The Time-Varying Ss Rule: a Semiparametric Hazard Function Estimation with the UK PPI Microdata

Kun Tian
Xiangtan University and CPI@Cardiff

March 14, 2015

Abstract

I examine the behaviour of individual producer prices in the UK by applying a semiparametric hazard function estimation. A number of stylized facts about price setting behaviour are uncovered, and a time-varying Ss model is set up in consistent with the micro evidence. Moreover, a semiparametric hazard function is specified according to the Ss model. I estimate the hazard function which controls for observed and unobserved heterogeneity across firms in assessing the effect of changes in inflation, interest rate, oil price, industrial output, and exchange rate on the hazard rate of price changes.

Keywords: PPI microdata; Ss rule; Cox model

1 Introduction

At the heart of New Keynesian models is the assumption that nominal rigidities - most notably price stickiness - are preventing resources from being allocated efficiently. There is a large amount of theoretical research which focused on the micro fundations of sticky prices, which is a key element in explanations of the real effects of monetary policy. However, the empirical literature on price stickiness has been relatively thin. In recent years, large-scale data sets of individual prices, in particular those assembled for the purpose of constructing price indices, have been made available to researchers. The empirical research has significantly broadened knowledge about the prevalence of price stickiness, and the characteristics of individual price changes.

One typical finding of the empirical studies using micro price data is that prices at the micro level remain unchanged for some periods. And this stylised fact was documented in, among many others, Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008), who study consumer prices in the U.S., and Dhyne *et al.* (2006) and Vermeulen *et al.* (2007), who give a synthesis of studies carried out in euro area. For example, Dhyne *et al.* (2006) find that the monthly frequency of consumer price changes is about 15% in the euro area. These results are consistent with evidence from survey data (see Fabiani *et al.* 2006).

The infrequent adjustment observed in micro price data is often described by an (S,s) rule. The (S,s) rule model indicating that there is a range of values of state variable for which it is optimal not to adjust. This range of state is called "band of inaction". Sheshinski and Weiss (1977) derived the (S,s) rule from optimal price setting problem in the prsence of adjustment cost. The ensuing empirical studies show that (S,s) rules are convenient reduced forms which can be confronted to the data.

However, the standard fixed (S,s) band model faces some empirical difficulties. It indeed predicts that prices become more likely to change the longer they have remained unchanged. If we define the hazard of a price change at time t is the probability that price will change after t periods given that it has survived for t periods. The standard fixed (S,s) band model suggests that the hazard function of price change is upward sloping. This prediction is at variance with patterns often observed in micro price data. Nakamura and Steinsson (2008) find that the hazard function of regular prices is somewhat *downward* sloping for the first few months and then mostly flat after that, and they do not find any evidence of upward-sloping hazard function. Furthermore, they find that "the hazard function including sales is much more steeply *downward* sloping than the hazard function of regular prices". Klenow and Kryvtsov (2008) confirm the finding of downward sloping hazard function and give a possible explaination that the downward sloping hazards reflect the time-varying Ss band. Gautier and Le Bihan (2011) also point out that the hazard decreases with the the size of the threshold.

In this article, I aim to analyze the determinants of hazard rate of price changes. Firm's decision to change its price is described as a time-varying Ss model. The time-varying Ss model is set up in a way that is consistent with the stylized fact I obtained from UK PPI micro data. Then a semiparametric hazard model is set up which is in line with the time-varying (S,s) model. More specifically, the hazard model is specified in form of Cox propotional hazard, which is formed by two parts: a baseline hazard function and a function with covariates of interest. The baseline hazard function can be seen as a term which captures the feature that the threshold is time-varying. I estimate the semiparametric hazard model which controls for observed and unobserved heterogeneity across firms in assessing the effect of changes in inflation, interest rate, oil price, industrial output, and exchange rate on the hazard rate of price changes.

The rest of this article is structured as follows. Section 2 provides a discription of the PPI micro data set and some stylized facts about price changes. Section 3 describes a time-varying (S,s) band model. Section 4 gives empirical specification of the time-varying (S,s) band model and describes the covariates of interst. In Section 5, I illustrate the estimated results. I conclude in Section 6.

2 The data set and some stylized facts

2.1 Data description

This study uses micro-dataset on producer prices collected by the Office for National Statistics (ONS). These individual price quotes are weigted and aggregated to form domestic Producer Price Index.[1] There are two types of PPI series: output price inices and input indeices. The output price indices measure the change in the price of goods *sold* by UK manufacturers, and input price indices measure the change in price of goods *bought* by manufacturers for use in the manufacturing process. Due to the data availability, this study only focus on the output prices. Products are grouped with the Standard Industrial Classification (SIC) with weighting patterns based on overall sales by manufactures within those groupings. The PPI uses sales data taken from PRODCOM survey

[1] The micro data that underlie the producer price index used in this research were made accessible via VML. The terms and condition of the VML is described in Richie (2008).

to update weights. Price quotes are collected from the products which are manufactured in the UK and sold to the home market, exlcuding VAT and after discounts. Price quotes reflect orders delivered in current month, and they reflect actual prices achieved rather than any notional list price. Exercise duties (on cigarettes, tobacco, alcoholic etc.) are included to complie PPI. Above all, service sector prices are not included in the PPI.

As stated in Morris and Green (2007), the output producer price index (PPI), produced by the Office for National Statistics (ONS), is exposed to several sorces of potential error. The total error consists of two elements, the sampling error and the non-sampling error. The random sampling techniques are used to minimise the sampling error. However, non-sampling errors are not easy to quantify and include errors of coverage, measurement processing and non-response. Various procedures are in place to ensure that errors are minimised. Validation checks on data, based on percentage movements from quarter to quarter,are conducted to highlight unusual price changes for items. Disparities in data are investigated by contracting respondents if not explained on the returned form. Letters are sent to respondents where no price change has been evident for eighteen months and analysts liaise with respondents to ensure that the prices they provide meet the specified criteria.

The final dataset that our analysis is based on included approximately $960,000$ individual producer price quotes, covering $24,000$ products by $12,000$ firms. Our sample covers the period between January 1998 and February 2008. The PPI basket is updated annually to incorporate new products and changes in demand patterns for existing products. While there are around $1,050$ products are present in our data set for all 122 months, less than 5% of total. On average, a product is included in our "raw"[2] data set for about 37 months.

The PPI computer programs impute for non-response in the most recent few months. Thus if the price £14.99 is recored for a specific item in date t, but the price information becomes unavailable for following 9 months. Then the PPI computer programs let the prices for that 9 months remain at £14.99. Imputation can help avoid the data gaps, mitigating the problem induced by censored price spells. However,as the duration of missing price quote keeps longer, an unobserved price change becomes more and more likely. Another disadvantage of imputation is that they are not true price observations but are "pseudo observations", which would introduce an upward bias in the estimation of the duration of price spells. Therefore, we discard the price spells with imputation

[2]Here "raw" data set means the data set provided by ONS without any fitering or manipulation.

prices. Above all, Imputation represents about 3% of our PPI research dataset.

