Price stickiness, and the hazard rate for price changes: evidence from qualitative survey data

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Draft date: October 26, 2010

Abstract

This paper develops a state-dependent pricing model of the type of Caplin & Spulber (1987) in which price changes are triggered by developments within the economy, and analyzes the determinants of the hazard rate of price changes using a duration model that allows for individual firm heterogeneity and the economic environment in which firms operate. The model is empirically estimated using a unique qualitative data set from quarterly business surveys in the manufacturing sector of the Dominican Republic. The results indicate that the hazard rate of price changes significantly increases with current and expected inflation, and this hazard also responds asymmetrically to changes in firms' costs, sales, and changes in business managers' perceptions about the economic environment. Finally, the empirical results are consistent with the predictions from state-dependent pricing models.

Keywords: Hazard Rate, Duration Models, Sticky Price

JEL Classification: C41, D21, E31

*I thank Neven Valev and participants at the Western Economic Association Annual Meeting for their suggestions. For comments, please contact the author at hav@gsu.edu.

Understanding the determinants of microeconomic price adjustment is necessary for fully specifying macroeconomic models based on aggregate price stickiness (Romer, 2006); for analyzing a set of macroeconomic issues, ranging from the welfare consequences of business cycles to optimal monetary policy (Nakamura & Steinsson, 2008); and for making policy recommendations. The approach for the analysis of the price behavior of firms shifted from studies of price adjustment for particular products (Cecchetti, 1986; Lach & Tisiddon, 1992) to studies of price adjustments based on consumer price indexes, which offer information on million of price quotes from a typical basket of consumer expenditures (Klenow & Kryvtsov, 2008; Gagnon, 2009). The general consensus from this literature is that inflation affects the probability and variability of price changes and that price adjustments takes on average about a year. However, some of the major determinants of price change decisions still remain unexplained, and the difficulties obtaining microeconomic price data that allows for individual firm characteristics continues to be an obstacle in understanding the pricing behavior of firms. In this paper, I try to address both problems.

I develop an state-dependent pricing model (or Ss model) of the type of Caplin & Spulber (1987), in which price changes are triggered by developments within the economy, to analyze the firm's decision to change its price. In order to empirically estimate this model, I use a unique data set of qualitative survey responses from quarterly business surveys in the manufacturing sector of the Dominican Republic. This data allows for individual firms' characteristics and the perception of business managers about the economic environment to estimate the determinants of the *hazard rate of price changes*. The hazard rate of price change is a measure of the probability of a firm changing its prices at time t, given the amount of time that has elapsed since the previous price change. The model also allows evaluation of differences across firms or economic sectors in the hazard rate of price changes, plus the asymmetries in the response of this hazard to changes in inflation and the economic environment in which firms operate.

I extend the work of Fougère, Bihan & Sevestre (2004), Klenow & Kryvtsov (2008), Nakamura & Steinsson (2008), Gagnon (2009) by analyzing the frequency of price changes across twenty manufacturing industries. This paper differs from previous studies in that I use a qualitative business survey that allows to track over time the firm's manager's decision to change prices.[1] The calculated mean (median) duration of price change is between 2 and 3 quarters (3 and 4 quarters), depending on the industry considered. One inconvenience of qualitative survey data is that it does not allow distinction between price changes associated with product substitutions or sales, which may significantly affect the estimates for the mean (median) price durations.[2] This information is easily inferred from Consumer Price Index (CPI) data, a common source in various studies. However, the CPI data provides no information on firms' observable heterogeneity, thus leaving unexplained some of the major determinants of price change decisions.

For this reason, the most important contribution of this paper is that I estimate a parametric hazard rate model that controls for observed firm heterogeneity to assess the effect of changes in inflation, costs, sales, and the perception of business managers about the economic environment on the hazard rate of price changes. That is, this paper shows how changes in economic conditions, like inflation, affect the timing of price changes, as suggested by state-dependent pricing models. I also examine how the hazard rate of price changes behaves over time by assuming that the baseline hazard function follows a Weibull distribution. The choice of the Weibull distribution is motivated by the work of Sichel (1991), who analyzed the duration of the United States business cycle during the post-war era.

The estimations indicate that the hazard rate of price changes significantly increases with inflation. Specifically, a 1% increase in the quarterly inflation rate raises the probability that a firm will increase its price at t, given that it has kept prices constant until that moment, by 3.5 percent. Moreover, the probability of a firm changing its price responds asymmetrically to changes in the firm's economic environment. For instance, an increase in firms' costs or sales raises the hazard rate of price changes by 13.6% and

[1] Blindet et al. 1998 also used survey data to analyze the pricing behavior of U.S. firms and to asses the validity of theories of price stickiness.

[2] See Nakamura & Steinsson (2008), Gaarder (2009), among others.

17.9%, respectively. However, when firm's cost or sales decreases, the magnitude of these effects on the hazard rate of price changes is significantly higher. The perception of firms' managers about the economic environment as favorable or unfavorable also affects this hazard. When business managers consider the economic situation to be favorable, the hazard rate of price changes increases by 11.2%, while if the economic situation is considered unfavorable, the hazard increases by 12.5 percent. The estimations also show that expectations about prices, employment, and the economic environment significantly affect business managers' price change decisions.

1 Literature Review

Until recently, the study of firm's pricing behavior was based on the collection and analysis on individual store-level prices of a consistent product over time, which limited the empirical literature on this subject. Sheshinski, Tishler & Weiss (1979) collected data on the price of noodles and instant coffee in Israel from 1965 to 1978, and they conducted one of the earliest studies on the relationship between the frequency of price changes and inflation. Although the study is criticized because the government of Israel highly controlled the prices during the period analyzed so that the data does not completely reflect individual decisions to change prices, the authors find evidence that inflation increases the frequency of price changes.

