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# Linking Individual and Aggregate Price Changes ♣


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**Abstract.** Standard macroeconomic forecasting indicators and techniques tend to perform poorly in predicting inflation in the short-run. The present paper shows that microeconomic price data placed in an empirical model rooted in (S,s) pricing theory convey extra information on inflation dynamics. The empirical model designed to capture the deviation between target and actual price, potentially applicable in other contexts where lumpy adjustment is prevalent, 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 are found to contribute to short-run inflation in the sample. Asymmetry in the density particularly matters. Idiosyncratic pricing shocks appear to impact on the size rather than the direction of inflation fluctuations.



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# 1 Introduction

Financial analysts and central bankers are all highly keen to learn about the nature of short-term, month-to-month or quarter-to-quarter, variation in aggregate inflation[1]. Despite its vital importance for business and policy, understanding the origin and determinants of short-term aggregate price changes has been a daunting task for macroeconomists. Investigating standard macroeconomic indicators and forecasting techniques, Cecchetti (1995) concludes that forecasting relationships for inflation in the US are unstable and time varying. The best, still highly imperfect predictor of inflation appears to be its own past. Cecchetti and Groshen (2000) report that the standard deviation of forecast errors in professional forecasters' one-year-ahead prediction of US inflation has been about one percentage point over the past decade. This latter fact is indicative as inflation during this period averaged about 3 percents.

Besides the displeasing performance of traditional approaches, motives are numerous for exploring new directions in understanding short-term inflation dynamics. The present analysis is motivated by results from two related strands of research. First, direct evidence on store level pricing patterns shows that nominal prices are lumpy in the sense that they often exhibit relatively long periods of inaction followed by discrete, intermittent and heterogeneous adjustments. This description of microeconomic pricing behavior suggests that the (S,s) pricing approach is able to serve as a particularly suitable framework for modeling store level pricing decisions[2].

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[1] This motive is especially strong in industrialized countries that adopted some form of explicit inflation-targeting regime.

[2] Microeconomic prices studied in this paper are unchanged for about three months on average, in an era when annual aggregate inflation varied between 15 to 35 percents. Moreover, prices are not altered in tandem; there exists a significant element of staggering in the timing of price changes (see Rátfai (1998)). For similar evidence in a highly inflationary period in Israel, see Lach and Tsiddon (1992). For US microeconomic price data see, for instance, Blinder (1991), Kashyap (1995).

Second, the literature on lumpy, (S,s)-type decision rules suggests that an 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. Indeed, several authors have recently emphasized the importance of exploiting micro level data in explaining the macroeconomy. 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 individual employment demand explain a sizeable portion of aggregate employment fluctuations in the US. Drawing on the same firm-level data set and utilizing a similar analytical framework, Caballero, Engel and Haltiwanger (1995) reach analogous conclusions regarding US 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 US in the early 1990s. The upshot of this literature is that the degree of coordination of lumpy and heterogeneous micro level actions matters in aggregate dynamics.

Over the past decades a vast amount of empirical research has been accumulated on the issue of inflation determination. Most of the studies appear to share two common features: the abstraction from microeconomic, behavioral considerations and the orientation towards aggregate data. The present study departs from the traditional literature in both respects and examines the issue of short-run inflation dynamics from a hitherto unexplored angle. First, the empirical model set up to estimate the determinants of microeconomic pricing decisions explicitly builds on implications of *two-sided (S,s) pricing rules*[3]. Second, the data analysis is structured around an explicit aggregation of *microeconomic price data*.

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[3] The non-smooth price adjustment in (S,s) models stems from the non-convexity of adjustment costs. See Ball and Mankiw (1994, 1995), Caballero and Engel (1992), Caplin and Leahy (1991) and Tsiddon (1993).

The central object of the empirical model developed in the paper is the price deviation - the log difference between the actual and the target price level[4]. The main idea, potentially instrumental in related macroeconomic applications, modeling the postulated imbalance between the actual and the target price is that the presence of menu costs in price adjustment implies two-sided (S,s)-type decision rules for price setters[5]. In this framework, stores alter their nominal price and pay the menu cost only when the difference between the target and the actual price level is sufficiently large and exceeds some threshold value. Otherwise, when shocks are not sufficiently large to move the price deviation outside the optimally determined (S,s) band, the current nominal price coincides with the preceding one and no actual pricing action takes place. This description of pricing behavior naturally lends itself to a Probit interpretation of microeconomic price data with the target price level being a latent variable[6].

The empirical model is applied to a unique, highly disaggregated panel sample of consumer prices. The data analysis is aimed at recovering and quantifying information that may be lost in merely taking averages of individual prices in constructing aggregate inflation indices. First, price deviations are estimated and the corresponding price adjustment functions and cross-sectional densities of price deviations are constructed. Price deviations, adjustment functions, and cross-sectional densities are then placed into an aggregating framework to obtain aggregate inflation. Given these constructs, three issues are investigated. First, to evaluate the relevance of the proposed empirical framework, the intertemporal stability of price adjustment functions and cross-sectional densities is analyzed. Then, the role of fluctuations in the price deviation

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[4] What is called price deviation here is often termed as relative or real price in the related literature. The current terminology appears to capture better the behavioral concept at hand (see also Caballero and Engel (1992)).

[5] The expressions of "menu cost" and fixed cost of adjustment are used interchangeably. Levy et al. (1996) provide *direct* empirical evidence on the nature and magnitude of menu costs.

[6] The present approach to model the deviation between actual and target behavior is markedly distinct from the ones advocated by Caballero, Engel and Haltiwanger (1995), (1997).

densities in shaping aggregate price dynamics is evaluated. Finally, the relative influence of idiosyncratic pricing shocks in aggregate price changes is briefly examined.

The rest of the paper is organized into eight sections. The new microeconomic data set used in the study is introduced in Section 2. Elements of the proposed empirical framework are developed in Section 3. The estimation procedure is described in Section 4. Sections 5 reports on the various pieces of empirical results, while Section 6 concludes and suggests directions for future research.

## 2 Data

Inferring the history of 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 stores. Samples that are representative of finished goods markets at large, or even for a specific sector of the economy, are simply inaccessible, thus shortage in appropriate data may explain the paucity of related research. To sidestep the data availability issue, this study examines a specific 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 different processed meat products[7] sold in eight distinct and geographically dispersed stores in Budapest, Hungary from January 1993 to December 1996. Observations are at the monthly frequency. Due to a five-month intermission in data collection from April 1995 to September 1995, the sample is split into two sub-periods covering 27 and 16 months. Out of the eight stores in the sample, five are larger department stores and three are smaller grocery stores, called Közért. All stores sell

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[7] The products include 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.

many other kinds of products besides the ones considered here. Whenever a particular store is visited, all the fourteen product prices are recorded. Throughout the sample period, there was no government control of the prices involved[8].

The data set is specified and does not represent the whole spectrum of economy-wide price movements. It still provides an excellent laboratory for the purposes of the present analysis. First, items in the sample are well-defined, homogeneous food products with insignificant variation in non-price characteristics such as quality. Second, products are manufactured by a technology that features a single basic input component, the underlying raw material. It implies that the fundamental source of aggregate pricing shocks is variation in raw material prices. Third, as products are taken from the same sector, inference about stores' pricing policies is less likely to be contaminated by major differences across production technologies. And finally, although being more volatile, the sample price index tracks movements in the overall CPI, especially its food component quite closely. For instance, the partial correlation coefficient between the average price level in the sample and the food component of the CPI in Hungary is 0.94[9].

## Descriptive Evidence

In a detailed descriptive, non-parametric study, Rátfai (1998) documents that prices in the sample exhibit both lumpiness and heterogeneity. To motivate the empirical approach adopted in this paper, it is instructive to briefly highlight some of the basic findings. First, nominal prices remain constant in 58 percent of the cases and the average duration of price quotations is about

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[8] Appendix A provides further details of the data.