In our PPI dataset, we do not have weights which are attached to individual price quotes before 2003. Following Nakamura and Steinsson (2008) and Gopinath and Rigobon (2008), we obtain value weights for the PPI at the four digit SIC commodity code, then divide the value weights equally within the four-digit code, calculating the weight for each price quote within the same item group by same method. Although the calculated weights are not necessarily equal to the actual PPI weights,as the result of a robustness check shows,the effect on aggregate measures of the statistics described in next section is trivial.

Censoring is an important characteristic of price data, and it needs to be taken into account. Censoring is defined as when the failure event occurs and the subject is not under observation. In our sample we have a total of 162,731 price spells. Of those, 122,462 (75.25%) are uncensored, 18,681 (11.48%) are left censored, 15,787 (9.7%) are right censored, and 5,801 (3.6%) are double censored.

2.2 The frequency of price changes

The frequency of price changes can be defined as the ratio of the number of non-zero price changes observations divided by the total number of observations.Following previous studies (e.g. Alvarez *et al*, 2010; Bunn and Ellis, 2012), the observations that there is no information on the price in the previous month are dropped from our sample. Because it is not possible to measure whether the prices has changed for these observations.As reported in Table 2.2, for all items in our sample of producer prices, the weighted average frequency of price change is 25.1%. It means that about a quarter of prices change each month. This result is similar to the estimate in Bunn and Ellis (2012), in which they claim that an average of 26% of UK producer prices changed each month. Moreover, our result is somewhat higher than Alverez *et al.*(2010) for Spain (21%), Cornille and Dossche (2008) for Belgium (24%), Dias *et al.* (2008) for Portugal (23%), Stahl (2006) for Germany (23%). Our result is almost the same as Gautier (2008) for France (25%), and Nakamura and Steinsson (2008) for the U.S.(25%).[3] Above all, the producer prices are changed infrequently, and this is against a few theoretical pricing models which predict that prices would change every period, (e.g. the sticky information (Mankiw and Reis, 2002); Calvo with indexation (Smets and Wouters, 2003); Quadratic costs of adjustment (Rotemberg, 1982). As

[3]However, we must notice that this is a very rough comparison. Because in each country's PPI data, the samplin scheme and the weight scheme are different. Furthermore, the time periods covered in each study are country specific.

Main component	All changes	Increases	Decreases	% of price decreases
Energy	65.9	39.0	26.9	40.8
Consumer food products	24.6	13.9	10.7	43.5
Consumer non-food non-durables	15.0	7.6	7.4	49.3
Consumer durables	17.7	8.9	8.8	49.7
Intermediate goods	25.1	14.1	11.0	43.8
Capital goods	18.6	10.1	8.5	45.7
All items	25.1	14.0	11.1	44.2

Table 1: Percentage of UK producer prices that change each month

discussed in Chapter2, a menu cost model can be easily calibrated to fit the observed frequency of micro price changes.

The frequency of price changes varies substantially across product sectors. The flexibility of prices is the largest for energy sector, in which about 66% of prices change each month. The prices of intermediate goods and consumer food products change more frequently than capital goods and consumer durables. Columns 3 and 4 of Table 2.2 report monthly frequencies of price increases and decreases respectively, for all items and the main product groups. Column five reports the proportion of price decreases over the total number of price changes. Over 44% of price adjustments are price decreases, which gives evidence against the downward nominal rigidity hypothesis.

There is also a considerable heterogeneity in the frequency of price changes at the 2 digit industry level. As can be seen from Table 2.2, the prices of clothing and lether change least often among all of the 2 digit industries. While the price of petrol and secondary raw materials change far more often than that of the other 2 digit industries. Clothing is the only industry with the share of price decreases over the total number of price changes larger than 50%. In another word, we are more likely to observe price cuts in clothing industry. In sharp contrast, we are more likely to observe price increases in tobacco industry.

2.3 The unconditional hazard function

A price reset hazard function gives the probability of resetting a price conditional on the time elapsed since last adjustment. As discussed in Chapter2 and 3, the hazard function is important for aggregate dynamics, since it is closely related to the distribution of price spells, which in turn affects how the economy reacts to nominal disturbances.

The classic Kaplan-Meier method is widely used to estimate the unconditional hazard function, excluding all left-censored spells, keeping all right censored spells, and treat the end of a right censored data as

Industry	All changes	Increases	Decreases
Food and beverages	24.2	12.9	11.3
Tobacco	28.2	22.0	6.2
Textiles	14.6	7.9	6.7
Clothing	9.1	4.4	4.7
Leather	13.0	6.8	6.2
Wood	15.5	9.3	6.2
Pulp and paper	18.0	10.0	8.0
Media	19.3	10.0	9.3
Petrol and fuel	65.9	39.0	26.9
Chemicals	24.8	13.4	11.4
Rubber and plastic	19.5	11.4	8.1
Other non-metallic mineral products	35.3	19.0	16.3
Basic metals	39.7	23.1	16.5
Fabricated metal products	19.3	10.7	8.6
Machinery and equipment	12.8	7.6	5.3
Office machinery and computers	22.7	11.5	11.3
Electrical machinery	14.9	8.2	6.7
Radio and TV equipment	17.6	9.1	8.5
Precision instruments	15.1	8.0	7.1
Vehicles	21.2	11.2	10.0
Other transport	21.4	10.5	10.8
Furniture	16.4	8.2	8.2
Secondary raw materials	65.8	34.9	30.9

Table 2: Percentage of UK producer prices that change each month by 2 digit industry

a 'loss' (or non-price-change). This treatment of right censored spells is not a good one, because it leads to an under-estimate of the hazard for each period. Dixon *et al.* (2012) proposed two alternatives treating censored data: (a) They exclude all censored data in estimating the hazard function. (b) They treat right-censoring as a price-change ('loss is failure' or LIF), which is also a strategy used by Dixon and Le Bihan (2012). Because the longer spells are more likely to be censored. The method (a) is more likely to overestimate the hazard in the short term. The method (b) is the opposite extreme to the classic KM assumption and more likely to overestimate the hazard. Figure 1 displays the hazard functions estimated under three methods. Even though the three methods differ in the treatment of right-censored spells, they all generate similar hazard functions. There are three main characteristics in Figure 1:

1 All three hazard functions display a downward sloping pattern.

2 All three hazard functions exhibit significant spikes at 12 months and at 24 months.

3 All three hazard functions exhibit that a large proportion of 1-month-length price spells.

As can be seen in Figure 1, the hazard generated from method 'LIF' lies between the estimates from 'Uncensored' and classic 'KM'. The method 'KM' tends to underestimate the hazard, while the method 'Uncensored' is more likely to overestimate the hazard in the short term. These findings suggest that the 'LIF' method is a better method to estimate the unconditional hazard function. Dixon *et al.* (2012) also find that the approaches of using only uncensored data and treating right censoring as a price-change both resultin very similar monthly cross-sectional distribution (distribution across firms). And the calibration in their paper actually uses the 'loss is failure' method.

