

INFLATION AND RELATIVE PRICE ASYMMETRY*

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Abstract. By placing store-level price data into structural VAR systems comprised of inflation and relative price asymmetry, this paper evaluates the quantitative importance of idiosyncratic pricing shocks in short-run inflation dynamics. Robustly to alternative definitions of the relative price, identification schemes dictated by (S,s) pricing theory and measures of asymmetry in the relative price distribution, idiosyncratic shocks explain about 25 to 30 percent of the forecast error variance in inflation at the 12-month horizon. They also lead to substantial build-up in inflation only after two to five months following the initial disturbance.

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

JEL Classification: E31

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This study seeks to contribute to a better understanding of short-run inflation dynamics, a relatively poorly understood issue in macroeconomics.¹ The specific focus of the analysis is on quantifying the empirical significance of idiosyncratic, store-specific pricing shocks as short-run determinants of aggregate price changes. In doing so, the paper analyzes the dynamic interaction between inflation and the asymmetry in relative price distribution using new store-level price data for a selected group of goods and services.

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 at least to the seminal work of Mills (1927). Initiating a voluminous literature, one of the first related studies in the modern era is Vining and Elwertowski (1976). By examining various forms of regression equations with some measure of cross-sectional variability in sector-specific inflation rates on the left hand and inflation on the right hand side, it is representative of many subsequent investigations. Studies following up on this of research have typically found that cross-sector price variability is positively related to inflation, the result often being interpreted as indicative of the welfare costs of inflation.²

There exist however several hitherto overlooked aspects of the comovement between inflation and price variation. The present paper seeks to make advances in three directions. First, the lack of solid theoretical priors seems to have led much of the previous literature to ignore the asymmetry in relative prices and focus only on the spread in it. Mainly inspired by the emergence

¹ See, for instance, Atkeson and Ohanian (2001) and Stock and Watson (2001).

² Weiss (1993) provides a survey of the literature.

of the (S,s) modeling framework and the microeconomic evidence supporting its foundations³, however, macroeconomists has recently started to investigate the importance of higher than second moments of relative price distributions.⁴ Indeed, this study draws on implications of the (S,s) pricing literature to study inflation dynamics through the interplay between relative price asymmetry and inflation.

Second, the earlier related literature has emphasized the direction of causality from inflation to relative price variation. The two-sided (S,s) pricing approach motivating the current analysis does not rule out the traditional channel, just points to the presence of the reverse direction as well and thus begs the question of controlling for the possibly simultaneous and time-varying determination of inflation and relative price variation. To get around these issues, this study analyzes bivariate structural VAR models of inflation and relative price asymmetry. The main virtue of the structural VAR approach is that it is able to isolate the underlying economic disturbances, without imposing strong constraints on the joint dynamics of the variables involved.

Finally, probably caused by the paucity of appropriate data, most previous studies focused on the cross-sectional variation in sector- or city-level price indices and neglected relative price measures based on establishment level samples.⁵ In contrast to this practice, the current work utilizes a new store-level retail price data set.

The rest of the paper proceeds as follows. To motivate the identification strategy in the VAR model, Section 2 explains the relevant implications of two-sided (S,s) pricing models.

³ For microeconomic evidence, for instance, see Kashyap (1995) and Lach and Tsiddon (1992).

⁴ See Amano and Macklem (1997), Ball and Mankiw (1995).

⁵ Notable exceptions include Danziger (1987), Fengler and Winter (2000), Lach and Tsiddon (1992), Reinsdorf (1994) and Tommasi (1993).

Section 3 covers measurement issues. The microeconomic price data are described in Section 4. The VAR model together with specification tests is discussed in Section 5. The baseline results are presented in Section 6 and their robustness is evaluated in Section 7. Section 8 provides a more detailed assessment of two related studies with a close bearing on the present work. Conclusions follow in Section 9.

2 IDENTIFICATION

Microeconomic evidence suggests that pricing decisions exhibit elements of both lumpiness and heterogeneity: stores tend to keep their prices unaltered for extended periods of time and when they change them, they do so in a non-uniform manner and by non-trivial amounts. The timing of price changes tends to be staggered across different stores selling the same product.⁶ The theoretical approach that matches the basic elements of this description of the data is developed in two-sided (S,s) models. The underlying idea here is that assuming monopolistically competitive markets and fixed cost to price adjustment (“menu cost”), optimizing stores trade off the benefit from adjusting the nominal price against the costs of this adjustment. The central object of the analyses is the relative price, the log difference between the actual and the target price level. Aggregate and idiosyncratic shocks continuously move the relative price through their impact on the target price. With small pricing shocks, the optimal pricing policy implies that the nominal price is temporarily held constant while the relative price keeps gradually moving in between the two optimally chosen bands (S and s). Actual pricing action is triggered only when the relative price gets sufficiently eroded to surpass one of the adjustment bands.

For the purposes of this study, two specific insights of the two-sided (S,s) literature are of particular interest. First, a central theme advanced in the literature is the joint determination of

⁶ For instance, see Kashyap (1995), Lach and Tsiddon (1992).

inflation and the shape of the relative price distribution. In an (S,s) model with symmetric pricing shocks as developed in Ball and Mankiw (1994) and Tsiddon (1993), the positive trend in the target price change continuously erodes the relative price making the non-adjustment band asymmetric with a more heavily populated downward and less populated upward portion. It follows that symmetrically distributed idiosyncratic shocks produce a right skewed relative price distribution, and more frequent nominal price increases than price decreases, thus higher inflation.⁷

An additional element of this argument is that a pure aggregate shock common to all price-setters has no contemporaneous impact on the shape of the relative price distribution. In other words, as illustrated in Figure I, the aggregate shock displaces all relative prices identically in the state space, leaving the shape of the distribution intact.⁸ This is the observation that serves as one of the identification assumptions in the structural VAR analysis of inflation and relative price skewness.

Second, assuming fixed cost of price adjustment, no trend in the target price change and potentially asymmetric idiosyncratic pricing shocks, Ball and Mankiw (1995) present a complementary model. They show that the optimal policy in the model is to change the nominal price only if the relative price moves outside the inaction bands. If the resulting inaction range is symmetric which is the case with no trend in inflation, the average price level is determined by the distribution of shocks to the target price. If for example this distribution is mean zero but is skewed to the right, more firms are likely to raise the nominal price. It follows that the aggregate

⁷ A multi-sector real business cycle model with an asymmetric input-output structure also delivers this result when relative prices are defined as sector-specific inflation rates. See Balke and Wynne (2000).

⁸ See Caballero, Engel and Haltiwanger (1995).

price level (and inflation) rises. A similar argument applies to left-skewed distributions and the possible decline in the aggregate price level. Using numerical simulations, Ball and Mankiw show that the same reasoning extends to the skewness of relative price distribution itself.⁹

A crucial 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 understand why this is the case, consider a situation where trend inflation is zero and there are only idiosyncratic shocks. Also assume that the population distribution of shocks and thus the distribution of relative prices are symmetric. The realization of this distribution however is not always symmetric; for instance, there will be periods dominated by a few large inflationary shocks together with many smaller deflationary ones. In this case the number of stores close to the lower adjustment boundary with a tendency for nominal price increase exceeds the number of stores close to the upper boundary with a tendency for price cut. When the inaction band is symmetric, such a realization of shocks makes the aggregate price level rise. However, once all actual changes have completed and relative prices are readjusted to their target level, relative prices will tend to bunch close to the lower, inflationary end of the distribution rather than to the upper, deflationary one. Then, assuming symmetric shocks again, fewer nominal price increases than price cuts are expected to take place in the upcoming period, implying a fall in price level. The adjustment process with alternating periods of rising and falling price levels continues until the original symmetric distribution of relative prices is restored and the aggregate price level returns to its original level.

The above line of reasoning implies that the impact of idiosyncratic shocks on the price level is mean reverting. In other words, any unit root in the log price level is driven solely by

⁹ The model also predicts that the variance of relative price shocks have no independent impact on inflation.

aggregate shocks. This is the insight that offers the second identifying assumption in the empirical analysis.

3 MEASUREMENT

The previous literature offers several approaches in empirically implementing the notion of relative price and its variation. This paper argues that the theory motivating empirical work of this kind imposes certain requirements on measurement. Three specific points bear on the current analysis.

First, as discussed above, most of the previous studies utilized *inter*-sector measures of relative price variation involving the standard deviation of the changes in sector level price indices. The focus on this object is problematic for two related reasons. On the one hand, cross-sector measures of variation are bound to draw on changes in some aggregate price measure with the outcome of heterogeneous microeconomic pricing decisions swamped into this index. Consequently, unless stores' pricing policies are fully synchronized within sectors, mere averages of microeconomic prices could mask important regularities in microeconomic behavior. On the other hand, the underlying theory motivating any analysis of this kind is a microeconomic one with heterogeneous agents, so its test should ideally draw on highly disaggregated, establishment level data and not on already aggregated indices.

As a second, related point, the correspondence between potentially measurable objects of price variation and the theoretical concepts motivating the use of these objects is in general obscured in much of the related literature. As economic theories do not necessarily have observationally equivalent implications regarding them, it is important to distinguish three concepts in this regard: variation in price *changes* (variability), variation in price *levels* (dispersion) and variation in relative prices. The vast majority of studies employ the cross-sector standard deviation of the *change* in sector level price indices. As opposed to the notion of cross-

sector price dispersion that would just compare apples to oranges, this measure certainly has the benefit of capturing a statistically meaningful object. At the same time, it does not adequately represent any of the theoretical concepts motivating the study of the correlation between inflation and relative price variation. From the perspective of (S,s) pricing models, it is the notion of the relative price, that is, the *deviation* between the actual and the target price level, and not the nominal price level or price change that is relevant for the purposes of empirical work.¹⁰

Finally, the interest in the relationship between the asymmetry in the relative price distribution and aggregate inflation is inspired by the relative novelty of the (S,s) approach and the microeconomic evidence supporting its foundations. There exist a few studies examining relative price skewness in relation to inflation but they define relative price distributions over sector-specific inflation rates, as opposed to establishment level price differences.¹¹ By focusing on univariate statistical models, these studies also fail to account for the joint determination of inflation and relative price asymmetry.

In light of the above considerations, the present study employs a definition of the relative price and its variability, which is not only feasible to measure but also consistent with the theory motivating the study of inflation dynamics. In particular, first, the relative price in store i of product j at time t is defined as the log deviation of the individual price level from the product-specific mean: $z_{ijt} = p_{ij,t-1} - p_{jt}$. The timing convention implicit in the definition captures the idea that the status of relative prices before potential adjustment in period t is the relevant variable of interest. The product-specific mean is an equally weighted index of nominal prices in sector j at

¹⁰ While theories of the (S,s) kind are built around the concept of the relative price, search models tend to have implications for intra-sector price dispersion, the variation in price levels.

