Asymmetries in Price-Setting Behavior: New Microeconometric Evidence from Switzerland*

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ABSTRACT

In this paper, we follow the recent empirical literature that has specified reduced-form models for price setting that are closely tied to (S, s)-pricing rules. Our contribution to the literature is twofold. First, we propose an estimator that relaxes distributional assumptions on the unobserved heterogeneity. Second, we use the estimator to examine the prevalence of positive price changes in a low-inflation environment. Our model estimates suggest that, if inflation falls from 0.9% to zero, the share of positive price changes in all price changes falls from 63.6% to 56.2%.

1. INTRODUCTION

Price increases are more frequent than price decreases. This is a common pattern documented for many low inflation countries.[1] In Switzerland, during a period where the average inflation rate amounts to only 0.9%, almost two-thirds of all price changes are positive.

The purpose of this paper is to empirically investigate to what extent aggregate inflation explains the prevalence of positive price changes. Tsiddon (1993) and Ball and Mankiw (1994) show theoretically in menu-cost models of price setting that price increases are more frequent than decreases because of positive aggregate inflation. This is because firms front load future inflation into the prices they currently set. It is thus an optimal choice to react less to negative shocks than to positive shocks of the same size, because inflation does part of the job of cutting relative prices without forcing firms to pay menu costs. However, price decreases would be just as frequent as price increases if inflation was stabilized at zero. This stands in contrast to models, where downward rigidities are simply assumed (see, e.g., Tobin 1972). In these models, price increases would be more frequent than price decreases, even in the absence of aggregate inflation.

In this paper, we contribute to the literature that has estimated reduced form models for price setting that are closely tied to (S, s)-pricing rules. In these models, the probability of observing a price adjustment depends on the deviation between the actual and the desired price. One of the challenges in estimating these types of models is that there is a large degree of unobserved heterogeneity across products. Making distributional assumptions about the heterogeneity is one way to take this unobserved heterogeneity into account. This approach has been pursued by Fehr and Goette (2005), Fougère, Gautier, and Le Bihan (2010) and Dhyne et al. (2011). An alternative, and less parametric, approach is to treat unobserved heterogeneity as fixed effects. This alternative is what we pursue in this paper. Specifically, we derive an estimator of the parameters of interest that does not make any assumptions on the relationship between the explanatory variables and the fixed effects. Thus, the estimation of these parameters will not be affected by incorrect distributional assumptions concerning the unobserved heterogeneity.

Estimation of nonlinear models with fixed effects is difficult in panel data situations where the number of time periods is small relative to the number of cross sectional units (see Arellano and Honoré 2001). This is because the nonlinearity invalidates any attempt to eliminate the fixed effects by differencing. The econometric literature has therefore proposed a number of other methods. These methods tend to be specific to the econometric model at hand and, unlike a maximum likelihood approach, they focus on particular features of the data that are independent of the fixed effects, while ignoring the features that may depend on the fixed effects. Using only some features of the data will typically lead to a statistical loss of information, but this seems to be a necessary cost of the flexibility provided by the fixed effects approach. For the model considered in this paper, the information about the parameters of interest is in the timing of the price changes. The information contained in the number and the sizes of the price changes is contaminated by the fixed effect. There is currently no known method for using this information for point estimation of the parameters of interest without additional, and often arbitrary, distributional assumptions.

The empirical contribution of this paper is to examine the impact of low but positive aggregate inflation on the prevalence of price increases. We use Swiss micro price data during a period of low inflation and examine the frequency of positive price changes as compared to that of negative price changes in a zero inflation environment. The extent to which aggregate inflation explains the prevalence of price increases is not yet well established empirically. So far, most studies have focused on the response of prices to measures of nominal marginal costs (see Peltzman 2000, Fougère, Gautier, and Le Bihan 2010, Dhyne et al. 2011) on high inflation environments (see Gagnon 2009) or on the relative frequency of wage increases (see Fehr and Goette 2005, ECB 2009). Other studies have assessed the relationship between inflation and price-setting behavior without specifying empirical price-adjustment rules (see Klenow and Kryvtsov 2008, Nakamura and Steinsson 2008, Chen et al. 2008). They usually find that the frequency of price increases comoves with inflation. Similarly, Lein (2010) shows that higher inflation reduces the probability of observing price decreases and raises the probability of observing price increases for Swiss manufacturing firms. With the exception of Chen et al. (2008), these studies do not, however, address the question whether price increases would still be prevalent if aggregate inflation was stabilized at zero.

Our results may be summarized as follows. Price increases are more frequent than price decreases because of positive aggregate inflation. Our counterfactual analysis shows that price decreases would be almost as frequent as price increases in the absence of aggregate inflation. The share of price increases in all price changes would fall from 63.6% to 56.2% if aggregate inflation was zero. This finding is robust to different specifications of the model and covariates. It suggests that already mild aggregate inflation combined with infrequent price adjustments imply that prices rise more frequently than they fall.

The remainder of this paper is structured as follows. Section 2 describes the model and Section 3 discusses the data. Section 4 presents the results and Section 5 offers some conclusions.

2. A FIXED EFFECTS APPROACH FOR ESTIMATING PRICE-ADJUSTMENT RULES

In this paper, we follow the recent empirical literature that has specified reduced form models for price setting that are closely tied to (S, s)-pricing rules. The main idea of an (S, s)-policy is that the probability of observing an adjustment at the microeconomic level is an increasing function of the gap between the actual value of a variable and its desired target level (see Caballero and Engel 1993a).[2] Such an adjustment behavior results from the assumption of non-convex adjustment costs. In the case of price setting, the estimated adjustment rule states that a price change occurs when the deviation between the desired price and the current one crosses an upper or lower adjustment threshold (see, e.g., Fehr and Goette 2005, Fougère, Gautier, and Le Bihan 2010, Dhyne et al. 2011).[3] These thresholds are motivated by assuming that firms have to pay menu costs for changing prices (see, e.g., Sheshinski and Weiss 1977), or by assuming that setting the desired price is prone to errors (see Costain and Nakov 2011). Simple specifications of such a model can be thought of as generalizations of well-understood limited dependent variable models, such as the censored regression model.[4]

The empirical approach used here is to use insights from the literature concerned with estimation of limited dependent-variable models to cast new light on the prevalence of positive price changes. Since one of the primary focuses will be on unobserved heterogeneity, the literature concerned with estimation of limited dependent-variable models using panel data will be especially relevant (see, e.g., Arellano and Honoré 2001, for an overview of that literature). Our approach differs from the recent empirical literature by assuming that the product-specific price-adjustment thresholds are deterministic, and we treat them as fixed effects. However, the approach is robust to these fixed effects changing slowly over time. This is in line with menu-cost models with deterministic menu costs (see, e.g., Sheshinski and Weiss 1977). Other authors have introduced stochastic price-adjustment thresholds that are allowed to change in every period, which is usually motivated by models with random menu costs (see, e.g., Dotsey, King, and Wolman 1999).[5]

Let p^*_{it} denote the log of the unobserved desired price for a product i at time t. We assume that this price can be modeled as a desired markup μ_i over nominal marginal cost $x'_{it}\beta$ and an idiosyncratic error:[6]

$$p^*_{it} = \mu_i + x'_{it}\beta + \varepsilon_{it} \quad . \tag{1}$$

In the spirit of an (S, s)-pricing rule, there is an interval for the desired price change, $p^*_{it} - p_{i,t-1}$, over which firms do not adjust prices. We denote this interval by $\left(\theta^-_{it}, \theta^+_{it}\right)$ and model the thresholds as

$$\theta^+_{it} = z'_{it}\delta^+ + u^+_i \tag{2}$$

$$\theta^-_{it} = z'_{it}\delta^- + u^-_i \quad , \tag{3}$$

where z_{it} denotes time-varying factors affecting the thresholds and u^+_i and u^-_i denote product-specific heterogeneity. Thus, the thresholds can vary over time and differ across products. It is implicit in equations (2)–(3) that $\theta_{it}^{+} \geq \theta_{it}^{-}$ for all t with probability 1. When the number of time periods for a product is large, this is a serious restriction on the possible values of u_i^{+} and u_i^{-}. One would have to explicitly deal with this restriction, if one were to treat u_i^{+} and u_i^{-} as parameters to be estimated or if one took a random effects approach and explicitly parameterized the distribution of u_i^{+} and u_i^{-}. The fixed effect approach taken here avoids this concern.