The downward sloping hazard function might reflect the "aggregation of heterogeneous price setter". There are firms with sticky pricing strategies and those with flexible pricing strategies. The firms with flexible pricing strategies are more likely to be in the "young age" zone. As firms become older, the share of price changes by firms with flexible pricing strategy will decrease. As argued in Alvarez (2008), only price changes which belong to sticky firms can be observed at high ages

An alternative explaination to the declining hazard is the time-varing "Ss band", or the width of the inaction region (Klenow and Krystov 2008). When a firm faces persistent idiosyncratic shock with high level, it tends to sell a large quantity under a low price. Therefore, the profit of the firm is mainly decided by chossing the right price. This will lead to a narrow (S,s) band. However, when the idiosyncratic shock is at low level, the firm's inaction region becomes wider. Furthermore, when

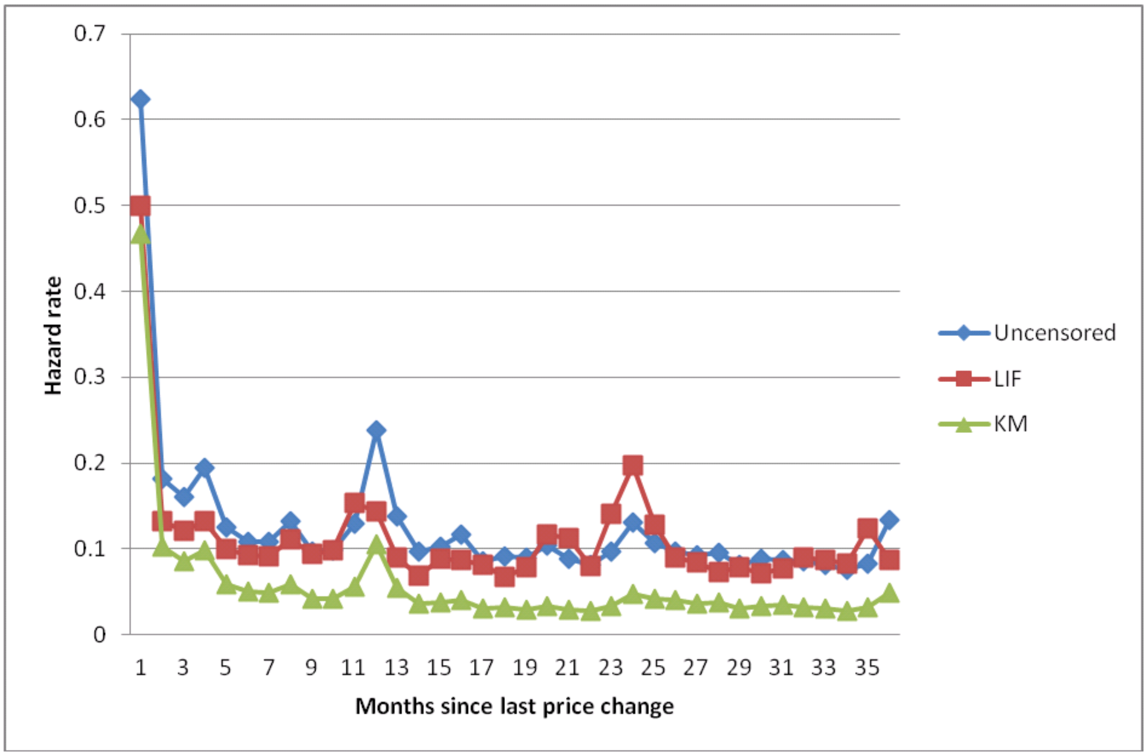

Figure 1: Unconditional hazard function

(S,s) band is narrow and hazard rate is high, the young prices are more common; while the old prices are more common when (S,s) band is wider and hazard rate is lower.

3 Time-varying (S,s) band model

The decison rule of price-setting can be described as an (S,s) rule model. (S,s) rules are convenient reduced forms that can be confronted to the micro data. Sheshinski *et al.* (1981) and Dahlby (1992) firstly estimate this class of reduced form models. Recently, Fisher and Konieczny (2006) and Dhyne *et al.*(2011) estimate (S,s) models with random thresholds using micro price data for many categories of product. As suggested by Caballero and Engel (1999) and Hall and Rust (2000), models assuming a random adjustment cost can rationalized the time-varying random (S,s) bands, which gives rise to hazard rates that vary over time for a given firm.

Let $p_{ij,t-1}$ is the actual price of a product i within the industry group j at time period $t-1$, p^*_{ijt} is the optimal price at period t. The actual price will keep the same as long as the difference between the actual price and optimal price is less or equal to the width of inaction s_t. Here we allow for time-varying pricing thresholds. Therefore, we have such a simple specification of (S,s) model, which can be written as

$$\begin{aligned} p_{ijt} &= p_{ij,t-1} \text{ if } |p^*_{ijt} - p_{ij,t-1}| \leq s_t \\ p_{ijt} &= p^*_{ijt} \quad \text{if } |p^*_{ijt} - p_{ij,t-1}| > s_t \end{aligned} \tag{1}$$

As we have seen in previous section, price setting is considerably heterogeneous across industries. At the industry level, some price trajectories represented by more frequently changing prices, while others are represented by less frequently changing prices. Therefore we can extend model (1) to allow for time-varying and industry-specific pricing thresholds, which can be written as

$$\begin{aligned} p_{ijt} &= p_{ij,t-1} \text{ if } |p^*_{ijt} - p_{ij,t-1}| \leq s_{jt} \\ p_{ijt} &= p^*_{ijt} \quad \text{if } |p^*_{ijt} - p_{ij,t-1}| > s_{jt} \end{aligned} \tag{2}$$

Let's assume such circumstance that the inflation rate is positive and steady. As time proceeds, $|p^*_{ijt} - p_{ij,t-\tau}|$ grows steadily[4] until it exceeds the level dictated by the rule. When the gap $|p^*_{ijt} - p_{ij,t-\tau}|$ surpasses the "adjustment threshold", the price will change. Therefore, the probability of observing a price change at time t, conditional on that the price has been kept the same for some time periods τ, will be the

[4] Caplin and Spulber (1987) assume the growth of money will raise p^*_{ijt} .

probability that the gap $|p^*_{ijt} - p_{ij,t-\tau}|$ is larger than the threshold s_{jt}, which is

$$\Pr\left\{|p^*_{ijt} - p_{ij,t-\tau}| > s_{jt}\right\} \tag{3}$$

We can use a semi-parametric survival function to develop an empirical specification of equation (3).However, to get a good understanding of the determinants of the hazard function, we need to analyze the factors which can affect the optimal price change.

