Linking Individual and Aggregate Price Changes*

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January 2003

Abstract

This paper develops an empirical model of price setting that captures the role of lumpiness and heterogeneity in retail store pricing decisions. The model designed to estimate the deviation between the target and the actual price is applied to a unique panel data set of store level retail prices. The results show that fluctuations in the shape of the cross-sectional density of price deviations convey extra information on inflation dynamics. Asymmetry in the density particularly matters. Idiosyncratic shocks alter the size but not the direction of fluctuations in inflation.

Key words: Inflation, (S,s) Pricing, Microeconomic Price Data, Simulated Maximum Likelihood

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* For many valuable discussions and suggestions at the early stage of this project I thank Matthew Shapiro. Robert Barsky, Susanto Basu, Ufuk Demiroglu, Gábor Körösi, Plutarchos Sakellaris, Todd Stinebrickner, and seminar participants at the Ente Einaudi, IGIER, Michigan, Southampton, the 2002 Econometric Society European Meeting in Venice, the 2002 International Conference on Panel Data in Berlin, the 2002 'Summer at CEU' Workshop in Budapest provided helpful insights to previous drafts. Ádám Reiff added excellent research assistance and useful comments. The usual caveat applies.

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1 Introduction

Especially in countries having adopted inflation targeting as the focus of their monetary regime, policymakers are seeking to possess advance knowledge of forthcoming price changes. Analysts engaged in projecting the real returns on investment in financial assets are also highly keen to learn about future inflation rates. Despite its central importance for policy and business, however, understanding the nature of short-term variation in inflation has been a daunting task for economists for a long period of time.[1]

While a vast amount of research has been amassed on the determinants of short-term inflation over the past decades, some recently documented empirical regularities cast doubt on existing approaches to inflation determination.[2] First, for example, in a review of standard macroeconomic indicators and forecasting techniques, Cecchetti (1995) argues that forecasting relationships for aggregate inflation are unstable and time varying. For the period 1982 to 1994 He concludes that the best, still highly imperfect predictor of inflation appears to be its own past. Cecchetti and Groshen (2000) also report on professional forecasters' prediction of U.S. inflation: the standard deviation of the forecast error in one-year-ahead forecast of inflation has been well above 1 percent in the 1990s, while inflation averaged at about 3 percent. More recently, Atkison and Ohanian (2001) examine standard Phillips curve-based U.S. one-year ahead inflation forecasts over the period of 1985 to 2000, and find that these models perform quite poorly, even when compared to a simple random walk reference.

There are several ways to get around these disappointing developments. Most studies on inflation determination tend to abstract from microeconomic considerations and draw on aggregate (national or sector) level data. In contrast, the present paper seeks to take a step

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[1] Short-term here refers to horizons not exceeding one year.

[2] A detailed review of the traditional literature is beyond the scope of this study, so it is omitted.

towards examining inflation dynamics from a more structural, hitherto unexplored angle. The distinctive features of the project are twofold. First, the empirical approach in it builds on a model of pricing behavior that conforms to evidence on microeconomic pricing patterns. Second, the data analysis is structured around an explicit aggregation of microeconomic price data.

By emphasizing the importance of fixed adjustment costs giving rise lumpiness and heterogeneity in micro level pricing decisions, the central object of the analysis is the price deviation, the postulated log difference between the actual and the target price level.[3,4] Potentially instrumental in related applications where lumpy and heterogeneous microeconomic adjustment is relevant, the main insight in empirically modeling the price deviation is that a generalized two-sided (S,s) pricing rule naturally lends itself to a trinomial latent variable interpretation of the microeconomic target price. Price deviations then bring about price adjustment functions and cross-sectional price deviation densities, all of these objects subsequently placed into an accounting framework to arrive at aggregate inflation. Using the proposed machinery, three main issues are investigated: the shape and the intertemporal stability of adjustment functions and cross-sectional densities, the role of fluctuations in price deviation densities in shaping inflation, and the importance of idiosyncratic pricing shocks in inflation dynamics.

Besides the displeasing performance of existing methods, what motivates the specific approach adopted in this study? First, direct microeconomic evidence shows that nominal price sequences exhibit relatively long periods of inaction followed by intermittent and discrete

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[3] The target price is the optimal price when adjustment costs momentarily removed. Following the rest of the empirical (S,s) literature, the target is assumed to be proportional to the frictional price obtained as the solution to the optimal price setting problem with adjustment costs removed at all horizons.

[4] What is called price deviation here is often termed as relative or real price in related studies. The present terminology appears to be more suitable to describe the behavioral concept at hand (cf. Caballero and Engel (1992)).

adjustments. Lumpiness in the timing of price changes is coupled with a significant element of heterogeneity, especially across different stores.[5] This basic description of pricing behavior in turn suggests that (S,s) pricing models based on fixed cost of price adjustment are likely to serve as a particularly suitable framework for modeling microeconomic pricing decisions.[6]

Second, several recent studies in the macroeconomics literature have highlighted the importance of drawing on microeconomic data in understanding the aggregate economy. For instance, Caballero, Engel and Haltiwanger (1997) examine employment dynamics using a large microeconomic data set of firm-level data and find that changes in the cross-sectional distribution of the deviation of actual from target employment demand explain a sizeable portion of aggregate employment fluctuations in the United States. Drawing on the same data set and utilizing a similar analytical framework, Caballero, Engel and Haltiwanger (1995) reach analogous conclusions regarding capital demand and investment dynamics. Eberly (1994) shows that simulated aggregate durable expenditures obtained from an explicit characterization of the cross-section of heterogeneous and lumpy individual automobile purchase decisions are consistent with the dynamics in aggregate durable expenditures in the United States in the early 1990s. The upshot of this line of research is that it is important to account for the degree of coordination of lumpy and heterogeneous microeconomic actions in explaining the dynamic behavior of macroeconomic aggregates.

The paper is organized into five further sections. The microeconomic price data set is introduced in Section 2. The empirical model is developed in Section 3. The estimation procedure is outlined in Section 4. Sections 5 reports on the results, while Section 6 concludes.

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[5] For a survey, see Wolman (2000).

[6] The non-smooth adjustment of nominal prices in (S,s) models originates from fixed adjustment costs. See, for instance, Ball and Mankiw (1994) and (1995), Caballero and Engel (1992), Caplin and Leahy (1991), Dotsey et al (2000) and Tsiddon (1993).

2 Data

Inferring the history of pricing shocks and their propagation through individual price sequences to aggregate inflation requires a long *panel* of microeconomic price data, ideally of many homogenous products sold in several distinct stores. Samples of prices that are representative of finished goods markets at large or even of a specific sector of the economy are however rarely available in practice. To sidestep the data availability issue, this paper offers a case study of a novel store level panel of processed meat product prices.[7]

The data set is a balanced panel of transaction prices of fourteen processed meat products sold in eight different, geographically dispersed stores in Budapest, Hungary.[8] Out of the eight stores, five are larger department stores and three are smaller grocery stores, called Közért. All stores sell many other products besides the ones considered here. Whenever a particular store is visited, all the fourteen product prices are recorded. Observations in the final sample are at the monthly frequency, they start in January 1993 and end in December 1996. Due to a five-month intermission in data collection from April 1995 through September 1995, the sample is split into two sub-periods covering 27 and 16 months. Throughout the sample period, there was no government control of processed meat product prices.[9]

While having clear limitations including its size and scope, the sample does serve as an excellent laboratory for the purposes of this paper. First, the items are well-defined, important, homogeneous food products with essentially no variation in non-price, physical characteristics such as quality. Second, the goods have low degrees of processing; producing them requires a single basic input component, the underlying raw material. Third, inference about stores' pricing

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[7] The shortage of appropriate store level price data may partly explain the paucity of closely related research.

[8] The products are boneless chop, center chop, leg, back ribs, thin flank, round, roast, brisket, hot dog, sausage for boiling, shoulder, spare ribs, smoked loin-ham, fat bacon.

[9] Appendix A provides further details of the sample.

policy is unlikely to be contaminated by major differences across production technologies. Finally, although it is more volatile, the sample price index tracks movements in the overall CPI, especially its food component.[10] The partial correlation coefficient between the sample average price level and the food component of the CPI in Hungary is 0.94. The time series properties of the sample price index also closely match the properties of a similar sector level index of processed meat product prices compiled by the Central Statistical Office, Hungary.

2.1 Descriptive Evidence

Rátfai (2001) provide a detailed non-parametric description of the sample at hand. To motivate the empirical model of price setting, it is instructive to briefly highlight some basic findings therein. First, nominal prices remain constant in 58 percent of the cases and the average duration of price quotations is about three months with the longest spell being 17 months. With the exception of months in the third quarter when the relevant raw material prices happen to spike, spells of adjustment are spaced irregularly across stores. The duration of price changes within stores is fairly dispersed over time, while contemporaneously it tends to be more synchronized.

The size of price changes is relatively homogenous across stores and products. The average size of non-zero price changes is about 9 percent in the whole sample, with the largest size being about 63 percent. The average size of positive changes is 10.85 percent in period 1 and 11.73 percent in period 2. Average negative changes are smaller: -8.24 percent in period 1 and -7.32 percent in period 2. These findings also suggest that price fixity can be well captured at the monthly frequency.

[10] The series obtained as an unweighted average of price changes is plotted in Figure 1a.

3 The Empirical Model

The semi-structural model designed to capture the role of lumpiness and heterogeneity in microeconomic pricing in inflation dynamics is developed in two stages. First, the microeconomic model for the target price and the price deviation is specified. Then, an aggregation framework is developed to organize price deviations into an inflation index[11].