Iwai (1982) develops a menu-cost model to analyze firms' pricing decisions, where he assumes that firms face two types of cost: first, the cost to firms when they set prices different from the profit-maximizing price, and second, a costs that firms incur by changing their prices. According to this model, when the actual firm's price is above or below some threshold (far away from the profit-maximizing price) the nominal price will change. His results show that changes in the short-term profit-maximizing price and the volatility of sales increase the probability of price changes.

Following the work of Iwai (1982), Cecchetti (1986) analyzes the effect of an increase in inflation on the frequency of price adjustments using annual data on newsstand prices of thirty-eight magazines for the period 1953 to 1979. The study suggests a high degree of price stickiness in the price of magazines, and he states that the cause might be related to the high menu cost of price changes in this industry. The author uses a fixed-effects logistic model and finds a positive and significant relationship between the probability of price changes and inflation. His results also indicate that an increase in the length of time since the magazine's last price change raises the probability of price changes. Moreover, the sales growth rate also has a positive and significant effect on the probability of price changes, as Iwai (1982) demonstrates. Cecchetti concludes that there are considerable short-run and long-run effects of increases in inflation on the frequency of price changes, and that high levels of inflation increase price adjustments and reduce price stickiness.

Lach and Tsiddon (1992) collected monthly store-level data on prices for 26 different products sold in Israel during periods of high inflation. The results show that both expected and unexpected inflation have a positive and significant impact on relative price changes, and the magnitude of this effect is stronger for expected inflation. In a more recent paper, Lach and Tsiddon (1996) examine the degree to which price changes are staggered or synchronized in retail stores that sell similar products.

More recent studies use survival methods or duration models to analyze the determinants of the hazard rate of prices changes. In this direction, Fougère, Bihan & Sevestre (2004), using monthly price quotes from French outlets for the period 1994 to 2003, find that inflation increases the hazard rate of price changes. According to this study, large stores adjust prices more quickly in response to changes in cumulative inflation than small stores. In addition, they found that the estimated non-parametric hazard function for food and manufactured goods decreases over time. As we mentioned before, this result suggests that a firm will have a lower probability of changing its price the longer it has kept it unchanged. However, Alvarez, Buriel & Hernando (2005) demonstrate that the decreasing hazard function is the result of aggregating firms with different pricing rules, as described by Calvo (1983) and Taylor (1980).

The objective of this paper is to estimate the determinants of the hazard rate of price changes and to analyze how this hazard behaves over time. I focused on how inflation affects the frequency of price adjustments. For this purpose, I extend the work of Fougère, Bihan & Sevestre (2004) and estimate a parametric model in which it is assumed that the hazard rate function follows a Weibull distribution. The selection of this distribution is based on the work of Sichel (1991) on the duration of the United State business cycle during the post-war era. The results indicate that inflation positively and significantly affects the hazard rate of price changes. A second contribution of this paper is that I show empirical evidence on the predictions of the Alvarez, Buriel & Hernando (2005) model. Specifically, when I estimated the hazard rate of price changes by nonparametric techniques, I found that the hazard decreases over time, as in Fougère, Bihan & Sevestre (2004). However, using a parametric model that allows for firm's observed heterogeneity, I found that the hazard rate of price changes increases over time. That is, the probability that a firm changes its price at time t increases with the time since the previous price change.

Finally, another contribution in this paper is that I use a qualitative data set, from opinion (or business tendency) surveys at the firm level, and I show that these results are consistent with other studies based on quantitative information. I did not find any other study that uses these surveys to analyze either the frequency or the hazard rate of price changes at the firm level. The data from opinion surveys have the advantage that it is more easily available than individual firm prices collected at retail stores, and it also allows to control for observed firm heterogeneity. In addition, the OECD is working on the harmonization of business tendency surveys in more than 60 countries worldwide (see Table 1-A in the appendix), which allows extension of the study of firms' pricing behavior in many other countries. For the purpose of this study, we will only use opinion survey information from the Dominican Republic.

2 The Model

Following the Caplin & Spulber (1987) state-dependent model where firms adjust their prices in response to economic developments, I assume that price-setting follows an Ss policy in which whenever a firm i adjusts its price, it sets the price so that the difference between the optimal price and the actual price at time t, $p^*_{it} - p_{it} = \delta_{it}$, equals some target level, S_{it}. The firm will keep its price fixed until p^*_{it} has increased to the point that δ_{it} reaches a trigger level, s_{it}. Then, the firm resets $\delta_{it} = S$, and the process repeats again.

In order to understand this mechanism, suppose we start with an observation of a price change at $t = 0$, and the actual price is set so that $\delta_{i0} = p^*_{i0} - p_{i0} = S_{i0}$, or $p_{i0} = p^*_{i0} - S_{i0}$. Then, under regular circumstances, a positive and steady inflation rate p_{i0} is set above p^*_{i0}, or $S_{i0} < 0$. As time proceeds, p^*_{i0} grows steadily until it exceeds the level dictated by the rule.[3] When the change in p^*_{i0} surpasses the distance from the trigger level to the target level, $p^*_{i0} - p_{i0} \geq s_{i0} - S_{i0}$, the price will change. Therefore, the probability of observing a price change at time t, given that some time has elapsed since the previous price change, will be the probability that the change in firm i's optimal price, Δp^*_{it}, exceeds the distance prescribed by $s_{it} - S_{it}$, that is:

$$Pr\{\Delta p^*_{it} > s_{it} - S_{it}\} \tag{1}$$

where the term on the right hand side of the inequality is firm i's pricing rule at time t. We can use a hazard rate model to develop an empirical specification of equation (1), but first, we need to analyze the determinants of the optimal price change, Δp^*_{it}.

