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Time-Dependency in Producers' Price Adjustments: Evidence from Micro Panel Data

Abstract

Existing micro evidence of firms' price changes tends to show a downward sloping hazard rate – the longer the price of a product has remained the same, the less likely it is that the price will change. Using a panel of Norwegian plant- and product-specific prices, we also find a downward sloping hazard when applying a Kaplan–Meier model. After having controlled for both observed and unobserved characteristics, we find flat hazards with spikes in the first and twelfth months. This suggests time-dependent price-setting by at least some of the producers. The spike after 12 months might be explained by seasonal demand effects, but also by the pricing season effect related to information acquisition and processing, negotiation and signing of price contracts. The revealed price adjustment pattern is at odds with the predictions of the Calvo model, a central element in many dynamic stochastic general equilibrium models, as this assumes constant frequencies of price adjustments over time. Our empirical findings instead point to a modified Calvo model where firms in some periods experience lower menu costs. Finally, the empirical findings may have implications for the effectiveness of monetary policy interventions.

JEL-Codes: E310, D220, C410.

Keywords: price-setting, micro data.

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1. Introduction

The field of inflation dynamics and price rigidity has triggered interest among economic researchers for several decades. A massive empirical literature has been devoted to shedding light on this subject. In recent years, access to good microeconomic datasets has increased significantly (see the discussion by Klenow and Malin, 2011). In the last decade, this has been especially evident through the empirical work conducted by the Inflation Persistence Network (IPN), a research team consisting of economists from the European Central Bank (ECB) and the national central banks of the European Union (see for instance Vermeulen *et al*. 2012).

Cornille and Dossche (2008) propose several reasons why it is important to study producer price adjustment.[1] First, these prices play an important role in macroeconomic models with intermediate goods. Price adjustments at the producer level responding to shocks to production costs and demand for intermediate goods transmit to prices at the consumer level. Cornille and Dossche show that the degree of producer price rigidity will be decisive in an inflation-targeting central bank's relative weighing of inflation at the producer level versus the consumer level. Furthermore, they stress the need for empirical evidence from both the consumer and producer levels, also in models ignoring the distinction between the two levels of pricing. Sixty per cent of the value of a consumer good is generated at the producer level in industrialized economies (Burstein *et al*. 2000). If adjustment of producer prices differs from that of consumer prices in the aftermath of monetary shocks, it is of great importance to combine evidence from both levels in the model design.

While consumer prices are important for central banks' inflation monitoring, producer-level prices are quite often the ones modelled in macroeconomic policy models (Vermeulen *et al*. 2012). Furthermore, as argued by Álvarez *et al*. (2006), most monetary macroeconomic

[1] See also Gautier (2008) for France and Sabbatini *et al*. (2005) for Italy for studies focusing on price adjustment at the producer level. Furthermore, Carlsson and Skans (2012) find support for the model of Maćkowiack and Wiederholt (2009) using Swedish firm-level data.

stabilizing policies today are still based on highly stylised assumptions about the micro-level pricing pattern of firms. Hence, the implications of these policies depend on generalized but inaccurate assumptions. It is therefore apparent that there is still a need for deeper insight into the field of price adjustment.

In this paper, we use monthly micro panel data from the Norwegian producer price index (PPI) to investigate price dynamics at the producer level. We take advantage of high-quality data, with wide coverage, a large number of observations and the possibility of disaggregation into products or industries. Descriptive statistics on price adjustment in Norway are presented and compared to the corresponding statistics in other European countries. In order to thoroughly analyse time-dependency in producers' price adjustments, we implement proportional hazard (PH) function models, which in our context, specify the probability of a price adjustment during a month, given the time lapse since the last price adjustment.

Our overall findings when comparing the descriptive statistics of the Norwegian PPI data to the European reference literature is that the pricing patterns of Norwegian producers are very similar to the pattern observed for the Euro area (see Vermeulen *et al*. 2012).[2] The descriptive statistics show quite a large degree of heterogeneity over seasons, types of goods and industries. Focusing on time-dependency in the price adjustment pattern, our non-parametric estimates of the hazard function indicate a decreasing function. Such a declining hazard may come as a consequence of imperfectly accounting for heterogeneity in the price-setting behaviour. Indeed, after having controlled for both observed and unobserved characteristics, we find flat hazards with spikes in the first and twelfth months. This suggests time-dependent price-setting, at least by some producers. These patterns remain when we split the sample into various types of goods. The extent of heterogeneity and the estimated shape of

[2] For other studies of price behaviour in Norway, see for example Langbraaten *et al*. (2008) and Wulfsberg (2016).

the price hazards suggests that macroeconomic price-setting models should also take pricing season effects into account. Such seasonality could be explained by seasonal demand variation. Furthermore, it might also be related to information acquisition and processing (see Mackowiak and Wiederholt (2009) and Mankiw and Reis (2002)), negotiation and the signing of price contracts as described by, for example, Zbaracki *et al*. (2004).

The remainder of the paper is structured as follows. Section 2 presents models found in the literature, building on theories of micro-level pricing. The econometric approaches used in this analysis are described in Section 3, while the data are presented in Section 4. Our empirical results are given in Section 5. Finally, in Section 6, some concluding remarks are made.

2. Theoretical background

A long-running debate in the field of nominal price rigidities is whether the pricing agents are following a state-dependent or time-dependent pattern in their behaviour. In state-dependent models, originally presented by Sheshinski and Weiss (1977, 1983), the firm's decision to change its price comes as a response to changes in the economic environment. Among the many time-dependent models that have been proposed in the last decades, two models stand out. In the first, by Taylor (1980), the firm decides its prices under contracts that remain fixed for a given number of periods. The hazard rate is thus zero for a certain time, and then switches to one after the given number of periods. With contemporaneous contracts of different lengths, the overall hazard might be increasing or decreasing at any time point. The second, by Calvo (1983), introduces the Calvo pricing rule, which is today the most used and commonly accepted derivation of the New Keynesian Phillips curve among the many so-called dynamic stochastic general equilibrium (DSGE) models. In this model, firms adjust their prices on a random basis. Price rigidity is thus introduced to the model by letting firms change their prices with a given probability.

A key feature of time-dependent models is that firms are forward-looking, aware that they will only be able to adjust their prices within certain intervals. Risking that they will be unable to increase their prices in the case of a future increase in marginal cost or expected future inflation, the firms choose to include the expected increase of marginal cost in today's prices. Assumptions about information diffusion is essential in these models. For example, changing economic conditions may be embedded in real variables such as prices and wages with a delay because information spreads slowly in the economy. Firms may also be reluctant to continuously update their set of information as it may be costly for the firm to obtain and process (see Mankiw and Reis 2002, 2003).[3]

3. Econometric procedures

We use hazard function models to study the price spell durations.[4] Price spells can be terminated, i.e. the price of goods may be changed at any particular time *t*. However, we observe the underlying continuous durations as discrete time intervals. Because the interval length is one month, the hazard functions estimated in this paper produce the probability that a price spell will end during the k^{th} month, given that the price of the good has remained unchanged until *k*-1.

The starting point of our hazard rate analysis consists of estimating the Kaplan–Meier empirical hazard function. However, Kaplan–Meier empirical hazard rates are mainly descriptive and assume that the sample is homogeneous. Hence, heterogeneity caused by either observable or unobservable factors may cause the empirical hazard rates to be misleading. In order to incorporate the effect of observed individual characteristics, we specify PH models. The discrete time representation of the hazard for month *k* can be expressed as:

[3] See also the related models by Reis (2006) and Maćkowiack and Wiederholt (2007).
[4] By the term *spell*, we mean the length of time during which the price is fixed.

$$h(k|\boldsymbol{x_k}) = 1 - \exp[-\exp(\beta_0 + \boldsymbol{x_k}\boldsymbol{\beta} + \gamma_k)]. \qquad (1)$$

where β_0 is an intercept term, $\boldsymbol{x_k}$ a vector of covariates (either fixed or time-varying) and $\boldsymbol{\beta}$ a vector of parameters. The term γ_k summarizes duration dependence in the discrete time hazard. Placing restrictions on the elements of γ_k can be regarded as making parametric assumptions about the baseline hazard (see Meyer 1990). More specifically, we are constructing 13 interval-specific dummies γ_k, one for each spell month at risk. The hazard is assumed to be constant within each duration interval but to vary between them. In our following estimations, we use the complementary log-log regression model implemented in STATA as cloglog. The baseline hazard is the hazard rate when all covariates $\boldsymbol{x}$ are equal to zero.

It should be mentioned that each plant may produce one or several products.[5] In the hazard model presented above, we treat each product as independent of each other. This means that we assume that the products within a plant's product portfolio are sufficiently differentiated and therefore, we abstract from strategic complementarity and substitution between the various products. However, we mitigate some of the potential problems related to the dependency between the various products within a plant by clustering at the plant level. To capture systematic cross-good-type variation, type-of-good-specific dummies are included. The vector of covariates includes a monthly type-of-good-specific PPI index for the relevant product that will proxy the prices of the products of a firm's competitors. The idea is that omitting the price level of similar products induces an omitted variable bias in the sense that the effects of these competitors' prices will be picked up by the hazard. Such a price index may also pick up the changes in competition in addition to potentially saying something about the relevant cost level in the industry. Moreover, as Fougère *et al.* (2007) indicate, the PPI index might act as a proxy

[5] The mean number of products per producer is 3.8, the maximum is 20.

variable for the state of the economy. We have used the PPI for intermediate goods, capital goods, durable consumer goods and non-durable consumer goods. These are matched to the various types of goods in our panel.