3.1 Measuring the Deviation

Potentially, there exist a number of approaches to model the deviation between actual and frictionless behavior. Caballero, Engel and Haltiwanger (1995), for instance, derive mandated investment, the log deviation between actual and target capital as a function of firm-specific variables that are individually highly persistent and argue that a (S,s)-type decision rule is bound to make mandated investment mean-reverting. This insight allows them to estimate the parameters of mandated investment in a cointegrating framework. Alternatively, Caballero, Engel and Haltiwanger (1997) identify the deviation between actual and target employment simply as a temporary fluctuation in hours per worker.

The hypothesized correlation between various measures, typically the dispersion of cross-sectional price deviation densities and aggregate inflation is an extensively studied issue in macroeconomics. Papers in this literature drawing on microeconomic price data tend to proxy, at least implicitly the target price with the across-store average of actual prices or the change in them (see Lach and Tsiddon (1992)). There are two related concerns with this *ad hoc* practice. First, in pricing models the target price is driven by the convolution of idiosyncratic and aggregate pricing shocks, so there is simply no structural reason to identify the target price with the product level average of prices in empirical analysis. Second, even if one abstracts from

[11] Throughout the data analysis, aggregate inflation refers to aggregate price changes in the sample at hand.

idiosyncratic pricing shocks, the target price tends to systematically differ across stores, due to geographical, financing, taxation or other considerations.

3.2 The Microeconomic Pricing Rule

The empirical framework developed in this paper markedly differs from previous attempts to measure the deviation.[12] It is based on the idea that fixed costs of changing prices create an imbalance between actual and target behavior and make pricing policies state-dependent. When shocks to the target price are symmetric, fixed adjustment costs result in a two-sided (S,s) pricing rule with the price deviation, the log difference between the actual and the target price typically differing from zero. Stores alter their nominal price and pay the fixed cost only when the state variable, the price deviation is sufficiently large to exceed one of the optimally determined threshold values. When shocks are unable to push the price deviation outside the (S,s) band, the current nominal price coincides with the preceding one and no actual pricing action takes place.

Formally, stores leave their nominal prices unaltered until the price deviation in store i of product j at time t, $z_{ijt} \equiv p_{ij,t-1} - p_{ijt}^{*}$, passes one of the two adjustment boundaries, S or s. If pricing shocks push z_{ijt} outside the band, stores will pay the adjustment cost and alter their nominal price either upwards when $z_{ijt} \leq s$ or downwards when $z_{ijt} \geq S$. The implied observation rule for the log nominal price level is then summarized as

[12] A close relative to this approach is the one explored in Bertola et al (2002) to study durable good expenditures. The differences between the current work and Bertola et al (2002) are still manifold. In short, they implement one-sided (S,s) policies in estimating microeconomic decision rules, abstract from the potential persistence in unobserved heterogeneity, focus on a Tobit specification of decision rules and are mainly concerned with microeconomic implications.

$$p_{ijt} \begin{cases} < p_{ij,t-1} & if \quad p_{ij,t-1} - p^*_{ijt} > S \\ = p_{ij,t-1} & if \quad s < p_{ij,t-1} - p^*_{ijt} < S \\ > p_{ij,t-1} & if \quad p_{ij,t-1} - p^*_{ijt} < s \end{cases}.$$

This description of pricing behavior suggests that the target price can be viewed as a latent variable, with the two-sided (S,s) rule translating into a trinomial probit panel model. Notice that the definition of the price deviation involves a special timing convention. As shocks to the target price are assumed to take place at the beginning of the current period, the price deviation does not to reflect stores' reaction to any pricing shock.

The key point in empirically implementing the price deviation model is the specification of the target price.[13] Besides lumpiness, the raw data suggest two fundamental regularities in price setting. First, the technology used to produce processed meat products dictates that the relevant raw material prices are basic elements in the product prices. Indeed, a crucial advantage of the data set used here is that the aggregate variable driving the target price is readily identified as the raw material price.[14] Second, certain stores are systematically more (or less) expensive than others, perhaps due to variation in the local tax-burden, the general quality of the store or simply the affluence of typical customers. Differences in consumer taste or production technology also cause certain product prices to be permanently different from others. To capture the persistent heterogeneity in price sequences, nominal prices are assumed to have a stochastic, time-varying residual term, ω_{ijt}, with homoskedastic variance, Ω and a constant store- *and* product-specific intercept term, a_{ij},. The residual term is interpreted as an idiosyncratic pricing

[13] Appendix B describes a simple model of the target log price, with monopolistically competitive stores with no friction in price.

[14] The raw material prices are the price of cattle for slaughter or pig for slaughter. Dunne and Roberts (1992) also emphasize the key role of raw material prices as determinants of plant level pricing behavior in the United States.

shock, specific to a particular product, store and month. In this sense the target price is driven by a combination of recurrent idiosyncratic and aggregate pricing shocks.

To ease estimation by reducing the number of parameters to be separately identified, the constant term, a_{ij}, is split into two parts: $a_{ij} = a_i + a_j$ where a_i is a store-specific and a_j is a product-specific component. Taken together, these considerations yield the following linear, fixed effect panel model for the log target price level:

$$p^*_{ijt} = a_{ij} + bm_{jt} + \omega_{ijt} = a_i + a_j + bm_{jt} + \omega_{ijt},$$

where m_{jt} denotes the log raw material price. Conforming to a model of optimal pricing decisions in a monopolistically competitive market with no frictions, entry or exit, the economic interpretation attached to this specification is one of markup over cost pricing. Overall, the fundamental elements of the specification are flexible enough to encompass a large class of two-sided (S,s) models.

3.3 State Dependence

The discrete choice decision rule associated with the latent variable framework exhibits both what Heckman (1981a) calls true and spurious state-dependence. As the current realization of the state variable is directly related to past actions, (S,s) type decision rules naturally give rise to *true* state-dependence by the lagged control variable entering the decision rule via the censoring thresholds. *Spurious* state dependence in general stems from the possibility that past realizations of heterogeneous unobservables impact on current decision variables. This type of intertemporal linkage appears here through serially correlated residuals, originating from persistent technology or demand driven disturbances. To comply with this characterization of unobservables, the

residual term in the regression model is assumed to follow an AR(1) process, with a constant auto-regressive parameter

$$\omega_{ijt} = \rho\omega_{ij,t-1} + \varepsilon_{ijt},$$

where ε_{ijt} is $N(0, \sigma_\varepsilon^2)$ i.i.d.. Overall, the resulting empirical model of the price deviation to be estimated is a multi-period, trinomial, fixed effect panel probit with serial correlation in the residual.[15]

3.4 Aggregation

At the microeconomic level, aggregate and idiosyncratic pricing shocks are filtered through the price deviation in a highly non-linear way. To capture the mechanism propagating microeconomic pricing shocks to the aggregate level, an accounting framework defining a measure of inflation as a weighted-average of the individual mean price changes with weights given by the cross-sectional density of price deviations is introduced. Analogously to Caballero, Engel and Haltiwanger (1995), (1997), omitting store- and product specific indices momentarily, aggregate inflation is defined as

[15] In general, the main advantage of a fixed over a random effect specification is that the former approach does not require the independence of latent heterogeneity and observed characteristics for consistent estimation. The main potential drawback of fixed effect specifications in many non-linear models is the incidental parameter problem: estimates of the individual effects are inconsistent for fixed T and this inconsistency is transmitted to other parameter estimates. Monte Carlo simulation results of a panel probit model in Heckman (1981b) indicate however that the bias is negligible in practice for $N = 100$ and $T = 8$; implying that inconsistency is unlikely to be a serious concern in the present application with $N = 112$, $T_1 = 27$ and $T_2 = 16$.

$$\Pi_t = \int z_t A_t(z_t) f(z_t, t) dz_t \ . \tag{1}$$

The aggregation formula features two fundamental building blocks, defined later in more detail: the cross-sectional empirical density of price deviations, $f(z_t,t)$, and the price adjustment function, $A_t(z_t)$. The price adjustment function is defined as the mean actual price change measured at particular realizations of price deviations normalized by the corresponding price deviation. The main advantage of this particular aggregation approach is that it allows for evaluating the role of fluctuations in price deviation densities and adjustment functions in inflation dynamics. Potentially, it also permits to account for the separate importance of idiosyncratic versus aggregate pricing shocks in inflation.[16]

4 Estimation

To motivate the estimation strategy, consider first the situation in which the residual in the model for the price deviation developed above is identically and independently distributed. In the absence of temporal dependence in the residual, the log-likelihood function can be simply written as the product of the appropriate marginal probabilities

$$L \equiv \sum_{\substack{i=1,\ldots,8 \\ j=1,\ldots,14}} \ln\left[prob(p_{ij1},\ldots,p_{ijT}) \right] = \sum_{\substack{i=1,\ldots,8 \\ j=1,\ldots,14}} \ln\left[\int_{p_{ijt}=\tau(p^*_{ijt})} f(p^*_{ijt} - a_i - a_j - bm_{jt}) dp^*_{ijt} \right] =$$

[16] The resulting weighted measure of inflation is plotted in Figure 1b. It is virtually identical to the simple unweighted index of aggregate price changes shown in Figure 1a. The correlation coefficient is 0.998.

