Department of Economics
University of Southampton
Southampton SO17 1BJ
UK

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Relative Price Skewness and Inflation: A Structural VAR Framework[♣]

ATTILA RÁTFAI

University of Southampton and

Institute of Economics, Hungarian Academy of Sciences

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Abstract. This study evaluates the empirical significance of idiosyncratic pricing shocks in inflation dynamics. To this end, using store-level price data for a selected group of products and employing identification schemes dictated by (S,s) pricing theory, product-level Structural Vector Autoregressions comprised of inflation and relative price skewness are estimated. Robustly to alternative identification assumptions, definitions of the relative price and measures of asymmetry in relative price distributions, idiosyncratic shocks tend to explain about 25 to 30 percent of the forecast error variance in inflation rates at the 12-month horizon. They also lead to substantial build-up in inflation after about 3 to 5 months following the initial disturbance.

Key words: inflation dynamics, (S,s) pricing models, Structural VAR analysis

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1 Introduction

Previous research indicates that (S,s) pricing models originally developed to provide behavioral foundations for business cycle analyses, are able to carry implications for the understanding of short-run fluctuations in inflation. Rátfai (1999) demonstrates that information contained in the cross-sectional distribution of relative prices is useful in explaining short-run inflation dynamics. By pressing for a balanced panel of store-level prices recorded in continuously operating stores, however, the semi-structural approach pursued in that study places strong requirements on the price data needed to construct relative prices and their cross-sectional distributions. Realistically, given current data collection practices of statistical agencies, it is almost impossible in practice to obtain such a data set for a broader set of product categories. The need to utilize the insights of the (S,s) pricing literature to learn about inflation dynamics for a broader set of products coupled with the lack of adequate data to pursue a more structural approach provides the motivation for the present analysis.

The specific goal of the present study is to assess the empirical significance of heterogeneity and idiosyncrasy in pricing shocks as short-run determinants of aggregate inflation. To this end, motivated by insights obtained from two-sided (S,s) models, bivariate structural Vector Autoregressions (VAR) comprised of inflation and relative price skewness are estimated and analyzed[1].

In a univariate context, the postulated correlation between various measures of cross-sectional relative price variation and aggregate inflation is an old and extensively studied issue in macroeconomics; its history goes back to the seminal work of Mills (1927). One of the first related studies in the modern era is by Vining and Elwertowski (1976). By examining various forms of regression equations with some measure of cross-sectional relative price variability in sector-specific price changes on the left hand and

[1] The term relative price is associated with the log difference between the actual and the target price level. Although much of the related literature uses the phrase relative (or real) price for the concept of *price deviation* originally envisioned by the (S,s) literature, to conform to the rest of the related literature, the standard terminology is adopted here.

inflation on the right hand side, the paper is representative of many subsequent investigations. These studies typically find that inflation is positively related to cross-sectoral price variability. The result is interpreted as being indicative of the welfare costs of inflation[2].

There exist several hitherto overlooked aspects of the comovement between inflation and relative price variation. Three of them are addressed in the present work. First, one of the neglected issues is the way the possibly simultaneous determination of inflation and relative price variation is controlled for. Indeed, it is *a priori* not obvious whether higher inflation causes increased relative price variation or the other way around. The main virtue of the structural VAR approach adopted in this study is that it is able to isolate structural disturbances with an economic interpretation without imposing strong constraints on the joint dynamics of the variables involved.

Second, presumably due to the lack of strong theoretical priors on relative price skewness, most of the previous related studies focused on the second moment of relative price variation and ignored higher ones. Mainly inspired by the emergence of the (S,s) modeling framework and the empirical microeconomic evidence supporting it[3], macroeconomists has just recently started to investigate the importance of higher than second moments of relative price variation. First, Ball and Mankiw (1994) and Tsiddon (1993) develop two-sided (S,s) pricing models based on fixed cost to price adjustment, symmetric shocks to relative price and positive trend inflation (to proxy for the change in the target price level). The model implies that the higher trend inflation, the more right skewed the relative price distribution is[4]. In a complementary fashion, Ball and Mankiw (1995) show that given symmetric inaction bands for relative prices and asymmetry in idiosyncratic pricing shocks, the third moment of shocks impacts on short-run aggregate

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[2] Weiss (1993) provides a comprehensive survey.

[3] See, for example, Lach and Tsiddon (1992), Tommasi (1993), Kashyap (1995) and Rátfai (1998).

[4] A multi-sector real business cycle model with an asymmetric input-output structure also implies this result. See Balke and Wynne (1996). Ball and Mankiw (1994) also note that an increase in the variance of relative prices could lead to higher inflation.

price changes. The paper demonstrates that this pattern extends to the relationship between the skewness of the relative price distribution and inflation.

Finally, possibly caused by the limited availability of appropriate data, most previous studies focused on the cross-sectional variation in sectoral or city-level price indices and neglected relative price measures based on microeconomic data[5]. The present study aims to address this potential shortcoming as well.

The plan of the paper is as follows. To motivate the estimation strategy in identifying the structural VAR model, Section 2 explains two-sided (S,s) pricing models and their relevant empirical implications. Section 3 covers measurement issues. The data set used is described in Section 4. Besides standard unit root and other specification tests, the time series model forming the basis of the empirical analysis is discussed in Section 5. The basic estimation results are presented in Section 6. Section 7 adds some further findings to help evaluate the robustness of the baseline results. Section 8 provides an assessment of two related papers that have a close bearing on the present study. Finally, conclusions are offered in Section 9.

2 Theory and Identification

The two-sided (S,s) pricing approach offers a novel perspective on modeling the relationship between relative price variation and inflation. On the one hand, it reverses the traditional direction of causality from inflation to relative price variation emphasized by the overwhelming majority of the empirical literature. It does not rule out the standard channel, just points to the presence of the reverse direction as well. On the other hand, by emphasizing the importance of the asymmetry in the relative price distribution, the (S,s) approach shifts the focus of discussion from the second moment of relative price variation to the third one. For the purposes of the present study, the predictions of two

[5] Exceptions include Lach and Tsiddon (1992) and Konieczny and Skrzypacz (2000).

interrelated (S,s) models are of particular interest. In what follows, the models and their implications for structural identification are discussed.

First, a central theme advanced in the two-sided (S,s) pricing literature is the interplay of trend inflation and the shape of the relative price distribution. The basic idea explored in Ball and Mankiw (1994) is the following. Given fixed costs to price adjustment and a positive trend in target price changes (as proxied by inflation), monopolistically competitive firms are relatively less inclined to pay the adjustment cost in response to a deflationary shock to the target price than to an inflationary shock. The reason for asymmetry in the distribution is that trend inflation continuously erodes relative prices, thereby making the non-adjustment band asymmetric with a relatively more heavily populated downward and less populated upward portion. It follows that even symmetrically distributed shocks produce an asymmetric distribution of relative prices. For instance, positive trend inflation results in a right skewed distribution of relative prices and more frequent price increases than price decreases.

In addition to higher trend in inflation making the distribution of relative prices more skewed to the right, the model also implies that an aggregate shock common to all price-setting units has no contemporaneous impact on the shape of the relative price distribution. To see why this is the case, first, consider the timing convention for shocks and nominal adjustments invoked in empirically implementing the notion of relative prices. According to this, relative prices in period t are defined as $z_{ijt} = p_{ij,t-1} - p^*_{ijt}$. It means that current relative prices reflect pricing shocks that occurred in period t but contain actual nominal prices inherited from period $t-1$. That is, z_{ijt} represents relative prices before nominal adjustments could have taken place. The definition implies that pricing shocks of the aggregate type filtered through p^*_{ijt} affect relative prices identically by displacing them exactly the same way in the state space. As illustrated in Figure 1, it means that any two different realizations of aggregate shocks in period t produce relative price distributions of the same shape but of different location. The observation that aggregate shocks do not alter the shape, including the asymmetry in it, of the relative price distribution serves as one of the two alternative identification assumptions in the data analysis.

Second, Ball and Mankiw (1995) outline a one-period model with monopolistically competitive firms with costly price adjustment. They posit that firms face shocks to their target price level and incur a fixed cost of adjustment ("menu cost") when they decide to alter their nominal price. The optimal pricing policy of firms in this setting is to change nominal price only if the relative price moves outside the boundaries of the optimally determined inaction bands. If the resulting inaction range is symmetric which is expected to be the case with no trend in inflation, then the average price level is determined by the distribution of shocks to firms' desired prices. If for example the distribution of idiosyncratic shocks is mean zero but is skewed to the right, more firms are likely to raise the nominal price. It follows that the aggregate price level rises. A similar argument applies to left-skewed distributions and the possible decline in the aggregate price levels. By presenting numerical simulation results, Ball and Mankiw (1995) show that this implication of the model extend to the skewness of relative price distributions themselves. Finally, the model also predicts that the variance of relative price shocks have no independent impact on aggregate inflation.

For identification purposes in the upcoming empirical analysis, an important corollary of the Ball and Mankiw (1995) analysis is that non-symmetric realizations of idiosyncratic shocks have no long run impact on the price level. To see why this is the case, consider a situation where trend inflation is zero and there are no aggregate but only idiosyncratic shocks. Again, in the presence of fixed costs, only shocks of a sufficiently extreme size push the relative price outside the adjustment boundaries and induce stores to make nominal adjustment. Now assume that the population distribution of shocks and thus the distribution of relative prices are symmetric in the cross-section. The realization of this distribution however is not necessarily symmetric; for instance, there will be periods dominated by a few large pricing shocks together with many smaller negative ones. In this case the number of stores close to the lower adjustment boundary and with a tendency for nominal price increase exceeds the number of similar stores close to the upper boundary and with a tendency for nominal price decrease. Consequently, such a realization of shocks makes the aggregate price level rise. However, once nominal adjustments have taken place in the current period and relative prices get readjusted to their target level, a relatively smaller number of relative prices will be bunching close to the inflationary end of the distribution than to the deflationary one. Given symmetric pricing shocks in the following periods, this implies that fewer nominal price increases are expected to take place relative to nominal price cuts in the upcoming periods. In the absence of further pricing shocks, this adjustment process continues until the original symmetric distribution of relative prices is restored and the aggregate price level returns to its original level.

The above reasoning implies that the impact of idiosyncratic shocks on the price level is mean reverting and that inflationary periods tend to be followed by deflationary ones. In other words, any unit root in the log price level is exclusively driven by aggregate shocks. This insight offers another identifying assumption in the structural VAR analysis of inflation and relative price skewness.

3 Measurement

As exemplified by previous studies in the literature, on top of the choice between the second and the third moment, one may choose among a number of empirical objects in studying cross-sectional relative price variation. First, possibly due to the unavailability of more disaggregated price data, most previous studies utilized *inter*-sectoral measures of relative price variation involving the cross-sectoral standard deviation of changes in sectoral price indices. Analyses of *intra*-sectoral microeconomic price variation of particular products are rare[6]. Examining aggregate price indices in this context is problematic for two related reasons. On the one hand, cross-sectoral measures of variation are bound to draw on changes in some aggregate price measure with the outcome of many microeconomic pricing decisions swamped into this index. And, unless stores' pricing policies are perfectly synchronized within sectors, sectoral price indices are not able to capture the aggregated implications of potentially heterogeneous microeconomic decisions. Consequently, utilizing mere averages of micro level prices

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[6] Exceptions include Lach and Tsiddon (1992), Tommasi (1993), Reinsdorf (1994).

before calculating their higher moments could mask regularities present in microeconomic pricing behavior with important aggregate consequences (see e.g. Parsley (1996)). On the other hand, as the underlying economic theory motivating any analysis of this kind is a microeconomic one under the assumption of optimizing individual agents, its test ideally should draw on highly disaggregated, micro level price data and not on already aggregated price indices.

Second, the correspondence between potentially measurable empirical objects of price variation and the theoretical concepts motivating their use appears to be an obscured issue in much of the related literature. However, as economic models do not necessarily have observationally equivalent implications regarding them, a fundamental distinction needs to be made among the concepts of cross-sectional variability, dispersion, and relative price variation. For instance, while theories of the (S,s) kind are built around the concept of relative price, that is, the *deviation* between the actual and the target price level, search theories tend to have implications for intra-sectoral price dispersion, variation in price *levels*[7]. Despite its conceptual ambiguity in fitting microeconomic pricing models, the vast majority of the empirical literature still draws on measures of cross-sectoral price variability as represented by the standard deviation of the *change* in sectoral price indices. Clearly, as opposed to cross-sectoral price dispersion (the variation in the *level* of sectoral price indices) which would just compare apples to oranges, the across-sector variability measure captures a statistically sensible object. Nonetheless, it does not seem to adequately represent the theoretical concepts motivating the study of the correlation between inflation and relative price variation. Indeed, from the specific perspective of (S,s) pricing models, it is the notion of variation in relative prices (or price deviations) and not in nominal price levels or nominal price changes that is relevant for the purposes of empirical studies like the present one.

Finally, the interest in the relationship between the skewness of relative price distributions and aggregate inflation is supported by the relative novelty of the (S,s)

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[7] In fact, given a panel of microeconomic price data, a potentially interesting exercise is to look at the dispersion of price levels within specific sectors. One example for the within-sector dispersion approach is Reinsdorf (1994). Lach and Tsiddon (1992) use microeconomic price data to study the variability in within-sector price changes.

approach pointing to the role of asymmetry in the relative price distribution. Although previous studies have examined skewness this issue[8], they measured skewness over sectoral inflation rates, as opposed to relative prices based on microeconomic data. Furthermore, these papers focused on univariate statistical models, often without explicit behavioral motivation.

