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Linking Individual and Aggregate Price Changes

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Abstract. Standard macroeconomic forecasting indicators and techniques perform poorly in predicting inflation in the short-run. In contrast, the present paper shows that microeconomic price data placed in an empirical framework rooted in (S,s) pricing theory convey extra information on inflation dynamics. The latent variable model designed to capture the gap between the target and the actual price is applied to a unique, highly disaggregated panel data set of consumer prices. Fluctuations in the shape of the cross-sectional density of price deviations contribute to short-run in-sample inflation. Asymmetry in the density particularly matters.

Key words: Simulated Maximum Likelihood estimation, panel data, inflation dynamics, (S,s) pricing

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1 Introduction

Especially in countries having adopted some form of inflation targeting monetary regime, policy makers in charge of controlling the macroeconomy need advance knowledge of the path of inflation. Financial analysts engaged in projecting the actions of central banks are also highly keen to learn about future month-to-month or quarter-to-quarter variation in inflation rates. Despite its vital importance for policy and business, understanding the nature of short-term inflation dynamics has been a daunting task for macroeconomists for a long period of time.

Over the past decades a vast amount of research, including mostly empirical studies drawing on aggregate (national or sector level) data and abstracting from microeconomic, behavioral considerations has been accumulated on the issue of inflation determination. In a review of standard macroeconomic indicators and forecasting techniques, Cecchetti (1995) concludes that forecasting relationships for inflation are unstable and time varying, and that the best, still highly imperfect predictor of inflation appears to be its own past. Cecchetti and Groshen (2000) find that the standard deviation of the forecast error in professional forecasters' one-year-ahead prediction of U.S. inflation has been about 1 percent in the 1990s, while inflation averaged at about 3 percent during this period of time. Most recently, Atkison and Ohanian (2001) examine Phillips-curve based out-of-sample inflation forecasts in the U.S. over the past fifteen years. They report that these forecasts have performed more poorly than a simple random walk reference model. Overall, the traditional literature seems to provide an inadequate account of the data.

Besides the overall displeasing performance of the traditional literature, on a more positive count, results from two recent strands of research point towards exploring new directions in the explanation of inflation dynamics. First, direct evidence on store level pricing patterns shows that nominal prices are lumpy in the sense that they tend to exhibit relatively long periods of inaction followed by discrete, intermittent and heterogeneous adjustments. There exists a significant element of heterogeneity in the timing of price changes, especially across different stores[1]. This description of microeconomic pricing behavior suggests that the (S,s) approach could serve as a particularly suitable framework for modeling store level pricing decisions.[2]

Second, several recent studies in macroeconomics have demonstrated the general importance of drawing on microeconomic data in explaining the aggregate economy. For instance, Caballero, Engel and Haltiwanger (1997) examine employment dynamics using a large microeconomic data set 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 firm-level 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 actual dynamics in aggregate durables in the United States in the early 1990s. The upshot of this line of research is that the degree of coordination of lumpy and heterogeneous microeconomic actions does matter in aggregate dynamics.

In light of these considerations, the present study radically departs from the traditional literature and examines inflation dynamics from a hitherto unexplored angle. First, the analysis is structured around an explicit aggregation of *microeconomic price data*. Second, by recognizing lumpiness and heterogeneity in micro level pricing behavior and building on implications of *two-*

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[1] The retail prices studied in the current paper are unchanged for about three months on average, at annual inflation rates of 15 to 35 percents (see Rátfai (2001)). For a more general survey, see Wolman (2000).

[2] In (S,s) pricing models, the non-smooth adjustment of nominal prices originates from fixed adjustment costs. See, for instance, Ball and Mankiw (1994), (1995), Caballero and Engel (1992), Caplin and Leahy (1991) and Tsiddon (1993).

sided (S,s) pricing rules, the study attempts to estimate directly microeconomic pricing decisions.

The central object of the empirical analysis is the price deviation, the postulated log difference between the actual and the target price level[3]. The main idea in empirically modeling the price deviation, potentially instrumental in related macroeconomic applications as well, is that the two-sided (S,s) pricing rule naturally lends itself to a trinomial Probit interpretation of the target price level. Price deviations are then estimated and the resulting price adjustment functions and cross-sectional price deviation densities are placed into an accounting framework to obtain aggregate inflation. Two specific issues are investigated: the relevance of the proposed empirical framework including the intertemporal stability of adjustment functions and cross-sectional densities and the role of fluctuations in price deviation densities in shaping inflation dynamics.

The rest of 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 described in Section 4. Sections 5 reports on the results, while Section 6 concludes.

2 Data

Inferring the history of pricing shocks and their propagation to individual price sequences requires a relatively long *panel* of microeconomic price data, ideally of many homogenous products sold in several distinct stores. However, samples of prices that are representative of finished goods markets at large or even of a specific sector of the economy are rarely available.

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

Indeed, the shortage of appropriate data may explain the paucity of related research. To sidestep the data issue, this study examines a small panel of microeconomic prices. The particular episode is the case of processed meat product prices in Hungary during the mid-1990s.

The data set investigated is a balanced panel of the transaction price of fourteen processed meat products[4] sold in eight different, geographically dispersed stores in Budapest, Hungary. Out of the eight stores in the sample, five are larger department stores and three are smaller grocery stores, called Közért. All stores sell many other kinds of products besides the ones considered here. Whenever a particular store is visited, all the fourteen product prices are recorded. Observations 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 prices present in the sample[5].

While the current prices represent only a small portion of economy-wide pricing patterns, they provide an excellent laboratory for the purposes of the current analysis.[6] First, the items are well-defined, homogeneous food products with essentially no variation in non-price, physical characteristics such as quality. Second, producing the items requires only one basic input component, the underlying raw material, implying that aggregate pricing shocks primarily come from variations in raw material prices. Third, as products are obtained from a single sector of the

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[4] 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.

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

[6] Moreover, although being more volatile, the sample price index tracks movements in the overall CPI, especially its food component quite closely. 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.

economy, inference about stores' pricing policies is unlikely to be contaminated by fundamental differences across production technologies.

Descriptive Evidence

In a detailed non-parametric, descriptive study, Rátfai (2001) documents that prices in the current sample exhibit both lumpiness and heterogeneity. To motivate the empirical model to come, it is instructive to briefly highlight some of the basic findings there. 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, the high raw material price season, spells of adjustment are spaced irregularly across stores. The duration of price changes within stores is fairly dispersed over time, 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.

Finally, price fixity appears to be adequately captured at the monthly frequency. First, given the average duration of price quotations, quarterly or lower frequency microeconomic price observations are likely to be heavily left-censored. Second, visualizing the price sequences indicates that higher, say weekly, frequency price data have little extra information to offer on microeconomic pricing patterns.

3 A Framework for Inflation Dynamics

The empirical model to study inflation dynamics is developed in two stages. First, the target price level and the resulting price deviation is specified and estimated. Second, following Caballero, Engel and Haltiwanger (1995), an aggregation framework is introduced to organize the distribution of microeconomic price deviations into an inflation index[7].