$$\sum_{\substack{i=1,\ldots,8\\ j=1,\ldots,14}} \ln\left[\int_{-\infty}^{\infty}\left\{\begin{array}{l}\prod_{p_{ijt}>p_{ij,t-1}}(1-F(p_{ij,t-1}-s-a_i-a_j-bm_{jt}))\times\prod_{p_{ijt}<p_{ij,t-1}}F(p_{ij,t-1}-S-a_i-a_j-bm_{jt})\times\\ \prod_{p_{ijt}=p_{ij,t-1}}(F(p_{ij,t-1}-s-a_i-a_j-bm_{jt})-(F(p_{ij,t-1}-S-a_i-a_j-bm_{jt}))\end{array}\right\}dp^*_{ijt}\right]$$

where *F(.)* denotes the normal cumulative density function. Here standard quadrature based Maximum Likelihood procedures serve as a straightforward solution method. Even if temporal dependence in the error term is neglected when it is actually present, parameter estimates are consistent.[17]

However, if the correlation structure is erroneously specified as i.i.d., *and* lagged dependent variables enter the model as they do here via the censoring thresholds, the standard ML estimation of the probit panel model leads to inconsistent parameter estimates (see Keane (1993)). This concern is especially troubling in the present application as the estimated parameters are used to form the cross-sectional density of price deviations and then aggregate inflation. These considerations call for a more careful treatment of the serial correlation in the residual. Once this is done, however, the log-likelihood function cannot be factored out in the usual fashion as evaluating the joint likelihood of consecutive price observations requires the computation of T (the number of time periods) dimensional integrals. Without imposing further simplifying restrictions on the covariance structure of residuals, the computation of these high dimensional integrals is numerically infeasible by standard procedures. Fortunately, simulation estimation techniques offer a suitable remedy.

A simple approach to consistently estimate model parameters is the direct simulation of choice sequence probabilities by the observed frequencies (Lerman and Manski (1981)). The problem with the direct simulation approach is that obtaining reasonably precise estimates of the possibly quite small probabilities entails a burdensome number of draws and thus excessive

[17] Nonetheless, parameter estimates and the estimated standard errors are biased.

computational efforts. In the absence of a large number of draws, the frequency simulator of the joint choice probabilities is discontinuous in the estimated parameters.[18]

The Simulated Maximum Likelihood (SML) estimator drawing on the Geweke-Hajivassiliou-Keane (GHK) simulator of importance sampling of univariate truncated normal variates offers a viable alternative. A brief outline of the GHK procedure tailored to the present context is as follows. The log-likelihood function to be maximized is

$$L \equiv \sum_{\substack{i=1,\ldots,8 \\ j=1,\ldots,14}} \ln\left[prob(p_{ij1},\ldots,p_{ijT}) \right] = \sum_{\substack{i=1,\ldots,8 \\ j=1,\ldots,14}} \ln\left[\int_{p_{ijt}=\tau(p^*_{ijt})} f(p^*_{ijt} - a_i - a_j - bm_{jt}) dp^*_{ijt} \right].$$

As described above, the serial correlation posited in the residual implies that estimating the parameters requires an indirect evaluation of the high dimensional integrals for the cross-sectional units. Consider now the sequence of prices of a single product in a single store. Dropping all subscripts for now, first, let us define recursively the normally distributed structural error term, ω, as $\omega = Ce$ where C is the lower triangular Cholesky decomposition of Ω satisfying $C'C = \Omega$, where e is a univariate i.i.d. standard normal variable. Then, instead of drawing directly from the original distribution of serially dependent truncated normals, the variable, e, is sampled R times sequentially and independently from the recursively restricted univariate standard normal distribution[19].

Assume that the nominal price remains constant for three consecutive periods. Then the draws of standard normal variates, e_1, e_2, e_3, are obtained as

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[18] Indeed, besides computational feasibility, smoothness (differentiability and continuousness) is a fundamental requirement to simulation estimators as it allows for applying standard hill-climbing or gradient methods in maximizing the log-likelihood function.

[19] In practice, sampling from the uniform distribution and then applying the inverse truncated normal distribution function to the outcome generates the required draws from a univariate, truncated normal distribution.

$$\alpha_1 = \frac{A_1^*}{c_{11}} \le e_1 = \frac{\omega_1^*}{c_{11}} \le \frac{B_1^*}{c_{11}} = \beta_1$$

$$\alpha_2 = \frac{A_2^* - c_{21}e_1}{c_{22}} \le e_2 = \frac{\omega_2^* - c_{21}e_1}{c_{22}} \le \frac{B_2^* - c_{21}e_1}{c_{22}} = \beta_2$$

$$\alpha_3 = \frac{A_3^* - c_{31}e_1 - c_{32}e_2}{c_{33}} \le e_3 \equiv \frac{\omega_3^* - c_{31}e_1 - c_{32}e_2}{c_{33}} \le \frac{B_3^* - c_{31}e_1 - c_{32}e_2}{c_{33}} = \beta_3 \ldots$$

where $A_t^* = p_{ij,t-1} - S - (a_i + a_j + bm_{jt})$ and $B_t^* = p_{ij,t-1} - s - (a_i + a_j + bm_{jt})$. The estimated joint probability of a price sequence is then the average of the simulated likelihood contributions factored as products of the simulated conditional probabilities:

$$prob(p_{ij1},...,p_{ijT} \,|\, m_{jt}, b, a_i, a_j, s, S, \rho, \Omega) =$$

$$\frac{1}{R}\sum_{r=1}^{R}\left[\prod_{p_{ijt} > p_{ij,t-1}} \{1 - F(\beta_t \,|\, e_r)\} \times \prod_{p_{ijt} < p_{ij,t-1}} \{F(\alpha_t \,|\, e_r)\} \times \prod_{p_{ijt} = p_{ij,t-1}} \{F(\beta_t \,|\, e_r) - F(\alpha_t \,|\, e_r)\}\right].$$

The computationally most burdensome stage of the estimation is the large number of simulations to estimate the joint occurrence of a sequence of price realizations. Börsch-Supan and Hajivassiliou (1993) report that relatively accurate likelihood estimates are obtained by employing a relatively small number of repetitive draws; 20 or 30 draws are often sufficient with three to seven alternative choices. In the current application, to use err at the conservative end, 50 sampling draws are employed. Although estimates of the implied truncated residuals are in general biased, the likelihood contribution is correctly simulated. Most importantly, the simulated log-likelihood is an unbiased and smooth estimate of the true log-likelihood function.[20]

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[20] Extensive comparisons by Börsch-Supan and Hajivassiliou (1993) of the accuracy and bias in the various possible simulation estimators of multivariate truncated normal probabilities show that the GHK approach performs best among similar estimators. Besides accommodating various correlation structures, the SML estimator is continuous in the parameters, relatively quick in reaching convergence, and provides consistent and efficient estimates even in the presence of lagged endogenous variables.

Identification of the intercept effects requires fixing at least one of the adjustment boundary parameters. While its exact position being constrained, the size of the band is still determined independently of this restriction. The initial values used in the simulation estimation are obtained from estimating the model with no serial correlation in the residual. Experimentation with alternative initial values confirms that the estimation results are robust to reasonable departures from these particular values.

Separately for the two periods, the estimated parameters of interest are reported in Table 1.[21] There are some notable points to highlight. First, the standard errors indicate that the parameters are fairly tightly estimated. Second, the autocorrelation parameters are sizeable and significantly different from zero, justifying the explicit account for the temporal dependence in the unobserved residual. Third, the slope estimates are somewhat larger than one indicating some increasing returns at the micro level. Fourth, the implied total size of the band is about 35% and 26% in the two periods. Finally, with the exception of the band parameters, the important point estimates in the two periods are about the same.

5 Results

5.1.1 The Cross-Sectional Density of Price Deviations

One of the fundamental implications of state dependent pricing models is that the impact of pricing shocks on aggregate price changes depends on the cross-sectional distribution of price deviations. In aggregating (S,s) pricing policies, Caplin and Spulber (1986) assume a uniform time-invariant distribution of price deviations and conclude that expected monetary policy may

[21] The estimations are performed in Gauss. The routine draws on a code simulating multivariate normal probabilities in a multinomial probit model supplied by Vassilis Hajivassiliou via his anonymous ftp-site. The parameter for the upper boundary is set to S = 0.13 in both periods. The results are robust to including monthly dummies in the baseline specification.

have no impact on aggregate output even when prices are sticky. Tsiddon (1993) demonstrates in a two-sided (S,s) pricing model that a positive trend in the target price forces price deviations to spend disproportionately more time closer to the lower adjustment band than to the upper one. The pressure exerted by the positive trend thus implies that the stationary distribution of price deviations has an asymmetric, in Tsiddon (1993) piece-wise exponential shape.

The sample of product prices used in this study appears to be ideal to learn more about the shape of price deviation densities observed in the data. To generate the empirical densities, one first needs to obtain an estimate of idiosyncratic shocks. While the exact realization of idiosyncratic shocks is directly unobserved by construction, their density is readily available. To obtain the probabilities defining the truncated densities, first, a discretized state space is defined with a bin width of one percent for price deviations between –70 and 60 percents. The conditional probabilities generating the truncated densities are evaluated at the middle-point of the bin intervals. Given the truncation points of $A_{ijt}^{*} = p_{ij,t-1} - S - (a_i + a_j + bm_{jt})$ and $B_{ijt}^{*} = p_{ij,t-1} - s - (a_i + a_j + bm_{jt})$, the probabilities defining the truncated normal densities are then obtained as the ratios of the probability of being in a particular bin interval and the probability of experiencing a particular pricing action. Averaging then the resulting truncated densities in the cross-section results in an empirical distribution of price deviations in each month.