In light of the above discussion, the present study employs a proxy for the relative price which is not only feasible to measure but also consistent with the (S,s) pricing approach motivating the analysis. Specifically, the relative price in store *i* of product *j* at time *t* is computed as the deviation of individual log price levels from their product-specific log mean: $z_{ijt} = p_{ij,t-1} - p_{jt}$. p_{jt} is an equally weighted index of sectoral price levels in sector *j* at time *t* and is defined as $p_{jt} = \frac{1}{n_{jt}} \sum_{i=1}^{n_{jt}} p_{ijt}$ where n_{jt} is the number of stores observed in sector *j* in month *t*. Note the timing convention implicit in the definition of z_{ijt}. Lagging actual prices by one period captures the idea that the position of relative prices exactly before (potential) nominal adjustment in period *t* is the object of interest. Then, separately for each sector *j*, the skewness statistic in the relative price distribution is defined as

$$S_{jt} = \frac{n_{jt}}{(n_{jt}-1)(n_{jt}-2)} \sum_{i=1}^{n_{jt}} \left(\frac{z_{ijt} - z_{jt}}{D_{jt}} \right)^3$$

where z_{jt} is the sector-specific mean of relative prices and D_{jt} is the across-store standard deviation of z_{ijt}. Inflation in sector *j*, Π_{jt}, is defined in the standard way by $\Pi_{jt} = p_{jt} - p_{j,t-1}$.

s[8] See, for instance, Blejer (1983) and Ball and Mankiw (1995).

4 Data

The empirical analysis builds on a large microeconomic data set of store level consumer prices of specific, narrowly defined and homogenous products. The sample consists of cross-sections of monthly frequency price observations of twenty-seven items, including mostly specific food products and some services. As stores in the sample are not longitudinally matched, the data in each product category can be considered as a series of cross-sections of microeconomic prices.

The sample of prices was drawn from the store level data set collected for the monthly computation of the CPI by the Central Statistical Office, Hungary. Products are selected from the full CPI database based on the criteria of being narrowly defined (according to size, branding, type and flavor), continuously available items with insignificant variation in non-price characteristics. An important advantage of the data set is that coupons were relatively infrequent during the sample period and thus pricing actions can be safely thought of as driven by considerations other than strategic ones.

The data are available from 1992:1 until 1996:7 at the monthly frequency. For each month, there are about 100-150 price observations (on average about 125) for each product. Observations are collected from 20 geographically dispersed locations in the country including all the 19 counties and the capital city, Budapest. Although stores in the sample are identified only by their geographic location and are not longitudinally matched, the staff of the CSO is instructed to make an effort to keep the set of stores appearing in the sample stable over time. Table 1 summarizes the products investigated including the expenditure weight attached to them in computing the aggregate CPI and their relative expenditure weight in the current sample as well.

Despite the turbulent economic environment during economic transition in the 1990s, aggregate inflation was relatively stable and moderate in Hungary. Year-to-year change in the monthly aggregate CPI and its food component are plotted in Figure 2. The graphs show that annual aggregate inflation initially decelerated until early 1994. Reaching a minimum of about 15 percent, the series eventually turned around and took on an increasing path reaching about 30 percent at a peak in early 1995. Starting in about the second quarter of 1995, shortly after an anti-inflationary fiscal adjustment package was introduced in March 1995, a steady disinflationary trend takes effect.

5 Empirical Specification and Estimation

Specified separately for each product *j* in the sample, consider the bivariate, structural VAR model of sectoral inflation (Π_{jt}) and relative price skewness (S_{jt}):

$$\begin{bmatrix} \Pi_{jt} \\ S_{jt} \end{bmatrix} = \begin{bmatrix} 0 & G^0_{\Pi S} \\ G^0_{S\Pi} & 0 \end{bmatrix} \begin{bmatrix} \Pi_{jt} \\ S_{jt} \end{bmatrix} + \begin{bmatrix} B_{\Pi\Pi}(L) & B_{\Pi S}(L) \\ B_{S\Pi}(L) & B_{SS}(L) \end{bmatrix} \begin{bmatrix} \Pi_{jt} \\ S_{jt} \end{bmatrix} + \begin{bmatrix} \varepsilon^{\Pi}_{jt} \\ \varepsilon^{S}_{jt} \end{bmatrix}$$

Dynamics in endogenous variables are assumed to be driven by contemporaneous and past values of an unobservable vector of serially uncorrelated and mutually orthogonal structural innovations $\varepsilon_{jt} = [\varepsilon_{jt}^{\Pi}, \varepsilon_{jt}^{S}]$ with variance-covariance matrix $D = E(\varepsilon_{jt}\varepsilon_{jt}')$[9]. Orthogonality of shocks implies that the off-diagonal elements of *D* are zero. The first of the structural shocks, ε_{jt}^{Π}, is interpreted as an aggregate pricing shock affecting all relative prices the same way. The second one, ε_{jt}^{S}, is assumed to reflect purely idiosyncratic disturbances to pricing policies that could impact on the shape of the relative price distribution[10]. Accordingly, $G^0_{S\Pi}$ captures the contemporaneous impact of aggregate shocks on relative price skewness and $G^0_{\Pi S}$ represents the contemporaneous impact of idiosyncratic shocks on inflation.

The structural VAR model written in a more compact form is

$$y_{jt} = G^0 y_{jt} + B(L) y_{jt} + \varepsilon_{jt}$$

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[9] All the parameters are specific to product categories. Product-specific indexes for parameters are omitted for convenience.

where $B(L)$ is a pth degree matrix polynomial in the lag operator L with $B(L) = 0$. The diagonal elements of G^0 are normalized to zero. Given some regularity conditions, the structural form VAR is readily transformed to the reduced form autoregressive one:

$$y_{jt} = H(L)y_{jt} + u_{jt} .$$

Here the u_{jt} are reduced form innovations with an unrestricted variance-covariance matrix Σ. They can be expressed as linear combinations of the structural innovations as

$$\varepsilon_{jt} = B^0 u_{jt}$$

where $B^0 = I - G^0$. As endogenous variables are written as combinations of their own past realizations and a prediction error, the reduced form VAR is suitable for estimation. From the reduced form VAR, it is straightforward to recover its Wold moving average representation as

$$y_{jt} = C(L)u_{jt}$$

where $C(L) = (I - H(L))^{-1}$. The infinite, structural form moving average representation of the VAR is obtained as

$$y_{jt} = M(L)\varepsilon_{jt}$$

where $M(L) = C(L)(B^0)^{-1}$. This form is of particular interest for both model identification and economic inference.

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[10] In discussing the specific identifying assumptions imposed on the model, these structural innovations are described in terms of explicit economic considerations.

Consistent estimates of the reduced form parameters are obtained by equation-by-equation Ordinary Least Squares estimation of the autoregressive form. The number of lags included in each product-specific system is dictated by a series of Likelihood Ratio tests. Based on estimates of $H(L)$ and u, the reduced form parameters in $C(L)$ and Σ are readily computed. However, there are four distinct primitive structural parameters (two of them in B^0 and another two in D) and the reduced form estimation provides only three separately identified parameters (the ones in Σ). For exact identification, it is necessary to place an extra piece of restriction on structural parameters. The discussion in Section 2 suggests two alternative restrictions stemming from explicit theoretical considerations. They amount to a particular economic interpretation of the primitive shocks governing the dynamics of the endogenous variables in the statistical model.

First, two-sided (S, s) pricing theory implies that on impact the skewness in the distribution of relative prices is shaped by idiosyncratic pricing shocks and is contemporaneously invariant to shocks of the aggregate kind. In terms of formal restrictions, it constrains the B^0 matrix by $B^0_{S\Pi} = 0$. This is what I call as the "Short Run" (*SR*) identification assumption. Second, two-sided (S,s) pricing theory also implies that idiosyncratic shocks have only transitory impact on the aggregate price level thus aggregate inflation is governed only by aggregate shocks in the long run. Formally, constraining the long-run impact of idiosyncratic shocks on the log price level to zero amounts to the restriction of $M_{\Pi S}(1) = 0$. This is called the "Long Run" (*LR*) identification assumption.

Specification Tests

To assure correct model specification in all the twenty-seven VARs, the stochastic properties of the product-specific inflation and skewness series are examined in a sequence of unit root tests. The specific testing procedure adopted is the Augmented Dickey-Fuller (ADF) test with the Schwartz Information Criterion used for selecting the number of lags included in the ADF regressions. By default, the maximum number of lags allowed in the tests is 12. Figures for the relevant ADF *t*-statistic and the largest autoregressive parameter are shown in Table 2. The results suggest the absence of a unit root in the inflation and the skewness series as well. Additional ADF test results reported in Table 3 indicate that the log price level series cannot be rejected to contain a unit root[11].

Three unit-root test issues deserve special attention, each of which having a bearing on model specification too. First, a visual inspection of the series suggests that with the exception of the skewness series *s10603* and *s52366*, the series do not appear to contain a deterministic time trend. Therefore, with the exception of these series, the ADF stationarity tests do not include a deterministic time trend.

Second, standard unit root tests do not reject the presence of a unit root in the case of three of the skewness series, *s10301*, *s14424* and *s66105*. However, visual inspection of the series also suggests that the three series are likely to contain a structural break[12]. To test for the stationarity of the three series, I use the unit root test of Perron (1997) that corrects for the presence of a break. The resulting *t*-statistic and autoregressive roots reported in Table 2 show that all the three series are better viewed as stationary with a structural break.

Finally, upon further inspection some of the inflation series, and interestingly virtually none of the skewness series, seem to exhibit seasonal fluctuations. This impression is confirmed by a set of seasonal regressions with inflation on the left and monthly seasonal dummies on the right hand side. The thirteen inflation series with at least two statistically significant monthly dummy coefficients and with an R^2 statistic of

[11] Further test results, not reported here, shows that the presence of unit-root in the stochastic component of the series can be rejected in all but one of these series even when deterministic seasonal effects are controlled for.

[12] Perron (1997) shows that not accounting for a break in the series when it is actually present may result in a false acceptance of unit root in standard ADF testing. To address this issue, he devised a modified ADF procedure and provided the appropriate critical values for the t-statistic. The procedure is based on a regression equation that includes dummies for capturing the break in the series, potentially of three different kinds (a pure intercept, a pure slope or a combination of the two), and chooses endogenously the break point in the series.

at least 0.4 are characterized as ones containing a deterministic seasonal component. To check whether the stochastic element in inflation series is stationary, a set of standard ADF tests for the estimated residuals obtained from the first stage seasonal regressions are conducted. Test results in Table 4 show no evidence of non-stationarity in the residuals. Based on these considerations, fifteen of the inflation series is modeled as stationary with a deterministic seasonal element.

Overall, besides the constant term and the raw data, thirteen of the VARs examined include seasonal dummies, one includes a pure time trend, one includes a time trend and seasonal dummies, two include dummies for a structural break, and one has dummies for a structural break and deterministic seasonals. Nine of the VARs exhibit none of these peculiarities and are estimated with only a constant added to the endogenous variables.

6 Baseline Results

This section reports on the structural VAR estimation results of short-run and long-run multipliers, forecast error variance decompositions and impulse response functions. First, the short-run multiplier parameters represent the contemporaneous conditional impact of a structural shock to variables in the system. Formally, they correspond to the appropriate elements of the G^0 matrix in the structural autoregressive representation of the time series model. Second, the long-run multipliers reflect the cumulative response in endogenous variables to structural shocks as reflected in the appropriate elements of $M(1)$.

Third, the forecast error variance decomposition (*FEVD*) function dividing the forecast error variance in a variable among all the individual structural shocks provides a measure of the quantitative importance of the particular structural shocks. Formally, the variance decomposition function gives the percentage of the k-step-ahead forecast error variance for variable j in the estimated VAR attributable to the structural shock i as

$$FEVD_{ij,k} = \frac{d_i^2 \sum_{h=0}^{k-1} m_{ij,h}^2}{\sum_{l=1}^{I} \left[d_l^2 \sum_{h=0}^{k-1} m_{lj,h}^2 \right]}$$

where $m_{ij,h}$ is the (i,j)th entry of the infinite moving average matrix $M(h)$ and d_i^2 is the diagonal element of the D matrix comprising of the variance of the structural innovations. In the present context, 12-month-ahead forecast errors are examined. And fourth, orthogonalized impulse response functions tracking the dynamics of the variables in response to structural shocks are studied. In a complementary fashion to forecast error decompositions, impulse response functions provide an answer to the following question: how does a current unitary structural shock make the econometrician revise the forecast of future realizations of variables in the VAR system. In terms of model parameters, the answer is recovered from the appropriate entry of the matrix, $M(L)$.

It is *a priori* not obvious how to present the results due to the large number ways they can be organized and grouped, a combinations of the four categories of inference, twenty-seven products and two identification schemes. The largest number of variation providing a practically non-digestible flow of information is clearly in the product dimension with twenty-seven units. To get around this issue, summary measures of parameter estimates are defined detecting the central tendency in the various pieces of product-specific results. Three different measures are examined including the median of the parameter estimates from product-specific VARs, direct parameter estimates from a VAR with aggregate inflation and the skewness in relative prices pooled together from all the products, and median results from a panel VAR regression. The summary measures are described in greater detail below[13].

Median Results

The median is chosen to capture the central tendency in parameter estimates as the across-product mean of the estimated parameters may be contaminated by extreme observations and easily give a distorted picture of the overall trend in the data. The median alleviates the impact of potential outliers, perhaps resulting from mis-specification in some of the individual VARs. It also preserves the product-level approach to analyzing price data advocated in the paper.

To formally assess the statistical significance of results involving the median of the parameters, non-parametric, confidence interval sign-tests are employed. This test determines a confidence interval for the median and tests the null hypothesis that the median of the parameter estimates is not different from zero against a two-sided alternative[14]. The test builds on the idea that if the number of sample observations larger than zero is sufficiently large then the null that the median is not different from zero can be rejected. To further evaluate the extent of the heterogeneity in point estimates and forecast error decompositions, the cross-product standard deviations of the estimated coefficients are also reported. For the impulse response function, the upper and the lower quartiles of the parameter estimates are displayed.