The starting month of price spells might be very different for bikinis and winter jackets. Thus, as a further measure to control for potential product-type heterogeneity, we include the starting month of a price spell when estimating the probability of a price change. Additionally, the time dependency picked up by the dependency parameters γ_k (for all k-s) might differ between seasons. For example, Olivei and Tenreyro (2007) assume that the probability of resetting wages varies between quarters. This time-dependency might affect the likelihood of seeing monetary interventions. Thus, we also include a set of dummies describing the current calendar month.

Heterogeneity is essential when analysing time-dependency. This is illustrated by Cameron and Trivedi (2005, p. 611), also referred to by Fougère *et al*. (2007) and Cooper *et al*. (1999). They all show that in an economy with two (or more) different types of products where each product type has a different time-constant hazard, the shape of the hazard is a direct function of the population at risk in every period. In other words, whether the overall hazard is decreasing or increasing is simply because of a composition effect at every period. The Taylor (1993) model introduces heterogeneity by letting the duration of price contracts differ between producers. Thus, the composition of products at risk changes over time such that the aggregate hazard rate is increasing. Another model is that of Álvarez and Burriel (2010), which combines different groups of Calvo agents in an annual model where the producers reset their prices every 12 months and maintain those prices for that time. The result is an aggregated hazard rate that is decreasing, with annual spikes every 12, 24, 36… periods. Thus, the introduction of explicit heterogeneity in these models has significant implications for the predicted form of their hazard rates.

Taking unobserved heterogeneity between the various products in the sample further into account, we allow for a random intercept, and therefore mitigate the potential problems of frailty/unobserved heterogeneity in our discrete time PH model. This random intercept v_i is assumed to be iid, $N(0, \sigma_v^2)$. This allows us to take advantage of potential observation of multiple spells for each product. This random-effects complementary log-log model is implemented in STATA as xtcloglog.

4. Data

The dataset was obtained from Statistics Norway (SSB). The price data consist of monthly micro product specific data collected from a large number of plants by SSB for calculation of the commodity price index for the Norwegian manufacturing sector (PPI). The PPI is a key part of the short-term statistics that monitor the Norwegian economy. These 5-digit price observations also include plant identifiers that make it possible to include information about the industry classification. Only data on products sold on the domestic market are used in this analysis. This is to minimise the influence of exchange rate fluctuations on prices and to reduce the heterogeneity of the data.

The PPI comprises all commodities and services produced by companies within manufacturing, mining, mining support service facilities, oil and gas extraction and energy supply (SSB 2013a). A selection of producers from these industries reports their prices on a monthly basis, and large, dominating, establishments are targeted to secure a high level of accuracy and relevance. The selection of respondents is updated on a regular basis to make sure that the indices are continuously being kept relevant with the development of the Norwegian economy. The required information is collected through both questionnaires and electronic reporting. Compulsory participation ensures a high response rate from the questioned producers. To make sure that the indices are of high quality, the gathered data is subject to several controls aiming at identifying extreme values and price changes owing to quality changes of the reported products.

The dataset used covers 19 different industries categorized by the SIC2002 standard, from the years 2004 to 2009. Before controlling for left censoring, the dataset includes 78 264 individual monthly price observations for a total of 1673 products. The corresponding numbers after controlling for left censoring are 19, 56 901 and 1545 (industries, individual monthly price observation, and products, respectively).

[Figure 1 "Monthly Frequency of Price Changes" about here]

The monthly averages of price change frequency – the number of price changes within a given month divided by the total number of price quotes in the month – ranging from January 2004 to December 2009, are plotted in Figure 1. The figure reveals a pattern similar to findings in the comparable literature from Europe (see Nakamura and Steinsson (2008) for a similar pattern for the U.S.). The price-setting of Norwegian producers follows a seasonal pattern, where the frequency of price changes is substantially higher at the beginning of the year.[6] Through the rest of the year, the change frequency seems to follow a similar pattern from one year to the next.

[Table 1 "Average Monthly Frequency of Price Changes in European Countries" about here]

The frequency of price changes alongside findings from other European countries, as found in Vermeulen *et al*. (2012), are presented in Table 1. We observe that approximately one

[6] The seasonal pattern is also clearly seen in Figure A1 in the Appendix. The change rate is at a peak in January (approx. 35 per cent). The change frequency decreases towards the summer months, then increases slightly again at the start of the second half of the year, before hitting a low point in November and December. This is a recognizable pattern from the literature for both consumer and producer levels.

quarter of prices change in a month. The change frequency among Norwegian producers is thus roughly the same as we observe for the rest of Europe, although it admittedly is the highest of all listed average frequencies.

[Table 2 “Average Monthly Frequency of Price Changes by Types of Good” about here]

Table 2 shows total change frequency and the frequency of increases and decreases separately, for intermediate goods, capital goods and consumer goods.[7] Consumer goods are further decomposed into non-durables and durables. Worth emphasizing is the fact that the frequency of price adjustments is never at a value close to one, regardless of product category. This means that price changes are not as frequent as several of the established DSGE models suggest. These findings indicate that there are indeed rigidities at the PPI level that several of the traditional macro models are unable to account for. The estimated frequencies range from 18 to over 32 per cent, indicating that manufacturers of non-durables and capital goods change their rates significantly more often than manufacturers in the other groups.

[Figure 2 “Average Monthly Price Change Frequencies by Industry” about here]

Figure 2 shows the price change frequency in different industries, defined by SIC2002 2-digit codes.[8] This figure underlines the fact that there is marked heterogeneity in price-setting across different types of producers. The difference between the industry with the lowest and highest average frequency is more than 40 percentage points. This figure thus supports the findings of Table 2, though focusing on industries rather than types of goods. The adjustment

[7] We use commodities, products and goods synonymously.
[8] See Table A1 in the Appendix for a complete listing of SIC2002 industry codes.

pattern of producers is clearly not as homogeneous as many DSGE models assume. There is marked heterogeneity, both between different types of goods and different industries, and the degree of price rigidity varies between producers.

5. Results

This section begins with Table 3 showing, in contrast to Tables 1 and 2, which is based on monthly observations, price spell characteristics.[9]

[Table 3: "Price Spell Durations by Types of Goods" about here]

We see that the mean spell length is 3.5 months. Note however, this is driven by some long-lasting spells (max 72 months) because the median duration is 1.0 month. If we look at the different types of goods, we see that both mean and median values vary substantially. Again, this is additional evidence of heterogeneity in price-setting between types of goods.

[Figure 3 "The Empirical Hazard Function" about here]

In Figure 3, we show the non-parametric estimates of the hazard rates based on all goods. We see that a considerable share of the prices dies out in a very short time, often after only one month. After the early peak, the hazard rates plunge down to a considerably lower level. It seems also to be evident that the aggregated hazard rate is a decreasing function of price duration, even after the initial drop. This is an important finding, as most macro models assume constant hazard rates. The longer the duration of a price spell, the lower the probability that the price will die. This is consistent with the findings of existing PPI analysis (see for

[9] Left-censored observations have been discarded from the dataset for this analysis.

example Álvarez *et al*. 2010 and Veronese *et al*. 2005). The declining hazard function can be explained by differences in adjustment probability between different manufacturers. The probability of price changes is by definition lower for products with high price duration than for products with low price duration. However, the hazard rate we show in Table 3 is the *aggregate* of different goods. In the construction of such an aggregated graph, it is therefore the case that the more the share of prices set by manufacturers with a more frequent change pattern decreases, the longer the time horizon.[10] Put differently, several heterogeneous producers with non-decreasing hazard functions yield a decreasing hazard function when aggregated. For long durations, manufacturers with relatively high change frequency have largely disappeared. A third observation is the existence of peaks every 12 months, which suggests that a proportion of plants apply annual pricing rules. This is also a well-known finding from the earlier PPI literature, indicating that a large proportion of price setters set prices only once a year. Furthermore, this could be interpreted as an acceptance of price-setting in a Taylor or Calvo pattern in the sense that many producers re-price their products at fixed intervals. However, this alone is not necessarily to reject these models in their original form.

[Table 4: "Estimation Results of the Proportional Hazard Models" about here]

In Table 4, we present our estimation results.[11] In this table, we report the predicted probability of a price change given the time since last price change for the same product, i.e. the marginal effects of the interval-specific dummies, γ_k, one for each spell month at risk, and the corresponding standard errors (calculated by the delta method). Furthermore, the variance–covariance matrix, and therefore also the standard errors, are based on clustered standard errors

[10] See Figure A2 in the Appendix for pictures of the non-parametric hazard functions for various types of goods. Even when separating by goods, we see no signs of constant hazard rates.
[11] The corresponding coefficient estimates are reported in the Appendix tables.

at the plant level to mitigate some of the potential problems related to the dependency between the various products within a plant.