To simply the notation, we drop the subject i, j, and let z be the indicator of the firm (product). Following Chapter2, we assume that a firm uses a linear technology to produce a differentiated good. And following most literature in this area, we strips out the capital, and leave the labor as the only input.

$$y_t(z) = A_t(z) L_t(z) \tag{4}$$

From this equation (4) , we define the following variables. The firm produce $y_t(z)$ output in period t. In order to produce this amount of output in period t, the firm need to employ a quantity of labour as $L_t(z)$. A labour combined technology in period t can be defined as $A_t(z)$. Differentiated goods $y_t(z)$ can be used to produce a final consumption good Y_t. We assume the production function exibit a CES love of variety over a continuum of differentiated goods y that are indexed by $z \in [0, 1]$:

$$Y_t = \left[\int_0^1 y_t(z)^{\frac{\eta-1}{\eta}} dz\right]^{\frac{\eta}{\eta-1}}.$$

And we assume the corresponding unit cost function P_t is:

$$P_t = \left[\int_0^1 p_t(z)^{1-\eta} dz\right]^{\frac{1}{1-\eta}}.$$

where $p_t(z)$ denotes the nominal price the firm charges in period t.As is standard in this setup, the demand for the output of firm z is given by

$$y_t(z) = \left(\frac{p_t(z)}{P_t}\right)^{-\eta} Y_t \tag{5}$$

where $y_t(z)$ denotes the quantity demanded of the firm's good.Given aggregate output level Y_t, aggregate nominal price index P_t, and the wage rate for each firm as $W_t(z)$, the firm will choose a price that maximize its profits:

$$\max_{p_t(z)} \left\{\frac{p_t(z)}{P_t} - mc_t\right\} y_t(z) \tag{6}$$

$$s.t.\ y_t(z) = \left(\frac{p_t(z)}{P_t}\right)^{-\eta} Y_t$$

where mc_t decribes the firm's marginal cost function. Solving the first order condition of the model (6), we can get the optimal price $p_t^*(z) = \frac{\eta}{\eta-1} mc_t P_t$, which is just the markup pricing condition of monopolistic competition. If we assume the P_t grows with the inflation rate $\dot{P}_t = \pi_t$, then we can describe the gap $|p_{ijt}^* - p_{ij,t-\tau}|$ as a function of inflation and the change in marginal cost. Since the change of optimal price is a function of the inflation and firm's marginal cost, the gap $|p_{ijt}^* - p_{ij,t-\tau}|$ is also an implicity function of the inflation and firm's marginal cost, given the actual price has remain as previous optimal price for some period.

$$|p_{ijt}^* - p_{ij,t-\tau}| = \mathbb{F}(\pi_t, \dot{m}c_t) = \mathbb{Z}(t)\beta \tag{7}$$

The vector $\mathbb{Z}(t)$ includes all the covariates of interest, and it will be specified in next section, and also the regression coefficient vector β will be estimated.

4 Empirical specification

In this section we develop an estimable model consisting of empirical versions of the equation(3) and (7). It is well known that OLS is not a good method to analyse survival data. Because it assumes the residuals to be distributed normally, which is equivalent to say that time to an event(failure) is assumed to follow a normal distribution. For example, if we are thinking about an case of Calvo pricing which the instantaneous risk of price changing is constant over time. Then the distribution of time (duration) would follow an exponential distribution. Moreover, the duration (time to failure) is always positive, while theoretically, the normal distribution is supported on the entire real line. Therefore, we will choose survival analysis (duration model). Similar approaches have been adopted in previous studies, such as Aucremmne and Dynne (2005), Dias *et al.* (2007),Fougere *et al.* (2005), Nakamura and Steisson (2008), Matsuoka (2010), and Vasquez-Ruiz (2011).At its core, survival analysis concerns nothing more than making a substitution for the normality assumption characterized by OLS with some more appropriate for the problem at hand.

We first recall that the general definition of hazard function. The hazard function, in our context, investigates the probability of a price change conditional on the elapsed duration of a price spell. The hazard function can be defined as $h(t) = \frac{f(t)}{S(t)}$, where $S(t)$ is the survival function, and $f(t)$ is the density function. The survival function can be defined as $S(t) = \Pr(T \geq t) = 1 - F(t)$ where $F(t)$ is the distribution function of the duration variable T, and $F(t) \in [0, 1]$. It is always a source of concern that the results of analyses are being determined by the assumption. We would prefer a method that do not require assumptions about the distribution of failure times. Cox (1972) provided such an option, so called Cox model. In Cox model, the effect of the exogenous variable is specified as multiplying a baseline hazard function by a function that depends on the exogenous variable. We can define the hazard function of the i^{th} cluster for the k^{th} failure type as

$$h_{ki}(t) = h_0(t)\, g(\mathbb{Z}, \beta)$$

where $h_0(t)$ is the baseline hazard function. The function $g(\mathbb{Z}, \beta)$ should be non-negative, and it can be specified as:

$$g(\mathbb{Z}, \beta) = \exp(\mathbb{Z}\beta)$$

Recall that the probability of observing a price change at time t, conditional on that the price has been kept the same for some time periods τ, will be the probability that the change in the gap between the optimal price and actual price, $|p^*_{ijt} - p_{ij,t-\tau}|$, is larger than the threshold s_{jt}. Therefore, we have

$$\begin{aligned} \Pr\left\{|p^*_{ijt} - p_{ij,t-\tau}| > s_{jt}\right\} &= h_0(t) \exp\left\{\mathbb{Z}_{ki}(t)\, \beta + \psi_j\right\} \\ &= \exp\left(\psi_j\right) h_0(t) \cdot \exp\left(\mathbb{Z}_{ki}(t)\, \beta\right) \end{aligned} \tag{8}$$

where ψ_j captures the variation of thresholds among industries. $h_0(t)$ can be seen as a term which is implicitly affected by the time-varying threshold. In Cox model, the baseline hazard function can be estimated separately[5] by performing an analysis at each failure and only concerning with the order in which the failures occurred. No assumption is made about the distribution of time to failure. We can obtain the maximum likelihood estimates of β from Cox's partial likelihood function, $L(\beta)$. As proved by Lin (1994), the estimator $\hat{\beta}$ is a consistent estimator and asymptotically normal as long as the marginal models are correctly specified.

