except that lagged inflation and expected oil price have positive effects on likelihood of price change for all sectors. Moreover, there are substantial heterogeneities within and between consumption goods and production goods. This is strong evidence supporting heterogeneous agent model, such as GTE or GCE. A representative firm might be able to capture the average degree of nominal friction, but it will fail in explaining the dispersion due to its simplicity. That is why simple Taylor or simple Calvo models cannot generate enough persistence of structural shocks within plausible calibrated values of price rigidity.

6.2.3. Baseline Hazard Function

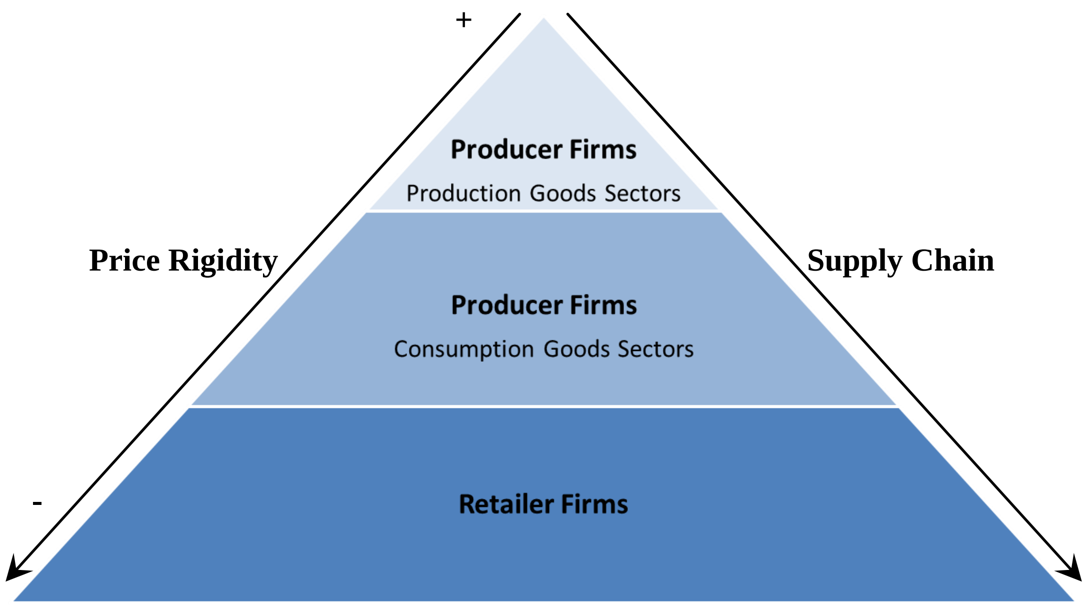
After controlling for all these covariates in Cox model, the leftovers are used to describe the pure hazard function which only depends on time t. This pure hazard function is termed as baseline hazard function $h_0(t)$. Both pooled and separate estimated $h_0(t)$ are shown in Figure 31.

Figure 31 Baseline Hazard Functions for Cox Models of Producer Price

The contrast within and among sectors shows a very similar pattern in baseline hazard function once the effects of various factors are purged off. It is also consistent with the features found in retailer price such as a downward slope and 4-month/12-month spikes. These common features between retailers and producers indicate that price setting behaviour in the whole economy tends to co-move and synchronised.

Despite little, the consumption goods sectors tend to have higher baseline hazard rates than that of production goods sectors. Recall that retailers have even less price rigidity, according to the cross-sectional measure (DAF). It is natural to infer that the upstream firms in the supply chain tend to have more nominal frictions in price setting than downstream firms. This conclusion not only holds in general, but also holds in particular industry. For example, although some sectors such as energy goods sector might have more flexible prices than retailer prices as a whole, the energy goods producers still have more rigidities than the energy goods retailers. As moving more towards the downstream of supply chain, the number of firms grows, and the products are more differentiated. Competition is greater due to more substitutable goods in the market. The structure of the supply chain looks like an “ecological pyramid”. The relationship between the position in supply chain and price rigidity be illustrated in Figure 32.

Figure 32 Supply Chain and Price Rigidity



The transmission of structural shocks, such as productivity shock and monetary policy shock, has multiple channels. Apart from a direct effect on the retailer firms, an indirect effect will be transmitted through producer firms in the upstream of supply chain. Hence, if there is even a small nominal friction in both producer and retailer firms, the effect of shocks could still be very persistent, due to the “container” role of producers.

On the other hand, producer firms split and mitigate the magnitude of impacts from the shock for retailer firms. This “buffer” effect reduces the volatility and fluctuations in price and output in the economy.

7. Conclusion

This chapter uses monthly microdata underlying PPI from 1998m1 to 2008m2 to investigate the price setting behaviour of producer firms in the UK. Two themes are explored: the outcome and the mechanism of price setting behaviour. For the first theme, both conventional and cross-sectional methods are applied. Under conventional method, it is found that producer price is more flexible than retailer price. However, this conclusion is illusionary because conventional method tends to oversample the short durations. In contrast, cross-sectional method (DAF) leads to an opposite conclusion that producer price on average lasts longer than retailer price.

Survival analysis is used for analysing the mechanism of price setting behaviour. To start with, nonparametric Kaplan-Meier approach is used to estimate the hazard function and survival function of producer's price setting. A very similar pattern is found in producer price with retailer price, i.e. downward sloping and typical 4-month spikes. Heterogeneity across sectors is also examined and consumption goods sectors have longer implied duration than production goods sectors.

To control for the factors that might influence the overall hazard function, semiparametric Cox model is used. After filtering out the effects from seasonality, macroeconomic and microeconomic covariates, the baseline hazard functions of different sectors turn out very similar. The downward slope and typical spikes features still remain, but the difference between consumption goods sectors and production goods sectors now vanishes. It is arguable to use baseline hazard functions to calibrate any heterogeneous price setting models in macroeconomic application, since they are "deep structural parameters" after removing policy dependent components.

A more systematic analysis of price rigidity is made in a wider perspective. In the economic system, as moving from upstream of supply chain to downstream, price rigidity is decreasing due to the growing degree of competition. Furthermore, as a shock hits the economy, the producer firms act as both "container" to prolong the persistence of shocks and "buffer" to reduce the fluctuations. Hence, the microdata evidence suggests that inclusion of producer firms and heterogeneity in price setting behaviour might greatly improve the performance of macroeconomic models.

CHAPTER III

Heterogeneous Price Setting Behaviour and Macrodata Analysis of DSGE Models

1. Introduction

The Dynamic Stochastic General Equilibrium (DSGE) models become more and more popular in both academia and policy making (e.g. Federal Reserve in US, Bank of England in UK and European Central Bank in Euro area), especially after the seminal works of Smets & Wouters (2003), Christiano, Eichenbaum & Evans (2005) and Smets & Wouters (2007). These models succeed in capturing some stylised facts of empirical persistence found in macroeconomic data, i.e. the hump shape impulse response functions of output, consumption, investment, employment, capital, inflation, interest rate and other important variables. These features rely on four modelling components of frictions in the DSGE models. Firstly, sticky price and wage setting behaviour are featured by Calvo model with partial indexation, following Kollmann (1997) and Erceg et al. (2000). This feature is essential to get persistence in inflation. Secondly, capital utilisation rate is employed to obtain persistence in capital accumulation, following Greenwood et al. (1988) and King & Rebelo (1999). Thirdly, adjustment costs are needed to get investment smoothing, in the spirit of Lucas (1967) and Gould (1968). Fourthly, habit formation, after Fuhrer (2000) and McCallum & Nelson (1999), is incorporated to achieve consumption smoothing.

A main controversial modelling component is the price setting behaviour. Indeed, the assumption of Calvo with indexation may be appropriate for wage setting, since it is arguable that wage negotiation is costly. Wage contracts cannot be flexibly reset within some duration, so indexation is necessary to account for the inflation risk. For instance, the minimum wage in the UK is reset every year according to the inflation. However, price setting behaviour is much more different, and little evidence is found from the microdata level for the usage of price indexation among firms. Another important drawback of these homogeneous type price setting models (including Calvo with indexation) is that the estimated degree of price rigidity is ridiculously high. For example, over 90% firms cannot reset prices at the optimal levels in Smets & Wouters (2003). This is inconsistent with microdata evidence and common sense. It seems to be a dilemma between enough persistence and reasonable degree of rigidity. In the light of a series of papers, e.g. Wolman (1999) and Dixon & Kara (2005), two price setting models with heterogeneous agent paradigm are developed, the Generalised Calvo Economy (GCE) and Generalised Taylor Economy (GTE). Both models provide a better description of the price setting behaviour, compared to homogeneous agent models such as simple Calvo, simple Taylor as well as Calvo with indexation (termed as ICE hereinafter). This paper develops a benchmark DSGE model based on Smets & Wouters (2003), with price setting mechanism replaced by different candidates. It is shown that heterogeneous agent framework has greatly improved the performance of DSGE model, especially in impulse response functions. The dilemma in homogeneous agent model can be resolved by heterogeneous price setting behaviour.

Along with the development of modelling, various macroeconometric tools are developed to estimate and test DSGE models. As classified by Geweke (1999), there is a distinction between *weak* and *strong* econometric interpretations of DSGE models. The strong interpretation applies system-based estimation and testing. This approach includes Classical maximum likelihood (ML) as in Sargent (1989) and Leeper & Sims (1994), and Bayesian inference proposed by Geweke (1999) and Schorfheide (2000). The weak interpretation, on the other hand, only focuses on some features of DSGE models of interested, such as Euler equation or impulse response functions. This approach encompasses the earliest calibration practice to match data moments adopted in Kydland & Prescott (1982), Generalised Method of Moments (GMM) in Hansen & Singleton (1982), Minimum Distance (MD) between VAR and DSGE impulse response functions in Christiano, Eichenbaum & Evans (2005), and indirect inference in Meenagh et al. (2009) and Le, Minford & Wickens (2010).

From another perspective regarding model testing, one could either test a DSGE model against the observed data in absolute sense, or test one model against another model in relative sense. As Meenagh & Minford (2011) argued, DSGE models fit data poorly and are usually rejected if they are tested in absolute sense. Nevertheless, models are not designed to be true, but to be useful in mimicking some important and interesting part of the real world. A model is useful if it outperforms the other competitors in the relative sense that it can better replicate various stylised facts found in data. Hence, relative testing provides a way of finding a useful model, rather than a true model.

This paper concentrates on the inferences based on Bayesian approach, while other approaches, such as maximum likelihood and indirect inferences, are also discussed to draw a comparison. Interestingly, all approaches lead to similar conclusion, i.e. DSGE model with heterogeneous price setting behaviour generates more persistence and performs econometrically better than homogeneous price setting model. This improvement greatly enhances the empirical validity and reliability of New Keynesian DSGE models, and also facilitates optimal monetary policy and welfare analysis.

Following the introduction, Section 2 discusses different approaches to macroeconometric inference and the chosen methodology for this chapter. Section 3 details the DSGE model framework and the 5 variants in price setting behaviour, and Section 4 describes the microdata and macrodata used to estimate and compare the models. Section 5 summarises the empirical findings in model comparison, estimation and other features of DSGE models. Section 6 concludes.

2. Methodology

Over the last 30 years, macroeconometric techniques have experienced revolutionary development. Some important and popular macroeconometric approaches are listed in Table 33. In particular, simulation-based methods have become possible, thanks to the growing computing power. One phenomenal consequence is the popularity of Bayesian inference, which was never so widely spread because the computation burden was unimaginably huge just several decades ago. Though Bayesian approach is controversial in using prior, its advantages in efficiency and flexibility are still very attractive to macroeconomists for estimating and evaluating DSGE models. Also, indirect inference, which belongs to Classical methodology based on simulation, has been greatly developed over the years. This chapter will focus on both ML and Bayesian inference to conduct macrodata analysis on DSGE models. Other popular tools, such as VAR, BVAR and indirect inference are also discussed.[①]

Table 33 Macroeconometric Approaches

Approach	Example
Calibration	Kydland & Prescott (1982)
VAR	Sims (1980)
BVAR	Doan et al. (1984)
GMM	Hansen & Singleton (1982)
Minimum Distance IRF	Christiano, Eichenbaum & Evans (2005)
Indirect Inference	Meenagh, Minford & Wickens (2009)
ML	Sargent (1989)
ML DSGE-VAR	Ireland (2004)
Bayesian	Smets & Wouters (2003)
Bayesian DSGE-VAR	Schorfheide (2000)

One can classify macroeconometric approaches into different categories in terms of different criteria. For example, according to the role of prior in obtaining the structural parameters, calibration is on one extreme treating prior as the only information source, while Classical ML is on the other extreme using nothing from prior. Bayesian approach lies in somewhere between calibration and ML, since it can be treated as a weighted average between the two approaches. For another example, according to the role of DSGE model in estimation, VAR is on one extreme using little information from DSGE model, while Bayesian and ML are on the other extreme with all conditions strictly derived from microfounded DSGE model. Approaches like GMM and minimum distance lie in somewhere between the two extremes, since they only focuses on some partial aspects of the DSGE model. For the last example of categorisation, most approaches including Bayesian are "direct" inference based on the forecasting

[①] I am obliged to Professor Patrick Minford's comments and critiques on this section.

criterion (smallness of forecast error), while indirect inference is based on the behaviour criterion (closeness of simulated behaviour with data).

The first and foremost advantage of Bayesian approach, compared to Classical approach, is its incorporation of prior information, which greatly mitigates the identification problem in estimating DSGE models. Identification problem is rooted in objective function, under which different values of structural parameters lead to the same joint distribution for the observables. Canova & Sala (2006) summarise different types of identification problems: (i) *observational equivalence*, which means that different structural models with different economic interpretations may not be distinguishable in terms of the chosen objective function; (ii) *partial identification*, which refers to the case where two or more structural parameters enter the objective function proportionally, making them separately unrecoverable; (iii) *under identification*, which occurs if a structural parameter disappears from a log-linearised solution; (iv) *limited information identification*, which is related to the situation where only a subset of the model's implications is used; and (v) *weak identification*, under which there is no unique solution, due to the lack of curvature in objective function. Bayesian inference is based on the likelihood function, which might also be flat, whereas even a weakly informative prior can introduce enough curvature in the posterior density surface that facilitates maximisation. In other words, Classical econometricians treat parameter space equally important, while Bayesian approach assigns different weights through prior distribution. This weighted maximisation procedure also avoids getting absurd estimates, which might happen under ML approach.

The second advantage of Bayesian approach is its easiness of model comparison between non-nested models. Bayes factor or posterior odds provide handy quantitative criteria to relatively evaluate the performance of models with totally disparate specifications. In contrast, likelihood ratio test is only useful when a model is a special case of the other. Note that Bayesian model comparison is a testing procedure in a relative sense, which means it cannot tell whether a model is verified or falsified by the observable data. If one tries to test DSGE models against data in an absolute sense, simulation-based indirect inference approach, among others, would be a nice choice.

The third advantage of Bayesian approach lies in its natural way of addressing misspecification of models. Quoting Fernández-Villaverde (2010), Bayesians are searching for the "right" rather than the "true" values of parameters to come up with good description of data. Indeed, all models are wrong, but some are useful. Bayesian approach is an efficient way of maximising one's ability to use the model as a tool to mimic the features of data and draw plausible policy implications.

However, there are several disadvantages of Bayesian inference. One big limitation of Bayesian approach, as mentioned above, is that it cannot test model in absolute sense, but only rank different models relatively. That is to say, a relatively best model might still be rejected by data, but one would never know that under Bayesian inference. In contrast, Classical or Frequentist approaches (including ML and indirect inference) test the models in both absolute and relative senses through likelihood ratio or Wald statistic. Another vital drawback of Bayesian inference is its reliance on prior. The validity and reliability of both estimation and testing depends on the correctness of prior. If prior is wrong, the posterior conclusions could be even more biased.

As a matter of fact, there is no absolutely best approach, but only relatively most appropriate approach. The choice depends on the question at hand. In this paper, the purpose is to compare and rank homogenous and heterogeneous price setting models in a common DSGE framework. Whether a model is rejected by data in absolute sense is less important in this thesis. The judgement relies on all the three dimensions, i.e. theory, data and prior. Hence, Bayesian approach[①] is chosen to provide an overall performance evaluation and system-based parameter estimation. At the same time, VAR and BVAR are employed to provide a comparison basis. Indirect inference is also discussed to reinforce the results obtained from Bayesian model comparison, while ML is used to highlight the advantage in parameter estimation of Bayesian approach.

Given the two disadvantages of Bayesian inference, future work may consider using simulation-based methods, such as indirect inference, to test these models against data in absolute sense. It is expected that some heterogeneous price setting models could survive the absolute tests and be estimated using prior-free methods. Moreover, estimation results can be used to check the robustness of the ranking, which might change after searching across the parameter space for the best combination to minimise the Wald statistics.

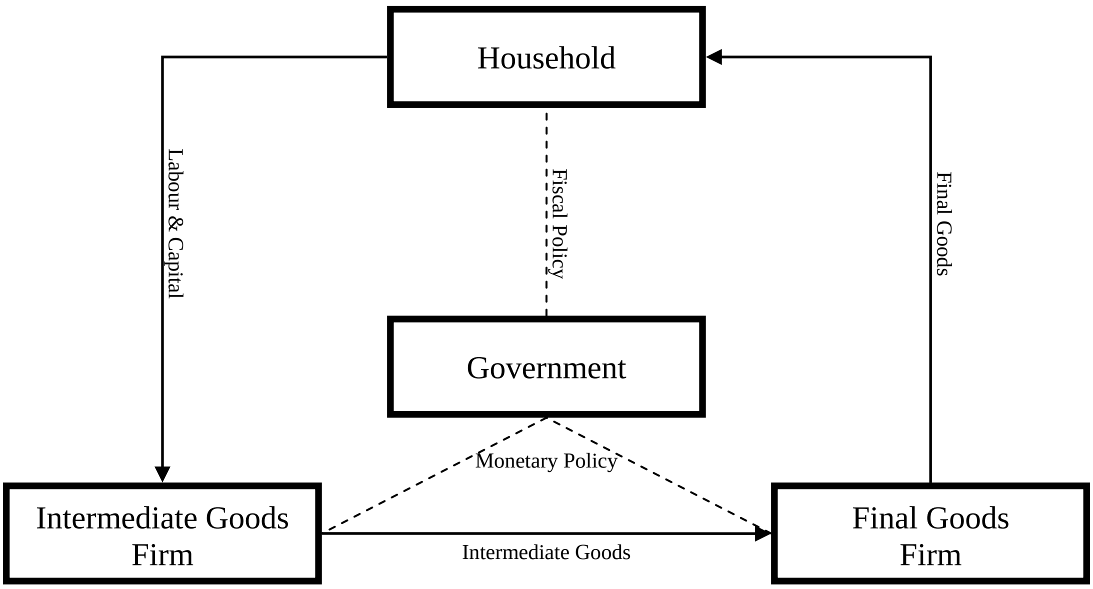
[①] Bayesian and ML estimation procedures are done with the help of Dynare, see **Adjemian, S.; H. Bastani; M. Juillard; F. Mihoubi; G. Perendia; M. Ratto and S. Villemot.** 2011. "Dynare: Reference Manual, Version 4," In *Dynare Working Papers*. CEPREMAP.

3. The Model

The DSGE models used in this paper are based on the benchmark model proposed by Smets & Wouters (2003), where the price setting behaviour is assumed to be Calvo with Indexation (ICE). As noted earlier, this simplification of price setting behaviour inconsistent with the micro level evidence of firm's price setting behaviour. In the light of Wolman (1999), Dixon & Kara (2005) and Coenen et al. (2007), a new paradigm for modelling price/wage setting behaviour is established. Generalised Taylor Economy (GTE) and Generalised Calvo Economy (GCE) are developed to capture the heterogeneity in price/wage setting behaviour. The idea of this paper is to replace the price setting component (ICE) in benchmark model by various candidates, such as simple Calvo, simple Taylor, GCE and GTE, resulting in 5 variants of the benchmark model, on which Bayesian econometric techniques can be used to draw model comparison as well as parameter estimation.

There are four agents in this modelling framework: (i) the household demands for final goods while supplying labour and capital to the intermediate goods firm; (ii) the intermediate goods firm demands for labour and capital from household, while supplying intermediate goods to final goods firm; (iii) the final goods firm demands for intermediate goods from intermediate goods firm, while supplying final goods to household; and (iv) the government influences the economy through fiscal policy and monetary policy. As in other New Keynesian monetary models, money is not modelled explicitly, but implicitly incorporated into the system via Taylor rule. To illustrate the model structure in Figure 33, the arrows indicates the flows of resources among the three market agents, and dash lines represent the government policies.

Figure 33 Logic Structure of the Model



3.1. The Household

It is assumed that there is a continuum of households indexed by $i \in [0,1]$. The households maximise the expected lifetime utility function over an infinite horizon[①]:

$$E_0 \sum_{t=0}^{\infty} \beta^t u_t^i \text{ , where } u_t^i \equiv \varepsilon_t^U \left[\frac{\left(c_t^i - h_t\right)^{1-\sigma_C}}{1-\sigma_C} - \varepsilon_t^L \frac{\left(l_t^i\right)^{1+\sigma_L}}{1+\sigma_L} \right]$$

Here, the instantaneous utility function u_t^i depends on the current consumption c_t^i and labour supply l_t^i as well as an external habit variable, which is defined as a proportion of the aggregate consumption $h_t = hC_{t-1}$, following Christiano, Eichenbaum & Evans (2005) and Smets & Wouters (2003). σ_C is the inverted intertemporal elasticity of substitution or coefficient of relative risk aversion in consumption, while σ_L is the inverted elasticity of labour. There are two shocks introduced in the utility function, i.e. the preference shock ε_t^U and labour supply shock ε_t^L. Both shocks follow a first order autoregressive process:

$$\varepsilon_t^U = \rho_{\varepsilon U} \varepsilon_{t-1}^U + \eta_t^U \text{ , where } \eta_t^U \text{ is } IID\left(0, \sigma_{\varepsilon U}^2\right);$$
$$\varepsilon_t^L = \rho_{\varepsilon L} \varepsilon_{t-1}^L + \eta_t^L \text{ , where } \eta_t^L \text{ is } IID\left(0, \sigma_{\varepsilon L}^2\right).$$

There are three constraints under this maximisation problem, i.e. the intertemporal budget constraint, capital accumulation equation, and labour demand function.