Let's assume that there is a continuum of monopolistic competitive firms that produce according to the CES production function $y_{it} = A_{it}e^{\theta_t}[k^{\rho}_{it} + l^{\rho}_{it}]^{\frac{\gamma}{\rho}}$, where k_{it} and l_{it} are capital and labor inputs, γ is a return to scale parameter, ρ is an elasticity of substitution parameter, and θ_t is the rate of technological progress, which is assumed to be constant. In addition, A_{it} is a scale component that indicates how firm i's manager perceives the

[3] In the original Caplin & Spulber (1987) model, money growth is assumed to raise p^*_{it}. In models with stochastic adjustments, p^*_{it} depends on the current state of the economy (see Caballero & Engel, 2007).

economic environment in which the enterprise operates at time t. That is, if the manager considers the economic environment as "favorable", A_{it} increases production in period t. Otherwise, production decreases.

Suppose also that firm i's demand function and cost function are given by $y_{it} = (\frac{p_{it}}{p_t})^{-\epsilon} y_t$ and $c(y_{it}, e^{\theta_t}, w_t) = y_{it}^{1/\gamma}(A_{it}e^{\theta_t})^{-1/\gamma} w_t$, respectively, where p_t is the aggregate CES price, or average price, y_t is aggregate sales (income), ϵ is the elasticity of demand, w_t denotes input prices, and γ is the same parameter defined above.[4] Now, the firm's problem is to choose a price that maximize its profits:

$$\underset{p_{it}}{\text{Max}} \{\frac{p_{it}}{p_t} - mc_t\} y_{it} \quad \text{s.t. } y_{it} = (\frac{p_{it}}{p_t})^{-\epsilon} y_t \tag{2}$$

where mc_t is the firm's marginal cost function. Setting the f.o.c. of the problem equal to zero, yields the firm optimal price, $p^*_{it} = \frac{\epsilon}{\epsilon - 1} mc_t p_t$, which is the markup pricing condition of monopolistic competition. Then, assuming that p_t grows with the inflation rate, $\dot{p}_t = \pi_t$, we can obtain an expression for the optimal price change that depends on inflation and on changes in the marginal cost function:

$$\Delta p^*_{it} = \beta_0 \pi_t + \beta_1 \dot{mc}_t = \mathbf{X}(t)\beta \tag{3}$$

Notice how the change in the firm's optimal price is positively affected by inflation. In addition, since mc_t is increasing in input prices and firm's sales, then $dp^*_{it}/dw_t > 0$ and $dp^*_{it}/dy_{it} > 0$, as well. Also, the optimal price change is negatively related to the firm manager's perception about the economic environment. That is, $dp^*_{it}/dA_{it} < 0$, if the firm's manager perceives the economic environment as "favorable"; and $dp^*_{it}/dA_{it} > 0$, otherwise.

To empirically estimate equation (3) with a hazard rate model, let T_{ki} and C_{ki} be the failure and censoring time of the k^{th} failure type ($k = 1, ..., K$) in the i^{th} cluster ($i = 1, ..., m$), and let $\mathbf{X}(t)_{ki}$ be a p-vector of (possibly time-dependent) covariates, for the i^{th} cluster with respect to the k^{th} failure type. "Failure type" is used here to mean

[4] Notice that $\epsilon > 1$ for a positive price to exist.

both failures of different types and failures of the same type, i.e., a price change. Assume that T_{ki} and C_{ki} are independent, conditional on the covariate vector, $\mathbf{X}(t)_{ki}$. Define $t_{ki} = min(T_{ki}; C_{ki})$ and $\delta_{ki} = I(T_{ki} \leq C_{ki})$ where $I(\cdot)$ is the indicator function, and let β be a p-vector of unknown regression coefficients.

The hazard rate function, which measures the probability that a firm will change its price at time t given that it has kept prices constant during the previous t periods, is defined as $\lambda(t) = \frac{f(t)}{S(t)}$, where $f(t)$ is the density function, or the frequency of firms changing prices at t, and $S(t)$ is the survival function.[5] The survival function indicates the frequency of firms which have kept prices constant during the previous t periods, and it can be defined as $S(t) = P(T \geq t) = 1 - F(t)$, where $F(t)$ is the c.d.f. of t. Cox (1972) demonstrated that the hazard function of the i^{th} cluster for the k^{th} failure type can be factored into two components: the base-line hazard $\lambda_0(t)$ that depends on time, and another function that depends on regressors alone $\phi(\mathbf{X}, \beta)$, which, for convenience, is defined as:

$$\phi(\mathbf{X}, \beta) = e^{\{\Delta p^*_{it} - (s_{it} - S_{it})\}} = e^{\{\zeta_{it} + \mathbf{X}(t)_{ki}\beta\}} \tag{4}$$

where ζ_{it} represents information about firm i's price change rule at time t. Thus, the hazard rate function is given by $\lambda_k(t, X_{ki}) = \lambda_0(t)e^{\{\zeta_{it} + \mathbf{X}(t)_{ki}\beta\}}$. To model the behavior of the base-line hazard, $\lambda_0(t)$, Kiefer (1988) suggests the use of hazard functions that adequately reflect (through their parameters) the possible events that we seek to characterize from the duration phenomenon under analysis.[6]

The economic theory will make explicit predictions about the shape of the hazard function. In other words, the pricing behavior of firms will suggest the pattern of the hazard function. For example, if firms negotiate price contracts for a fixed period, as described by Taylor (1980), we will expect the hazard rate to be zero for the initial periods, and then, to exhibit a spike at the termination of the contract. With a significant number

[5] Formally, $f(t)$ is the p.d.f. of the random variable T_{ki} at time t. This way of defining the hazard is convenient because we can find the density function by $f(t) = \lambda(t)S(t)$.

[6] For instance, if the hazard function were approximated by a normal distribution, we would find that the risk distributions obtained may not generate constant hazard rate values, which may or may not be a desirable outcome.

of firms signing multiple contracts of different lengths, we should observe multiple spikes in the hazard rate function. On the other hand, if firms have a constant probability of changing their price, as described in Calvo (1983), the hazard function will be flat. In this case, the assumption of an exponential distribution for the hazard rate function would be more suitable. For these reasons, the parametric model used in this paper assumes that the hazard rate function follows a Weibull distribution. The Weibull distribution is very convenient in statistical applications because of its ability to generate both constant and non-constant hazard rate functions (see equations 5 and 6 below). Moreover, Sichel (1991) suggested the Weibull distribution for the analysis of macroeconomic variables that are related to the business cycle.