It may be too restricted to assume that the baseline hazard function is the same across different industries. An alternative specification would be to assume that there are industry-specified baseline functions $h_{j0}(t)$. Therefore, we have following so-called stratified-Cox model

$$h_{ki}(t) = h_{j0}(t) \cdot \exp\left(\mathbb{Z}_{ki}(t)\, \beta\right) \tag{9}$$

In order to account for unobservable heterogeneity, we follow Nakamura and Steinsson (2008) and Matsuoka (2010) to build a semiparametric hazard model with shared fraility. At the observation level, frailty is

[5] We drop all the left and double censored spells. And we apply the "LIF" method when right-censoring is treated.

introduced as an unobservale multiplicative effect α on the hazard function. And the frailty α is a random positive quantity. For purposes of model identifiability, α is assumed to have mean one and variance θ. In line with Nakamura and Steinsson(2008), we specify the unobserved heterogeneity as being common to all observations within the same product. In another word, we assume that the heterogeneities are not specificto a price spell, but are shared along the same price trajectory. Frailty model can be written as

$$h_{ki}(t) = \alpha_i \cdot h_{j0}(t) \cdot \exp\left(\mathbb{Z}_{ki}(t)\,\beta\right) \tag{10}$$

where α_i follow a gamma distribution. We can test the exsitence of unobserved heterogeneity by using a likelihood-ratio test of $H_0 : \theta = 0$.

The vector $\mathbb{Z}(t)$ includes some regressos varying with time which economic theory suggests may be relevant factors in explaining the conditional probability of price change over time. From previous section, the derivation of the time-varying Ss band model suggests that $\mathbb{Z}(t)$ should includes: a) Inflation rate, which is measured as the monthly growth rate of the producer price index. It can be expected that the inflation rate will have a positive and significant effect on the hazard rate of price changes. The lead and lag of inflation rate could also affect the probability of price change, these should also be taken into consideration. b) Interest rate, the three-month Libor rate is chosen. Because the aggregate demand is more responsive to the Libor rate than to the base rate as it is the benchmark interest rate that influences the interest rate at which the private sector, both corporate and personal, can borrow. c) Oil price, a Brent series from Bloomber (Ticker:CO1 Comdty) is used. To construct the monthly series, daily closing prices for all trading days are averaged within the month. It is suggested that the sharp increase of oil prices is more like past supply shocks. And high oil price may change inflation expectations. d) Industiral production index. The industrial production index has been used as a proxy to measure demand pressure. And previous finding suggests that the probability of changing prices varies positively with the industry sales growth. e) Nominal effective exchange rate. It represents the relative value of a home country's currency compared to the other major currencies being traded. Two nominal effective exchange rate series (pound vs. U.S. doolar, pound vs. euro) are used. A higher nominal effective exchange rate means that the pound is worth more than an imported currency. The change in the effective exchange rate would have both supply side and demand side effect.

5 Estimates

Figure 2 presents the aggregate baseline hazard function estimated from model 8. It is very similar to the unconditional hazard function. It shows that the probability of a firm to change its price after one month is about 60%. This probability drops sharply to a level lower than 20% for the second and third month. The hazard rate jumps above 20% at the 12th month. Afterwards, the hazard function becomes relatively flat. After 60 months, the hazard function becomes more and more volatile. Because large amount of price spells are either ended with price change or censored. All price spell will definitely ends before or at the end of our sample period. Therefore, the baseline hazard rate equals to 1 at the end of sample period.

Figure3 shows the sectoral baseline hazard functions. The baseline hazard function in each product group (main sector) displays a downward sloping pattern which is similar to the aggregate baseline hazard. Our finding is consistent with the finding in Nakamura and Steinsson (2008). We can find that the 12-month spikes in baseline hazard are quite significant in all sectors, except for the energy. The baseline hazard function for energy goods differs greatly from the other sectors. In particular, the spike at 1-month is more pronounced for energy sector. In the energy sector, the firms change their price more frequently. Furthermore, the energy sector is characerised by very short durations and within this sector, very few price spells are observed with duration longer than 18 months, which makes the estimation of the hazard rates for longer durations very imprecise. There is no price spell in energy sector with a duration longer than 36 months. We also conduct the log rank test to see whether the baseline hazard functions are the same across 6 main sectors. The test result rejects the null hypothesis that

$$H_0 : h0_1\left(t\right) = h0_2\left(t\right) = ... = h0_6\left(t\right)$$

Table6 reports the main estimation results under different specification of the Cox model. The column (1) and (2) report the estimation from the equation (8). The column (3) and (4) shows the estimated hazard rate model for price changes using the stratified Cox model (equation 9). The last two column (5) and (6) report the estimation result for the shared frailty model. The table 6 report the estimated hazard ratio rather than coefficient β. The hazard ratio equivalent to $\exp\left(\beta\right)$. Therefore, a hazard ratio greater than one means that the variable has a positive effect on the hazard rate of price changes. While a hazard ratio less than one implies that the variable has a negtive effect on the hazard rate of price changes. Above all, hazard ratio equals to one when variable has no effect on the hazard rate of price changes.

It can be seen that the estimated hazard ratio for the inflation variable are highly significant across all specifications. And all hazard ratios for inflation variable are relatively larger than one. It shows that the PPI inflation rate positively and significantly affect the hazard rate of price changes. Specifically, if the monthly PPI inflation rate increases by 1%, it will raise the probability that a firm will change its price about 7% (hazard ratio lies with a range from 5% to about 9%), given that the price remains the same until that time. Our result is economically large in magnitude comparing with the previous findings. For example, Cecchetti (1986) find that a 5% increase in the inflation rate raises the instantaneous probability of price changes by 10%. However, Cecchetti (1986) only have price data on several magzines. In our research data set, there are over 240,000 products. Moreover, Ceccetti's research focus on the retail shop, while our study focus on the factory gate. The firms at an earlier point in the supply chain may be more sensitive to the changes in aggregate price level. However, we also find that, neither the change of one-period lagged inflation rate nor the change of one-period ahead inflation rate has a significant effect on the probability of price changes.

The estimates show that the change in the interest rate will significantly affect the hazard rate of price changes. An 1% increase in interest rate (Libor) rate, will lead to about 4% to 8% increase in hazard rate of price changes. The change in oil price has a significant but very small positive effect on the probability of changing prices. Moreover, the change in industrial production and effective exchange rate do have significant effect on the hazard rate of price changes.