[9] The time series properties of the sample price index also closely match the properties of a similar sectoral index of processed meat product prices compiled by the Central Statistical Office, Hungary.

three months with the longest spell being 17 months. With the exception of months in the third quarter when a raw material price shock hits in, spells of adjustment are spaced irregularly across stores. The duration of price changes is dispersed over time within stores but contemporaneously tends to be 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. Positive changes tend to be larger than negative ones. 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.

The above observations suggest that price fixity is adequately captured at the monthly frequency. In particular, first, quarterly or lower frequency microeconomic price observations are likely to be heavily left-censored as the average duration of price quotations is about three months. Second, visualizing price sequences in the data indicates that higher, say weekly, frequency price data have little to offer in providing new information on microeconomic pricing patterns. Also, the time series for the underlying raw material prices are available only at the monthly frequency.

## 3 The Empirical Model of Inflation Dynamics

The empirical model of inflation dynamics is developed in two stages. First, the target price level is specified and the resulting price deviation is estimated. Second, an aggregation framework is set up to organize price deviations into an inflation index[10].

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[10] Throughout the data analysis, aggregate inflation is meant to refer to aggregate price changes in the particular sample at hand.

### 3.1 Specification and Estimation of Price Deviations

The (S,s) model assumes that there exists a target price that would be implemented in the absence of fixed adjustment costs. To capture the 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. First, there is no apparent behavioral reason to identify the target price level with the product level average price. And second, there exist several factors including location or technological ones that make the target price level heterogeneous across price setters and products as well. In the investment literature, Caballero, Engel and Haltiwanger (1995) derive mandated investment, the log deviation between the actual and the target capital level, as a function of two firm-specific variables that are individually both highly persistent and argue that the (S,s) decision rule makes mandated investment mean-reverting. This is the insight that allows them to identify parameters of mandated investment in a cointegrating framework.

The empirical framework developed below radically departs from both of the above two strands of literature. The various pieces of the model revolve around the idea that fixed costs of changing prices create an imbalance between actual and target pricing behavior and make actual price adjustment state-dependent. Stores follow two-sided (S,s) pricing policies and leave their nominal price 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 shocks to the target price are sufficiently large then $z_{ijt}$ is pushed outside one of the bands that in turn induces stores to pay the menu cost and adjust their nominal price either upwards when $z_{ijt} \leq s$ or downwards when $z_{ijt} \geq S$. The observation rule for the (log) nominal price level is summarized as

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

This description of pricing behavior suggests that the target price level can be viewed as a latent variable. Clearly, the two-sided (S,s) pricing rule translates into a trinomial Probit estimation problem.

It is important to give emphasis to the timing convention adopted in the definition of price deviations. As shocks to the target price are assumed to occur at the beginning of the current 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 are able to respond to current shocks.

The starting point to actually estimate price deviations under the organizing framework of (S,s) pricing rules is specifying the individual target price level for processed meat products. To do so, first, recurrent aggregate and idiosyncratic shocks are assumed to drive the stochastic process for the target price level. An important advantage of the data set used in this paper is that the aggregate forcing variable is easily characterized and the specific product prices are readily matched with it. Indeed, aggregate shocks are identified by the change in the relevant raw material price, the price of cattle or pig for slaughter [11]. Idiosyncratic shocks are independent from aggregate shocks and specific to the particular product in the particular store at the particular time.

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

Second, individual price sequences are assumed to contain both product *and* store specific components. The fact that certain stores may happen to be systematically more (or less) expensive than others could be due to differences in the local tax-burden or in the affluence of customers at a particular location. Similarly, differences in consumer taste or production technology could perhaps cause certain products to be priced systematically higher than other ones. To capture these effects, nominal price sequences are assumed to contain a deterministic, store- and product-specific nuisance term. Therefore, the log target price level is a linear combination of the nuisance term, $c_{ijt}$, and the relevant raw material price, $M_{jt}$. The economic interpretation attached to this specification is a fixed markup over cost story[12].

Third, the nuisance term, $c_{ijt}$, is defined as the sum of a time-invariant intercept term, $a_{ij}$, and a residual term, $\omega_{ijt}$, with homoskedastic variance, $\Omega$. The residual is then interpreted as an idiosyncratic pricing shock. To ease estimation by reducing the number of parameters, the store- and product-specific intercept parameter, $a_{ij}$, is split into two parts. 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 fixed effect model for the target price level:

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

### 3.2 True versus Spurious State Dependence

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

As past realizations of nominal prices have a genuine behavioral effect on the probability of initiating a pricing action in the present, 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 estimation procedure adopted here accommodates both sources of temporal dependence.

In general, decision rules of the (S,s) type naturally give rise to "true" state-dependence in the decision variable of interest. In the present application, the current realization of the state variable, the price deviation is directly related to past pricing actions by $z_{ijt} \equiv p_{ij,t-1} - p_{ijt}^{*}$. Nonetheless, as the lagged control variable does not directly enter the true behavioral model but it affects decisions through the censoring thresholds, the discrete choice model reflects state-dependence in a non-standard form.

The possibility of "spurious" state dependence appears in the model in the form of serially correlated residuals. In general, this form of intertemporal linkage stems from the fact that past realizations of heterogeneous unobservables can persistently affect current decision variables. In the present application, local technological or demand shocks may result in increased persistence in the residual term of the target price model. To comply with this presence of temporal dependence in idiosyncratic unobservables, the residual in the fixed effect regression model, $\omega_{ijt}$, is specified as an AR(1) process in the form of

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

where $\varepsilon_{ijt}$ is i.i.d. Normal with mean zero and variance $\sigma_{\varepsilon}^{2}$. The auto-regressive parameter, $\rho$, is constant across stores and products.

Taken together, these considerations yield an empirical model of price deviations estimated as a multi-period, trinomial panel Probit model with serial correlation in the residual.

### 3.3 Aggregation Framework

To complete the description of the empirical model, a general accounting framework of price deviations is introduced to arrive at a definition of aggregate inflation. In the proposed framework both aggregate and idiosyncratic pricing shocks are filtered through the single state variable, $z_t$, in a non-linear manner. First, 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[13].

The propagation pricing shocks in the model is reflected in the time and state dependent adjustment function and cross-sectional density of price deviations. The principal advantage of aggregating individual price changes in this particular framework is that it permits a rich evaluation of the mechanism driving aggregate price changes, including the study of the role of fluctuation in $A_t(z_t)$ and $f(z_t,t)$. Potentially, the framework also permits to separate the importance of idiosyncratic versus aggregate shocks in driving inflation.

Clearly, the above definition of aggregate inflation is not a conventional one. It 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. Nonetheless, the index is virtually

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[13] As opposed to $A_t(z)$, $z$ and $f(z,t)$ explicitly enter (S,s) pricing models. See Tsiddon (1993).

identical to a simple unweighted index of aggregate price changes in the present sample. The correlation coefficient between the two indices is 0.99.

## 4 Estimation

To motivate the estimation strategy for the empirical model, consider the situation in which the residual in the target price model, $\omega_{ijt}$, is assumed to be Normal with variance $\Omega$ and identically and independently distributed. In the absence of temporal dependence in the error term, the log-likelihood function for the model can be simply written as the product of the appropriate marginal probabilities:

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

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

where *F(.)* denotes the multivariate cumulative density function. In this setup, standard quadrature based Maximum Likelihood procedures serve as a relatively straightforward estimation method. Even if temporal dependence in the error term is neglected when it is actually present, parameter estimates are consistent. However, standard error estimates are biased and parameter estimates are inefficient. More importantly, if the serial correlation structure is erroneously specified to be i.i.d. *and* lagged dependent variables enter the model, as they do here, then standard ML estimation may lead to inconsistent parameter estimates (see Keane (1993)). These concerns are especially troubling in the current context as the estimated parameters are used for prediction purposes in forming the cross-sectional density of $z_{ijt}$ and then aggregate inflation.