Under the Weibull distributional assumption, the hazard rate function and the survival function can be represented as:

$$\lambda_k(t, \mathbf{X}_{ki}) = \alpha t^{\alpha-1} e^{\mathbf{X}_{ki}\beta} \tag{5}$$

$$S(t, \mathbf{X}_{ki}) = e^{-t^{\alpha} e^{\mathbf{X}_{ki}\beta}} \tag{6}$$

respectively. The shape of the Weibull hazard function depends on the parameter α. If $\alpha = 1$, the Weibull distribution will reduce to an exponential distribution and the hazard function will not depend on time. The hazard rate function increases or decreases monotonically according to whether $\alpha > 1$ or $\alpha < 1$, respectively. In other words, if the probability of a firm changing its prices increases, stay constant, or decreases over time, then the shape parameter, α, will be greater than, equal to, or lower than one, respectively.

To test the consistency of my results, I estimate two additional models: (i) the exponential hazard model, and (ii) the Cox(1972) proportional hazard model. The first, as previously mentioned, is a special case of the Weibull in which the hazard rate function is assumed to be constant ($\alpha = 1$), and the second makes no specific assumption about the distribution of the baseline hazard.

Based on the hazard and survival functions defined in 5 and 6, respectively, the density function for the i^{th} observation can be written as

$$f(t, \mathbf{X}_{ki}) = \lambda(t, \mathbf{X}_{ki})S(t, \mathbf{X}_{ki}) = \alpha t^{\alpha-1} e^{\mathbf{X}_{ki}\beta} e^{-t^{\alpha} e^{\mathbf{X}_{ki}\beta}} \quad (7)$$

Taking logs and summing, the likelihood function becomes

$$lnL = \sum_{i} \sum_{k} [\delta_{ki}\{\mathbf{X}_{ki}\beta + ln\alpha + (\alpha-1)lnt_{ki} - e^{\mathbf{X}_{ki}\beta} t_{ki}^{\alpha}\} - (1-\delta_{ki})e^{\mathbf{X}_{ki}\beta} t_{ki}^{\alpha}] \quad (8)$$

Under the assumption of independence of failure times, we can obtain the maximum likelihood estimates of β from Cox's partial likelihood function, $L(\beta)$. Lin (1994) showed that the estimator $\hat{\beta}$ is a consistent estimator for β and is asymptotically normal as long as the marginal models are correctly specified. Since the model allows for multiple failures of the same type, failure times might be correlated within individual firms. Therefore, the resulting estimated covariance matrix, obtained as the inverse of the information matrix $I^{-1} = -\frac{\partial logL(\beta)}{\partial\beta\partial\beta'}$, will not take into account the additional correlation in the data, and would not be appropriate for testing or constructing confidence intervals for multiple failure data. However, Lin and Wei (1989) proposed a modification to this estimate. The resulting robust variancecovariance matrix is obtained from $V = I^{-1}U'UI^{-1}$ where U is an $n \times p$ matrix of efficient score residuals. This formula assumes that the n observations are independent. When observations are not independent, but can be divided into m independent groups $(G_1, G_2..., G_m)$, then the robust covariance matrix takes the form $V = I^{-1}G'GI^{-1}$.

The Ss model predicts that firms will keep nominal prices fixed until the point that inflation increases the firm's optimal price p^{*}_{it} to a critical level, at which time the firm will change the nominal price. For this reason, the vector X_{ki} introduces the variable $Inflation_t$, which is measured as the quarterly growth rate of the consumer price index (CPI) at time t. Similar to the empirical results from non-conditional probabilistic models, such as Cecchetti (1986), I expect that the inflation rate will have a positive and significant effect on the hazard rate of price changes.

If the managers of firms and retail shops freely adjust prices in response to economic events, then this pricing behavior can be captured by variables reflecting the economic situation that is currently facing the company. The model shows that a favorable economic environment decreases the firm's marginal cost function, mc_t, and an unfavorable economic environment increases mc_t. Therefore, the firm's optimal price is inversely related to the manager's perception of the economic situation as well. That is, $dp^*_{it}/dA_{it} < 0$, if the firm's manager perceives the economic environment as "favorable", and $dp^*_{it}/dA_{it} > 0$, otherwise. I introduce the variables $Favorable_{it}$, which equals 1 if firm i's manager perceives the economic situation as favorable at time t, and zero otherwise, and $Unfavorable_{it}$, which equals -1 if the economic situation is perceived as unfavorable, and zero otherwise. I expect that a favorable (unfavorable) economic environment will decrease (increase) the hazard rate of price changes. In addition, since mc_t is increasing in input prices and firm sales, then $dp^*_{it}/dw_t > 0$ and $dp^*_{it}/dy_{it} > 0$, as well. Thus, the model includes $Cost\_inc_{it}$ ($= 1$ if cost increases, 0 otherwise), $Cost\_dec_{it}$ ($= -1$ if cost decreases, 0 otherwise), $Sales\_inc_{it}$ (=1 if sale increases, 0 otherwise), and $Sales\_dec_{it}$ ($= -1$ if sale decreases, 0 otherwise). Similar to the results from Iwai (1982), Cecchetti (1986), and Buckle & Carlson (2000), I expect that an increase (decrease) in firm sales and input prices will affect this hazard rate positively (negatively) and significantly.