In Column 1, we see the probability of a price change in the first month is as high as 0.720. The marginal effects and the corresponding 95% confidence intervals are shown in Figure 4.[12] Given that the price remains unchanged in the first month, the probability of a price change drops to 0.270 in the second month. We see that the hazard remains low until it spikes again in the twelfth month. The evolution of the predicted hazard rates mirrors what we have already seen in Figure 3, the Kaplan–Meier estimates, which also showed a very high probability of a price change in the first month after a price change. It is also consistent with the median duration of a price spell of 1.0 month reported in Table 3. The non-constant hazard, i.e. the price spikes at the first and twelfth months after an initial price change, is at odds with the predictions of the standard Calvo model. One could think, however, that such a pattern would be consistent with the so-called "fixed-price time-dependent" rule (see for instance Bonomo *et al*. (2010) and Alvarez *et al*. (2011)).[13] The underlying mechanisms driving such a pattern are both costs related to observing and processing information about the state of the economy and a physical menu cost for price changes such as negotiation and signing of price contracts, described by, for example, Zbaracki *et al*. (2004). These latter authors also point to the convexity of price adjustment costs that induce firms to favour slow adjustment, i.e. two subsequent small price changes rather than one large price change. Such a convexity might be related to customer behaviour, i.e. that a larger price increase is more likely to make customers search for more attractive outside offers. The managerial costs related to a price change might also be convex because a larger price change will involve more people, more internal discussion, more attention and controversy and additional actions to handle customers'

[12] The full set estimation results, i.e. parameter estimates for all covariates, are not reported here, but are available from the authors on request. This applies also to all estimated hazard models reported from here on.

[13] For a related paper, see Midrigan (2010).

complaints and concerns (see Zbaracki *et al*. 2004).[14] If this is true, then we would expect to see a relatively high probability of a price change in the first month. One could, of course, think that seasonal demand effects might explain the spike at the twelfth month; however, in our model, we have included both the current and starting month of the price spell. Thus, the importance for seasonal effects on the hazards should be minimized.

[Figure 4 “Complementary log-log Regression Model Hazards” about here]

As already seen in Figure 2, the monthly frequencies of price changes are quite different from one type of industry to the next, and even more across products. Thus, we estimate the same model, but now with 30 different product dummies to better control for product specific heterogeneity. The estimation results, where we include a set of much more detailed product control dummies, are reported in Column 2 of Table 4. It is hard to see any differences between the hazard rates in Columns 1 and 2.

So far, we have not taken advantage of our ability to observe multiple spells for each product in our sample. Doing so, we might better control for product specific heterogeneity than we can when ignoring this fact, as we do in Columns 1 and 2 of Table 4. The results of using the random-effects complementary log-log model are reported in Column 3 of Table 4. Now we see that the spike at the first month has disappeared almost completely, and therefore, the hazard is constant except for the spike at the twelfth month. This means that that the downward sloping hazard we observed in Figure 3 using the Kaplan–Meier approach has disappeared. This reconfirms that composition effects, at every period in time, critically affect whether the overall hazard is decreasing or increasing. The disappearance of the spike in period

[14] See also Nilsen and Vange (2018) for a model including both fixed and convex price adjustment costs, tested on the same data used in this paper.

1, and therefore also the reduced occurrence of price adjustments in the two subsequent months, also makes it hard to argue for the convexity in the price adjustment costs discussed earlier. The pattern of the spike in the prize hazard in the twelfth month might still be consistent with the theories that focus on staggered contracts (see Taylor 1980, 1999) with a duration of one year, and of course, the "pricing season effect" described by Zbaracki *et al*. (2004). These latter results are also in line with those of Fougère *et al*. (2007), who state that "allowing for such specific peaks [in some given months] makes the constancy of the hazard an acceptable assumption."

[Figure 5 "Random Effects Complementary log-log Regression Model Hazards by Types of Goods" about here]

As a first robustness check, we have estimated the PH model, similar to those used to produce the results reported in Column (3) of Table 4, for four groups of disaggregated types of goods: non-durable consumer goods, durable consumer goods, capital goods and intermediate goods. The predicted hazard rates are reported in Figure 5 in the Appendix.[15] From the figure, we see that the predicted hazards for the four different types of goods are quite similar, showing flat hazards with spikes in the first and twelfth months.

As an additional robustness check, we look more closely at the competing risk aspect of price changes. That means we split the sample into two sub-samples and then estimate a random effects complementary log-log regression model for each of the two sub-samples. In the first sub-sample, we have removed all price decreases. We are therefore implicitly treating the price decrease transitions as censored. Similarly, for the second sub-sample, we begin with the full sample but remove the price increase observations. Thus, we treat the price increase transitions

[15] The full set of estimation results are not reported, but available from the authors on request.

as censored. Admittedly, such a competing risk analysis based on the two subsamples builds on a set of discussable and partly unrealistic and unverifiable assumptions. Thus, this latter robustness check should only be taken as an informal assessment rather than as hard evidence for the competing risk aspect of the observed pricing behaviour. The predicted hazards for the two sets of estimates are reported in Figure 6.

[Figure 6 “Competing Risk: Complementary log-log Regression Model Hazards” about here]

The first thing to notice is that the hazard rates for the price increases are larger than those for the price decreases for all months. The probability of a price decrease is less than 10 per cent (except for the first month). However, most important is the fact that the spike in the price hazard at the twelfth month is driven solely by price increases. Thus, our former discussion of the “pricing season phenomenon” seems to be related to price increases but not to price decreases. The asymmetry might also be relevant to the discussion of asymmetric response to upward and downward demand and cost shocks (see Peltzman (2000) and Loy *et al.* (2016)). Thus, our later analysis questions the underlying assumptions in many models that treat price increases and decreases symmetrically.

6. Concluding remarks

In this paper, we have analysed time-dependency in producers’ price adjustments. Using a relatively unexplored sample of plant-level data of Norwegian producers within the manufacturing sector, we have provided empirical evidence on price adjustment behaviour.

Norwegian producers’ price adjustment behaviour is more or less in line with the rest of Europe, according to the European reference literature. Norwegian price change frequency is slightly above 28 per cent every month. Our analysis also reveals that price increases are more common than price decreases. Price change frequency shows great heterogeneity between different types of goods and industries. This means that there are differences in the degree of rigidity, and thus in the reaction pattern of different producers in the wake of macroeconomic shocks. Furthermore, there are also clear signs of seasonality in the price adjustment pattern of firms, as the frequency has substantial peaks in January every year.

We have also analysed price adjustment behaviour more thoroughly by estimating piecewise linear hazard rate models. Focusing on the empirical hazard rates using a Kaplan–Meier approach, it seems that the probability of a price change declines with the duration since the last price change. However, this decreasing pattern is a consequence of imperfectly accounting for heterogeneity in price-setting behaviour. In order to accommodate this issue, we specified several PH models where we controlled for both observed and unobserved heterogeneity between price spells. Using a complementary log-log model, we found flat hazards with spikes in the first and twelfth months. The spike in period 1 might be related to convex price adjustment costs. After having taken the repeated spell feature into account using a random effects complementary log-log model, the spike in period 1 disappears. Thus, we are left with a rather constant hazard with a spike only in period 12. This latter finding is consistent with the theories focusing on staggered contracts (Taylor 1980, 1999) with a duration of one year, and of course, the "pricing season effect" described by Zbaracki *et al*. (2004). Finally, there are strong indications that the seasonal pattern is mainly related to price increases, while the hazards of price decreases are rather constant.

Our findings point towards the importance of taking heterogeneity seriously because it affects the estimated hazard. Furthermore, the competing risk aspect, and therefore also asymmetric responses to macroeconomic shocks, are also important for addressing price adjustment behaviour. Ignoring these features might have consequences for the effectiveness of monetary policy. As a result, even the most famous and widely adopted macro pricing models require revision.

References

Álvarez, L. J., E. Dhyne, M. Hoeberichts, C. Kwapil, H. Le Bihan, P. Lünnemann, F. Martins, R. Sabbatini, H. Stahl, P. Vermeulen, and Jouko Vilmunen (2006). "Sticky Prices in the Euro Area: A Summary of New Micro-Evidence", *Journal of the European Economic Association*, 4(2-3):575-584.

Álvarez, L. J. and P. Burriel (2010). "Is a Calvo Price Setting Model Consistent with Individual Price Data?", *The B.E. Journal of Macroeconomics*, 10(1) (Advances), Article 13.

Álvarez, L. J., P. Burriel and I. Hernando (2010). "Price Setting Behaviour in Spain. Evidence from Micro PPI Data", *Managerial and Decision Economics*, 31:105-121.

Alvarez, F. E., F. Lippi and L. Paciello (2011). "Optimal Price Setting with Observation and Menu Costs", *The Quarterly Journal of Economics*, 126(4):1909-1960.

Bonomo, M., C. Carlos and G. Rene (2010). "State-Dependent Pricing under Infrequent Information: A Unified Framework", Staff Report no. 455, Federal Reserve Bank of New York.

Burstein, A., J. Neves and S. Rebelo (2003). "Distribution Costs and Real Exchange Rate Dynamics During Exchange-Rate-Based-Stabilizations", *Journal of Monetary Economics*, 50(6):1189–1214.