Unfortunately, the residual in the target price model is likely to exhibit a non-trivial serial correlation structure here. Moreover, the pricing model features lagged dependent variables that appear in the censoring thresholds. These two considerations raise significant econometric problems in the ML estimation of the Probit panel model. First, once the serial correlation in the error term is properly taken into account, the log-likelihood function cannot be factored in the standard fashion. It implies that estimating the joint likelihood of consecutive price observations requires the evaluation of $T$ (the number of time periods) dimensional integrals. Without further simplifying restrictions imposed on the correlation structure of residuals, the computation of these high dimensional integrals by standard numerical procedures is numerically infeasible. An obvious resolution to this problem could be to directly simulate the choice sequence probabilities by the observed frequencies. However, 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. In general, besides computational feasibility, smoothness (differentiability and continuousness) is an important feature of the estimator as it implies that standard hill-climbing or gradient methods can be directly applied to maximize the resulting simulated log-likelihood function. Fortunately, simulation estimation techniques such as the Simulated Maximum Likelihood (SML) estimator employing the Geweke-Hajivassiliou-Keane (GHK) simulator of importance sampling of univariate truncated normal variates offer a feasible remedy. Most importantly, the SML estimator is not only relatively quick and continuous in the parameters but it is also able to accommodate various correlation structures and provide consistent and efficient parameter estimates even in the presence of lagged endogenous variables. Extensive comparisons investigating the accuracy and bias in the various possible simulation estimators of multivariate truncated normal probabilities found that the SML estimator performs the best of the available ones (see Börsch-Supan and Hajivassiliou (1993)). 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 the following. 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 presence of serial correlation in the residual implies that estimating the parameters of this problem requires the evaluation of $T$ dimensional integrals for each cross-sectional unit where $T$ is either 27 or 16 here.

To understand the simulation estimation procedure, consider the sequence of prices of a single product in a single store. First, dropping subscripts for the moment, the normally distributed structural error term, $\omega$, is defined recursively as $\omega = Ce$ where $C$ is the lower triangular Cholesky decomposition of $\Omega$ satisfying $C'C = \Omega$, and $e$ is a univariate i.i.d. standard normal residual. Then, instead of drawing directly from the original distribution of serially dependent truncated normals, $e$ sequentially and independently is sampled $R$ times from the recursively restricted univariate standard normal distribution[14]. For instance, if the nominal price remains constant during the first three periods then the consecutive draws of $e_1$ ,$e_2$, and $e_3$ are obtained from:

[14] 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 $B_t^* = p_{ij,t-1} - s - (a_i + a_j + bM_{jt})$. To scale the size of the dependent variable for identification purposes, 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[15].

In general, the SML procedure requires $R$ distinct simulations to estimate the joint occurrence of a particular sequence of nominal price realizations. 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:

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

This stage of the estimation computationally is quite time consuming. Still, relatively accurate likelihood estimates are obtained by employing only a small number of repetitive draws.

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[15] See Tsiddon (1993), Lach and Tsiddon (1992). The parameters are set as s = -0.11 and S=0.08 (period 1) and S=0.07 (period 2). Experimentation with alternative numerical values for the boundaries suggests that the qualitative results are insensitive to reasonable departures from these values. For parameter values that significantly differ from the original ones, the SML estimator was not able to converge after several repeated trials.

Börsch-Supan and Hajivassiliou (1993) report that only twenty or thirty draws are likely to be sufficient in the case of three to seven alternative choices. To use err at the conservative end, fifty sampling draws is employed in the simulations.

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 presented in Table 1 separately for *Period 1* and *Period 2*. There are a few points that clearly stand out here. First, standard errors reported in the table indicate that the parameters are fairly tightly estimated. Second, the autocorrelation parameters are sizeable and significantly different from zero[16]. The substantial persistence found in the residual clearly justifies accounting explicitly for the temporal dependence in residual term. And third, the slope estimates are larger than one indicating the possibility of some form of increasing returns to scale in the production technology.

## 5 Empirical Results

### 5.1.1 The Cross-Sectional Density of Price Deviations

In (S,s) pricing models, histories of shocks and the potentially heterogeneous response of stores to these shocks are summarized in the cross-sectional distribution of price deviations. It implies that the shape of this distribution is likely to serve as an important determinant of aggregate price dynamics. Indeed, a novel element of the two-sided (S,s) approach is the way individual pricing

[16] The results remain intact to experimentation with monthly dummies in the regression equation. Therefore, only the baseline specification is considered in the rest.

decisions are aggregated. Tsiddon (1993) develops a continuous time model in which trend inflation (used to proxy the trend change in the target price level) is non-negative. Due to the presence of occasional deflationary shocks, the optimal price setting rule is a two-sided (S,s) policy, featuring both downward and upward actual price adjustments. The paper demonstrates that the presence of non-zero trend inflation implies that the stationary distribution of price deviations has an asymmetric, non-uniform, piece-wise exponential shape. Intuitively, this feature of his model follows from the fact that the pressure exerted by positive trend inflation forces price deviations to spend disproportionately more time closer to the lower adjustment band than to the upper one. In another two-sided (S,s) model with no trend inflation, Caplin and Leahy (1991) assumes a uniform time-invariant distribution of price deviations in aggregating (S,s) pricing policies.

To provide microeconomic evidence on the shape of the cross-sectional distribution of price deviations, first, recall that price deviations are defined as the log difference between the actual lagged price level and the predicted target price levels. Aggregate shocks to the target price are observable and represented by the change in raw material prices. However, the exact realization of idiosyncratic shocks cannot be recovered, only their conditional density is identified in the form of a truncated normal distribution. Consequently, target price levels are directly unobservable as well.

Despite that target price levels and price deviations are not observed, the cross-sectional density of price deviations can be calculated in a straightforward manner by averaging the 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, $k = -35, -30, -25, -24, -23, \ldots, 23, 24, 25, 30, 35$. Formally, the empirical densities at $z_{ijt} = k$ can be computed as

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

The definition of price deviations implies the truncation points for $\omega_{ijt}$ of $A_{ijt}^{*} = p_{ij,t-1} - S - (a_i + a_j + bM_{jt})$ and $B_{ijt}^{*} = p_{ij,t-1} - s - (a_i + a_j + bM_{jt})$. Then, for each bin interval and price observation, the conditional truncated normal densities are computed[17]. Adding up the individual densities at each bin interval and normalizing the resulting empirical distribution so that it sums to unity produces the empirical distribution of price deviations in each time period.

Summary statistics show that the average of the mean price deviation calculated separately for each product-store specific sequence of price deviation is –3.05 percent in the whole sample with an average standard deviation of 8.74. On the one hand, the first figure indicates that there is a substantial upward trend built in the target price levels and a corresponding downward trend in target price changes. This observation is in accordance with the predominance of inflationary periods in the sample. On the other hand, the standard deviation figure confirms that there is considerable cross-sectional heterogeneity both across stores and products in the sample.

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, the upper panel in Figure 2 shows the histogram of all price deviations pooled together[18]. The empirical density clearly does not take on a symmetric, rectangular shape implied by much of the literature on one-sided (S,s) pricing policies. Indeed, it appears to be asymmetric. This feature of the distribution is actually consistent with two-sided (S,s) models that motivate the empirical structure imposed on the data.

How the shape of the empirical densities of price deviations evolves over time? To ease interpretation, only densities at the *quarterly* frequency are examined[19]. The graphs in Figure 3

[17] The masses at the two tails represent the respective cumulative densities.

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

[19] To ease visual interpretation, monthly histograms are not reported here.

displaying densities show that price deviations are asymmetric and non-uniform. 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 decreases.