- Constraint 1: Intertemporal Budget Constraint

$$\underbrace{w_t^i l_t^i}_{\text{labour income}} + \underbrace{\left(R_t^K z_t^i k_{t-1}^i - \Psi\left(z_t^i\right) k_{t-1}^i\right)}_{\text{capital income}} + \underbrace{div_t^i}_{\text{dividend}} + \underbrace{a_t^i}_{\text{insurance}} = c_t^i + \underbrace{inv_t^i}_{\text{physical inv.}} + \underbrace{\left(\frac{P_t^B}{P_t} b_t^i - \frac{b_{t-1}^i}{P_t}\right)}_{\text{financial investment}} + tax_t^i$$

The left hand side is the income flow (inflow), consisting of labour income, capital income from the physical investment, dividend received from the monopolistically competitive firms and a state contingent security payoff (perfect insurance). The right hand side is the expenditure flow (outflow), including consumption, physical investment, financial investment on government bonds and a real lump-sum tax. In general, there should be another income flow (direct transfer) from the government. However, it is nothing but a constant, and it makes no difference at all. Since this paper's focus is not on public finance, it is then ignored and simply assumed that the tax revenue will be consumed by the government without giving back to households.

[①] The notational convention in this chapter is that lower case is used for individual-level variables, and upper case for aggregate-level variables.

Note that z_t^i is the utilisation rate of capital, and $\Psi(\bullet)$ represents the cost of capital utilisation. As in Christiano, Eichenbaum & Evans (2005), the steady state of capital utilisation rate is set as 1 ($\bar{z}=1$), and the cost is equal to 0 ($\Psi(1)=0$).

Also note that the assumption of perfect insurance market (frictionless financial market) leads to equalised inflows and outflows across households by a_t^i. As a result, the individual levels are just equal to the aggregate levels for the following variables:

$$c_t^i = C_t,\ b_t^i = B_t,\ div_t^i = DIV_t,\ inv_t^i = I_t, k_t^i = K_t,\ z_t^i = Z_t$$

- Constraint 2: Capital Accumulation Equation

$$\underbrace{K_t - K_{t-1}(1-\delta)}_{\text{change in capital stock}} = \underbrace{\left[1-\Gamma\left(\varepsilon_t^I \frac{I_t}{I_{t-1}}\right)\right]I_t}_{\text{net investment flow}}$$

The left hand side is the change in capital stock, with a constant depreciation rate δ. The right hand side is the net investment flow, with an investment adjustment cost function $\Gamma(\bullet)$ depending on the ratio between investments in current and last periods. In steady state, investment level is constant over time and $\Gamma(1)=0$. Following Smets & Wouters (2003), a first order autoregressive process is introduced to disturb the adjustment cost function:

$$\varepsilon_t^I = \rho_{\varepsilon I}\varepsilon_{t-1}^I + \eta_t^I, \text{ where } \eta_t^I \text{ is } IID\left(0, \sigma_{\varepsilon I}^2\right).$$

This constraint has two features. On the one hand, the physical investment needs time to build, which is the typical feature of any RBC-paradigm models since Kydland & Prescott (1982). On the other hand, adjustment of investment is costly, which is the typical feature in the spirit of Gould (1968) and Lucas (1967). To change the supply of rental services of physical capital, household could either change the utilisation rate of capital Z_t, or change the investment I_t, but both incur costs.

- Constraint 3: Labour Demand Function

The households are assumed to supply differentiated labour, so they have certain wage setting power in the monopolistically competitive labour market. These differentiated labour will be combined somehow into a composite labour L_t, which is then employed by intermediate goods firms. Each household faces a labour demand function, which will be derived later from the intermediate goods firm's cost minimisation problem. For now, this constraint is presented without proof.

$$l_t^i = \left(\frac{w_t^i}{W_t} \right)^{-\frac{1+\lambda_{W,t}}{\lambda_{W,t}}} L_t$$

This condition simply says that the demand for household i's labour is a proportion of the aggregate labour demand. The wage mark-up shock $\lambda_{W,t}$ is assumed to move around a constant λ_W by a normal white noise error:

$$\lambda_{W,t} = \lambda_W + \eta_t^W \text{, where } \eta_t^W \text{ is } IID\left(0, \sigma_W^2\right).$$

To summarise, there are two roles of the household. It is both the demand side of final goods market and the supply side of the factor (labour and capital) markets. The optimal consumption and investment behaviour is based on expected utility maximisation subject to intertemporal budget constraint and capital accumulation equation, while the optimal wage setting behaviour is subject to labour demand function as well. The Lagrangian of household's maximisation problem can be written as:

$$L^H = E_t \left\{ \begin{array}{l} \beta^t \varepsilon_t^U \left[\dfrac{\left(C_t - hC_{t-1}\right)^{1-\sigma_C}}{1-\sigma_C} - \varepsilon_t^L \dfrac{\left(L_t\right)^{1+\sigma_L}}{1+\sigma_L} \right] \\ -\beta^t \Lambda_t \left[\begin{array}{c} w_t^i l_t^i + \left(R_t^K Z_t K_{t-1} - \Psi\left(Z_t\right) K_{t-1} \right) + DIV_t + a_t^i \\ -C_t - I_t - \left(\dfrac{P_t^B}{P_t} B_t - \dfrac{B_{t-1}}{P_t} \right) - tax_t^i \end{array} \right] \\ -\beta^t \mathrm{M}_t \left[K_t - (1-\delta) K_{t-1} - I_t \left(1 - \Gamma\left(\varepsilon_t^I \dfrac{I_t}{I_{t-1}} \right) \right) \right] \\ -\beta^t \mathrm{N}_t \left[l_t^i - \left(\dfrac{w_t^i}{W_t} \right)^{-\frac{1+\lambda_{W,t}}{\lambda_{W,t}}} L_t \right] \end{array} \right\}$$

3.1.1. Final Goods Demand and Consumption Behaviour

The first order conditions obtained from the Lagrangian with respect to consumption C_t and bond B_t can be used to derive the intertemporal condition:

$$E_t \left[\frac{\beta \varepsilon_{t+1}^U \left(C_{t+1} - hC_t\right)^{-\sigma_C}}{\varepsilon_t^U \left(C_t - hC_{t-1}\right)^{-\sigma_C}} \frac{P_t}{P_{t+1}} R_t^B \right] = 1$$

This dynamic marginal condition describes the trade-off between present consumption and future consumption. In addition, it is also known as "Lucas asset pricing for bond". Note that the first term in the expectation operator is the real "stochastic discount factor" (SDF), while the nominal SDF also takes into account the inflation $1+\pi_{t+1} \equiv \frac{P_{t+1}}{P_t}$. This equation is popular in financial economics to determine the price P_t^B of the discount bond, or equivalently, the nominal return on bond $R_t^B \equiv \frac{1}{P_t^B}$.

3.1.2. Capital Supply and Investment Behaviour

Also from the first maximisation problem (consumption and investment), first order conditions with respect to investment I_t, capital stock K_t and capital utilisation rate of capital Z_t generate the following equilibrium conditions.

$$I_t : \frac{\Lambda_t}{\mathrm{M}_t} + \Gamma\left(\varepsilon_t^I \frac{I_t}{I_{t-1}}\right) + \Gamma'\left(\varepsilon_t^I \frac{I_t}{I_{t-1}}\right)\frac{\varepsilon_t^I I_t}{I_{t-1}} = 1 + E_t\left[\frac{\beta \mathrm{M}_{t+1}}{\mathrm{M}_t}\Gamma'\left(\varepsilon_{t+1}^I \frac{I_{t+1}}{I_t}\right)\frac{\varepsilon_{t+1}^I I_{t+1}^2}{I_t^2}\right]$$

$$K_t : E_t\left[\frac{\beta \mathrm{M}_{t+1}}{\mathrm{M}_t}\left(1 + \frac{\Lambda_{t+1}}{\mathrm{M}_{t+1}} R_{t+1}^K Z_{t+1} - \frac{\Lambda_{t+1}}{\mathrm{M}_{t+1}} \Psi\left(Z_{t+1}\right) - \delta\right)\right] = 1$$

$$Z_t : R_t^K = \Psi'\left(Z_t\right)$$

The first condition implies that the optimal investment adjustment must gain a balance between marginal benefit and marginal cost in a dynamic fashion. The second condition is an extension of typical RBC intertemporal condition, which focuses on the return on physical investment R_t^K. Note that the second term inside the expectation operator is the net return after deducting the capital utilisation costs and depreciation. It is also known as "Lucas asset pricing for capital", in contrast to that for bond. The last condition simply describes that the optimal capital utilisation rate is such that marginal cost equal to the marginal revenue.

The Lagrangian multipliers Λ_t and M_t can be respectively interpreted as the shadow price of income and the shadow price of capital (or Tobin's Q). It is handy to define a relative shadow price of capital with respect to income $Q_t \equiv \mathrm{M}_t / \Lambda_t$.

3.1.3. Labour Supply and Wage Setting Behaviour

In the labour market, each household offers a differentiated type of labour with a monopolistic power on wage setting. Following Christiano, Eichenbaum & Evans (2005) and Smets & Wouters (2003), the there is a proportion (ξ_W) of wages which cannot adjust optimally, but follow a simple indexation rule:

$$w_t^i = \left(\frac{P_{t-1}}{P_{t-2}}\right)^{\gamma_W} w_{t-1}^i$$

The degree of indexation is measured by γ_W, which is equal to 0 if there is no indexation and reduces to simple Calvo wage setting as in Calvo (1983). On the other extreme, if $\gamma_W = 1$, then there is perfect indexation to inflation in past period. The rest $1-\xi_W$ of the wages are randomly picked, and they can be adjusted optimally. The optimal nominal wage $\tilde{w}_t$ is set to maximise the expected utility function subject to all the three constraints.

$$\frac{\tilde{w}_t}{P_t} E_t \left[\sum_{\tau=0}^{\infty} \beta^{\tau} \xi_W^{\tau} \frac{\left(P_t / P_{t-1}\right)^{\gamma_W}}{\left(P_{t+\tau} / P_{t+i-1}\right)} \frac{l_{t+\tau}^{i} MU_{C,t+\tau}}{1+\lambda_{W,t+\tau}} \right] = E_t \left[\sum_{\tau=0}^{\infty} \beta^{\tau} \xi_W^{\tau} l_{t+\tau}^{i} MU_{L,t+\tau} \right]$$

The intuition behind this equilibrium condition is that the luckily chosen household resets its wage such that the present value of marginal benefit of labour is equal to a mark-up over the present value of marginal cost. This dynamic marginal condition is nothing but an extension of Classical intratemporal condition between consumption and leisure without wage rigidity. Accordingly, the law of motion of the aggregate wage W_t is:

$$\left(W_t\right)^{-\frac{1}{\lambda_{W,t}}} = \xi_W \left[W_{t-1} \left(\frac{P_{t-1}}{P_{t-2}} \right)^{\gamma_W} \right]^{-\frac{1}{\lambda_{W,t}}} + \left(1-\xi_W\right)\left(\tilde{w}_t\right)^{-\frac{1}{\lambda_{W,t}}}$$

In fact, the wage setting behaviour could also take GTE or GCE form, instead of Calvo with Indexation (ICE). However, due to the lack of data, it is very difficult to conduct empirical studies on wage setting behaviour. As a result, this paper will keep wage setting in line with Smets & Wouters (2003), but it should not limit the potential to apply more general wage setting models in the future if wage data is available.

3.2. The Final Goods Firm

The final goods market is assumed perfectly competitive. The firms produce a composite output from the intermediate goods produced by the intermediate goods firms. Therefore, the final goods firms are both the supply side in final goods market and the demand side in intermediate goods market. This duality results in two equivalent optimisation problems. On the one hand, the firms choose the optimal output level to maximise the profit. On the other hand, the optimal input levels are chosen to minimise the total cost. A representative final goods firm's optimisation problem can be formulated as:

$$\max_{y_t^j} \Pi_t = P_t Y_t - \int_0^1 p_t^j y_t^j dj \text{, subject to: } Y_t = \left[\int_0^1 \left(y_t^j\right)^{\frac{1}{1+\lambda_{P,t}}} dj \right]^{1+\lambda_{P,t}}$$

Here, P_t is the aggregate price level (treated as given by the final goods firms) and Y_t is the aggregate output or final goods level, while p_t^j and y_t^j are the price and goods produced by intermediate goods firm j. The inputs are not perfectly substitutable, so the production function takes a popular form proposed by Dixit & Stiglitz (1977). Note that a price mark-up shock is also introduced here, echoing the wage mark-up shock[①]. The degree of substitutability between intermediate goods is now random.

$$\lambda_{P,t} = \lambda_P + \eta_t^P \text{, where } \eta_t^P \text{ is } IID\left(0, \sigma_P^2\right).$$

The first order condition derived from this optimisation problem gives the intermediate goods demand, which will be used as a constraint in intermediate goods firm's optimisation problem.

$$y_t^j = \left(\frac{p_t^j}{P_t}\right)^{-\frac{1+\lambda_{P,t}}{\lambda_{P,t}}} Y_t$$

Due to the perfect competition market structure in final goods market, a zero profit is obtained for all final goods firms.

3.3. The Intermediate Goods Firm

Assume that there is a continuum of intermediate goods firms indexed by $j \in [0,1]$. Each firm produces differentiated goods and sets its own price with certain monopolistic power to maximise its profit. Meanwhile, the intermediate goods firm demands for a composite labour and capital as inputs in production function.

Given the two roles of intermediate goods firms, two equivalent optimisation problems are simultaneously formulated. As the demand side of labour and capital, each firm minimises its total cost subject to production function. On the other hand, as the supply side of intermediate goods, each firm maximises its expected profit by setting a possibly fixed price, subject to production function as well as the intermediate goods demand function derived from final goods firm's problem.

3.3.1. Cost Minimisation Problem

$$\min_{L_t^j, Z_t K_{t-1}^j} TC_t^j = W_t L_t^j + R_t^K \left(Z_t K_{t-1}^j\right) \text{, subject to: } y_t^j = \varepsilon_t^A \left(Z_t K_{t-1}^j\right)^{\alpha} \left(L_t^j\right)^{1-\alpha} - \Phi$$

Here, each firm only decides on how much composite labour L_t^j to employ and how much is the effective utilisation of the capital stock $Z_t K_{t-1}^j$. The composite labour L_t

[①] This shock is also termed as "goods mark-up shock" or "cost-push shock".

is formed by all the differentiated labour supplied by households, and the aggregate wage W_t for this composite labour can also be obtained in a Dixit & Stiglitz (1977) fashion:

$$L_t = \left[\int_0^1 \left(l_t^i \right)^{\frac{1}{1+\lambda_{W,t}}} di \right]^{1+\lambda_{W,t}} \text{ and } W_t = \left[\int_0^1 \left(w_t^i \right)^{-\frac{1}{\lambda_{W,t}}} di \right]^{-\lambda_{W,t}}$$

Note that the Cobb-Douglas neoclassical production function with fixed cost Φ is stochastic due to the productivity shock ε_t^A, which also follows a first-order auto-regressive process:

$$\varepsilon_t^A = \rho_{\varepsilon A} \varepsilon_{t-1}^A + \eta_t^A, \text{ where } \eta_t^A \text{ is } IID\left(0, \sigma_{\varepsilon A}^2\right).$$

The first order conditions of this cost minimisation problem imply the equalisation of capital-labour ratio and marginal cost across all intermediate goods firms, because these two quantities are independent of j.

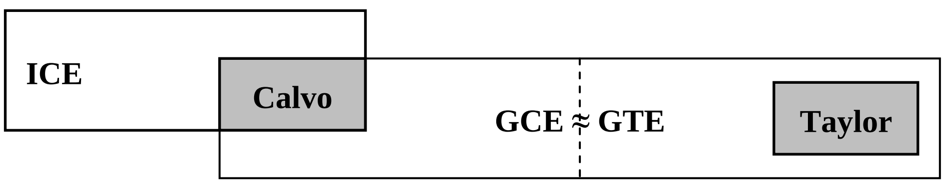
$$\frac{W_t L_t^j}{R_t^K \left(Z_t K_{t-1}^j \right)} = \frac{1-\alpha}{\alpha} \Rightarrow \frac{W_t L_t}{R_t^K \left(Z_t K_{t-1} \right)} = \frac{1-\alpha}{\alpha}$$

$$MC_t^j \equiv \frac{\partial TC_t^j}{\partial y_t^j} = \frac{1}{\varepsilon_t^A} \left(\frac{W_t}{1-\alpha} \right)^{1-\alpha} \left(\frac{R_t^K}{\alpha} \right)^{\alpha} \Rightarrow MC_t = \frac{1}{\varepsilon_t^A} \left(\frac{W_t}{1-\alpha} \right)^{1-\alpha} \left(\frac{R_t^K}{\alpha} \right)^{\alpha}$$

3.3.2. Profit Maximisation Problem

Each firm j has some monopolistic power on price setting in the intermediate goods market. The simplest two models are Taylor (1979) and Calvo (1983). An extension of simple Calvo, Calvo with Indexation Economy (ICE), is developed by Christiano, Eichenbaum & Evans (2005). This section introduces two more price setting models developed recently by a series of papers, i.e. Generalised Calvo Economy (GCE) and Generalised Taylor Economy (GTE). The two models become increasingly popular because of their heterogeneous agent features. The topological relationship among these 5 models is illustrated below.

Figure 34 Topological Relationship among Price Setting Models



Firstly, it can be seen that simple Calvo is a special case of both ICE (if indexation degree is zero) and GCE (if hazard rate is constant), while simple Taylor is a special case of GTE (if there is only one sector with homogenous duration across firms).

Secondly, it is shown by that GCE is very close to GTE in the sense that they both describe an economy with heterogeneous firms. In particular, GCE assumes that firms have time-varying hazard rates, in contrast to the constant hazard rate as in simple Calvo model. At a particular point in time, prices in this economy have different ages and, thus, different hazard rates. On the other hand, GTE assumes that there are several sectors with different durations, in contrast to the homogenous duration across firms as in simple Taylor model. Dixon (2010) argues that it is always possible to find a unique GTE for a given GCE with the same distribution of durations, and vice versa. However, there is a subtle difference between GCE and GTE in the mechanism of price setting behaviour, though exactly the same in the outcome. As noted in Dixon & Le Bihan (2010), firms do not know when to reset the prices ex ante in GCE, while they know exactly when to reset the price in GTE. This uncertainty makes firms in GCE more forward looking than those in GTE. Consequently, the impulse response functions of the two models also differ.

The following equations present the optimal price setting behaviour under these 5 models. They are all derived from the intermediate goods firm's dynamic profit maximisation problem, subject to the demand function of intermediate goods derived in previous section. As a benchmark case, the optimal price p_t^* under flexible price can be derived when marginal revenue is equal to marginal cost:

$$p_t^* = MC_t\left(1+\lambda_{P,t}\right) = \frac{1}{\varepsilon_t^A}\left(\frac{W_t}{1-\alpha}\right)^{1-\alpha}\left(\frac{R_t^K}{\alpha}\right)^{\alpha}\left(1+\lambda_{P,t}\right)$$

- **Simple Calvo**

It is assumed that there is a proportion $1-\xi_P$ of current prices can be reset by firms, while the rest ξ_P will stay the same as last period. This ξ_P is called survival rate, and $1-\xi_P$ is termed hazard rate. They are constant and independent of how long the price duration is. In other words, the proportion $1-\xi_P$ is randomly picked each period without discrimination. As a result, there might be some prices lasting forever, while some prices are reset very frequently.

Due to the uncertainty of price change, firms have to maximise the discounted profits in the future. The first order conditions give the equilibrium condition of optimal reset price $\tilde{p}_t$ for firm j:

$$E_t\left[\sum_{\tau=0}^{\infty}\beta^{\tau}\xi_P^{\tau}\Lambda_{t+\tau}y_{t+\tau}^{j}\frac{\tilde{p}_t}{P_{t+\tau}}\right]=E_t\left[\sum_{\tau=0}^{\infty}\beta^{\tau}\xi_P^{\tau}\frac{MC_{t+\tau}}{P_{t+\tau}}\left(1+\lambda_{P,t+\tau}\right)\right]$$

Note that this optimal reset price $\tilde{p}_t$ is the same for all intermediate goods firms, since they share the same marginal costs and market conditions. Basically, the optimal reset price is obtained when the expected sum of discounted marginal revenue (left hand side) is equal to the expected sum of discounted marginal cost (right hand side). This is a straightforward extension of the condition under flexible price.