We capture the unobservable heterogeneity by using frailty model. Notice that regarless of the choice of frailty distribution, the frailty model reduces to non-frailty model when variance of frailty equals to zero. That is to say, if $\theta = 0$, then $h_\theta(t) = h(t)$. The last two columns of table 6 report the estimation of θ. The likelihood ratio test suggests that the null hypothesis that there is no heterogeneity present is strongly rejected. The estimated hazard ratios from frailty model are generally higher than the estimates from the other two models. This facts indicate that failure to account for the unobservable heterogeneity may result in an underestimate of hazard ratio.

Overall, it is important to stress a point that the coefficents associated to the time varying regressors, which measure the state of the economy, are in general individually significant, using the likelihood ratio test, the null hypothesis that the included time varying regressors are not jointly significant is strongly rejected. Further more, even controlling for different sources of heterogeneity, coefficients associated to the time varying regressors are statistically very significant, suggests that the state dependent models are likely to proved a reasonable approximation to the micro price data underlying the UK PPI.

6 Conclusion

This study documents the main stylised facts of price-seting behaviour of British firms over the period Janurary 1998 to Febrary 2008. We develop a time-varying Ss band model and use the individual prices underlying the UK PPI to analyze the factors which can affect the hazard rate of price changes through a semiparametric survival analysis model that fully capture observable and unobservable heterogeneities among the individual firms. Instead of assuming the distribution for the baseline hazard function, we let "data speak" and avoid the situation that the results of analyses are being determined by the assumptions and not the data. The study presents stastistically significant evidence that the economic environment affects the hazard rate of price changes, which is consistent with the predictions in state-dependent pricing models. We can summarized the key empirical findings as follows.

First, producer prices are moderately sticky. The weighted average frequency of price change is 25.1%. The frequency of price changes varies substantially across product sectors. There are about 44% of price adjustments are price decreases, which gives evidence against the downward nominal rigidity hypothesis.

Second, the unconditional hazard function displays a downward sloping pattern with annual spikes. The hazard rate is quite high at the first month, which indicates that a large proportion of firms reset their price in short period. After correcting for firm's heterogeneity and estimate a semiparametric semiparametric hazard model, the baseline hazard functions still exihibit a downward slope with relativley large 12-month spike. The downward sloping hazard can be explained by a time-varying Ss band model with persistent strong idiosyncratic shock.

Third, the inflation rate affects the instantaneous probability of price change conditional on that the price has been kept constant until that time period. Specifically, a 1% increase in the inflation rate significantly increase the hazard rate of price change by about 7%. This result is consistent with the analysis of the pricing behaviour of firms using qualitative surveys, and previous probabilistic and non-parametric studies.

Fouth, the factors that can affect firm's cost or demand will significantly affect the hazard rate of price change, but in different magnitude.The change in interest rate will have a large effect on the hazard rate of price change. While the change in oil price, industrial production, and exchange rate only have very small effect on the probability of

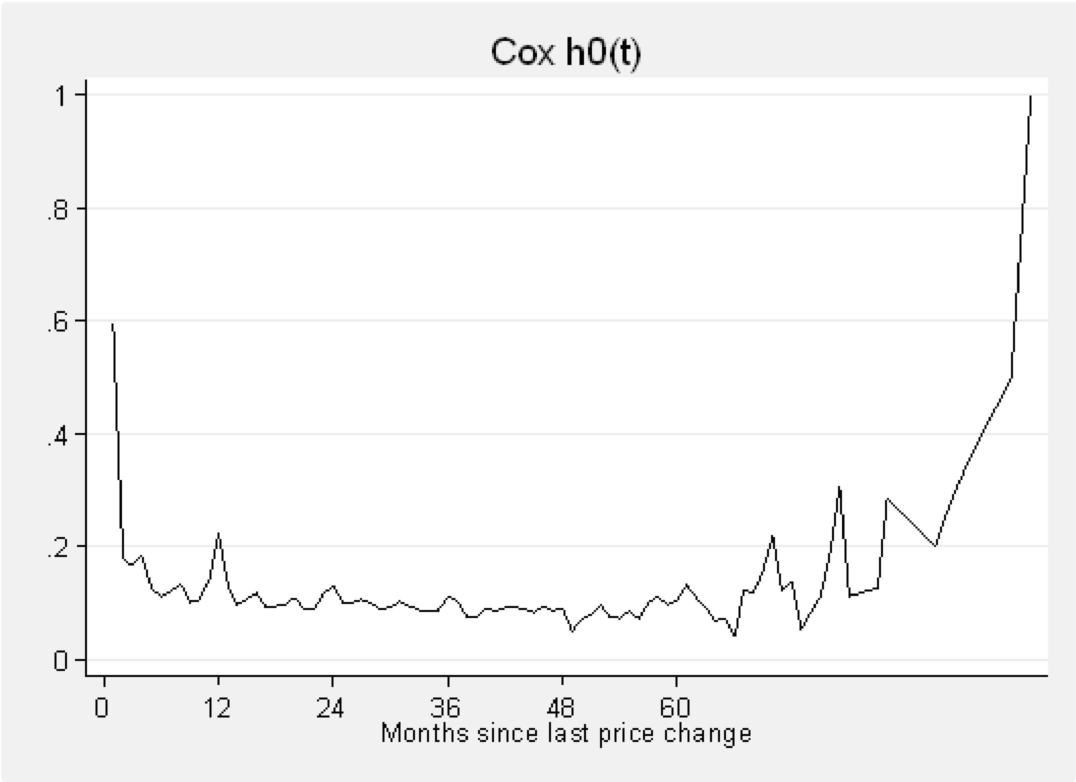

Figure 2: Aggregate baseline hazard function

changing prices.

Five, the unobservable heterogeneity is captured by using frailty model. Given the significance level of the likelihood-ratio test, we reject the null hypothesis that no such heterogeneity present.

Finally, our estimation results of hazard ratio are quite robust under different specifications of the empirical semiparametrical hazard models.