A few further episodes of interest can also be identified in the histograms in Figure 3. For instance, Figure 1a suggests that the accelerating burst in annual food price inflation in early 1994 was eventually terminated by the middle of 1995[20]. By many price deviations bunching in the neighborhood of the lower adjustment boundary, histograms of price deviations in the present sample quite clearly pick up this story, especially between late 1994 and early 1995. Alternatively, at the beginning of 1993 and 1996 the large number of price deviations bunched on the right end of the empirical densities witness deflationary pressures on meat product prices. As evidenced by the sample inflation series displayed in Figure 6, the deflationary pressure eventually resulted in disinflation in early 1993 or even deflation in the first two quarters of 1996. An interesting episode is 1994 when the graph actually signals pressure on subsequent price increases.

### 5.1.2 The Price Adjustment Function

Dropping individual specific subscripts momentarily, for all $k = -35, -30, -25, -24, -23, \ldots, 23, 24, 25, 30, 35$, the adjustment function is defined as

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[20] Although less dramatically, this acceleration and then stopping is also detectable in the case of the aggregate CPI.

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

In the present framework, $DP_t\,(z_{ijt} = k,\ \forall\, i, j)$ is computed as a weighted average of all nominal price changes (including zeros) in month $t$ when the price deviation is equal to $k$. The weights are supplied by the corresponding empirical densities. Formally,

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

Note that this definition implies that $A_t(z_t)z_t$ measures the expected value of the size of price changes taking place at price deviation $z_t$.

As its curvature determines the extent to which fluctuations in non-uniform price deviation densities are able to impact on aggregate inflation, the shape of the adjustment function may have important aggregate consequences. The Probit model imposed on the data implies specific predictions on the shape of the adjustment function. In particular, if prices were perfectly flexible then the middle portion of the adjustment function would contain no realization of price deviation. However, if prices were sticky in one way or another then the adjustment function would be hat- (or reverse-U) shaped. Intuitively, in this case stores are willing to tolerate small deviations between the actual and the target price level but a large deviation induces them to alter their nominal price. It implies that the adjustment function would take on large absolute values for more extreme price deviations, outside the (S,s) band, and zero values for a range of intermediate price deviations, side the (S,s) band. In reality, stores may not be fully intolerant towards small deviations. They are more likely to have average adjustment functions that evolve less smoothly in the neighborhood of the boundaries and look less concave and symmetric.

In general, 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 CEH (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 $z_t$. In fact, if the adjustment function were fully flat then in the proposed aggregating framework higher moments of the cross-sectional density of price deviations would be irrelevant to aggregate inflation.

Figure 4 portrays the average adjustment functions in the sample. They are constructed by pooling monthly observations of $A_t(z)$ from the whole sample or from the same quarters in different years. The upper four panels show average adjustment functions at the quarterly frequency, while the bottom panel shows all observations pooled together. In general, the shape of the adjustment functions appear to be consistent with the implication of two-sided (S,s) models. Visual inspection of the graphs suggests that the adjustment functions do take on a hat-shaped form and reflect the inaction region implied by the Probit structure imposed on the data. Most importantly, the average adjustment functions are relatively stable across quarters. The discontinuity at the adjustment boundaries is due to the assumption that the boundaries are fixed.

Figure 5 displays the same information separately for all the fourteen quarters in the sample. Despite the noise in constructing these graphs, the emerging picture clearly indicates that adjustment functions are remarkably stable over time and 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 reasonably well captures the underlying microeconomic structure that governs stores' pricing behavior.

### 5.2 Aggregate Implications

As two-sided (S,s) pricing models predict that they exert pressure on aggregate price changes, fluctuations in the shape of the cross-sectional density of price deviations are of considerable interest for the study of inflation dynamics. Using sectoral level inflation data, Ball and Mankiw (1995) show that the standard deviation and the skewness of a particular cross-sectoral measure of price deviations do impact on changes in aggregate inflation. They find strong evidence that inflation is related to the asymmetry in the distribution and somewhat weaker evidence that it is related to dispersion in the distribution.

My focus is also on the same features of price deviation densities: dispersion and asymmetry. Dispersion is measured as the standard deviation of the cross-sectional distribution of price deviations. As *a priori* it is not straightforward which statistic captures better the fundamental concept of interest here, the relative bunching of price deviations to one of the two adjustment boundaries, two alternative measures of asymmetry are considered, the inter-deciles difference, and the standard skewness coefficient[21].

First, the three panels in Figure 6 show the time path of the above three summary measures along with the corresponding aggregate inflation series. To assess if the price deviation series exhibit any sort of cyclical relationship with respect to inflation, first, Table 2 summarizes 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 third central moment of price deviations and aggregate inflation. At the same time, the correlation coefficient between the inter-deciles difference and aggregate 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. To sort them out, by case of example, consider the empirical density of price deviations in the third quarter of 1993 shown in Figure 3. Clearly, the large number of price deviations bunching at the lower end of the distribution translates into substantial aggregate price increases during that quarter. As the top panel of Figure 6 indicates, the bunching is evidenced in the jump of the

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[21] The inter-deciles difference statistic is the upper 10 percentile of the distribution minus the lower 10 percentile of the distribution. Results with alternative percentile measures of asymmetry are omitted from here as they lead to qualitatively similar results to the inter-deciles one. The skewness coefficient is defined as the third central moment of the distribution of price deviations scaled by the third power of the corresponding standard deviation.

inter-deciles statistic. At the same time, the skewness coefficient turns into negative in the quarter that does not reflect the observed bunching of price deviations around the lower boundary. This episode and other ones as well suggest 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 coefficient to capture asymmetry in the empirical density, results using both potential measures are report.

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 general form of the regression equation is

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

where *StDev* denotes the standard deviation and *Asym* denotes the asymmetry measure of price deviation densities. Six distinct regressions are considered, all of which include a constant, $b_0$, and lagged inflation, $\Pi_{t-1}$ as well. The six cases differ in what measures of the price deviation density are included as explanatory variables in the equation.

The parameter estimates along with their standard error and the goodness-of-fit measure of the regression are displayed in Table 3. Results for the benchmark regression are reported in the first column of the table. 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 leads to a worse goodness-of-fit than the one including only the standard deviation. However, in both cases the parameter estimates are statistically insignificant at conventional levels. Column four shows that adding only the inter-deciles statistic 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 inter-deciles 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 variable is supplemented with the inter-deciles difference one. 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. In this sense, they match the empirical results of Ball and Mankiw (1995).

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[22]. For example, replacing the actual $A_t(z_t)$ in my 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 CEH (1995, 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 $\Pi_t^{cf}$ ($cf = s$ (seasonal), $oa$ (overall average)) is the counterfactual and $\Pi_t$ is the actual aggregate price change and $\sigma^2$ denotes the variance of the series. To the extent that it is not

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

constrained by zero from below[23], the proposed statistic, *G(.)*, is different from the traditional goodness-of-fit measure, $R^2$.

Table 4 displays the results obtained for goodness-of-fit in the various counterfactual cases. First, note that 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 upper right and lower left corner of the table show statistics obtained by removing all (seasonal and non-seasonal) fluctuations either in the cross-sectional density or in the adjustment function. The figures indicate a dramatic deterioration in fit when all fluctuations in the cross-sectional distribution of price deviations are eliminated. In the other parallel 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 in understanding 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.

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[23] 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).

### 5.3 Idiosyncratic versus Aggregate Shocks

Idiosyncratic shocks average to zero by definition. In addition, in a frictionless neoclassical world their aggregate impact cancels out by relative price adjustment. However, though they are still zero on average, idiosyncratic shocks are not neutral any more if there are fixed costs to price adjustment. Two-sided (S,s) behavior implies that 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 are idiosyncratic shocks in shaping aggregate inflation dynamics after having been filtered through the cross-sectional distribution of price deviations? What fraction of fluctuations in aggregate inflation can be attributed to idiosyncratic shocks, after having them filtered through the cross-sectional density of price deviations? The strategy in answering these questions is to split aggregate fluctuations into two parts, one is due to idiosyncratic and the other to aggregate shocks. Idiosyncratic shocks are identified with the residual in the panel Probit regression, while aggregate shocks with the change in raw material prices. Inflation is defined the same way as before:

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

First, idiosyncratic pricing shocks are suppressed in computing price deviations[24]. Using the counterfactual price deviations with no idiosyncratic shocks, the cross-sectional density, *f(oa)*, is constructed. The adjustment functions assumed to be the same as in the baseline case, *A(a)*. By sticking the above two building blocks into the aggregating framework, the counterfactual inflation series, $\Pi_t'$ are readily computed.