The top panel in Table 5 summarizes the information obtained on the median of the estimated coefficients of the short-run and the long-run cross-multipliers. Independently of the identification assumption chosen, the contemporaneous impact of a structural inflation shock to relative price skewness is small with a small variance. Under the *SR* identification assumption it is zero by construction. In the *LR* case, parameter estimates appear to be indistinguishable from zero. Indeed, the non-parametric sign-test shows that this result is statistically significant at the 5 percent level. Finding a universally small contemporaneous response under the *LR* identification schemes not *a*

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[13] In preliminary calculations, I experimented with looking at estimation results excluding the three items from the sample representing services. As the results remained qualitatively unchanged, I do not pursue further this issue.

[14] See Gibbons and Chakraborti (1992).

priori imposing the constraint of no impact of inflationary shocks to relative price skewness is reassuring to the extent that the *SR* identification assumption is a sensible one. The contemporaneous impact of an idiosyncratic shock to inflation is less clear-cut. Prior considerations motivated by (S,s) pricing theory suggest that increased relative price skewness should lead to higher inflation. Although neither of them is significant, the median measures are of the expected, positive, sign for impulse responses estimated under both the *SR* and the *LR* identification scheme. The median estimates in the third and fourth column of the table suggest that the long run impact of idiosyncratic shocks on inflation is relatively modest. Estimated under the *SR* identification scheme, the small long-run response of inflation to idiosyncratic shocks indicates that imposing the *LR* identification assumption is actually borne out by the data.

Next, median estimates of forecast error variance decompositions are examined. The estimates in the top panel of Table 6 show that idiosyncratic shocks explain about 19 to 26 percent of the variation in inflation forecasts at the sectoral level. Note that the total impact of structural shocks to a particular variable does not necessarily have to add up to exactly 100 percent for the median of product-specific measures. Idiosyncratic shocks appear to be the fundamental determinant of the forecast error variance in relative price skewness. They are less important under the *LR* identification assumption where, for instance, their median contribution is 66 percent to forecast error variance. In the *SR* case, however, more than 80 percent of the median forecast error variance in relative price skewness is attributed to idiosyncratic pricing shocks.

Calculated under the two different identification schemes, Figures 3a and 3b show the median of the product-specific impulse responses of inflation, relative price skewness and the price level to one standard deviation idiosyncratic and aggregate shocks. From the perspective of this study, the top-left panels in the figures are of primary interest. They depict the median of the 12-month-ahead impulse response of inflation to idiosyncratic shocks. The impulse responses portray a remarkably uniform picture across different identification assumptions. To slightly different extent depending on the identification assumption chosen, idiosyncratic shocks induce a surge in aggregate inflation that start to dissipate only after about four to five months. The impulse effects tend to peak at about three to four months after the initial idiosyncratic shock has occurred. The medium size of the impulse responses at the peak is economically significant. According to the sign-test, the positive responses at the fourth month are statistically different from zero under both identification assumptions.

Pooled Relative Prices

Another way to capture the central tendency in the data is to estimate a bivariate structural VAR model comprised of aggregate inflation and the skewness of pooled relative prices. The latter variable is computed by first calculating relative prices the same way it is done for the product level analysis, then pooling all of the resulting relative prices together and calculating their cross-sectional skewness statistic. More formally, assuming that all relative prices are drawn from the same underlying distribution, the pooled skewness measure is defined as

$$S_t = \frac{N_t}{(N_t - 1)(N_t - 2)} \sum_{j=1}^{J} \sum_{i=1}^{n_{jt}} \left(\frac{z_{ijt} - z_{jt}}{D_t} \right)^3 .$$

As before, $z_{ijt} = p_{ij,t-1} - p_{jt}$ is the relative price of store i of product j at time t and z_{jt} is its mean across stores. For each product $j = 1, \ldots, J$, p_{jt} is the sectoral average price level and $N_t = \sum_{j=1}^{J} n_{jt}$ is obtained as the total number of price observations all the sectors in month t. D_t stands for the standard deviation of pooled relative prices at time t. Aggregate inflation, Π_t, is defined as the across-product mean of product-specific inflation rates:

$$\Pi_t = \frac{1}{J} \sum_{j=1}^{J} \left(\ln(p_{jt}) - \ln(p_{j,t-1}) \right).$$

Now, estimated under the two distinct identification assumptions, the relevant multipliers for the pooled data are displayed in the middle panel of Table 5. First, in contrast to the median results reported above, the short-run coefficients shown in the first two columns of the table indicate a sizeable and statistically significant deflationary impact of a unitary idiosyncratic shock. The corresponding forecast error variance decompositions are displayed in the middle panel of Table 6. The figures indicate that the relative share of idiosyncratic shocks is even more sizeable than for the median measure. For instance, it moves up to as large as 64 percent in the case of *LR* identification assumption.

As portrayed in Figures 4a and 4b, impulse response results based on the pooled data are similar to the corresponding cross-product median results[15]. In particular, independently of the identification assumption chosen, one can detect a sizeable and statistically significant inflationary effect of the idiosyncratic shock, occurring at about the third and fourth months following the initial shock. At the same time, for the *LR* identification scheme, there appears to be a second sizeable peak occurring at the fifth month. As compared to the across-product median results, impulse responses show a slightly longer lasting and larger effect of the idiosyncratic shock. The graphs also feature a statistically significant initial deflationary effect that seems to disappear after the first month in the *SR* identification case and after the second month in the *LR* identification case. This is the impact that has been captured in the short-run median multipliers.

Finally, one may note that imposing both identifying restrictions dictated by economic theory results in an overidentified VAR model. To test for the relative merit of the two restrictions, a set of simple exclusion tests are conducted on the pooled data. The resulting *t*-test statistic indicates that the restriction of no impact from aggregate shocks to relative price skewness cannot be rejected at the 10 percent level of significance. Similarly, the *F*-test statistic for the *LR* restriction indicates non-rejection.

[15] To evaluate the uncertainty associated with the parameter estimates, 90 percent confidence bands for the impulse response functions are reported. Confidence bands are constructed using Runkle's (1987) bootstrap procedure with 500 repetitions.

Panel VAR

Finally, cross-equation restrictions on the product level VAR models are imposed resulting in a panel VAR. The specific restrictions are that the reduced form autoregressive coefficients appearing in the *H(L)* matrix are the same across the different products. Correspondingly, the number of lags in *H(L)* are also specified to be the same for all the time series models. In estimating the panel VARs, the appropriate structural break dummies, seasonal parameters and deterministic time trend are also included. To identify the VAR model, the same assumptions (*SR* and *LR*) are employed as in the baseline product-level specification.

In practice, the system is estimated as two separate panels by standard Dummy Least Square methods. One of the panels comprises of all the inflation series, the other of all the relative price skewness series. Estimating the models by DLS is likely to produce unbiased estimates as the time dimension of the panel well exceeds 30 observations (cf. Judson and Owen (1997)). The procedure leads to structural parameter estimates that are different across products. Therefore, impulse response functions and forecast error variance decompositions are bound to differ across products as well. To characterize the central tendency in the dynamics of the variables in the model, similarly to the unrestricted case, cross-product percentiles including the median and the lower and upper quartiles are presented.

Results for the impulse response functions are reported in Figures 5a through 5b. From the perspective of this paper, the top-left graphs are again the most relevant ones. The pictures portrayed therein are remarkably similar to the ones in the unconstrained case. A notable feature of the graphs is the relatively strong homogeneity in the impulse response functions. For instance, in the case of the *LR* identification constraint impulse responses universally start out negative, then turn to positive for the horizons of one to four months and again negative for the next six months. Although the emerging picture is less clear-cut here, the *SR* identification case produces similar results. In particular, for the horizons of two to four months the impulse responses are positive, afterwards the results are somewhat more mixed. The initial impulse responses tend to be mostly positive, according to the median sign-test, becoming significantly so after one month having elapsed.

Overall, invariantly to the identification assumption adopted, the central results of the impulse response analyses in the panel VAR approach are in accordance with previous findings obtained from the baseline VARs with no cross-equation constraint. The major difference is that the resulting parameter estimates portray a more homogeneous picture of inflation dynamics across products.

7 Robustness

To evaluate the power of the above results, further results are impulse response and forecast error decompositions results are presented from alternative definitions of relative prices and of the asymmetry in their distribution. For simplicity, in what follows only one summary measure of the central tendency in the data is examined, pooled relative prices in relation to aggregate inflation.

Other Measures of Asymmetry

The standard skewness statistic is introduced to represent the relative bunching of relative prices in the mass of observations in the tails of the empirical distribution. However, a potential problem with the skewness statistic is that it could be sensitive to outliers in the distribution and may actually capture something different from the concept it is meant to measure. To evaluate if the main results of the analysis are robust to alternative definitions of asymmetry, an additional, non-parametric measure of asymmetry in the relative price distributions is examined. The specific asymmetry measure is the difference between the mean and the median of the pooled relative price distribution scaled by its standard deviation, *mm*[16]. It is expected to be larger, the more intensive the bunching of relative prices in the lower tail of the distributions is. Importantly, the series is positively correlated with the standard skewness coefficient with partial correlation coefficients of 0.58.

Utilizing the alternative asymmetry measure, the VAR system of inflation and relative price asymmetry is estimated subject to the two identification restrictions introduced before. The resulting impulse response functions are depicted in Figures 6a and 6b. First, a direct comparison of the impulse responses reveals that the impulse response functions obtained for the *mm* measure here are strikingly similar to the one derived from the standard skewness measure as depicted in Figures 4a and 4b. Most importantly, the top-left panels in Figures 6a and 6b demonstrate that there is a peak in the response of inflation to idiosyncratic shocks after about four months following the initial shock. An additional notable feature of the impulse responses is the sizeable though imprecisely measured contemporaneous response of inflation under both identification constraints.

Finally, the top panel of Table 7 shows decompositions of 12-month-ahead forecast error variances of the structural VARs. The figures corroborate the baseline results in that idiosyncratic shocks are quantitatively important determinants of aggregate inflation dynamics.

Timing in the Measurement of Relative Prices

Another potential objection to the generality of the baseline results is that they are obtained by assuming a particular timing convention in the definition of relative prices. To address this issue, relative prices are defined in a slightly different but still plausible

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[16] I also experimented with another related measure, $W = (Q_1\ \ Q_3 - 2M)/(Q_3\text{-}Q_1)$, where Q_1 and Q_3 are the lower and the upper quartiles and M is the median of the distribution. (see Stuart and Ord (1987), p. 112). As this measure leads to almost identical results, I

way, and examine how the resulting impulse response and variance decomposition compare to the ones arrived at under the original definition. The modified measure of relative prices is $z_{ijt} = p_{ij,t-1} - p_{j,t-1}$ where $p_{j,t-1}$ is the one-period lagged sectoral average price level and is meant to proxy the target price level.

As before, findings from impulse response analyses and forecast error decompositions are examined solely for the pooled relative price measure and aggregate inflation measures. First, Figures 7a and 7b display the impulse responses for relative price skewness, inflation and the price level. Clearly, the impulse responses obtained under the *LR* identification scheme here are indistinguishable from the ones obtained in the baseline case. Aggregate inflation responds to idiosyncratic shocks with a five months lag following the structural shock and that this response is statistically significant. In general, impulse responses under the *SR* assumption differ from the *LR* case to the extent that the lagged response of inflation materializes only two months after the initial disturbance and that there is a statistically significant direct impact too. Forecast error variance figures displayed in the bottom panel of Table 7 confirm that idiosyncratic shocks are important determinants of inflation dynamics for the modified definition of relative prices as well.

8 Inter-Sectoral Variation in Relative Inflation

In an influential study, Ball and Mankiw (1995) develop a theory of relative price skewness and inflation and estimate the impact of the skewness in sectoral inflation rates on aggregate inflation using industry level inflation data. Robustly to alternative measures of asymmetry in relative inflation distributions, they find that asymmetry has a statistically significant impact on aggregate inflation. The OLS estimation results in their baseline specification is

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confine my attention to the mean-median difference measure defined in the text. I thank John Aldrich for bringing this measure of asymmetry to my attention.

$$\pi_t = 0.013 + 0.569\pi_{t-1} + 0.012 s_t, \quad \overline{R}^2 = 0.584$$
$$\quad (0.006)\,(0.101) \qquad (0.002)$$

where π_t denotes aggregate inflation and s_t denotes the skewness coefficient of the distribution of inter-sectoral relative inflation rates. In what follows, the data exercise of Ball and Mankiw is replicated and connected to the present analysis.

First, the *inter-sectoral relative inflation* as a measure of relative price is adopted to estimate the above univariate regression equation in the present sample[17]. Here the product categories represent the different sectors of the economy. The estimated regression equation is

$$\pi_t = 0.566 + 0.442\pi_{t-1} + 0.565 s_t, \quad \overline{R}^2 = 0.382$$
$$\quad (0.339)\,(0.112) \qquad (0.177) \qquad .$$

Clearly, the result is qualitatively identical to the one obtained by Ball and Mankiw: skewness impacts on inflation and the impact is statistically significant.

As a next step, the current aggregate inflation and inter-sectoral relative inflation skewness data is placed into the structural VAR framework developed above. The relevant results are mixed and sensitive to the identification assumption chosen. In particular, as shown in the top-left panels of Figures 8a and 8b, the identification scheme that produces impulse responses consistent with the univariate regression results is the one where aggregate shocks are constrained to have no contemporaneous effect on cross-sectional skewness. Under the *LR* identification assumption, the impulse response of inflation to an idiosyncratic shock exhibits a drop on impact and a peak only after 5 months following the initial disturbance.

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[17] As the main focus of this paper is on the asymmetry in relative price distributions, I set aside examining the second moment of relative sectoral inflation rates and its interaction with the third moment, an issue emphasized by Ball and Mankiw (1995).

Finally, for the sake of comparison, the univariate approach is also applied to the pooled *intra*-sectoral relative price measure in the current sample. The estimation results are the following:

$$\underset{}{\pi_t} = \underset{(0.427)}{1.118} + \underset{(0.117)}{0.538}\pi_{t-1} + \underset{(0.931)}{1.410}s_t, \quad \overline{R}^2 = 0.291.$$

The parameter estimates show a positive relationship between inflation and relative price skewness. They also indicate a relatively good fit of the regression equation. Although the estimated coefficient on skewness is insignificant at conventional levels, when the skewness statistic is replaced by the alternative asymmetry measure proposed above the estimates becomes highly significant and the R^2 statistic increases to about 0.6. This result is in contrast to the corresponding structural VAR estimates. There, independently of the identification scheme chosen, the contemporaneous estimated impact of skewness on inflation is negative in both VAR specifications considered.