3.1 Specification and Estimation of Price Deviations

In capturing the log deviation between the actual and the target price, the literature on relative prices tends to associate the target price with the across-store average of actual prices (see, for instance, Lach and Tsiddon (1992)). There are two, interrelated concerns with this naïve practice of measurement. First, various factors including geographical, technological, financing and tax considerations are likely to make the target price level heterogeneous across stores and products. Second, there is no fundamental behavioral reason to identify the target price level with the product level average of prices. Indeed, in (S,s) models the target price is typically driven by the convolution of aggregate and idiosyncratic pricing shocks.

There exist other, somewhat more structural approaches to model the deviation between actual and some frictionless behavior. Caballero, Engel and Haltiwanger (1995) derive mandated investment, the log deviation between actual and target capital as a function of two firm-specific variables that are individually both highly persistent and argue that a (S,s)-type decision rule makes mandated investment mean-reverting. This insight allows CEH 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.

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

The empirical framework developed below radically departs from earlier attempts to measure the deviation. In particular, the various pieces of the empirical model revolve around the idea that fixed costs of changing prices create an imbalance between actual and target pricing behavior and make price adjustment policies state-dependent. When shocks to the target price are symmetric, fixed price adjustment costs (menu costs) result in a two-sided (S,s) pricing rule with the price deviation typically differing from zero. Stores alter their nominal price and pay the fixed cost only when the log difference between the actual and the target price is sufficiently large and exceeds some optimally determined threshold value. Otherwise, when shocks are not able to move the price deviation outside the (S,s) band, the current nominal price coincides with the preceding one and no actual pricing action takes place.

More formally, stores leave their nominal prices unaltered until the state variable, 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 the shock to the target price is sufficiently large to push z_{ijt} outside one of the band, stores will pay the menu cost and adjust their nominal price either upwards when $z_{ijt} \leq s$ or downwards when $z_{ijt} \geq S$. This description of pricing behavior suggests that the log target price can be viewed as a latent variable with the two-sided (S,s) pricing rule translating into a trinomial Probit estimation problem. The implied observation rule for the (log) nominal price level is then summarized as

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

It is important to give emphasis to the timing convention adopted in the definition of the price deviation. As shocks to the target price are assumed to take place at the beginning of the period, the price deviation is bound *not* to reflect stores' reaction to pricing shocks of any kind. That is, prices inherited from the preceding period are in effect before stores can respond to current shocks.

The starting point in actually estimating the price deviation is to specify the individual target price level driven by recurrent aggregate and idiosyncratic shocks. First, an important advantage of the data set used in here is that the aggregate forcing variable is easily identified by the change in the relevant raw material price, that is, the price of cattle or pig for slaughter[8].

Second, certain stores may happen to be systematically more (or less) expensive than others, perhaps due to variation in the local tax-burden or the affluence of local customers. Similarly, consumer taste or production technology could cause certain products to be priced systematically differently from other ones. To capture these effects, nominal prices are assumed to contain a store- *and* product-specific intercept term. That is, the log target price is defined as a linear combination of the intercept term, c_{ijt}, and the relevant raw material price, m_{jt}.

Third, the intercept term, c_{ijt}, is specified as the sum of a time-invariant nuisance term, a_{ij}, and a residual term, ω_{ijt}, with homoskedastic variance, Ω. The residual is then interpreted as an idiosyncratic pricing shock, specific to a particular product, store and month. Splitting the store- and product-specific constant, a_{ij}, into two parts, reduces the number of parameters and thus eases estimation. In particular, $a_{ij} = a_i + a_j$ where a_i is a store-specific and a_j is a product-specific component. Taken together, the above considerations yield the following simple fixed effect model for the target price level:

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

[8] Dunne and Roberts (1992) also emphasize the key role of raw material prices as determinants of plant level pricing behavior in the US.

The economic interpretation one can attach to this specification is a fixed markup over cost argument[9].

3.2 True versus Spurious State Dependence

As past realizations of nominal prices have a genuine behavioral effect on the probability of initiating a pricing action, the discrete choice decision rule associated with the empirical Probit framework exhibits both what Heckman (1981) calls "true" and "spurious" state-dependence. It is important to stress that the current estimation procedure accommodates both sources of temporal dependence.

In general, as the current realization of the state variable, the deviation between actual and target behavior is directly related to past actions, (S,s) type decision rules naturally give rise to "true" state-dependence in the decision variable of interest. The current discrete choice model reflects true state-dependence in a somewhat non-standard form: the lagged control variable enters the decision rule through the censoring thresholds.

The possibility of "spurious" state dependence generally stems from the possibility that past realizations of heterogeneous unobservables are able to affect current decision variables. This form of intertemporal linkage appears here in the form of serially correlated residuals, perhaps due to persistent local technological or demand shocks. To comply with this form of temporal dependence, the residual in the fixed effect regression model, ω_{ijt}, is specified as an AR(1) process

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[9] The interpretation is consistent with a model of optimal pricing decisions in a frictionless, monopolistically competitive market with no entry and exit. Appendix B describes a simple static pricing model along these lines.

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

where ε_{ijt} is Normal i.i.d. with mean zero and variance σ_ε^2. The auto-regressive parameter ρ is assumed to be invariant across stores and products. Taken together, these considerations yield an empirical model of price deviations to be estimated as a multi-period, trinomial panel Probit model with serial correlation in the error term.

3.3 Aggregation

In the above model, aggregate and idiosyncratic pricing shocks are filtered through the single state variable, z_t, in a non-linear way. To complete the empirical model and arrive at a measure of aggregate inflation, a simple accounting framework is introduced. In particular, analogously to Caballero, Engel and Haltiwanger (1995), (1997) and momentarily omitting store- and product specific indices, aggregate inflation is defined as

$$\Pi_t = \int z_t A_t(z_t) f(z_t, t) dz_t \ .$$

The aggregation formula features two fundamental building blocks: the cross-sectional density of price deviations, $f(z_t,t)$, and the so-called 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.

Importantly, aggregating individual price changes in this particular way allows for a rich evaluation of the mechanism propagating microeconomic shocks to aggregate price changes, including the study of the role of fluctuation in $A_t(z_t)$ and $f(z_t,t)$. Potentially, the approach also permits to separate the importance of idiosyncratic versus aggregate shocks in driving inflation.

Finally, although aggregate inflation is constructed as a weighted-average of the individual mean price changes with weights given by the cross-sectional density of the appropriate price deviation, the index is virtually identical to a simple unweighted index of aggregate price changes in the sample. The correlation coefficient between the two indices is 0.99.

4 Estimation

To motivate the estimation strategy for the price deviation, consider the situation in which the residual in the target price model, ω_{ijt}, is Normal with variance Ω, identically and independently distributed. In the absence of temporal dependence in the residual, the log-likelihood function for the model can be simply written as the product of the appropriate marginal probabilities:

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

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

where *F(.)* denotes the multivariate cumulative density function. In this setup, standard quadrature based Maximum Likelihood procedures serve as a straightforward estimation method. Even if temporal dependence in the error term were actually present when it is neglected in estimation, parameter estimates are still consistent.[10] At the same time, if the serial correlation structure is erroneously specified to be i.i.d. *and* lagged dependent variables enter the model, as they do here via the censoring thresholds, then standard ML estimation of the Probit panel model

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

leads to inconsistent parameter estimates (see Keane (1993)). These concerns are especially troubling in the current context as the estimated parameters are used for forming the cross-sectional density of z_{ijt} and then aggregate inflation.