With this specification, the decision rule can be written as

$$p_{it} = \begin{cases} p_{it}^{*} & \text{if} \quad p_{it}^{*} > p_{it-1} + \theta_{it}^{+} \\ p_{it}^{*} & \text{if} \quad p_{it}^{*} < p_{it-1} + \theta_{it}^{-} \\ p_{it-1} & \text{if} \quad \text{otherwise} \end{cases}. \tag{4}$$

In a cross-sectional model, this is the model proposed by Rosett (1959) and later applied by Udry (1994). In a panel data setting, it is closely related to a censored regression model with fixed effects of the generic form $y_{it} = \max\{0, y_{it}^{*}\}$, where y_{it}^{*} is the dependent variable in a linear fixed effect panel data model. Estimation of β in this model was considered in Honoré (1992). The main challenge in equation (4) relative to the censored regression model is the presence of the fixed effect in the threshold as well as in the desired price equation. This makes a trivial extension of the ideas in Honoré (1992) impossible.

There are a number of ways to approach estimation of the model defined by equations (1)–(4). If the number of time periods is large, then the μ_i's, u_i^{+}'s and u_i^{-}'s can be treated as parameters to be estimated, and the model can be estimated by maximum likelihood. However, as pointed out by Neyman and Scott (1948), this procedure will generally lead to inconsistent estimation of all the parameters of the model if one thinks of the number of time periods as fixed. This suggests that such an approach may not be a good starting point in situations with relatively short panels. On the other hand, it is possible to proceed with maximum likelihood estimation if one is willing to make distributional assumptions on $\left(\{\varepsilon_{it}\}, \mu_i, u_i^{+}, u_i^{-}\right)$. This is usually referred to as a random effects approach and it will result in asymptotically efficient estimation of the model parameters provided that the distributional assumptions are correct. Unfortunately, the random effects approach mentioned above will typically lead to an inconsistent estimator of the parameters if the distribution of the product-specific heterogeneity is misspecified. It is therefore interesting to investigate whether it is possible to make progress without distributional assumptions. This is the approach that we pursue in this paper.

Specifically, let y_{1it} be 1 if there is a price increase for product i in time period t and 0 otherwise. Then

$$\begin{aligned} y_{1it} &= 1\{\triangle p_{it} > 0\} = 1\left\{\mu_i + x_{it}'\beta + \varepsilon_{it} > p_{it-1} + z_{it}'\delta^+ + u_i^+\right\} \qquad (5) \\ &= 1\left\{x_{it}'\beta - z_{it}'\delta^+ - p_{it-1} + \mu_i - u_i^+ + \varepsilon_{it} > 0\right\} \quad , \end{aligned}$$

where $1\{A\}$ equals 1 if A is true and 0 otherwise. Equation (5) has the structure of a discrete choice model with fixed effects. Manski (1987) shows how to consistently estimate the parameters β and δ^+ of such a model with a fixed number of time periods for each i.[7] His approach allows $\mu_i - u_i^+$ to be a fixed effect that can be arbitrarily correlated with the explanatory variables and the only real assumption is that $\{\varepsilon_{it}\}_{t=1}^{T_i}$ is stationary conditional on the explanatory variables for each i. The weakness of this approach is that the resulting estimator is not asymptotically normal and converges to the true parameter values at a rate that is slower than the usual $\sqrt{N}$, where N is the number of products. On the surface, this then seems like a poor estimator. However, Chamberlain (2010) showed that even with a parametric distributional assumption on ε_{it}, it is essentially impossible to estimate the parameters of a fixed effect version of equation (5) at the usual $\sqrt{N}$ rate unless ε_{it} is i.i.d. logistic.

Therefore, we proceed by specifying

$$\begin{aligned} y_{1it} &= 1\left\{x_{it}'\beta - z_{it}'\delta^+ - p_{it-1} + \mu_i - u_i^+ + \varepsilon_{it} > 0\right\} \qquad (6) \\ &= 1\left\{x_{it}'\beta/\kappa - z_{it}'\delta^+/\kappa - p_{it-1}/\kappa + \left(\mu_i - u_i^+\right)/\kappa + \varepsilon_{it}/\kappa > 0\right\} \quad , \end{aligned}$$

where $\{\varepsilon_{it}/\kappa\}$ is i.i.d. with a standard logistic distribution. With this assumption β/κ, δ^+/κ and $1/\kappa$ can be estimated by the conditional maximum likelihood estimator introduced by Rasch (1960) and studied by Andersen (1970). Note that with this parameterization, $V\left[\varepsilon_{it}\right] = \frac{\pi^2\kappa^2}{3}$. For this reason, the standard deviation of the idiosyncratic error is given by $\sigma_\varepsilon = \frac{\pi\kappa}{\sqrt{3}}$.

Rather than focusing on price increases, we could also consider whether a price decreases in time period t. Let y_{2it} be 1 if the price of product i does not decrease in time period t and 0 otherwise. Then

$$y_{2it} = 1\left\{x_{it}\beta/\kappa - z_{it}'\delta^-/\kappa - p_{it-1}/\kappa + \left(\mu_i - u_i^-\right)/\kappa + \varepsilon_{it}/\kappa \geq 0\right\} \quad . \tag{7}$$

which can be estimated as above.

The conditional likelihood approach can be computationally burdensome if each product is observed over many time periods. It is therefore useful to proceed by using a slightly less efficient approach that uses all pairs of time periods (t, s) for a given i rather than the whole series simultaneously. Writing equation (6) as $y_{it} = 1\left\{w_{it}^+\gamma^+ + \alpha_i^+ + v_{it} > 0\right\}$ where $v_{it} = \varepsilon_{it}/\kappa$ is logistic, $w_{it}^+ = (x_{it}, z_{it}, p_{it-1})$, $\gamma^+ = (\beta/\kappa, \delta^+/\kappa, 1/\kappa)$ and $\alpha_i^+ = \left(\mu_i - u_i^+\right)/\kappa$, we have

$$P\left(y_{1it} = 1 \middle|\, w_{it}^+, w_{is}^+, \alpha_i^+\right) = \frac{\exp\left(w_{it}^{+\prime}\gamma^+ + \alpha_i^+\right)}{1 + \exp\left(w_{it}^{+\prime}\gamma^+ + \alpha_i^+\right)}$$

and

$$P\left(y_{1it}=1,y_{1is}=0\right|y_{1it}+y_{1is}=1,w_{it}^{+},w_{is}^{+},\alpha_{i}^{+}\Big)$$

$$= \frac{P\left(y_{1it}=1,y_{1is}=0\right|w_{it}^{+},w_{is}^{+},\alpha_{i}^{+}\Big)}{P\left(y_{1it}=1,y_{1is}=0\right|w_{it}^{+},w_{is}^{+},\alpha_{i}^{+}\Big)+P\left(y_{1it}=0,y_{1is}=1\right|w_{it}^{+},w_{is}^{+},\alpha_{i}^{+}\Big)}$$

$$= \frac{\frac{\exp\left(w_{it}^{+\prime}\gamma^{+}+\alpha_{i}^{+}\right)}{1+\exp\left(w_{it}^{+\prime}\gamma^{+}+\alpha_{i}^{+}\right)}\frac{1}{1+\exp\left(w_{is}^{+\prime}\gamma^{+}+\alpha_{i}^{+}\right)}}{\frac{\exp\left(w_{it}^{+\prime}\gamma^{+}+\alpha_{i}^{+}\right)}{1+\exp\left(w_{it}^{+\prime}\gamma^{+}+\alpha_{i}^{+}\right)}\frac{1}{1+\exp\left(w_{is}^{+\prime}\gamma^{+}+\alpha_{i}^{+}\right)}+\frac{1}{1+\exp\left(w_{it}^{+\prime}\gamma^{+}+\alpha_{i}^{+}\right)}\frac{\exp\left(w_{is}^{+}\gamma^{+}+\alpha_{i}^{+}\right)}{1+\exp\left(w_{is}^{+\prime}\gamma^{+}+\alpha_{i}^{+}\right)}}$$

$$= \frac{\exp\left(\left(w_{it}^{+}-w_{is}^{+}\right)'\gamma^{+}\right)}{1+\exp\left(\left(w_{it}^{+}-w_{is}^{+}\right)'\gamma^{+}\right)} \quad .$$