An Anticipated Criticism

Results from a structural VAR analysis of inflation and relative price skewness suggest that a "favorable" idiosyncratic shock can cause an initial fall in aggregate inflation and then an eventual increase only in a few months afterwards. This conclusion markedly differs from the univariate inter-sectoral empirical results obtained in Ball and Mankiw (1995), reproduced above and confirmed in the present data set.

In a recent paper Bryan and Cecchetti (1996) argue that the empirical results in Ball and Mankiw (1995) documenting a positive correlation between inflation and relative price skewness are statistical artifacts and suffer from small-sample bias. Their statistical argument stands on statistical grounds and is motivated by the following thought experiment. Consider a sample of price changes that is drawn from a zero-mean symmetric distribution and actually has a sample mean of zero. In this case, by construction, the mean and the skewness of the distribution are uncorrelated. One can easily show that if an extra draw is made from the far positive (or negative) tail of the underlying distribution then it may induce a simultaneous increase (or fall) in measured inflation and in measured skewness. The example illustrates the possibility of a spuriously measured positive unconditional correlation between inflation and the skewness of the distribution of price changes when the distribution has fat tails. Motivated by these considerations, Bryan and Cecchetti go on and use Monte Carlo simulations to demonstrate that the suspected bias is not only a theoretical possibility but also an actual concern in the Ball and Mankiw data. Indeed, after having corrected for small-sample bias, they find negative correlation between the skewness of sectoral price changes and aggregate inflation. As a behavioral explanation for their findings, Bryan and Cecchetti suggest that if price setters were fully reluctant to cut their nominal prices, a fall in aggregate inflation would induce the distribution of nominal price changes bunching around zero implying increased skewness. They then draw the conclusion that "the recent focus on the correlation between the mean and skewness of the cross-sectional distribution of inflation is unwarranted".

Though the criticism of Bryan and Cecchetti does appear to invalidate the empirical results of Ball and Mankiw (1995), its main thrust is not applicable in the context of this paper. First, the finding of negative contemporaneous, unconditional correlation between inflation and relative price skewness does not preclude the presence of more complex dynamic relationship between the two variables. Indeed, to the extent that they highlight the lagged response of inflation to idiosyncratic shocks and the potential presence of negative contemporaneous correlation between inflation and relative price skewness, one might view the findings of this paper as complementary to the small-sample simulation exercise performed by Bryan and Cecchetti[18].

As a more general point, in accordance to the discussion in Section 3, the particular construct Bryan and Cecchetti (following Ball and Mankiw) use to measure the relative price actually makes their argument immaterial to the assessment of (S,s) pricing models, models that actually motivate studies of asymmetry in relative price distributions like the present one. There are two issues to consider in this regard, both of them related to the problem of the correspondence between theory and measurement. On the one hand, defining relative prices at the inter-sectoral level is inconsistent with the firm level focus of pricing models in the literature. Indeed, the sectoral level approach ignores an important element of microeconomic reality, the intra-sectoral heterogeneity price setting practices (see Rátfai (1998)). On the other hand, although the idea of downward rigid price adjustment is appealing intuitively, so far only models of the (S,s) type have had success in rigorously modeling rather than just assuming downward rigidity[19]. Therefore, it is difficult to determine how any inter-sectoral argument regarding the distribution of *price changes* would directly bear on the intra-sectoral concept envisioned by (S,s) theory, the distribution of *relative prices*.

9 Conclusions

This study aimed at using implications of two-sided (S,s) pricing models to learn about idiosyncratic determinants of aggregate inflation dynamics in the short run. Based on two distinct identification assumptions, both of them explicitly motivated by (S,s) pricing theory, bivariate dynamic systems of equations including current and lagged values of aggregate inflation and relative price skewness are studied. In the baseline specification, product-level VARs are estimated, and then the median values of the product-level estimates are presented. In addition to the baseline specification, two further types of estimates are examined. The first one is based on a pooled measure of relative prices. The skewness of the distribution of the pooled relative price data and aggregate inflation placed into in the proposed structural VAR model. The other alternative specification is a

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[18] Nonetheless, it remains to be seen how their small-sample bias argument applies to the distribution of relative prices measured in microeconomic data. This exercise is left for future research.

panel VAR model with the reduced form slope parameters constrained to be the same across the different products. The estimated structural parameters are different across products here, so the focus is on the median values of product-specific parameter estimates.

To examine the relative importance of idiosyncratic and aggregate pricing shocks in inflation dynamics, standard impulse response analysis and historical variance decomposition are utilized. The main findings are that idiosyncratic pricing shocks explain a non-negligible portion of the forecast error variance in inflation and that these shock lead to substantial inflationary responses in about three to five months after the occurrence of the shock. These results are robust to plausible identification assumptions, alternative definition of the relative price and to an alternative measure of asymmetry in the relative price distribution.

A potential explanation for the strong and robust lagged response of sectoral inflation to idiosyncratic shocks could be that price setters are slow to recognize or learn of shocks of an idiosyncratic nature, or they just adjust sluggishly to these shocks. This argument still leaves the initial response of inflation unexplained. Overall, the results give emphasis to conducting further theoretical research on the macroeconomic consequences of heterogeneous pricing behavior within individual sectors. More specifically, they provide a motivation for modeling price setters' sluggish response to idiosyncratic pricing shocks.

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[19] See Ball and Mankiw (1994), Tsiddon (1993).

Table 1
Products in the Sample

Product Code	Product Name	Absolute Weight in CPI	Relative Weight in Sample
10001	Pork, Chops	0.49	9.39
10002	Spare Ribs, with Bone	0.19	3.64
10003	Pork, Leg without bone and hoof	0.77	14.75
10102	Beef, Round	0.04	0.77
10103	Beef, Shoulder with Bone	0.04	0.77
10301	Pork Liver	0.12	2.30
10401	Chicken Ready to Cook	0.41	7.85
10601	Sausage, Bologna type	0.25	4.79
10603	Sausage, Italian type	0.17	3.25
10605	Sausage, Boiling	0.17	3.26
10801	Carp, living	0.06	1.15
11302	Curd, 250g	0.16	3.07
12101	Lard, pork	0.13	2.49
12201	Fat Bacon	0.07	1.34
12203	Smoked Boiled Bacon	0.07	1.34
12301	Sunflower Oil	0.37	7.09
13002	Flour, prime quality	0.28	5.36
13301	Roll, 52-56g, 10 pieces	0.21	4.02
13501	Sugar, white, granulated	0.53	10.15
13801	Dry Biscuits, without Butter, Packed	0.05	0.96
14424	Tomato Paste	0.03	0.57
15208	Vinegar, 10 hydrate	0.05	0.96
17001	Coffee, Omnia type, 100g	0.21	4.02
19001	Cigarette, Kossuth type, 25 pieces	0.17	3.26
52366	Broom, Horsehair-synthetic Mix	0.01	0.19
66105	Car Driving School, Full Course	0.16	3.07
66301	Movie Ticket, Evening, 1-6 Rows	0.01	0.19
		5.22	100.00

Notes: 1. Information compiled in this table is taken from various consumer price statistic booklets of the Central Statistical Office, Hungary.
2. Weights are expenditure-based. Absolute weights are the same as in the CPI. Relative ones reflect weight in this particular sample.
3. Having selected by these criteria, products are narrowly defined items according to size, branding, type and flavor.

Table 2
Unit Root Tests for Inflation and Relative Price Skewness

Inflation			Skewness		
Product Code	ADF t-statistic	Largest AR Root	Product Code	ADF t-statistic	Largest AR Root
dp10001	-4.94	0.45	s10001	-2.61	0.74
dp10002	-4.95	0.44	s10002	-3.77	0.56
dp10003	-4.88	0.46	s10003	-2.71	0.73
dp10102	-3.92	0.53	s10102	-4.32	0.54
dp10103	-4.02	0.44	s10103	-8.83	0.70
dp10301	-4.06	0.50	s10301[b]	-8.91	-0.87
dp10401	-5.83	0.21	s10401	-4.26	0.47
dp10601	-4.50	0.43	s10601	-3.86	0.55
dp10603	-4.50	0.43	s10603[a]	-3.22	0.69
dp10605	-4.24	0.48	s10605	-2.67	0.63
dp10801	-4.19	0.46	s10801	-5.16	0.23
dp11302	-7.21	0.07	s11302	-4.71	0.39
dp12101	-3.88	0.64	s12101	-3.67	0.59
dp12201	-3.98	0.52	s12201	-3.70	0.57
dp12203	-4.78	0.39	s12203	-3.03	0.69
dp12301	-5.77	0.21	s12301	-3.10	0.66
dp13002	-4.14	0.48	s13002	-3.96	0.50
dp13301	-6.37	0.11	s13301	-3.88	0.55
dp13501	-4.46	0.35	s13501	-5.91	0.19
dp13801	-5.95	0.18	s13801	-3.59	0.60
dp14424	-4.48	0.42	s14424[c]	-5.02	0.38
dp15208	-5.40	0.27	s15208	-2.81	0.75
dp17001	-3.46	0.63	s17001	-4.17	0.68
dp19001	-7.03	0.02	s19001	-2.68	0.78
dp52366	-8.20	0.12	s52366[a]	-3.71	0.56
dp66105	-6.66	0.07	s66105[d]	-5.58	0.43
dp66301	-7.06	0.02	s66301	-2.70	0.75

[a] ADF regression includes deterministic time trend.
[b] ADF regression includes dummies for a structural "intercept and slope" break at 94:12. The 5% t-sig critical value is –5.59 for T = 70. See Perron (1997).
[c] ADF regression includes dummies for a structural "intercept break" at 93:01. The 5% t-sig critical value is –4.83 for T = 100. See Perron (1997).
[d] ADF regression includes dummies for a structural "slope break" at 93:01. The 5% t-sig critical value is –5.23 for T = 60. See Perron (1997).

Notes: 1. *dp*<code> refers to the monthly percentage change in the average price level of the product denoted by <code>. Similarly, *s*<code> refers to the relative price skewness measure of the product denoted by <code>.
2. The number of lags in the regressions is based on the Schwartz Information Criterion allowing for a maximum number of lags of 12.
3. Unless otherwise indicated, regressions do not include a time trend.

Table 3
Unit Root Tests for Log Price Levels

	Log Price Level	
Product Code	ADF t-statistic	Largest AR Root
log_p10001	-3.85	0.81
log_p10002	-2.92	0.82
log_p10003	-3.82	0.82
log_p10102	-1.42	0.94
log_p10103	-1.34	0.94
log_p10301	-2.93	0.86
log_p10401	-1.68	0.90
log_p10601	-1.62	0.91
log_p10603	-1.92	0.89
log_p10605	-1.62	0.92
log_p10801	-2.76	0.84
log_p11302	-6.22	0.52
log_p12101	-3.82	0.83
log_p12201	-2.79	0.85
log_p12203	-3.39	0.82
log_p12301	-2.48	0.84
log_p13002	-1.74	0.94
log_p13301	-3.40	0.79
log_p13501	-1.96	0.94
log_p13801	-2.19	0.86
log_p14424	-0.63	0.98
log_p15208	-2.11	0.88
log_p17001	-2.19	0.93
log_p19001	-2.73	0.78
log_p52366	-2.15	0.88
log_p66105	-1.81	0.89
log_p66301	-0.97	0.94

Notes: 1. *log_p*<code> refers to the log of the average price level of the product denoted by <code>.
2. Each of the ADF regressions includes a constant and a deterministic time trend.
3. The number of lags in the regressions is based on the Schwartz Information Criterion with a maximum number of lags of 12.

Table 4
Unit Root Tests for Residuals from Seasonal Dummies Regressions

Residuals from Seasonal Dummy Regressions		
Product Code	ADF t-statistic	Largest AR Root
res_dp10001	-3.95	0.54
res_dp10002	-4.30	0.48
res_dp10003	-3.98	0.53
res_dp10102	-3.79	0.46
res_dp10103	-4.19	0.49
res_dp10301	-4.25	0.48
res_dp10401	-5.30	0.28
res_dp10601	-4.70	0.40
res_dp10603	-4.95	0.35
res_dp10605	-4.50	0.43
res_dp10801	-4.58	0.40
res_dp11302	-9.51	-0.13
res_dp12101	-3.67	0.59
res_dp12201	-3.57	0.52
res_dp12203	-4.51	0.43
res_dp12301	-2.90	-0.26
res_dp13002	-3.77	0.54
res_dp13301	-7.15	0.00
res_dp13501	-4.79	0.29
res_dp13801	-6.20	0.16
res_dp14424	-4.46	0.44
res_dp15208	-5.22	0.30
res_dp17001	-3.26	0.65
res_dp19001	-7.71	-0.07
res_dp52366	-8.44	-0.14
res_dp66105	-6.50	0.09
res_dp66301	-7.31	0.00

Notes: 1. *res_dp*<code> refers to the residual obtained from a seasonal dummy regression of the change in the log average price level of the product denoted by <code>.
2. ADF regressions include a constant and no time trend.
3. The number of lags in the regressions is based on the Schwartz Information Criterion with a maximum number of lags of 12.

Table 5
Short-Run and Long-Run Multipliers

MEDIAN OF PRODUCT-SPECIFIC ESTIMATES

	Short Run		Long Run	
Identification Restriction	$G^0_{\Pi S}$	$G^0_{S\Pi}$	$M(1)_{\Pi S}$	$M(1)_{S\Pi}$
SR: $B^0_{S\Pi} = 0$	0.74	0	-0.16	-0.16
	[1.45]	[0]	[2.81]	[1.08]
LR: $M(1)_{\Pi S} = 0$	0.18	-0.01	0	-0.14
	[3.03]	[0.07]	[0]	[1.49]

Note: The across-product standard deviations of the estimated parameters are in parentheses. *SR* and *LR* refer to the identification scheme chosen.