A natural remedy here would be to account properly for the serial correlation in the residual. Once this is done, however, the log-likelihood function cannot be factored in the standard fashion, estimating the joint likelihood of consecutive price observations requires the evaluation of T (the number of time periods) dimensional integrals. Without imposing further simplifying restrictions on the correlation structure of residuals, the computation of these high dimensional integrals is numerically infeasible by standard procedures.

The next natural step towards consistent estimation could be the direct simulation of choice sequence probabilities by the observed frequencies. The problem with this approach is that obtaining reasonably precise and consistent estimates of the possibly quite small probabilities entails a computationally burdensome number of draws and thus excessive efforts. In the absence of a large number of draws, the frequency simulator of the joint choice probabilities is discontinuous in the estimated parameters.

Fortunately, simulation estimation techniques such as the Simulated Maximum Likelihood (SML) estimator drawing on the Geweke-Hajivassiliou-Keane (GHK) simulator of importance sampling of univariate truncated normal variates offer a feasible remedy here. Besides computational feasibility, smoothness (differentiability and continuousness) is an important requirement to simulation estimators as it allows for applying standard hill-climbing or gradient methods in maximizing the simulated log-likelihood function. In general, the SML estimator is not only continuous in the parameters and relatively quick in reaching convergence, it is also able to accommodate various correlation structures and provide consistent and efficient estimates even in the presence of lagged endogenous variables. Extensive comparisons by Börsch-Supan and Hajivassiliou (1993) investigating the accuracy and bias in the various possible simulation estimators of multivariate truncated normal probabilities show that the SML approach performs best among similar estimators. Therefore, in estimating the panel Probit model with serial correlation in the error term the smooth Simulated Maximum Likelihood estimator employing the GHK simulator of univariate truncated standard normals is used.

A brief outline of the SML procedure is as follows. The log-likelihood function to be maximized is

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

As described above, the serial correlation posited in the residual implies that estimating the parameters here requires the evaluation of T dimensional integrals for each cross-sectional unit (T is 27 and 16 here). Consider now the sequence of prices of a single product in a single store. First, dropping all subscripts for now, 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 residual. Then, instead of drawing directly from the original distribution of serially dependent truncated normals, the variable, e, is sampled sequentially and independently R times from the recursively restricted univariate standard normal distribution[11].

For example, assume that the nominal price remains constant during the first three periods. Then the consecutive draws of the standard normal residuals, e_1 ,e_2, and e_3, are obtained from:

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

[11] 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.

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

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

where $A_t^* = p_{ij,t-1} - S - (a_i + a_j + bm_{jt})$ and $B_t^* = p_{ij,t-1} - s - (a_i + a_j + bm_{jt})$. To scale the size of the dependent variable for identification, the adjustment boundaries are fixed to the average size of actual price changes. This restriction can be thought of as resulting from a discrete time approximation to the width of the band obtained in a continuous time (S,s) model[12].

The SML procedure in general requires R distinct simulations to estimate the joint occurrence of a particular sequence of nominal price realizations.[13] The estimated joint probability is then given by the average of the R distinct probability simulations factored as the products of the simulated univariate probabilities:

$$prob(p_{ij1},\ldots,p_{ijT} \mid M_{jt}, b, a_i, a_j, s, S, \rho, \Omega) =$$
$$\frac{1}{R}\sum_{r=1}^{R}\left[\prod_{p_{ijt} > p_{ij,t-1}}\{1 - F(\beta_t \mid e_r)\} \times \prod_{p_{ijt} < p_{ij,t-1}}\{F(\alpha_t \mid e_r)\} \times \prod_{p_{ijt} = p_{ij,t-1}}\{F(\beta_t \mid e_r) - F(\alpha_t \mid e_r)\}\right].$$

Börsch-Supan and Hajivassiliou (1993) report that relatively accurate likelihood estimates are obtained by employing only a small number of repetitive draws, twenty or thirty draws are often sufficient in the case of three to seven alternative choices. To use err at the conservative end,

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[12] The parameters are set as s = -0.11 and S=0.08 (period 1) and S=0.07 (period 2). (Cf. Lach and Tsiddon (1992).) Experimentation with alternative boundaries shows that the estimation results are insensitive to reasonable departures from the particular numerical values. For parameter values that significantly differ from the above ones, the SML estimator is unable to converge even after extensive experimentation with alternative initial values.

[13] This stage of the estimation is computationally quite burdensome.

fifty sampling draws is employed in the current simulation estimation. Although estimates of the implied truncated structural errors are biased in general, the likelihood contribution is correctly simulated by the joint probability of the corresponding truncated standard normal variates. As shown by Börsch-Supan and Hajivassiliou (1993), the simulated log-likelihood is an unbiased and smooth estimate of the true likelihood function.

The estimated parameters of interest are shown in Table 1, separately for *Period 1* and *Period 2*. There are a few points that stand out. First, the standard errors indicate that the parameters are fairly tightly estimated. Second, the autocorrelation parameters are sizeable and significantly different from zero, thus justifying the explicit account for the temporal dependence in the residual term. And third, the slope estimates are larger than one indicating some form of increasing returns to scale[14].

5 Results

5.1.1 The Cross-Sectional Density of Price Deviations

A novel element of the two-sided (S,s) pricing approach is the way individual pricing decisions are aggregated. Caplin and Leahy (1991) assume a uniform time-invariant distribution of price deviations in aggregating two-sided (S,s) pricing policies. Tsiddon (1993) demonstrates that the 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, non-uniform, piece-wise exponential shape.

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[14] The results remained intact when experimenting with monthly dummies in the baseline specification.

As the individual target prices and thus price deviations are directly unobservable, the exact realization of idiosyncratic shocks cannot be recovered, only their conditional density is identified. Cross-sectional densities of price deviations are indeed obtained by averaging the individual conditional densities.

First, a discretized state space is defined with a bin width of one percent for price deviations between –25 and 25 percents and of five percents for the rest of the state space. The densities are evaluated at the middle-point of the bin intervals, k = -35, -30, -25, -24, -23, …, 23, 24, 25, 30, 35. Formally, the empirical densities at $z_{ijt} = k$ are computed as

$$f(z_{ijt} = k) = f(\omega_{ijt} = p_{ij,t-1} - (a_i + a_j + bM_{jt}) - k).$$

Given the truncation points of $A_{ijt}^* = p_{ij,t-1} - S - (a_i + a_j + bm_{jt})$ and $B_{ijt}^* = p_{ij,t-1} - s - (a_i + a_j + bm_{jt})$ for ω_{ijt}, the truncated normal densities are calculated for each bin interval and price observation. Averaging individual conditional densities produces the empirical distribution of price deviations in each month or quarter.

Price deviations are constructed by imposing a decision rule of the (S,s) type on actual price data. Is the resulting shape of the empirical density consistent with implications of two-sided (S,s) theory? First, summary statistics show that the average of the mean price deviation calculated separately for each product-store specific sequence is –3.05 percent in the whole sample with an average standard deviation of 8.74. The first figure reflects the upward trend built in the target price levels and accords well with the predominance of inflationary periods in the sample. The standard deviation figure indicates that there is considerable cross-sectional heterogeneity both across stores and products in the sample. The upper panel in Figure 2 shows the histogram of pooled (over time, store and product) price deviations[15]. The density appears to

[15] To smooth the visual appearance in the graphs, a third degree polynomial is fitted to all densities.

be asymmetric, consistently with two-sided (S,s) models actually motivating the statistical structure imposed on the data.