Other studies suggest that firms' observe heterogeneity, such as size and industry sector, will affect the hazard rate of price changes. For instance, Fougère, Bihan & Sevestre (2004) find that firm size is an important determinant of the frequency of price adjustments. Specifically, they show evidence that large outlets adjust prices more often than small ones, and also modify prices more promptly in response to inflation than their smaller counterparts. This suggests a faster adjustment to changes in the competitiveness of one group of firms with respect to other firms in the same group. According to these authors, large firms may have a better ability to observe and react to those changes than small firms. Their study also indicates that the hazard rate for price changes differs across different types of products, such as food and clothing. Thus, I include $Empl50_{it}$ and $Empl250_{it}$ as dummy variables that capture if the firm's total number of employees is either less or equal to 50, or greater than 250 at time t, respectively, to account for the effect of industry size on the hazard rate. Moreover, I control for 20 industry sectors in which the sample is classified to account for observed heterogeneity effects on the hazard rate. I expect that the hazard rate will be higher for firms with more than 250 employees compared to small firms with less than 50 workers. Finally, if the industry's competitiveness is relevant to the determination of prices, we can expect that companies exposed to international markets will not only modify their prices according to changes in the local economy, but in response to changes in the international environment as well. I include the variable $Export_i$, which takes the value 1 if company i exports its main product, and 0 otherwise, to account for the effect of international competitiveness on the hazard rate. I expect that exporter firms will have a higher hazard rate than non-exporter companies.

3 The Data

The sample consists of an unbalanced panel with quarterly information from the first quarter of 1995 (1995q1) to the third quarter of 2007 (2007q3). The information is obtained from managers who report whether their firm's main product price has increased, not changed, or decreased during the current period. The same information is reported on costs, sales, and production for the firm's main product. In addition, the survey includes information on the number of employees from each firm, and whether or not the firm exports its product (net exporter). All responses are coded so that any variable reported as increasing is coded as +1, no change as 0, and decreasing as -1. The sample corresponds to the manufacturing sector of the Dominican Republic and it is divided into 20 industries, according to the International Standard Industrial Classification (ISIC, 3rd revision), with a total of 10,650 observations. The Central Bank of the Dominican Republic conducts this survey.

Table 1 shows summary statistics for the variables of interest. To obtain the duration variable, $Duration_{it}$, I recorded the number of periods that a firm takes to change its price. According to this information, manufacturing firms take an average of 3.7 quarters to change their prices, which is similar to the information reported in Blinder (1998), Bils & Klenow (2004), and Klenow & Kryvtsov (2004). These authors used information from firm surveys and the CPI basket index, and they found the frequency of price adjustments is between 6 months and a year for firms in the United States. The variable $Price\_change_{it}$ indicates the time of occurrence of the price change and it takes the value of 1 if firm i increases or decreases its prices at time t, and zero otherwise. Since firms are followed for the period 1995q1 to 2007q3, the data includes multiple price-change events for the same firm, i. In other words, firm i might have changed its price on more than one occasion during the period analyzed. In this study, I consider additional failures as different firms change their prices over time.

Figure 1 shows the annualized quarterly inflation rate and the consumer price index series of the Dominican Republic, during the period 1995q1 to 2007q3. The shaded area highlights the quarters between 2002q3 and 2004q3, in which the country went through the worst banking and currency crisis in its history. In these two-years, the average quarterly annualized inflation rate was 41.1%, which contrasts significantly with the average of 6.9% observed during the pre-crisis period from 1995q1 to 2002q2. In August 2004, new authorities took control of the central bank, and re-oriented the monetary and exchange rate policies of the country. Their inmediate response was to sell certificates of deposits (CD's) to the public and to reduce the money supply, in order to return the inflation rate close to its long-term growth rate. As a result, the average annualized inflation rate dropped to 5.5% in the post-crisis period from 2004q4 to 2007q3.

Table 2 illustrates the manufacturing sector industrial classification adopted in this paper. The sample excludes government enterprises, sugar production factories, oil refinement companies and free-zone (maquilas) firms. The Central Bank of the Dominican Republic surveys 280 companies every quarter, of which 68% are located in the capital (Santo Domingo), and 32% are located in the rest of the country. Due to their high representation, 40% of the firms in the sample are chosen by obligatory selection, and the remaining 60% are selected randomly. The interviews are personal (or direct), at the

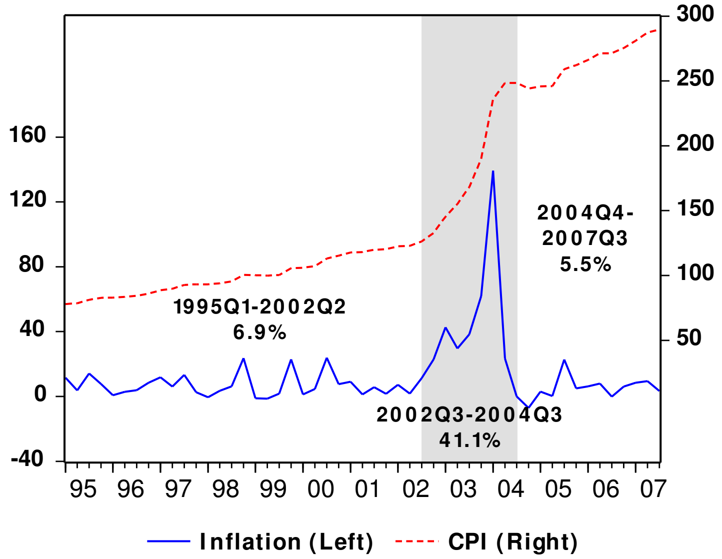

Figure 1: Annualized Inflation Rate & Consumer Price Index.