Calvo, G. A. (1983). "Staggered Pricing in a Utility Maximizing Framework", *Journal of Monetary Economics*, 12:383-398.

Cameron C. A. and P. K. Trivedi (2005). "Microeconometrics: Methods and Applications", Cambridge, New York.

Carlsson, M. and O. N Skans (2012). "Evaluating Microfoundations for Aggregate Price Rigidities: Evidence from Matched Firm-Level Data on Product Prices and Unit Labor Cost", *American Economic Review*, 102(4):1571–1595.

Cooper, R., J. Haltiwanger and L. Power (1999). "Machine Replacement and the Business Cycle: Lumps and Bumps", *The American Economic Review*, 89(4):921-946.

Cornille, D. and M. Dossche (2008). "Some Evidence on the Adjustment of Producer Prices", *Scandinavian Journal of Economics*, 110:489-518.

Eurostat (2005). "Statistical Classification of Economic Activities in the European Community, Rev. 1.1 (2002) (NACE Rev. 1.1)". <http://www.ec.europa.eu/eurostat/ramon/nomenclatures/index.cfm?TargetUrl=LST_CLS_DLD&StrNom=NACE_1_1>, (03.07.13).

Fougère D., H. Le Bihan and P. Sevestre (2007). "Heterogeneity in Consumer Price Stickiness: A Microeconomic Investigation", *Journal of Business and Economics Statistics*, 25(3):247-264.

Gautier, E. (2008). "The Behaviour of Producer Prices: Evidence from French PPI Micro Data", *Empirical Economics*, 35:301-332.

Klenow, P. and B. Malin (2011). "Microeconomic Evidence on Price-Setting", *Handbook of Monetary Economics*, 3:231-284.

Langbraathen, N., E. W. Nordbø and F. Wulfsberg (2008). "Price-Setting Behaviour of Norwegian Firms – Results of a Survey", *Economic Bulletin*, 2/2008, Norges Bank.

Loy, J. P., C. R. Weiss and T. Glauben (2016). "Asymmetric Cost Pass-Through? Empirical Evidence on the Role of Market Power, Search and Menu Costs", *Journal of Economic Behavior and Organization*, 123:184–192.

Maćkowiack, B. and M. Wiederholt (2009). "Optimal Sticky Prices under Rational Inattention", *American Economic Review*, 99(3):769-803.

Mankiw, N. G. and R. Reis (2002). "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve", *Quarterly Journal of Economics*, 107:1295-1328.

Mankiw, N. G. and R. Reis (2003). "Sticky Information: A Model of Monetary Nonneutrality and Structural Slumps", National Bureau of Economic Research Working Paper No. 8614.

Meyer, B. D. (1990). "Unemployment Insurance and Unemployment Spells", *Econometrica*, 58(4):757-782

Midrigan, V. (2010). "Is Firm Pricing State or Time Dependent? Evidence from US Manufacturing", *Review of Economics and Statistics*, 92:643-656.

Nakamura E. and J. Steinsson (2008). "Five Facts about Prices: A Reevaluation of Menu Cost Models", *The Quarterly Journal of Economics*, 123(4):1415-1464.

Nilsen, Ø. A. and M. Vange (2018). "Intermittent Price Changes in Production Plants: Empirical Evidence using Monthly Data", *mimeo*, Department of Economics, Norwegian School of Economics.

Olivei, G. and S. Tenreyro (2007). "The Timing of Monetary Policy Shocks", *American Economic Review*, 97:636–663.

Peltzman, S. (2000). "Prices Rise Faster Than They Fall", *Journal of Political Economy*, 108(3):466.

Reis, R. (2006). "Inattentive Producers", *Review of Economic Studies*, 73:793-821.

Sabbatini R., S. Fabinani, A. Gatulli, and G. Veronese (2005). "Producer Price Behaviour in Italy: Evidence from Micro PPI Data", *mimeo*, Banca d'Italia.

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

Sheshinski, E. and Y. Weiss (1983). "Optimum Pricing Policy Under Stochastic Inflation", *Review of Economic Studies*, 50(3):513-529.

SSB (2013a). "Commodity Price Index for the Industrial Sector". <http://www.ssb.no/en/priser-og-prisindekser/statistikker/vppi?fane=om>.

SSB (2013b). "Standard for Næringsgruppering (SN2002)". <http://www4.ssb.no/stabas/Items Frames.asp?ID=5556001&Language=nb>.

Taylor, J. B. (1980). "Aggregate Dynamics and Staggered Contracts", *Journal of Political Economy*, 88(1):1-23.

Taylor, J. B. (1993). "Macroeconomic Policy in a World Economy: From Econometric Design to Practical Operation", W. W. Norton.

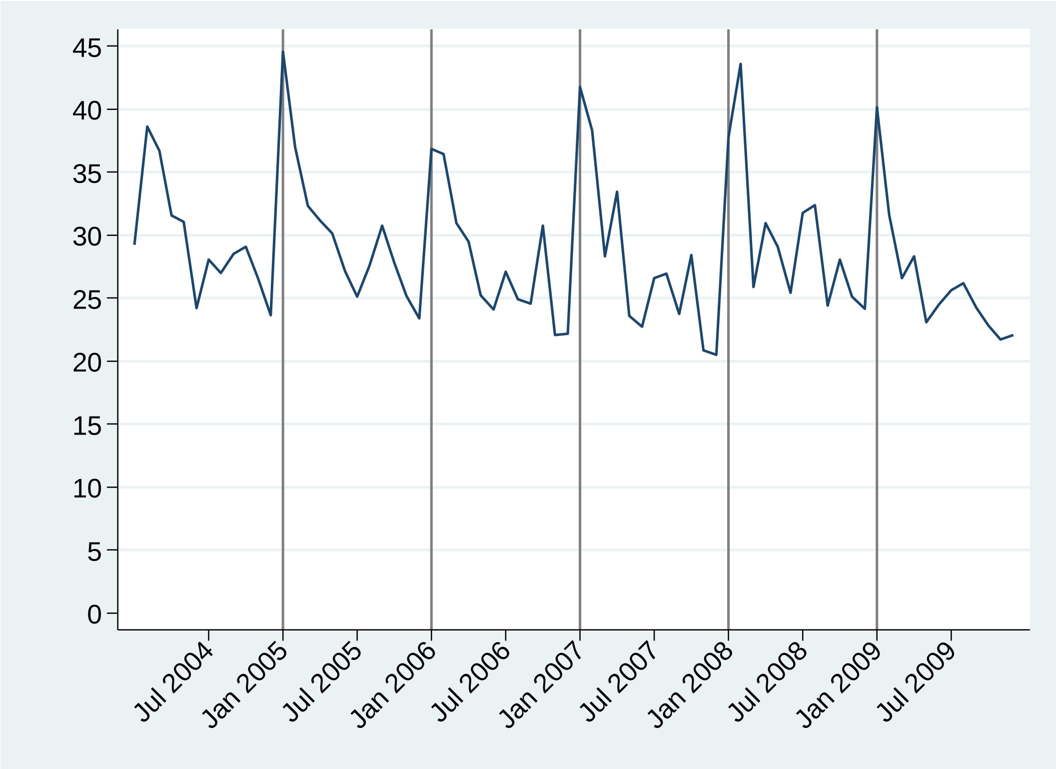
Vermeulen, P., D. Dias, M. Dossche, E. Gautier, I. Hernando, R. Sabbatini and H. Stahl (2012). "Price Setting in the Euro Area: Some Stylised Facts from Individual Producer Price Data", *Journal of Money, Credit and Banking*, 44(8):1631-1650.

Veronese, G., S. Fabiani, A. Gattulli and R. Sabbatini (2005). "Consumer Price Behaviour in Italy: Evidence from Micro CPI Data", European Central Bank Working Paper No. 449.

Wulfsberg, F. (2016). "Inflation and price adjustments: Micro evidence from Norwegian consumer prices 1975-2004", *American Economic Journal: Macroeconomics*, 8(3):175–194.