How the shape of the empirical densities of price deviations evolves over time? To ease interpretation, only *quarterly* frequency densities are examined here. The graphs in Figure 3 show that quarterly price deviation densities tend to have an asymmetric and non-uniform shape. Changes in the shape of the histograms are suggestive of the evolution of aggregate inflation. For instance, third quarter histograms tend to feature strongly leftward warped distributions with many price deviations bunching towards the lower end of the distribution. Conversely, the rightward warped second quarter histograms tend to indicate a pressure on nominal price cuts.

A few interesting episodes of aggregate inflation dynamics as shown in Figures 1a and 6 also stand out in the histograms in Figure 3. By many price deviations bunching in the neighborhood of the lower adjustment boundary, the histograms pick up this story of the accelerating burst in inflation in early 1994 eventually terminated by the middle of 1995. Also, the large number of price deviations bunching on the right end of the empirical 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 actually 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. The weights are given by the corresponding empirical densities. Formally,

$$DP_t(z_t = k, \forall\, i, j) = \sum_{j=1}^{14} \sum_{i=1}^{8} (p_{ijt} - p_{ij,t-1}) f(z_{ijt} = k) \,.$$

The definition implies that $A_t(z_t)z_t$ measures the expected value of the size of price changes at price deviation z_t.

The latent variable model imposed on the data implies tight predictions on the shape of the adjustment function: it should take on a hat (or reverse-U) shape. Intuitively, 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. This implies that the adjustment function would show large absolute values for extreme price deviations outside the (S,s) band, and zero values for a range of intermediate price deviations, inside the band. In reality, stores may not be fully intolerant towards small deviations. They are likely to have average adjustment functions evolving more smoothly in the neighborhood of the boundaries, perhaps looking less symmetric as well.

As its curvature determines the extent to which fluctuations in price deviation densities impact on inflation, the shape of the adjustment function may have important aggregate consequences. If the adjustment function is assumed to be an nth 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 and quarterly averages of adjustment functions. The upper four panels show average quarterly adjustment functions, while the bottom panel shows the pooled function. They are constructed by collecting together monthly price deviations from identical quarters in the different years and from the whole sample, respectively. Visual inspection of the graphs shows that the shape of the adjustment functions is in general consistent with the implication of two-sided (S,s) models, the adjustment functions do take on a hat-shaped form and reflect the inaction region implied by the Probit structure imposed on the data. The discontinuity at the adjustment boundaries is due to the assumption that the boundaries are fixed. In addition, it also apparent that the average adjustment functions are relatively stable across the quarters.

Figure 5 displays the same information separately for all the fourteen quarters available in the sample. Despite the noise in constructing these graphs, the emerging pictures again indicate that adjustment functions are remarkably stable over time and that they 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 reasonably well the underlying microeconomic structure governing stores' pricing behavior.

5.2 Aggregate Implications

As histories of shocks and the heterogeneous response of stores to these shocks are summarized in the cross-sectional density of price deviations, (S,s) pricing models imply that the shape of the density is expected to serve as an important determinant of aggregate price dynamics. Indeed, drawing on sector level inflation data in the U.S., Ball and Mankiw (1995) show that the higher moments of a particular cross-sector measure of price deviation densities do impact on inflation. They argue that inflation is primarily related to the asymmetry in the distribution.

The focus here is also on the higher moments including the dispersion and the asymmetry in price deviation densities. Dispersion is associated here with the standard deviation of the cross-sectional distribution of price deviations. Regarding asymmetry, as it is *a priori* not straightforward what is the statistic that captures best the fundamental concept of interest, the relative bunching of price deviations to one of the two adjustment boundaries. Therefore, two alternative measures of asymmetry are considered: the standard skewness coefficient and the mean-median difference scaled by the standard deviation.

First, the three panels in Figure 6 show the time path of the dispersion and asymmetry measures along with the corresponding aggregate inflation series. To better assess if the price deviation series exhibit any sort of cyclical relationship with respect to inflation, Table 2 displays the unconditional correlation coefficients among the series depicted in Figure 6. The table shows that there is positive correlation between the second but negative correlation between the skewness of price deviations and inflation. At the same time, the correlation coefficient between the mean-median difference and inflation is positive and sizeable.

Apparently, the two alternative asymmetry statistics, the inter-deciles difference and the skewness coefficient, have quite different cyclical properties relative to aggregate inflation. Consider, for example, the third quarter of 1993. The large number of price deviations bunching at the lower end of the distribution clearly translates into substantial aggregate price increases during the quarter. As Figure 6 indicates, the bunching is also evidenced in the hike of the mean-median measure. At the same time, the skewness coefficient turns into negative in the quarter. This episode, along with some others, suggests that changes in the skewness coefficient may reflect other behavioral considerations than the pressure on price setters to change their nominal price. Nonetheless, as much of the related literature employs the standard skewness statistic to capture asymmetry, results using both potential measures are reported next.

To assess the robustness of the partial correlation results, a set of horse-race regressions is run with aggregate inflation as the dependent and the various measures of price deviation densities as the explanatory variables. Following Ball and Mankiw (1995), the basic regression equation takes the form of

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

where *StDev* denotes the standard deviation and *Asym* denotes the asymmetry measure of price deviation densities. Six distinct regressions are considered, all of them include a constant term, b_0, lagged inflation, Π_{t-1} and various measures of the price deviation density as explanatory variables.

The estimatation results are displayed in Table 3. Results for the benchmark regression not including any of the measures characterizing the shape of the price deviation density are reported in the first column. First, a simple comparison of the adjusted R^2 statistics reported in the first and the second column of the table shows that adding the standard deviation to the benchmark regression slightly improves the fit of the model. The equation augmented solely by the skewness coefficient as shown in the third column leads to a worse goodness-of-fit than the one including only the standard deviation. In both cases however the parameter estimates are statistically insignificant at conventional levels. The results reported in column four show that adding only the mean-median measure as an explanatory variable results in a better fit than either the pure standard deviation or skewness regressions. Moreover, the relevant parameter estimate is of the expected sign and statistically significant. Results in column five indicate that including both the standard deviation and the skewness coefficient in the regression equation leaves the parameter estimate statistically insignificant and the fit about the same. Indeed, the model with only the mean-median difference measure provides a better fit than the model with both the standard deviation and the skewness coefficient included in it. Finally, a dramatic improvement in the goodness-of-fit is revealed when the standard deviation is supplemented with the mean-median difference measure. In addition, all parameter estimates are highly significant. These findings suggest that the asymmetry in the cross-sectional distribution is a more important determinant of aggregate inflation than the corresponding dispersion.

Next, the importance of fluctuations in $A_t(z_t)$ and $f(z,t)$ in shaping aggregate dynamics is examined. The strategy followed here is to construct counterfactual aggregate inflation series by replacing actual cross-sectional distributions and adjustment functions with their seasonal (quarterly) or overall average and then compare the proximity of these series with the true one[16]. For example, replacing the actual $A_t(z_t)$ in the aggregating framework with the corresponding seasonal average $A_t^s(z_t)$ amounts to shutting down cyclical but retaining seasonal fluctuations in the adjustment function. Following Caballero, Engel and Haltiwanger (1995) and (1997), the following goodness-of-fit measure is used to evaluate the proximity of actual and counterfactual price dynamics

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

where Π_t^{cf} ($cf = s$ (seasonal), oa (overall average)) is the counterfactual and Π_t is the actual aggregate price change and σ^2 denotes the variance of the series. To the extent that it is not constrained by zero from below[17], the proposed statistic is different from the traditional goodness-of-fit measure, R^2.