Therefore, the law of motion of the aggregate price index P_t is:

$$\left(P_t\right)^{-\frac{1}{\lambda_{P,t}}}=\xi_P\left(P_{t-1}\right)^{-\frac{1}{\lambda_{P,t}}}+\left(1-\xi_P\right)\left(\tilde{p}_t\right)^{-\frac{1}{\lambda_{P,t}}}$$

- **Calvo with Indexation Economy (ICE)**

In addition to the assumption of simple Calvo, it is also assumed that the ξ_P proportion of prices, which could not be reset, will be automatically adjusted according to a predetermined indexation rule:

$$p_t^j=\left(\frac{P_{t-1}}{P_{t-2}}\right)^{\gamma_P}p_{t-1}^j$$

The optimal reset price condition under ICE, as an extension of simple Calvo where $\gamma_P=0$, now becomes:

$$E_t\left[\sum_{\tau=0}^{\infty}\beta^{\tau}\xi_P^{\tau}\Lambda_{t+\tau}y_{t+\tau}^{j}\frac{\tilde{p}_t}{P_{t+\tau}}\left(\frac{P_{t-1+\tau}}{P_{t-1}}\right)^{\gamma_P}\right]=E_t\left[\sum_{\tau=0}^{\infty}\beta^{\tau}\xi_P^{\tau}\Lambda_{t+\tau}y_{t+\tau}^{j}\frac{MC_{t+\tau}}{P_{t+\tau}}\left(1+\lambda_{P,t+\tau}\right)\right]$$

Accordingly, the law of motion of the aggregate price index P_t is now:

$$\left(P_t\right)^{-\frac{1}{\lambda_{P,t}}}=\xi_P\left[P_{t-1}\left(\frac{P_{t-1}}{P_{t-2}}\right)^{\gamma_P}\right]^{-\frac{1}{\lambda_{P,t}}}+\left(1-\xi_P\right)\left(\tilde{p}_t\right)^{-\frac{1}{\lambda_{P,t}}}$$

- **Generalised Calvo Economy (GCE)**

GCE is another way of generalising simple Calvo model, in addition to ICE. Initially proposed by Wolman (1999) and popularised by Guerrieri (2006), GCE assumes a duration dependent hazard function $h(t)$ and survival function $S(t)$. Compared to the simple Calvo model, hazard rate is constant $h(t)=1-\xi_P$, and so is survival rate $S(t)=\xi_P$. Here, it is assumed that the maximum duration is T, i.e. all prices will be reset at the end of period T. In other words, $h(T)=1$ or $S(T)=0$. Based on the previous microdata studies, it is appropriate to set $T=20$ quarters. Under this time-varying hazard/survival rates, the optimal reset price $\tilde{p}_t$ for any intermediate goods firm in GCE becomes:

$$\tilde{p}_t = \frac{1}{\sum_{\tau=0}^{T} \beta^{\tau} S(\tau)} \sum_{\tau=0}^{T} \beta^{\tau} S(\tau) E_t\left[p_{t+\tau}^{*} \right]$$

Note that it is simply a weighted average of future optimal flexible prices p_t^{*}, and the aggregate price index P_t is:

$$P_t = \frac{1}{\sum_{\tau=1}^{T-1} S(\tau)} \sum_{\tau=1}^{T-1} S(\tau)\, \tilde{p}_{t+1-\tau}$$

- **Simple Taylor**

Instead of assuming uncertainty of when to reset the price, simple Taylor explores another possible fashion of incorporating price rigidity. Following the seminal papers of Taylor (1979) and Taylor (1980), it is assumed that the price duration is fixed and known ex ante by the firms. There is a staggering structure in price setting across the economy, resulting in a steady state distribution of price duration. Suppose T is the fixed price duration for all firms, and then there exist T cohorts in the economy resetting their prices in a staggering fashion. The optimal reset price is simply a weighted average over the future optimal flexible prices:

$$\tilde{p}_t = \frac{1}{\sum_{\tau=0}^{T-1} \beta^{\tau}} \sum_{\tau=0}^{T-1} \beta^{\tau} E_t\left[p_{t+\tau}^{*} \right]$$

The aggregate price index P_t turns out to be:

$$P_t = \frac{1}{T} \sum_{\tau=1}^{T} \tilde{p}_{t+1-\tau}$$

Compared to the condition in GCE, it is easy to see that simple Taylor is just a special case of GCE, when $S(t)$ is constant for $t \in [1, T-1]$ and $S(T)=0$. Note that weight of each cohort is the same for simple Taylor, but different for GCE (decreasing in τ) and GTE (varying). It will be shown soon that simple Taylor is also a special case of GTE there is only one sector.

- **Generalised Taylor Economy (GTE)**

The GTE is developed by a series of works, such as Taylor (1993), Coenen, Levin & Christoffel (2007) and Dixon & Le Bihan (2010). It is an extension of simple Taylor model in the sense that it allows heterogeneous firms, or multiple sectors, in terms of fixed price duration. To be consistent with previous illustration, assume that there are T sectors, which are only different in the price duration. The minimum price duration is 1 period, and the maximum is T. In fact, each sector is a simple Taylor economy, which has the same number of cohorts as the length of price duration. For example, for sector 2, all the firms reset prices every 2 periods, so there are 2 cohorts. In general, for sector $1 \le \tau \le T$, the firms reset prices every τ periods, and there are τ cohorts resetting prices in a staggering fashion. The proportion of each sector α_τ is different, but constant in steady state. The optimal reset price for sector τ is exactly the same as that in simple Taylor model with price duration equal to τ:

$$\tilde{p}_t^\tau = \frac{1}{\sum_{k=0}^{\tau-1} \beta^k} \sum_{k=0}^{\tau-1} \beta^k E_t \left[p_{t+k}^* \right], \text{ where } \tau \in [1, T]$$

It is also necessary to derive the sector price index P_t^τ, which is an average over the τ cohorts in the sector:

$$P_t^\tau = \frac{1}{\tau} \sum_{k=0}^{\tau-1} \tilde{p}_{t-k}^\tau \text{ , where } \tau \in [1, T]$$

Hence, the aggregate price index can be defined as:

$$P_t = \sum_{\tau=1}^{T} \alpha_\tau P_t^\tau$$

If there is only one price duration, then the economy will be homogenous, GTE reduces to simple Taylor. In this case, $\tilde{p}_t^\tau = \tilde{p}_t$ and $P_t^\tau = P_t$.

To summarise, there are two basic traditions in time dependent models of price rigidity, i.e. Calvo and Taylor. Their extensions, both GCE and GTE generalise to heterogeneous agent framework, while ICE is another way to extend simple Calvo. In general, Calvo type models are more forward looking due to the uncertainty of price duration. Under different modelling paradigms, profit maximisation problems of the intermediate goods firms lead to four typical conditions: (i) the optimal flexible price equation for p_t^* (the same for all models), (ii) optimal reset price equation for $\tilde{p}_t$ (different for different models), (iii) aggregate price index equation for P_t (different for different models), and (iv) inflation definition π_t (the same for all models).

$$\pi_t \equiv \frac{P_t - P_{t-1}}{P_{t-1}} \text{ or } \pi_t \approx \ln P_t - \ln P_{t-1}$$

By the way, to complete the circulation system of resources as illustrated in Figure 33, the monopolistic profits of intermediate goods firms are paid to households as dividends DIV_t, which is an inflow in budget constraint.

3.4. The Government

Government is able to influence the macroeconomic system through both fiscal policy and monetary policy. Since the focus of this paper is not on optimal policy, the mechanism is simplified as much as possible.

3.4.1. Fiscal Policy

As noted in household's budget constraint, the government spending G_t does not enter household's budget constraint, and it is assumed to be used by government elsewhere. It does not change the final results, since it is nothing but an exogenous quantity, which will drop out when taking derivatives.

To finance this government spending, tax authority can levy a lump-sum tax tax_t^i on household. This simplification avoids the complicated effects of distortionary taxes, such as labour income tax, capital income tax and consumption tax. On the other hand, Treasury can also issue government bonds or "Gilts" B_t to finance its expenditure. Households purchase the government bonds as a tool of financial investment. Hence, the government's budget constraint in the perspective of public finance can be written as an equation of outflow (left hand side) and inflow (right hand side):

$$G_t = \left(\int_0^1 tax_t^i di\right) + \left(B_t - B_{t-1} R_t^B\right) + \varepsilon_t^G$$

Note that ε_t^G is the government expenditure shock, which is an autoregressive process:

$$\varepsilon_t^G = \rho_{\varepsilon G} \varepsilon_{t-1}^G + \eta_t^G \text{, where } \eta_t^G \text{ is } IID\left(0, \sigma_{\varepsilon G}^2\right).$$

3.4.2. Monetary Policy

Money can be modelled in various ways in general equilibrium models, such as Money in Utility proposed by Samuelson (1958) and Eckstein & Leiderman (1992), or

Cash in Advance (CIA) proposed by Lucas (1980) and Goodfriend & McCallum (1987), which are popular in New Classical literature among many others. However, in canonical New Keynesian monetary models, money is usually not modelled explicitly. Instead, a Taylor rule for monetary policy is assumed to describe how nominal interest rate R_t^B is set by monetary authority. The change in nominal interest rate implies a change in money holdings, through which the role of money is embedded. The instrument of monetary policy is usually thought to be interest rate, rather than money supply.

In the light of Taylor (1993), an empirical monetary policy reaction function is added into the system to complete the model. The nominal interest rate R_t^B is set based on previous nominal interest rate R_{t-1}^B, inflation gap between actual inflation π_{t-1} and inflation target $\bar{\pi}_t$, output gap between the actual GDP Y_t and potential GDP Y_t^*, as well as the change of these gaps. The parameter ρ measures the degree of interest rate smoothing. In fact, the nominal interest rate is a sort of weighted average between the past interest rate and the optimal interest rate, which in turn depends on the inflation target and the gaps. Note that the potential output Y_t^* is defined as the level of output that would occur under flexible price and wage in the absence of shocks. The interest rate rule is written in the form of log-deviation from steady state:

$$\begin{aligned}\hat{R}_t^B = \rho \hat{R}_{t-1}^B + (1-\rho)\left[\bar{\pi}_t + r_\pi\left(\hat{\pi}_{t-1} - \bar{\pi}_t\right) + r_Y\left(\hat{Y}_t - \hat{Y}_t^*\right)\right] \\ + r_{\Delta\pi}\left(\hat{\pi}_t - \hat{\pi}_{t-1}\right) + r_{\Delta Y}\left[\left(\hat{Y}_t - \hat{Y}_t^*\right) - \left(\hat{Y}_{t-1} - \hat{Y}_{t-1}^*\right)\right] + \eta_t^R\end{aligned}$$

There are two sources of monetary policy shocks in this generalised Taylor rule. The first is an autoregressive permanent inflation target shock $\bar{\pi}_t$, and the other is an IID temporary interest rate shock η_t^R.

$$\bar{\pi}_t = \rho \bar{\pi}_{t-1} + \eta_t^\pi \text{, where } \eta_t^\pi \text{ is } IID\left(0, \sigma_{\bar{\pi}}^2\right);$$
$$\eta_t^R \text{ is } IID\left(0, \sigma_R^2\right).$$

3.5. General Equilibrium

The general equilibrium requires that all markets clear, or equivalently, supply equals demand for factor markets and goods market.

- **Labour Market**

$$\underbrace{\int_0^1 L_t^j dj}_{\text{labour demand}} = L_t = \underbrace{\left[\int_0^1 \left(l_t^i\right)^{\frac{1}{1+\lambda_{W,t}}} di\right]^{1+\lambda_{W,t}}}_{\text{labour supply}}$$

- **Capital Market**

$$\underbrace{\int_0^1 K_{t-1}^j dj}_{\text{capital demand}} = K_{t-1} = \underbrace{\int_0^1 k_{t-1}^i di}_{\text{capital supply}}$$

- **Goods Market**

$$\underbrace{C_t + I_t + G_t + \Psi\left(Z_t\right) K_{t-1}}_{\text{goods demand}} = Y_t = \underbrace{\left[\int_0^1 \left(y_t^j\right)^{\frac{1}{1+\lambda_{P,t}}} dj\right]^{1+\lambda_{P,t}}}_{\text{goods supply}}$$

Given fiscal and monetary policies, G_t, R_t^B and tax_t^i, an equilibrium is defined as an allocation $\left\{C_t, H_t, B_t, l_t^i, L_t^j, L_t, k_t^i, K_t^j, K_t, Z_t, I_t, y_t^j, DIV_t, Y_t\right\}_{i\in[0,1],\, j\in[0,1]}$ and wages/prices $\left\{b_t, R_t^B, R_t^K, w_t^i, W_t, p_t^j, P_t\right\}_{i\in[0,1],\, j\in[0,1]}$, such that:

i. Given wages/prices and the demand function for labour l_t^i, the allocation maximises the utility of the household, subject to the budget constraint;

ii. Given wages/prices and the demand function for intermediate goods y_t^j, the allocation maximises the profits of the firms, subject to the technology constraint;

iii. The policy rules, G_t, R_t^B and tax_t^i, are consistent with allocation and wages/prices;

iv. All markets clear.

3.6. Summary of the Model

To solve the system of equations by perturbation method and apply Bayesian inferences, the structural equilibrium conditions derived above is log-linearised around the steady state. The full list of the linearised model is presented below. Note that to investigate the difference resulting from price setting behaviour, the intermediate goods firm’s optimal reset price has 5 variants. However, the other parts of the model are exactly the same.

- **Equation (1): Consumption**

$$\hat{C}_t = \frac{h}{1+h}\hat{C}_{t-1} + \frac{h}{1+h}E_t\left[\hat{C}_{t+1}\right] - \frac{1-h}{(1+h)\sigma_C}\left(\hat{R}_t^B - E_t\left[\hat{\pi}_{t+1}\right]\right) + \frac{1-h}{(1+h)\sigma_C}\hat{\varepsilon}_t^U$$

- **Equation (2): Investment**

$$\hat{I}_t = \frac{1}{1+\beta}\hat{I}_{t-1} + \frac{1}{1+\beta}E_t\left[\hat{I}_{t+1}\right] + \frac{\gamma}{1+\beta}\hat{Q}_t + \hat{\varepsilon}_t^I$$

Note that γ is the inverted investment adjustment cost, and it arises from the investment adjustment cost function $\Gamma(\bullet)$.

- **Equation (3): Capital Shadow Price**

$$\hat{Q}_t = -\left(\hat{R}_t^B - E_t\left[\hat{\pi}_{t+1}\right]\right) + \frac{1-\delta}{1-\delta+\bar{R}^K}E_t\left[\hat{Q}_{t+1}\right] + \frac{\bar{R}^K}{1-\delta+\bar{R}^K}E_t\left[\hat{R}_{t+1}^K\right] + \eta_t^Q$$

Note that η_t^Q is an IID equity premium shock, which is introduced here to capture other sources of risk omitted in the model.

- **Equation (4): Capital**

$$\hat{K}_t = (1-\delta)\hat{K}_{t-1} + \delta\hat{I}_{t-1}$$

- **Equation (5): Wage**

$$\begin{aligned}
\hat{W}_t - \hat{P}_t = {} & \frac{\beta}{1+\beta}E_t\left[\hat{W}_{t+1} - \hat{P}_{t+1}\right] + \frac{1}{1+\beta}\left(\hat{W}_{t-1} - \hat{P}_{t-1}\right) \\
& + \frac{\beta}{1+\beta}E_t\left[\hat{\pi}_{t+1}\right] - \frac{1+\beta\gamma_W}{1+\beta}\hat{\pi}_t + \frac{\gamma_W}{1+\beta}\hat{\pi}_{t-1} \\
& - \frac{1}{1+\beta}\frac{(1-\beta\xi_W)(1-\xi_W)}{\left(1+\frac{1+\lambda_W}{\lambda_W}\sigma_L\right)\xi_W}\left[\hat{W}_t - \hat{P}_t - \sigma_L\hat{L}_t - \frac{\sigma_C}{1-h}\left(\hat{C}_t - h\hat{C}_{t-1}\right) + \hat{\varepsilon}_t^L\right] + \eta_t^W
\end{aligned}$$

- **Equation (6): Labour**

$$\hat{L}_t = -\hat{W}_t + (1+\psi)\hat{R}_t^K + \hat{K}_{t-1}$$

- **Equation (7): Flexible Price**

$$\hat{p}_t^* - \hat{P}_t = \alpha\hat{R}_t^K + (1-\alpha)\left(\hat{W}_t - \hat{P}_t\right) - \varepsilon_t^A + \eta_t^P$$

- **Equation (8): Inflation**

$$\hat{\pi}_t = \hat{P}_t - \hat{P}_{t-1}$$

- **Equation (9): Goods Demand**

$$\hat{Y}_t = \left(1 - \delta \frac{\overline{K}}{\overline{Y}} - \frac{\overline{G}}{\overline{Y}}\right)\hat{C}_t + \delta \frac{\overline{K}}{\overline{Y}} \hat{I}_t + \hat{\varepsilon}_t^G$$

- **Equation (10): Goods Supply**

$$\hat{Y}_t = \phi\alpha\hat{K}_{t-1} + \phi\alpha\psi\hat{R}_t^K + \phi(1-\alpha)\hat{L}_t + \phi\hat{\varepsilon}_t^A$$

Note that ϕ is equal to 1 plus the share of fixed cost in production, and it arises from the Φ component in production function. Also note that ψ is the inverted elasticity of capital utilisation cost, and it arises from the capital utilisation cost function $\Psi(\bullet)$.

- **Equation (11): Monetary Policy**

$$\begin{aligned}\hat{R}_t^B = {} & \rho\hat{R}_{t-1}^B + (1-\rho)\left[\overline{\pi}_t + r_\pi\left(\hat{\pi}_{t-1} - \overline{\pi}_t\right) + r_Y\left(\hat{Y}_t - \hat{Y}_t^*\right)\right] \\ & + r_{\Delta\pi}\left(\hat{\pi}_t - \hat{\pi}_{t-1}\right) + r_{\Delta Y}\left[\left(\hat{Y}_t - \hat{Y}_t^*\right) - \left(\hat{Y}_{t-1} - \hat{Y}_{t-1}^*\right)\right] + \eta_t^R\end{aligned}$$

The 11 linearised equations above are common to all the models considered in this paper. The only difference among simple Calvo, ICE, GCE, simple Taylor and GTE lies in price setting behaviour. Note that in simple Calvo and ICE, the price setting equation can be rewritten in the form of rational expectation augmented Phillips curve, but the other three cases are not. It does not make much difference, since Phillips curve is nothing but a transformation by combining with other equations. The 5 variants of price setting equation (12) are linearised and listed below.

- **Equation (12-Calvo): Price**

$$\hat{\pi}_t = \beta E_t\left[\hat{\pi}_{t+1}\right] + \frac{(1-\beta\xi_P)(1-\xi_P)}{\xi_P}\left[\alpha\hat{R}_t^K + (1-\alpha)\left(\hat{W}_t - \hat{P}_t\right) - \hat{\varepsilon}_t^A\right] + \eta_t^P$$

- **Equation (12-ICE): Price**

$$\begin{aligned}\hat{\pi}_t = {} & \frac{\beta}{1+\beta\gamma_P} E_t\left[\hat{\pi}_{t+1}\right] + \frac{\gamma_P}{1+\beta\gamma_P}\hat{\pi}_{t-1} \\ & + \frac{1}{1+\beta\gamma_P}\frac{(1-\beta\xi_P)(1-\xi_P)}{\xi_P}\left[\alpha\hat{R}_t^K + (1-\alpha)\left(\hat{W}_t - \hat{P}_t\right) - \hat{\varepsilon}_t^A\right] + \eta_t^P\end{aligned}$$

- **Equation (12-GCE): Price**

$$\hat{P}_t = \frac{1}{\sum_{\tau=1}^{T-1} S(\tau)} \sum_{\tau=1}^{T-1} S(\tau)\, \hat{\hat{p}}_{t+1-\tau} \text{, where } \hat{\hat{p}}_t = \frac{1}{\sum_{\tau=0}^{T} \beta^\tau S(\tau)} \sum_{\tau=0}^{T} \beta^\tau S(\tau) E_t\left[\hat{p}^*_{t+\tau}\right]$$

- **Equation (12-Taylor): Price**

$$\hat{P}_t = \frac{1}{T} \sum_{\tau=1}^{T} \hat{\hat{p}}_{t+1-\tau} \text{, where } \hat{\hat{p}}_t = \frac{1}{\sum_{\tau=0}^{T-1} \beta^\tau} \sum_{\tau=0}^{T-1} \beta^\tau E_t\left[\hat{p}^*_{t+\tau}\right]$$

- **Equation (12-GTE): Price**

$$\hat{P}_t = \sum_{\tau=1}^{T} \alpha_\tau \hat{P}_t^\tau \text{, where } \hat{P}_t^\tau = \frac{1}{\tau} \sum_{k=0}^{\tau-1} \hat{\hat{p}}_{t-k}^\tau \text{ and } \hat{\hat{p}}_t^\tau = \frac{1}{\sum_{k=0}^{\tau-1} \beta^k} \sum_{k=0}^{\tau-1} \beta^k E_t\left[\hat{p}^*_{t+k}\right]$$

There are 12 equations in the simplified and linearised system, so 12 endogenous control variables: $\left\{\hat{C}_t, \hat{I}_t, \hat{K}_t, \hat{L}_t, \hat{Y}_t; \hat{Q}_t, \hat{R}_t^B, \hat{R}_t^K, \hat{W}_t, \hat{p}_t^*, \hat{P}_t, \hat{\pi}_t\right\}$. Meanwhile, there are 10 orthogonal exogenous shocks: $\left\{\hat{\varepsilon}_t^U, \hat{\varepsilon}_t^L, \hat{\varepsilon}_t^I, \hat{\varepsilon}_t^G, \hat{\varepsilon}_t^A; \eta_t^W, \eta_t^P, \eta_t^Q, \eta_t^R, \bar{\pi}_t\right\}$. They are derived respectively from preference shock, labour supply shock, investment shock, government expenditure shock, productivity shock, wage mark-up shock, price mark-up shock, equity premium shock, interest rate shock and interest rate target shock.

Preference shock: $\varepsilon_t^U = \rho_{\varepsilon U} \varepsilon_{t-1}^U + \eta_t^U$, where η_t^U is $IID\left(0, \sigma_{\varepsilon U}^2\right)$;

Labour supply shock: $\varepsilon_t^L = \rho_{\varepsilon L} \varepsilon_{t-1}^L + \eta_t^L$, where η_t^L is $IID\left(0, \sigma_{\varepsilon L}^2\right)$;

Investment shock: $\varepsilon_t^I = \rho_{\varepsilon I} \varepsilon_{t-1}^I + \eta_t^I$, where η_t^I is $IID\left(0, \sigma_{\varepsilon I}^2\right)$;

Government expenditure shock: $\varepsilon_t^G = \rho_{\varepsilon G} \varepsilon_{t-1}^G + \eta_t^G$, where η_t^G is $IID\left(0, \sigma_{\varepsilon G}^2\right)$;

Productivity shock: $\varepsilon_t^A = \rho_{\varepsilon A} \varepsilon_{t-1}^A + \eta_t^A$, where η_t^A is $IID\left(0, \sigma_{\varepsilon A}^2\right)$;

Wage mark-up shock: $\lambda_{W,t} = \lambda_W + \eta_t^W$, where η_t^W is $IID\left(0, \sigma_W^2\right)$;

Price mark-up shock: $\lambda_{P,t} = \lambda_P + \eta_t^P$, where η_t^P is $IID\left(0, \sigma_P^2\right)$;

Equity premium shock: η_t^Q is $IID\left(0, \sigma_Q^2\right)$;

Temporary monetary shock: η_t^R is $IID\left(0, \sigma_R^2\right)$;

Permanent monetary shock: $\bar{\pi}_t = \rho \bar{\pi}_{t-1} + \eta_t^\pi$, where η_t^π is $IID\left(0, \sigma_{\bar{\pi}}^2\right)$.