Since the right-hand side does not depend on α_i^+, this allows one to estimate $\gamma^+ = (\beta/\kappa, \delta^+/\kappa, 1/\kappa)$ without assumptions on α_i^+. In practice, this is done by maximizing the pseudo log-likelihood for all pairs of observations for which $y_{1it} + y_{1is} = 1$.

Likewise, $(\beta/\kappa, \delta^-/\kappa, 1/\kappa)$ can be estimated by considering y_{2it}. We impose the constraint that β/κ and $1/\kappa$ should be the same when using y_{1it} and when using y_{2it} by maximizing the sum of the two pseudo log-likelihood functions. Specifically, we can estimate β, κ, δ^+ and δ^- by maximizing the pseudo log-likelihood function

$$\sum_{i=1}^{N}\sum_{1\le s\le t\le T_i} \begin{array}{l} q_{ist}^{1}\left(\beta,\delta^{+},\delta^{-},\kappa\right)+q_{ist}^{2}\left(\beta,\delta^{+},\delta^{-},\kappa\right) \\ +q_{ist}^{3}\left(\beta,\delta^{+},\delta^{-},\kappa\right)+q_{ist}^{4}\left(\beta,\delta^{+},\delta^{-},\kappa\right) \quad , \end{array} \tag{8}$$

where

$$q^1_{ist}\left(\beta,\delta^+,\delta^-,\kappa\right) = 1\left\{\triangle p_{it} \geq 0, \triangle p_{is} < 0\right\}$$
$$\log\left(\frac{\exp\left(\left(x_{it}-x_{is}\right)'\beta/\kappa - \left(z_{it}-z_{is}\right)'\delta^-/\kappa - \left(p_{it-1}-p_{is-1}\right)/\kappa\right)}{1+\exp\left(\left(x_{it}-x_{is}\right)'\beta/\kappa - \left(z_{it}-z_{is}\right)'\delta^-/\kappa - \left(p_{it-1}-p_{is-1}\right)/\kappa\right)}\right),$$

$$q^2_{ist}\left(\beta,\delta^+,\delta^-,\kappa\right) = 1\left\{\triangle p_{it} < 0, \triangle p_{is} \geq 0\right\}$$
$$\log\left(\frac{1}{1+\exp\left(\left(x_{it}-x_{is}\right)'\beta/\kappa - \left(z_{it}-z_{is}\right)'\delta^-/\kappa - \left(p_{it-1}-p_{is-1}\right)/\kappa\right)}\right),$$

$$q^3_{ist}\left(\beta,\delta^+,\delta^-,\kappa\right) = 1\left\{\triangle p_{it} > 0, \triangle p_{is} \leq 0\right\}$$
$$\log\left(\frac{\exp\left(\left(x_{it}-x_{is}\right)'\beta/\kappa - \left(z_{it}-z_{is}\right)'\delta^+/\kappa - \left(p_{it-1}-p_{is-1}\right)/\kappa\right)}{1+\exp\left(\left(x_{it}-x_{is}\right)'\beta/\kappa - \left(z_{it}-z_{is}\right)'\delta^+/\kappa - \left(p_{it-1}-p_{is-1}\right)/\kappa\right)}\right),$$

and

$$q^4_{ist}\left(\beta,\delta^+,\delta^-,\kappa\right) = 1\left\{\triangle p_{it} \leq 0, \triangle p_{is} > 0\right\}$$
$$\log\left(\frac{1}{1+\exp\left(\left(x_{it}-x_{is}\right)'\beta/\kappa - \left(z_{it}-z_{is}\right)'\delta^+/\kappa - \left(p_{it-1}-p_{is-1}\right)/\kappa\right)}\right).$$

Assuming random sampling across i, the asymptotic variance of this estimator can be derived and calculated using standard methods for extremum estimators (see, e.g., Amemiya 1985).

The assumption that the product-specific fixed effect is constant over time is strong when a product is observed over a large number of periods. We therefore estimate β, κ, δ^+ and δ^- by maximizing a modification of equation (8) that only uses pairs of time periods that differ by less than some number k:

$$\sum_{i=1}^{N} \sum_{\substack{1 \leq s \leq t \leq T_i \\ t-s \leq k}} q_{ist}^{1}\left(\beta, \delta^{+}, \delta^{-}, \kappa\right) + q_{ist}^{2}\left(\beta, \delta^{+}, \delta^{-}, \kappa\right) + q_{ist}^{3}\left(\beta, \delta^{+}, \delta^{-}, \kappa\right) + q_{ist}^{4}\left(\beta, \delta^{+}, \delta^{-}, \kappa\right) \quad . \tag{9}$$

If the model above is correctly specified, then this estimator is still consistent and asymptotically normal, but it is likely to be less efficient than that defined by maximizing equation (8).[8] However, the intuition is that the estimator defined by equation (9) is likely to be much more robust to a misspecification in which μ_i, u_i^{+} and u_i^{-} change slowly over time.

While estimating β, κ, δ^{+} and δ^{-} by minimization of equation (9) is attractive because the resulting estimator is consistent under very weak assumptions on the product-specific effects, there is a trade-off between this robustness and some of the advantages associated with other approaches. Naturally, it is reasonable to treat the product-specific effects as parameters to be estimated and proceed by using likelihood-based methods, if the number of time periods (T) is large relative to the number of products (N). This approach will lead to inconsistent estimation in an asymptotic exercise in which T is fixed and N grows to infinity. As a result, this approach is probably not advisable when T is much smaller than N. But when T is not too small, various methods exist for removing some of the asymptotic bias. See, for example, Hahn and Newey (2004), Fernández-Val (2009), Carro (2007) and the general discussion in Arellano and Hahn (2007). The advantage of this approach is that a likelihood-based method uses all features of the data, while the approach pursued here focuses on the specific aspects that cleanly identify the parameters of interest without assumptions on the product-specific effects.

For a maximum likelihood approach to be useful when T is small, it is necessary to specify the distribution of the product-specific effects conditional on the explanatory variables. If this distribution is correctly specified, then this approach will have all the usual desirable properties of maximum likelihood. Moreover, this approach will lead to an estimate of a fully specified model which can be used for any kind of counterfactual simulation. In contrast, without additional assumptions the approach taken here will not be directly informative about counterfactuals that depend on the product-specific effects. On the other hand, if the distribution of the product-specific effects is misspecified, then the parameters of the model will be inconsistently estimated, and one needs to resort to interpretations in terms of pseudo-true parameters. Even in a specific application, it therefore seems questionable that one can declare one of these approaches as unambiguously superior to the others.

3. DATA

3.1 Empirical Specification

In this paper, we use the micro price data underlying the Swiss CPI to model the desired price conditional on a price adjustment.[9] The sampling decisions leave us with more than 3.2 million quarterly price quotes from Q1 1994 to Q4 2007 covering almost 50% of the CPI basket at average CPI expenditure weights (see Table 1).