¹¹ See, for instance, Blejer (1983). As discussed above, Ball and Mankiw (1995) also use the (S,s) approach to motivate their data analysis.

time t and is computed as $P_{jt} = \frac{1}{n_{jt}} \sum_{i=1}^{n_{jt}} P_{ijt}$, where P_{ijt} is the nominal price in store i of product j at time t and n_{jt} is the number of stores in sector j in month t .

Then the standard skewness statistic capturing the asymmetry in the relative price distribution in sector j 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} . Finally, inflation in sector j , Π_{jt} , is computed as

$$\Pi_{jt} = p_{jt} - p_{j,t-1}.$$

4 DATA

The empirical analysis builds on a data set of store level consumer prices recorded in Hungary. The actual sample consists of cross-sections of monthly frequency price observations of twenty-seven homogenous items, mostly specific food products and a few services. It is drawn from the larger sample of consumer prices collected for the monthly computation of the CPI by the Central Statistical Office, Hungary. Products are selected from the full CPI database with an eye to obtaining very narrowly defined (according to size, branding, type and flavor), continuously available items with negligible variation in non-price characteristics. Table I lists the products investigated including the expenditure weight attached to them in computing the aggregate CPI and their relative expenditure weight in the current sample.

The data are available from 1992:1 until 1996:7 at the monthly frequency. In each month, there are 100-150 price observations (on average about 125) for each product. The number of stores is stable over time, the average standard deviation is less than 3. The data are recorded in 20 geographically dispersed locations including all the 19 counties in Hungary and the capital city, Budapest. Although stores in the sample are identified only by their location and are not longitudinally matched, the data collectors are formally instructed to try to keep the set of stores visited as stable as possible over time.

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

5 SPECIFICATION AND ESTIMATION

To fix notation, consider the bivariate, structural VAR model of the stationary variables of inflation (Π_{jt}) and relative price skewness (S_{jt}) specified separately for each product j ¹²

$$y_{jt} \equiv \begin{bmatrix} \Pi_{jt} \\ S_{jt} \end{bmatrix} = \begin{bmatrix} 0 & G_{\Pi S}^0 \\ G_{S\Pi}^0 & 0 \end{bmatrix} \begin{bmatrix} \Pi_{jt} \\ S_{jt} \end{bmatrix} + \begin{bmatrix} B_{\Pi\Pi}(L) & B_{\Pi S}(L) \\ B_{S\Pi}(L) & B_{SS}(L) \end{bmatrix} \begin{bmatrix} \Pi_{jt} \\ S_{jt} \end{bmatrix} + \begin{bmatrix} \varepsilon_{jt}^{\Pi} \\ \varepsilon_{jt}^S \end{bmatrix} \equiv G^0 y_{jt} + B(L)y_{jt} + \varepsilon_{jt}$$

¹² Product-specific parameter indices are omitted for convenience.

where $B(L)$ is a p th degree matrix polynomial in the lag operator L with $B(L) = 0$. The diagonal elements of G^0 are normalized to zero. Dynamics in inflation and relative price skewness are assumed to be driven by contemporaneous and past realizations of an unobservable vector of serially uncorrelated and mutually orthogonal structural innovations $\varepsilon_{jt} = [\varepsilon_{jt}^I, \varepsilon_{jt}^S]$ with variance-covariance matrix $D = E(\varepsilon_{jt}\varepsilon_{jt}')$. The orthogonality assumption implies that the off-diagonal elements of the variance-covariance matrix are zero. In economic terms, ε_{jt}^I is interpreted as a pure aggregate shock affecting relative prices identically and ε_{jt}^S as the outcome of store-specific, idiosyncratic disturbances to pricing policies. Accordingly, G_{SI}^0 captures the contemporaneous impact of aggregate shocks on relative price skewness and G_{IS}^0 the contemporaneous impact of idiosyncratic shocks on inflation.

Under standard regularity conditions, the structural model is transformed to the reduced form autoregressive one as

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

Here u_{jt} represents reduced form innovations with an unrestricted variance-covariance matrix Σ .

Reduced form innovations are linearly related to structural ones by

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

where $B^0 = I - G^0$.

From the Wold moving average representation $y_{jt} = C(L)u_{jt}$ with $C(L) = (I - H(L))^{-1}$, the infinite order, structural form moving average representation is obtained as

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

where $M(L) = C(L)(B^0)^{-1}$. This form is of particular interest for model identification and economic inference. To exactly identify the four distinct primitive structural parameters (two in B^0 and another two in D) from the three reduced form parameter estimates (the ones in Σ), it is necessary to place one extra restriction on the structural parameters.

The discussion in Section II suggests two alternatives, both of them amounting to a particular economic interpretation of the primitive shocks governing the dynamics of the endogenous variables. First, the skewness in the distribution of relative prices is assumed to be contemporaneously invariant to shocks common to all stores: $B^0_{SI} = 0$ (“Short Run” (SR) identification assumption). Second, idiosyncratic shocks have only transitory impact on the aggregate price level thus aggregate inflation is governed only by aggregate shocks in the long run: $M_{IS}(1) = 0$ (“Long Run” (LR) identification assumption).

5.1 Specification Tests

The VAR model described above assumes the stationarity of the series involved. The stochastic properties of product-specific inflation and relative price skewness series are examined in a sequence of univariate unit root tests for all the twenty-seven products. The testing procedure adopted is the Augmented Dickey-Fuller (ADF) test with the Schwartz Information Criterion used for selecting the number of lags. By default, the maximum number of lags allowed is 12. Results for the relevant ADF t -statistic and the largest autoregressive parameter are shown in Table II. Overall, the results suggest the absence of a unit root in the inflation and the skewness

series as well.¹³ Additional ADF test results reported in Table III indicate that the log price level series cannot be rejected to have a unit root.

Three issues in unit-root testing deserve special comments, each of which with a bearing on model specification. First, a visual inspection of the series suggests that with the exception of the skewness series *s10603* and *s52366*, the series appear to exhibit no trend. Therefore, with the exception of these series, the ADF stationarity tests and then the VARs do not include a deterministic time trend.

Second, preliminary tests did not reject the presence of a unit root in three of the skewness series, *s10301*, *s14424* and *s66105*. However, eyeballing the series also suggests that they are likely to contain a structural break.¹⁴ To test for the stationarity of these series, the modified unit root test of Perron (1997) is used that account for the presence of structural breaks. The resulting *t*-statistics and autoregressive roots reported in Table II indicate that all the three series can be viewed as stationary with a structural break.

Finally, upon further inspection, some of the inflation series and virtually none of the skewness series seem to exhibit seasonal fluctuations. To confirm this impression, a series of

¹³ Further test results, not reported here, show that the presence of unit-root in the stochastic component of the series can be rejected practically in all of the series when deterministic seasonal effects are controlled for.

¹⁴ Perron (1997) shows that not accounting for a break in the series when it is actually present may result in false acceptance of the unit root in standard ADF tests. To address this issue, he devised a modified ADF procedure choosing endogenously the break point in the series 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.

deterministic seasonal regressions are run with inflation on the left and 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 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 IV show no evidence of non-stationarity in the residuals. Based on these considerations, fifteen of the inflation series are modeled as stationary with seasonal dummies.

Overall, in the product level analysis, thirteen of the VARs are specified with seasonal dummies, one with a pure time trend, one with a time trend and seasonal dummies, two with dummies for a structural break, and one with dummies for a structural break and deterministic seasonals as well. Nine of the VARs exhibit none of these peculiarities and are estimated with only a constant added to the endogenous variables and their lagged values. Given these considerations, consistent estimates of the reduced form parameters are obtained by equation-by-equation Ordinary Least Squares. The number of lags included in each product-specific system is dictated by a series of Likelihood Ratio tests.

6 BASELINE RESULTS

The VAR estimations deliver four specific objects of interest including short-run multipliers, long-run multipliers, forecast error variance decompositions and impulse response functions. To fix ideas, 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 VAR model. The long-run multipliers reflect the cumulative response in endogenous variables to structural shocks as reflected in the appropriate elements of $M(I)$. The forecast error variance decomposition (*FEVD*) function

provides a measure of the quantitative importance of a particular structural shock. 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. Here, 12-month-ahead forecast errors are examined. Finally, orthogonalized 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. In terms of model parameters, the answer is recovered from the appropriate entries of the $M(L)$ matrix.

Now, how should the relevant product-specific estimates be presented if one aims at detecting the central tendency in the data? The large number ways the results could be grouped, at the minimum a combination of twenty-seven products, four categories of inference and two identification schemes, results in a practically non-digestible flow of information.¹⁵ The largest number of variation is clearly in the product dimension. To handle this issue, the various pieces of product-specific information are merged in three distinct ways. The first approach combines data, the other two combine parameter estimates.

¹⁵ In preliminary calculations, I also experimented with examining food and non-food prices separately. The results were qualitatively unchanged, so this issue is not pursued any further.

6.1 VAR Results with Pooled Data

Under the assumption that all microeconomic prices are drawn from the same underlying distribution, first, all nominal price and relative price data in a given month are pooled into two separate series, aggregate inflation and skewness in the relative price distribution. Aggregate inflation, Π_t , is defined as the mean of product-specific inflation rates

$\Pi_t = \frac{1}{J} \sum_{j=1}^J (\ln(p_{jt}) - \ln(p_{j,t-1}))$. The relative price skewness variable is obtained by calculating

product-level relative prices as $z_{ijt} = p_{ij,t-1} - p_{jt}$, then pooling all of these together and computing their cross-sectional skewness statistic. Formally, the skewness measure is defined as

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

where $N_t = \sum_{j=1}^J n_{jt}$ is the total number of price observations all the sectors in month t and D_t is

the standard deviation of relative prices at time t .¹⁶

The parameter estimates are thus obtained from a single bivariate structural VAR comprised of these two variables. The short run and the long run multipliers for the pooled data, estimated under the two distinct identification assumptions are displayed in the top panel of Table V. Notice here that the short-run coefficients shown in the first two columns of the table indicate a sizeable and statistically significant deflationary impact of idiosyncratic shocks. The corresponding forecast error variance decompositions are displayed in the top panel of Table VI.

¹⁶ ADF-tests suggest that both series are stationary without deterministic time trends and structural breaks.

The figures indicate that the relative share of idiosyncratic shocks is quite sizeable. Under the *LR* restriction, it is as large as 64 percent.

Figures IIIa and IIIb portray the relevant impulse response functions based on the pooled data.¹⁷ Independently of the identification assumption chosen, one can detect a sizeable and statistically significant inflationary effect of idiosyncratic shocks, taking place at about the third month following the initial disturbance. For the *LR* identification scheme, there appears to be a second sizeable peak occurring at the fifth month. The graphs also feature a statistically significant initial deflationary effect that disappears after the first month in the *SR* identification case and after the second month in the *LR* identification case. This is the direct impact also captured in the short-run multiplier.