ESTIMATES BASED ON POOLED DATA

	Short Run		Long Run	
Identification Restriction	$G^0_{\Pi S}$	$G^0_{S\Pi}$	$M(1)_{\Pi S}$	$M(1)_{S\Pi}$
SR: $B^0_{S\Pi} = 0$	-2.38	0	1.60	0.06
LR: $M(1)_{\Pi S} = 0$	-3.39	0.06	0	0.39

Note: *SR* and *LR* refer to the identification scheme chosen.

PANEL ESTIMATES

	Short Run		Long Run	
Identification Restriction	$G^0_{\Pi S}$	$G^0_{S\Pi}$	$M(1)_{\Pi S}$	$M(1)_{S\Pi}$
SR: $B^0_{S\Pi} = 0$	0.14	0	0.33	-0.25
	[0.56]	[0]	[0.78]	[0.14]
LR: $M(1)_{\Pi S} = 0$	-0.18	0.03	0	-0.17
	[0.06]	[0.08]	[0]	[0.23]

Note: The across-product standard deviations of the estimated parameters are in parentheses. *SR* and *LR* refer to the identification scheme chosen.

Table 6
Forecast Error Decomposition -
Median, Pooled, Panel Estimation

MEDIAN OF PRODUCT-SPECIFIC ESTIMATES

		Variance Share in Percentage Terms 12 month horizon	
Identification Restriction	Source of Shocks	Aggregate Inflation	Relative Price Skewness
SR: $B^{0}_{S\Pi} = 0$	Aggregate (Π)	0.81	0.19
		[0.13]	[0.23]
	Idiosyncratic (S)	0.19	0.82
		[0.13]	[0.23]
LR: $M(1)_{\Pi S} = 0$	Aggregate (Π)	0.74	0.34
		[0.22]	[0.22]
	Idiosyncratic (S)	0.26	0.66
		[0.22]	[0.22]

Note: Cross-product standard deviations of the estimated parameters are in parentheses.

ESTIMATES BASED ON POOLED DATA

		Variance Share in Percentage Terms 12 month horizon	
Identification Restriction	Source of Shocks	Aggregate Inflation	Relative Price Skewness
SR: $B^{0}_{S\Pi} = 0$	Aggregate (Π)	0.66	0.10
	Idiosyncratic (S)	0.34	0.90
LR: $M(1)_{\Pi S} = 0$	Aggregate (Π)	0.36	0.58
	Idiosyncratic (S)	0.64	0.42

PANEL ESTIMATES

		Variance Share in Percentage Terms 12 month horizon	
Identification Restriction	Source of Shocks	Aggregate Inflation	Relative Price Skewness
SR: $B^{0}_{S\Pi} = 0$	Aggregate (Π)	0.73	0.19
		[0.04]	[0.05]
	Idiosyncratic (S)	0.27	0.82
		[0.03]	[0.05]
LR: $M(1)_{\Pi S} = 0$	Aggregate (Π)	0.74	0.24
		[0.04]	[0.02]
	Idiosyncratic (S)	0.26	0.76
		[0.05]	[0.03]

Note: Cross-product standard deviations of the estimated parameters are in parentheses.

Table 7

Forecast Error Decomposition - Alternative Measures of Asymmetry and Timing, Pooled Data

S: mm

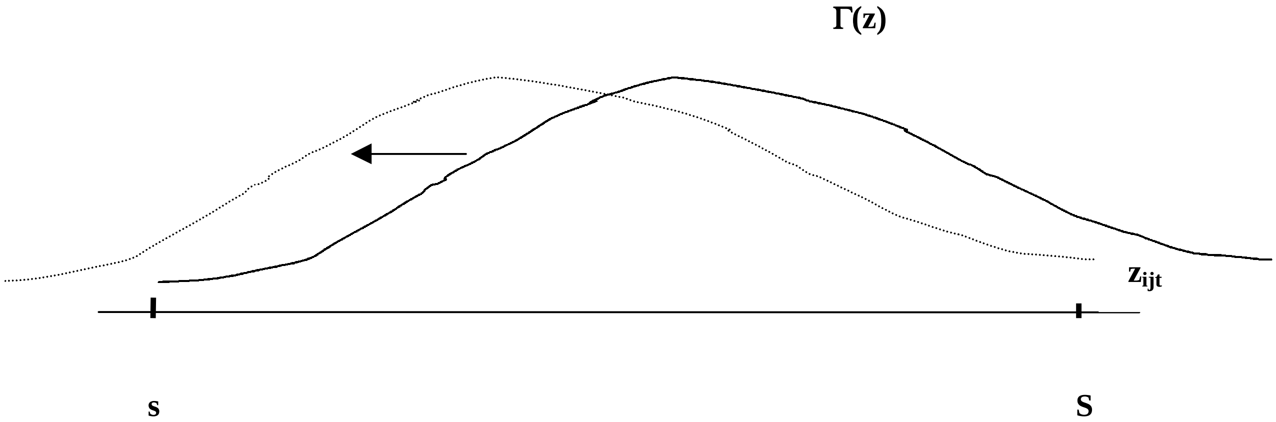
		Variance Share in Percentage Terms 12 month horizon	
Identification Restriction	Source of Shocks	Aggregate Inflation	Relative Price Skewness
SR: $B^{0}_{S\Pi} = 0$	Aggregate (Π)	0.72	0.18
	Idiosyncratic (S)	0.28	0.82
LR: $M(1)_{\Pi S} = 0$	Aggregate (Π)	0.62	0.20
	Idiosyncratic (S)	0.38	0.80

S: p*-1

		Variance Share in Percentage Terms 12 month horizon	
Identification Restriction	Source of Shocks	Aggregate Inflation	Relative Price Skewness
SR: $B^{0}_{S\Pi} = 0$	Aggregate (Π)	0.68	0.21
	Idiosyncratic (S)	0.32	0.79
LR: $M(1)_{\Pi S} = 0$	Aggregate (Π)	0.66	0.40
	Idiosyncratic (S)	0.34	0.60

Figure 1

Impact of an Aggregate Shock on the Distribution of Relative Prices



Note: The solid line represents relative price distribution before the aggregate shock, the dashed line after the aggregate shock. z_{ijt} is the relative price of product j in store i at time t defined as $z_{ijt} = p_{ij,t-1} - p^*_{ijt}$. S and s are the two adjustment boundaries.

Figure 2

Annual CPI Inflation in Hungary, Monthly Data

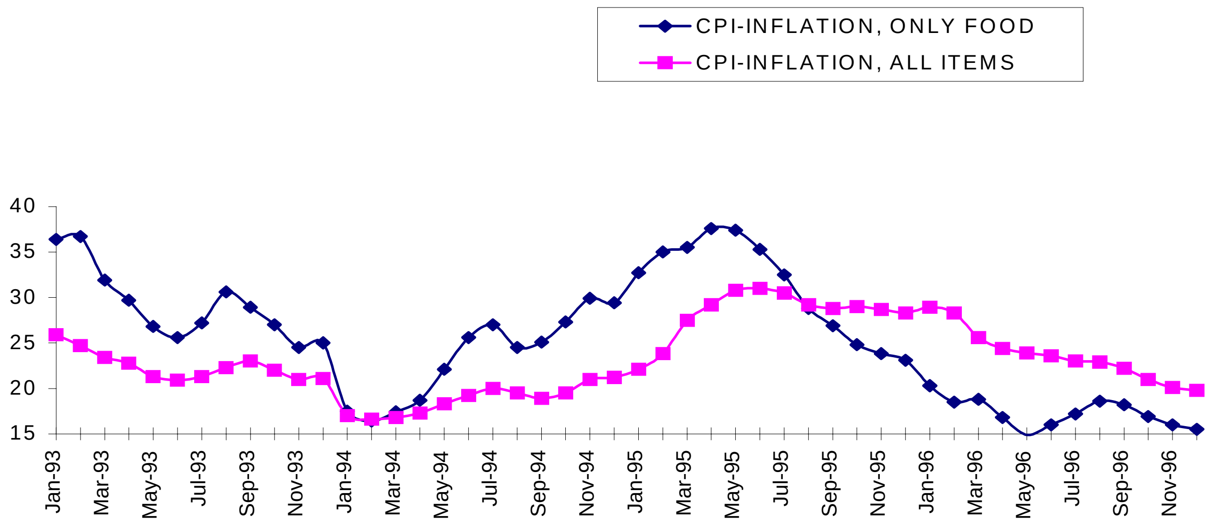
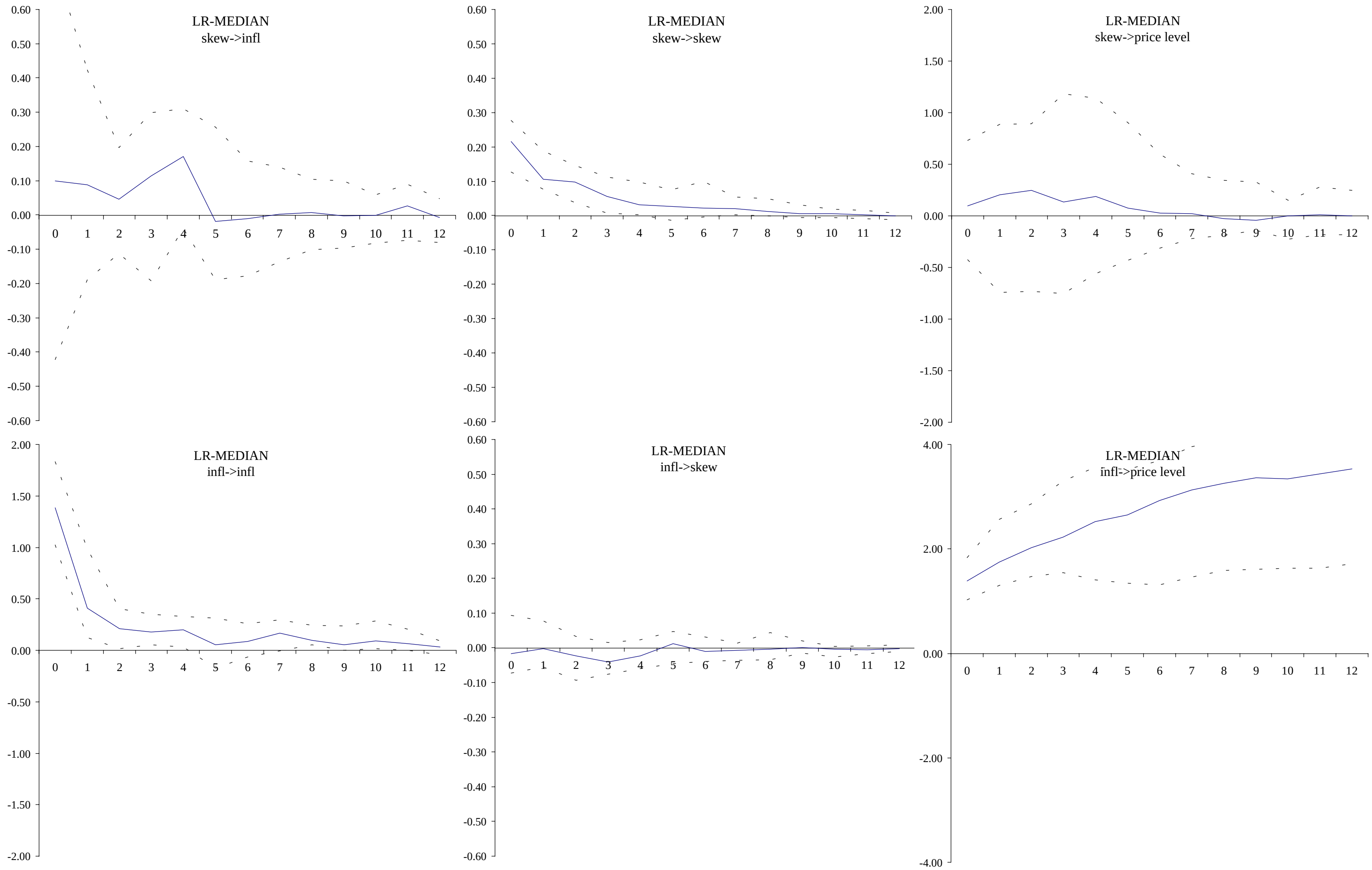
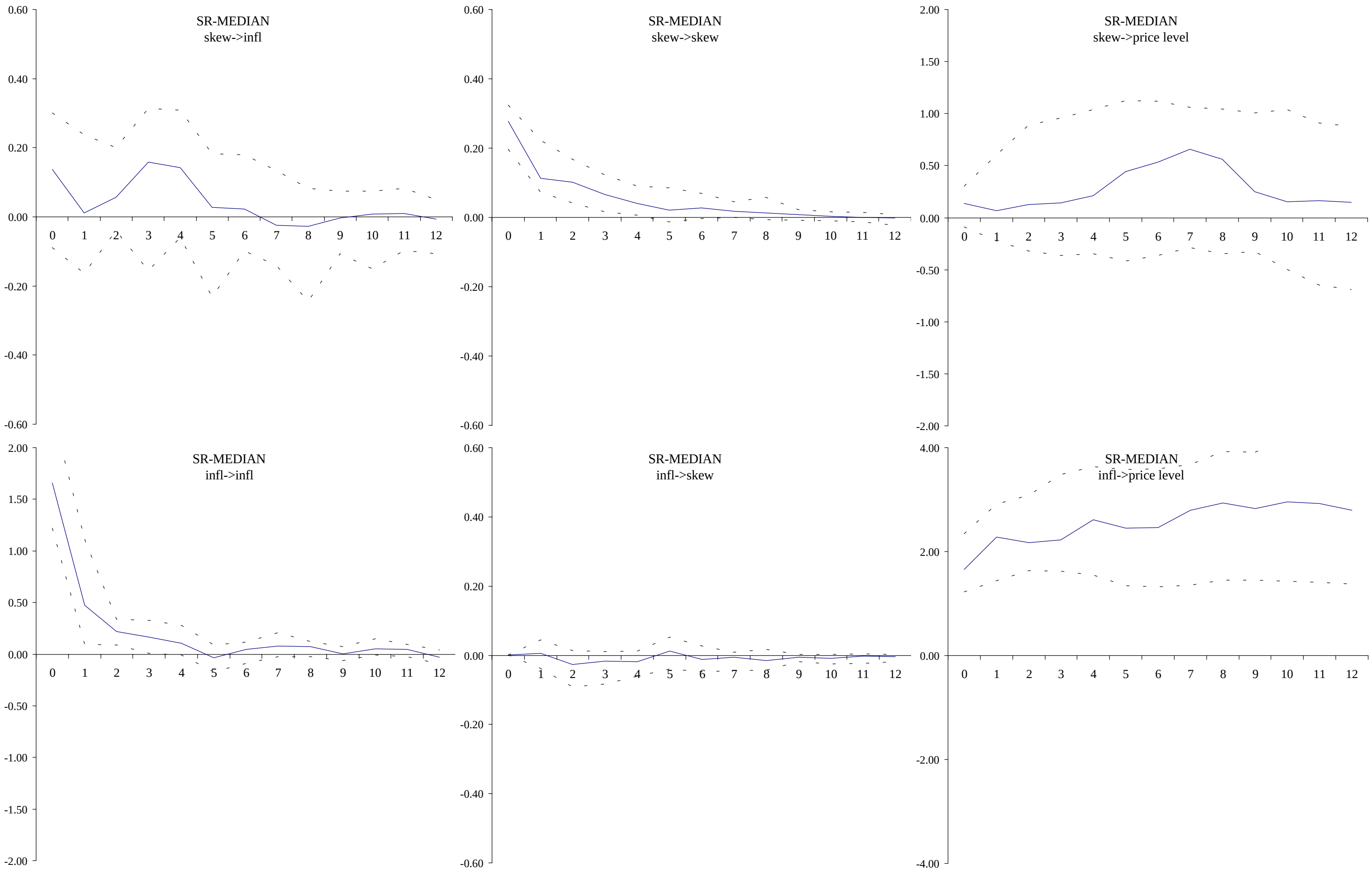