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[24] Eliminating idiosyncratic shocks implies that the only source of heterogeneity in counterfactual price deviations stems from the store- and product-specific fixed effects.

Figure 7 displays the counterfactual series, $\Pi_t'$, together with the actual one, $\Pi_t$. Visual inspection of the graph suggests that the underlying dynamics in inflation remains relatively intact. The visual impression is confirmed by simple partial correlation coefficients reported in Table 5. The figures show that the actual and the counterfactual series closely move together, the partial correlation coefficient is 0.83. By displaying the difference between the true and the counterfactual inflation series, Figure 8 shows the relative contribution of idiosyncratic shocks. Their effect appears to be sizeable. For instance, had idiosyncratic shocks not mitigated aggregate surprises between September 1994 and March 1995, inflation would have been higher by about 4 to 5 percent. At the same time, idiosyncratic shocks seem to have prevented an even more drastic deflation in meat product prices during the first eight months of 1996. Analogously to the exercise performed in Section 5.2, the goodness-of-fit statistic, *G(.)*, is constructed here to measure the proximity of the true and the counterfactual series. As reported in Table 6, the resulting statistic is 0.29 indicating that the elimination of all variation in idiosyncratic disturbances significantly alters inflation dynamics. All of this suggests that idiosyncratic shocks do not alter the basic features of inflation dynamics but rather play a role in determining the magnitude of fluctuations in inflation.

## 9 Conclusions

Traditionally, the study of short-run inflation has focused on aggregate data and abstracted from microeconomic, behavioral considerations. In contrast, the present study examined the implications of lumpiness and heterogeneity in micro level price setting for inflation dynamics in the short-run. It differs from traditional approaches in that the empirical framework explicitly builds on implications of two-sided (S,s) pricing models *and* that microeconomic price data are used in the data analysis. The (S,s) pricing framework was originally designed to provide microeconomic foundations for business cycle models derived under the assumption of price stickiness. Here the (S,s) approach is exploited to gain a better understanding of a different phenomenon in the aggregate economy, inflation. In this sense, the analysis demonstrates the power of this approach in macroeconomic modeling.

The most important goal of the paper is to demonstrate the value of an empirical technique that is applied to the study of inflation dynamics based on microeconomic price data[25]. What can one take away from the data analysis? Most importantly, the empirical 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 matters. And finally, pricing shocks impact rather on the magnitude than the timing of fluctuations in aggregate inflation.

The analysis has clear implications for monetary policy as well. 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 that no particular pattern is observed in past average prices; still, a significant amount of pressure builds up in the directly unobservable price deviations. Therefore, provided that appropriate microeconomic price data are available on a timely basis, the empirical approach proposed in this study suggest that the direction and intensity of bunching in price deviations are able to signal forthcoming aggregate price changes. Of course, detecting the correct signal requires a careful specification of the target price level for the different product prices appearing in the price index.

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[25] The technique is potentially applicable in other contexts where lumpy microeconomic adjustment plays a role as well.

## APPENDIX A – DATA

The data were originally collected for commercial purposes by the price-watch service of Solvent Rt. (Solvent Inc.), Budapest. In its original form, the sample of prices in 8 stores selling 14 products over 27 (Period 1) and then 16 (Period 2) months is unbalanced in month-store specific observations. However, no two consecutive observations are missing. Despite their relatively sporadic occurrence[26] missing price data pose a formidable obstacle to the Simulated Maximum Likelihood estimation procedure adopted in the study. To resolve this issue, missing observations are imputed to produce a balanced panel of price data.

There appears to be two straightforward 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 taking excessively long intervals of nominal inaction. Instead, to avoid the shortcomings associated with these procedures missing data are imputed the following way for each product $j$. Assume that $p_{ijt}$ is missing. The case when $p_{ij,t-1} = p_{ij,t+1}$ is an innocuous one. Here $p_{ijt}$ 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 compared separately to both $p_{ij,t-1}$ and $p_{ij,t+1}$ in all stores other than store $i$. There are three different possible ways to set $p_{ijt}$: (a) $p_{ijt} = p_{ij,t-1}$, (b) $p_{ijt} = p_{ij,t+1}$, (c) $p_{ijt} \neq p_{ij,t-1}, p_{ij,t+1}$. If the number of non-missing price changes between period $t-1$ and $t$ and between $t$ and $t+1$ exceeds the number of unchanged prices in these periods then option (c) is selected. In particular, $p_{ijt}$ is set according to $(p_{ijt}- p_{ij,t-1})/p_{ij,t-1})/((p_{ij,t+1}- p_{ijt})/p_{ijt}) = ((p^{-i}_{ijt}- p^{-i}_{ij,t-1})/p^{-i}_{ij,t-1})/( p^{-i}_{ij,t+1}- p^{-i}_{ijt})/p^{-i}_{ijt})$, where superscript $-i$ denotes the average price level in all the stores but store $i$. This simply amounts to assuming that the relative size of imputed price changes

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[26] They occur in 11 cases out of the 344 month-store specific data points.

between periods *t-1* and *t* and periods *t* and *t+1* is proportional to the average non-missing price changes in these periods. 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.

## APPENDIX B - A MODEL OF TARGET PRICE

The target price level of an optimizing store operating in an imperfectly competitive market and using a frictionless price adjustment technology is specified in the following framework. For simplicity, the profit function of a multi-product store is assumed to be separable across products and no explicit aggregate demand linkage is allowed across product markets. It implies that a store-product specific price sequence can be considered as the outcome of a single-product store's optimal decision.

The simple, illustrative model defining the target price level is as follows. In the absence of adjustment costs, an imperfectly competitive store producing a single product maximizes its profit subject to a demand constraint as

$$\max_{P_{ijt}} \pi_{ijt}(M_{jt}, W_t, Q_{ijt}) = P_{ijt}Q_{ijt} - \Theta M_{jt}^{b} W_t^{1-b} Q_{ijt} \,,$$

$$s.t. \qquad Q_{ijt} = P_{ijt}^{-\eta_{ij}} \delta_{ijt} \,, \qquad\qquad \eta_{ij} > 1 \,.$$

Note that both prices ($P_{ijt}$) and quantities ($Q_{ijt}$) are 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, like labor ($W_t$), and marginal costs ($\Theta\, M_{jt}^{b}\; W_t^{1\text{-}b}$) that are the same across different stores. Markets are imperfectly competitive, demand is unit specific with $\eta_{ij}$ being the demand elasticity of product $j$ sold in store $i$. $\delta_{ijt}$ is a multiplicative demand shock. Given this setup, the instantaneously optimal frictionless log price is obtained as

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

The nature of the products examined implies that the price of raw materials ($M_{jt}$) is dominates other cost elements, thus in the empirical specification the first term on the right hand side is assumed to be a nuisance term. Then, the target log price is further simplified to

$$p_{ijt}^{*} = c_{ijt} + bM_{jt} \, .$$

The equation states that the target price level prevailing prior to the potential adjustment is determined by the price of raw materials up to an intercept term. The latter is interpreted here interpreted as an individual specific markup.