Finally, imposing both identifying restrictions on the bivariate system results in an over-identified VAR model. To test for the relative merit of the two restrictions, a set of simple exclusion tests are conducted, using again 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.

6.2 Product-Specific VAR Results

To merge information from product-specific VARs, the cross-product median of product-specific estimates are presented. The median measure is designed to capture the central tendency in parameter estimates while preserving the product-level approach to analyzing price and inflation

¹⁷ 90 percent confidence bands using the Runkle (1987) bootstrap procedure with 500 repetitions are reported on the graphs.

data. It is superior to the mean as the latter statistic is more likely to be contaminated by outliers, resulting perhaps from the mis-specification of some of the individual VARs.

The middle panel in Table V summarizes the median estimates of the short-run and the long-run cross-multipliers. To capture the extent of the heterogeneity in point estimates, the cross-product standard deviation of the estimated coefficients are also reported. To formally assess the statistical significance of the results, non-parametric confidence interval sign-tests are employed.¹⁸ The results in the table show, first, that irrespectively of the identification assumption, the contemporaneous impact of an aggregate shock to relative price skewness is small with a small variance. In the *SR* case the impact is zero by construction. In the *LR* case, however, it is also indistinguishable from zero. The non-parametric sign-test shows that this result is statistically significant at the 5 percent level. Finding a small contemporaneous response of this kind under the *LR* constraint is reassuring as it suggests that the *SR* identification assumption is a sensible one. The contemporaneous impact of idiosyncratic shocks to inflation is more ambiguous. Although the median estimates are of the expected, positive, sign under both identification constraints, none of them are significantly so.

The median estimates in the third and fourth column of the table suggest that the long run impact of idiosyncratic shocks to inflation is modest. Estimated under the *SR* identification scheme, the small long-run response of inflation to idiosyncratic shocks indicates that the *LR* identification assumption is also borne out by the data.

¹⁸ The test determines a confidence interval for the median and evaluates the null hypothesis that the median of the parameter point-estimates is not different from zero against a two-sided alternative. It builds on the idea that the number of observations larger than zero must be sufficiently frequent to reject the null that the median is not different from zero. See Gibbons and Chakraborti (1992).

Next, the median estimates of the forecast error variance decompositions are shown in the middle panel of Table VI. The cross-product standard deviations of the estimated coefficients are again reported. The figures show that idiosyncratic shocks explain about 19 to 26 percent of the variation in inflation forecasts at the sector level.¹⁹ Less surprisingly, idiosyncratic shocks appear to be fundamental determinants of the forecast error variance in relative price skewness. They are less important under the *LR* identification assumption where their median contribution is 66 percent. 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 for the two different identification schemes, Figures IVa and IVb show the median of the product-specific impulse responses of inflation and relative price skewness to one standard deviation idiosyncratic and aggregate shocks. Besides the median, the graphs also display the upper and the lower quartiles of the parameter estimates. Depicting the median of the 12-month-ahead impulse response of inflation to idiosyncratic shocks, the top-left panels in the graphs are of primary interest here. The impulse responses portray a remarkably uniform picture with a peak at about three to four months after the initial shock has occurred. The medium size of both impulse responses at the peak is economically significant. Moreover, the sign-test indicates that the positive response at the fourth month is statistically different from zero under both identification assumptions.

6.3 Panel VAR Results

Assuming that the different product markets exhibit similar price-setting dynamics, an alternative way of combining information from the individual product markets is to estimate the product-

¹⁹ Note that the total effect of structural shocks to a particular variable does not have to add up to exactly 100 percent for the median of measures.

specific VARs as a panel with the appropriate cross-equation constraints imposed on the system. The specific restriction here amounts to constraining the reduced form autoregressive coefficients in the $H(L)$ matrix to be the same across items.

In practice, the system is estimated as two separate panels together with the relevant structural break dummies, seasonal parameters and deterministic time trend by standard Dummy Least Square methods. For simplicity, the number of lags is the same for all products. The dependent variables in one of the panels comprise of all the inflation variables, in the other panel all the relative price skewness ones. The DLS approach produces asymptotically unbiased estimates even with lagged dependent variables. As the current panel is long with a time dimension well exceeding 30 observations, the estimator is expected to perform well here (cf. Judson and Owen (1997)). To identify the model at the product level, the same identifying restrictions are employed as before.

The procedure leads to structural parameter estimates, impulse response functions and forecast error variance decompositions that are different across products. To summarize the information from all these estimates, the cross-product median of parameter estimates are considered again. First, the bottom panel in Table V shows the median of forecast error variance decompositions. The results here resemble the unconstrained case: idiosyncratic shocks explain about 26-27 percent of the forecast error variance in inflation. The panel constraints result in structural parameters that are tighter across products with small, 3 to 5 percent cross-product variation.

Impulse response functions are depicted in Figures Va and Vb. To characterize the central tendency in impulse responses, three different cross-product percentiles including the median and the lower and upper quartiles of point estimates are presented. Again, the focus is on the top-left graphs displaying the impact of idiosyncratic shocks on inflation. First, the pictures here are remarkably similar to the ones in the unconstrained case. Another notable feature of these graphs is the relatively strong homogeneity in the impulse response functions. Under the LR

identification, impulse responses universally start out in the negative territory, then turn to significantly positive at the horizons of one to four months and again negative for the next six months. Although the emerging picture is less unambiguous for the *SR* identification case, it produces similar results. At the horizons of two to four months the impulse responses are positive, afterwards the results are more mixed. The initial impulse response tends to be positive, significantly so after one month according to the median sign-test.

7 ROBUSTNESS

To evaluate the robustness of the above results, alternative definitions of the relative price and of the asymmetry in the relative price distribution are introduced. For simplicity, only the VAR system with pooled relative prices and aggregate inflation is considered here.

7.1 Alternative Measure of Asymmetry

The standard skewness statistic is designed to capture the degree of bunching of relative prices in the tails of the distribution. A potential problem with this measure is that it could be sensitive to outliers in the distribution and thus might capture something different from the concept it is initially intended to represent. To evaluate if the main results of the analysis are robust to the definition of asymmetry, an alternative non-parametric measure is examined here: the difference between the mean and the median of the pooled relative price distribution scaled by its standard deviation.²⁰ The statistic, denoted by *mm*, is expected to be larger the more intensive the bunching of relative prices in the lower tail of the distributions is.

²⁰ I also experimented with another related measure, $W = (Q1 - Q3 - 2M)/(Q3 - Q1)$, where *Q1* and *Q3* are the lower and the upper quartiles and *M* is the median of the distribution. (see Stuart and

First, importantly, the new series is positively correlated with the standard skewness statistic, the correlation coefficient is 0.58. Next, utilizing the alternative asymmetry measure, the VAR model of inflation and relative price asymmetry is estimated subject to the two identification restrictions used earlier. The top panel of Table VII shows the decompositions of 12-month-ahead forecast error variances. The figures corroborate the baseline results in that idiosyncratic shocks are quantitatively important determinants of aggregate inflation dynamics. Finally, the impulse response functions are depicted in Figures VIa and VIb. First, a direct comparison to Figures IIIa and IIIb reveals that the impulse response functions obtained for the alternative of asymmetry measure are strikingly similar to the one derived from the original one.

7.2 Alternative Timing in the Measurement of Relative Prices

On the ground of real-time data availability, another potential objection to the baseline results is that they are contingent on a particular timing convention in the definition of target price. To address this issue, the target price and thus the relative price is defined in a slightly different but still plausible way now. In particular, the new measure of relative price is $z_{ijt} = p_{ij,t-1} - p_{j,t-1}$ where $p_{j,t-1}$ is the average product-specific price lagged by one period.

As in the previous subsection, findings from impulse response analyses and forecast error decompositions are examined solely for the pooled relative price measure and aggregate inflation. First, Figures VIIa and VIIb display the impulse responses for relative price skewness and inflation. The impulse responses here under the *LR* identification are clearly indistinguishable from the ones obtained in the baseline case. Aggregate inflation responds to idiosyncratic shocks

Ord (1987), p. 112). As this one makes virtually no difference, I confine my attention to the standard scaled mean-median difference measure. I thank John Aldrich for bringing both measures to my attention.

with a five months lag following the shock in a statistically significant way. Impulse responses under the *SR* assumption differ from the *LR* case in that the lagged response of inflation materializes only two months after the initial disturbance and that there is a statistically significant direct impact as well. Forecast error variance figures displayed in the bottom panel of Table VII again confirm that idiosyncratic shocks are important determinants of inflation dynamics.

8 THE UNIVARIATE APPROACH

Ball and Mankiw (1995) develop a theory of relative price skewness and inflation, and estimate the impact of asymmetry in the distribution of sector-specific inflation rates on aggregate inflation using U.S. sector level data in an univariate regression framework. Robustly to alternative definitions of asymmetry, they conclude that asymmetry has a sizeable and statistically significant contemporaneous effect on inflation.

By placing microeconomic price data into a structural VAR framework, the current paper takes issue with the analysis of Ball and Mankiw (1995) on two grounds: measurement and dynamics. The univariate regression results reported below put these points further into perspective.

The finding that relative price asymmetry impacts on inflation holds in the current sample as well. Using the skewness in *inter*-sector relative inflation rates as a measure of relative price asymmetry in the present data, the preferred specification of Ball and Mankiw, the OLS estimation results in

$$\pi_t = 0.566 + 0.442\pi_{t-1} + 0.565s_t, \quad \bar{R}^2 = 0.382$$

$$(0.339)(0.112) \quad (0.177)$$

where π_t denotes aggregate inflation and s_t the standard skewness statistic. Replacing the inter-sector relative inflation rate measure with the pooled microeconomic measure of relative prices in the current sample, the results remain qualitatively unchanged:

$$\pi_t = 1.118 + 0.538\pi_{t-1} + 1.410s_t, \quad \bar{R}^2 = 0.291$$

(0.427) (0.117) (0.931)

Moreover, when the skewness statistic is replaced by the scaled mean-median difference, the positive coefficient on asymmetry becomes highly significant and the fit increases to about 0.6. Taken together, the contemporaneous impact of relative price asymmetry on inflation is significantly positive both in sector level and microeconomic data.

The above univariate results suggest that having better data allowing for relative price measurement that is closer to what the theory mandates is not sufficient in itself. What is also needed is the explicit account for the dynamic interplay between inflation and relative price asymmetry.