Table 4 displays the goodness-of-fit results in the various counterfactual cases. First, shutting down only cyclical and keeping 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, $G(.)$ falls by 18 percent, while in the latter case it gets reduced only by 2 percent. This observation again reflects the intertemporal stability of the adjustment function. Entries in the top right and bottom left corner of the table show the goodness-of-fit statistics obtained by removing all (seasonal and non-seasonal) fluctuations either in the cross-sectional density or in the adjustment function, respectively. The results indicate a dramatic deterioration in fit in the former case, when all fluctuations in the cross-

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[16] For this exercise, all price deviations from the same quarter are pooled together.

[17] The statistical reason for this is that the residual part here is not necessarily uncorrelated with the predicted part. See Caballero, Engel and Haltiwanger (1997).

sectional distribution of price deviations are eliminated. In the latter case, with no time-series variation in the adjustment function, the proximity of the two series is only slightly reduced. Indeed, removing all fluctuations in the adjustment function results in a slightly better fit than taking away only cyclical and leaving seasonal fluctuations in the cross-sectional distributions.

Overall, the goodness-of-fit statistics indicate that swings in both the cross-sectional density and the adjustment function are non-trivial ingredients of aggregate price dynamics and ignoring them results in loss of information of inflation dynamics. Seasonal and cyclical fluctuations in the adjustment function contribute relatively little to aggregate price dynamics, while fluctuations in the cross-sectional distribution are of fundamental importance both at the seasonal and the cyclical frequency.

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 short-run fluctuations in inflation? 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.[18] The data analysis is specifically aimed at recovering and quantifying information potentially lost in merely taking averages of individual prices in constructing aggregate inflation indices

What can one carry away from the analysis? The results demonstrate that microeconomic price data do contain extra information on aggregate inflation dynamics not present in aggregate indexes. More in particular, first, the shape of the price adjustment function is relatively stable over time. Second, fluctuations in the shape of cross-sectional distribution of price deviations contribute to aggregate inflation dynamics. Asymmetry in the cross-sectional density particularly

[18] The econometric approach is potentially instrumental in other contexts where lumpy and heterogeneous microeconomic adjustment is relevant.

matters. Overall, the findings confirm that the explicit aggregation of intermittent *and* heterogeneous individual actions is able to yield new insights for a more adequate understanding of dynamic patterns in aggregate economic activity.

The current analysis has clear implications for monetary policy making. In particular, provided that appropriate microeconomic price data are available on a timely basis, it suggests that the direction and intensity of bunching in price deviations provide useful signals for forthcoming aggregate price changes. In formulating short-term inflation forecasts, besides some other non-price indicators, central banks today merely tend to look at the history of aggregate inflation and ignore information contained in the cross-sectional distribution of price deviations. It may well happen however that no particular pattern is observed in past average prices; still, a significant amount of pressure builds up in the directly unobservable price deviations. Of course, detecting the correct signal requires a careful specification of the target price for the various product prices at hand.

Finally, an important limitation of the empirical analysis in the paper is the specificity and size of the sample. Further research should examine a richer sample of prices with a broader set of product categories and more stores involved.

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[19] missing price data pose a significant obstacle to the Simulated Maximum Likelihood estimation procedure. To resolve this issue, missing observations are imputed to produce a balanced panel of price data.

There appears to be three different ways to get around the imputation issue. 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 excessively long intervals of inaction.

Third, to avoid the shortcomings associated with the first two possible procedures, missing data are imputed for each product j the following way. Assume that p_{ijt} is missing. The case when $p_{ij,t-1} = p_{ij,t+1}$ is straightforward, p_{ijt} is simply set so as $p_{ijt} = p_{ij,t-1} = p_{ij,t+1}$. If $p_{ij,t-1} \neq p_{ij,t+1}$ then p_{ijt} is computed in one of the following three distinct 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 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

[19] They take place in 11 cases out of the total of 344 month-store specific data points.

store *i* exceeds the number of unchanged prices in these periods then option (c) is selected. This approach is based on the 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 two options. 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. [20]

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[20] The approach adopted here is admittedly *ad hoc*. Developing a procedure that imputes missing data within the simulation estimation framework is the subject of ongoing research.

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 across product markets, implying that a particular price sequence can be considered as the outcome of a single-product store's optimal decision. Prices (P_{ijt}) and quantities (Q_{ijt}) are then store- *and* product-specific. Stores are assumed to operate a two-factor Cobb-Douglas technology with unit factor prices of raw materials (M_{jt}) and of other inputs (e.g. labor) (W_t). 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 static profit subject to the demand constraint as

$$\max_{P_{ijt}} \pi_{ijt}(M_{jt}, W_t, Q_{ijt}) = P_{ijt}Q_{ijt} - \Theta M_{jt}^{b} W_t^{1-b} Q_{ijt} \,,$$
$$s.t. \qquad Q_{ijt} = P_{ijt}^{-\eta_{ij}} \delta_{ijt} \,, \qquad\qquad \eta_{ij} > 1 \,.$$

The instantaneously optimal frictionless log price is easily obtained as

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

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}. To ease estimation, the individual effect, a_{ij}, is decomposed into a store-specific (a_i) and product-specific (a_j) component, identified separately from each other. All of these considerations yield a fixed effect specification for the target price:

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

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Table 1

Estimation Results

	PERIOD 1		PERIOD 2	
	no AR(1) -ML a_i,i=1,…,14, a_j,j=1,…,8	AR(1) - SML a_i,i=1,…,14, a_j,j=1,…,8	no AR(1) - ML a_i,i=1,…,14, a_j,j=1,…,8	AR(1) - SML a_i,i=1,…,14, a_j,j=1,…,8
sigma	0.117	0.092	0.099	0.086
	(0.0023)	(0.0021)	(0.0026)	(0.0025)
rho	-	0.712	-	0.636
	-	(0.0228)	-	(0.0295)
b	1.040	1.343	0.961	1.528
	(0.0098)	(0.0275)	(0.0269)	(0.0357)
lnL	-95.160	-87.608	-89.211	-85.557

Notes:
1 Trinomial Probit panel regressions by ML and SML with actual nominal prices as dependent and raw material prices as explanatory variables.
2 sigma: standard deviation of residual, lnL: log-likelihood value, rho: autocerrelation parameter, b: slope parameter.
3 All estimation were carried out in Gauss. Standard errors are in parenthesis.

Table 2
Correlation between Aggregate Inflation and
Three Summary Statistics of the Density of Price Deviations

	Π	*mm(z)*	*stdev(z)*	*skew(z)*
Π	1.000			
mm(z)	0.278	1.000		
stdev(z)	0.120	0.941	1.000	
skew(z)	-0.343	0.273	0.271	1.000

Note: Π denotes inflation, "stdev(z)" denotes standard deviation, "skew(z)" denotes skewness, "mm(z)" denotes the scaled difference of the distribution of desired price changes.