Figure 3a
Impulse Response Functions



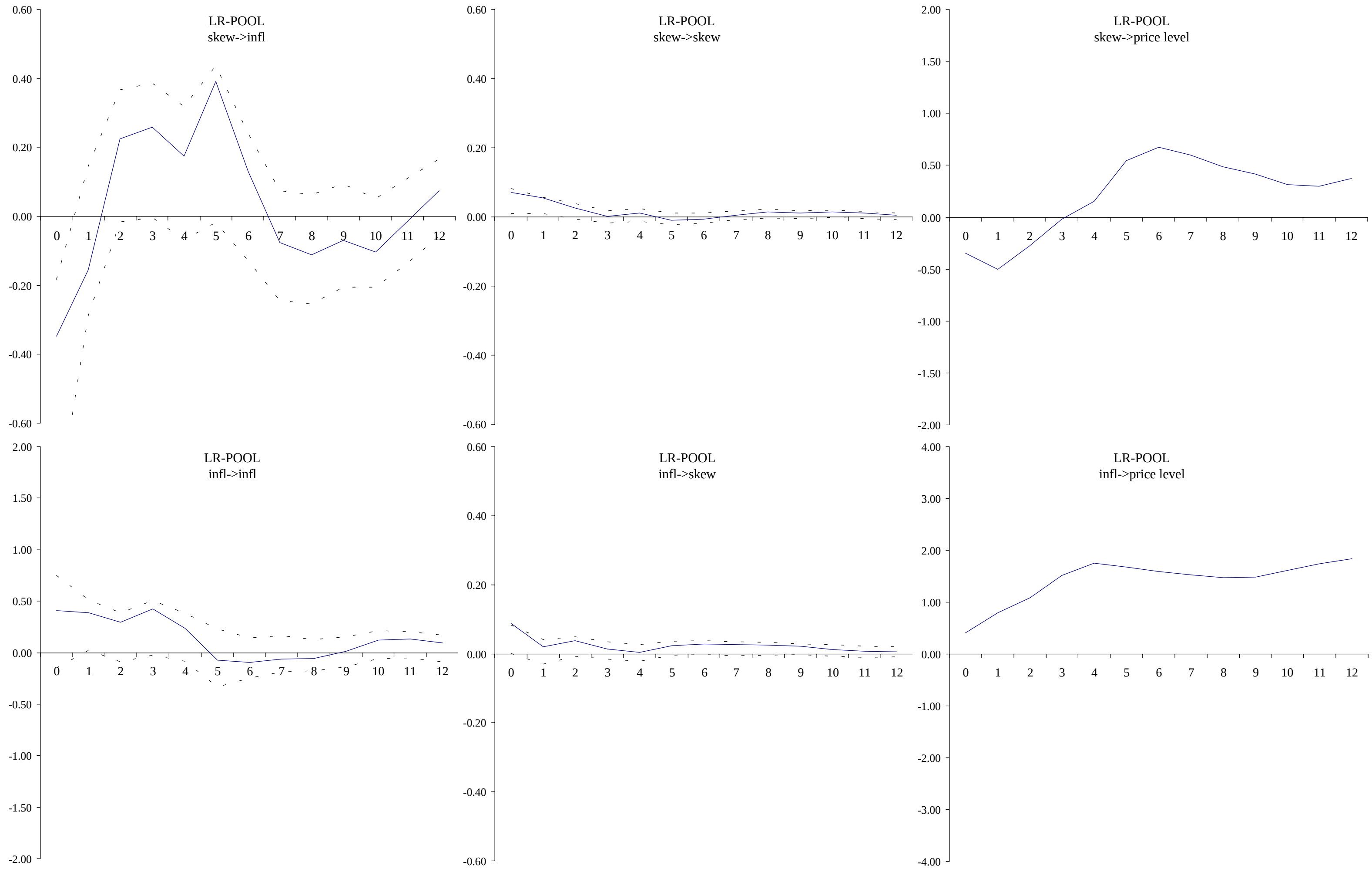
Note: Dashed lines are the upper and lower quartiles, the solid line is the median of impulse responses across products.

Figure 3b
Impulse Response Functions



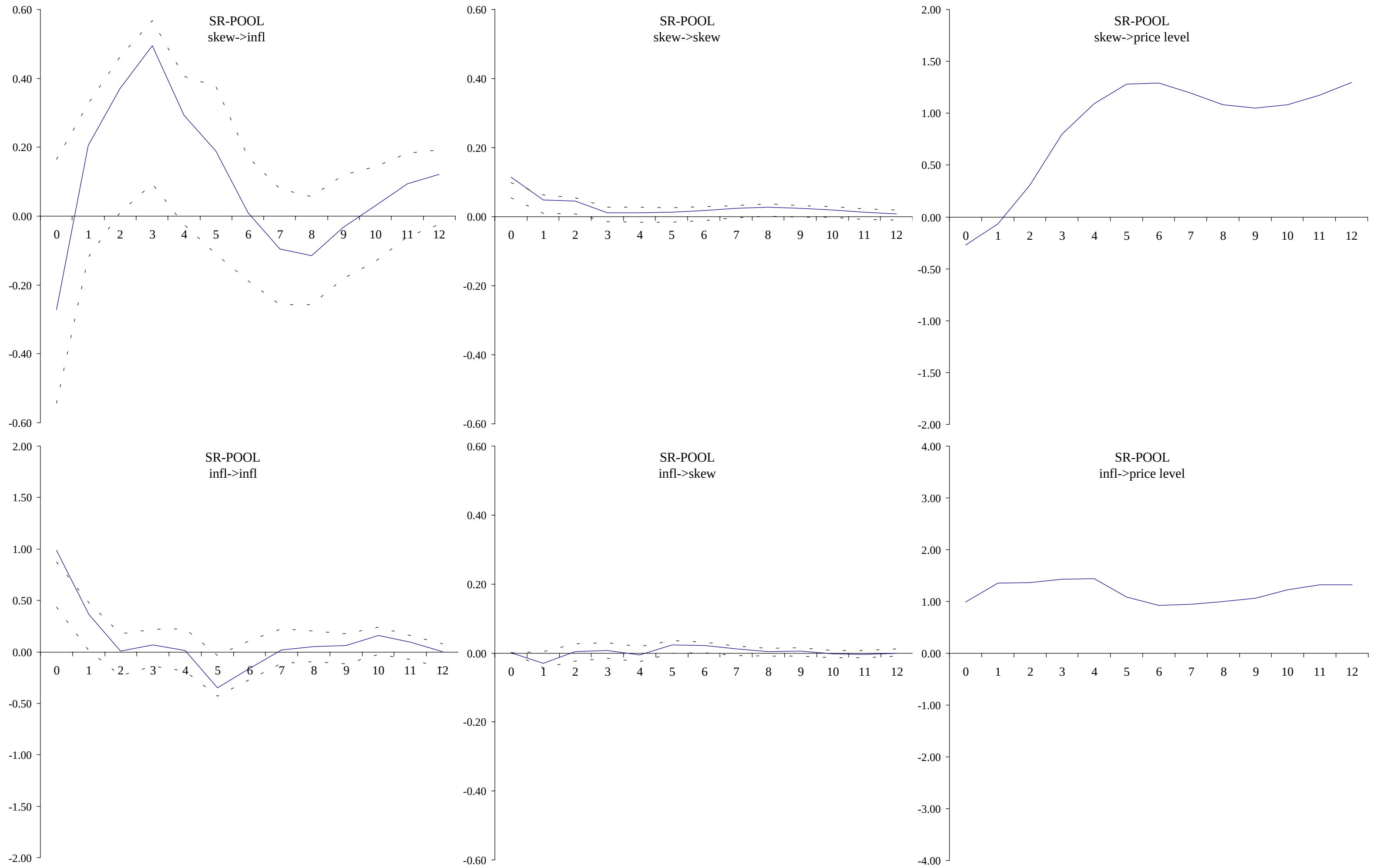
Note: Dashed lines are the upper and lower quartiles, the solid line is the median of impulse responses across products.

Figure 4a
Impulse Response Functions



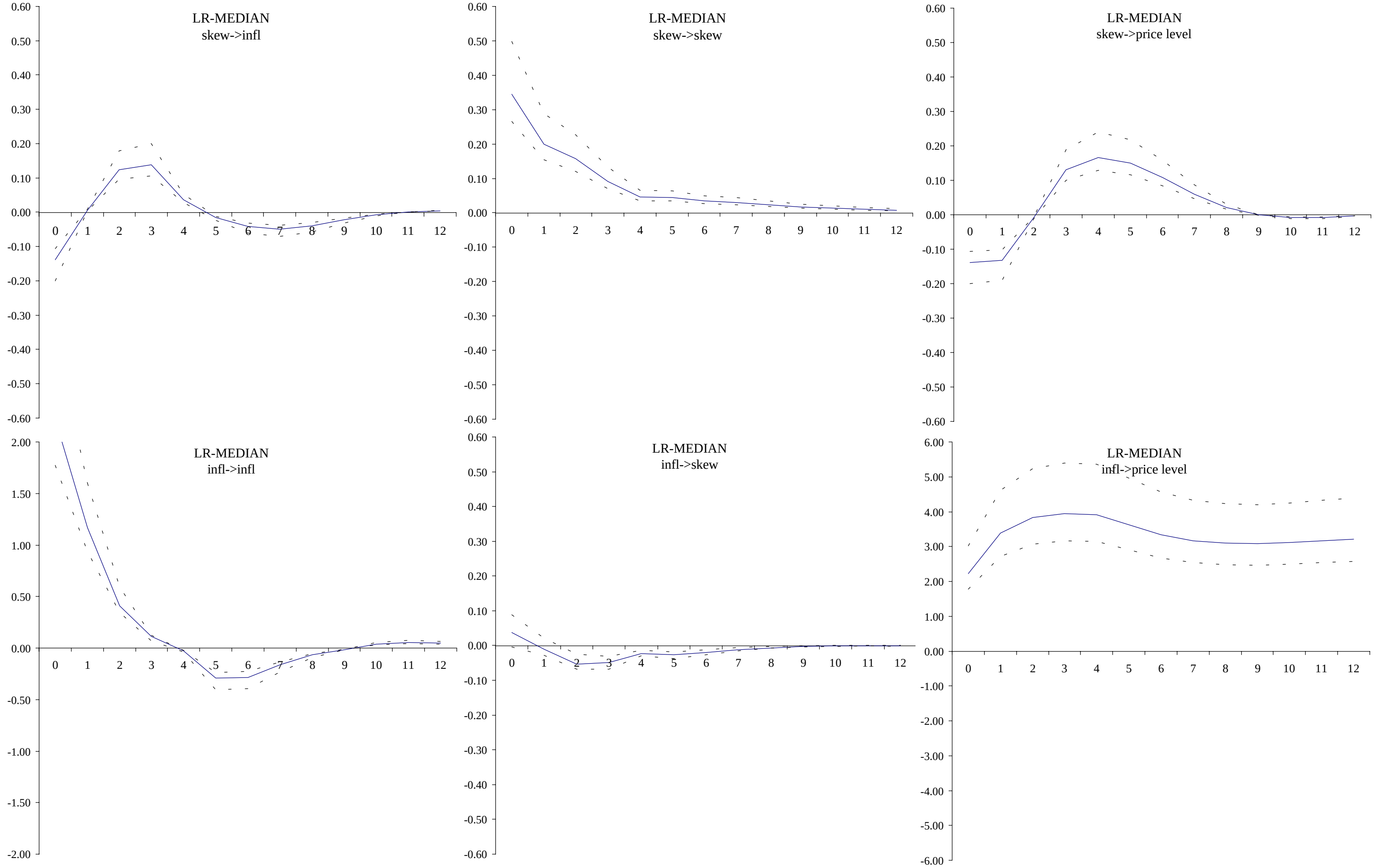
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.