8.1 An Anticipated Criticism

Bryan and Cecchetti (1999) argue that the empirical results in Ball and Mankiw (1995) documenting a positive and statistically significant contemporaneous correlation between inflation and relative price asymmetry are statistical artifacts and suffer from small-sample bias. The argument standing on purely statistical grounds is motivated by the following thought experiment. Consider a sample of price changes drawn from a zero-mean symmetric distribution, actually having a sample mean of zero. By construction, the mean and the skewness of the distribution are uncorrelated here. It is straightforward to 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 skewness. The example illustrates the possibility of a spuriously measured positive unconditional correlation between inflation and the skewness in the distribution of price changes, when the distribution has fat tails. Motivated by these considerations, Bryan and Cecchetti go on and employ Monte Carlo simulations to demonstrate that the suspected bias is an actual concern in the Ball and Mankiw data set. After correcting for the small-sample bias, they actually find negative correlation between skewness and 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, its main thrust is not applicable in the present context. In particular, any 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 emphasize the lagged response of inflation to idiosyncratic shocks and the potential of negative contemporaneous correlation between inflation and relative price skewness, one may view the findings of the current paper as complementary to the small-sample simulation exercise performed by Bryan and Cecchetti.²¹

As a more general point, the particular construct Bryan and Cecchetti (and Ball and Mankiw) use in measuring the relative price renders their empirical results immaterial to the

²¹ Nonetheless, it remains to be seen how the small-sample bias argument applies to the distribution of relative prices measured in the current microeconomic data. This exercise is left for future research.

assessment of (S,s) pricing models motivating the study of asymmetry in relative price distributions. There are two points to consider in this regard; both of them pertain to the correspondence between theory and measurement. On the one hand, although the idea of downward rigid price adjustment is intuitively appealing, so far only models of the (S,s) type have been capable of rigorously modeling rather than just assuming downward price rigidity.²² Therefore, it is difficult to determine how arguments regarding the distribution of *price changes* would bear on the concept envisioned by (S,s) theory, the distribution of *relative prices*. On the other hand, as discussed before, besides that it ignores an important element of microeconomic reality, the within-sector heterogeneity in price setting, identifying relative prices with sector-specific inflation rates is inconsistent with the store level focus of the relevant microeconomic pricing models.²³

9 CONCLUSION

In order to learn about the role idiosyncratic pricing shocks play in short-run inflation dynamics, the broad goal of this study has been to quantitatively explore the aggregate consequences of lumpiness and heterogeneity in microeconomic price setting. The approach adopted here differs from traditional ones in explicitly building on basic implications of two-sided (S,s) pricing models and using microeconomic price data in a structural VAR analysis of inflation and relative price asymmetry.

The study arrives at two main findings. First, robustly to alternative identification schemes, definition of the relative price and measures of asymmetry in the relative price

²² See Ball and Mankiw (1994), Tsiddon (1993).

²³ See Fengler and Winter (2000), Lach and Tsiddon (1992).

distribution, store-specific pricing shocks explain a substantial portion, about one-third of the forecast error variance in inflation. This result is good news for theories emphasizing the aggregate importance of lumpy and heterogeneous microeconomic behavior. Second, quite robustly again, idiosyncratic shocks lead to sizeable response in inflation only with a lag of two to five months. The corresponding *contemporaneous* impact is either insignificant or ambiguous in sign. This second set of results does not match well with the univariate regression evidence presented in Ball and Mankiw (1995), and confirmed in the current data and Amano and Macklem (1997) as well. Indeed, the results suggest that existing two-sided, fixed-band (S,s) pricing models predicting a contemporaneous impact here miss an important element of reality, the delayed response of inflation to idiosyncratic shocks.

One possible explanation for the lagged aggregate response might be that some price setters are slow to learn of idiosyncratic shocks, perhaps due to some sort of local-aggregate misperception problem. An alternative story could be that the (S,s) bands are not fixed and may also respond to pricing shocks as in Carroll and Dunn (1997). For instance, besides reshuffling the relative price distribution by making relative prices bunch closer to the lower adjustment boundary, an inflationary shock may also result in the concurrent widening of the bands. Intuitively, this effect could be due to increased uncertainty about the target price resulting in a more cautious attitude towards initiating a price change, implying in turn a wider optimal non-adjustment band.

Overall, the results of this paper give emphasis to conducting further theoretical research on the macroeconomic consequences of lumpy and heterogeneous pricing behavior, including the modeling of sluggishness in price setters' response to idiosyncratic shocks.

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TABLE I
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 here 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 II
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 III
UNIT ROOT TESTS FOR LOG PRICE LEVELS

Product Code	Log Price Level	
	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 IV
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 V
SHORT-RUN AND LONG-RUN MULTIPLIERS

ESTIMATES BASED ON POOLED DATA

	Short Run		Long Run	
Identification Restriction	G^0_{DS}	G^0_{SD}	$M(1)_{DS}$	$M(1)_{SD}$
<i>SR</i> : $B^0_{SD} = 0$	-2.38	0	1.60	0.06
<i>LR</i> : $M(1)_{DS} = 0$	-3.39	0.06	0	0.39

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

MEDIAN OF PRODUCT-SPECIFIC ESTIMATES

	Short Run		Long Run	
Identification Restriction	G^0_{DS}	G^0_{SD}	$M(1)_{DS}$	$M(1)_{SD}$
<i>SR</i> : $B^0_{SD} = 0$	0.74 [1.45]	0 [0]	-0.16 [2.81]	-0.16 [1.08]
<i>LR</i> : $M(1)_{DS} = 0$	0.18 [3.03]	-0.01 [0.07]	0 [0]	-0.14 [1.49]

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

PANEL ESTIMATES

	Short Run		Long Run	
Identification Restriction	G^0_{DS}	G^0_{SD}	$M(1)_{DS}$	$M(1)_{SD}$
<i>SR</i> : $B^0_{SD} = 0$	0.14 [0.56]	0 [0]	0.33 [0.78]	-0.25 [0.14]
<i>LR</i> : $M(1)_{DS} = 0$	-0.18 [0.06]	0.03 [0.08]	0 [0]	-0.17 [0.23]

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

TABLE VI
FORECAST ERROR DECOMPOSITION

ESTIMATES BASED ON POOLED DATA

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

Note: SR and LR refer to the particular identification scheme.

MEDIAN OF PRODUCT-SPECIFIC ESTIMATES

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

Note: Cross-product standard deviations of the estimated parameters are in parentheses. SR and LR refer to the particular identification scheme.

PANEL ESTIMATES

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

Note: Cross-product standard deviations of the estimated parameters are in parentheses. SR and LR refer to the particular identification scheme.

TABLE VII

FORECAST ERROR DECOMPOSITION - ALTERNATIVE MEASURES OF ASYMMETRY
AND TIMING, POOLED DATA*S: mm*

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

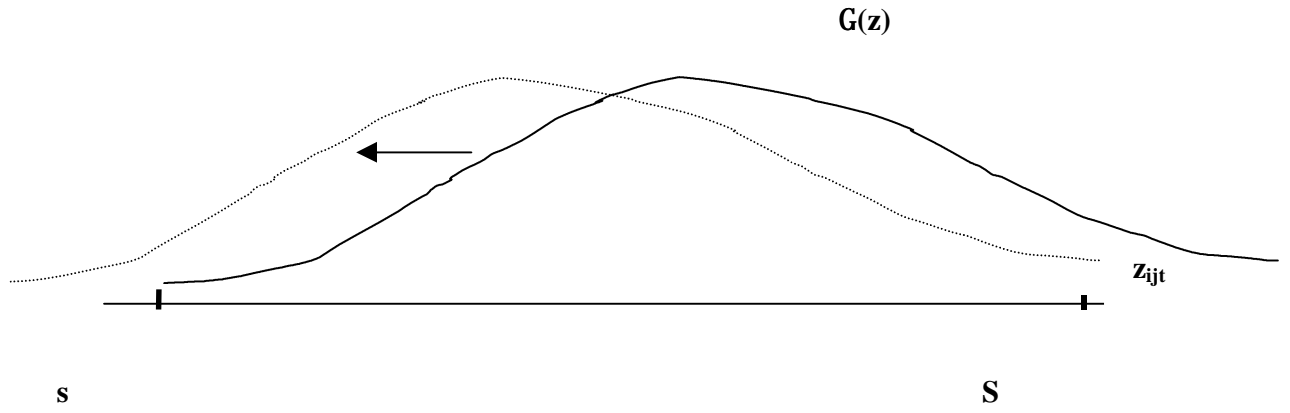
*Note: SR and LR refer to the particular identification scheme.**S: p*-1*

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

Note: SR and LR refer to the particular identification scheme.

FIGURE I

Impact of an Aggregate Shock on the Distribution of Relative Prices



Note: z_{ijt} denotes the relative price of product j in store i at time t as defined in the text. S and s are the adjustment boundaries. $\Gamma(z)$ is the density of relative prices. The solid line shows the relative price distribution before, the dashed line after an aggregate shock.