Microeconomic price deviations are constructed by imposing a microeconomic decision rule of the (S,s) type on the data. Is the shape of the resulting empirical densities consistent with any of the possible approaches to aggregating microeconomic (S,s) pricing rules? First, summary statistics show that the average standard deviation of price deviations in the sample is 15.23 percent, reflecting the fact that there is considerable cross-sectional heterogeneity in pricing both across stores and products. The two panels in Figure 2 show the histogram of price deviations in the two periods, pooled over time, stores and products[22]. The density appears to be highly non-

[22] To facilitate visual inspection, a third degree polynomial is fitted to all empirical densities.

uniform and asymmetric, consistently with the presumption made in aggregating two-sided (S,s) policies.

How does the shape of the empirical densities of price deviations evolve over time? To ease visual interpretation, first, the *quarterly* frequency densities are displayed in Figure 3. Simple eyeballing of the graphs indicates that the densities tend to have non-uniform, often asymmetric shape. Histograms in the third quarter tend to feature leftward warped distributions with many price deviations bunching towards the lower end of the density. This shape of the distribution is consistent with the presence of strong inflationary pressures. Conversely, the rightward bent second quarter histograms typically reflect the pressure on nominal price cuts.

Changes in the shape of the histograms are suggestive of the evolution of aggregate inflation. A few interesting episodes indeed stand out. By many price deviations bunching in the neighborhood of the lower adjustment boundary, the histograms in Figure 3 pick up the story of accelerating inflation in early 1994 eventually terminated by the middle of 1995. Also, the relatively large number of price deviations bunching on the right end of the densities at the beginning of 1993 and 1996 witness deflationary pressures on meat product prices. In contrast, in the first part of 1994, the histograms rather signal pressure on subsequent price increases.

5.1.2 The Price Adjustment Function

Dropping store- and product-specific subscripts, the adjustment function is defined as

$$A_t(z_t = k) = \frac{DP_t(z_t = k, \forall i, j)}{z_t}.$$

where k denotes the bin points described above. The average price change, $DP_t(z_{ijt} = k, \forall i, j)$, is computed as a weighted average of all nominal price changes (including zeros) in month t at price deviation k, where the weights are obtained from the corresponding cross-sectional

densities. The definition implies that $A_t(z_t)z_t$ measures the expected size of price changes at particular price deviations.

Models of optimal price setting deliver meaningful predictions on the shape of the adjustment function. When stores follow two-sided (S,s) pricing rules, stores are willing to tolerate small deviations between the actual and the target price level, but a sufficiently large deviation induces them to alter their nominal price. The implication of this reasoning is that one observes large price changes in absolute value for extreme price deviations outside the (S,s) band, and zero values for a range of intermediate price deviations inside the band. That is, the adjustment function takes on a hat (or reverse-U) shape. In reality, stores may not be fully intolerant to adjusting at small deviations or not fully adjusting at large ones. Instead, they are likely to have average normalized price changes evolving more smoothly outside and in the neighborhood of the boundaries, perhaps in a less symmetric manner as well.

As it determines the extent to which fluctuations in price deviation densities impact on inflation, changes in the shape of the adjustment function may have important aggregate consequences. If the adjustment function is assumed to be an *n*th degree polynomial then aggregate inflation depends on all the $(n+1)$ moments of price deviations (see Caballero, Engel and Haltiwanger (1995), (1997)). For instance, if adjustment costs were nonexistent or simply convex, $A_t(z_t)$ would follow a smooth path and be virtually invariant to z_t. Then higher moments of the cross-sectional density of price deviations would be irrelevant to inflation.

Figure 4 portrays the total adjustment functions, separately for the two periods. The functions are constructed by pooling all price deviations in the two parts of the sample. Visual inspection of the graphs suggests that the shape of the adjustment functions is in general consistent with the implication of two-sided (S,s) models, taking on a hat-shaped form and

reflecting the inaction region implied by the latent variable structure imposed on the data.[23] It is also apparent that the average adjustment functions are relatively stable across the quarters.

Figure 5 displays the same information separately for the fourteen quarters available. Despite the noise in constructing the graphs, the pictures again indicate that adjustment functions are remarkably stable over time and that they are broadly consistent with (S,s) theory motivating their construction. The intertemporal stability of the adjustment function indicates that the empirical specification imposed on the data captures well the underlying microeconomic structure governing stores' pricing behavior.

5.2 Aggregate Implications

With fixed price adjustment costs, histories of pricing shocks and the heterogeneous response of stores to these shocks are summarized in the cross-sectional density of price deviations, implying that the shape of these densities is likely to serve as an important determinant of aggregate price dynamics. Drawing on sector level inflation data in the U.S., Ball and Mankiw (1995) indeed find that the higher moments of cross-sector relative inflation rate densities impact on inflation. They conclude that inflation is primarily related to the asymmetry in the distribution.

The following analysis also asks how the shape of microeconomic price deviation densities determines inflation dynamics. The main focus of analysis is on the dispersion and asymmetry in the densities. Dispersion is captured by the standard deviation statistic. Measuring asymmetry is less straightforward; it is not *a priori* obvious what statistic captures best the fundamental concept of interest, the relative bunching of price deviations near to the adjustment boundaries. In what follows two alternative measures of asymmetry are considered, the standard skewness coefficient and the mean-median difference.

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[23] The discontinuity is due to the assumption that the boundaries are fixed.

First, the three panels in Figure 6 show the time path of the dispersion and asymmetry measures along with the corresponding aggregate inflation series. The graphs suggest that inflation is positively correlated with all the three different measures of the shape of the density. Table 2 displaying the unconditional correlation coefficient among the series confirms this presumption. Moreover, the correlation is sizeable and significant for both asymmetry measures.

To assess the robustness of the simple correlation results, conforming to Ball and Mankiw (1995), a set of horse-race regressions is run with aggregate inflation as the dependent and the various measures of the shape of price deviation densities as independent variables. While the specification is clearly simple, it highlights the role higher moments of price deviation densities may play in inflation dynamics. The basic regression equation takes the form of

$$\Pi_t = b_0 + b_1 \Pi_{t-1} + b_2 StDev_t(z) + b_3 Asym_t(z) + u_t$$

where *StDev(z)* denotes the standard deviation and *Asym(z)* denotes the asymmetry measure of price deviation densities.

Six different specifications are considered. All of them include a constant, lagged inflation and measures of the shape of price deviation densities as explanatory variables. The findings are summarized in Table 3. Estimates from the benchmark AR(1) model reported in the first column. The coefficient on the lagged inflation term points to the persistence in the inflation process. The R^2 statistic indicates a respectable fit. The second column shows results with a model appended with the standard deviation in price deviations. Comparing the adjusted R^2 statistics reported in the first two columns indicates that adding the standard deviation provides no progress in goodness-of-fit and the standard deviation parameter is insignificant. The results for the equation augmented solely by the skewness statistic are displayed in the third column. This specification substantially improves goodness-of-fit when compared to the preceding ones. In addition, the parameter estimates for skewness are statistically significant. The findings for the model that includes both skewness and standard deviation as independent variables are in

column five. Having measures of both dispersion and skewness in the regression equation leaves the standard deviation parameter insignificant and the fit of the model virtually unchanged. The final two models use the alternative measure of asymmetry in the price deviation distribution, the mean-median difference. The results show that the parameter estimates are of the expected sign, the ones for the asymmetry measure are statistically significant. The models with or without the standard deviation provide a better fit than either the AR(1) or the pure standard deviation model, but a poorer fit then implied by the models with the skewness statistic.

It is instructive to examine how fluctuations in $A_t(z_t)$ and $f(z,t)$ shape inflation dynamics from yet another angle. The idea is to construct counterfactual aggregate inflation series by replacing the actual monthly frequency cross-sectional distributions and adjustment functions with their seasonal (i.e. quarterly) or overall average counterpart, and then compare the proximity of these counterfactual series with the true one. For example, replacing the actual adjustment function, $A_t(z_t)$ in the aggregating framework with the corresponding seasonal average amounts to shutting down cyclical but retaining seasonal fluctuations in it. Following Caballero, Engel and Haltiwanger (1997), the goodness-of-fit measure used to evaluate the proximity of the resulting counterfactual and actual price dynamics is

$$G(.)=1-\frac{\sigma^2(\Pi_t^{cf}-\Pi_t)}{\sigma^2(\Pi_t)}$$

where Π_t^{cf} ($cf = s$ (seasonal), oa (overall average)) is the counterfactual, Π_t is the actual aggregate price change and σ^2 denotes the time-series variance of the series. To the extent that it is not constrained by zero from below, the statistic is different from the traditional goodness-of-fit measure, R^2.[24]

[24] The reason for this is that the residual part here is not necessarily uncorrelated with the predicted one.

Table 4 displays the goodness-of-fit results. First, shutting down cyclical and keeping only seasonal movements in $f(z,t)$ distracts aggregate inflation from its true dynamics by a much larger extent than playing down similar cyclical fluctuations in $A_t(z_t)$. In the former case, reflecting again the intertemporal stability of the adjustment function, $G(.)$ falls by 26 percent, while in the latter case only by 10 percent. Entries in the top right and bottom left corner of the table show the goodness-of-fit measures obtained by removing all (seasonal and non-seasonal) fluctuations in the cross-sectional density or in the adjustment function, respectively. The results indicate a dramatic deterioration in fit in the former case, $G(.)$ falling to 0.37. In contrast, the proximity of the two series is only moderately reduced with no time-series variation in the adjustment function. The goodness-of-fit statistic is 0.79 here. Indeed, removing all fluctuations in the adjustment function and keeping the original density results in a better fit than taking away only cyclical and leaving seasonal fluctuations in the cross-sectional distributions.