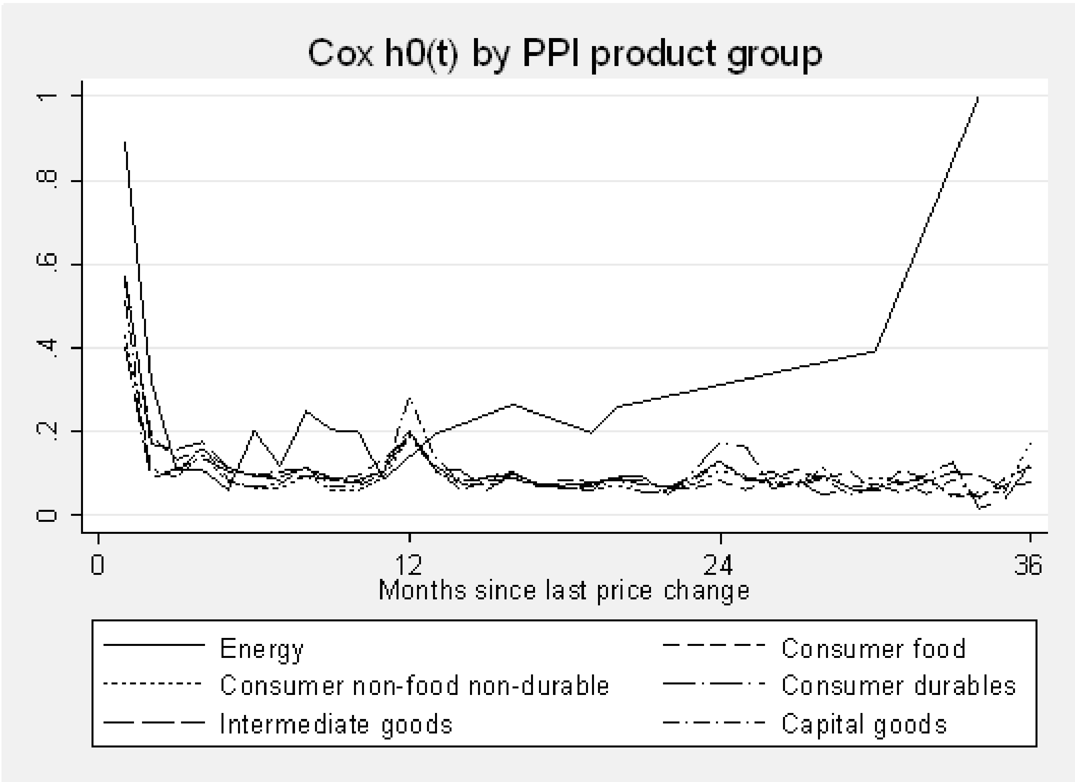

Figure 3: Sectoral baseline hazard function.

	(1)	(2)	(3)	(4)	(5)	(6)
Inflation	1.075***	1.05***	1.077***	1.059***	1.089***	1.078***
Interest	1.039***	1.049***	1.053***	1.061***	1.083***	1.079***
Oil_price	1.003***	1.004***	1.003***	1.005***	1.006***	1.005***
Industry_production	1.002***	1.007***	1.003***	1.005***	1.004***	1.006***
eff_exchange_euro	1.005***	1.007***	1.006***	1.07***	1.012***	1.011***
eff_exchange_us	0.994***	0.996***	1.002***	1.001***	1.004***	1.003***
Inflation(t+1)		0.965		0.964		0.986
Inflation(t-1)		1.007		1.006		1.003
Theta					0.089***	0.059***

Table 3: Hazard rate for price changes

*significant at 10%; **significant at 5%; ***significant at 1%.

7 Reference

Aucremmane, L., and Dhyne E., (2005), "Time-dependent versus state-dependent pricing: A panel data approach to the determinants of Belgian consumer price changes", European Central Bank, WP. No. 462.

Alvarez LJ. 2008. "What do micro price data tell us on the validity of the New Keynesian Phillips Curve?" *Economics-The Open-Access, Open-Assessment E-Journal* 2:1-36

Alvarez, L. J., Burriel. P., and Hernando, I., 2010, "Price setting behaviour in Spain: evidence from micro PPI data." *Managerial and Decision Economics*, 31: 105-121

Alvarez, LJ., Hernando I. 2006. " Price setting behaviour in Spain: evidence from consumer price micro-data." *Economic Modelling*, 23: 699-716.

Alvarez, Luis J., Emmanuel Dhyne, Marco M. Hoeberichts, Claudia Kwapil, Harve Le Bihan, Patrick Lunnemann, Fernando Martins, Roberto Sabbatini, Harald Stahl, Philip Vermeulen, and Jouko Vilmunen, 2006,"Sticky Prices in the Euro Area: A Summary of New Micro Evidence," *Journal of the European Economic Association*, 4, 575-584.

Baudry L, Le Bihan H, Sevestre P and Tarrieu S (2007). What do thirteen million price records have to say about consumer price rigidity? *Oxford Bulletin of Economic Statistics,* 69, 139-183.

Bils, Mark, and Peter J. Klenow, 2004, "Some Evidence On the Importance of Sticky Prices," *Journal of Political Economy* 112, 947-985.

Bunn, Philip, and Colin Ellis, (2010), "How Do Individual UK Producer Price Behave?", Working Paper, Bank of England.

Bunn P, Ellis C. (2012a). "Examining The Behaviour Of Individual UK Consumer Prices." *Economic Journal*, 122, F35-F55.

Bunn P, Ellis C. (2012b). "How do individual UK Prices behave?", *Economic Journal*, 122(558), F16-F34.

Calvo, Guillermo A., 1983 "Staggered Prices in a Utility-Maximizing Framework," *Journal of Monetary Economics,* 12, 383-398.

Caplin, Andrew, and Daniel Spulber, 1987, "Menu Costs and the Neutrality of Money," *Quarterly Journal of Economics,* 102, 703-725.

Cecchetti, Stephen G., 1986, "The Frequency of Price Adjustment: A Study of the Newsstand Prices of Magazines," *Journal of Econometrics,* 31, 255-274.

Cornille D, Dossche M. 2008, "some evidence on the adjustment of producer prices." *Scandinavian Journal of Economics* 110:489-518.

Cox, D., 1972, "Regression Models and Life-Tables." *Journal of the Royal Statistical Society,* 34(2), 187-220.

Dahlby, B., 1992, "Price adjustment in an automobile insurance market: a test of the Sheshinski-Weiss model." *Canadian Journal of Eco-*

nomics 25: 564-583.

Dhyne, E., Alvarez, L.J., Le Bihan, H., Veronese, G., Dias, D., Hoffman, J., Jonker, N., Lunnemann, P., Rumler, F. and J. Vilmunen, 2005, "Price-Setting in the Euro Area: some Stylized Facts from Individual Consumer Price Data", *ECB Working Paper No. 524.*

—–, 2006, "Price Setting in the Euro Area and the United States: Some Facts from Individual Consumer Price Data," *Journal of Economic Perspective,* 20, 171-192.

Dhyne, E., Fuss, C., Pesaran, H., Sevestre, P., 2011, "Lumpy price adjustments: a microeconomic analysis." *Journal of Business and Economics Statistics,* 29:4, 529-540.

Dias, Daniel A., Carlos Robalo Marques, and Joao M. Santo Silva, 2007, "Time or State Dependent Price Setting Rules? Evidence from Micro Data," *European Economic Review,* 51, 1589-1613.