FIGURE II

Annual CPI Inflation in Hungary, Monthly Data

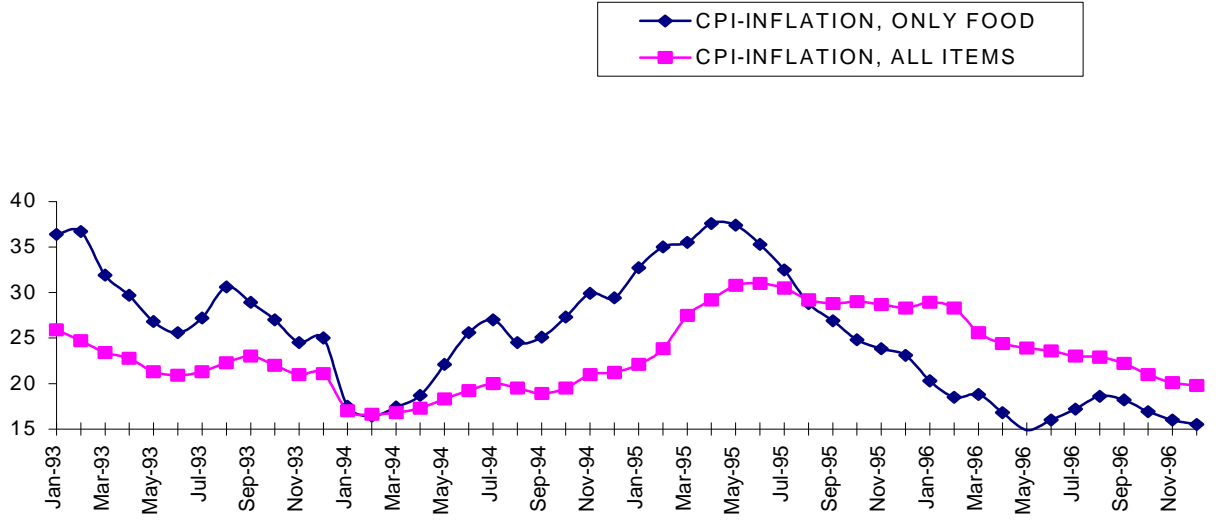
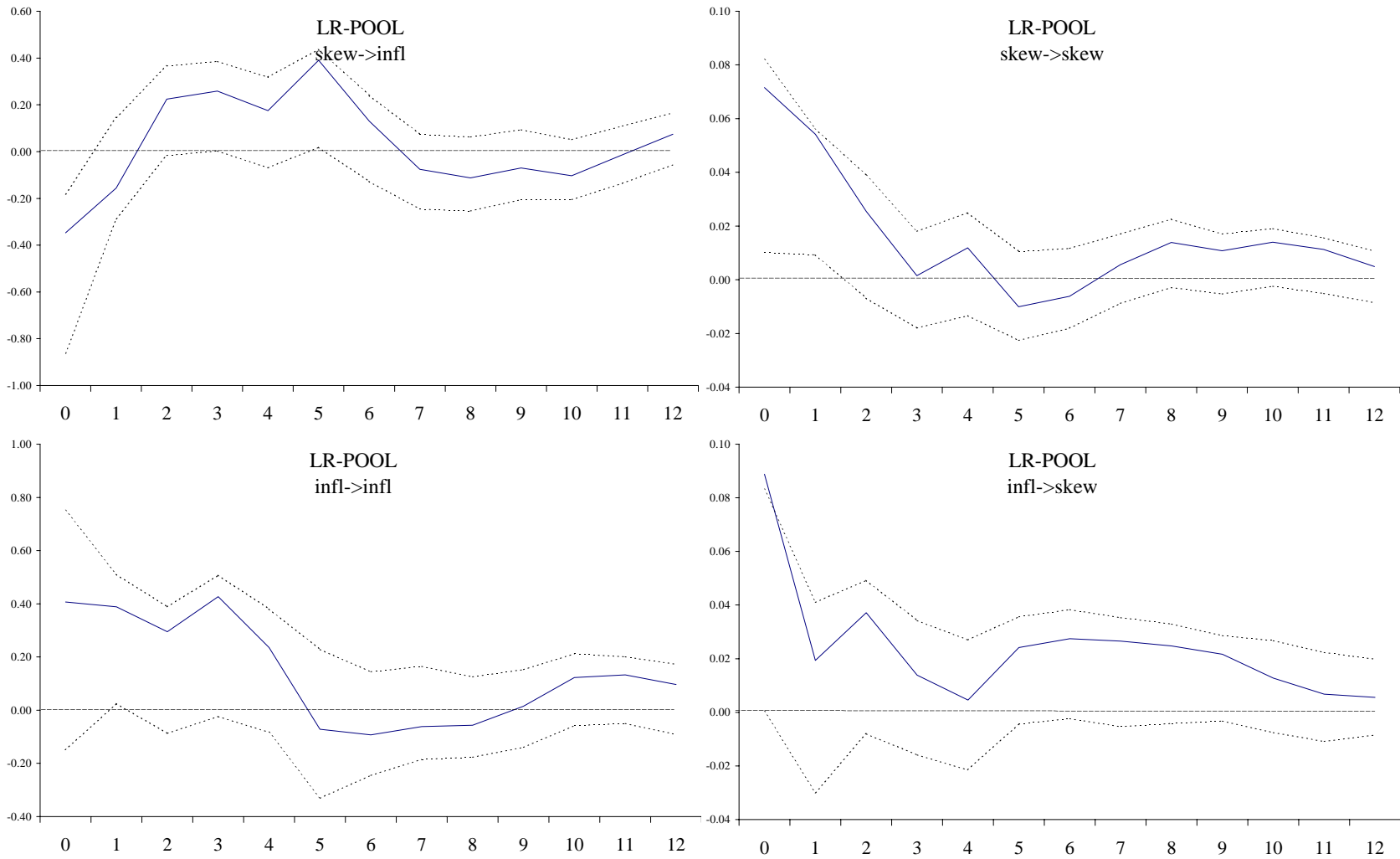
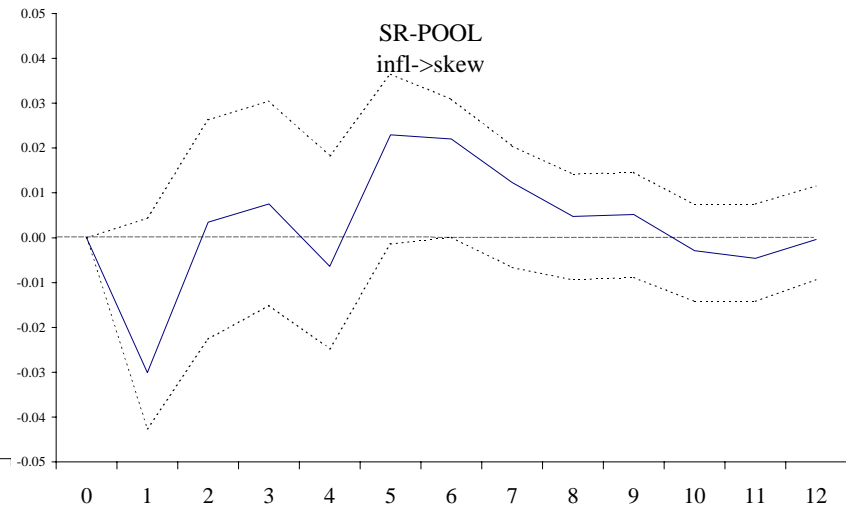
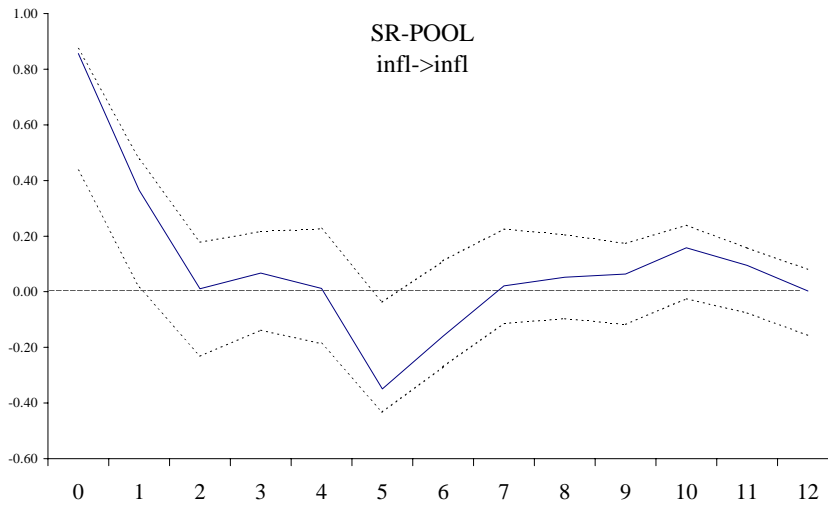
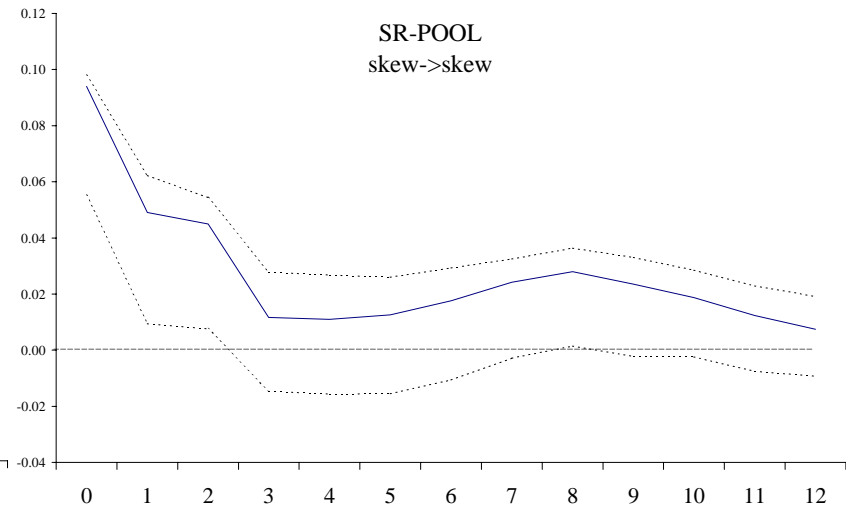
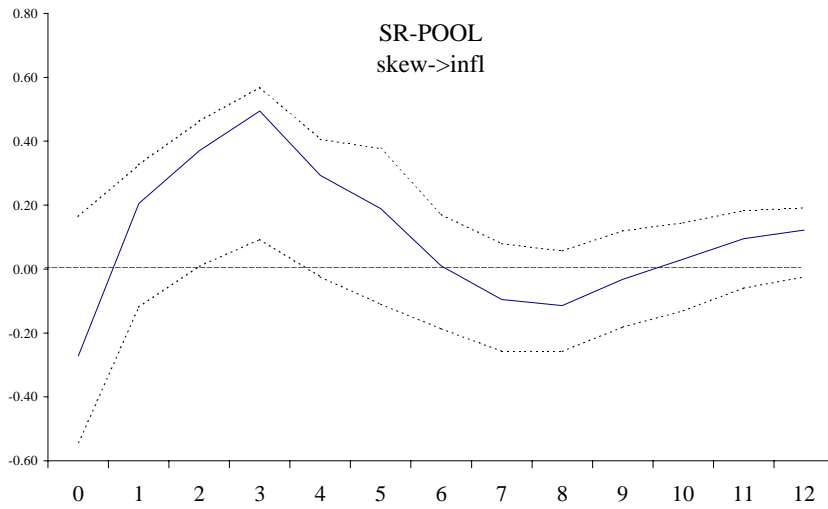