The model suitable for estimation is obtained by specifying $c_{ijt}$ as the sum of an idiosyncratic error $\omega_{ijt}$ with variance $\Omega$ 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. Formally, the fixed portion of the price of product $j$ in store $i$ is assumed to be a convolution of separately identified store and product specific effects. All of these considerations yield a fixed effect specification for estimation:

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

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# Table 1

## Estimation Results

| | **PERIOD 1** | | **PERIOD 2** | |
|---|---|---|---|---|
| | no AR(1) -ML<br>$a_i$,i=1,…,14,<br>$a_j$,j=1,…,8 | AR(1) - SML<br>$a_i$,i=1,…,14,<br>$a_j$,j=1,…,8 | no AR(1) - ML<br>$a_i$,i=1,…,14,<br>$a_j$,j=1,…,8 | AR(1) - SML<br>$a_i$,i=1,…,14,<br>$a_j$,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* | *dec-diff* | *stdev(z)* | *skew(z)* |
|---|---|---|---|---|
| *Π* | 1.000 | | | |
| *dec-diff* | 0.278 | 1.000 | | |
| *stdev(z)* | 0.120 | 0.941 | 1.000 | |
| *skew(z)* | -0.343 | 0.273 | 0.271 | 1.000 |

*Note:* "stdev(z)" denotes the standard deviation, "skew(z)" denotes the skewness, "dec-diff" denotes the inter-deciles 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 the standard deviation, *Asym* denotes the selected measure of 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 inter-deciles 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

## Table 5

Correlation between Actual

and Counterfactual Series

| *Π aggregate* | *A(a) , f(a)* | *A(a) , f(no-idios)* |
|---|---|---|
| A(a) , f(a) | 1 | |
| A(a) , f(no-idios) | 0.832 | 1 |

## Table 6

Fit between Actual

and Counterfactual Series

| *f(.)* | *G(.)* |
|---|---|
| f(a) | 1 |
| f(no-idios) | 0.29 |

*Note: a* denotes actual, *no-idios* denotes no idiosyncratic shocks

The counterfactual series is constructed by removing idiosyncratic shocks in constructing the price deviations density

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

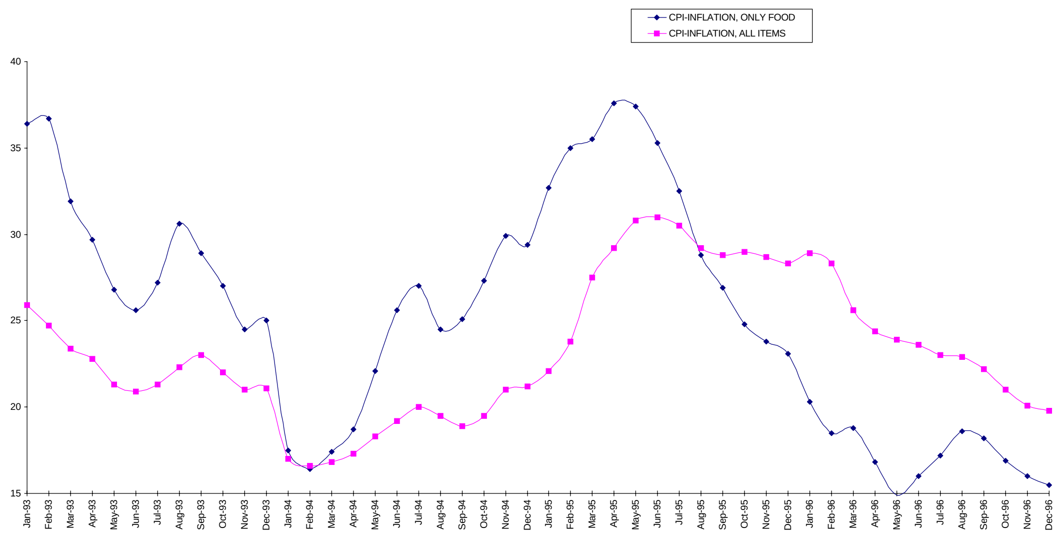
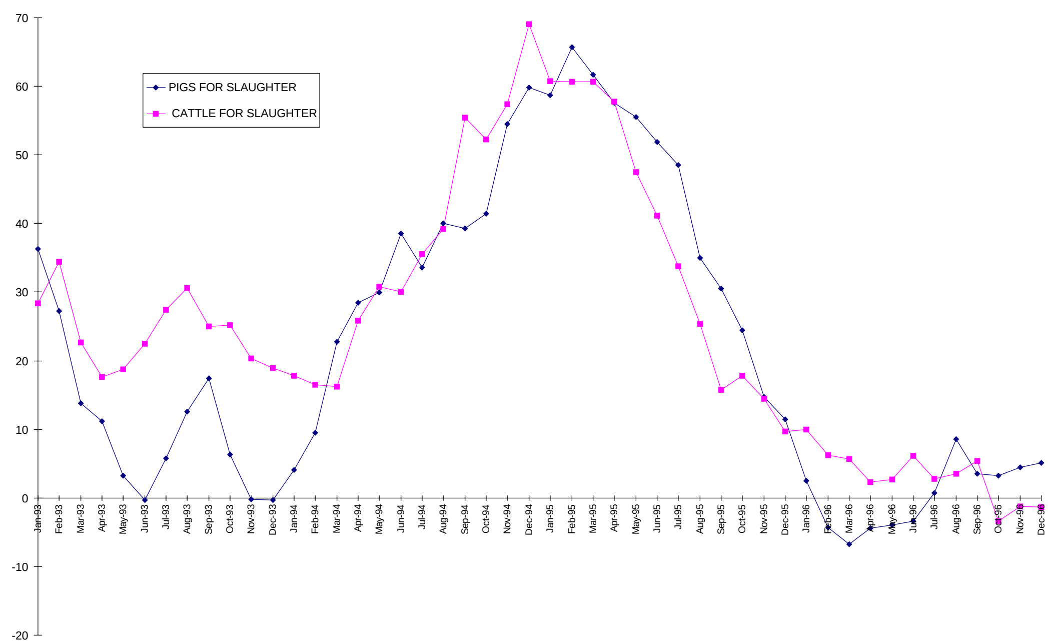


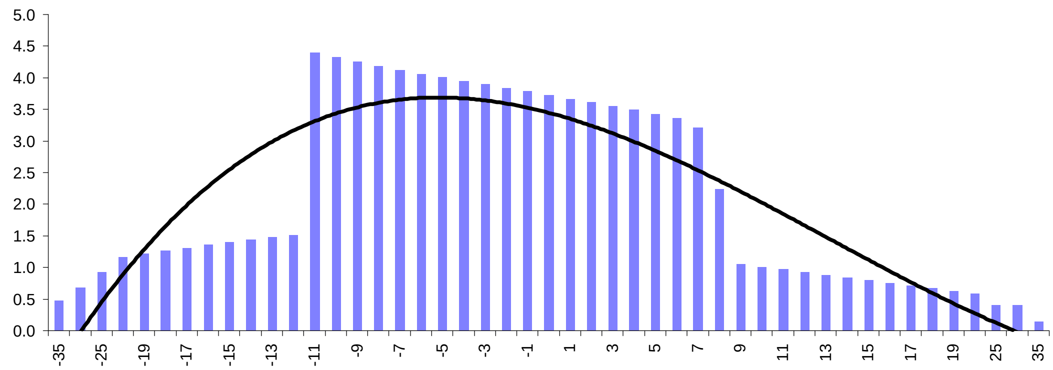

Figure 1b
Inflation in Pigs and Cattle for Slaughter, 1993-1996
(annual growth rate; in percentage)