Finally, a summary of parameters used in the model is listed in Appendix Table 41 and Table 42. Thus, the three structural components—12 endogenous controls, 10 exogenous shocks and parameters—form the dynamic stochastic general equilibrium system through the 12 equilibrium equations with 5 variants in price setting.

4. Data

In prevailing literature, macrodata are usually used in macroeconometric studies to estimate the structural parameters and evaluate models. Pure calibration based on microdata research in the traditional RBC literature is less popular now. Yet, some well-established parameter calibrations are still used to reduce the dimensionality of estimated parameters. In this chapter, both microdata and macrodata are emphasised.

4.1. Microdata

Microdata are referred to the empirical results obtained based on individual-level observations on consumer's behaviour and firm's behaviour. Some well-established estimated structural parameters are calibrated in this chapter. These calibrated parameters are shown in Table 41 and Table 42, including subjective discount factor ($\beta = 0.99$), depreciation rate of capital ($\delta = 0.025$), capital output ratio ($\alpha = 0.3$), capital output ratio ($\bar{K}/\bar{Y} = 8.8$), share of investment in GDP ($\bar{I}/\bar{Y} = 0.22$), share of consumption in GDP ($\bar{C}/\bar{Y} = 0.6$), and share of government expenditure in GDP ($\bar{G}/\bar{Y} = 0.18$).

Moreover, the survival rates $S(\tau)$ for GCE come from the estimated survival function, and the sector shares $\alpha(\tau)$ for GTE are based on the estimated distribution of duration across firms. To make the model comparison coherent, the average survival rate for simple Calvo is also calibrated using the implied value from $S(\tau)$, and the average duration for simple Taylor is based on $\alpha(\tau)$. However, for ICE, prices are assumed to change every period, which is not supported by microdata evidence. Thus, the share of optimally changed price is not calibrated but estimated.

In the microdata research on firm's price setting behaviour in Chapter I, both nonparametric analysis and semiparametric analysis are applied to estimate the survival function and distribution of DAF in the UK from 1996m1 to 2008m1. The nonparametric approach directly estimates the survival function and distribution of DAF, without controlling for factors which might affect firms' behaviour. In contrast, the semiparametric approach considers various factors in estimation, such as inflation, interest rate, oil price, etc. Thus, baseline survival function of semiparametric analysis is more appropriate for calibrating the "deep structural parameters" in DSGE models. Meanwhile, corresponding distribution of DAF can be implied from baseline survival function in the light of the formula of Dixon (2010). Nevertheless, for the purpose of sensitivity analysis, the estimation results of both nonparametric analysis (Figure 35) and semiparametric analysis (Figure 36) will be used in estimation and testing.

Figure 35 Survival Function from Microdata Research

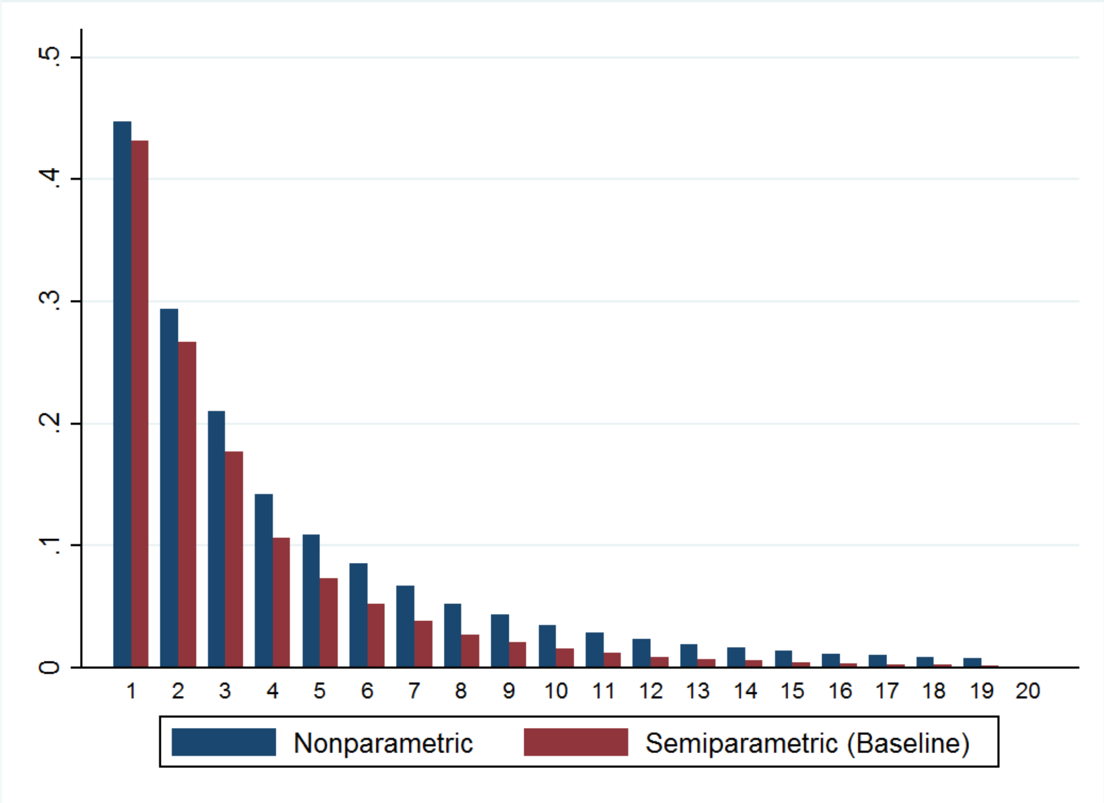
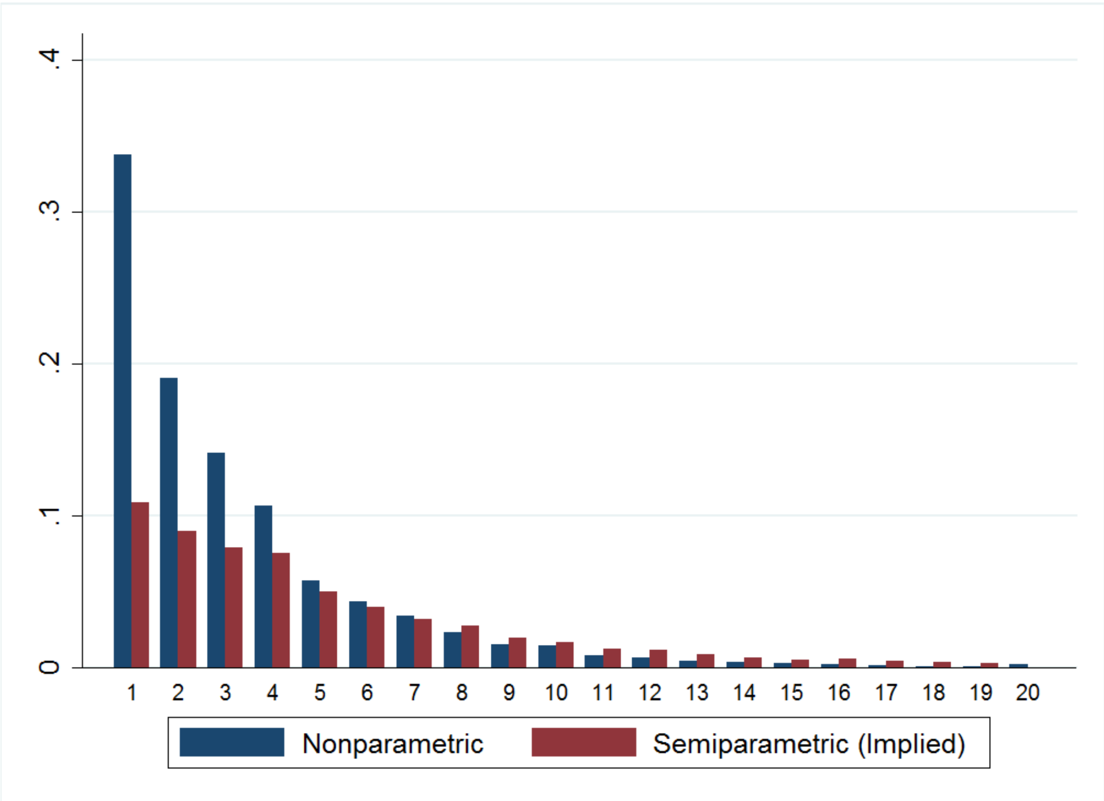


Figure 36 Distribution of Duration across Firms from Microdata Research



4.2. Macrodata

7 key macroeconomic variables (output, consumption, investment, labour, inflation, interest rate and wage) and 108 observations (1981Q1-2007Q4) in the UK are used. The macrodata are collected by Office for National Statistics ONS) in the UK. This sample period covers the "Great Moderation" before the recent global financial crisis. It also overlaps with the microdata period (1996-2007), making the calibrations plausible and coherent.

All the observables are nonstationary, according to Augmented Dickey-Fuller test. A simplified but standard way of dealing with nonstationarity is to use Hodrick-Prescott (HP) filter. Indeed, this method is not the best choice theoretically, since it takes away too much information which does not belong to "trend". However, this paper's focus is not exploring the optimal method of detrending, but to compare different price setting models. Therefore, HP filter will not harm the generalisability.

To summarise, both microdata and macrodata are used to evaluate and compare the price setting models under a common DSGE framework. It provides a microfoundation for macroeconometric analysis in an empirical sense, echoing the theoretical microfoundation from microeconomics for macroeconomic modelling.

5. Results

The general equilibrium is characterised by the 12 linearised equations with 5 variants in price setting mechanism. While confronted with microdata and macrodata, econometric techniques based on strong econometric interpretation, i.e. Classical maximum likelihood and Bayesian estimation procedures are applied to estimate the structural parameters as well as the processes governing structural shocks. The estimation subsection focuses on GCE and GTE results, since the heterogeneous agent models are decisively supported in model comparison.

Next, impulse response functions are presented and compared across the 5 competing models using Bayesian approach. The closeness between model-based and data-based impulse response functions can be used to check the performance of DSGE models.

Moreover, variance decomposition is also conducted following Bayesian approach to identify the contribution of various structural shocks to the variances of endogenous variables of interest. These two subsections provide another perspective for model comparison by only focusing on some partial features of rather than the whole DSGE model, following the philosophy of weak econometric interpretation.

Lastly, the 5 models are first evaluated relatively using Bayes Factor (BF). Robustness of the test is checked by various dimensions, such as different calibrations, different prior distributions and different observables. At the same time, indirect inference approach for model testing (following the philosophy of weak econometric interpretation) is also briefly discussed, based on a PhD colleague's work. The relative ranking between models turns out exactly the same.

5.1. Parameter Estimation

Following the results from model comparison, this subsection will focus on estimation of heterogeneous price setting models, i.e. GTE and GCE. Both Bayesian and Classical maximum likelihood (ML) estimation procedures are applied to the 5 models.

5.1.1. Maximum Likelihood Approach

ML estimation procedure is applied to all the 5 models, following Sargent (1989). Kalman filter is used to obtain the log-likelihood function for given set of parameter values, and the paramter values are varied across the parameter space within preset bounds to maximise the log-likelihood function. The estimation results are listed in Appendix Table 43. Two issues related to ML estimation are addressed here.

The most important feature of ML estimation is its identification issues. Identification problems are typical for non-Bayesian approach to estimating DSGE models. Firstly, two structural parameters cannot be estimated by ML procedure due to identification: the inverted elasticity of capital utilisation rate (ψ) and the inverted investment adjustment cost (γ). After the DSGE model is solved and written in state space form, the two structural parameters enter objective function (log-likelihood) only proportionally, making them separately unrecoverable. This is termed as "partial identification problem" by Canova & Sala (2006). Therefore, these two parameters are fixed at its calibration values, $\psi = 0.2$ and $\gamma = 4$. Moreover, another parameter, the steady state level of price mark-up (λ_P), is also not estimated, but due to another type of identification problem. The objective function turns out to be independent of λ_P, which disappears from the log-linearised solution. This is called "under identification problem" by Canova & Sala (2006). As introduced in Methodology, there are another three types of identification problem, i.e. observational equivalence, limited information identification and weak identification. It is very likely that weak identification problem also arises in applying ML to these 5 DSGE models. Due to lack of curvature in objective function, the standard errors are quite big. Many parameters are not significantly different from zero. The identification problems greatly reduced the reliability of ML estimation.

Another problem with ML estimation is the existence of corner solutions. As seen from Appendix Table 43, several parameters (e.g. SD of inflation target shock $\sigma_{\bar{\pi}}$, AR coefficienct of productivity shock $\rho_{\varepsilon A}$, and output gap growth coefficient $r_{\Delta Y}$) are equal to zero. It is because the preset lowerbounds for these parameters are zero. However, it is obvious that the productivity shock is supposed to be persistent and $\rho_{\varepsilon A}$ must be close to 1. These corner solutions do not make any economic sense, because ML approach treats the whole parameter space equally important. As a result, the corner solution is more a mathematical optimum than an economic optimum. Arguably, the probability of parameter values are different across the paramter space according to related economic theory and empirical findings. It is another comparative advantage of Bayesian approach over ML approach.

In spite of the two shortcomings above, ML has an advantage that its computational burden[①] is much less than simulation-based Bayesian approach. In addition to using it as comparison basis, there are also some meaningful results worth pointing out.

[①] ML estimation usually takes 5-10 minutes, but Bayesian estimation takes at least 5-10 hours. For the GTE model with 20 price setting sectors, it takes more than 1 week to get the results!

Firstly on nominal rigidity, the average survival rate ξ_P in ICE has to be extremely high (0.998) to capture the persistence in data. Yet, it is quite similar to the estimate (0.908) in Smets & Wouters (2003). It is because in homogeneous price setting models, it is difficult to have realistic average price rigidity on one hand and enough persistence on the other. Also, the degree of price indexation (γ_P) is estimated to be zero, suggesting no evidence for indexation in price setting. In contrast, indexation in wages setting behaviour is much more supported, and the estimates for ξ_W (0.733) and γ_W (0.431) make economic sense and are consistent with previous studies. This finding verifies the earlier prediction that ICE is more appropriate for wage setting, but not for price setting.

Secondly on habit persistence, the estimate of habit portion of past consumption (h) ranges from 0.609 (GCE) to 0.801 Calvo), which are higher than that (0.573) found in Smets & Wouters (2003). It might suggest a greater habit persistence of consumers in the UK, relative to the Euro area. The habit persistence component in the DSGE model is vital in explaining consumption smoothing. Note that ψ and γ are not identified, so the other two modelling components to generate persistence in capital and investment cannot be discussed.

Thirdly on the Taylor rule coefficients, the response of interest rates to inflation (r_π) is around 1.5-1.6, which satisfies the Taylor principle. The inflation growth coefficient ($r_{\Delta\pi}$) is also significant mainly around 0.25. However, the estimates of output gap coefficient (r_Y) and output gap growth coefficient ($r_{\Delta Y}$) are quite different across models. Moreover, a high AR coefficient of past interest rate (ρ) implies an interest rate smoothing feature in monetary policy.

5.1.2. Bayesian Approach

Bayesian approach makes use of both data information and prior information to obtain the posterior distributions of structural parameters. In contrast to ML, Bayesian approach solves identification problem by assigning different weights over the parameter space, so that the curvature of objective function is strong enough to identify all the structural parameters. Meanwhile, the use of prior also effectively prevents the cases of corner solution. In some sense, Bayesian approach includes ML approach as a special case. The prior distributions (listed in Table 45) used in this chapter are exactly the same as those in Smets & Wouters (2003), which are quite standard in current literature. The posterior modes and Hessian matrix are obtained through Monte Carlo based optimisation routine, and the posterior distributions including means are based on 500,000 draws through Metropolis Hastings algorithm.

Based on the results listed in Appendix Table 44 and Table 45, this subsection focuses on three issues: (i) the four modelling components to generate persistence, (ii) monetary policy, and (iii) structural shocks.

Firstly, nominal rigidity in price setting is reflected in the average price survival rate (ξ_P), which is only estimated for ICE. It is because ξ_P in simple Calvo has to be calibrated to be consistent with the calibration of baseline survival function in GCE. The estimated mode of ξ_P under ICE is 0.868, a bit lower than that that (0.908) in Smets & Wouters (2003). However, it is still too high compared to the implied ξ_P 0.556 implied from microdata. Similarly, wage setting is characterised by the estimated average wage survival rate (ξ_W) shown in Figure 37, ranging from 0.677 (GCE) to 0.705 (ICE), also lower than that in the Euro area (0.737). The estimated degrees of indexation, γ_P and γ_W, are also lower than Euro area. All these evidence suggests a more flexible price and wage setting behaviour in the UK.

Secondly, persistence in capital accumulation is measured by the inverted elasticity of capital utilisation rate (ψ). The estimates are quite close to the prior mean (0.2), a bit higher than that found in Euro area (0.169). This implies a less capital utilisation cost and less persistence in capital accumulation in the UK.

Thirdly, persistence in investment can be seen from the inverted elasticity of investment adjustment cost (γ). The posterior modes and MH means for all the models are between 4, which are lower than that in Euro area (6.771). This suggests a higher investment adjustment cost and more persistence in investment in the UK. ψ and γ (Figure 38) describe the real rigidity.

Fourthly, persistence in consumption behaviour depends on the habit portion of past consumption (h). Similar to the findings in ML estimation, the estimates are over 0.8 (Figure 39), much higher than that in the Euro area (0.573). Thus, consumption smoothing is stronger in the UK.

Figure 37 Posterior Distributions of Nominal Rigidity Parameters

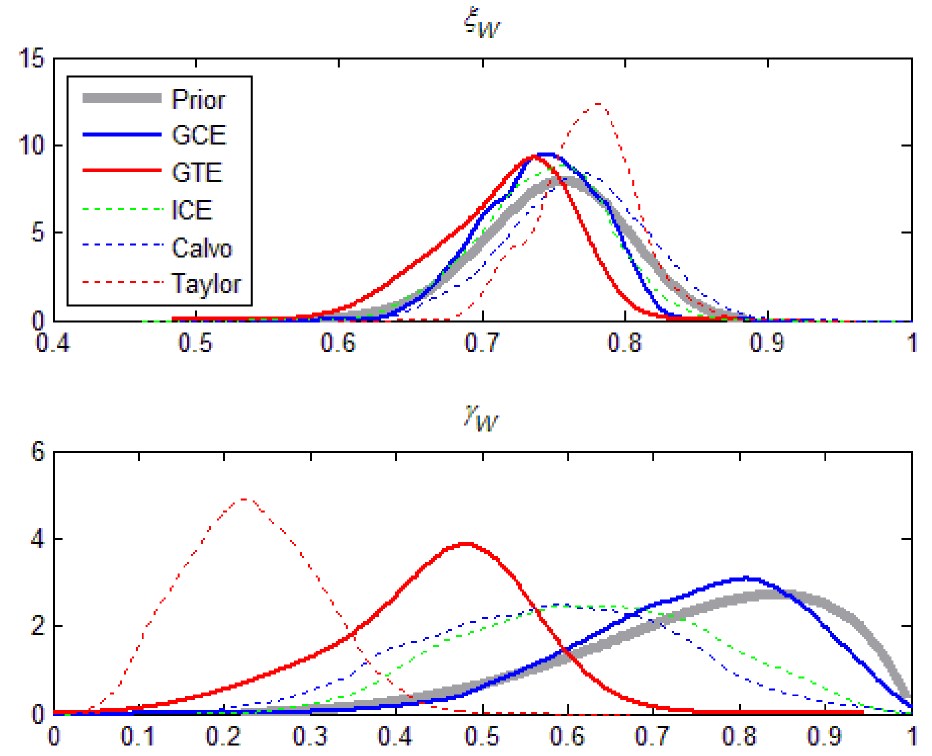


Figure 38 Posterior Distributions of Real Rigidity Parameters

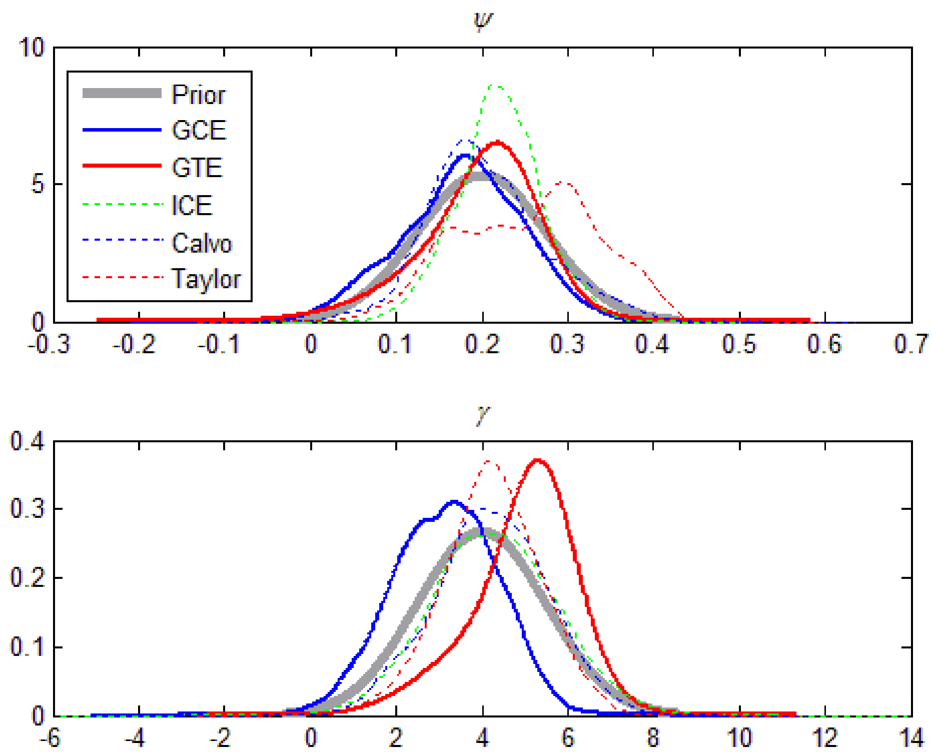
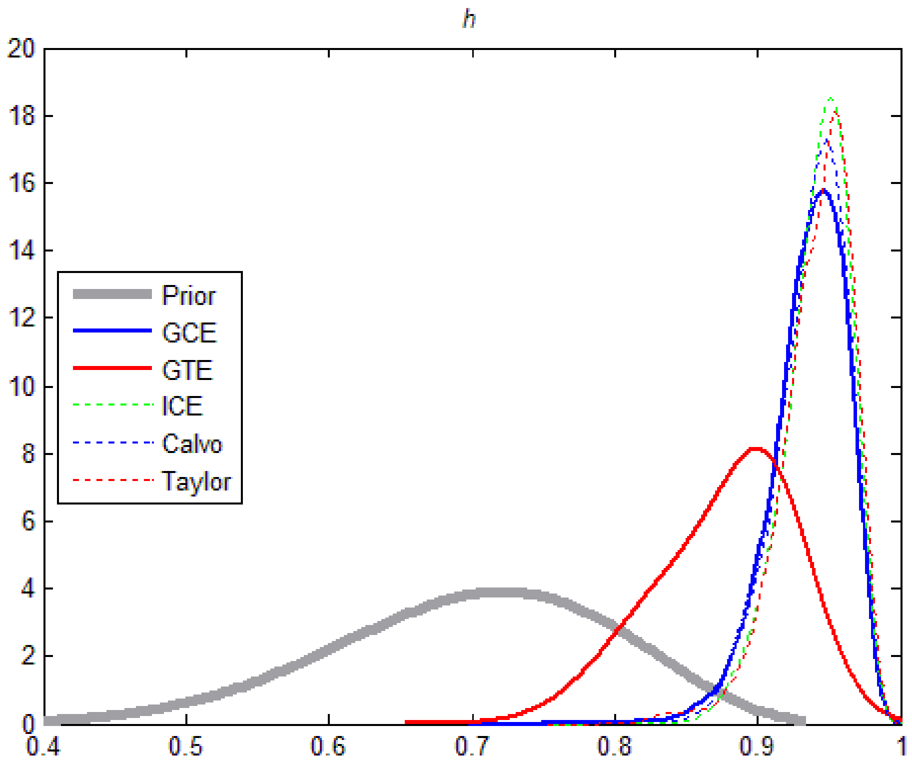