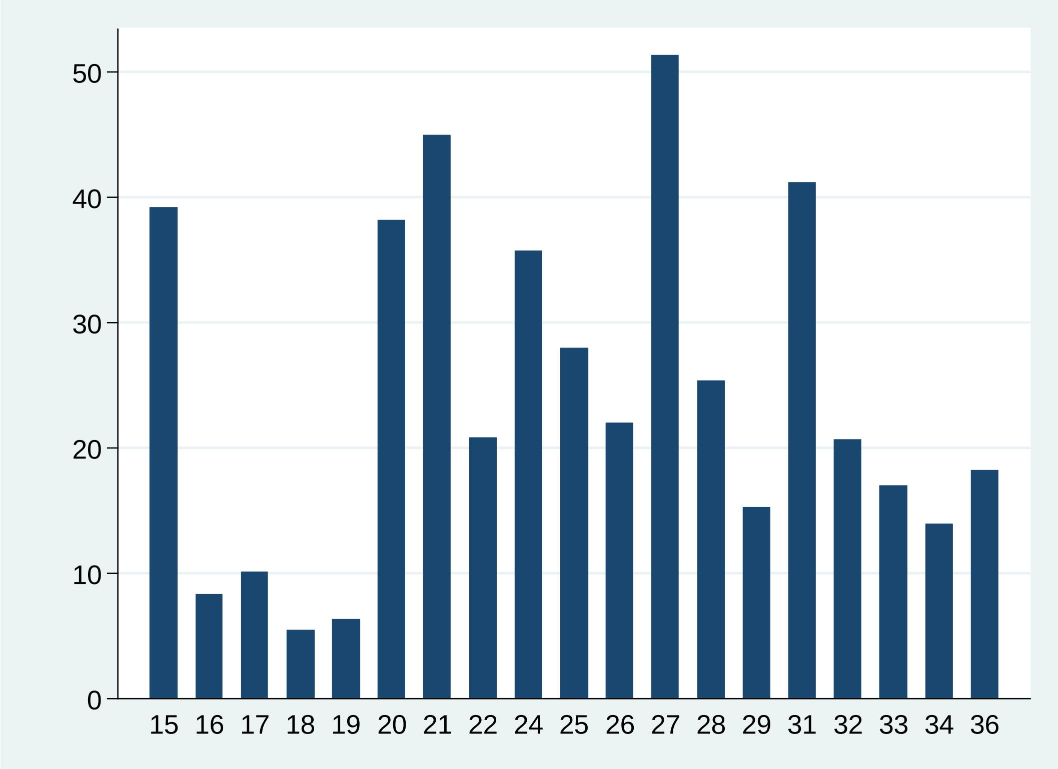
Zbaracki, M. J., M. Ritson, D. Levy, S. Dutta and M. Bergen (2004). "Managerial and customer costs of price adjustment: Direct evidence from industrial markets", *Review of Economics and Statistics*, 86(October 2015):514–533.

Figure 1: Monthly Frequency of Price Changes



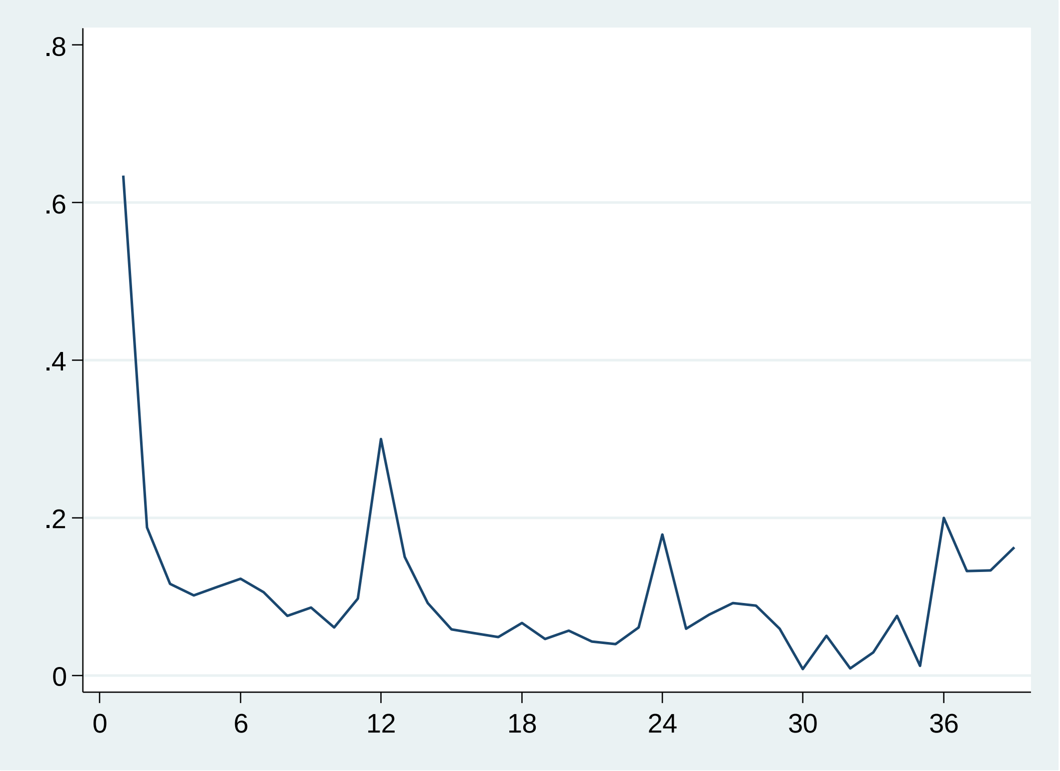
Note: Monthly frequency of producer price changes are given as the number of price changes within a month divided by the total number of price quotations in the month.

Figure 2: Average Monthly Price Change Frequencies by Industry



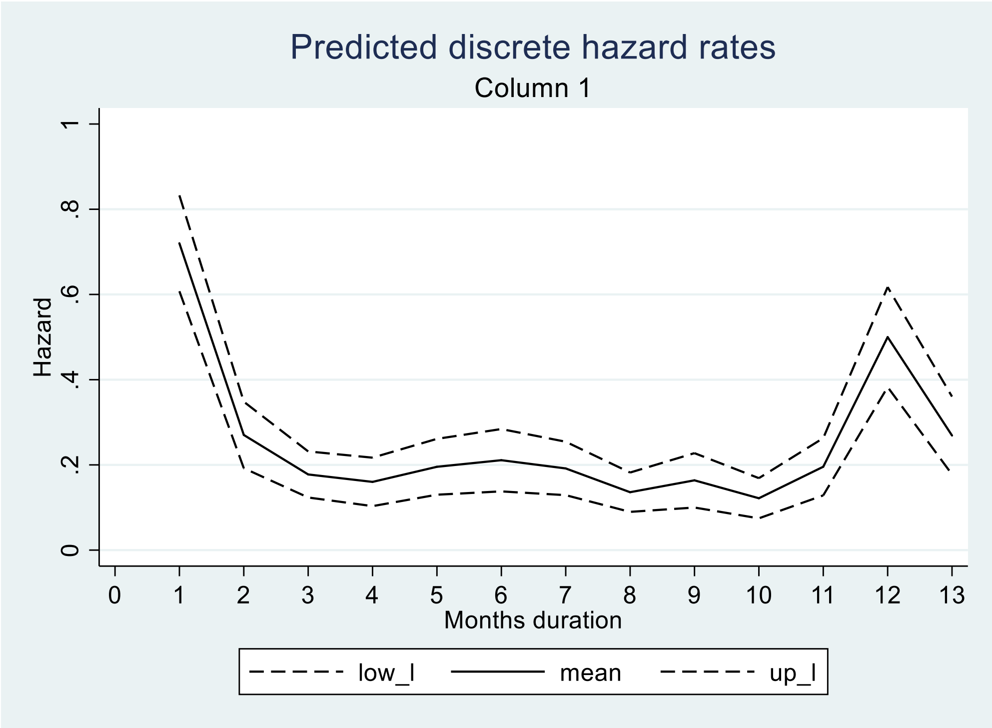
Note: The figure shows the average monthly frequency of producer price changes by different industries in the period 2004–2009. The industry codes and the number and share of price quotes corresponding to each industry are detailed in Appendix Table A1.