The data set comprises price quotes of products. A product has a specific quality and quantity, and it is on offer in a specific outlet. An example of a product is a 600ml family-size package of ice cream of a certain brand and flavor in a particular outlet. When products are out of stock, the statistical office collects prices for close substitutes. The statistical office provides a variable that indicates whether the price quotes of close substitutes can be linked directly because they are of the same quality. If this is not the case, a new product series starts. We call the products that are close substitutes across all outlets a product group. For example, a product group would be a 600 ml family-size package of ice cream.

The data set does not cover the whole Swiss CPI basket because the statistical office uses other data sources to construct some of the price indices. The largest of these sectors are rents, telecommunication and books. Furthermore, some sectors drop out of the sample because they are not available over the whole sample period. We also only include products that were surveyed on a quarterly basis, at least. In our sample period, prices for some food items are available on a monthly basis. We use the last month of the quarter as the quarterly observation. Finally, we remove a few products with price changes larger than 200% and with missing data.

We restrict the analysis to permanent rather than temporary price changes because they are more important for aggregate predictions of menu-cost models (see Kehoe and Midrigan 2007). A temporary price change is followed by the nominal price returning to its pre-period level. This definition identifies temporary price increases as well as decreases. In addition, the statistical office provides an indicator variable for sales. In periods with either temporary price changes or sales, we carry forward the pre-period price.

The micro price data yields the desired price conditional on observing a price change. For periods with no price change, we model the desired price according to equation (1). We follow Cecchetti (1986) and use the accumulated sectoral inflation rate as a proxy for the change in nominal marginal costs.[10] We match the inflation rates with the micro data at the three-digit COICOP level.[11] This yields 70 sectors, which are listed in Table A1 in the Appendix.

We decompose the sectoral inflation rate into a sectoral inflation trend and sector-specific deviations from trend. The sectoral inflation trend is persistent and captures macroeconomic factors as well as relative price trends. This accounts for the fact that price trends may be an important factor in explaining why price increases are more frequent than price decreases (see Tsiddon 1993, Ball and Mankiw 1994). The sector-specific deviations from trend are not persistent and capture sector-specific shocks to marginal costs. All variables are accumulated from the beginning of each product series and therefore the empirical specification reads

$$p^*_{it} = \mu_i + \beta_1 \Sigma\bar{\pi}_{jt} + \beta_2 \Sigma\hat{\pi}_{jt} + \varepsilon_{it} \quad , \tag{10}$$

where $\bar{\pi}_{jt}$ denotes the sectoral inflation trend and $\hat{\pi}_{jt}$ denotes the sector-specific shock in sector j.

To decompose the sectoral inflation rates, we follow Boivin, Giannoni, and Mihov (2009) and use a principal components approach.[12] We extract a vector of four factors ($\mathbf{C}_t$) from a large macroeconomic data set including our sectoral inflation rates, and estimate the corresponding factor loadings for each variable ($\boldsymbol{\lambda}_j$). Each sectoral inflation rate can be decomposed into an average ($\bar{\pi}_j$), a common component ($\boldsymbol{\lambda}_j \mathbf{C}_t$) and an idiosyncratic component (e_{jt}):

$$\pi_{jt} = \underbrace{\bar{\pi}_j + \boldsymbol{\lambda}_j \mathbf{C}_t}_{\bar{\pi}_{jt}} + \underbrace{e_{jt}}_{\hat{\pi}_{jt}} . \tag{11}$$

The sectoral inflation trend for sector j is defined as the sum of the common component of the sectoral inflation rate and its mean. The sector-specific shocks are measured by the idiosyncratic component of the sectoral inflation rate. Our approach differs from Dhyne et al. (2011), who estimate a sector-specific price trend directly from micro price data.

The price-adjustment thresholds are modelled by including the sectoral trend inflation rate, seasonal time dummies, and dummies for periods with VAT changes. Therefore, the price-adjustment thresholds may differ not only across products, but also over time. We include sectoral trend inflation to test whether the thresholds vary with the level of inflation. According to Ball and Mankiw (1994), higher inflation leads to an asymmetric adjustment range by reducing the upper threshold and raising the lower threshold in absolute terms.[13] We include dummies for periods with VAT changes because such events give firms an opportunity to change prices as managerial and customer costs are particularly low (see Zbaracki et al. 2004, Fougère, Gautier, and Le Bihan 2010, Karadi and Reiff 2010). Similarly, the seasonal dummies reflect the fact that menu costs may be low in certain months because of end-of-season sales or seasonal product replacements.

3.2 Descriptive Statistics

The micro price data show that positive price changes are more frequent than negative price changes (see Table 2).[14] On average, the relative frequency of price increases, that is, the share of price increases in all price changes, is 63.6%.[15] However, there are considerable differences across product types. For services, we find a relative frequency of price increases of 78.2%. For non-durable goods, this frequency is lower, at 58.9%. The relative frequency of price increases for semi-durable and durable goods is in between.

Against the backdrop of the high share of positive price changes, it may seem surprising that Swiss CPI inflation was very low during the sample period (on average 0.9%). The two observations can be reconciled by the fact that price increases are on average smaller than price decreases. The difference between the absolute size of price increases and decreases is more pronounced for those product types with a higher relative frequency of price increases. This observation is in line with asymmetric price-adjustment thresholds in a menu-cost model. If the lower threshold is larger in absolute size than the upper threshold, this leads to infrequent price decreases relative to price increases. Moreover, conditional on a price adjustment, a price decrease would on average be larger than a price increase.

According to Ball and Mankiw (1994), we would expect those sectors with positive inflation rates to exhibit a majority of price increases and those sectors with negative inflation rates to exhibit a majority of price decreases. In 49 out of 70 sectors, we find that a positive sectoral inflation rate is associated with more price increases than decreases. Moreover, a negative sectoral inflation rate is associated with more price decreases than increases in eight sectors. However, in the remaining 13 sectors, a negative sectoral inflation rate is associated with a relative frequency of price increases which is higher than 50%. This is partly related to our sampling decisions; the official sectoral inflation rates do not perfectly correspond to our underlying micro data. Alternatively, we could use the average price change observed in each sector instead of the sectoral inflation rate. In that case a negative average price change would be associated with a relative frequency of price increases higher than 50% in only four sectors.

Moreover, sectors with a higher inflation rate should exhibit more asymmetric price-adjustment thresholds and therefore a higher relative frequency of price increases. Panel (a) in Figure 1 shows, in a scatter plot, the relationship between the relative frequency of price increases and the average inflation rate across sectors. We find a significantly positive relationship. The R^2 suggests that the sectoral inflation rate explains 34% of the cross-sectional variation in the relative frequency of price increases. We can use the scatter plot to gauge the relative frequency of price increases for a sector with zero sectoral inflation. According to the intercept of the regression line, a sector with zero sectoral inflation displays a relative frequency of price increases of 64.1%.

The scatter plot provides some descriptive evidence for the predictions of the Ball and Mankiw (1994) model. It does not, however, reveal what the relative frequency of price increases would be if aggregate inflation was stabilized at zero. The reason is that firms with larger menu costs have a more pronounced front-loading motive because the duration between two price adjustments is on average longer. For those firms, the relative frequency of price increases is higher despite identical productivity trends and identical sectoral inflation rates. The multi-sector menu-cost model by Nakamura and Steinsson (2010) has this implication. Although all firms in their model are faced with the same trend inflation rate, the relative frequency of price increases varies substantially across sectors. For sectors with larger menu costs, we observe a higher relative frequency of price increases. For sectors with low menu costs, price increases are almost as frequent as decreases despite positive aggregate inflation. Therefore, a simple regression of the sectoral inflation rate on the relative frequency of price increases gives wrong predictions if there is heterogeneity in menu costs.[16]

Alternatively, we can look at the relative frequency of price increases during periods with zero aggregate inflation.[17] Panel (b) shows that the aggregate inflation rate is indeed correlated with the relative frequency of price increases over time. The R^2 amounts to 0.24, but the slope of the regression line is only significant at the 10% level. Taking this regression line at face value, we may argue that in periods with zero aggregate inflation, the relative frequency of price increases amounts only to 52.9%. Admittedly, the result may be driven by one year with zero inflation and a surprisingly low relative frequency of price increases of 40%. When excluding this observation, the intercept would rise to 61.3% and the R^2 would be close to 0.