Source: Central Statistical Office, Hungary

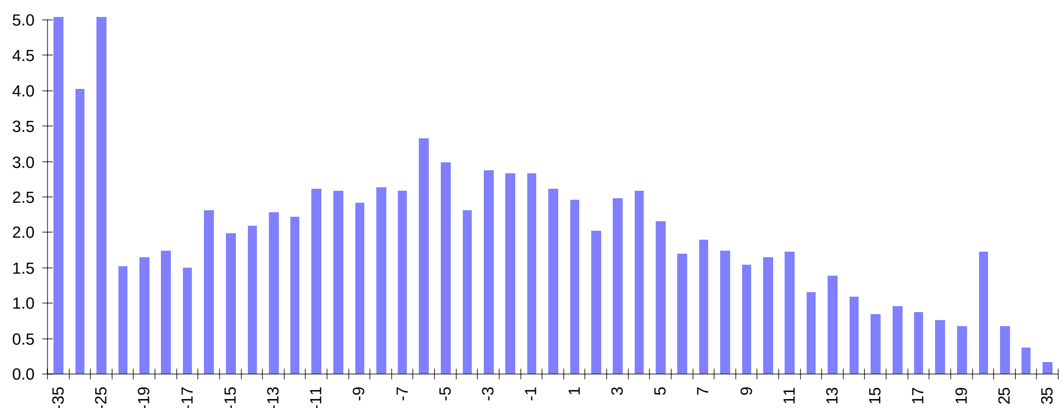
Figure 2

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



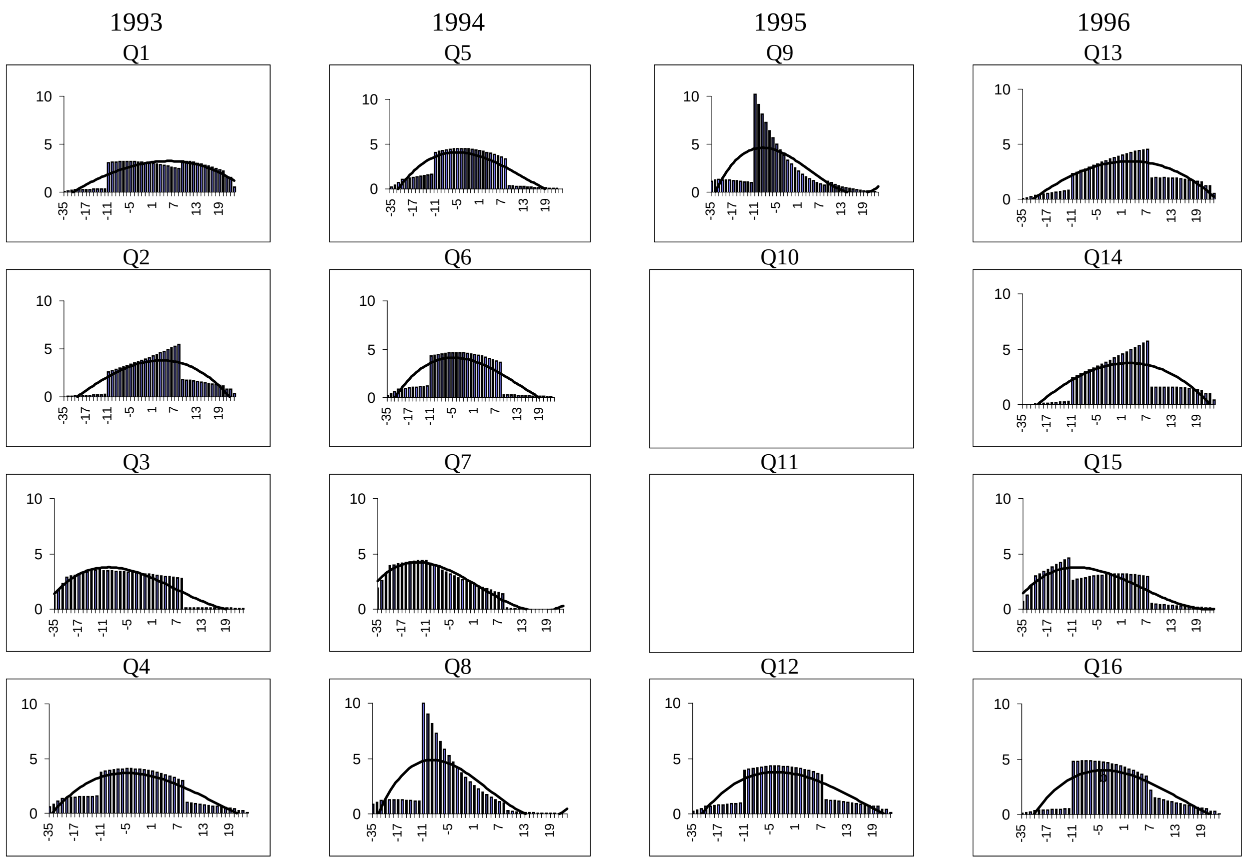

Note: The solid line represents a third degree polynomial fitted to the empirical density function

Empirical Density of Price Deviations - Full Sample,
no idiosyncratic shocks (in percentage)



# Figure 3

## Empirical Densities of Price Deviations - Quarterly
(in percentage)




*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)