Figure 39 Posterior Distribution of Habit Persistence



Regarding the monetary policy, the estimated inflation coefficient (r_π) and inflation growth coefficient ($r_{\Delta\pi}$) are higher than those in Euro area. Again, Taylor principle in monetary policy is verified since r_π is greater than 1 (around 1.6). The responses to output gap (r_Y) and output gap growth ($r_{\Delta Y}$) are both significant (Figure 40). It does not show evidence for an independent role of Bank of England during the sample period. Furthermore, the estimated AR coefficient of past interest rate (ρ) is around 0.6, suggesting a widely found interest rate smoothing (Figure 41).

Lastly, the structural shocks in the UK tend to have similar persistence, measured by the AR(1) coefficients, but quite different standard deviations. The AR(1) coefficients of productivity shock ($\rho_{\varepsilon A}$), government spending shock ($\rho_{\varepsilon G}$), labour supply shock ($\rho_{\varepsilon L}$) and inflation target shock ($\rho_{\bar{\pi}}$) are all very close to 0.9, as found in Euro area. However, the coefficients of preference shock ($\rho_{\varepsilon U}$) and investment shock ($\rho_{\varepsilon I}$) are much lower, ranging from 0.3 to 0.4. Moreover, the standard deviations of structural shocks are quite different except for productivity shock ($\sigma_{\varepsilon A}$). Shocks with lower standard deviations include labour supply shock ($\sigma_{\varepsilon L}$), equity premium shock ($\sigma_{\varepsilon Q}$) and wage mark-up shock (σ_W). Shocks with higher standard deviations include preference shock ($\sigma_{\varepsilon U}$), government spending shock ($\sigma_{\varepsilon G}$), investment shock ($\sigma_{\varepsilon I}$), interest rate shock (σ_R) and price mark-up shock (σ_P).

Figure 40 Monetary Policy Responses to Inflation and Output

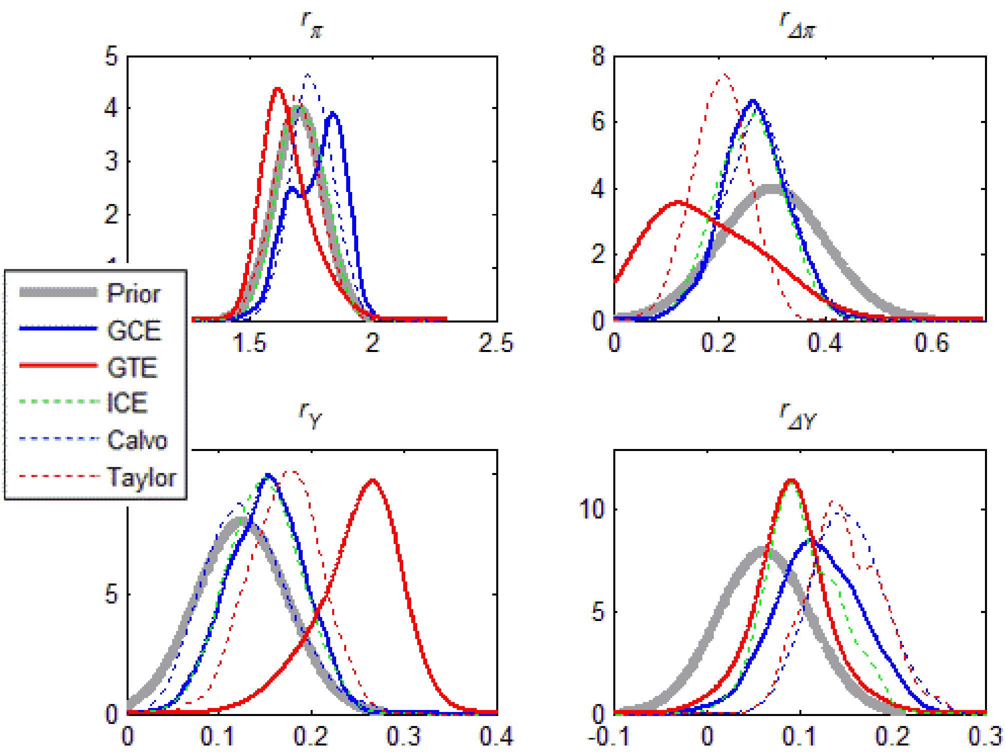
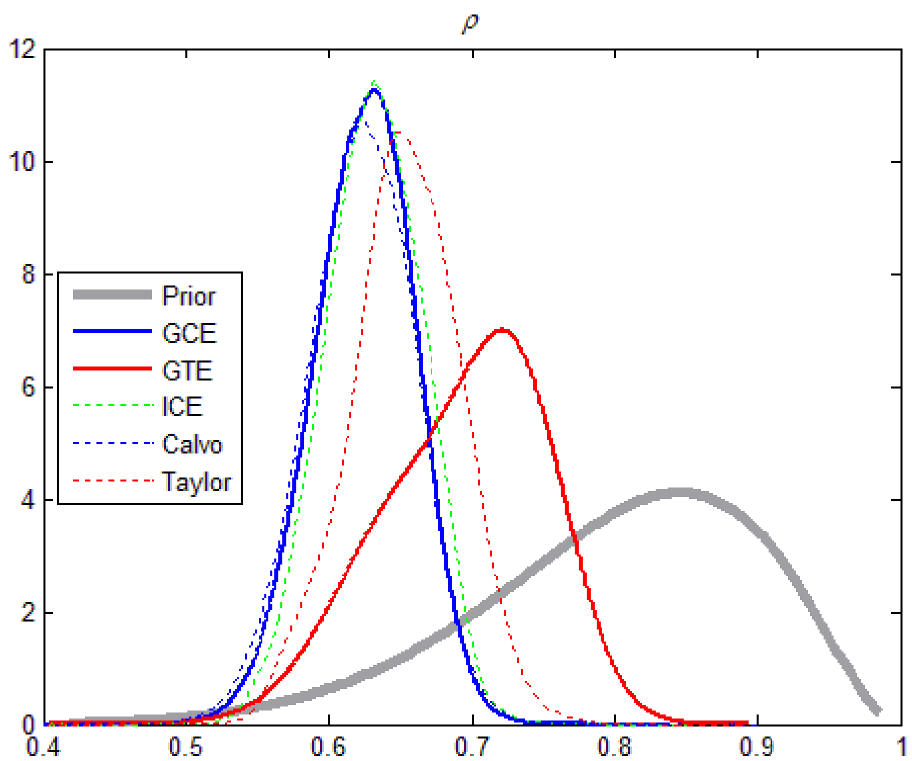


Figure 41 Monetary Policy Interest Rate Smoothing



5.2. Impulse Response Function

This subsection compares the impulse response functions both among DSGE models and against unrestricted VAR models. The estimated impulse response functions for GCE, GTE, ICE and simple Calvo models are listed in Appendix from Figure 42 to Figure 46. The first four graphs are responses of selected "quantities" (output Y, consumption C, investment I and labour L), and the other 4 graphs below a demarcation line are the responses of selected "prices" (inflation π, wage W, nominal interest rate R^B and shadow price of physical capital Q). There are 10 structural shocks, but this paper will focus on productivity, mark-up and monetary policy shocks. Also, the impulse response functions of unrestricted VAR based on the 7 observables are listed in Appendix Figure 47. Since VAR summarises the dynamic features of observable data without any restriction, the stylised facts could be used as comparison basis. Moreover, a relative comparison among the candidate models could provide a deeper insight into which aspects each model could better capture. It complements the Bayesian approach, which is based on strong econometric interpretation and evaluates the *overall* performance of DSGE models.

5.2.1. Empirical Stylised Facts

The unrestricted VAR includes 3-period lags after an iterative selection according to AIC and BIC criteria. There are 7 observables (Y, C, I, L, W, R, π), so there are 7 reduced shocks, which are respectively ($e^Y, e^C, e^I, e^L, e^W, e^R, e^\pi$)[①]. As shown in Appendix Figure 47, four important stylised facts can be identified from the impulse response functions of the VAR estimation.

The first feature is the strong persistence in VAR impulse response functions. Most shocks (e.g. output, consumption, labour, etc.) do not die out even after 40 quarters. The only exception is the response of inflation π to inflation shock e^π, whose effects disappear after 5 quarters.

The second feature is the hump shape at the beginning of the responses. The effects of most shocks do not peak on the arrival of the shock. Rather, the maximum is obtained after around 4-8 quarters for most impulse response functions. However, the responses to their own shocks (i.e. Y to e^Y, C to e^C and all the diagonal graphs) peak immediately when the shocks occur.

[①] Note that these shocks are reduced form shocks and do not correspond to any structural shocks as there is no identification scheme. Here it only shows the effect of reduced form shocks to output, inflation, etc. It is used to see that in general there are humps and persistence in response to linear combinations of structural shocks.

The third feature is the cyclical oscillation over time. The impulse response functions do not converge to steady state monotonically, but jump around the long run equilibrium (red horizontal lines).

The last feature is the typical hump around 20 quarters in the impulse response functions. Most response functions experience a local hump around 60 months. This is a very interesting phenomenon, because this spike echoes the findings in microdata. As shown in Chapter I, the firms in the UK tend to reset prices every 4 months resulting in a minor peak, and most firms reset prices every 12 months resulting in a major peak. It is found that over 95% prices will change (from the directly estimated distribution of duration across firms). Hence, 20 quarters (or 60 months) is a critical point where the effects of shocks will decline, since most firms could adjust their prices finally. This persistence is induced by the nominal frictions.

5.2.2. Homogeneous V.S. Heterogeneous

Under homogeneous price setting behaviour, such as simple Calvo, simple Taylor and ICE, there is only one representative firm and one unique price setting mechanism. To generate a high persistence close to stylised facts (stylised fact 1), it needs either a ridiculously high survival rate (over 0.9) for Calvo-type models or an impossibly long price duration (around 20 quarters) for simple Taylor model. If not, the responses to shocks are lack of persistence as shown in Appendix.

In contrast, heterogeneous price setting models do not have this dilemma. Due to its flexibility of having heterogeneity in price duration, these models are not only able to generate persistent impulse response functions, but also able to have a plausible average duration or survival rate at the same time. As shown in Appendix Figure 42 to Figure 46, heterogeneous price setting models, especially GTE, have more persistent responses to various structural shocks.

Another advantage of heterogeneous models is its ability to generate hump shape responses (stylised fact 2), especially to the monetary policy shocks (Figure 45 and Figure 46). Interestingly, a key difference between GCE and GTE is also seen here. GTE seems to have higher reactions in quantities (Y, C, I, L) but smaller reactions in prices (π, W, R^B, Q). More importantly, GTE displays a hump shape responses of inflation to both permanent and temporary monetary shocks, whilst GCE does not. This might be the reason why GTE fits the data better than GCE if only output, inflation and interest rate are used as observables as in 5.4.2.

Two remarkable features of GTE are identified here, i.e. only GTE exhibits the other two stylised facts found in data-based impulse response functions, i.e. cyclical oscillation (stylised fact 3) and 20-quarter spike (stylised fact 4). The cyclical oscillation can be seen in, for instance, the responses to productivity shock (Figure 42) and to price mark-up shock (Figure 43). Also, only GTE model exhibits 20-quarter humps, which might be due to the 20 price setting sectors in the model. Note that the share of each sector is calibrated from the empirical research in Chapter I and consistent with microdata evidence. These special favourable features make GTE a better heterogeneous price setting model than GCE, if one only focuses on the impulse response dynamics, especially of output, inflation and interest rate. This is consistent with Dixon & Le Bihan (2010), who also find that GTE performs the best in a specific scenario.

5.2.3. Other Features

Apart from the four stylised facts discussed above, DSGE impulse response functions can be evaluated in some other well-known empirical claims.

Consumption smoothing can be seen in both VAR and DSGE models. The response of consumption is about half of that in output after a productivity shock (Figure 42). The effect obtains the maximum about 5 quarters after the shock, similar to the findings in Euro area. This feature is a consequence of intertemporal link in consumption resulting from habit persistence. Both homogeneous and heterogeneous models have similar qualitative property with a little quantitative difference. In particular, the responses of GTE seem to be greater than other models. This is because of higher shares of short price duration sectors. These firms can react quickly to the positive productivity shock and attenuate the consumption smoothing.

Investment smoothing is well documented in Finance literature, such as Das (1991) and Fazzari & Petersen (1993). An important reason for this feature is the adjustment costs, resulting in hump shape responses of investment to various shocks. An unexpected rise in productivity leads to a positive response in investment, which peaks around 4 quarters after the shock. A positive shock in temporary monetary policy (η_t^R) will reduce the investment for the first 4 quarters after shock, but overshoot above zero after 10 quarters (Figure 46). However, a positive shock in permanent monetary policy (η_t^π) will raise investment until the 8th quarter, and converge back to steady state (Figure 45).

Labour market fluctuations are found persistent in VAR impulse response function. In this model, labour supply component follows Smets & Wouters (2003) and use ICE as nominal friction. It works well for responses of labour to monetary policy shock, but there is a lack of persistence for responses to price and wage mark-up shocks, which die away around 10 quarters (Figure 43 and Figure 44). Traditional RBC models with flexible price also fail to capture this, because income effect offsets substitution effect. Many attempts are made in literature to address this problem, such as indivisible labour in Hansen (1985), human capital in Lucas (1988) and searching costs in Merz (1995) and Andolfatto (1996). There are many other ways of improving the performance of labour. This paper, however, only focuses on the price setting behaviour, so ICE is good enough for this purpose. In fact, one could also use GTE or GCE to model the wage setting behaviour and labour market. Due to the lack of microdata in wage, this is left for future research.

The existence of liquidity effect and Fisher effect of monetary policy is a long and controversial literature (see Christiano & Eichenbaum (1992)). Following a rise in money supply, liquidity effect refers to the negative effect on interest rate in the short run, while Fisher effect refers to the positive effect on interest rate in the long run due to the expected increase in future inflation. However, in New Keynesian monetary models, there is no explicit money. Rather, money is implicitly assumed through a nominal interest rate setting rule. In this Taylor-type monetary policy, a permanent monetary shock (inflation target shock) and a temporary monetary shock (interest rate shock) are equivalent to the money supply shock in New Classical monetary models. Note that a positive inflation target shock or a negative interest rate shock implies a positive money supply shock. The data-based impulse response function of nominal interest rate to a negative money supply shock (row 6, column 6 of Figure 47) evidences both liquidity effect in the short run and Fisher effect in the long run. For temporary monetary policy shock (Figure 46), only liquidity effect is seen. For permanent monetary policy shock (Figure 45), both liquidity and Fisher effects are shown. Note that only GTE has a hump shape in the response, and it is quantitatively closer to that in VAR. This favourable feature suggests that GTE outperforms the other candidates in mimicking interest rate dynamics. That is to say, if one is more interested in monetary policy rather than the overall performance, GTE is preferred to the other models including GCE.

5.3. Variance Decomposition

To investigate the importance of the 10 structural shocks in explaining endogenous variables, variance decomposition is done for the 5 models. Table 46 compares the results of an asymptotic decomposition of unconditional variance of selected endogenous variables.

In general, investment shock (η_t^I) and government spending shock (η_t^G) seem to be the most important shocks for output, consumption, investment and labour, accounting for over 60% of the variations. In contrast, the mark-up shocks (η_t^W and η_t^P) and equity premium shock (η_t^Q) contribute little, less than 5%, to the variations in the 4 quantities. As for prices (inflation and nominal interest rate), price mark-up shock (η_t^P) and interest rate shock (η_t^R) are now the most important sources of variation, account for more than 80% of the variance in inflation and nominal interest rate.

In particular, the variance of inflation is almost determined (over 85%) by the price mark-up shock, and little by productivity or preference shocks. This result is exactly the same as Smets & Wouters (2003), who argue that monetary policy responds "quite strongly to those shocks, thereby helping to close the output gap and to avoid inflationary or deflationary pressures that may otherwise arise".

Among the 5 models, Taylor behaves in a very distinctive way from the other models. Indeed, due to lack of persistence, most shocks die away fast in 3-cohort simple Taylor model. Hence, the variances under simple Taylor model are mainly determined by persistent shocks, such as productivity shock and preference shock. Differently, Calvo-type models, including GCE, ICE and simple Calvo, have longer implied mean duration, so the variances are explained by shocks with higher volatility, such as investment shock and government expenditure shock. GTE is almost the same as GCE, but with an important exception. The variance of consumption is mainly explained by preference shock in GTE (73.66%), whilst, under Calvo-type models, investment shock is considered to be the most important source of variation (over 50%). In this regard, GTE is more plausible and consistent with the empirical findings in the US and Euro area.

Regarding the policy implications, the government expenditure shock (fiscal policy) contributes a substantial amount of variations in real side of economy (output, consumption, investment and labour), while monetary policy shocks seem to affect only the nominal side of economy (inflation and interest rate). Hence, to reduce the economic fluctuations, it is critical to have smoothed fiscal and monetary policy.

5.4. Model Comparison

5.4.1. Bayesian Approach

Following Geweke (1999), this subsection focuses on Bayesian techniques to evaluate and compare DSGE models, which might be fundamentally misspecified. The basic criterion for model comparison is the marginal likelihood, defined as:

$$M_i \equiv p\left(data_{T\times N}\left|model_i\right.\right) = \int\limits_{\theta\in\Theta} p\left(\theta\left|model_i\right.\right) p\left(data_{T\times N}\left|\theta, model_i\right.\right) d\theta$$

Here, $\theta \in \Theta$ is the structural parameters of model i to be estimated, $p\left(\theta\left|model_i\right.\right)$ is the prior probability of model i, and $p\left(data_{T\times N}\left|\theta, model_i\right.\right)$ is the likelihood function of the observable data $data_{T\times K}$ given the model and parameter, assuming T observations (row) and N observable variables (column). In this chapter, $T = 108$ observations from 1981Q1 to 2007Q4 are collected for $N = 7$ key macroeconomic variables in the UK: output, consumption, investment, labour, inflation, interest rate and wage.

The marginal likelihood measures the prediction performance of a model, so it can be used to relatively evaluate and compare models. Two popular ways are adopted to calculate the marginal likelihood for these models, as discussed in Geweke (1999). The first method is Laplace approximation, which assumes a functional form (Gaussian density) of the posterior kernel to be integrated, usually used before Metropolis-Hastings algorithm but after estimating the mode of parameters ($\hat{\theta}$).

$$\hat{M}_i = \left(2\pi\right)^{\frac{K}{2}} \left|\Sigma_{\hat{\theta}}\right|^{\frac{1}{2}} p\left(\hat{\theta}\left|data_{T\times N}, model_i\right.\right) p\left(\hat{\theta}\left|model_i\right.\right)$$

The second approach is modified harmonic mean estimator, based on Metropolis-Hastings simulation, where each draw of parameter vector $\theta^{(d)}$ ($d \in [1, D]$) comes from a candidate probability density function f. In this chapter, the number of Metropolis-Hastings draws is $D = 500{,}000$ and half of them are dropped to allow a 50% burn-in phase.

$$\hat{M}_i = \left[\frac{1}{D}\sum_{d=1}^{D} \frac{f\left(\theta^{(d)}\right)}{p\left(\theta^{(d)}\left|model_i\right.\right) p\left(data_{T\times N}\left|\theta^{(d)}, model_i\right.\right)}\right]^{-1}$$

To apply model comparison or relative testing, Bayes Factor (BF) between two competing models i and j is usually used:

$$BF_{i,j} = \frac{M_i}{M_j}$$

The Bayes factors of the 5 competing models, in terms of the two approaches of calculating marginal likelihood, are listed in Table 34. To calibrate the GCE and GTE parameters, semiparametric baseline survival function $h_0\left(t\right)$ and implied distribution of duration across firms (DAF) estimated in Chapter I are used. A full list of calibrated parameters and free parameters to be estimated is shown in Table 41 and Table 42.