To make more precise statements about the relative frequency of price increases in the absence of aggregate inflation, we would need more observations with zero or negative inflation rates. Evidence from Japan indeed shows that when inflation was zero or even negative, consumer price decreases were just as frequent as price increases (see Higo and Saita 2007). Moreover, workers started to accept nominal wage cuts (see Kuroda and Yamamoto 2003). Despite low aggregate inflation in Switzerland, only one year with zero aggregate inflation is available. We therefore proceed by estimating price-adjustment rules for each of the 70 sectors. These rules takes the heterogeneity in sectoral price trends and menu costs into account. We then use these estimates to make counterfactual predictions of the relative frequency of price increases at zero aggregate inflation.

4. RESULTS

This section first discusses the estimation results and the covariates which are most important for explaining the relative frequency of price increases. We then conduct a counterfactual analysis, showing the extent to which the relative frequency of price increases would fall if aggregate inflation was zero. Finally, we offer some robustness tests.

4.1 Estimation Results

We estimate the coefficients of the desired price equation, controlling for heterogeneity at the level of individual products. As discussed in Section 2, it is potentially desirable to use only pairs of time periods that are fairly close. We therefore use pairs that differ by no more than 12 quarters. This makes the results more robust to the assumption that the fixed effects in the thresholds, as well as the fixed effects in the pricing equation, are constant over the whole sample period.

Table 3 reports the estimation results for the 70 sectors. The first panel summarizes the estimates of the desired price equation and the second panel the estimates the threshold equations. The third panel gives averages of the estimated standard deviation of the idiosyncratic errors and of the price-adjustment thresholds. The last panel provides some summary statistics. All statistics are weighted by the corresponding average CPI expenditure weights.

The estimated coefficients of the desired price and threshold equations are summarized as follows. For each model and for each coefficient, we perform a one-sided test with the alternative hypothesis that the coefficient is larger (or smaller) than zero. The table reports the weighted average of the coefficients across all sectors conditional on this alternative hypothesis.[18] As a measure of significance, we report in brackets the share of sectors for which we reject the null hypothesis at the 5% level.

The relative price trends have a significantly positive impact on desired prices, in almost all sectors. At the 5% level, the share of sectors with a positive coefficient amounts to 91%. On average, a 1% increase in the sectoral price trend raises the firm's desired price by 1.17%. This suggests that desired prices move one-for-one with the sectoral price trend. This finding is common across product types. For three out of four product types, the share of sectors that react significantly to the sectoral price trend is larger than 90% and the average coefficient is close to 1. For durable goods, the coefficient is somewhat higher, at 1.54, and for semi-durable goods, the share of significant coefficients amounts to only 63%.

The coefficients are also mostly significant for sector-specific shocks. In 84% of the sectors, firms' desired prices react significantly to sector-specific shocks. The coefficient is 1.39 on average and significant in almost all sectors. Only for durable goods is the share of sectors with a significantly positive coefficient somewhat smaller (54%).

The thresholds vary with the level of sectoral inflation. We find that a higher sectoral inflation rate reduces both thresholds in more than 50% of all sectors. This implies that the upper threshold becomes smaller and the lower threshold becomes larger in absolute terms, which makes price increases more likely than price decreases. This is in line with menu-cost models in the spirit of Ball and Mankiw (1994). The effect of sectoral inflation on the upper threshold is significantly negative for most non-durable goods, durable goods and services, but only for 20% of the semi-durable goods. Meanwhile, the effect on the lower threshold is relatively homogeneous across product types. Only for services do less than 50% of the products have a significantly negative effect of inflation.

The third panel displays the average thresholds at actual sample values of the covariates. One must be careful in interpreting these averages as they include the fixed effect μ_i. However, if we assume that μ_i, the desired log-markup, is positive, the average price-adjustment thresholds are asymmetric. The upper threshold is smaller in absolute terms than the lower threshold, which makes positive price changes more likely, on average, than negative price changes. The asymmetry of the price-adjustment thresholds is more pronounced for semi-durable goods and services than for non-durable and durable goods.

4.2 Explanatory Power of the Covariates

The cross-sectional dispersion of the relative frequency of price increases is mostly driven by sectoral price trends rather than asymmetric price-adjustment thresholds. To illustrate this, we calculate the probability of a price increase as well as the probability of a price decrease at actual sample values of the covariates. The simulated relative frequency of positive price changes is then given by the average probability of a price increase divided by the average probability of a price change.

To simulate the relative frequency of price increases, we have to obtain a value for the fixed effects. Equations (6) and (7) show that we only need to know $\left(\mu_i - u_i^+\right)$ and $\left(\mu_i - u_i^-\right)$ instead of all three fixed effects separately. We calibrate the two differences by matching the probability of positive and negative price changes. This boils down to re-estimating the model by maximum likelihood including dummy variables for the fixed effects and restricting all other coefficients to the values from the fixed effects estimator.

Calibrating a different fixed effect for each product is problematic, because for some products we only observe price increases, price decreases or no changes. We therefore calibrate the fixed effects for each product group rather than for each product.

The first column of Table 4 shows the results of regressing the relative frequency of price increases on the model predictions at actual sample values. The R^2 equals almost 1 by construction because we calibrated the fixed effects to match the probability of positive and negative price changes. In the remaining columns, we set one of the covariates to zero to simulate the relative frequency of price increases. The size of the drop in the R^2 shows to what extent the corresponding covariate helps in explaining the cross-sectional variation of the relative frequency of price increases.

Sectoral price trends explain a large share of the cross-sectional variation in the relative frequency of price increases. If we set the sectoral inflation trend to zero, the model explains only 76% of the cross-sectional variation ($\bar{\pi}_{jt} = 0$). The reason for this is that, in our model, sectoral inflation trends imply that the desired price changes between two price adjustments. If we set sectoral trend inflation to zero in the desired price equation, but not in the threshold equation, the R^2 falls to 0.74. If we set the sectoral trend inflation to zero only in the threshold equations, the R^2 remains unchanged. Finally, if we set sector-specific shocks to zero ($\hat{\pi}_{jt} = 0$), the R^2 falls only slightly, to 0.94. This suggests that the sectoral inflation trends are more important for fitting the cross-sectional variation in the relative frequency of positive price changes than the sector-specific shocks.

4.3 Counterfactual Predictions at Zero Aggregate Inflation

The estimated price-setting rules can be used to show whether the relative frequency of price increases is mainly driven by positive aggregate inflation. The first two columns in Table 5 give the actual relative frequency of price increases and the model predictions at actual sample values, respectively. The remaining columns give the counterfactual predictions at zero aggregate inflation. The third column sets aggregate inflation to zero in the desired price equation as well as in the threshold equations. This is done by subtracting aggregate inflation from the sectoral inflation trend in the desired price equation ($\beta_1[\Sigma\bar{\pi}_{jt} - \Sigma\pi_t]$) and in the threshold equations ($\delta_1^+[\bar{\pi}_{jt} - \pi_t]$, $\delta_1^-[\bar{\pi}_{jt} - \pi_t]$). We subtract aggregate inflation from the sectoral inflation trend, because it captures macroeconomic factors and relative price trends rather than sector-specific shocks. We repeat the exercise by setting inflation to zero separately in the desired price equation or the threshold equations in the fourth and fifth columns, respectively.