Table 1: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
$Duration_{it}$	3.69	4.11	1	19
$Price\_change_{it}$	0.38	0.49	0.00	1.00
$Inflation_t$	11.85	13.37	-0.98	62.32
$Cost\_up_{it}$	0.70	0.46	0.00	1.00
$Cost\_down_{it}$	0.00	0.07	0.00	1.00
$Sales\_up_{it}$	0.34	0.47	0.00	1.00
$Sales\_down_{it}$	0.40	0.49	0.00	1.00
$Employees_{it}$	174.28	360.29	0.00	6171.00
$Empl50_{it}$ (=1 if Empl $\leq$ 50)	0.41	0.49	0.00	1.00
$Empl250_{it}$ (=1 if Empl $\geq$ 250)	0.18	0.39	0.00	1.00

Source: Author's calculations from the sample.

managerial level, and the average response rate of the survey is approximately 71%.[7] As noted, the food industry is the largest in terms of the number of companies in the sector, representing 33.8% of the sample. The chemical products industry is the second largest. These industries are time-invariant regressors and they are introduced through dummy

[7] The average response rate of the survey is computed as the average percentage of all enterprises that completely responded to the questionnaire for the period 2000q1 to 2007q3.

variables.

Table 2: Industrial classification

Industry	Freq.	Percent	Cum.
Food	3,604	33.84	33.84
Tobacco	228	2.14	35.98
Textiles	397	3.73	39.71
Clothing	704	6.61	46.32
Leather	269	2.53	48.85
Wood	185	1.74	50.58
Paper	248	2.33	52.91
Publishing	588	5.52	58.43
Coke	11	0.1	58.54
Chemicals	1,107	10.39	68.93
Plastic	588	5.52	74.45
Mineral	717	6.73	81.18
Metals	123	1.15	82.34
Metal Products	700	6.57	88.91
Machinery	109	1.02	89.93
Electrical Machinery	96	0.9	90.84
Communication equipments	11	0.1	90.94
Medical Instruments	128	1.2	92.14
Vehicle	178	1.67	93.81
Furniture	659	6.19	100
Total	**10,650**	**100**	—

Source: International Standard Industrial Classification (ISIC), 3rd revision, and author's calculations from the sample.

4 Results

Before estimating the full model presented in equation (8), it is useful to observe the shape of the non-parametric hazard rate (or survival) function to understand how the process of price changes evolves over time. Figure 2 shows the Kaplan-Meier survival estimate for price changes as a function of time. This indicator shows the probability that a firm does not change its price (survival) beyond the first two quarters decreases by more than 50 percent. In other words, the probability that a firm does not change its price in the period of one quarter is almost 100%. However, for the second quarter this probability is less than 50%, and it has a slow decay thereafter. Figure 3 presents the hazard function for price changes. The hazard rate function is initially increasing, up to approximately 8 periods, and then continuously declines over time. As mentioned earlier, the decreasing shape of the hazard rate suggests that a firm will have a lower probability of changing its price the longer it has kept it unchanged, which is a common finding in empirical studies using micro level information.

Alvarez, Burriel & Hernando (2005) state that the decreasing hazard rate of price changes is the result of aggregating heterogeneous firms that use different pricing rules, such as those of Calvo (1983) and Taylor (1980). They demonstrate that the aggregation of agents following different pricing rules with non-decreasing hazard functions generates a decreasing hazard function. Intuitively, the probability of a price change is higher for companies with flexible pricing rules than for firms with sticky pricing schemes, and therefore, when they estimate the hazard function for all firms in aggregate, the proportion of price changes corresponding to firms that follow flexible pricing rules decreases over time. Consequently, we observe initially that the hazard rate increases and then decreases consistently as the time horizon expands. Finally, Figure 4 shows the hazard rate function for food ($Food = 1$) and non-food ($Food = 0$) industries.

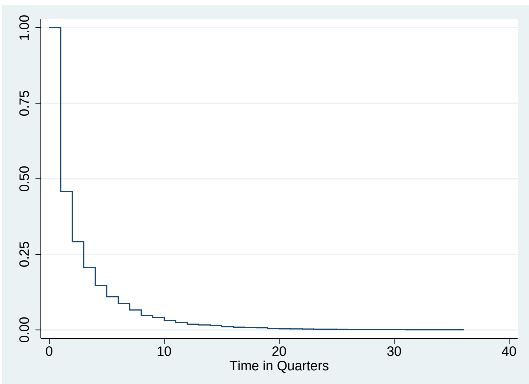

Figure 2: Kaplan-Meier survival estimate for price change.

Figure 4 shows the estimated hazard rate for price changes using the Cox (1972),

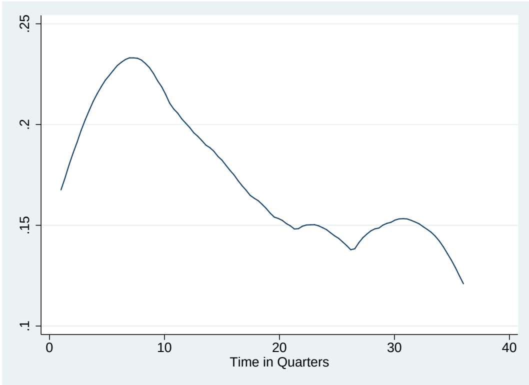

Figure 3: Smoothed estimated hazard rate for price changes.

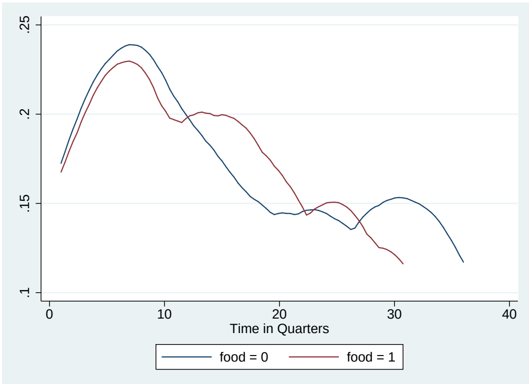

Figure 4: Smoothed estimated hazard rate for price changes.