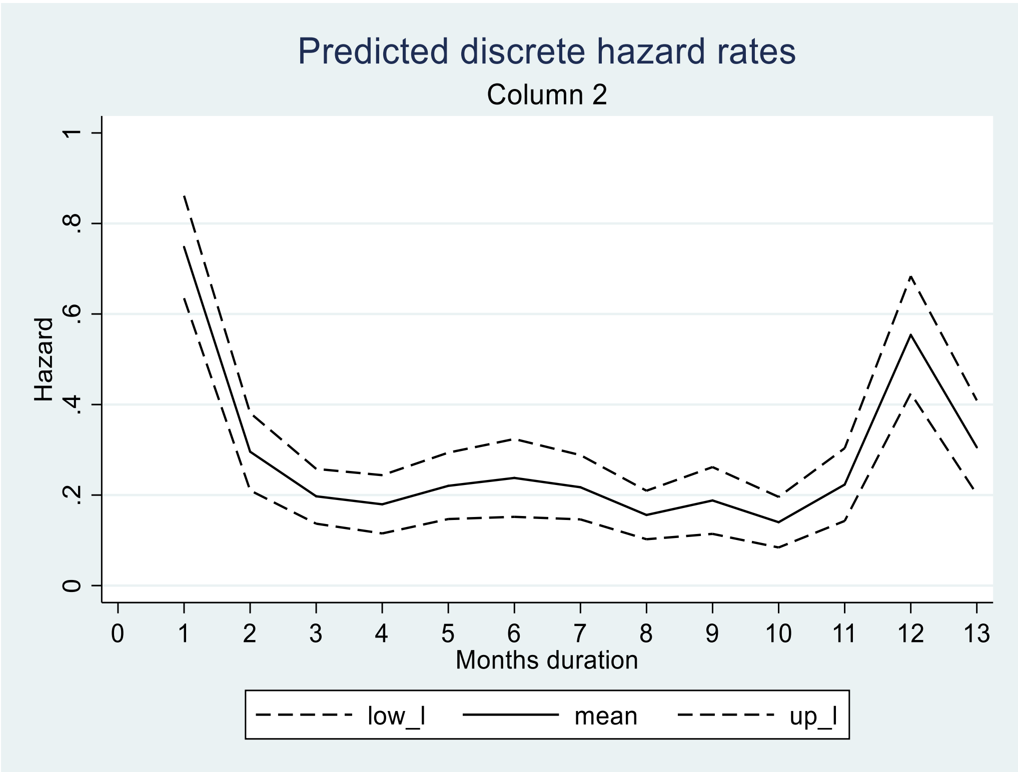
Figure 3: The Empirical Hazard Function

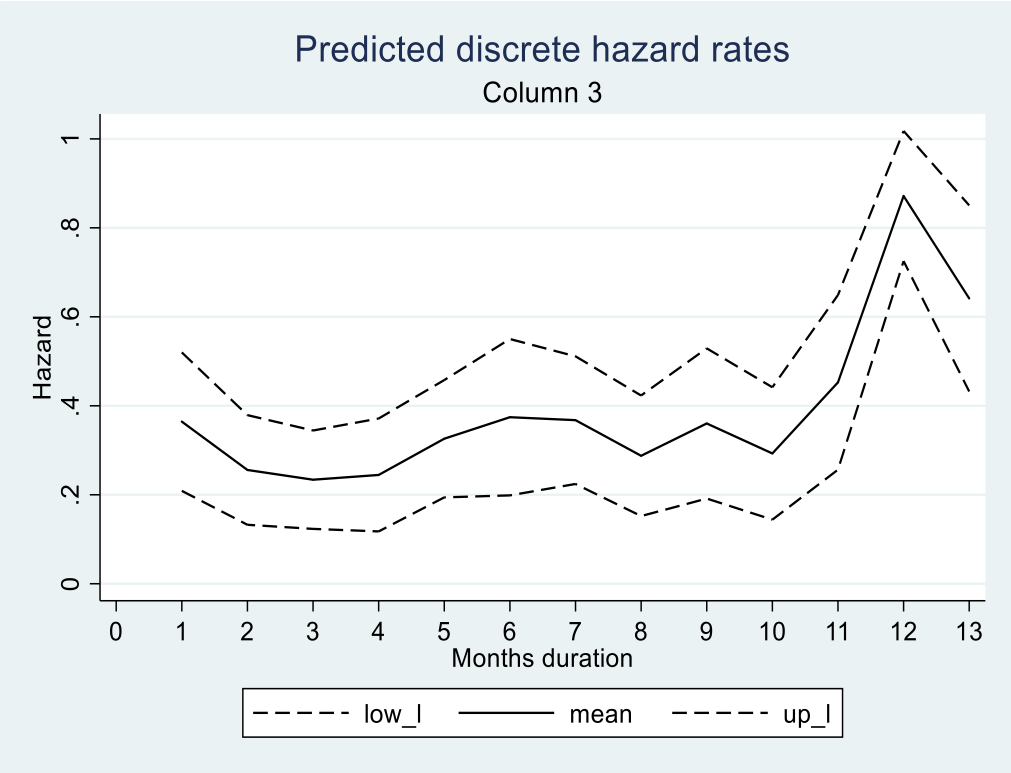


Note: The figure shows the average empirical hazard at different durations when all goods are considered together. Hazard rates are given as percentages. The horizontal axis has been terminated at 40 because of the low number of observations for older prices. Left-censored spells are discarded from the dataset.