Figure 4b
Impulse Response Functions



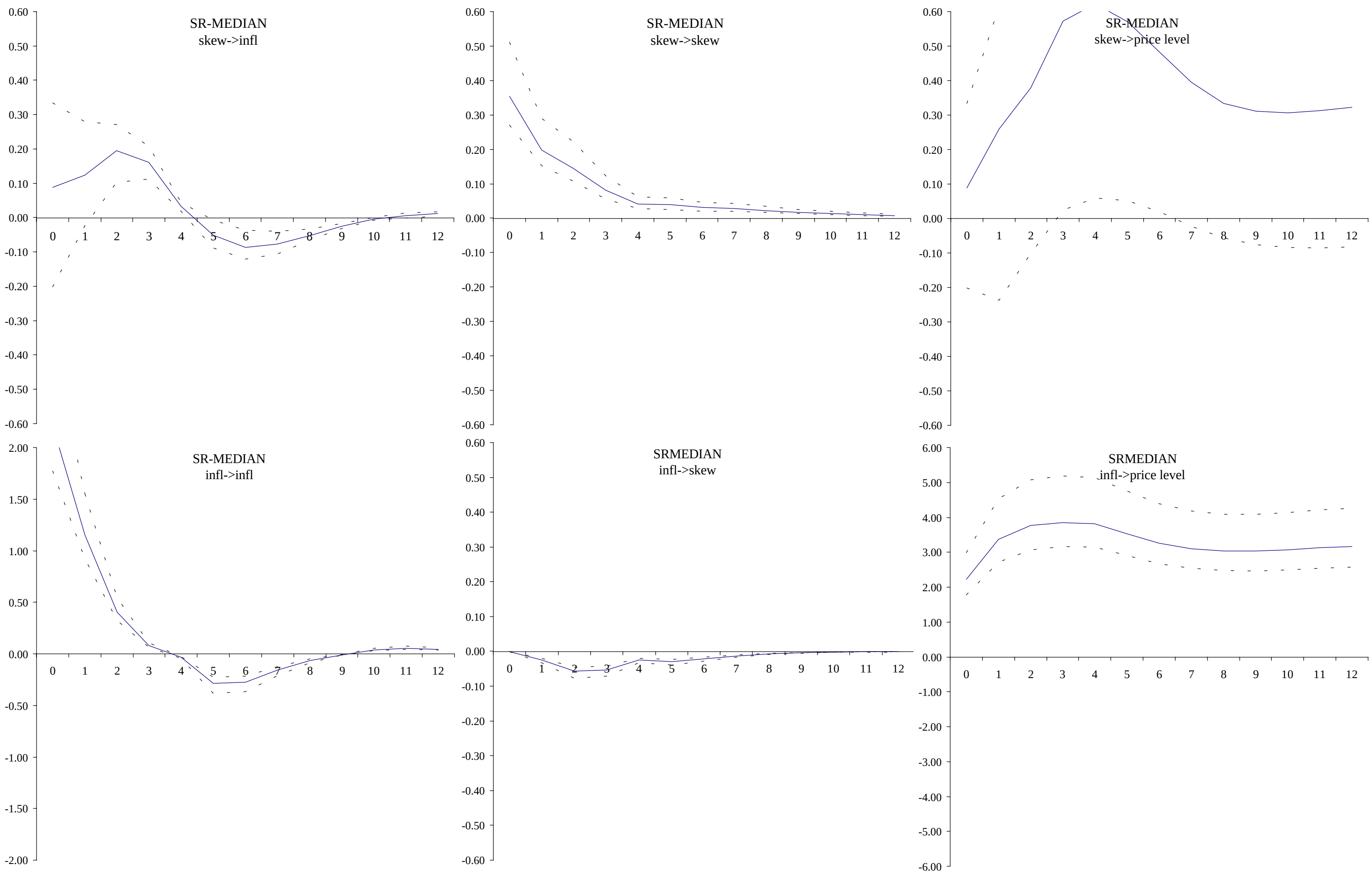
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.

Figure 5a
Impulse Response Functions
Panel VAR



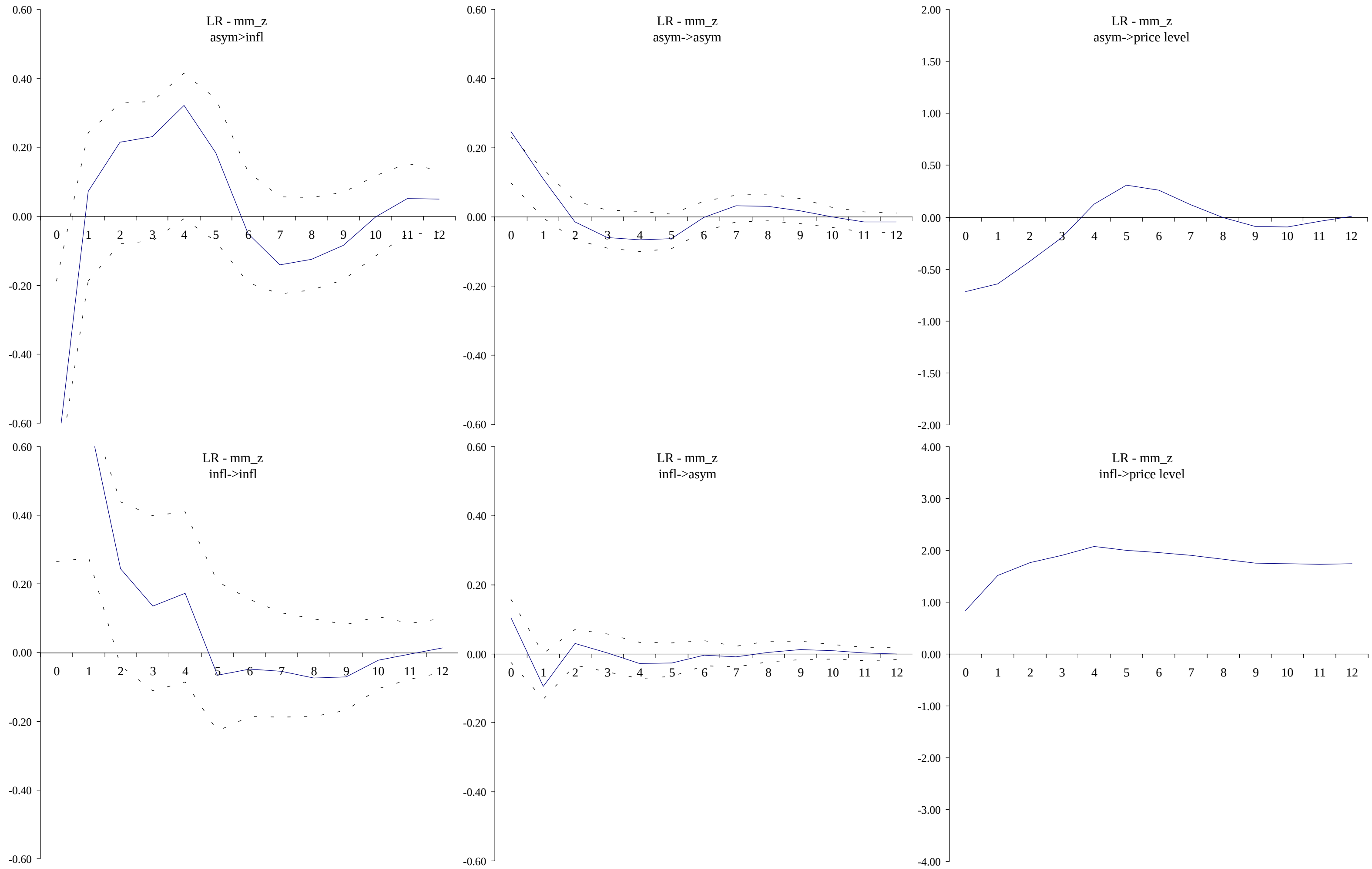
Note: Dashed lines are the upper and lower quartiles, the solid line is the median of impulse responses across products.

Figure 5b
Impulse Response Functions
Panel VAR



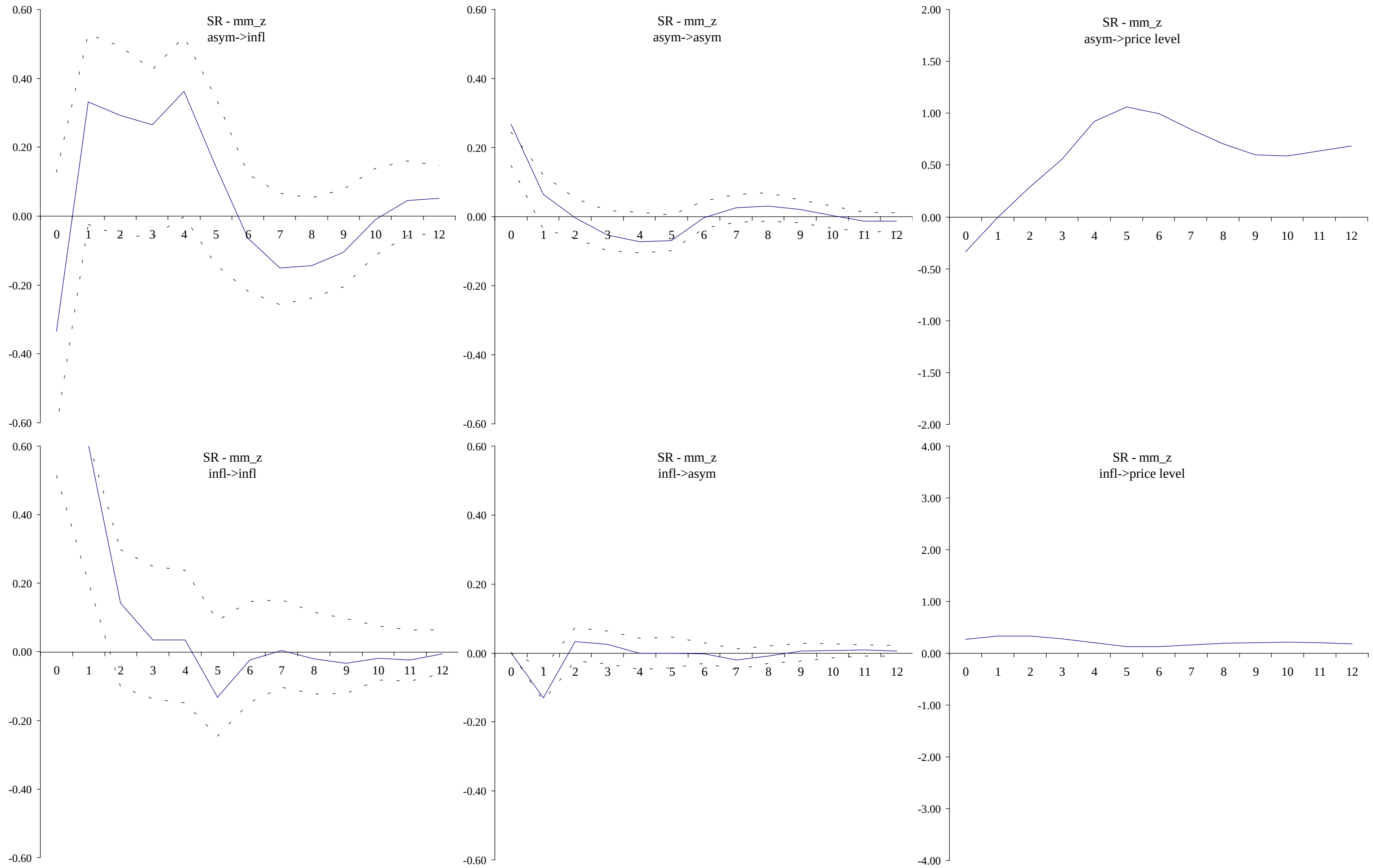
Note: Dashed lines are the upper and lower quartiles, the solid line is the median of impulse responses across products.