Table 3
Regression Results -
Aggregate Inflation and the Distribution of Price Deviations

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

b_0	0.67	-4.20	0.90	-5.01	-5.57	7.05
	0.54	3.81	0.63	2.39	3.84	4.43
b_1	0.57	0.57	0.54	0.56	0.49	0.52
	0.12	0.12	0.13	0.12	0.13	0.11
b_2	-	56.08	-	-	76.75	-357.23
	-	43.38	-	-	44.67	114.35
b_3	-	-	-50.18	25.82	-2.60	112.21
	-	-	63.79	10.62	1.67	29.30
Adjusted R^2	0.320	0.330	0.315	0.388	0.353	0.492
R^2	0.335	0.360	0.346	0.416	0.396	0.526
F statistic	22.194	12.102	11.352	15.287	9.177	15.521

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 scaled mean-median difference in the fourth and the sixth columns.

Table 4

Aggregate Price Changes:
True vs. Counterfactual Series

G(.)	*A(oa)*	*A(s)*	*A(a)*
f(oa)	0.00	0.25	0.31
f(s)	0.67	0.77	0.82
f(a)	0.88	0.98	1.00

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

Figure 1a
CPI Inflation
(annual growth rate; in percentage)

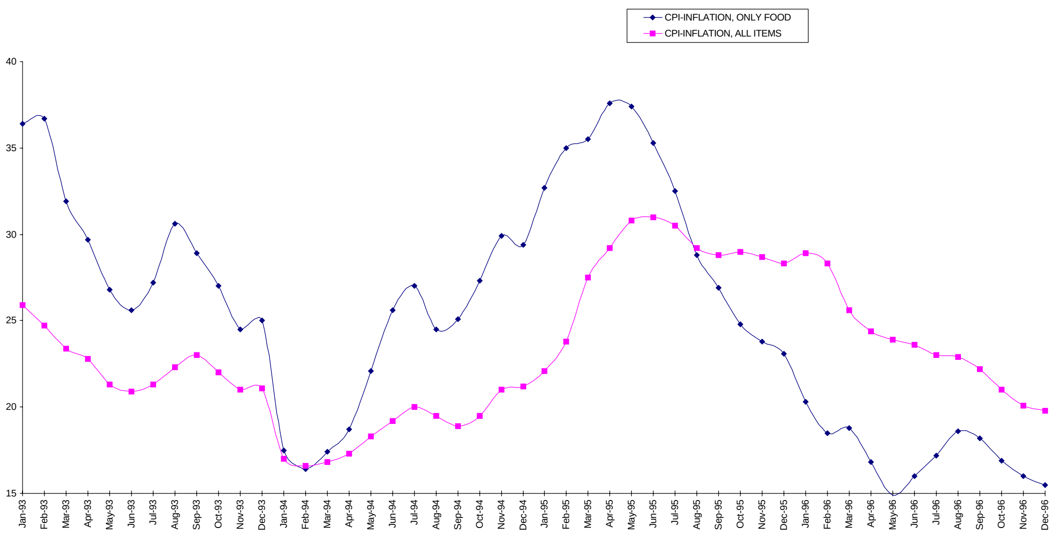
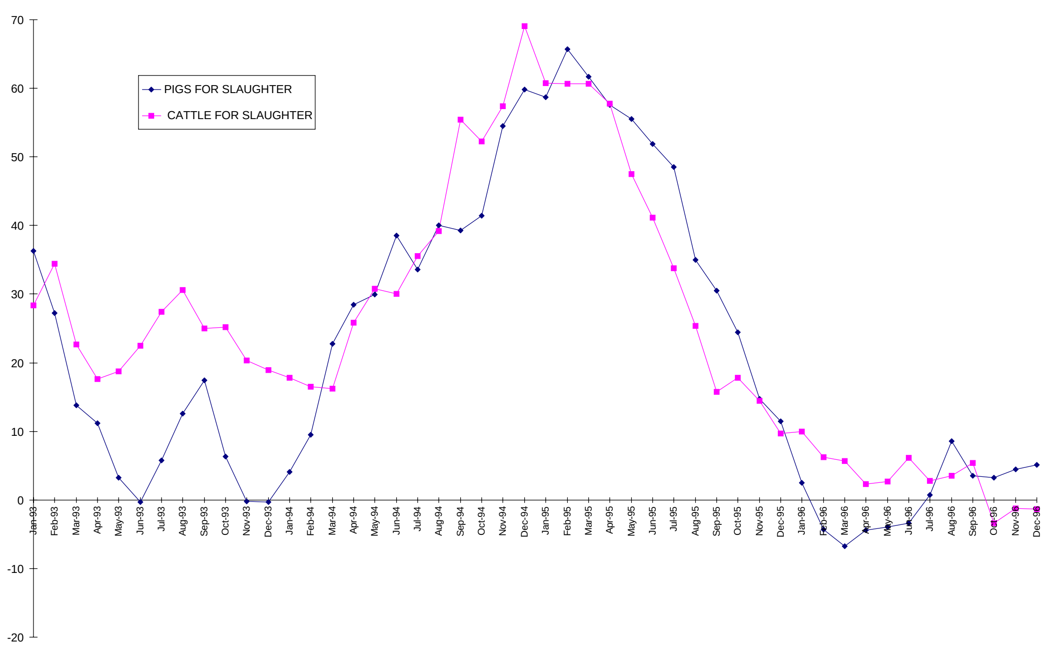


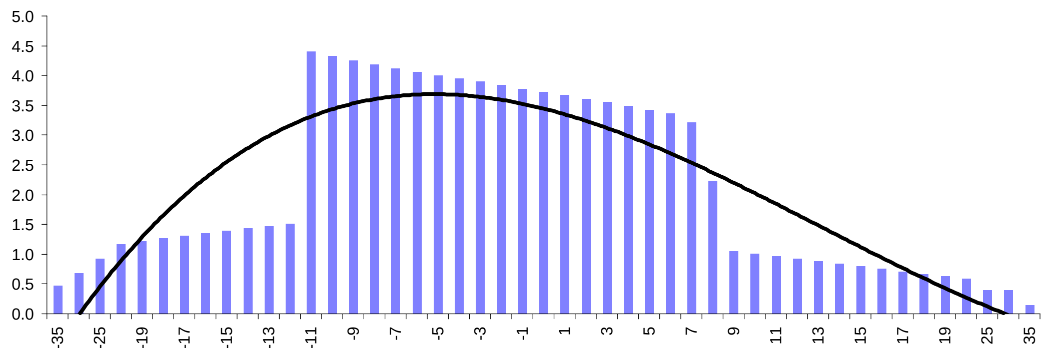
Figure 1b
Inflation in Pigs and Cattle for Slaughter, 1993-1996
(annual growth rate; in percentage)