Note that GCE is chosen as the reference model, since it performs the best among the 5 models.

Table 34 Model Comparison by Bayes Factors

Marginal Likelihood	Taylor	Calvo	ICE	GTE	GCE
Laplace Approximation	-1120.91	-1053.49	-1034.73	-1008.14	-1001.31
BF relative to GCE	$e^{119.60}$	$e^{52.18}$	$e^{33.42}$	$e^{6.83}$	1
Modified Harmonic Mean	-1083.74	-1023.79	-1006.38	-1004.03	-998.38
BF relative to GCE	$e^{85.36}$	$e^{25.41}$	$e^{8.00}$	$e^{5.65}$	1

A rule of thumb is proposed by Jeffreys (1961) to interpret the BF while comparing two models. Table 35 summarises the guideline to conduct model comparison in terms of BF.

Table 35 Jeffrey's Guideline for Interpreting Bayes Factor

BF	Interpretation
1 to 3.2	Not worth more than a bare mention
3.2 to 10	Substantial
10 to 100	Strong
> 100	Decisive

According to Jeffrey's guideline, the first and foremost conclusion drawn from Table 34 is that simple Calvo, ICE, simple Taylor and GTE are "decisively" rejected against GCE. However, note that GTE has the closest marginal likelihood to GCE, though the implied BF ($e^{5.65}$=284.29) is significantly higher than 100. The closeness between GCE and GTE is not surprising, because both models imply heterogeneous price setting behaviour. A given distribution of durations can always be derived from a GTE or a unique corresponding GCE. The only difference between GTE and GCE is the uncertainty while setting prices. Under GTE, firms are assumed to know how long the price will last ex ante, while under GCE, firms only know the duration dependent probability of resetting price. Hence, GCE is more forward looking due to this uncertainty. Heterogeneity in price setting models, especially GCE, is supported based on the 7 observable macroeconomic variables in 1981Q1-2007Q4. Evidence shows that, on average, firms do not know when to reset the prices in the future, but they know the varying probability of price change, with some periodic peaks every 4 months.[①]

Secondly, ICE performs relatively better than simple Calvo, since it is more flexible due to its unrestricted value of price indexation γ_P. Nevertheless, ICE is still strongly

① This argument is based on the survival analysis of microdata underlying CPI and PPI in UK, as found in Chapter I.

rejected against heterogeneous price setting models. Arguably, indexation in price setting is neither empirically supported nor logically consistent. If there is no nominal friction like menu costs, firms will always reset the prices to the optimal level. However, ICE assumes, on the one hand, no nominal friction—firms can and will reset prices every period, while it assumes, on the other hand, that some firms cannot reset the prices to optimal level. Hence, although ICE behaves econometrically better than simple Calvo and simple Taylor, it is less supported from a theoretical point of view.

Lastly, simple Taylor is the worst model among all the candidates. The disadvantage of simple Taylor is obvious. Since the estimated average price duration across firms (DAF) in the UK is around 9 months or 3 quarters, the simple Taylor model has three cohorts. That means any monetary shock dies away in 3 quarters under simple Taylor model. It fails to generate enough persistence, compared to heterogeneous agent models and even simple Calvo. Taylor-type models fix the price duration ex ante, resulting in less flexibility and worse fit of data. This point also reinforces the first conclusion that firms do not know exactly when to change the price.

In Smets & Wouters (2003) and Smets & Wouters (2007), DSGE models are found to perform at least as good as standard unrestricted VAR and Bayesian VAR (BVAR). However, as shown in Table 36, BVAR based on the 7 observables in the UK performs far better than all DSGE models, including heterogeneous GTE and GCE.

Table 36 Log Marginal Likelihood of Bayesian VAR

GCE	BVAR(1)	BVAR(2)	BVAR(3)	BVAR(4)	BVAR(5)	BVAR(6)
-998.38	-815.153	-765.465	-772.165	-758.492	-761.701	-759.653

These BVAR models are estimated for 1981Q1-2007Q4 using Minnesota prior, as in Doan, Litterman & Sims (1984). It turns out that BVAR(4) performs the best, but all DSGE models, including GCE and GTE, are strongly rejected compared to BVAR model. This is not a surprise, because DSGE models are restricted by economic theory and very likely to be misspecified, compared to unrestricted VAR or BVAR.

Hence, if one tries to justify DSGE models by absolute tests, they are usually rejected definitely. This unfortunate result is consistent with other types of tests in most empirical studies[①], including likelihood ratio test (strong interpretation) and indirect inference test (weak interpretation). However, as argued previously, models are not designed to be true but to be useful in policy analysis and welfare analysis. VAR and

[①] For a detailed discussion, see **Le, V. P. M.; P. Minford and M. Wickens.** 2010. "The 'Puzzles' Methodology: En Route to Indirect Inference?" *Economic Modelling*, 27(6), pp. 1417-28.

BVAR are not that useful, since they merely summarise the past information in real data and cannot be used in policy analysis due to the famous critique of Lucas (1976). In contrast, DSGE models might do a bad job in some aspects, but do a good job in other aspects in which researchers and policy makers are interested. Relative tests like Bayes factor provide a handy criterion to identify the most useful model with least *overall* misspecification. GCE and GTE are justified relative to other homogenous agent models in this spirit. Regarding which aspects the heterogeneous agent models match data better, impulse response function and variance decomposition will be discussed in 5.2 and 5.3.

5.4.2. Robustness of Bayesian Approach

To check the robustness of the Bayesian model comparison or relative testing, four dimensions of the original estimation procedures are investigated. It is shown that the model ranking is not sensitive to calibration, prior distribution or macroeconometric approach, but might be different if different observables are used.

Firstly, different calibrations for survival function are used. Bayesian inference in 5.4.1 is based on the semiparametric baseline survival function after controlling for microeconomic and macroeconomic factors, which might affect the survival rates. Hence, it is directly used for calibrating GCE duration dependent survival function, while the implied distribution of DAF is used for calibrating GTE sector shares. Also, the implied average survival rate is used to calibrate simple Calvo, and the implied average duration (around 9 months) is used to calibrate simple Taylor. It is the most reasonable calibration, since the nonparametric survival function does not control for these factors and is not "deep" structural parameter. The nonparametric survival function will change if, say, monetary policy has changed. Semiparametric baseline survival function does not have this problem, since it is the pure relationship between survival rates and analytical time. However, the nonparametric survival function could be used to provide robustness analysis of the test. It is shown in Table 37 that the relative ranking among models are exactly the same, in spite of slight differences in magnitudes in marginal likelihood.

Table 37 Model Comparison by Bayes Factors (Robustness to Calibration)

Marginal Likelihood	Taylor	Calvo	ICE	GTE	GCE
Laplace Approximation	-1115.45	-1110.22	-1001.06	-999.00	-997.50
BF relative to GCE	$e^{117.95}$	$e^{112.72}$	$e^{3.56}$	$e^{1.50}$	1
Modified Harmonic Mean	-1098.69	-1090.63	-992.55	-980.62	-972.46
BF relative to GCE	$e^{126.23}$	$e^{118.17}$	$e^{20.09}$	$e^{8.16}$	1

Notice that the Bayes factors of GTE and ICE (Laplace) are quantitatively closer to GCE. Compared to the results based on semiparametric analysis, the difference between GTE and GCE now lies in the second category, “substantial”, rather than “decisive” according to Jeffrey’s guideline. Also, the difference in statistical performance between GCE and ICE is now only “strong”. However, the relative ranking among models are not changed, and the close relationship between GCE and GTE is again verified. In this practice, nonparametric survival function is not substantially different from semiparametric baseline survival function. However, it is possible that relative ranking between models may change if the calibration is far away enough. Given that possibility, it is very important to choose the right calibration for use. Another implication is that, different models might be favoured for different countries, since the current calibration is based on the microdata findings in the UK. Thus, the role of microdata is of equal importance with macrodata.

Another useful check for robustness to calibration is to make the parameter of price rigidity (ξ_P) in simple Calvo and ICE free to be estimated, rather than calibrated to be consistent with microdata evidence. It turns out that, even if the homogeneous price setting models are free to vary ξ_P to maximise marginal likelihood, heterogeneous price setting models still outperform: Calvo (-1039.15) and ICE (-1017.69), versus GCE (-1001.31) and GTE (-1008.14).

Secondly, different prior distributions are tried to check the reliance of BF on the prior information. The priors used in the previous tests are exactly the same as those used in Smets & Wouters (2003). Now if, instead, posterior modes or Metropolis-Hastings means in Smets & Wouters (2003) are used to specify prior distributions, the relative ranking still turns out exactly the same. In particular, Table 38 shows the estimated marginal likelihood and BF, when Metropolis-Hastings means are used in the prior distributions.

Table 38 Model Comparison by Bayes Factors (Robustness to Prior)

Marginal Likelihood	Taylor	Calvo	ICE	GTE	GCE
Laplace Approximation	-1118.18	-1081.86	-1017.90	-1003.57	-999.41
BF relative to GCE	$e^{118.78}$	$e^{82.45}$	$e^{18.49}$	$e^{4.16}$	1
Modified Harmonic Mean	-1091.22	-1057.21	-999.47	-992.33	-985.42
BF relative to GCE	$e^{105.80}$	$e^{71.79}$	$e^{14.04}$	$e^{6.90}$	1

Indeed, Bayesian inference is mainly criticised in the usage of prior, which is said to have significant influence on parameter estimation and model comparison. If an absurd prior is used, then any absurd conclusion might be drawn. However, in this paper, prior distributions are chosen to have adequately large variances, so that estimation procedures travel across a vast range of parameter space. Moreover, the relative ranking is proven robust to different choices of prior distributions within a reasonable range. Therefore, the disadvantage of Bayesian approach does not affect the reliability of this chapter.

Thirdly, instead of evaluating models directly in terms of model's goodness of fit to data as in maximum likelihood and Bayesian inference, indirect inference approach compares some partial features simulated by DSGE models with actual data indirectly through an auxiliary model, usually using VAR à la Sims (1980). It is called "indirect" because VAR acts as a window through which DSGE model is confronted with data. The DSGE model is used to generate pseudo data by bootstrapping, and each simulation is used to run a VAR, resulting in a Wald statistic. Since simulation is run for many times, distribution of the Wald statistic could be obtained. On the other hand, the actual data is all used to run a VAR to calculate the Wald statistic. If the Wald statistic from the actual data lies in the 95% confidence interval of the simulated distribution, the model cannot be rejected in an absolute sense. If two models are compared in a relative sense, then the model with the highest probability value or smallest Wald statistic is favoured.

Indirect inference approach is developed by a research team of faculty and PhD students in Cardiff Business School, led by Professor Patrick Minford. The results used here is based on the work done by a PhD student in this research team, Jing Jiao, who has been working on indirect inference testing of the same set of models as in this paper. The results quoted in Table 39 is based on calibrations of survival function from Dixon & Le Bihan (2010) and observables of quarterly France data from 1978 to 2010 on output, consumption, investment, inflation and interest rate. The auxiliary model used is VAR(1), and the specifications of the 5 models are exactly the same.

Table 39 Model Comparison by Indirect Inference

	Taylor	**Calvo**	**ICE**	**GTE**	**GCE**
Wald Statistic	16.75	15.47	16.12	11.48	7.70
P-Value	100%	100%	100%	100%	100%

Unfortunately, all the models are rejected in an absolute sense according to the Wald statistics (note that normalised Mahalanobis distances are not reported), similar to the findings based on Bayesian approach. However, relatively speaking, GCE performs the best relative to the other candidates. In fact, relative ranking among the 5 models is exactly the same as that by Bayes factor. In spite of different approaches, microdata and macrodata, heterogeneous price setting models always perform better than homogeneous pricing models. This practice greatly reinforces the robustness of the model comparison result in a stronger sense.

Note that a future extension of this study is to use simulation-based approach (e.g. indirect inference) to re-estimate the 5 models, so that they pass overall tests of fit to the data, either Likelihood ratio or Wald. It is important to check whether the ranking of the 5 model still holds.

Lastly, different observables are used to check whether model comparison depends on observable data to be fitted. All the tests above are confronted with the 7 observable macroeconomic variables (output, consumption, investment, labour, inflation, interest rate and wage), so the relative ranking is, to some extent, comparing the goodness of fit of the 5 models in terms of these 7 observables as a whole. However, if one is only interested in a subset, rather than all, of these variables, then the relative ranking might change, since these models perform differently in fitting different aspects of reality. To be comparable to the findings in Dixon & Kara (2011), three variables (output, inflation and interest rate) are selected to check the robustness of model comparison. Table 40 summarises the results.

Table 40 Model Comparison by Bayes Factors (Robustness to Observable)

Marginal Likelihood	Taylor	Calvo	ICE	GCE	GTE
Laplace Approximation	-510.82	-443.59	-375.24	-354.058	-348.44
BF relative to GTE	$e^{162.38}$	$e^{95.15}$	$e^{26.80}$	$e^{5.61}$	1
Modified Harmonic Mean	-458.24	-396.73	-325.41	-323.223	-317.62
BF relative to GTE	$e^{140.62}$	$e^{79.11}$	$e^{7.79}$	$e^{5.60}$	1

The relative model ranking changes this time, thought heterogeneous agent models still outperform the homogeneous agent models. GTE performs better than GCE if only output, inflation and interest rate are used as observables. This result is in line with the findings of Dixon & Kara (2011), who maintain that GTE is strongly favoured by data relative to some variants of Calvo. A key reason is that GTE is able to generate more persistence in inflation in response to productivity shocks and monetary shocks. This feature greatly improves the performance of GTE, especially when more weights are put on explaining the dynamics of output, inflation and interest rate. In some sense, the choice of the three observables is logically similar to using weak interpretation approaches, such as minimum distance of impulse response and indirect inference. It is because the choice of specific set of observables only focuses on some partial features of the model. Question determines method, so the “best” model depends on what one tries to explain. If one is more interested in persistence of inflation, then GTE performs the best. However, if one cares about the overall performance, not just the three observables, then he might better go for GCE.

The examination of robustness suggests that model comparison is robust to calibration and prior within a wide range. However, if different observables are chosen, the relative ranking might change due to higher weights on some specific model features.

6. Conclusion

Following the theoretical framework in Smets & Wouters (2003) and Dixon & Le Bihan (2010), this paper proposes a DSGE model with either homogeneous or heterogeneous price setting behaviour. Based on the microdata findings in Chapter I, calibrations for heterogeneous price setting models (GTE and GCE) become possible.

Both maximum likelihood and Bayesian estimation procedures are conducted to estimate the structural parameters and processes driving shocks. Bayesian results are preferred because there are less corner solutions and more stable with fewer identification problem. The structural parameters are shown to be not very different from those found in the Euro area, whilst the standard deviations of structural shocks are quite different. In particular, more nominal frictions, less persistence in capital accumulation, more persistence in investment and more habit persistence are found in the UK. A Taylor principle is discovered in monetary policy of Bank of England with a higher weight on inflation. Preference shock, investment shock and price mark-up shock in the UK have significantly higher variance than those in Euro area.

An unrestricted VAR is employed to generate the data-based impulse response functions, from which four stylised facts are found, i.e. persistence, hump shape, oscillation and a hump around the 20^{th} quarter. GTE seems to be the best model in matching these four stylised facts in impulse response functions. In addition, smoothing in consumption, investment and monetary policy are found in both data-based and model-based impulse response functions. Moreover, the DSGE models are able to generate both short run liquidity effect and long run Fisher effect after a permanent shock in monetary policy.

Variance decomposition is obtained to identify the most influential structural shocks in the UK economy. Variations in quantities, such as output, consumption, investment and labour, are mainly determined by demand side shocks such as investment shock and government expenditure shock. In contrast, fluctuations in prices, like inflation and interest rate, are more related to price mark-up shock and monetary policy shocks. An effective feedback policy greatly reduced the impact of productivity shocks, but as a cost, it increases the volatility of inflation.

With a focus on Bayesian approach, various macroeconometric methods are applied to draw model comparison and relative evaluation. It is proven that heterogeneous price setting component remarkably improves the performance of DSGE models, but all models are still rejected against data. Interestingly, Bayesian and indirect inference approaches give exactly the same relative ranking among the 5 candidate models. If all the 7 macroeconomic observables are used, GCE then performs the best and GTE follows. In homogeneous price setting models, simple Taylor is the worst, because it generates the least persistence. This model ranking is also robust to different calibrations and priors. However, GTE could be the best model if one puts more weight on explaining output, inflation and interest rate.

Overall, the heterogeneous price setting component (GCE and GTE) has significantly enhanced the explanatory power and prediction precision of DSGE models. It overcomes the dilemma of homogenous price setting models that one cannot have plausible degree of nominal rigidity and enough persistence simultaneously. Which variant to use depends on the scope of the policy maker. GCE tends to fit the data better as a whole, but GTE performs the best if one only cares about the dynamics of output, inflation and interest rate.

Due to the unavailability of microdata on wage, this model keeps the ICE feature in wage setting. Indeed, ICE is logically more plausible in wage setting than in price setting. However, it is still possible to improve the model's overall performance if GTE and GCE are tried. On the other hand, all the candidates considered here are time dependent models. As found in the microdata, firm's price setting behaviour is likely to be state dependent. A future study including state dependent price setting behaviour, such as menu cost model, would be interesting. Furthermore, in addition to retailer's price setting behaviour based on CPI microdata, a research on wholesaler's price setting behaviour based on PPI microdata could also be informative to the transmission of shocks in the economy. Incorporating this microdata evidence could be promising to improve the persistence in DSGE model.

GENERAL CONCLUSION

This thesis has addressed nominal friction in price setting behaviour from both microdata and macrodata perspectives. The link between microdata analysis and macrodata analysis are built through the estimated distribution of duration across firms and the hazard function of price change. In fact, microdata study provides an empirical microfoundation for macrodata study. The novelties in microdata analysis are the use of cross-sectional method for descriptive measures of price rigidity and survival analysis method for estimating price setting mechanism. The contributions in macrodata analysis are improvement of performance of DSGE models by incorporating in heterogeneous price setting behaviour and application of various macroeconometric approaches to model comparison, estimation and dynamic analysis. It is shown that heterogeneous agent models can better mimic both microdata and macrodata stylised facts simultaneously.

Regarding the outcome of price setting behaviour, degree of price rigidity is measured by the conventional method based on the frequency of price change, which implies a short duration less than 6 months. However, this measure is criticised as downward biased due to oversampling of short durations by Dixon (2010). Alternatively, cross-sectional method uses the distribution of duration across firms, resulting in much longer durations, i.e. over 9 months for retailer price and 15 months for producer price. These findings are strong evidence of rigidity in frequency of price change. There is little evidence for rigidity in direction of price change, i.e. the nominal frictions are symmetric in both price increases and decreases. Retailer prices tend to have higher rigidity in magnitude of price change than producer prices in the light of attractive pricing. Also, significant cross-sectional heterogeneity is observed, but little regional difference or time-series heterogeneity is found in the UK during the sample period 1997-2007.

To investigate the mechanism of price setting behaviour, hazard functions are estimated by different approaches of survival analysis. For retailer price, the hazard function can be decomposed into decreasing component from goods sectors and the cyclical component from services sectors. For producer price, the hazard function also takes similar features of deceasing and cyclical, but not separable across sectors. There are minor cycles every 4 months and major cycles every 12 months, which are common to both retailer and producer prices. Seasonal peaks in Christmas sales and summer sales are revealed in calendar months. Both microeconomic and macroeconomic covariates have significant effects on the conditional probability (hazard function) of price change, which are supports for both time dependent and state dependent pricing models.

In the economic system with both retailer and producer firms, as moving from upstream of supply chain to downstream, price rigidity is decreasing due to the growing degree of competition. Furthermore, as a shock hits the economy, the producer firms act as both "container" to prolong the persistence of shocks and "buffer" to reduce the fluctuations. Hence, the microdata evidence suggests that inclusion of producer firms and heterogeneity in price setting behaviour might greatly improve the performance of macroeconomic models.

Turning to the macrodata analysis of DSGE models with different price setting behaviour, heterogeneous agent models (GCE and GTE) performs much better than the homogeneous agent models (ICE, simple Calvo and simple Taylor). This result is robust to different calibration, prior and method. Both Bayesian inference and indirect inference give exactly the same model ranking. If, instead of using 7 observables to estimate the model, only output, inflation and interest rate are used, GTE will perform the best, but heterogeneous agent models still outperforms homogeneous agent models.

Unrestricted VAR is employed to identify the stylised facts of dynamics of the 7 observables. Firstly, strong persistence is found in impulse response functions to shocks. The second feature is the hump shape at the beginning of the responses. The third feature is the cyclical oscillation over time after shocks. The last feature is the typical hump around 20 quarters in the impulse response functions. It is shown that homogeneous agent models fail to generate enough persistence and hump in model-based impulse response functions. In contrast, heterogeneous price setting models, especially GTE, could better capture these dynamic stylised facts found in macrodata.

To conclude, heterogeneous price setting behaviour is an effective way of improving the performance of DSGE models. On the one hand, it can generate both persistent impulse responses to structural shocks and various stylised facts found in macrodata. On the other hand, it can also be consistent with the evidence found in microdata.

Numerous extensions of this study could be done in the future. To name a few, firstly, in addition to nominal frictions in price setting, a heterogeneous wage setting model (GTE or GCE) could also be used. Secondly, the findings in producer price could also be incorporated into a more sophisticated model with multiple sectors. Thirdly, the DSGE model with heterogeneous agent can be used in optimal monetary policy analysis, accounting for both average price rigidity and distribution of price rigidity.