The results overall indicate that swings in both the cross-sectional density and the adjustment function are non-trivial ingredients of aggregate price dynamics. Seasonal and cyclical fluctuations in the adjustment function contribute relatively little to aggregate price dynamics, while fluctuations in the cross-sectional distribution are fundamental both at the seasonal and the cyclical frequency.

5.3 Idiosyncratic Shocks

In a frictionless neoclassical economy the aggregate impact of idiosyncratic shocks cancels out by relative price adjustment. Although they still average to zero by definition, the impact of idiosyncratic shocks on pricing decisions is not neutral any more if there are fixed costs to price adjustment. Many small idiosyncratic shocks in one direction may have no aggregate effect at all, while only a few large ones in one direction actually does have.

How important idiosyncratic shocks are in shaping aggregate price dynamics? In particular, what fraction of fluctuations in inflation can be attributed to idiosyncratic shocks, after having them filtered through the cross-sectional density of price deviations?[25] To address this issue, first, idiosyncratic shocks are suppressed in computing the counterfactual price deviation densities, *f(y)*, under the maintained assumption that adjustment functions remain the same as in the baseline case, *A(a)*. Then the counterfactual inflation series are obtained as a weighted average of price changes with weights provided by *f(y)*.

Figure 7 displays the counterfactual series together with the actual one. A simple visual inspection of the graph suggests that the series closely moves together. This impression is confirmed by the partial correlation coefficient of 0.88. Figure 7 also suggests that idiosyncratic shocks alter the size of inflation changes. Had idiosyncratic shocks not mitigated aggregate surprises, for instance, inflation would have been higher by 3 to 9 percents between July and October 1994. At the same time, during the first six months of 1993 idiosyncratic shocks seem to have prevented an even more drastic deflation in processed meat product prices. The proximity of the true and the counterfactual series is also assessed by the goodness-of-fit statistic introduced earlier. The resulting figure of 0.62 indicates that eliminating all variation in idiosyncratic disturbances fundamentally alters the size of inflation changes, though not their direction. Finally, Figure 8 displays the empirical density when price deviations are fully purged from idiosyncratic shocks. The graph features a non-uniform distribution suggesting that it is not the particular functional form imposed on the residual term that drives the basic shape of price deviation densities.

5.4 A Comparison

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[25] Idiosyncratic shocks are identified with the residual obtained in the panel model. Eliminating idiosyncratic shocks means that the only source of heterogeneity in counterfactual price deviations stems from the time-invariant individual effects.

Given the simplicity and popularity of the approach to proxy the target price in an *ad hoc* manner, it is worthwhile asking the question: does higher cross-sectional moments of price deviations contain information on inflation, when the target price is defined as the across-store average of actual prices? To address the issue, a set of univariate linear regression models are estimated again with inflation as the dependent and measures of the shape of the deviation densities as independent variables

$$\Pi_t = b_0 + b_1 \Pi_{t-1} + b_2 StDev_t(x) + b_3 Asym_t(x) + u_t .$$

StDev(x) again denotes the standard deviation and *Asym(x)* one of the usual asymmetry measures of the density. The price deviation is defined as $x_{ijt} = p_{ij,t-1} - \overline{p}_{jt}$, where $\overline{p}_{jt}$ is the across-store average of actual prices for product *j*.

The findings summarized in Table 5. Besides the ones for lagged inflation, all parameter estimates prove to be statistically insignificant. The point estimates for the asymmetry parameters even have the wrong sign. In addition, as indicated by the adjusted R^2 statistics, higher moments of price deviation densities are in general unable to improve the goodness of fit of the benchmark AR(1) model. Clearly, the results are unable to go anywhere close neither to the ones reported by Ball and Mankiw (1995) using less disaggregated data nor to the current results employing a more structural measure of the price deviation.

6 Conclusions

Are (S,s) pricing models originally designed to provide behavioral foundations for business cycle analysis able to carry implications for the understanding of inflation dynamics? By applying an empirical technique rooted directly in (S,s) considerations to a unique, highly disaggregated panel sample of consumer prices, the study gives an affirmative answer.

The empirical model is specifically aimed at recovering and quantifying information potentially lost by merely taking averages of individual prices when modeling inflation determination. What can one carry away from the analysis? The findings in general confirm the argument that an explicit aggregation of intermittent *and* heterogeneous individual pricing actions yields new insights for a more adequate understanding of aggregate price changes. More in particular, first, the shape of the price adjustment function is relatively stable over time. Second, fluctuations in the shape of the cross-sectional distribution of price deviations contribute to aggregate inflation dynamics. Asymmetry in the cross-sectional density particularly matters. Finally, though idiosyncratic shocks do not alter the direction of aggregate inflation dynamics, they do determine the magnitude of fluctuations.

Provided that the appropriate microeconomic price data are available on a timely basis, the analysis also has clear implications for monetary policy making. In formulating short-term inflation forecasts, central banks currently rely on only histories of aggregate variables, often mainly inflation itself. Prior evidence indicates however that the usual macroeconomic variables are unable to reliably forecast short-term aggregate price changes. In contrast, the findings of this study show that even when no particular pattern is observed in past average prices, the latent pressure built up in directly unobservable price deviations can provide a useful signal for forthcoming inflation. In practice, detecting the correct signal requires a careful specification of the target price for the product prices at hand and a forecasting procedure that accounts for the specific features of the timing of microeconomic data release.[26]

Finally, a clear limitation of the analysis is the specificity and the size of the sample. Future research should also investigate a richer sample of prices with a broader set of product categories and more stores involved.

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[26] Implications of the model for out-of-sample forecasting are the subject of ongoing research.

APPENDIX A – DATA IMPUTATION

The data were originally collected for commercial purposes by the price-watch service of Solvent Rt. (Solvent Inc.), Budapest. The current sample consists of the consumer prices of 14 products in 8 stores over 27 (Period 1) and then 16 (Period 2) months (see Rátfai (2001) for further details). The sample is unbalanced in month-store specific observations with no two consecutive observations missing. Observations are missing only when no price data was recorded in a particular store in a particular month. That is, when a product-store-month specific observation is missing, it is missing along with all other observation in the particular store-month specific entry. Despite their sporadic occurrence[27] missing price data pose a significant obstacle to the Simulated Maximum Likelihood estimation procedure. To resolve this issue, missing observations have to be imputed to produce a balanced panel of price data.

The imputation issue can potentially be resolved in a number of different ways. First, the analysis could be restricted to stores with no missing observation. Unfortunately, this approach would lead to the loss of all but one store in the sample. Second, the last available price could be carried forward to the present. This procedure would extend the actual frequency of observations to two months in the particular instances and so introduce a bias towards having artificially long intervals of inaction.

To avoid the shortcomings associated with the above two options, missing data are actually imputed the following way.[28] Assume that p_{ijt} is missing. The case when $p_{ij,t-1} = p_{ij,t+1}$ is straightforward, p_{ijt} is simply set to $p_{ijt} = p_{ij,t-1} = p_{ij,t+1}$. If $p_{ij,t-1} \neq p_{ij,t+1}$ then p_{ijt} is computed in one of the following ways: (a) $p_{ijt} = p_{ij,t-1}$, (b) $p_{ijt} = p_{ij,t+1}$, (c) $(p_{ijt} - p_{ij,t-1})/p_{ij,t-1})/((p_{ij,t+1} - p_{ijt})/p_{ijt}) = ((p^{-i}_{ijt} - p^{-i}_{ij,t-1})/p^{-i}_{ij,t-1})/(p^{-i}_{ij,t+1} - p^{-i}_{ijt})/p^{-i}_{ijt})$, where superscript $-i$ denotes the average price level in all

[27] They take place in 11 out of the total of 344 month-store specific data points; that is, in about 3.2 percent of the cases.

[28] Admittedly, the approach adopted is still *ad hoc*. Developing an endogenous procedure imputing missing data within the simulation estimation framework is the subject of current research.

the stores but store *i*. If the number of non-missing price changes between period *t-1* and *t* and between *t* and *t+1* in all stores other than store *i* exceeds the number of unchanged prices in these periods then option (c) is selected. This approach is based on the implicit assumption that the ratio of the unobserved price changes between periods *t-1* and *t* and periods *t* and *t+1* in store *i* corresponds to the similar ratio of the average of non-missing price changes.

If the number of non-missing price changes between period *t-1* and *t* and between *t* and *t+1* does not exceed the number of unchanged prices then the choice is between the first options (a) and (b). Option (a) is selected if the number of pairs of non-missing observations with price fixity between month *t-1* and *t* outnumbers the number of similar cases between month *t* and *t+1*. Otherwise, option (b) is selected.