Dias M, Dias, D, Neves P. 2008. "Stylised features of prcie setting behaviour in Portugal: 1992-2001." *Poutuguese Economic Journal* 7:75-99.

Dixon H. (2012), "A unified framework for using micro-data to compare dynamic time-dependent price-setting models," *BE Journal of Macroeconomics* (Contributions), volume 12.

Dixon, H., Franklin, J., and Millard, S, 2012, "Sectoral shocks and monetary policy in the United Kingdom", Working paper, Bank of England.

Dixon, H and Le Bihan, H, 2012, "Generalized Taylor and generalised Calvo price and wage-setting: Micro evidence with macro implications." *Economic Journal,* 122(560): 532-544.

Dotsey, M., King, R., and Wolman, a., 1999, "State-Dependent Pricing and the General Equilibrium Dynamics of Money and Output," *Quarterly Journal of Economics,* 655-90.

Fabiani, S., Druant, M., Hernando, I., Kwapil, C., Landau, B., Loupias, C., Martins, F., Matha, T., Sabbatini, R., Stahl, H., and Stockman, A., 2005, "The pricing behaviour of firms in the euro area: new servey evidence", Working Paper.

Fougere, D., Le Bihan, H., and Sevestre, P. (2007), "Heterogeneity in Price Stickiness: A Microeconometric Investigation," *Journal of Business & Economic Statistics, 25(3), 247-264.*

Gautier E. 2008, "The behaviour of producer prices: evidence from the French PPI micro data." *Empirical Economics* 35: 301-332.

Gautier, E., and Le Bihan, H., 2011, "Time-varying (S,s) band models: Properties and interpretation", *Journal of Economic Dynamics & Control*, 35, 394-412.

Gertler, M., and Leahy, J., 2006, "a Phillips Curve with and Ss

Foundation," *NBER Working Paper*, 11971.

Goette, Lorenz, Rudolf Minsch, and Jean-Robert Tyran, 2005, "Micro Evidence on the Adjustment of Sticky-Price Goods: It's How Often, Not How Much," Discussion Paper, University of Copenhagen.

Gopinath, Gita, and roberto Rigobon, 2008, "Sticky Borders," *Quarterly Journal of Economics,* 123, 531-575.

Hall, G., rust, J., 2000, "An empirical model of inventory investment by durable commodity intermediaries." *Carnegie-Rochester Conference Series on Public Policy,* 52: 171-214.

Hofstetter, Marc, (2010), "Sticky prices and moderate inflation", *Economic Modelling*,27, 535-546

Kiefer, Nicholas M., (1988), "Economic Duration Data and Hazard Functions," *Journal of Economic Literature*, 26, 646-679.

Klenow, Peter J., and Oleksiy Kryvstov, (2005), "State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation," NBER Working Paper No. 11043.

Klenow, Peter J., and Oleksiy Kryvtsov, (2008), "State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation?" *Quarterly Journal of Economics, 123, 863-904.*

Kolmogorov, A. (1933) "Sulla determinazione empirica di una legge di distribuzione" G. Inst. Ital. Attuari, 4, 83

Lach, Saul, and Daniel Tsiddon, (1992), "The Behavior of Prices and Inflation: An Empirical Analysis of Disaggregated Price Data," *Journal of Political Economy*, 100, 349-389.

Lancaster, Tony, (1979), "Econometric Methods for the Duration of Unemployment," *Econometrica*, 47, 939-956.

Lin, D. Y. (1994), "Cox Regression Analysis of Multivariate Failure Time Data: The Marginal Approach." *Statistics in Medicine*, 13, 2233-2247.

Mankiw, N. Gregory, and Ricardo Reis, (2002), "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *Quarterly Journal of Economics,* 117, 1295-1328.

Matusoka T (2009) "Goodness-of-fit test for price duration distributions", Mimeo

Matsuoka, T., 2010, "Unobserved heterogeneity in price-setting behavior: A duration analysis approach". *Japan and the World Economy,* 22: 13-20.

Meyer, Bruce D., (1986), "Semiparametric Estimates of Hazard Models," Mimeo, MIT.

Meyer, Bruce D., (1990), "Unemployment Insurance and Unemployment Spells," *Econometrica*, 58, 757-782.

Morris, J. and Green, T. (2007):'Measuring the quality of the producer price index', *Economic & Labour Market Review* 1(10), pp 31-5

Nakamura, Emi, and Jon Steinsson, (2007), "Monetary-Non-Neutrality in a Multi-Sector Menu Cost Model," Working Paper, Columbia Universtiy.

Nakamura, Emi, and Jon Steinsson, 2008, "Five Facts About Prices: a Reevaluation of Menu Cost Models", *Quarterly Journal of Economics* 123(4), 1415-1464.

Ritchie, F 200, "Secure access to confidential microdata: four year of the Virtual Microdata Laboratory", *Economic & Labour Market Review*, 2(5), May.

Rotemberg, Julio J. (1982), "Sticky prices in the United States", *Journal of Political Economy*, 90, 1187-1211.

Rotemberg, Julio J. (2005), "Customer anger at Price Increases, Changes in the Frequency of Price Adjustment and Monetary Policy", *Journal of Monetary Economics*, 829-852.

Sheshinski, Eytan, and Yoram Weiss, (1977) "Inflation and Costs of Price Adjustment," *Review of Economic Studies*, 44, 287-303.

Sheshinski, E., Tishler, A., Weiss, Y., 1981, "Inflation, costs of price adjustment, and the amplitude of real price changes: an empirical analysis." In: Flanders, M.J., Razin, A. (Eds.), *Development in an inflationary world.* Academic Press, New York, pp.195-207.

Smets, F., and Wouters, R, (2003) "An estimated dynamic stochastic general equilibrium model of the euro area." *Journal of the European Economic Association,* 1(5): 1123-1175.

Smirnov, N.V. (1948) "Tables for estimating the goodness of fit of empirical distributions", *Annals of Mathematical Statistic*, 19, 279.

Stahl H. 2006. "Producer price adjustment at the micro level: evidence from individual price records underlying the German PPI." Mimeo, Deutsche Bundesbank.

Stigler, George J., and James K. Kindahl, *The Behavior of Industrial Press* (New York, NY: Columbia University Press).

Vasquez-Ruiz, H.A., 2011, "Price Stickiness And The Hazard Rate For Price Changes: Evidence From Qualitative Survey Data." mimeo.

Vermeulen, Philip, Daniel Dias, Maarten Dossche, Erwan Gautier, Ignacio Hernando, Roberto Sabbatini, and Harald Stahl, (2006), "Price Setting in the Euro Area: Some Stylised Facts from Individual Producer Price Data and Producer Surveys," ECB Working Paper.