Figure IIIa
Impulse Response Functions



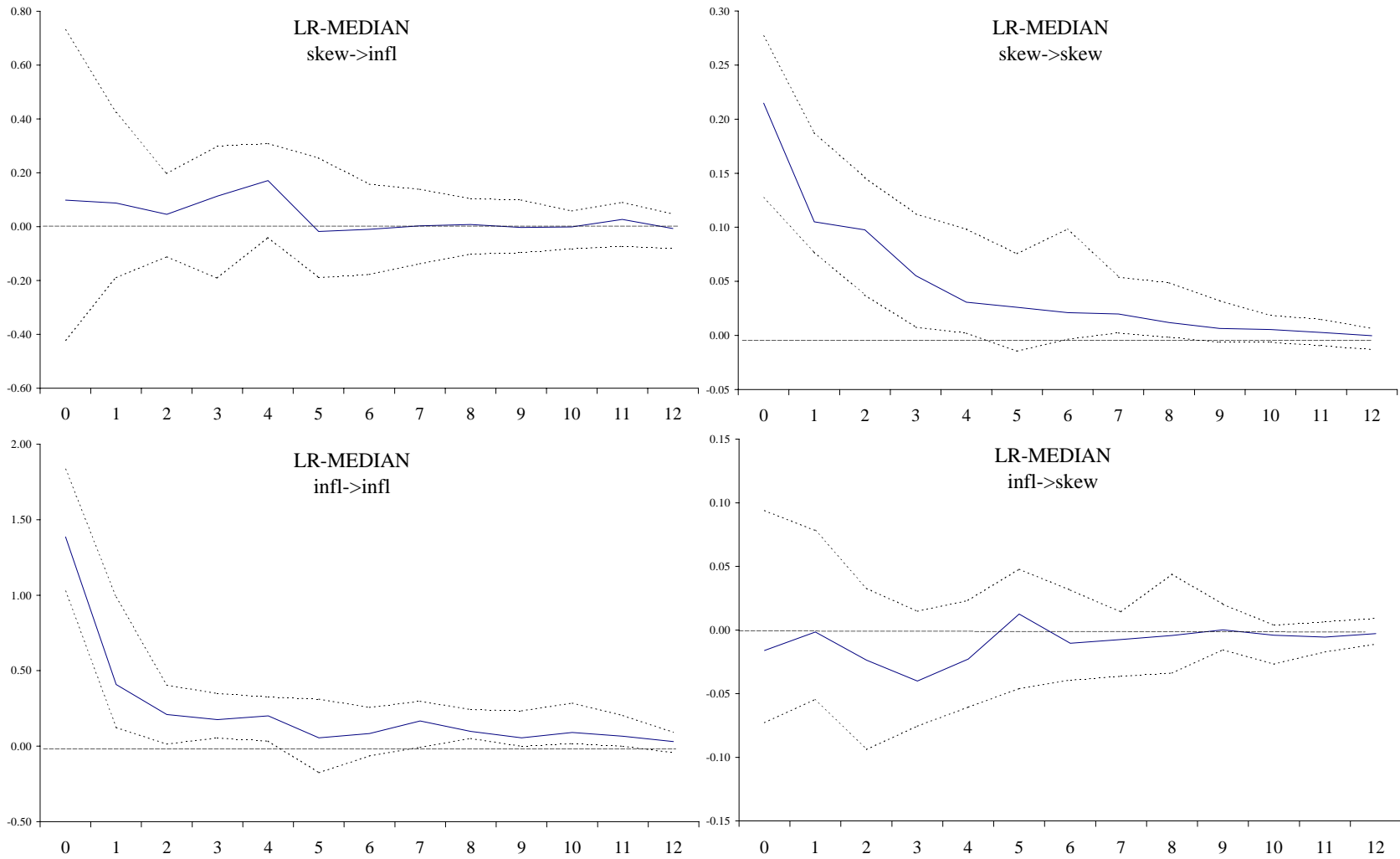
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.
Horizontal axis: months following shock

Figure IIIb
Impulse Response Functions



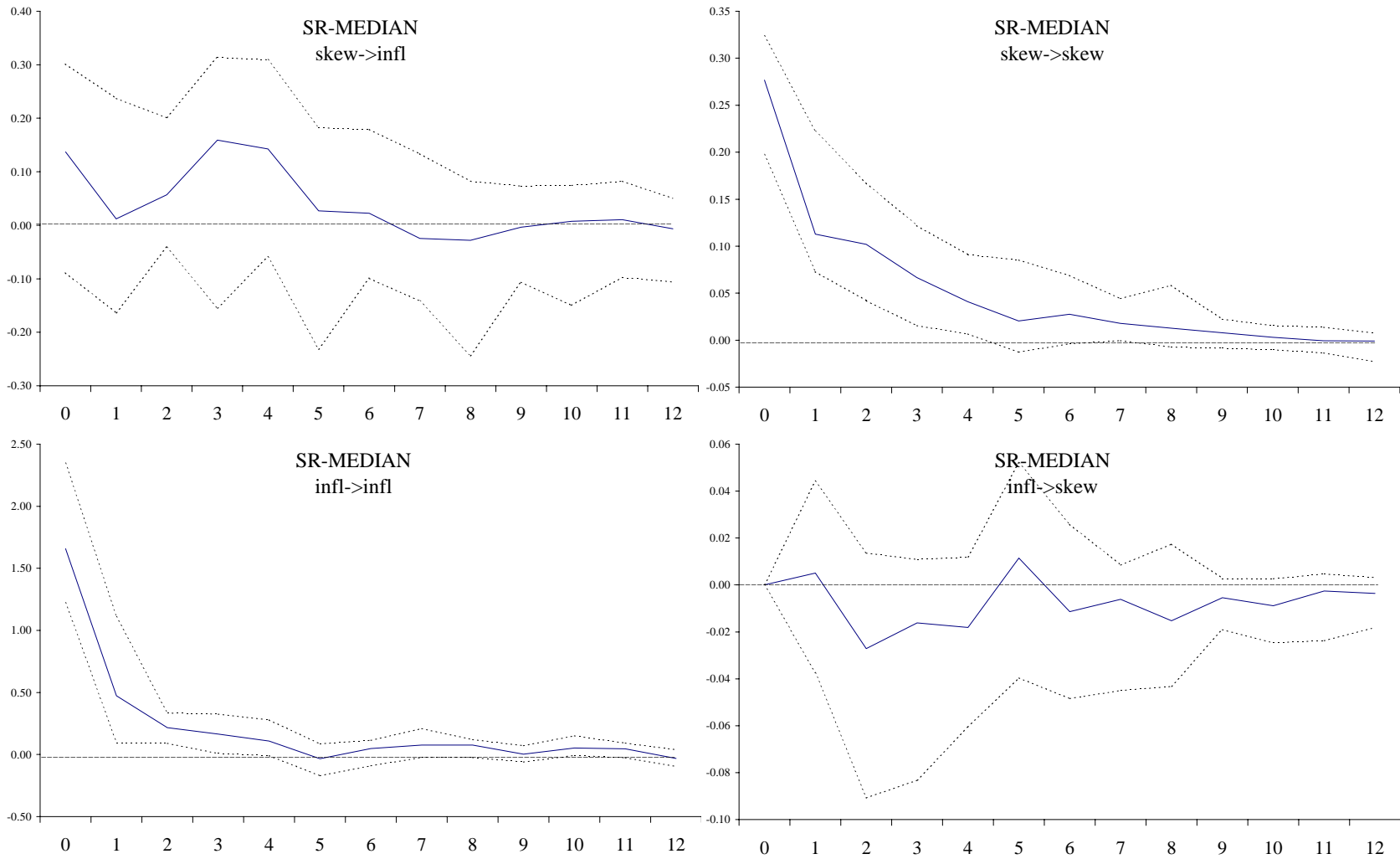
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.
Horizontal axis: months following shock

Figure IVa
Impulse Response Functions



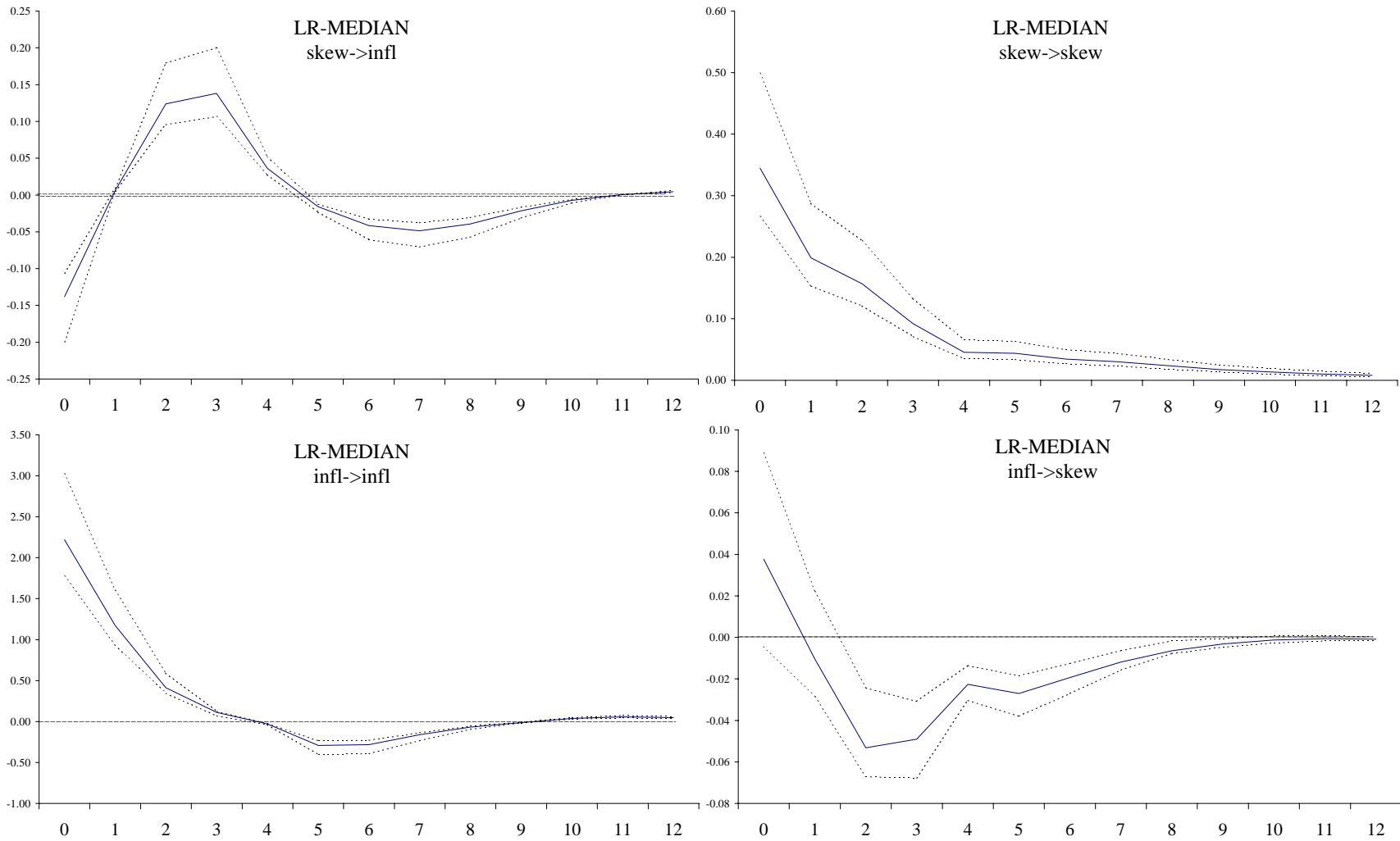
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.
Horizontal axis: months following shock