APPENDIX B – THE TARGET PRICE

Assume that the profit of a multi-product store is separable across products and that no explicit aggregate demand linkage is allowed to exist across product markets: a particular store- *and* product-specific price sequence is treated as the outcome of a single-product store's optimal decision. Store- and product-specific profit centers are assumed to operate a two-factor Cobb-Douglas technology with unit factor prices of raw materials (M) and of other inputs. e.g. labor (W). Markets are imperfectly competitive, η_{ij} is the unit specific demand elasticity of product j sold in store i and δ_{ijt} is a multiplicative demand shock. In the absence of adjustment costs, a single-product store maximizes its profit subject to a demand constraint as

$$\max_{P_{ijt}} \left[V_{ijt} = P_{ijt} Q_{ijt} - \Theta M_{jt}^{b} W_t^{1-b} Q_{ijt} \right]$$
$$s.t. \qquad Q_{ijt} = P_{ijt}^{-\eta_{ij}} \delta_{ijt}, \qquad \eta_{ij} > 1 .$$

The first order condition easily simplifies to the frictionless optimal log price as[29]

$$p_{ijt}^{*} \equiv \ln(P_{ijt}^{*}) = \ln(\frac{-\eta_{ij}}{1-\eta_{ij}})\Theta W_t^{1-b} + b\ln(M_{jt}) = c_{ijt} + bm_{jt} .$$

The model suitable for estimation is obtained by specifying c_{ijt} as the sum of an idiosyncratic residual term ω_{ijt} with variance Ω and a store- and product-specific dummy, a_{ij}, the latter decomposed into a store-specific (a_i) and product-specific (a_j) component. These considerations combined with the assumption that the target price is proportional to the frictionless optimal price yield a fixed effect empirical specification for the target price:

$$p_{ijt}^{*} = a_{ij} + bm_{jt} + \omega_{ijt} = a_i + a_j + bm_{jt} + \omega_{ijt} .$$

[29] Assuming a Leontief technology would produce the same result.

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Table 1
Estimation Results

	PERIOD 1		PERIOD 2	
	AR(0)	AR(1)	AR(0)	AR(1)
sigma	0.216	0.161	0.155	0.120
	(0.011)	(0.009)	(0.009)	(0.007)
b	1.211	1.124	1.185	1.081
	(0.025)	(0.024)	(0.043)	(0.049)
S	0.349	0.248	0.213	0.151
	(0.023)	(0.02)	(0.017)	(0.015)
rho	-	0.340	-	0.332
	-	(0.025)	-	(0.031)
lnL	-87.930	-84.649	-89.729	-86.342

Notes:
1. Trinomial Probit panel regressions with actual nominal prices as dependent and raw material prices as explanatory variables.
2. The AR(0) model is estimated by ML, the AR(1) by SML.
3. sigma: standard deviation of residual, rho: autocerrelation parameter, b: slope parameter, s: lower adjusment boundary, lnL: mean log-likelihood.
4. The lower adjustment boundary is fixed at s = -0.11.
5. Estimations are carried out in Gauss. Standard errors are in parenthesis.

Table 2
Partial Correlation

	Π	*mm(z)*	*stdev(z)*	*skew(z)*
Π	1.000			
mm(z)	0.352	1.000		
stdev(z)	0.219	-0.106	1.000	
skew(z)	0.336	0.689	0.036	1.000

Note: Π denotes inflation, *stdev(z)* denotes standard deviation, *skew(z)* denotes skewness, *mm(z)* denotes the mean-median difference in price deviation densities.

Table 3
Higher Moments of Price Deviations. The Baseline Case

$$\Pi_t = b_0 + b_1 \Pi_{t-1} + b_2 StDev(z)_t + b_3 Asym(z)_t + u_t$$

b_0	0.51	-1.69	0.45	0.45	-1.55	-2.94
	0.51	2.81	0.48	0.51	3.38	3.58
b_1	0.60	0.58	0.58	0.54	0.56	0.51
	0.12	0.13	0.11	0.12	0.12	0.13
b_2	-	1.46	-	-	1.33	2.25
	-	2.37	-	-	2.22	2.35
b_3	-	-	3.83	5.83	3.81	6.48
	-	-	1.42	3.51	1.44	3.62
Adjusted R^2	0.34	0.33	0.42	0.36	0.42	0.36
F	24.57	12.30	17.58	14.10	11.67	9.69

Notes: Estimated parameters are underlied. Standard errors are underneath the corresponding parameter estimates. *StDev* denotes standard deviation, *Asym* asymmetry in the price deviation distribution. For the latter variable, the standard skewness coefficient is used in the third and the fifth columns and the mean-median difference in the fourth and the sixth columns.

Table 4

Counterfactual Inflation with Time Variation in *f(.)* and *A(.)* Suppressed

G(.)	*A(oa)*	*A(s)*	*A(a)*
f(oa)	0.00	0.32	0.37
f(s)	0.50	0.69	0.74
f(a)	0.79	0.90	1.00

Note: *a* denotes actual, *s* seasonal average, *oa* overall average

Table 5

Higher Moments of Price Deviations. The *Ad Hoc* Case

$$\Pi_t = b_0 + b_1 \Pi_{t-1} + b_2 StDev(z)_t + b_3 Asym(z)_t + u_t$$

b_0	0.37	-2.36	0.49	1.59	-2.05	-0.42
	0.38	2.58	0.43	5.93	2.73	6.20
b_1	0.54	0.56	0.52	0.53	0.54	0.55
	0.13	0.13	0.13	0.13	0.13	0.13
b_2	-	0.37	-	-	0.33	0.38
	-	0.34	-	-	0.35	0.35
b_3	-	-	-0.09	-0.49	-0.55	-0.83
	-	-	0.14	2.39	1.40	2.40
Adjusted R^2	0.276	0.278	0.266	0.260	0.262	0.263
F	18.155	9.684	9.148	8.901	6.313	6.364

Notes: Price deviations are computed the as the log deviation of actual prices from the average price.
Estimated parameters are underlied. Standard errors are underneath the corresponding parameter estimates.
StDev denotes standard deviation, *Asym* asymmetry in the price deviation distribution.
For the latter variable, the standard skewness coefficient is used in the third and the fifth columns
and the mean-median difference in the fourth and the sixth columns.

Figure 1a
Inflation, month-to-month
(unweighted average of price changes)

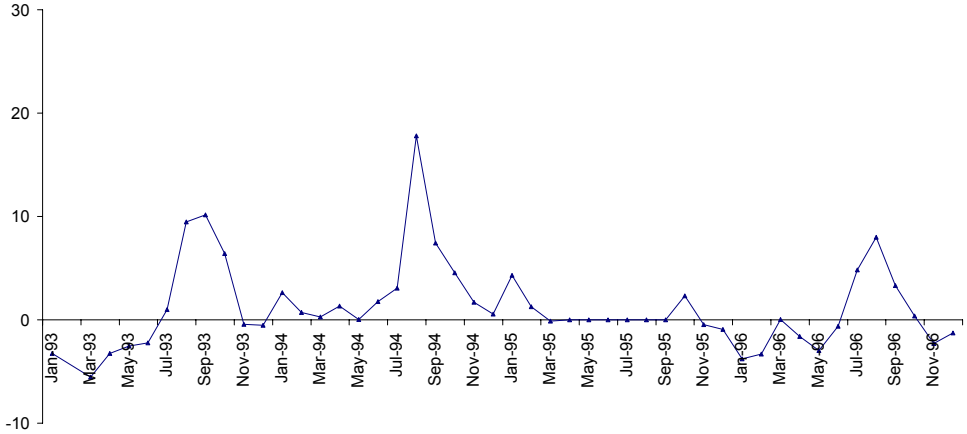


Figure 1b
Inflation, month-to-month
(price changes weighted by price deviation densities)

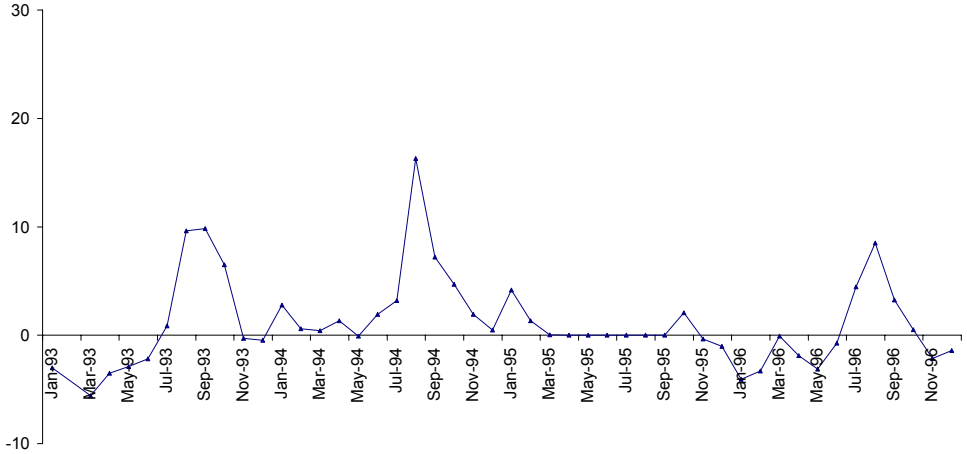
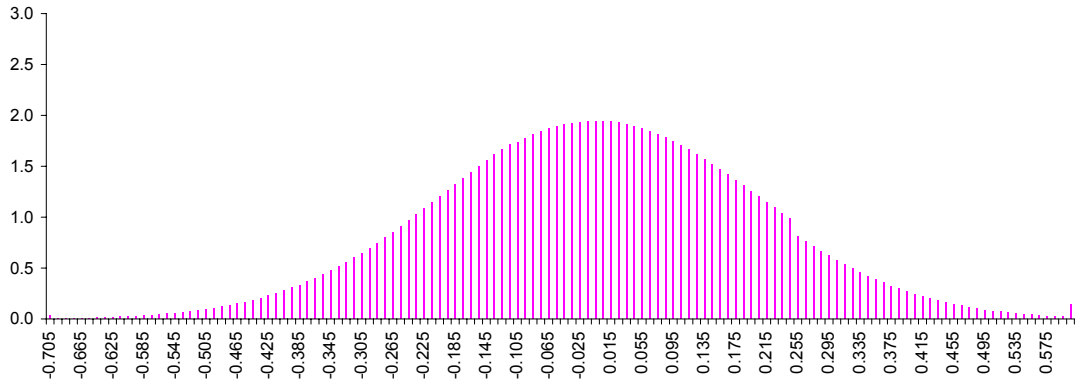