If we set aggregate inflation to zero, the relative frequency of price increases drops by 7.2 percentage points to 56.2%. This drop is significant, but we would still observe somewhat more price increases than decreases. The effect of positive aggregate inflation is approximately equal in magnitude in the desired price equation and in the threshold equations.

Across product types, the drop is largest for durable goods and services. In fact, for durable goods, we would observe more price cuts than price increases. Meanwhile, the relative frequency of price increases is still considerably higher than 50% for services, which may be because of positive relative price trends or because of downward rigid wages (see, e.g., Fehr and Goette 2005). For semi-durable and non-durable goods, the drop of the relative frequency of price increases is smaller. For semi-durable goods, this may be related to frequent end-of-season sales which are excluded from the analysis. We examine the impact of including sales in the next section as a robustness test.

Even in a zero inflation environment, we find somewhat more price increases than decreases. In our model, this reflects asymmetric price-adjustment thresholds which are present even with zero aggregate inflation. A theoretical explanation for asymmetric adjustment thresholds with zero inflation can be found in Golosov and Lucas (2007). They show that the region of inaction is cone-shaped as a function of productivity. For low levels of productivity, the band of inaction is wider than it is for high levels of productivity because high-productivity firms have low prices and sell high quantities, while the opposite is the case for low-productivity firms. Klenow and Kryvtsov (2008) show that the (S, s)-band becomes increasingly asymmetric with higher elasticity of demand, which implies that the profit function is more asymmetric.

Another explanation stressed by Chen et al. (2008) is that time-constrained consumers may be inattentive to small price changes. As a consequence, a retailer would find it beneficial to implement small price increases and large price decreases because consumers respond only to large price changes. Indeed, they find that the prevalence of price increases is mostly concentrated in small price changes.

4.4 Robustness Tests

To examine the robustness of our results, we also estimate five alternative specifications.[19] First, we estimate our models on the sample including all sales prices and temporary price changes. The counterfactual prediction of the relative frequency of price increases at zero inflation is slightly lower (55.0%) than in the main specification. This is not surprising, perhaps, as the observed relative frequency of price increases including sales (61.9%) is lower than excluding sales (63.6%). However, the estimates across products types contain some interesting information. Services is the only product type for which we observe a relative frequency of price increases that is significantly higher than 50%. For all other product types, positive price changes are about as frequent as negative price changes. For durable goods, price decreases are even more frequent than price increases.

Second, we estimate the models using all price changes, not only those within a range of 12 quarters. In doing this, we assume that the fixed effects remain constant over a period of 14 years. As a consequence, the estimated standard deviation of the idiosyncratic error becomes unrealistically large. Moreover, the average price-adjustment thresholds increase in absolute size. This is an undesirable feature of the more restrictive model because it implies price changes of large magnitude. As a result, we are less likely to fit the prevalence of small price changes observed in the data. Nevertheless, the counterfactual predictions with respect to the relative frequency of price increases are not qualitatively affected by using the more restrictive model. Equations (6) and (7) show that the standard deviation of the idiosyncratic errors scales all parameters by the same amount so that the probability of observing a price increase or decrease is not greatly affected, even though the size of price adjustments may well be.

Third, we add accumulated aggregate inflation as well as accumulated personal consumption expenditures to our empirical specification. Even though the effect of aggregate inflation on the desired price is significantly larger than zero in only about one-fourth of the sectors, sectoral trend inflation remains significant in almost 68% of all sectors. The counterfactual predictions of this specification imply that the relative frequency of price increases falls to 57.4% at zero aggregate inflation.

Fourth, we use a Hodrick-Prescott filter to obtain an alternative estimate of the sectoral price trend. With this alternative decomposition, deviations from trend are not necessarily sector-specific. Most of the results prove robust to this alternative. The effect of aggregate inflation on the relative frequency of price increases is even larger than with our main specification. The counterfactual prediction of the relative frequency of price increases falls to 51.1%. This, is driven mainly by durable goods and services, where the relative frequency of price increases drops substantially to 29.8% and 57.8%, respectively.

Our main specification uses the official sectoral inflation rates published by the statistical office. Because of our sampling decisions, these inflation rates do not have to fully correspond to our micro data set. As a fifth robustness test, we therefore approximate the desired price change by the average price change observed in our data set instead of the sectoral inflation rate. As a consequence, the share of sectors in which we find a significantly negative sign in the desired price equation is zero. In particular, this affects our parameter estimates for semi-durable goods. All coefficients in the desired price equation are now larger than zero and most coefficients for inflation in the threshold equations are significantly negative. Our counterfactual predictions remain largely unchanged. Setting aggregate inflation to zero results in a relative frequency of price increases of 55.7%.

5. CONCLUSIONS

This paper is motivated by the empirical regularity that price increases are more frequent than price decreases. While this observation is not surprising for inflationary environments, it is also present in countries, and over periods, in which inflation is very low. For example, 63.6% of all price changes in Switzerland are increases during a period where the average inflation rate amounts only to 0.9%. One explanation for this observation is that firms, which face menu costs and therefore reset their price irregularly, front load future trend inflation into the prices they currently set. In this paper, we examine whether low but positive inflation is sufficient to explain the prevalence of positive price changes.

The large amount of unobserved heterogeneity poses a challenge for estimating a price-adjustment model using micro price data. To deal with this heterogeneity, we develop an estimator for a price-adjustment model with fixed effects. The innovation relative to the existing econometric literature is that both the main equation and the thresholds for price changes contain fixed effects. As such, the approach relies on weaker assumptions than other approaches. While existing estimators of censored regression model with fixed effects do not generalize, the particular structure of the model makes it possible to estimate the main parameters by applying estimation strategies for discrete choice models with fixed effects. This approach uses the particular scale normalization that the desired (latent) price should be compared to the actual price without a multiplicative coefficient. This normalization has the implication that we can base the estimation on the direction of the price change, while ignoring its magnitude. However, it is clear that such a scale normalization will not be available in generic applications of panel data censored regression models with fixed effects in the unobserved thresholds. It would therefore be desirable to develop an alternative estimation strategy that estimated the scale of the parameters of the model from the magnitude of the dependent variable. We leave this for future research.

The empirical contribution of this paper is to examine the impact of aggregate inflation on the prevalence of price increases in a low inflation environment. Our findings suggest that the fact that price increases are more frequent than price decreases is caused by positive aggregate inflation. A counterfactual analysis shows that price decreases would be almost as frequent as price increases in the absence of aggregate inflation.

According to our estimates, the share of price increases among all price changes would fall from 63.6% to 56.2% if aggregate inflation was zero. This finding is robust to different specifications of the model and of the covariates. The evidence suggests that even in Switzerland, where aggregate inflation was below 1% on average over the sample period, trend inflation implies that prices rise more frequently than they fall.

Because positive aggregate inflation largely explains the prevalence of positive price changes, the policy implication follows from the discussion in Ball and Mankiw (1994). Stabilizing CPI inflation at zero is optimal in their model. Positive inflation increases relative price variability and lowers output, as the distorted price signal does not allocate resources efficiently. This stands in contrast to the argument put forward by Tobin (1972) and Akerlof, Dickens, and Perry (1996), for example, that a central bank should adopt a positive inflation target if prices are downwardly rigid in nominal terms.

There are other reasons why a central bank may adopt a positive inflation target. Therefore, the welfare loss due to distortions resulting from low, but positive, inflation may be smaller than the welfare gains along other dimensions. For example, the CPI probably overestimates the actual inflation to some degree, because quality changes may be imperfectly accounted for. Moreover, with higher inflation and thus higher nominal interest rates, the probability is lower for a central bank to be constrained by the zero lower bound (see Summers 1991). Finally, downwardly rigid wages may have large welfare consequences which call for a positive inflation target. Using our estimation strategy to gauge the effect of aggregate inflation on wages would be an interesting future application.