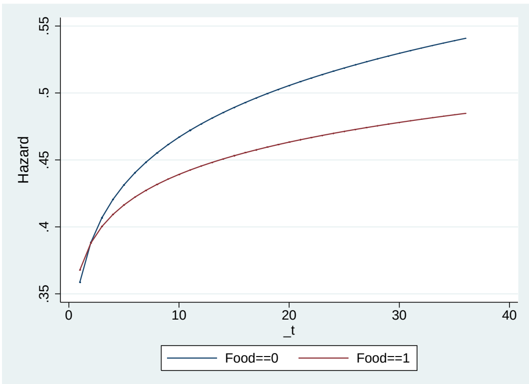

Figure 5: Base-line hazard rate for Food & non-Food industries.

Weibull, and Exponential models. Although the Cox (1972) model presents the highest log-likelihood (LL) ratio, the Akaike and Bayes information criteria suggest that the

Weibull is the best fit. Moreover, most of the estimated coefficients are highly significant even at the 1% confidence level with this model. For these reasons, and based on the results of the Weibull specification, I conclude that the inflation rate positively and significantly affects the hazard rate of price changes. Specifically, a 1% increase on the inflation rate raises the hazard rate of price changes by 1.8%. This result is consistent with Cecchetti (1986), who determines that a 5% increase in inflation raises the probability of price changes by 0.1 (or 10%), and Kashyap (1995), who concluded that the price of a good is changed by almost 10 percent after inflation has eroded its real price.

As the model predicted, an increase in firms' costs or sales raises the hazard rate of price changes. However, the results suggest that firms appear to be less likely to modify their prices when their costs decrease, since the coefficient in the $Cost\_down_{it}$ variable is negative and not statistically significant. Also, an increase or decrease in sales has almost a symmetrical effect on the hazard of price changes. That is, an increase in firm sales raises the hazard by 18.3%, while a drop in firm sales raises this hazard by 17.4 percent. Furthermore, the economic environment affects the firm's decision to modify its prices. For instance, a favorable economic situation reduces the hazard rate of price changes by 8.2%, while an unfavorable economic situation increases the hazard rate by almost 18 percent. In other words, firms seem to have less incentive to modify their prices when they perceive a good economic environment, compared to an unfavorable environment. This is because, in the model, a favorable (unfavorable) economic environment is associated with exogenous factors that decrease (increase) the firm's marginal cost function and, therefore, affect the firm's optimal price, p^*_{it}.

The estimations support the hypothesis about how the degree of industry's competitiveness affects the hazard rate of price changes. The coefficient on $Exporter_i$ indicates that exporting firms have a higher hazard rate (4% higher) than non-exporting companies, which might be attributed to the higher degree of competition faced by exporting firms on international markets. That is, exporting firms seem to adjust their prices more frequent than non exporters as a response to changes in international markets. However, the coefficient on this variable is not statistically significant. In addition, the estimates of the coefficients of company size variables proved to be very different from those found by Fougère, Biham & Sevestre (2004). First, these estimates indicate that firm size does not significantly affect the hazard rate of price changes. Second, unlike Fougère et al., I found that small firms are more likely to modify their prices than their larger counterparts. That is, firms with less than 50 employees have a higher hazard rate of price changes than firms with more than 250 employees. Also, observed heterogeneity in industry sector significantly affects the hazard rate. The coefficient on the variable $Food_i$ indicates that the hazard rate for manufacturing food industries is 60% less than the hazard rate of non-food industries. Similarly, the hazard rate of the Tobacco and Mineral industries are 79% less and 42% less, respectively, than that of the industries outside these groups.

Finally, when I estimated the parametric baseline hazard under the Weibull distributional assumption, $\lambda_0(t) = \alpha t^{\alpha-1}$, I found that the parameter α of the distribution is significantly greater than one ($\alpha = 1.175$), suggesting that the hazard rate of price changes increases with the time elapsed between price changes. Figure 5 shows the estimated baseline hazard for food and non-food industries under the Weibull distributional assumption. As noted, the hazard rate of price changes is significantly higher for non-food industries than for food manufacturing industries. This chart stands in contrast to the nonparametric hazard rate estimated in Figures 2 and 3, which are decreasing due to the aggregation of heterogeneous firms with different pricing rules, as discussed above.

5 Conclusions

This paper develops an Ss model of the type of Caplin & Spulber (1987) and uses a unique data set from business opinion surveys in the manufacturing sector of the Dominican Republic to analyze the determinants of the hazard rate of price changes through a duration model that allows for individual firm characteristics and the economic environment in which these firms operate. Based on the work of Sichel (1991), I assumed that the hazard function follows a Weibull distribution. To test the consistency of the results,

Table 3: Estimated hazard rate for price changes under different distributional assumptions.

	Cox	**Weibull**	**Exponential**
$Inflation_t$	1.010***	1.018***	1.015***
	(0.001)	(0.001)	(0.001)
$Cost\_up_{it}$	1.131***	1.173***	1.158***
	(0.033)	(0.039)	(0.036)
$Sales\_up_{it}$	1.144***	1.183***	1.166***
	(0.039)	(0.045)	(0.042)
$Cost\_down_{it}$	0.94	0.99	0.98
	(0.195)	(0.228)	(0.212)
$Sales\_down_{it}$	1.160***	1.174***	1.170***
	(0.038)	(0.042)	(0.040)
$Situation\_up_{it}$	0.96	0.918**	0.936**
	(0.030)	(0.033)	(0.031)
$Situation\_down_{it}$	1.155***	1.175***	1.168***
	(0.036)	(0.040)	(0.038)
$Exporter_i$	1.02	1.04	1.03
	(0.031)	(0.047)	(0.039)
$Empl50_{it}$ (=1 if Empl $\leq$ 50)	0.99	1	0.99
	(0.029)	(0.045)	(0.037)
$Empl250_{it}$ (=1 if Empl $\geq$ 250)	0.98	0.93	0.95
	(0.037)	(0.058)	(0.048)
$Food$	0.589***	0.396***	0.475***
	(0.064)	(0.070)	(0.069)
$Tobacco$	0.391***	0.208***	0.277***
	(0.070)	(0.060)	(0.066)
$Textiles$	0.561***	0.382***	0.454***
	(0.068)	(0.074)	(0.072)
$Clothing$	0.541***	0.345***	0.422***
	(0.065)	(0.068)	(0.068)
$Leather$	0.496***	0.313***	0.386***
	(0.068)	(0.071)	(0.071)
$Wood$	0.550***	0.350***	0.430***
	(0.077)	(0.080)	(0.080)
$Paper$	0.606***	0.430***	0.503***
	(0.076)	(0.086)	(0.082)
$Publishing$	0.563***	0.379***	0.453***
	(0.067)	(0.073)	(0.072)
$Chemicals$	0.532***	0.342***	0.418***
	(0.060)	(0.063)	(0.063)