Figure IVb
Impulse Response Functions



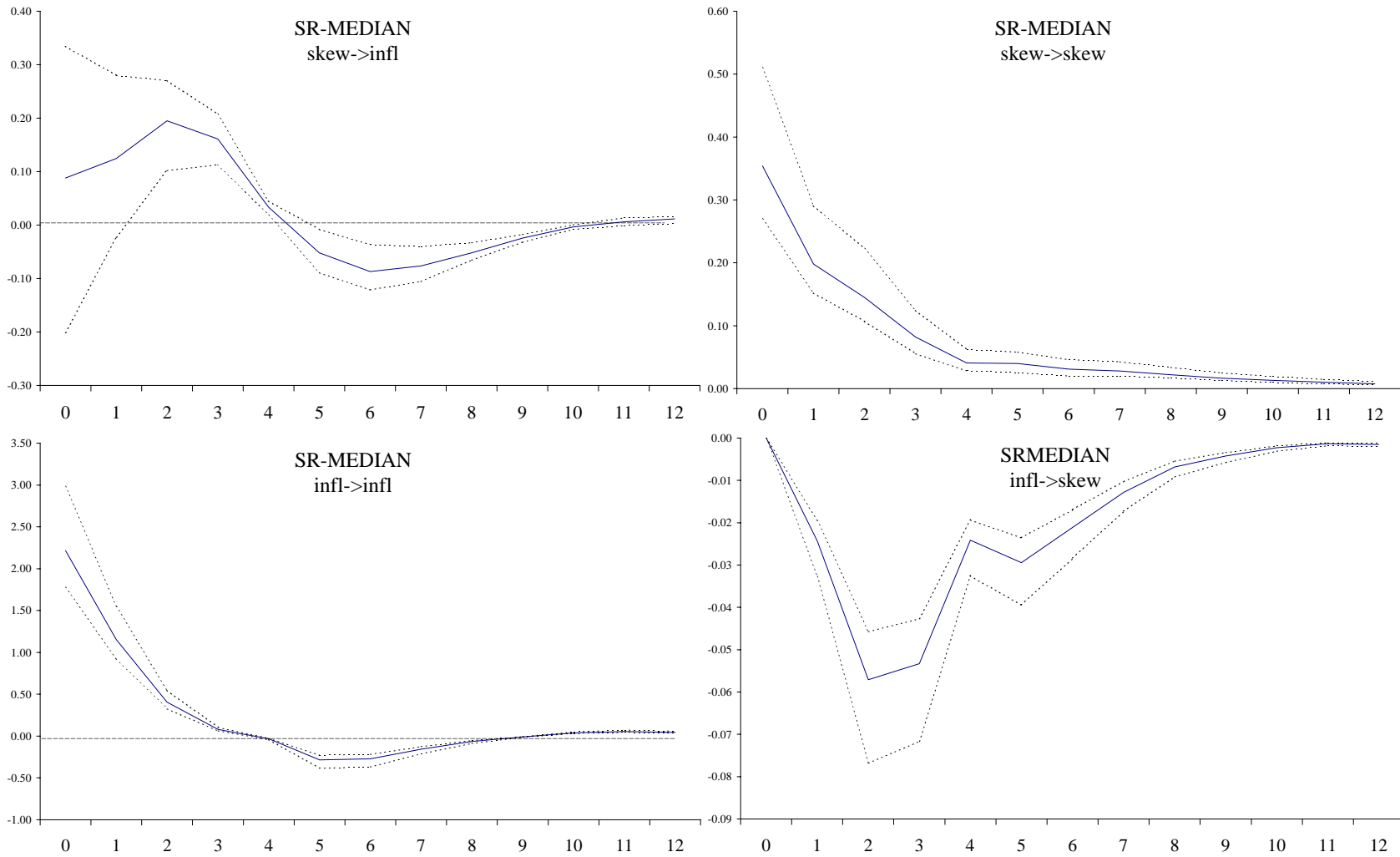
Note: Dashed lines are the upper and lower quartiles, the solid line is the median of impulse responses across products.
Horizontal axis: months following shock

Figure Va
 Impulse Response Functions
 Panel VAR



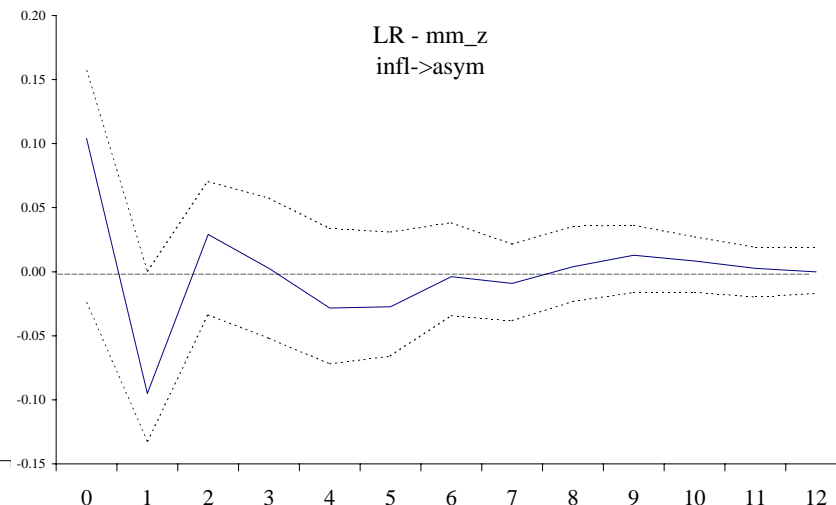
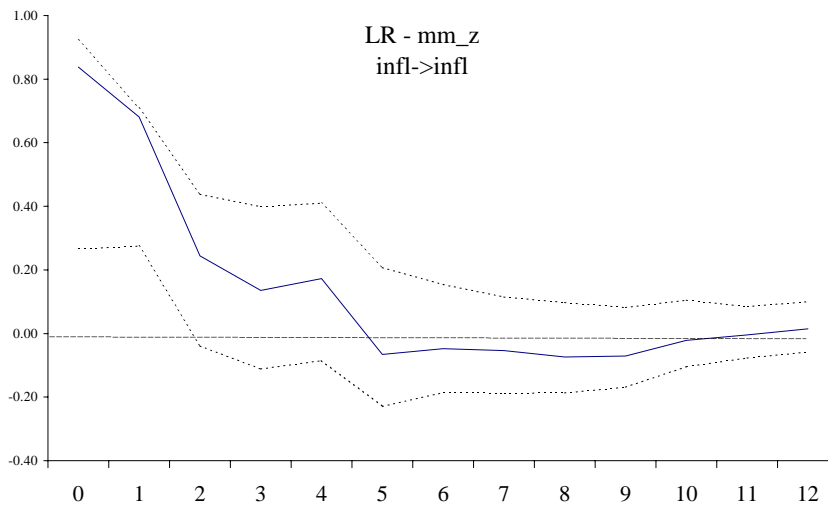
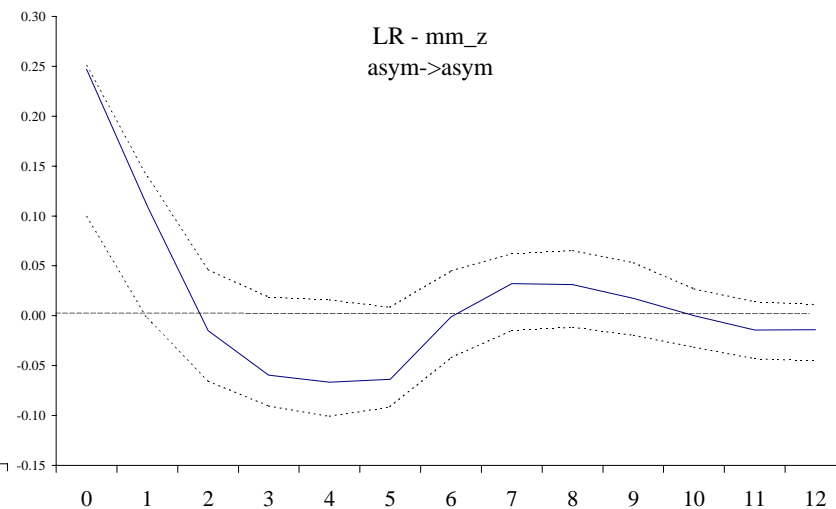
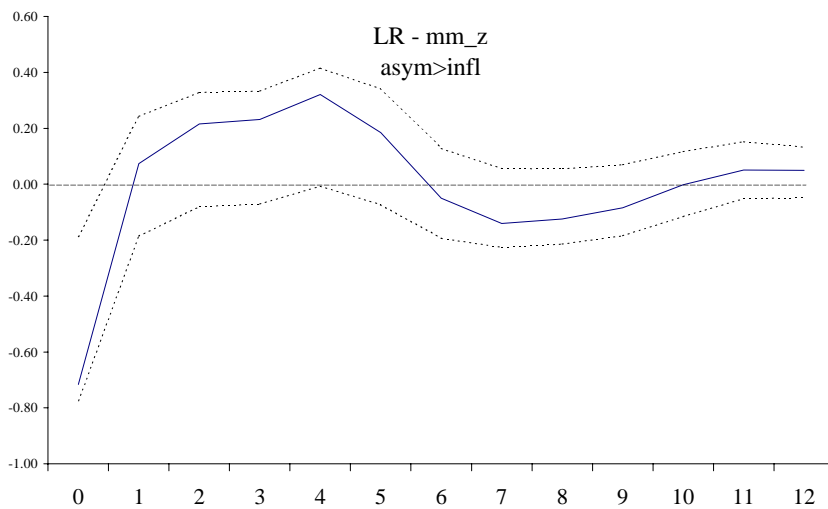
Note: Dashed lines are the upper and lower quartiles, the solid line is the median of impulse responses across products.
 Horizontal axis: months following shock