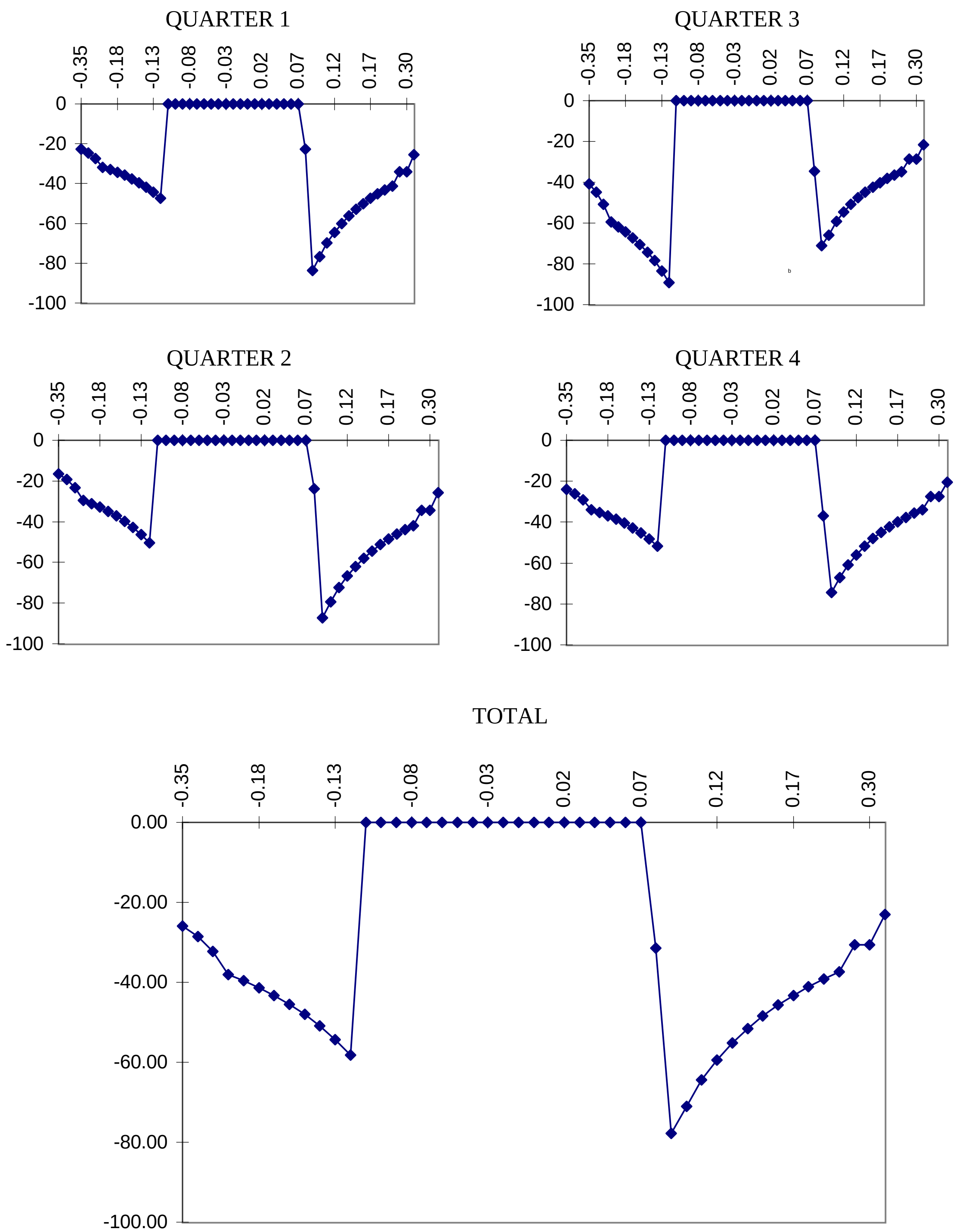
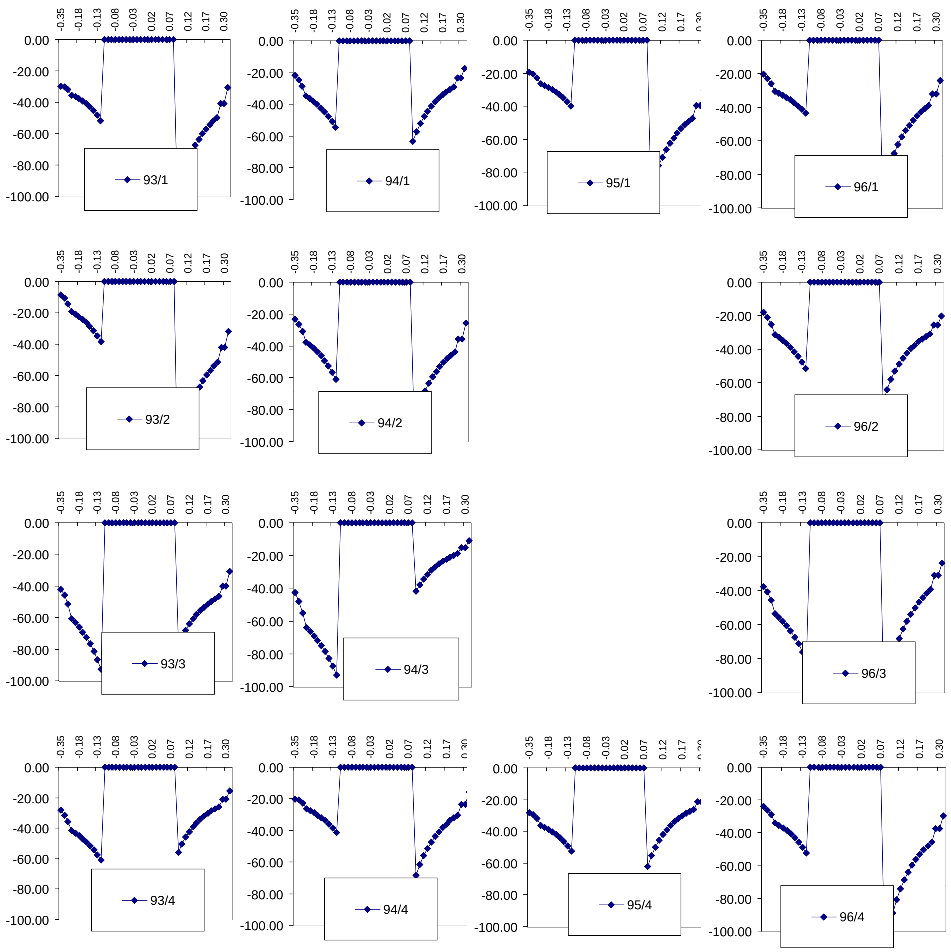
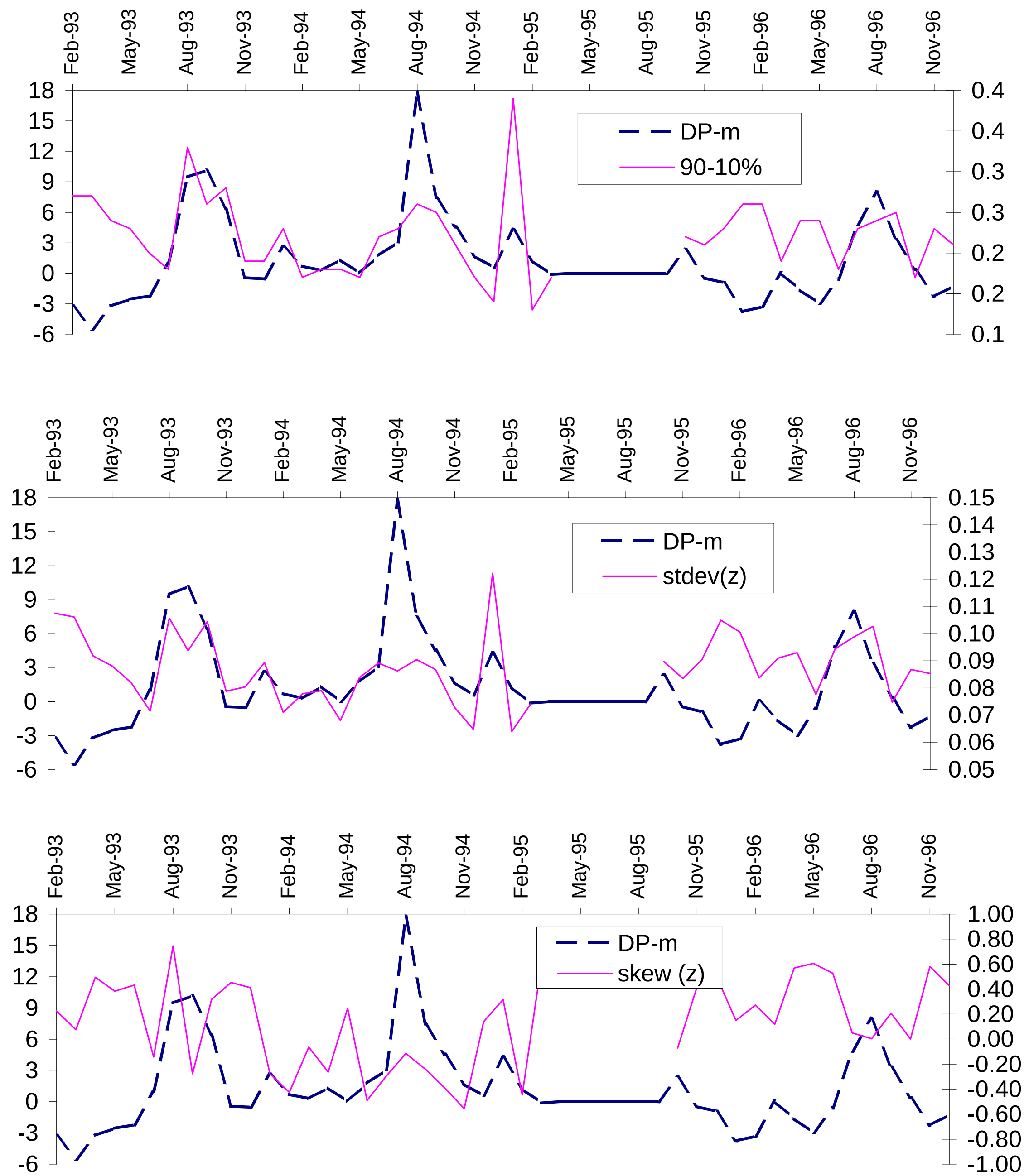


Figure 5
Adjustment Functions
(quarterly data)



# Figure 6

Inter-Deciles Difference, Moments of Price Deviations
and Aggregate Inflation




*Notes.* Aggregate inflation is measured on the left axes.
"90-10%" denotes the difference between the upper and the lower deciles of the distribution of price deviations.
"stdev(z)" and "skew(z)" denote the standard deviation and the skewness of the distribution of price deviations, respectively.