Plastic	0.624***	0.453***	0.523***
	(0.073)	(0.086)	(0.081)
Mineral	0.712***	0.576***	0.635***
	(0.080)	(0.105)	(0.094)
Metals	0.536***	0.344***	0.419***
	(0.082)	(0.081)	(0.083)
Metal_Products	0.545***	0.337***	0.420***
	(0.065)	(0.067)	(0.068)
Machinery	0.664***	0.490***	0.563***
	(0.092)	(0.109)	(0.103)
Electrical_Machinery	0.467***	0.319***	0.376***
	(0.084)	(0.079)	(0.081)
Communication_equipment	0.511**	0.382***	0.438***
	(0.140)	(0.106)	(0.120)
Medical	0.562***	0.383***	0.454***
	(0.088)	(0.091)	(0.091)
Vehicle	0.681***	0.518***	0.588***
	(0.087)	(0.109)	(0.101)
Furniture	0.560***	0.369***	0.445***
	(0.065)	(0.068)	(0.067)
LL	-30582.46	-5268.798	-5371.02
AIC	61222.92	10599.6	10802.03
BIC	61433.84	10825.07	11020.23
Observations	10,650	10,650	10,650

Robust standard errors in parentheses

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

I also estimate the Cox (1972) proportional hazard model and the Exponential hazard model. The Log-Likelihood ratio and the Akaike and Bayes information criteria indicated that the the Weibull form is the best fit. The results can be summarized as follows:

(i) The estimated non-parametric hazard rate of price changes is decreasing over time (negative duration dependence), which suggests that a firm will have a lower probability of changing its price the longer it has kept it unchanged. This behavior is explained by the process of aggregating heterogeneous firms that follow different pricing rules, as described by Taylor (1980), Calvo (1983), and Alvarez, Buriel & Hernando (2005). Under the Weibull distributional assumption, the base line hazard is increasing over time (positive duration dependence) implying that the probability of a firm's price change at time

t increases with the time since the last price change. This result is consistent with state dependent pricing models in which the firm's optimal price, p^*_{it}, grows steadily over time until it exceeds a level imposed by the price setter causing the firm to modify its actual price, as predicted in Caplin & Spulber (1987). Therefore, by comparing our first results of decreasing hazard function, correcting for firms' heterogeneity, and then finding evidence of an increasing hazard rate for price changes, this paper offers empirical empirical evidence on the predictions from state-dependent pricing models.

(ii) The results show that a 1% increase in the inflation rate significantly increases the hazard of price changes by almost 1.8 percent. This result is consistent with the predictions found in Cecchetti (1986), Lach & Tsiddon (1992), Buckle & Carlson (2000), and Fougère, Bihan & Sevestre (2004), who analyze the determinants of the probability of a firm's price change using non-conditional probabilistic, or non-parametric, models.

(iii) Increases in firms' costs or sales raise the hazard rate of price changes. However, the estimations indicate that firms are less likely to modify their prices when costs decrease, suggesting some degree of asymmetry in the response of the hazard rate to changes in production costs. As shown in Iwai (1982), the increase or decrease in firms' sales positively and significantly affects this hazard. Moreover, the economic environment affects companies' decision to change their prices, as suggested in state dependent models where the pricing behavior of firms depends on the economic situation. Specifically, when employers consider the economic situation as favorable, the hazard rate of price changes decreases by 8.2%, while if the economic situation is considered unfavorable, the hazard rate increases by 18 percent.

(iv) Finally, the estimations of the hazard rate of price changes using qualitative data are consistent with other quantitative empirical studies, suggesting that business opinion surveys contain important and useful information for analyzing the pricing behavior of individual firms. The OECD has standardized these surveys over 60 countries worldwide, thus facilitating the study of the pricing policies of firms. As Caballero & Engel (2007) indicate, it is important to understand the relationship between price stickiness at the firm level and aggregate price stickiness in order for studies documenting the frequency of price changes to be useful in macroeconomics. For instance, although the standard Ss state-dependent model shows a degree of price rigidity at the firm level, under certain circumstances this model shows that monetary expansions have no effect on output. This is because the process of firm aggregation erases the impact of microeconomic price stickiness. Therefore, it is important to understand these conditions in order to fully specify macroeconomic models with nominal price rigidities for policy analysis.

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Appendices

Table 1-A: Countries conducting business surveys

Region	Number	Countries
Western Europe	17	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, U.K.
Central & Eastern Europe	12	Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Russian Fed, Slovak Rep., Slovenia, Ukraine
North America	3	Canada, Mexico, USA
Central & Latin America	8	Argentina, Bolivia, Brazil, Colombia, Dom. Rep., Ecuador, Peru, Venezuela
Central Asia	2	Kazakhstan, Uzbekistan
South Asia & Pacific	15	Australia, China P.R., Chinese Taipei, Hong Kong (China), India, Indonesia, Malaysia, New Zealand, Philippines, Singapore, Thailand, Vietnam
West Asia	2	Lebanon, Saudi Arabia
Africa	1	South Africa
Total	**60**	

Source: OECD (2003).