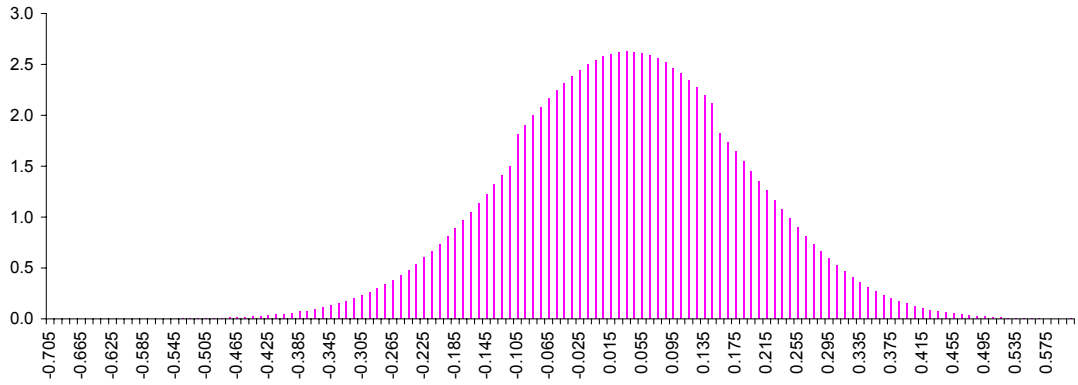
Figure 2

Empirical Density of Price Deviations
Period 1



Note: The lower adjustment band is fixed at s=-0.11, the upper one estimated to be S=0.248.

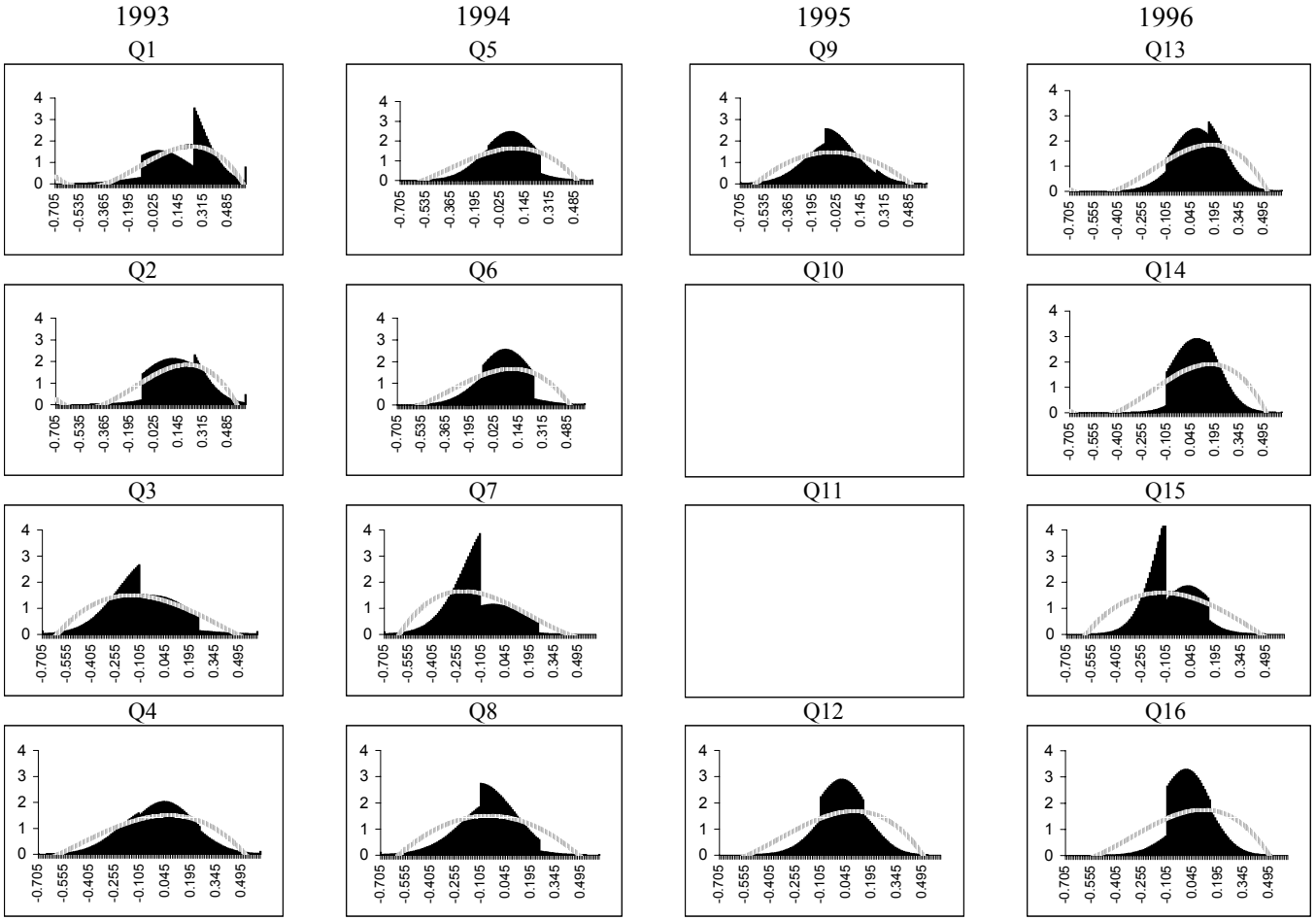
Empirical Density of Price Deviations
Period 2



Note: The lower adjustment band is fixed at s=-0.11, the upper one estimated to be S=0.151.

Figure 3

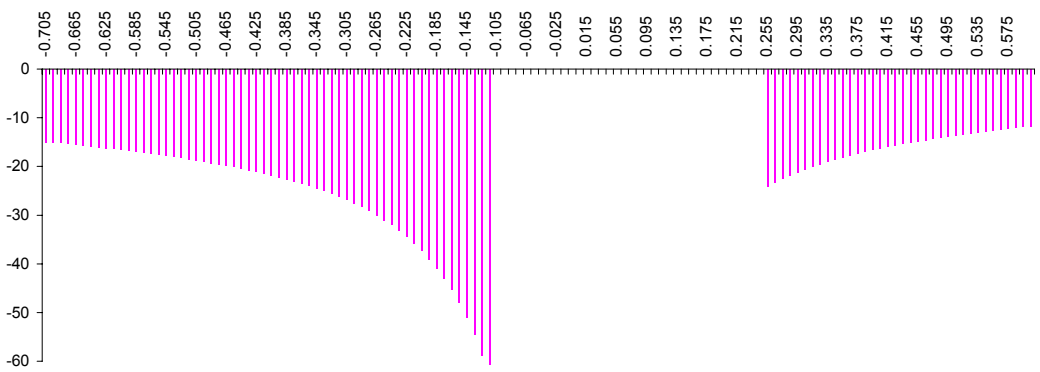
Empirical Densities of Price Deviations - Quarterly



Notes The solid lines are third degree polynomials fitted to the empirical densities.
Data from Q10 and Q11 are missing. The lower adjustment bands are fixed at s=-0.11.

Figure 4

Adjustment Function
Period 1



Note: The lower adjustment band is fixed at s=-0.11, the upper one estimated to be S=0.248.

Adjustment Function
Period 2

Note: The lower adjustment band is fixed at s=-0.11, the upper one estimated to be S=0.151.