Source: Central Statistical Office, Hungary

Figure 2

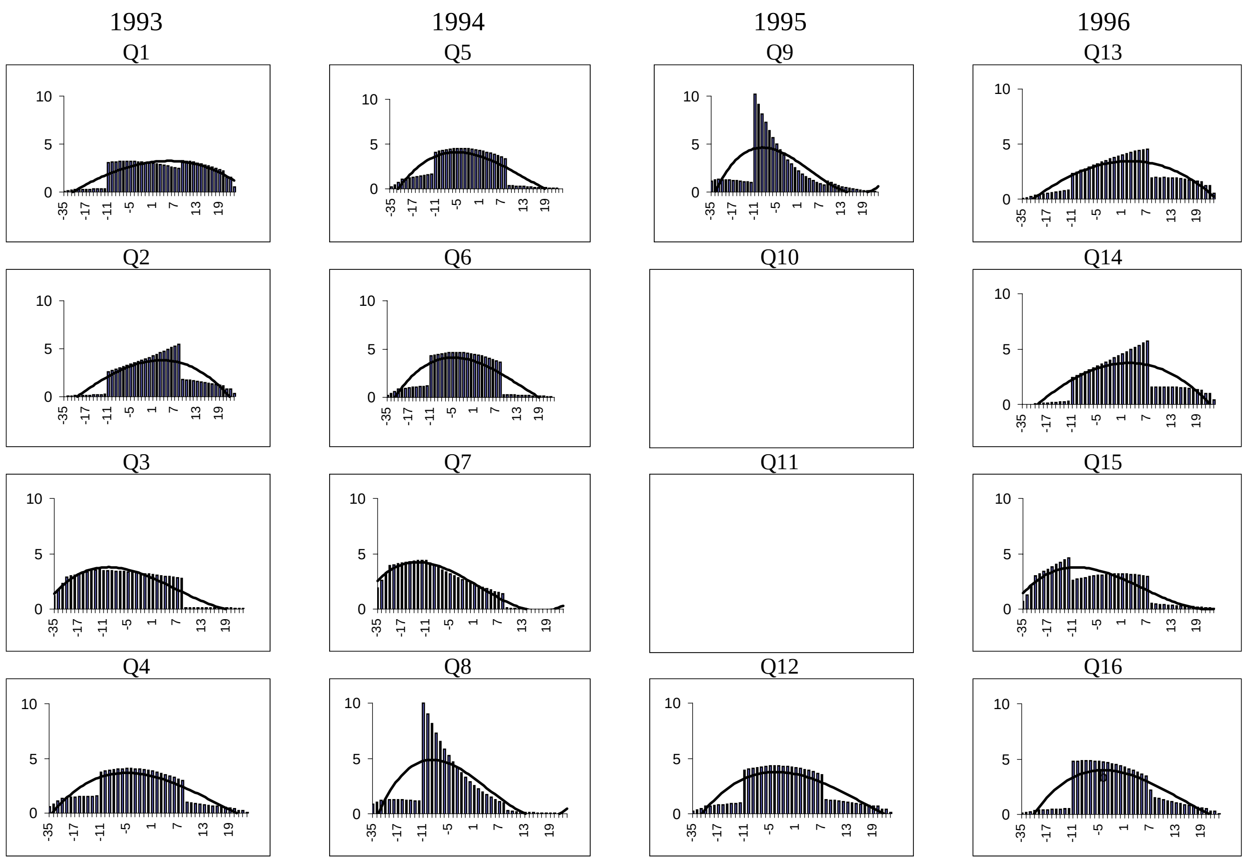
Empirical Density of Price Deviations -
Full Sample (in percentage)



Note: The solid line represents a third degree polynomial fitted to the empirical density function

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.

Figure 4

Average Adjustment Functions

(quarterly average, total average)

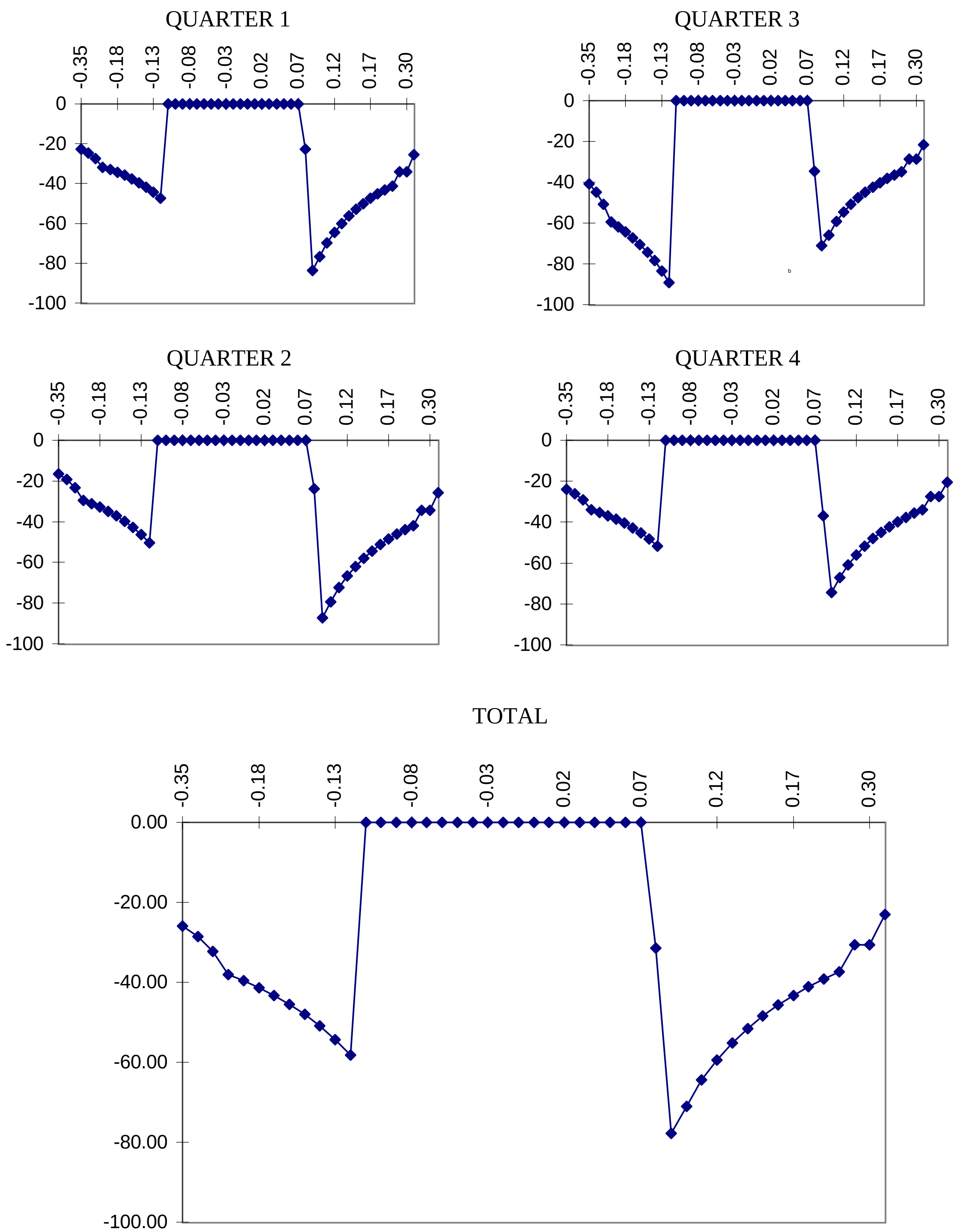


Figure 5
Adjustment Functions
(quarterly data)