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APPENDIX

Table 41 Structural Parameters (Coefficients)

Parameter	Value	Description
β	0.990	Subjective discount factor
δ	0.025	Depreciation rate of capital
α	0.300	Capital output ratio
ψ	TBE	Inverted elasticity of capital utilisation rate
λ_P	TBE	Steady state level of price mark-up
λ_W	TBE	Steady state level of wage mark-up
γ_P	TBE	Degree of partial indexation of price
γ_W	TBE	Degree of partial indexation of wage
ξ_P	Micro	Calvo price stickiness (average survival rate)
ξ_W	TBE	Calvo wage stickiness (average survival rate)
σ_L	TBE	Inverted elasticity of labour supply
σ_C	TBE	Coefficient of relative risk aversion
h	TBE	Habit portion of past consumption
ϕ	TBE	1 + share of fixed cost in production
γ	TBE	Inverted elasticity of investment adjustment cost
$\bar{R}^K$	TBE	Steady state return on capital
$\bar{K}/\bar{Y}$	8.800	Capital output ratio
$\bar{I}/\bar{Y}$	0.220	Share of investment in GDP
$\bar{C}/\bar{Y}$	0.600	Share of consumption in GDP
$\bar{G}/\bar{Y}$	0.180	Share of government expenditure in GDP
ρ	TBE	AR coefficient of past interest rate (Taylor rule)
r_π	TBE	Inflation coefficient (Taylor rule)
$r_{\Delta\pi}$	TBE	Inflation growth coefficient (Taylor rule)
r_Y	TBE	Output gap coefficient (Taylor rule)
$r_{\Delta Y}$	TBE	Output gap growth coefficient (Taylor rule)
$S(\tau)$	Micro	Survival rate at date τ (GCE)
α_τ	Micro	Sector share for duration τ (GTE)

Note: *TBE* stands for "To Be Estimated", and *Micro* strands for to be calibrated by microdata results in Chapter I.

Table 42 Structural Parameters (Shocks)

Parameter	Value	Description
$\rho_{\varepsilon A}$	TBE	AR coefficient of productivity shock
$\sigma_{\varepsilon A}$	TBE	Standard deviation of productivity shock
$\rho_{\varepsilon U}$	TBE	AR coefficient of preference shock
$\sigma_{\varepsilon U}$	TBE	Standard deviation of preference shock
$\rho_{\varepsilon L}$	TBE	AR coefficient of labour supply shock
$\sigma_{\varepsilon L}$	TBE	Standard deviation of labour supply shock
$\rho_{\varepsilon I}$	TBE	AR coefficient of investment shock
$\sigma_{\varepsilon I}$	TBE	Standard deviation of investment shock
$\rho_{\varepsilon G}$	TBE	AR coefficient of government expenditure shock
$\sigma_{\varepsilon G}$	TBE	Standard deviation of government expenditure shock
ρ_{W}	0	AR coefficient of wage mark-up shock
σ_{W}	TBE	Standard deviation of price mark-up shock
ρ_{P}	0	AR coefficient of price mark-up shock
σ_{P}	TBE	Standard deviation of wage mark-up shock
ρ_{Q}	0	AR coefficient of return on equity
σ_{Q}	TBE	Standard deviation of return on equity
ρ_{R}	0	AR coefficient of interest rate shock
σ_{R}	TBE	Standard deviation of interest rate shock
$\rho_{\bar{\pi}}$	TBE	AR coefficient of inflation target shock
$\sigma_{\bar{\pi}}$	TBE	Standard deviation of inflation target shock

Note: *TBE* stands for “To Be Estimated”.

Table 43 Maximum Likelihood Estimation Results

Parameter	Taylor		Calvo		ICE		GTE		GCE	
	Mode	**S.E.**	**Mode**	**S.E.**	**Mode**	**S.E.**	**Mode**	**S.E.**	**Mode**	**S.E.**
$\sigma_{\varepsilon A}$	0.933	0.191	0.602	0.227	0.507	0.269	0.422	0.046	0.501	0.342
$\sigma_{\bar{\pi}}$	0.062	0.021	0.000	0.020	0.034	0.048	0.027	0.036	0.000	0.085
$\sigma_{\varepsilon U}$	0.590	0.091	1.461	0.107	0.697	0.210	0.286	0.065	0.589	0.343
$\sigma_{\varepsilon G}$	0.819	0.125	0.672	0.216	0.642	0.222	0.443	0.055	0.547	0.356
$\sigma_{\varepsilon L}$	1.616	0.053	1.194	0.065	0.999	0.006	1.039	0.024	1.274	0.133
$\sigma_{\varepsilon I}$	0.978	0.148	1.420	0.100	0.752	0.236	0.380	0.085	0.664	0.353
σ_R	1.078	0.091	0.760	0.189	0.674	0.270	0.276	0.172	0.496	0.498
σ_Q	0.408	0.009	0.397	0.001	0.403	0.580	0.391	0.003	0.404	0.014
σ_P	1.591	0.499	0.697	0.110	0.563	0.265	0.462	0.121	0.283	0.064
σ_W	0.919	0.245	0.774	0.168	0.526	0.258	0.460	0.047	0.478	0.492
$\rho_{\varepsilon A}$	0.000	0.034	0.621	0.260	0.935	0.246	0.744	0.037	0.656	0.324
$\rho_{\bar{\pi}}$	0.857	0.006	0.847	0.065	0.850	0.031	0.855	0.002	0.845	0.000
$\rho_{\varepsilon U}$	0.942	1.811	0.637	0.399	0.856	0.881	0.954	0.235	0.825	1.052
$\rho_{\varepsilon G}$	0.939	0.353	0.941	0.294	0.762	0.090	0.884	0.016	0.952	0.706
$\rho_{\varepsilon L}$	0.966	0.855	0.990	1.303	0.840	0.076	0.967	1.150	0.999	1.625
$\rho_{\varepsilon I}$	0.634	0.146	0.000	1.065	0.493	0.192	0.847	0.093	0.622	0.369
r_π	1.550	0.159	1.448	0.135	1.516	0.042	1.665	0.008	1.568	0.211
$r_{\Delta\pi}$	0.407	0.019	0.156	0.122	0.299	0.140	0.276	0.034	0.264	0.184
ρ	0.418	0.187	0.587	0.288	0.581	0.313	0.678	0.067	0.624	0.460
r_Y	0.606	0.226	0.669	0.100	0.067	0.300	0.160	0.079	0.821	0.178
$r_{\Delta Y}$	0.000	6.354	0.117	0.068	0.047	0.093	0.041	0.023	0.000	2.174
γ	N/I	N/I	N/I	N/I	N/I	N/I	N/I	N/I	N/I	N/I
σ_C	1.020	0.177	1.021	0.122	1.140	0.111	1.015	0.011	0.962	0.119
h	0.686	0.396	0.801	0.707	0.788	0.659	0.711	0.033	0.609	0.317
σ_L	1.953	0.044	1.942	0.029	2.002	0.009	1.989	0.019	1.901	0.049
ϕ	1.549	0.131	1.598	0.052	1.590	0.059	1.482	0.019	1.509	0.090
λ_W	0.555	0.153	0.555	0.027	0.500	0.038	0.507	0.013	0.482	0.068
ψ	N/I	N/I	N/I	N/I	N/I	N/I	N/I	N/I	N/I	N/I
ξ_W	0.299	0.581	0.653	0.243	0.733	0.237	0.790	0.077	0.598	0.320
ξ_P	N/A	N/A	N/A	N/A	0.998	0.011	N/A	N/A	N/A	N/A
γ_W	0.771	0.093	0.571	0.077	0.431	0.058	0.738	0.013	0.705	0.103
γ_P	N/A	N/A	N/A	N/A	0.000	1.897	N/A	N/A	N/A	N/A
Log Likelihood	-1096.502		-1085.391		-973.047		-944.863		-935.973	

Notes: *N/A* denotes “Not Applicable”, and *N/I* denotes “Not Identified”.

Table 44 Bayesian Estimation for Homogeneous Price Setting Models

Parameter	Taylor			Calvo			ICE		
	Mode	S.E.	MH Mean	Mode	S.E.	MH Mean	Mode	S.E.	MH Mean
$\sigma_{\varepsilon A}$	0.464	0.034	0.469	0.493	0.036	0.504	0.459	0.034	0.468
$\sigma_{\bar{\pi}}$	0.009	0.009	0.020	0.009	0.011	0.018	0.009	0.009	0.017
$\sigma_{\varepsilon U}$	3.417	0.370	3.462	3.687	0.333	4.112	3.760	0.503	3.754
$\sigma_{\varepsilon G}$	0.646	0.039	0.644	0.646	0.044	0.641	0.651	0.043	0.651
$\sigma_{\varepsilon L}$	0.468	0.305	0.664	0.467	0.996	0.731	0.469	0.244	0.750
$\sigma_{\varepsilon I}$	1.027	0.074	1.059	1.028	0.073	1.051	1.020	0.069	1.053
σ_R	0.732	0.060	0.743	0.728	0.051	0.743	0.733	0.057	0.748
σ_Q	0.184	0.191	0.382	0.186	0.144	0.358	0.188	0.298	0.410
σ_P	12.272	0.997	12.382	1.438	0.132	1.455	0.516	0.036	0.524
σ_W	0.453	0.036	0.461	0.487	0.033	0.497	0.480	0.033	0.488
$\rho_{\varepsilon A}$	0.877	0.037	0.876	0.766	0.032	0.760	0.875	0.014	0.862
$\rho_{\bar{\pi}}$	0.915	0.040	0.790	0.901	0.029	0.849	0.884	0.018	0.857
$\rho_{\varepsilon U}$	0.441	0.055	0.459	0.419	0.036	0.402	0.412	0.048	0.430
$\rho_{\varepsilon G}$	0.889	0.031	0.838	0.897	0.024	0.829	0.916	0.031	0.873
$\rho_{\varepsilon L}$	0.866	0.027	0.839	0.852	0.028	0.755	0.893	0.049	0.817
$\rho_{\varepsilon I}$	0.347	0.028	0.338	0.338	0.038	0.342	0.326	0.031	0.310
r_π	1.564	0.026	1.588	1.713	0.042	1.721	1.678	0.070	1.686
$r_{\Delta\pi}$	0.227	0.031	0.217	0.230	0.044	0.228	0.241	0.048	0.240
ρ	0.657	0.037	0.658	0.684	0.030	0.678	0.656	0.041	0.647
r_Y	0.228	0.011	0.242	0.187	0.022	0.182	0.231	0.020	0.213
$r_{\Delta Y}$	0.111	0.010	0.126	0.140	0.032	0.120	0.117	0.018	0.099
γ	4.304	0.400	4.382	3.938	0.587	4.075	4.023	0.604	3.939
σ_C	1.515	0.109	1.592	1.503	0.161	1.527	1.416	0.189	1.547
h	0.831	0.020	0.819	0.840	0.042	0.841	0.851	0.019	0.831
σ_L	2.531	0.394	2.489	2.599	0.301	2.520	2.766	0.208	2.812
ϕ	1.870	0.065	1.947	1.788	0.174	1.786	1.991	0.091	2.008
λ_W	0.550	0.038	0.509	0.619	0.078	0.585	0.568	0.025	0.510
ψ	0.201	0.023	0.190	0.225	0.017	0.216	0.224	0.015	0.185
ξ_W	0.698	0.017	0.713	0.681	0.015	0.683	0.705	0.017	0.701
ξ_P	N/A	N/A	N/A	N/A	N/A	N/A	0.868	0.012	0.861
γ_W	0.139	0.036	0.149	0.135	0.046	0.151	0.287	0.028	0.290
γ_P	N/A	N/A	N/A	N/A	N/A	N/A	0.145	0.045	0.167
Laplace		-1120.91			-1053.49			-1034.73	
Harmonic		-1083.74			-1023.79			-1006.38	

Table 45 Bayesian Estimation for Heterogeneous Price Setting Models

Parameter	Prior Distribution			S&W (2003)			GTE			GCE		
	Form	**Mean**	**S.D.**	Mode	S.E.	MH Mean	**Mode**	**S.E.**	**MH Mean**	**Mode**	**S.E.**	**MH Mean**
$\sigma_{\varepsilon A}$	invg	0.4	2	0.598	0.113	0.639	0.472	0.035	0.443	0.522	0.043	0.521
$\sigma_{\bar{\pi}}$	invg	0.02	2	0.017	0.008	0.033	0.009	0.040	0.019	0.518	0.107	0.324
$\sigma_{\varepsilon U}$	invg	0.2	2	0.336	0.096	0.407	3.527	0.443	5.035	5.013	0.656	5.248
$\sigma_{\varepsilon G}$	invg	0.3	2	0.325	0.026	0.335	0.644	0.044	0.624	0.646	0.041	0.646
$\sigma_{\varepsilon L}$	invg	1	2	3.520	1.027	3.818	0.496	0.623	0.745	0.477	0.439	3.047
$\sigma_{\varepsilon I}$	invg	0.1	2	0.085	0.030	0.113	1.039	0.091	1.172	1.027	0.071	1.031
σ_{R}	invg	0.1	2	0.081	0.023	0.090	0.733	0.056	0.736	0.686	0.049	0.718
σ_{Q}	invg	0.4	2	0.604	0.063	0.613	0.186	0.148	0.642	0.187	0.311	0.379
σ_{P}	invg	0.15	2	0.160	0.016	0.165	2.354	0.218	2.398	1.075	0.473	0.589
σ_{W}	invg	0.25	2	0.289	0.027	0.297	0.517	0.043	0.561	0.645	0.044	0.667
$\rho_{\varepsilon A}$	beta	0.85	0.1	0.823	0.065	0.811	0.813	0.024	0.8245	0.699	0.029	0.712
$\rho_{\bar{\pi}}$	beta	0.85	0.1	0.924	0.088	0.855	0.902	0.054	0.824	0.996	0.004	0.9602
$\rho_{\varepsilon U}$	beta	0.85	0.1	0.855	0.035	0.838	0.418	0.051	0.3788	0.384	0.025	0.3672
$\rho_{\varepsilon G}$	beta	0.85	0.1	0.949	0.029	0.943	0.888	0.036	0.7499	0.895	0.041	0.8535
$\rho_{\varepsilon L}$	beta	0.85	0.1	0.889	0.052	0.881	0.912	0.041	0.8675	0.904	0.030	0.8804
$\rho_{\varepsilon I}$	beta	0.85	0.1	0.927	0.022	0.910	0.300	0.088	0.2708	0.382	0.058	0.374
r_{π}	norm	1.7	0.1	1.684	0.109	1.688	1.717	0.046	1.6549	1.661	0.056	1.667
$r_{\Delta\pi}$	norm	0.3	0.1	0.140	0.053	0.151	0.246	0.050	0.1747	0.337	0.054	0.2968
ρ	beta	0.8	0.1	0.961	0.014	0.956	0.650	0.025	0.6936	0.568	0.031	0.6138
r_{Y}	norm	0.125	0.05	0.099	0.041	0.098	0.230	0.032	0.2504	0.214	0.035	0.2154
$r_{\Delta Y}$	norm	0.063	0.05	0.159	0.027	0.158	0.094	0.018	0.0916	0.137	0.024	0.1421
γ	norm	4	1.5	6.771	1.026	6.962	3.874	0.447	4.9525	3.966	1.051	3.8422
σ_{C}	norm	1	0.375	1.353	0.282	1.391	1.463	0.071	1.3874	1.500	0.274	1.4787
h	beta	0.7	0.1	0.573	0.076	0.592	0.836	0.016	0.8767	0.877	0.021	0.8718
σ_{L}	norm	2	0.75	2.400	0.589	2.503	1.867	0.342	1.5916	2.847	0.248	2.7693
ϕ	norm	1.45	0.25	1.408	0.166	1.417	1.991	0.116	2.2938	1.767	0.094	1.8596
λ_{W}	beta	0.5	0.15	0.599	0.050	0.597	0.562	0.074	0.639	0.602	0.085	0.5601
ψ	norm	0.2	0.075	0.169	0.075	0.201	0.206	0.032	0.1965	0.200	0.033	0.1909
ξ_{W}	beta	0.75	0.05	0.737	0.049	0.742	0.686	0.023	0.7166	0.677	0.025	0.7146
ξ_{P}	beta	0.75	0.05	0.908	0.011	0.905	N/A	N/A	N/A	N/A	N/A	N/A
γ_{W}	beta	0.75	0.15	0.763	0.188	0.728	0.355	0.050	0.4411	0.683	0.079	0.717
γ_{P}	beta	0.75	0.15	0.469	0.103	0.477	N/A	N/A	N/A	N/A	N/A	N/A
Laplace								-1008.14			-1001.31	
Harmonic								-1004.03			-998.38	