Figure 4: Complementary log-log Regression Model Hazards

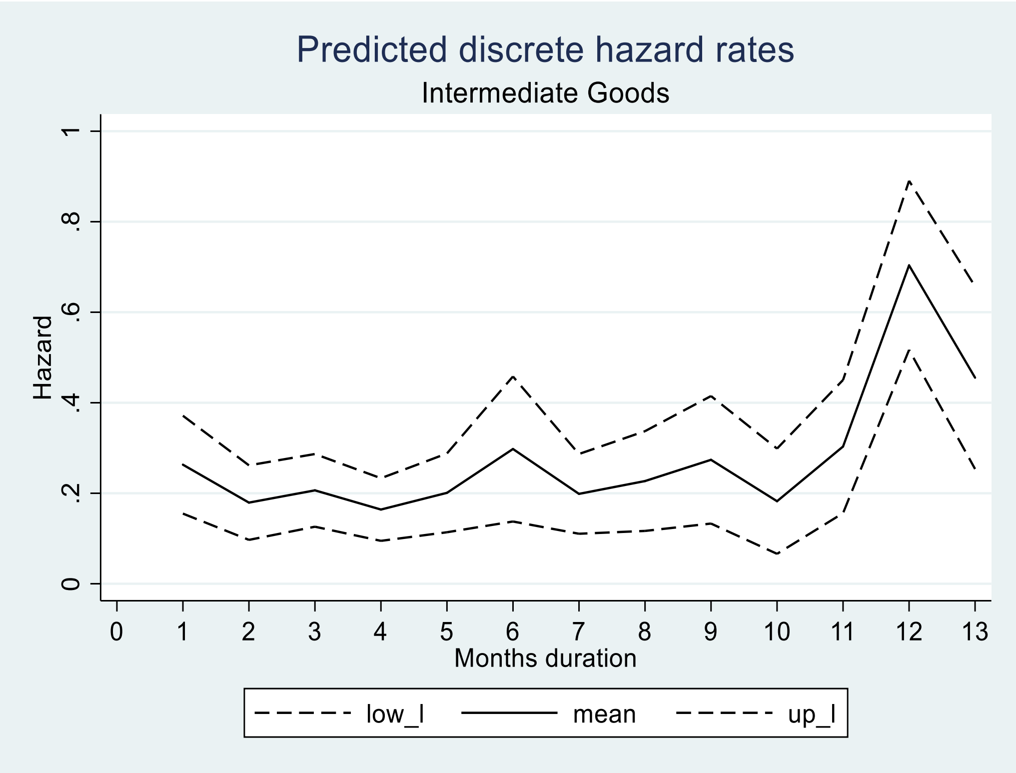


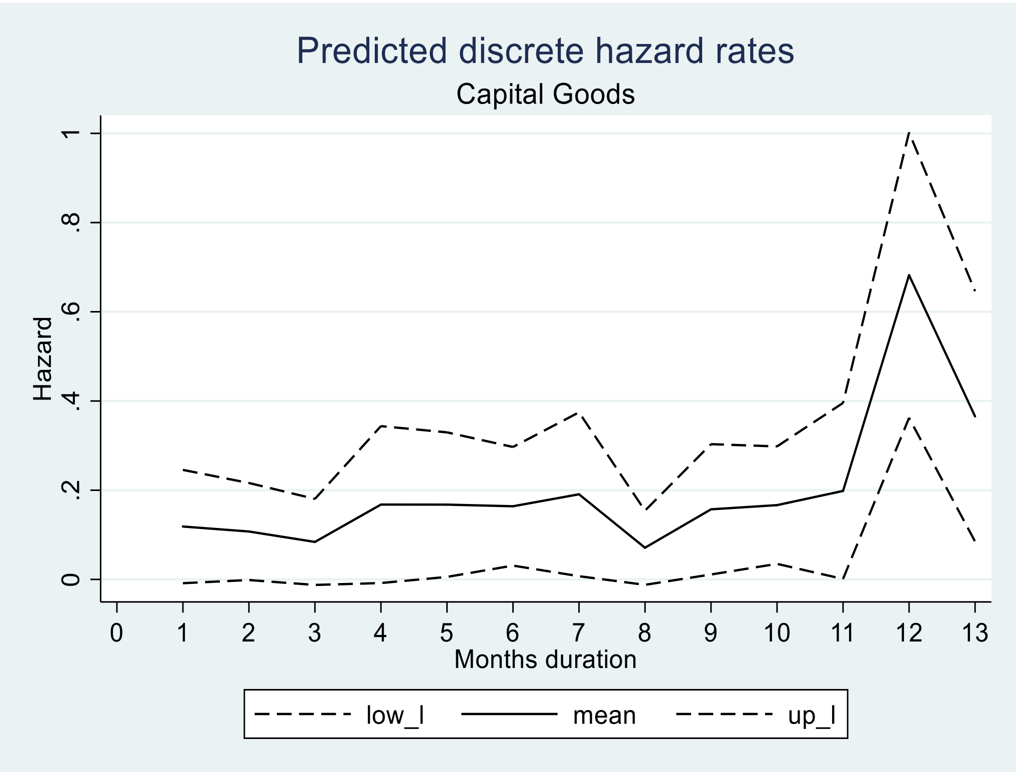


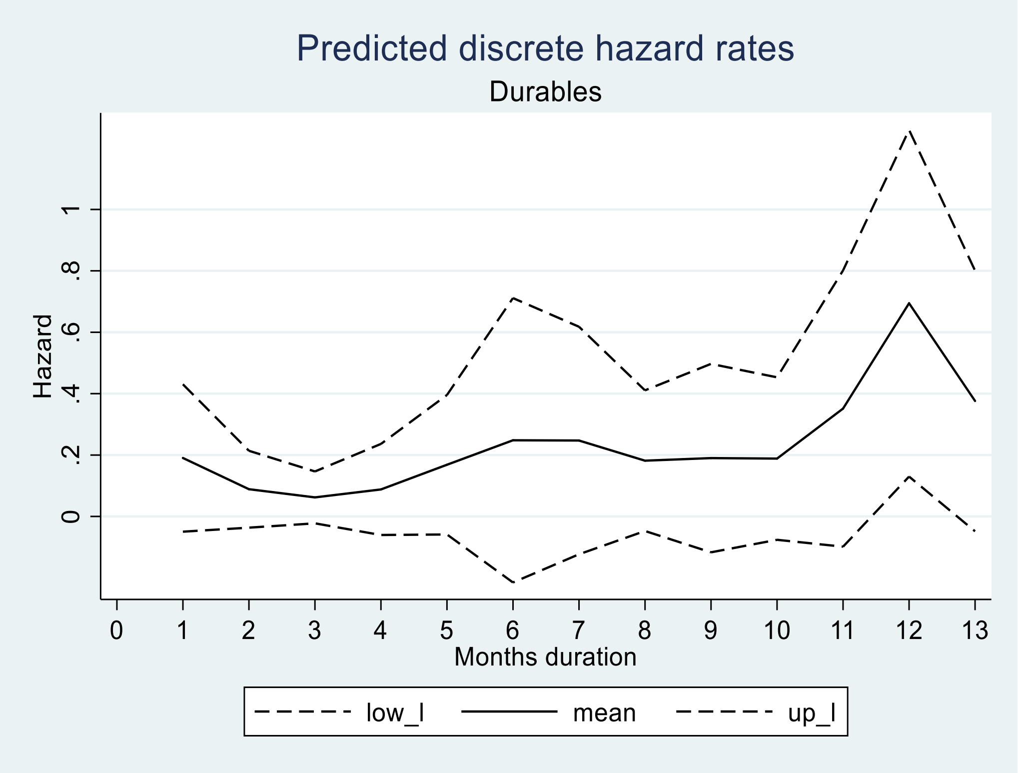


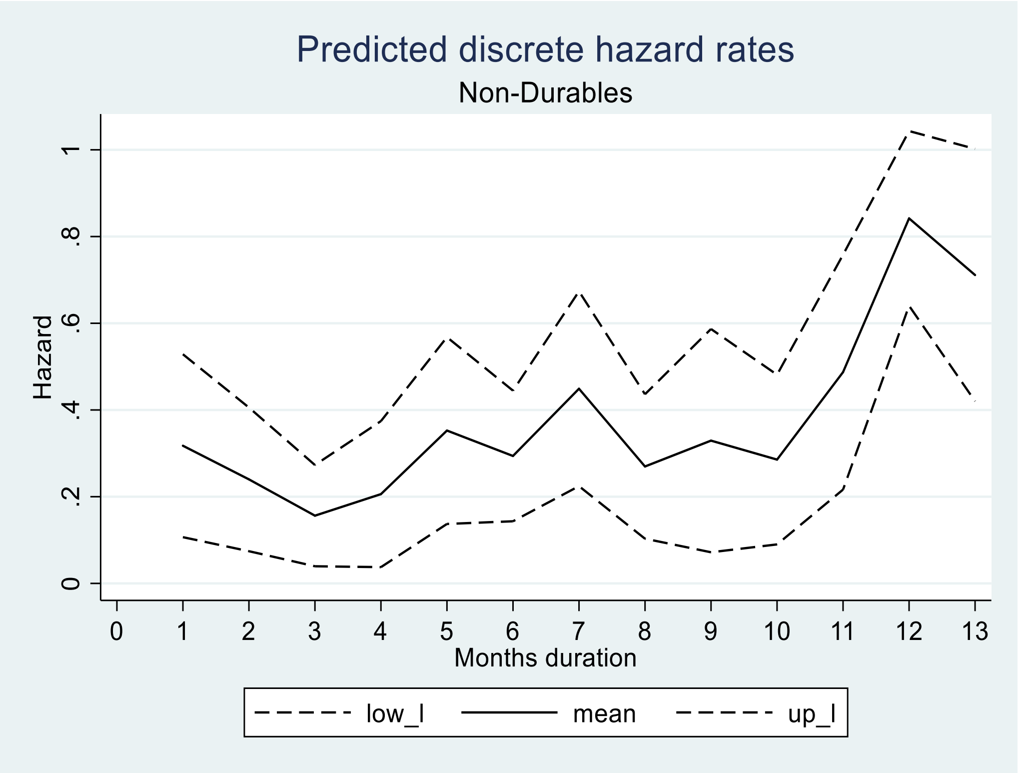
Note: The figures show the predicted hazard function for the baseline scenario, i.e. non-durable price spells that began in January (PPI are equal to 100 and the type-of-good, and starting-month dummies are equal to zero). The estimates are based on the results reported in Table 4. Hazard rates are given as percentages, and dotted lines denote the 95% confidence interval. Left-censored spells are discarded from the dataset.

Figure 5: Random Effects Complementary log-log Regression Model Hazards by Types of Goods









Note: See also notes to Figure 4.

Figure 6: Competing Risk: Complementary log-log Regression Model Hazards

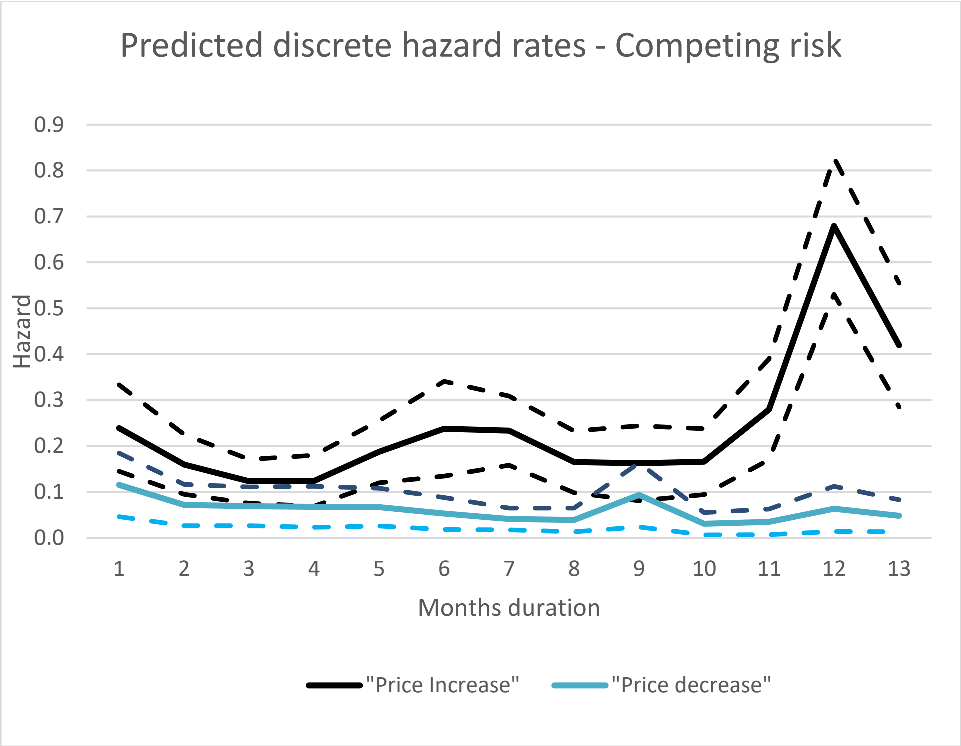


Table 1: Average Monthly Frequency of Price Changes in European Countries

	Frequency of price adjustments				
	Changes	Increases	Decreases	Fraction of price decreases	Inflation
Belgium	23.6	12.8	10.9	45.9	0.12
France	24.8	13.8	11.0	41.9	0.09
Germany	21.2	11.8	9.4	44.4	0.09
Italy	15.3	8.5	6.8	45.0	0.14
Portugal	23.1	13.6	9.5	41.2	0.17
Spain	21.4	12.2	9.2	43.2	0.17
Euro area	20.8	11.6	9.2	43.8	0.11
Norway	28.4	16.1	10.4	36.7	0.17

Note: The table reports the average monthly frequency of price changes in the years 2004 to 2009. Estimates are given in percentage. For the other European countries, the estimates are taken from Vermeulen *et al.* (2012). The Norwegian inflation figure is the monthly change in CPI in the same years.

Table 2: Average Monthly Frequency of Price Changes by Types of Goods

	Frequency of price adjustments		
	Changes	Increases	Decreases
Consumer goods			
Non-durables	31.7	17.5	12.3
Durables	18.4	10.9	5.7
Capital goods	16.1	9.6	4.6
Intermediate goods	32.1	18.0	11.9

Note: The table reports the monthly frequency of price changes in the years 2004 to 2009 for four different goods categories. Estimates are given in percentage.