APPENDIX A: LIST OF SECTORS

Table A1: List of sectors

Label	Description
	Non-durable goods
A001	Rice
A002	Flour
A003	Bread and pastries
A004	Pasta
A005	Other cereal products
A006	Beef
A007	Veal
A008	Pork
A009	Lamb
A010	Poultry
A011	Other meat
A012	Fish
A013	Milk
A014	Cheese
A015	Other dairy products
A016	Cream
A017	Eggs
A018	Fats and edible oils
A019	Fruits
A020	Vegetables and potatoes
A021	Dried, frozen, tinned vegetables
A022	Sugar, jam, honey/other sugary foods
A023	Other food products
A024	Coffee, tea, cocoa and nutritional beverages
A025	Mineral waters, soft drinks and juices
B001	Spirits
B002	Wine
B003	Beer
B004	Tobacco
D002	Products for housing maintenance and repair
D003	Electricity
D004	Natural gas
D005	Heating oil
E012	Goods for routine household maintenance
F001	Medicines and first-aid material
G005	Fuels
I007	Plants and flowers
I008	Pets and related products
I010	Daily newspapers and periodicals
I011	Writing and drawing materials
I014	Articles for personal hygiene
	Semi-durable goods
C001	Clothing
C002	Other articles of clothing/fabrics
E007	Household textiles
E009	Smaller electric household appliances
E010	Glassware, tableware and household utensils

Continued on next page

Table A1 – *continued from previous page*

Label	Description
G003	Spare parts
G004	Tires and accessories
I004	Recording media
I005	Games, toys and hobbies
I006	Equipment for sport, camping and open-air recreation
I013	Personal care appliances, electric
	Durable goods
E006	Furniture, furnishings, floor coverings and carpets
E008	Major electric household appliances
E011	Tools, equipment and accessories for house and garden
F002	Medical products
G001	New cars
G002	Motorcycles and bicycles
I001	Television sets and audiovisual appliances
I002	Photographic, cinematographic equipment and optical instruments
I003	Personal computers and accessories
I015	Watches and other personal effects
	Services
C003	Dry-cleaning and repair of garments and shoes
D001	Rental of garages, parking spaces
F003	Health services
G006	Repair services and work
G007	Repair services and work
G008	Transport services
I009	Sports, leisure, cultural and other services
I012	Beverages in canteens

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NOTES

1. See, for example, Álvarez et al. (2006) for the euro area, Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) for the US, Kaufmann (2009) for Switzerland, and Klenow and Malin (2010) for a survey.
2. Caballero and Engel (1993a) present a generalized (S, s)-adjustment policy and show the implications for aggregate dynamics using the example of employment adjustment. Caballero and Engel (1993b) show the aggregate implications of the adjustment policy for pricing decisions. Estimates of these rules based on microeconomic data can be found in Caballero, Engel, and Haltiwanger (1995) for investment decisions, in Caballero, Engel, and Haltiwanger (1997) for employment adjustment decisions, and in Eberly (1994) and Attanasio (2000) for households' durable purchases.
3. See also Midrigan (2010) and Midrigan (2011) for calibration results of (S, s)-pricing rules.
4. See, for example, Amemiya (1985) for a general discussion of limited dependent-variable models, and Rosett (1959) for an early discussion of how transaction costs can lead to generalizations of the censored regression model.
5. Gautier and Le Bihan (2011) emphasize that it is necessary to allow for time-varying stochastic price-adjustment thresholds because otherwise (S, s)-pricing rules have difficulty in matching the prevalence of small price changes. In particular, the price-adjustment thresholds tend to be too wide and the variance of the idiosyncratic shocks tends to be too large (see the online supplement to Dhyne et al. 2011). However, Eichenbaum et al. (2012) show for US micro data that the prevalence of small price changes is largely due to sampling error and quality adjustment. They argue that the importance of small price changes for evaluating macroeconomic models is therefore overrated.
6. We model the desired price – the price the firm sets once it pays the menu cost – rather than the optimal frictionless price. However, in structural models such as the one presented in Sheshinski and Weiss (1977), the desired price equals the optimal frictionless price plus a positive constant if aggregate inflation is positive (see Gautier and Le Bihan 2011).
7. Formally, Manski (1987) showed how to estimate the parameters of such a model up to scale. Here, the scale is identified from the fact that the coefficient on p_{it-1} is -1.
8. Since both equation (8) and equation (9) are pseudo log-likelihood functions, it is not guaranteed that estimation based on equation (9) will lead to a less efficient estimator even though it uses strictly less information than equation (8).
9. Source: Swiss Federal Statistical Office: data collection for the Swiss CPI, 1994–2007.
10. The sectoral inflation rate is not necessarily a good approximation to changes in nominal marginal costs for two reasons. First, it would be desirable to obtain actual cost measures. For example, Fougère, Gautier, and Le Bihan (2010) use changes in minimum wages and producer price indices to model marginal costs for restaurants. However, we were not able to match our 70 sectors with corresponding producer price indices or wage indices. Second, the sectoral inflation rate is an average of changing prices and constant prices. If pass-through from desired prices to posted prices is slow, then sectoral inflation seems to be a bad proxy for desired prices. However, Bils, Klenow, and Malin (Forthcoming) find that actual inflation and reset price inflation are equally persistent, which is in line with rapid pass-through from desired prices to posted prices.
11. Classification of Individual Consumption According to Purpose; see `unstats.un.org/unsd/cr/registry/regcst.asp?Cl=5`.
12. The detailed approach and the data set are described in Kaufmann and Lein (2011).
13. See also Gautier and Le Bihan (2011). The price-adjustment thresholds do not necessarily depend on inflation in menu-cost models with idiosyncratic shocks as in Danziger (1999) or Gertler and Leahy (2008).
14. These statistics broadly repeat the findings in Kaufmann (2009). Some differences emerge because of different sampling decisions. In particular, the relative frequency of price increases is higher than in the earlier study (1993–2000: 56.2%; 2000–2005: 58.7%).
15. The descriptive statistics for all sectors and statistics including sales are available in an online appendix from the journal website. For all product types, the relative frequency of price increases is slightly lower when we include sales prices.
16. We are grateful to Emi Nakamura and Jón Steinsson for sharing simulated data from their model. The corresponding figures are available in an online appendix from the journal website.
17. Chen et al. (2008), for example, examine retail scanner price data during periods with low aggregate inflation. They find that, even after accounting for inflation, small price increases are still

more frequent than small price decreases.

18. The estimates for each model and more tests of hypotheses are available in an online appendix from the journal website.

19. All results of the robustness tests are available in an online appendix from the journal website.

TABLES AND FIGURES

Table 1: Sample

	Weight	Sectors	Product groups	Products	Observations
Total	48.0	70	1,018	193,583	3,219,722
Non-durable	27.4	41	588	120,830	2,194,817
Semi-durable	4.5	11	181	32,535	469,807
Durable	7.9	10	179	32,367	379,643
Services	8.2	8	70	7,851	175,455

Table 2: Frequency and size of price changes

	fpc^+	fpc^-	$\%\text{fpc}^+$	size^+	size^-	$\%\text{size}^+$	$\bar{\pi}$
Total	11.4	7.1	63.6	8.1	9.9	-1.8	0.7
Non-durable	13.8	9.6	58.9	9.1	9.9	-0.8	0.9
Semi-durable	6.4	3.6	64.2	10.1	12.0	-1.9	0.0
Durable	9.7	5.4	64.2	5.5	8.2	-2.7	-0.5
Services	8.0	2.2	78.2	6.3	10.6	-4.3	1.6

Note: The table gives statistics on the frequency and size of price changes. The statistics are calculated for 70 sectors and then aggregated using average CPI expenditure weights. fpc^+: frequency of price increases; fpc^-: frequency of price decreases; $\%\text{fpc}^+$: relative $\text{fpc}^+ = 100 \times \text{fpc}^+/(\text{fpc}^+ + \text{fpc}^-)$; size^+: absolute size of positive price changes; size^-: absolute size of negative price changes; $\%\text{size}^+$: relative $\text{size}^+ = \text{size}^+ - \text{size}^-$; $\bar{\pi}$: average inflation.