Figure 6a
Impulse Response Functions
(Pooled Data)



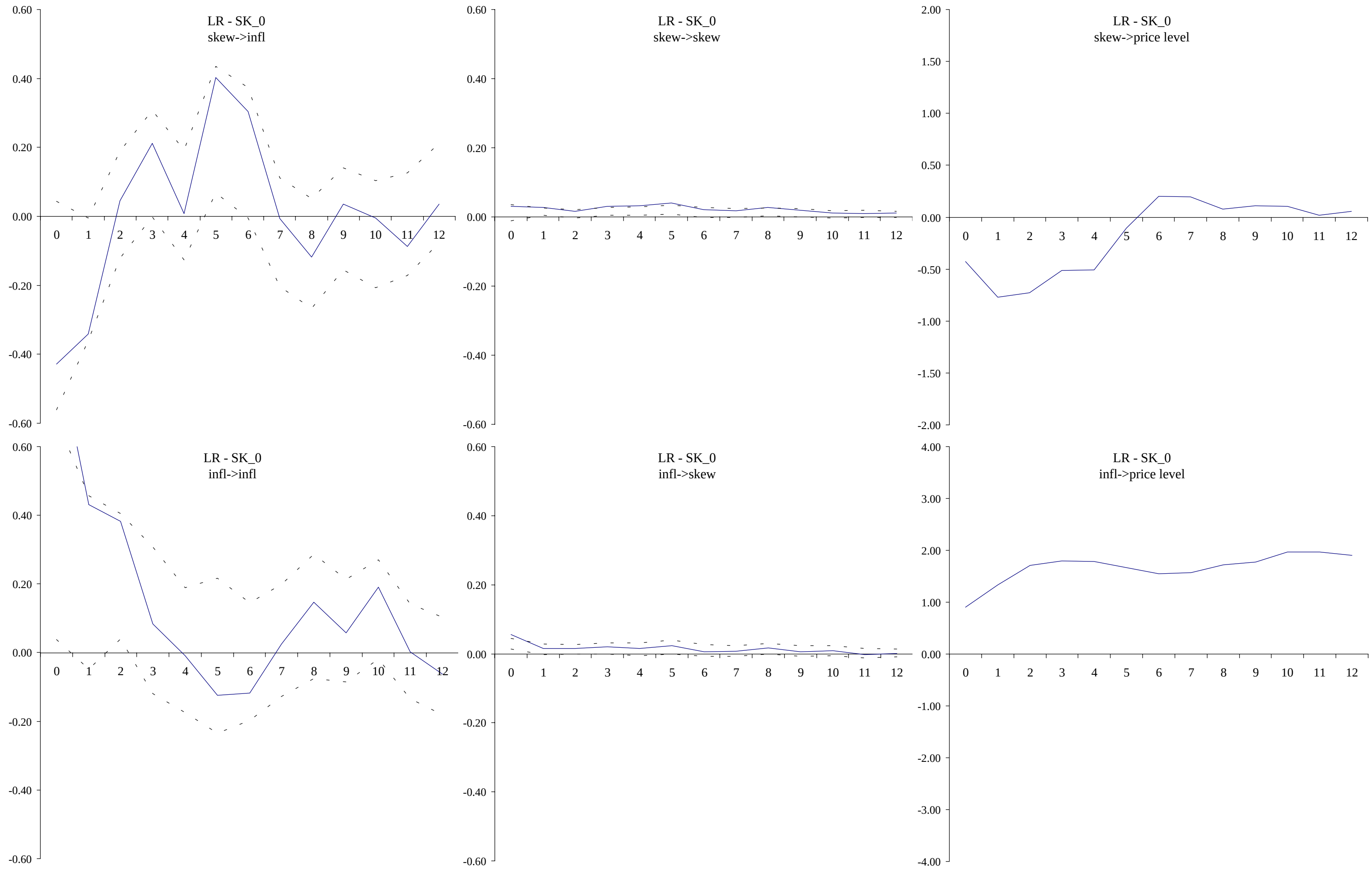
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.

Figure 6b
Impulse Response Functions
(Pooled Data)



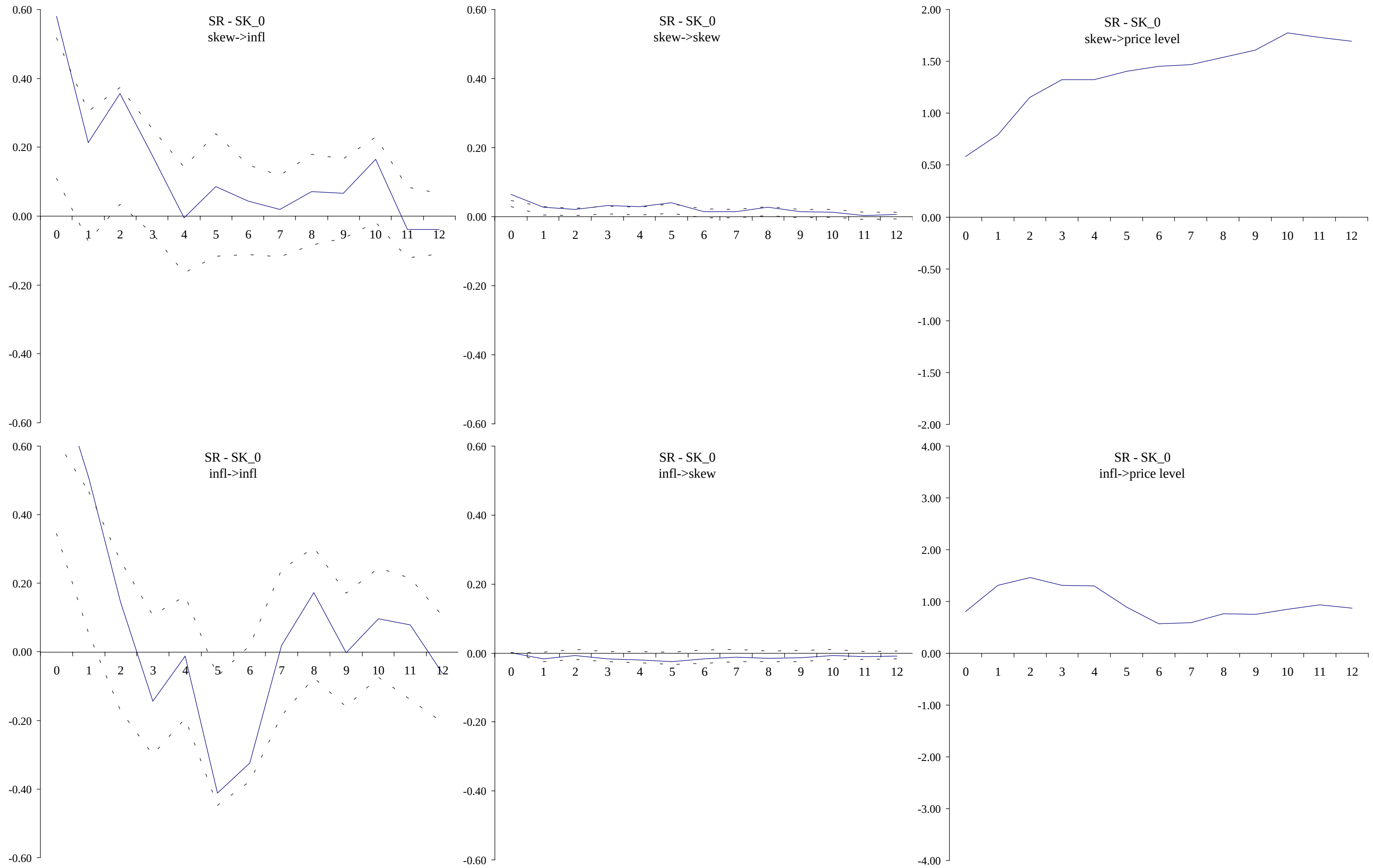
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.

Figure 7a
Impulse Response Functions
(Pooled Data)



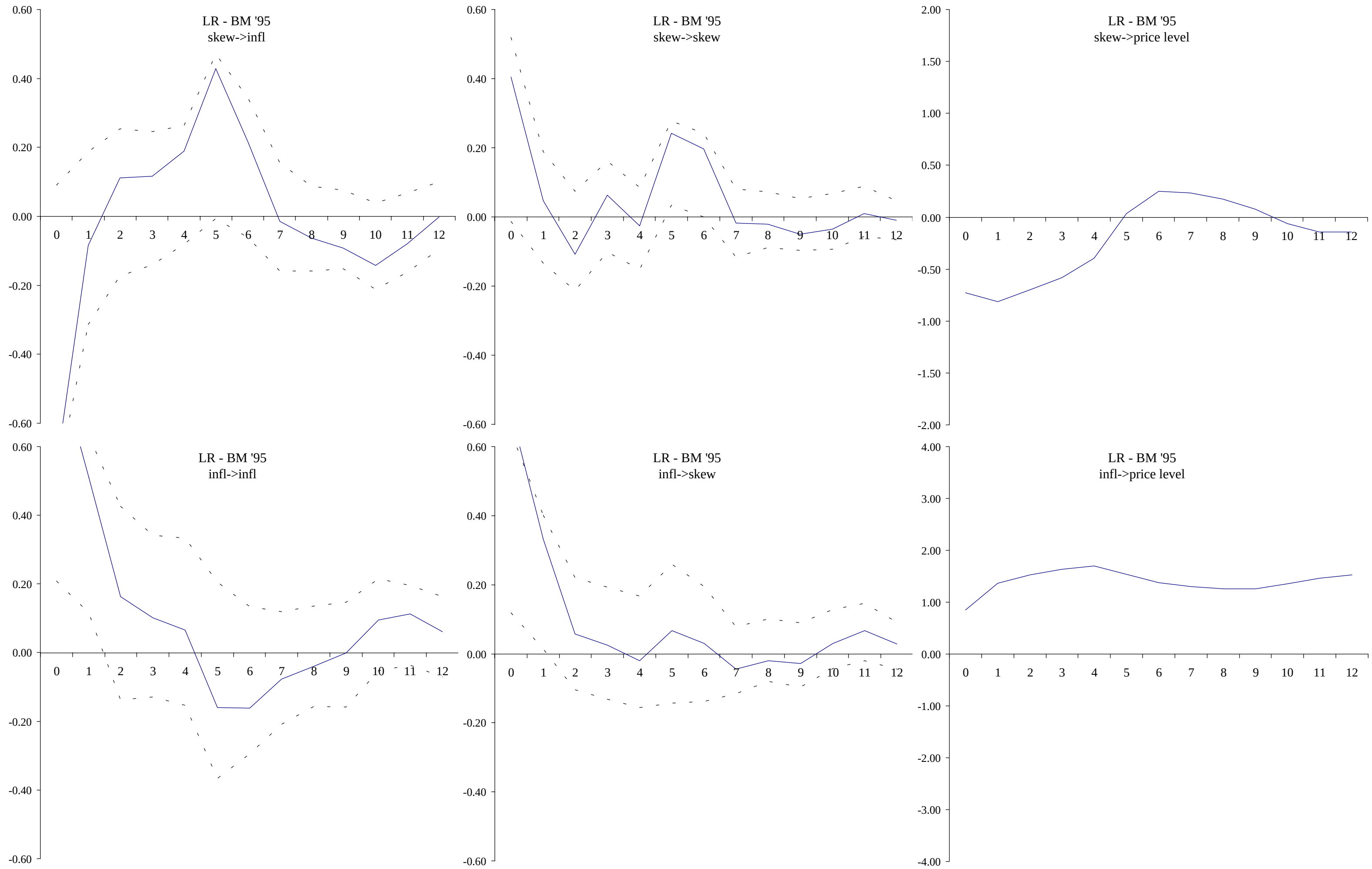
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.

Figure 7b
Impulse Response Functions
(Pooled Data)



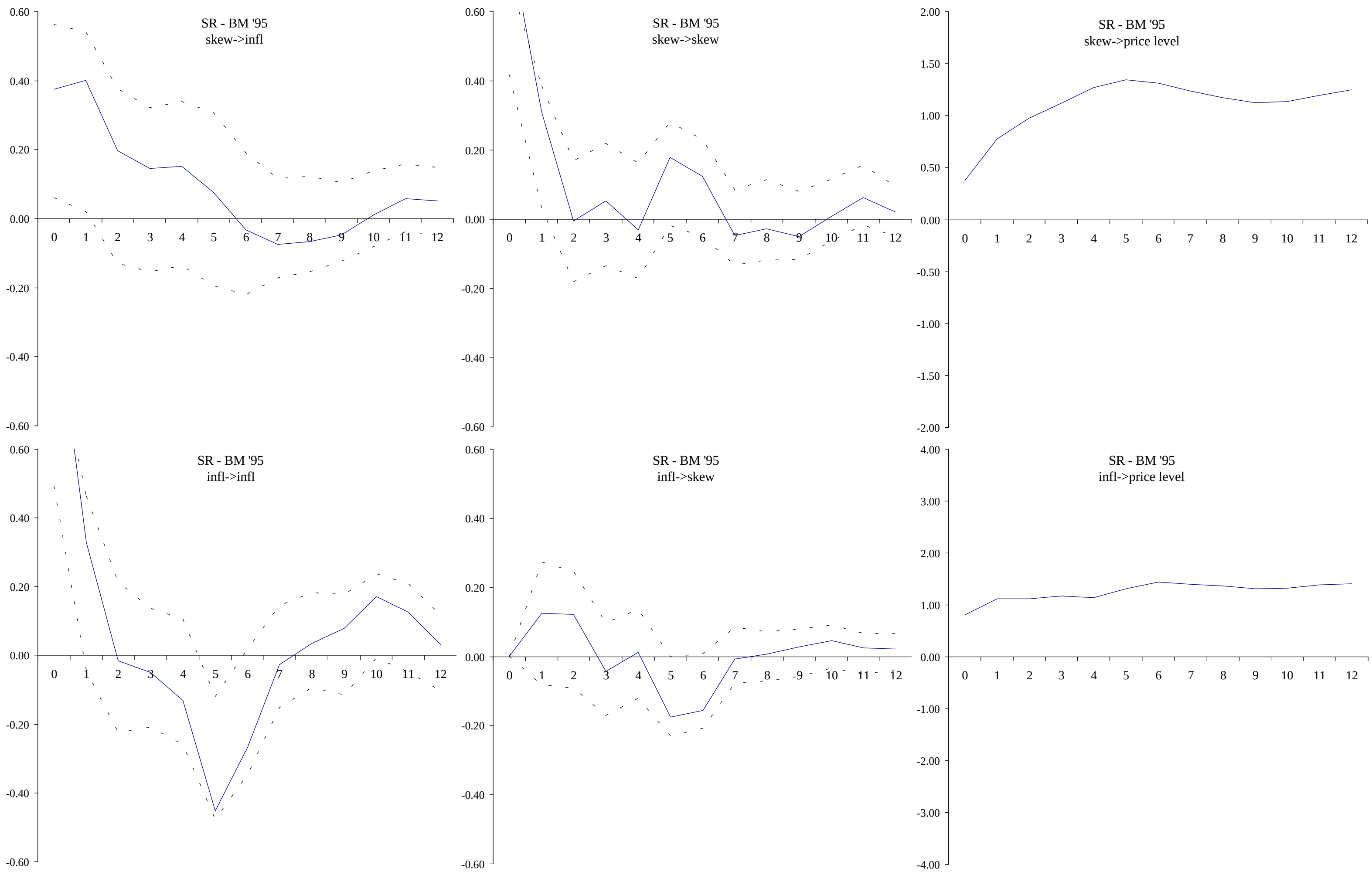
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.

Figure 8a
Impulse Response Functions
(Pooled Data)



Note: Dashed lines are 90 percent Runkle (1987) confidence bands.

Figure 8b
Impulse Response Functions
(Pooled Data)



Note: Dashed lines are 90 percent Runkle (1987) confidence bands.

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