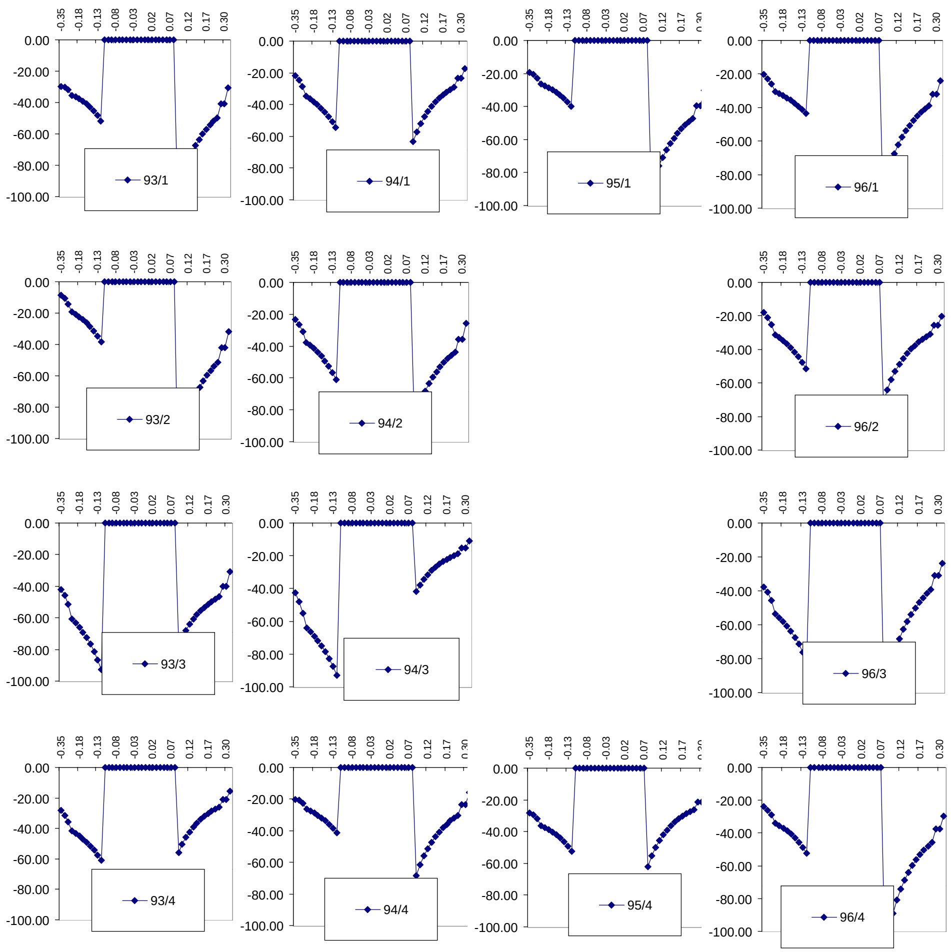
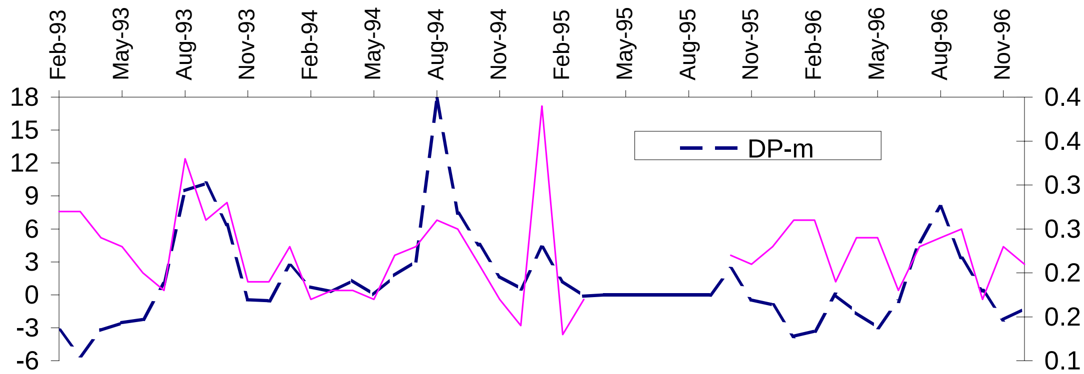
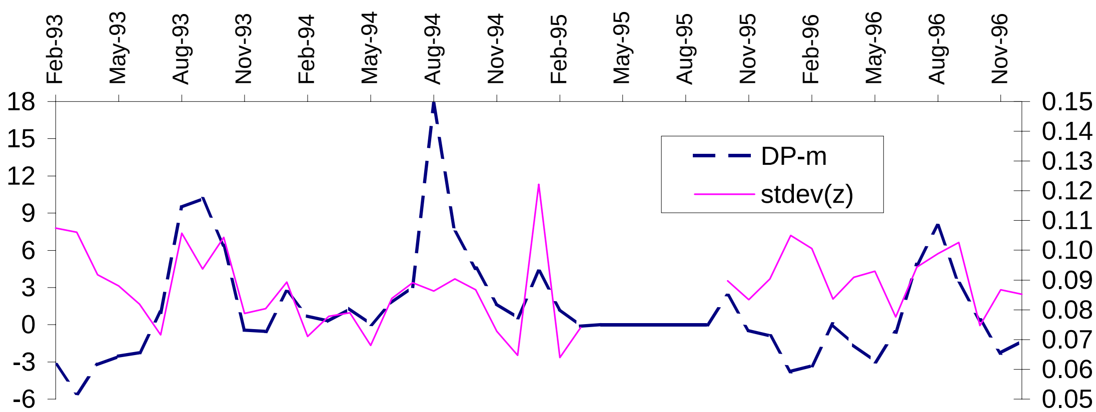
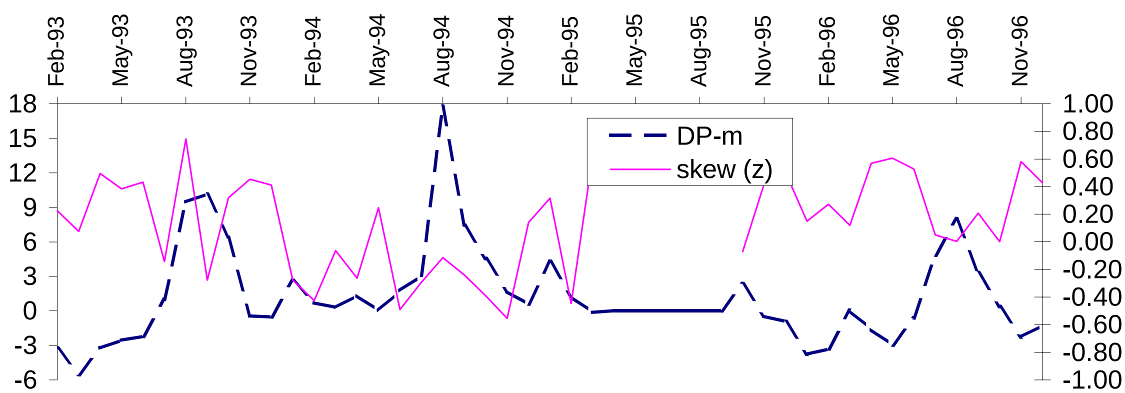


Figure 6

Dispersion, Asymmetry and Aggregate Inflation







Notes. Month-to-month inflation (DP-m) is measured on the left axes.
"mm(z)" in the top graph denotes the scaled mean-median difference in the distribution of price deviations.
"stdev(z)" and "skew(z)" denote the standard deviation and the skewness of the distribution of price deviations, respectively.