Table 3: Estimation results

	Total	Product types: Non-durable	Semi-durable	Durable	Services
$\Sigma\bar{\pi}_{jt}$ (sectoral price trends)					
Avg. $\beta_1 \vert \beta_1 > 0$	1.17	1.13	1.00	1.54	1.04
	(0.91)	(0.91)	(0.63)	(0.97)	(1.00)
$\Sigma\hat{\pi}_{jt}$ (sector-specific shocks)					
Avg. $\beta_2 \vert \beta_2 > 0$	1.39	1.35	1.34	1.13	1.71
	(0.84)	(0.85)	(0.98)	(0.54)	(0.99)
$\bar{\pi}_{jt}$ (sectoral inflation trend upper threshold)					
Avg. $\delta_1^+ \vert \delta_1^+ < 0$	-4.50	-3.24	-8.08	-6.98	-5.76
	(0.62)	(0.60)	(0.20)	(0.76)	(0.75)
$\bar{\pi}_{jt}$ (sectoral inflation trend lower threshold)					
Avg. $\delta_1^- \vert \delta_1^- < 0$	-5.05	-5.09	-5.73	-5.68	-3.71
	(0.56)	(0.60)	(0.65)	(0.57)	(0.36)
Avg. σ_ε	12.47	13.13	16.09	12.35	8.40
Avg. $\theta_{it}^+ - \mu_i$	22.88	22.11	30.12	21.60	22.72
Avg. $\theta_{it}^- - \mu_i$	-27.84	-26.60	-37.24	-25.05	-29.48
Sectors	70	41	11	10	8
Observations	3,219,722	2,194,817	469,807	379,643	175,455

Note: The table summarizes the estimation results for 70 sectoral models. The first panel gives the estimates for the desired price equation ($p_{it}^* = \mu_i + \beta_1\Sigma\bar{\pi}_{jt} + \beta_2\Sigma\hat{\pi}_{jt} + \varepsilon_{it}$). The second panel gives the estimates on the sectoral inflation trend in the threshold equations ($\theta_{it}^{+/-} = \delta_1^{+/-}\bar{\pi}_{jt} + \ldots$). All explanatory variables are measured in logarithms multiplied by 100. For each model, we perform tests for which the alternative hypothesis is given in the first column. We then report averages of the coefficients, weighted by the average CPI expenditure weights, conditional on this alternative hypothesis. We report in brackets the share of sectors where we reject the null hypothesis at the 5% level. The third panel gives averages of the estimated standard deviation of the idiosyncratic errors and the average thresholds.

Table 4: Explanatory power of covariates

	Model	$\bar{\pi}_{jt} = 0$			$\hat{\pi}_{jt} = 0$
		All equations	Desired price	Thresholds	
Constant	-0.73	-14.61	-11.85	-0.87	9.45
Slope	1.01	1.27	1.23	1.02	0.85
R^2	0.99	0.76	0.74	0.99	0.94

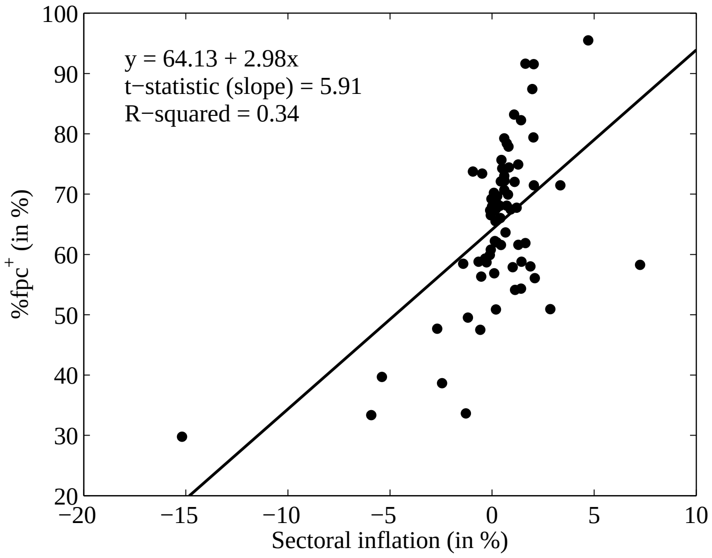
Note: The table shows coefficients and the R^2 from a regression of the actual relative frequency of price increases (%fpc$^+$) on the simulated %fpc$^+$ and a constant. The first column shows the results at actual sample values of the covariates. In the subsequent columns we repeat the regression with a simulated %fpc$^+$, where the corresponding covariate shown in the first row is set to zero.

Table 5: Counterfactual predictions for the relative frequency of price increases

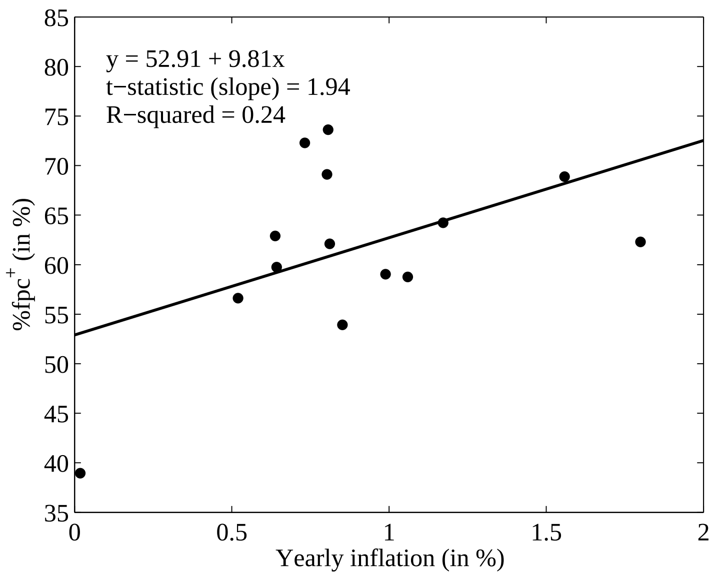
	Data	Model	$\pi_t = 0$		
			All equations	Desired price	Thresholds
Total	63.6	63.4	56.2	59.4	59.9
Non-durable	58.9	59.0	54.3	56.7	56.7
Semi-durable	64.2	63.8	58.7	61.2	61.4
Durable	64.2	63.7	46.1	54.5	54.7
Services	78.2	77.3	71.0	71.9	74.8

Note: The table gives model predictions of the relative frequency of price increases (%fpc$^+$) for various paths of aggregate inflation. The first two columns give the actual %fpc$^+$ and the model predictions at actual sample values of the covariates, respectively. The third column assumes that aggregate inflation is zero by subtracting aggregate inflation from the sectoral inflation trend in the desired price equation ($\beta_1[\Sigma\bar{\pi}_{jt} - \Sigma\pi_t]$) and in the threshold equations ($\delta_1^+[\bar{\pi}_{jt} - \pi_t]$, $\delta_1^-[\bar{\pi}_{jt} - \pi_t]$). The fourth and fifth columns repeat the exercise by setting inflation to zero separately in the desired price equation or the threshold equations.

Figure 1: Relative frequency of price increases and inflation



(a) Across sectors



(b) Across time

Note: The figures give scatter plots and regression lines of the relative frequency of price increases ($\%fpc^+$) on inflation. Panel (a) shows a scatter plot of the sectoral $\%fpc^+$and the sectoral average inflation rate. Panel (b) shows a scatter plot of the yearly aggregate $\%fpc^+$and the yearly aggregate inflation rate.