Figure 5

Adjustment Functions - Quarterly

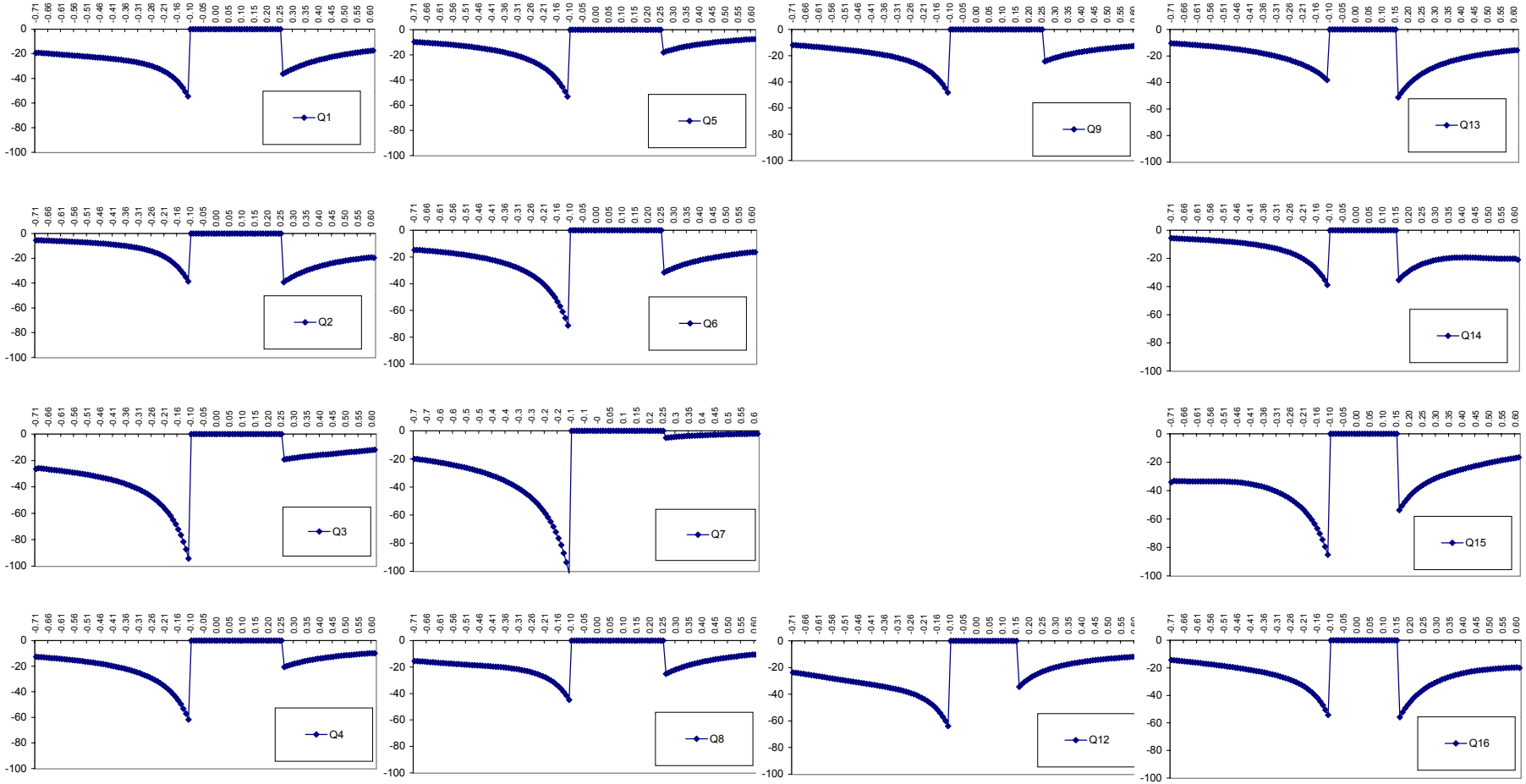
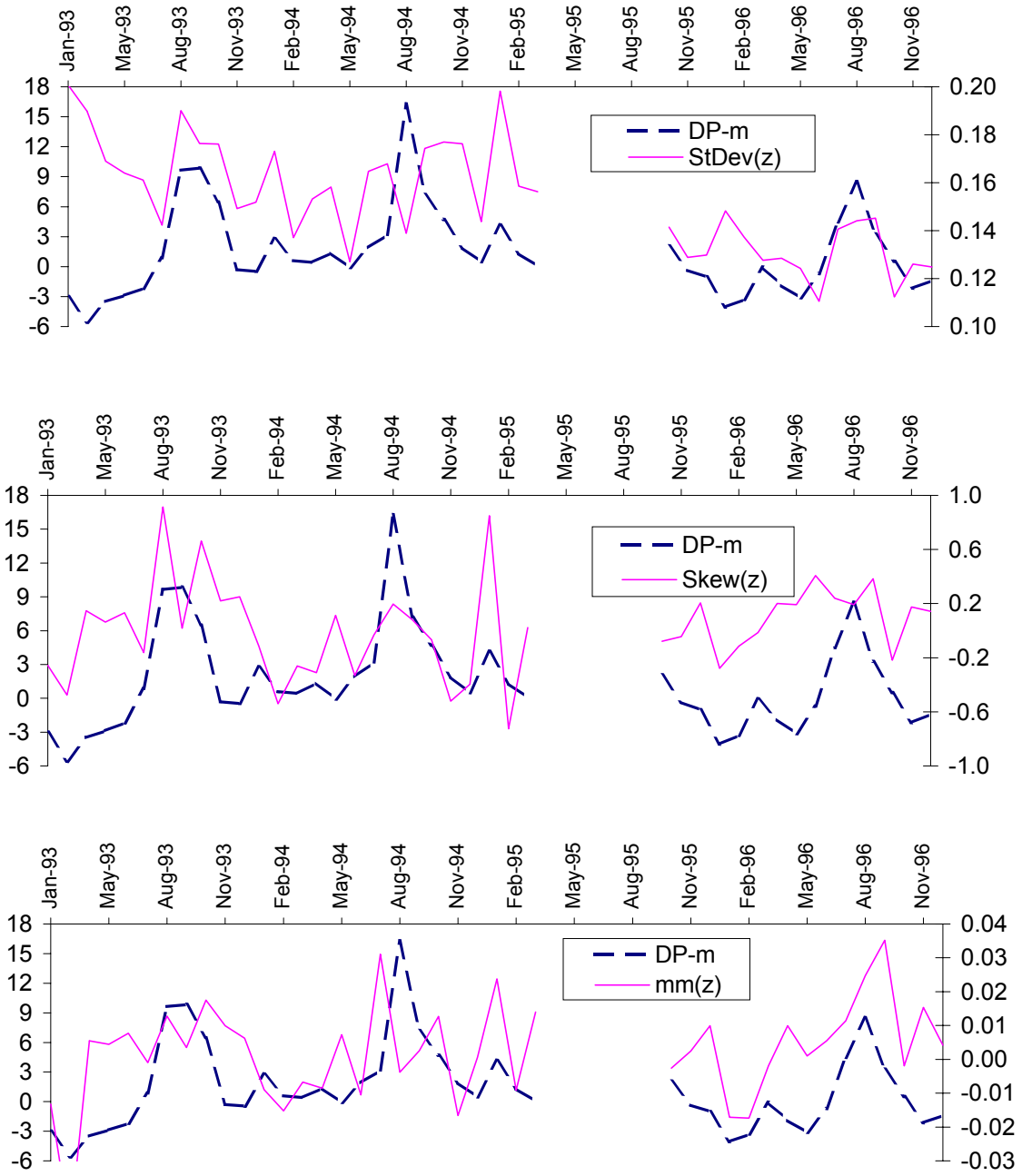


Figure 6

Dispersion, Asymmetry and Aggregate Inflation



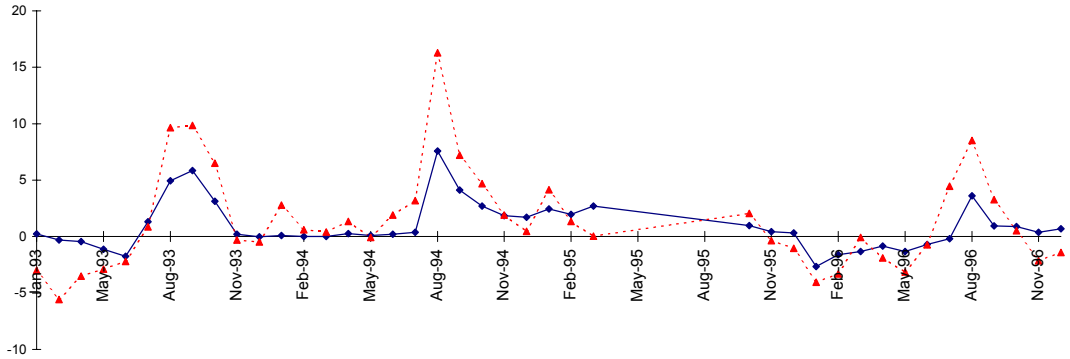
Notes. Inflation, month-to-month (DP-m) is measured on the left axes, other variables on the right ones.

"stdev(z)" and "skew(z)" denote the standard deviation and the skewness of the distribution of price deviations, respectively.

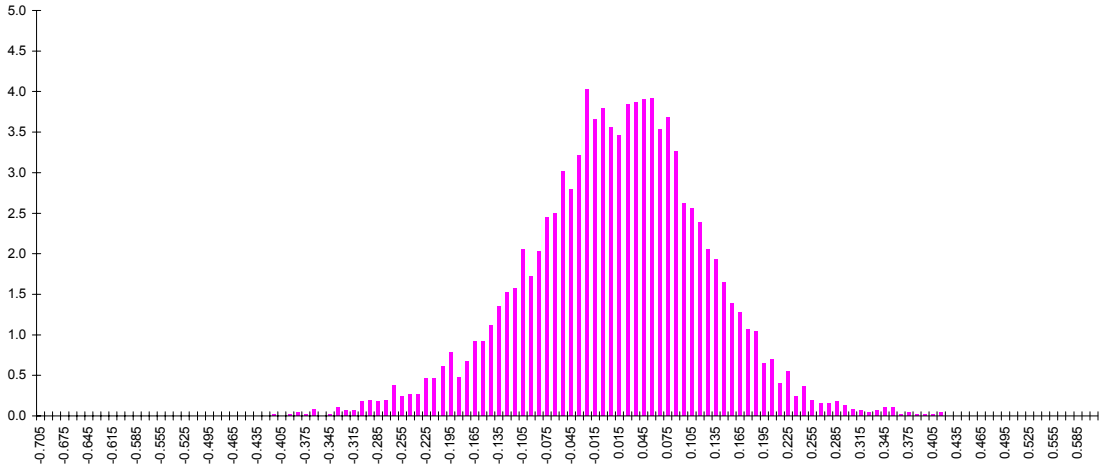
"mm(z)" denotes the mean-median difference in the distribution of price deviations.

Figure 7

True vs. Counterfactual Aggregate Inflation



Note : The dashed line is the true aggregate inflation series, the solid line is the counterfactual one. The counterfactual is constructed by replacing the benchmark cross-sectional density of price deviations with the one computed by suppressing idiosyncratic shocks.

Figure 8

Empirical Density of Price Deviations -
Full Sample, Idiosyncratic shocks suppressed