Table 3: Price Spell Durations by Types of Goods

	Spells	Mean	Min.	1st quartile	Median	3rd quartile	Max.
All items	19370	3.5	1.0	1.0	1.0	3.0	72.0
Consumer goods							
Non-durables	5984	3.1	1.0	1.0	1.0	2.0	72.0
Durables	1079	5.3	1.0	1.0	2.0	9.0	52.0
Capital goods	1551	6.1	1.0	1.0	4.0	10.0	72.0
Intermediate goods	10756	3.1	1.0	1.0	1.0	2.0	72.0

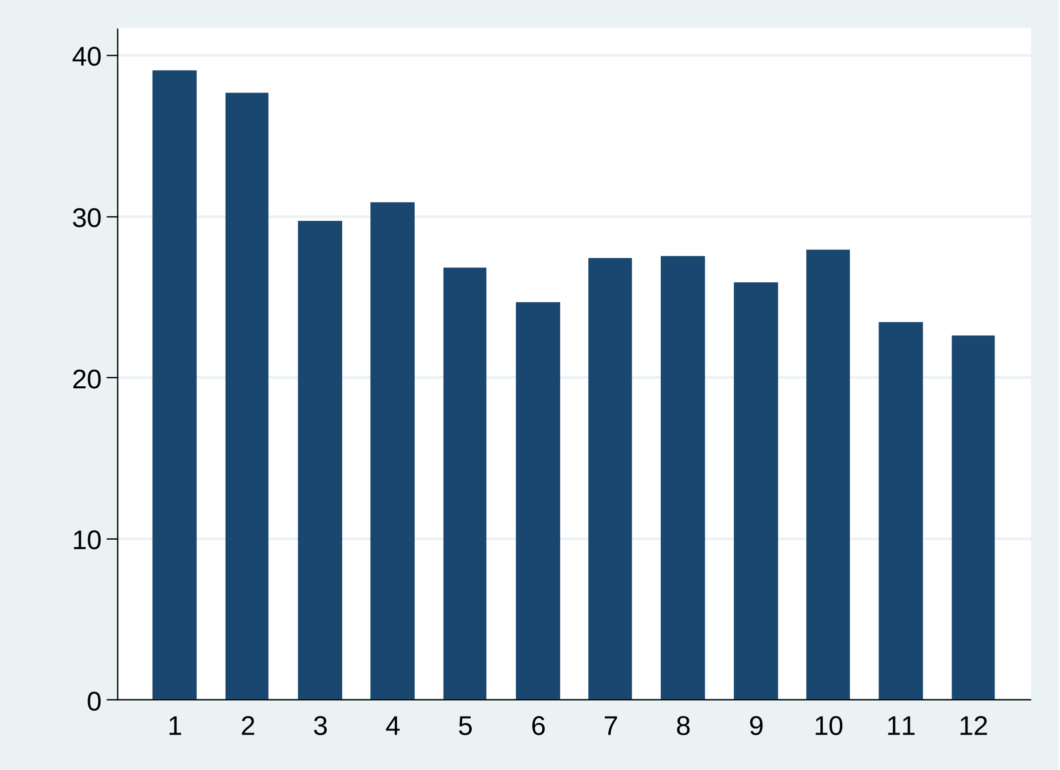
Note: Durations are given in months. The estimates are based on price spell observations in the years 2004 to 2009.

Table 4: Estimation Results of the Proportional Hazard Models

	Column 1		Column 2		Column 3	
	Margin	Std. Err.	Margin	Std. Err.	Margin	Std. Err.
Dur1	0.720	0.057	0.748	0.058	0.365	0.079
Dur2	0.270	0.040	0.296	0.044	0.256	0.063
Dur3	0.178	0.028	0.197	0.031	0.234	0.056
Dur4	0.160	0.029	0.180	0.033	0.245	0.065
Dur5	0.196	0.033	0.220	0.037	0.326	0.067
Dur6	0.211	0.037	0.238	0.044	0.374	0.090
Dur7	0.192	0.032	0.217	0.036	0.368	0.073
Dur8	0.136	0.024	0.156	0.027	0.288	0.069
Dur9	0.164	0.033	0.188	0.038	0.360	0.086
Dur10	0.122	0.024	0.140	0.029	0.293	0.076
Dur11	0.196	0.034	0.223	0.041	0.453	0.100
Dur12	0.500	0.060	0.554	0.066	0.872	0.075
Dur13	0.269	0.047	0.306	0.053	0.641	0.107

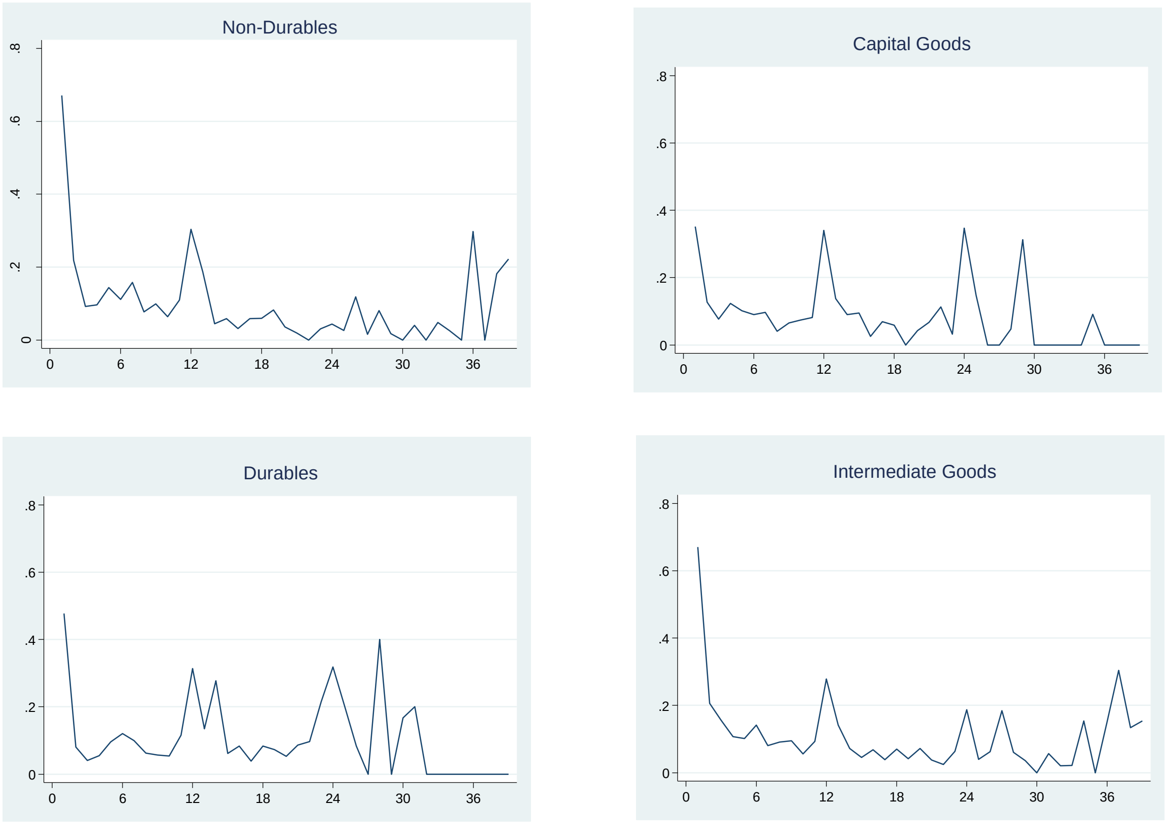
Note: Table 4, panel A reports the results from the estimation of proportional hazard models. The first row represents the hazard at month one, when all covariates are equal to zero. The reported numbers on covariates are exponentiated coefficients, while the numbers on the standard errors are those from the coefficient estimates. Duration-month dummies to characterize duration dependence are included in the regression of column 4 and 5. Exponentiated coefficient estimates of these dummies are reported in panel B.

Figure A1 – Average Frequency of Price Changes by Month



Note: The figure shows the average frequency of producer price changes in the years 2004 to 2009 by calendar month.

Figure A2 – Empirical Hazard Functions, Types of Goods



Note: The figure shows the average empirical hazards at different durations for four types of goods. Hazard rates are given as percentages. The horizontal axis has been terminated at 40 because of the low number of observations for older prices. Left-censored spells are discarded from the dataset.

Table A1: Industries Represented in the Dataset, 2-Digit SIC2002

2-digit code	Industrial activity	Number of price quotes	Share of dataset
15	Manufacture of food products and beverages	18,852	20.48
16	Manufacture of tobacco products	264	0.29
17	Manufacture of textiles	3540	3.85
18	Manufacture of wearing apparel; dressing and dyeing of fur	2064	2.24
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	360	0.39
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	9744	10.59
21	Manufacture of pulp, paper and paper products	3540	3.85
22	Publishing, printing and reproduction of recorded media	60	0.07
24	Manufacture of chemicals and chemical products	6312	6.86
25	Manufacture of rubber and plastic products	5868	6.38
26	Manufacture of other non-metallic mineral products	9228	10.04
27	Manufacture of basic metals	1104	1.20
28	Manufacture of fabricated metal products, except machinery and equipment	8664	9.41
29	Manufacture of machinery and equipment n.e.c.	9240	10.04
31	Manufacture of electrical machinery and apparatus n.e.c.	1608	1.75
32	Manufacture of radio, television and communication equipment and apparatus	1464	1.59
33	Manufacture of medical, precision and optical instruments, watches and clocks	2628	2.86
34	Manufacture of motor vehicles, trailers and semi-trailers	1944	2.11
36	Manufacture of furniture; manufacturing n.e.c.	5556	6.04

Note: Industry codes and classifications have been collected from SSB (2013b) (Norwegian classification SIC2002) and Eurostat (2005) (NACE Rev. 1.1 classification).