Figure 42 Impulse Response Functions to Productivity Shock

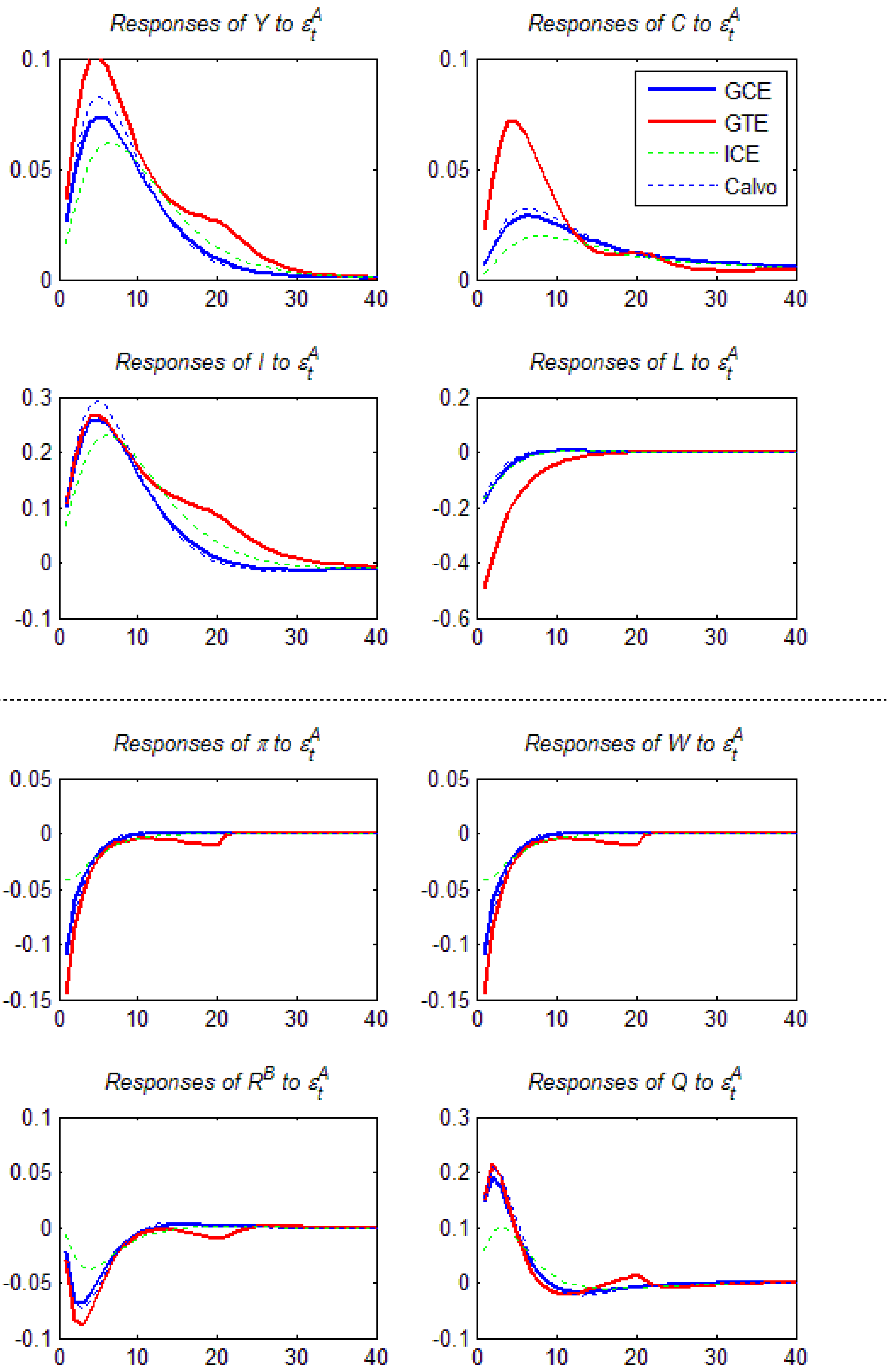


Figure 43 Impulse Response Functions to Price Mark-Up Shock

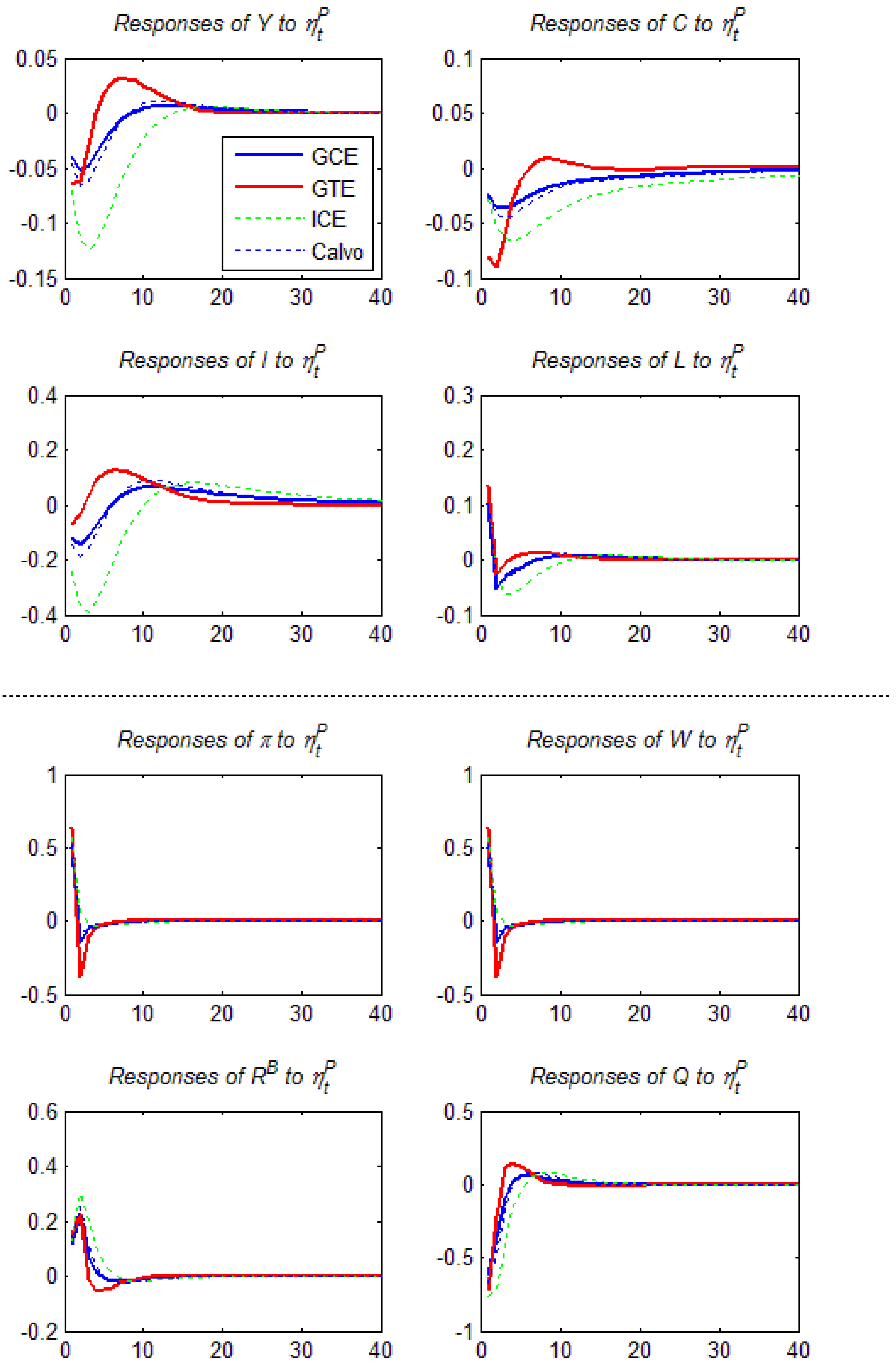


Figure 44 Impulse Response Functions to Wage Mark-Up Shock

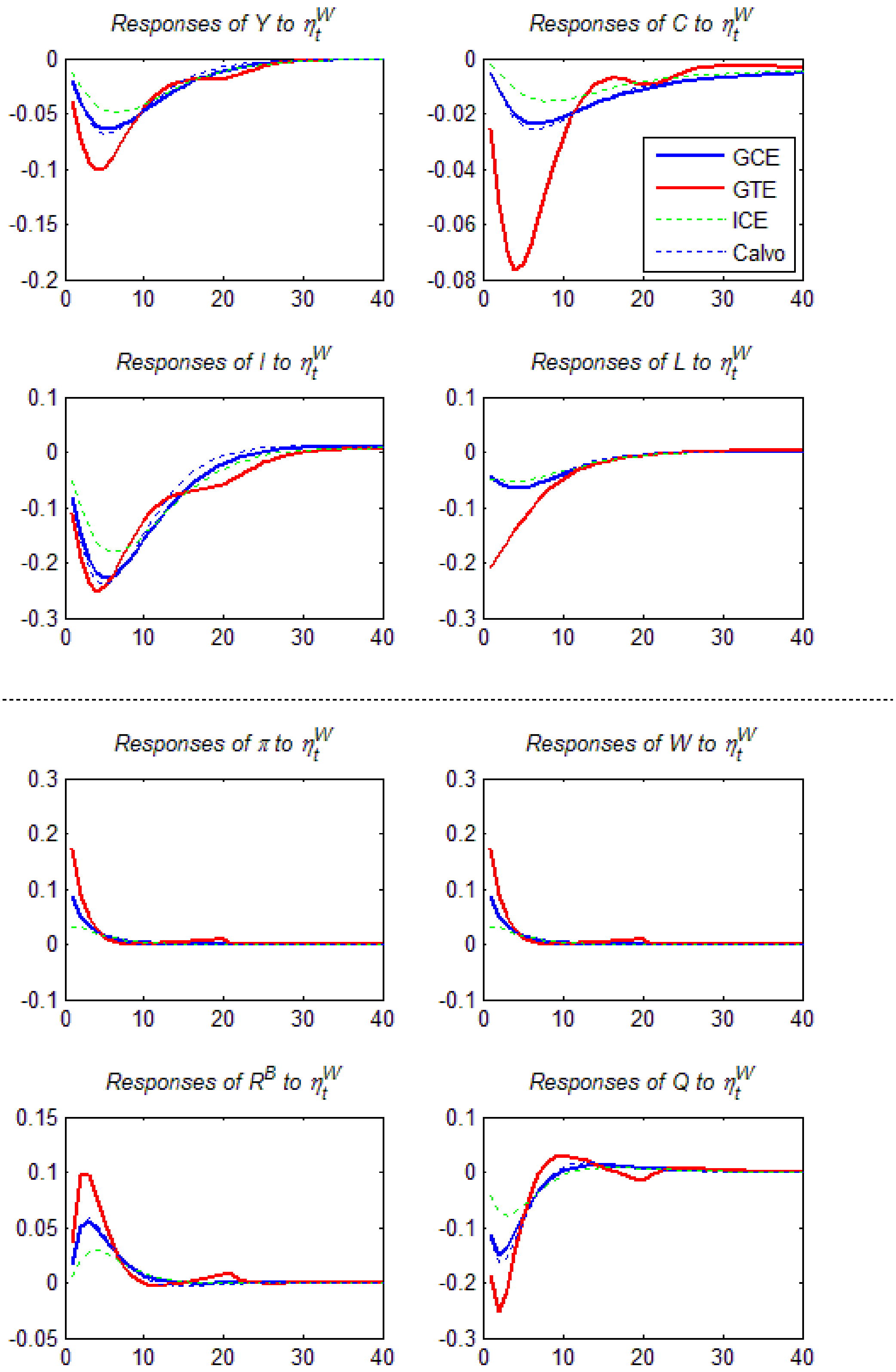


Figure 45 Impulse Response Functions to Permanent Monetary Policy Shock

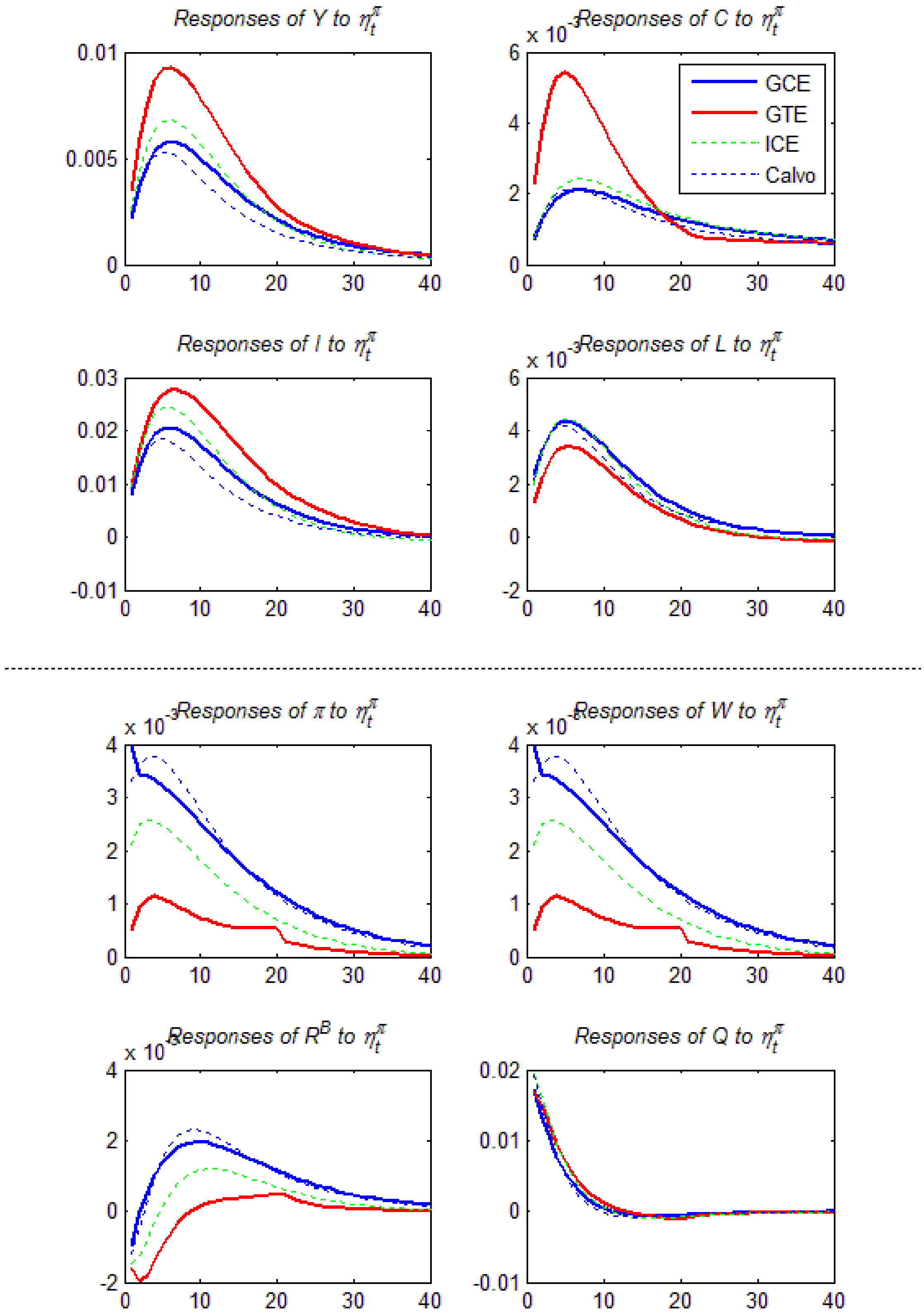


Figure 46 Impulse Response Functions to Temporary Monetary Policy Shock

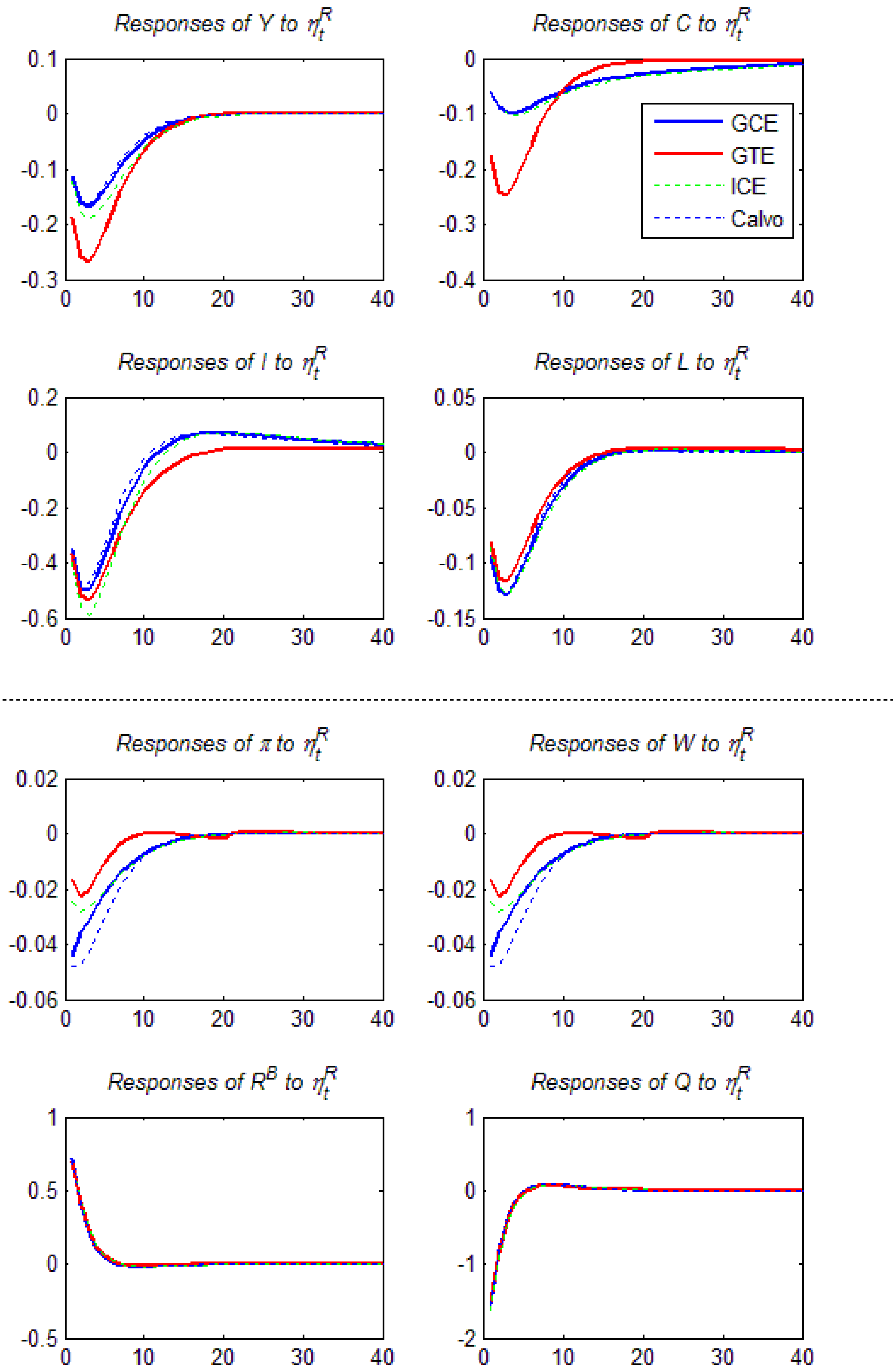
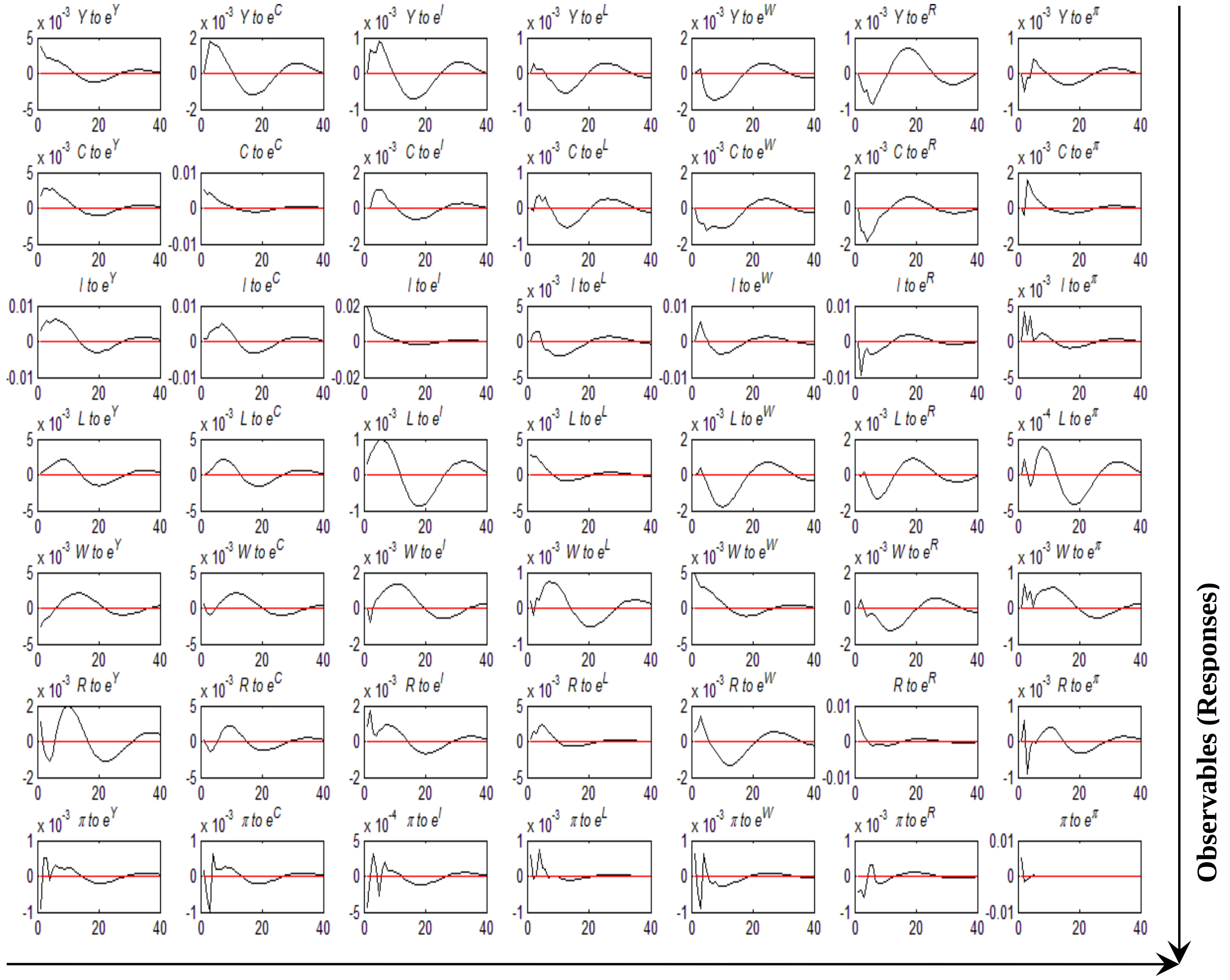


Figure 47 Impulse Response Functions of Unrestricted VAR



Note: The rows are the 7 observable variables (Y, C, I, L, W, R, π), while the columns indicate to which shocks ($e^Y, e^C, e^I, e^L, e^W, e^R, e^\pi$) the impulse response functions are describing. Each impulse response function is based on a positive shock equal to 1 standard deviation. VAR(3) is used, which has the highest information criterion.

Table 46 Variance Decomposition

Variable	Model	Structural Shocks									
		η_t^A	η_t^U	η_t^I	η_t^L	η_t^G	η_t^W	η_t^P	η_t^Q	η_t^π	η_t^R
Y	**GCE**	3.76	0.39	41.66	1.62	35.79	3.08	0.80	0.01	0.03	12.87
	GTE	2.92	15.25	38.27	1.10	26.58	2.38	0.52	0.00	0.03	12.93
	ICE	2.59	0.52	43.87	1.55	30.68	1.62	5.10	0.01	0.03	14.04
	Calvo	4.39	0.64	43.20	1.07	35.16	3.05	1.29	0.01	0.02	11.17
	Taylor	29.34	23.20	2.30	0.34	25.28	1.94	0.00	0.00	0.01	17.58
C	**GCE**	2.04	10.75	54.41	0.55	11.54	1.54	1.68	0.00	0.02	17.48
	GTE	0.98	73.66	9.94	0.18	4.88	0.99	0.57	0.00	0.01	8.80
	ICE	1.14	11.20	51.81	0.54	8.80	0.71	6.73	0.00	0.02	19.04
	Calvo	2.12	8.90	58.32	0.32	12.23	1.42	2.19	0.00	0.01	14.48
	Taylor	2.97	94.20	0.17	0.01	1.03	0.09	0.00	0.00	0.00	1.54
I	**GCE**	1.91	3.36	74.19	0.96	12.98	1.61	0.37	0.01	0.02	4.60
	GTE	1.34	7.82	75.90	0.72	9.91	0.94	0.24	0.00	0.02	3.09
	ICE	1.53	3.53	75.48	0.98	9.70	0.95	2.27	0.01	0.02	5.54
	Calvo	2.06	3.45	73.76	0.58	14.56	1.44	0.58	0.01	0.01	3.56
	Taylor	6.99	83.48	1.87	0.07	5.61	0.30	0.00	0.00	0.00	1.67
L	**GCE**	7.96	0.37	36.28	1.69	35.92	4.55	2.02	0.01	0.03	11.17
	GTE	41.07	4.41	20.15	1.73	14.74	12.00	1.38	0.00	0.01	4.50
	ICE	7.46	0.63	39.97	1.90	31.99	3.31	3.24	0.01	0.02	11.47
	Calvo	5.67	0.58	39.22	1.12	36.96	4.01	1.96	0.01	0.02	10.44
	Taylor	99.47	0.19	0.01	0.00	0.19	0.02	0.00	0.00	0.00	0.12
π	**GCE**	5.76	0.42	0.69	0.56	0.72	3.71	86.18	0.00	0.04	1.92
	GTE	5.30	0.75	0.08	0.55	0.01	6.36	86.70	0.00	0.00	0.25
	ICE	1.67	0.37	0.20	0.43	0.30	1.01	94.84	0.00	0.02	1.16
	Calvo	5.62	0.49	0.94	0.35	0.99	3.51	85.05	0.00	0.05	3.00
	Taylor	98.33	1.27	0.00	0.02	0.01	0.33	0.00	0.00	0.00	0.04
R^B	**GCE**	1.99	0.24	3.47	0.23	2.85	1.32	7.98	0.00	0.01	81.92
	GTE	2.86	4.77	4.20	0.37	3.18	3.17	8.09	0.00	0.00	73.36
	ICE	0.70	0.22	2.38	0.18	2.02	0.43	16.82	0.00	0.00	77.26
	Calvo	2.21	0.29	3.80	0.16	3.07	1.39	10.57	0.00	0.01	78.50
	Taylor	68.33	6.48	0.04	0.03	0.66	0.47	0.00	0.00	0.00	23.99

Note: This is an asymptotic decomposition of the unconditional variance of endogenous variables in an infinite time horizon. Shocks are supposed to happen in every period between now and infinity, not only once. It is obtained by solving a Lyapunov equation in Dynare.