Figure Vb
Impulse Response Functions
Panel VAR



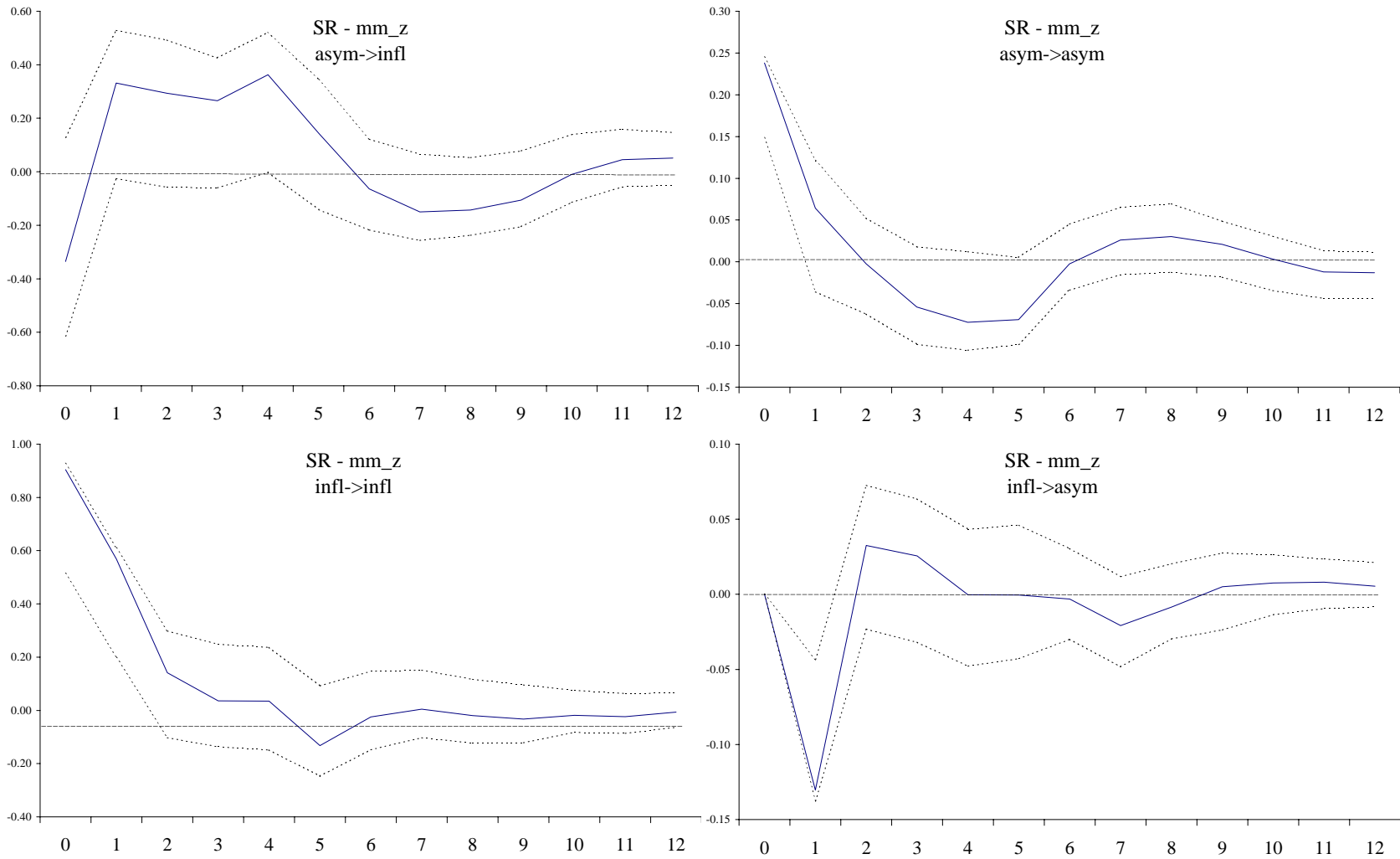
Note: Dashed lines are the upper and lower quartiles, the solid line is the median of impulse responses across products.
Horizontal axis: months following shock

Figure VIa
Impulse Response Functions
(Pooled Data)



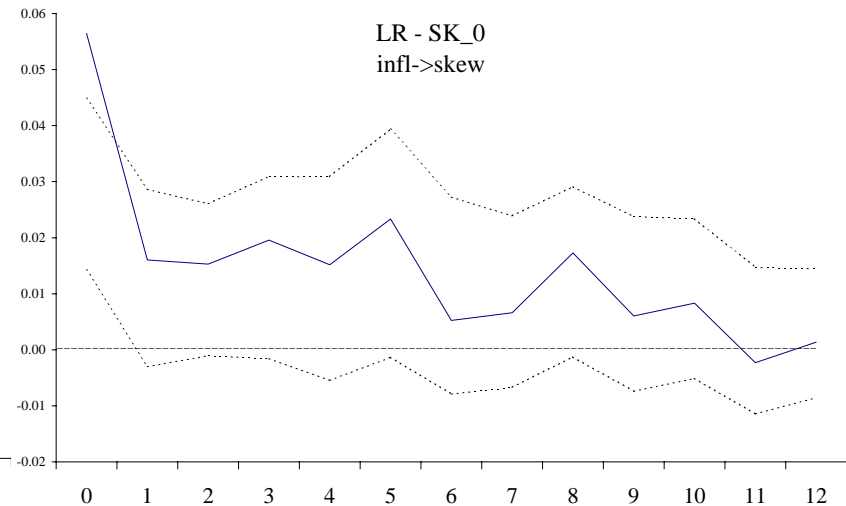
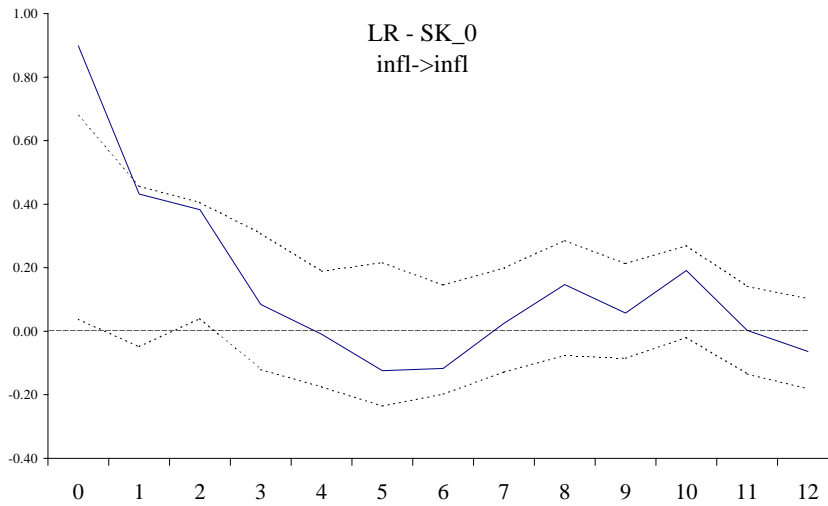
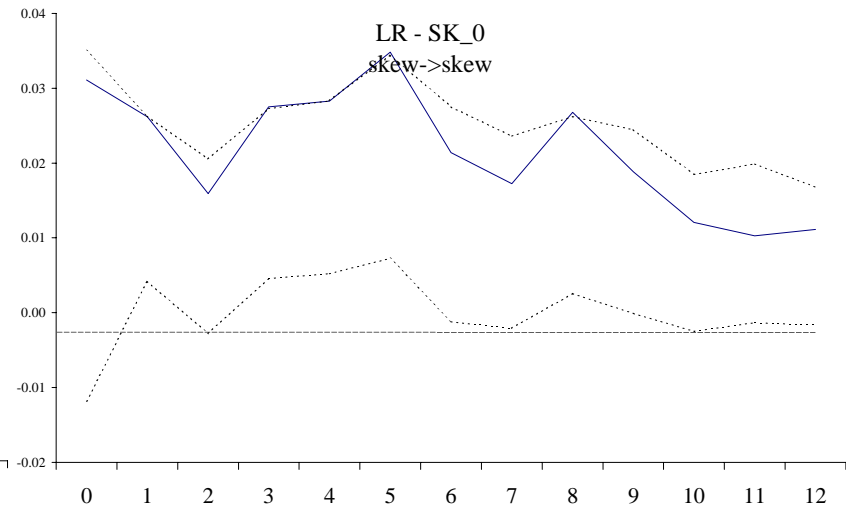
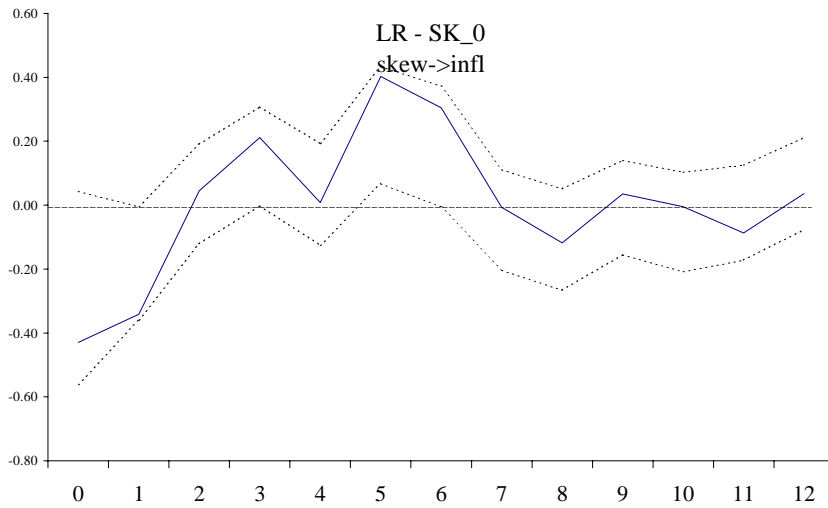
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.
Horizontal axis: months following shock

Figure VIb
Impulse Response Functions
(Pooled Data)



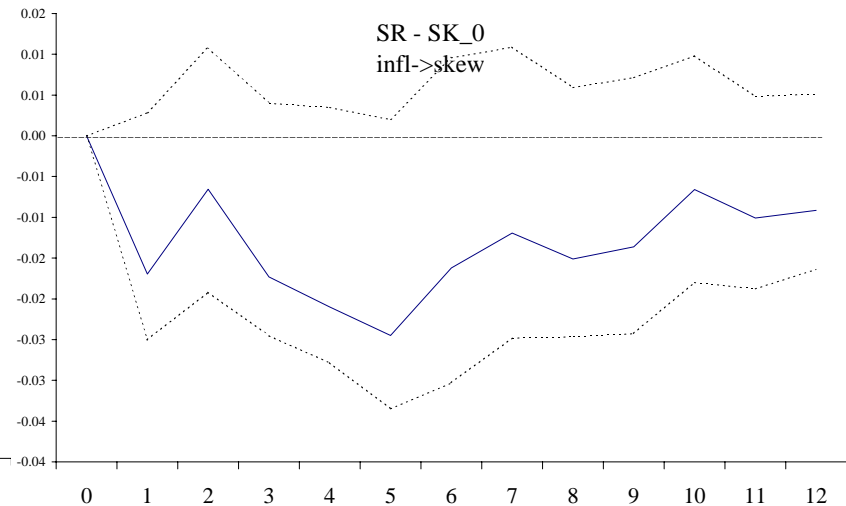
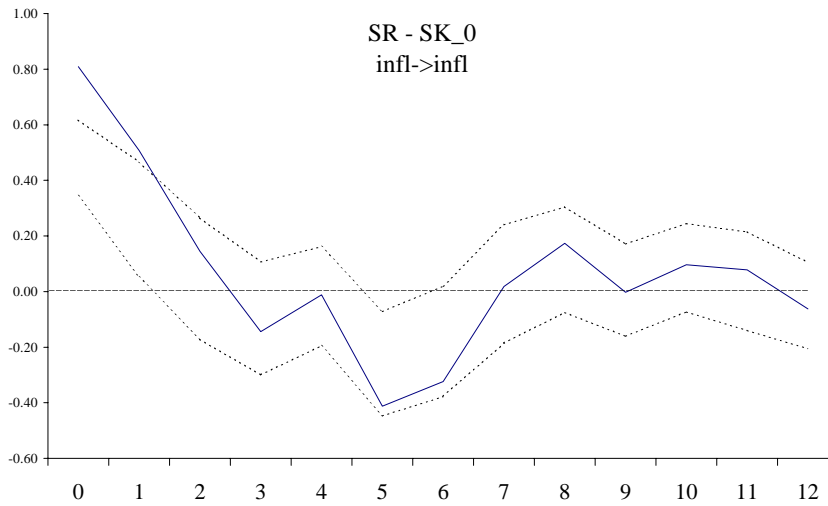
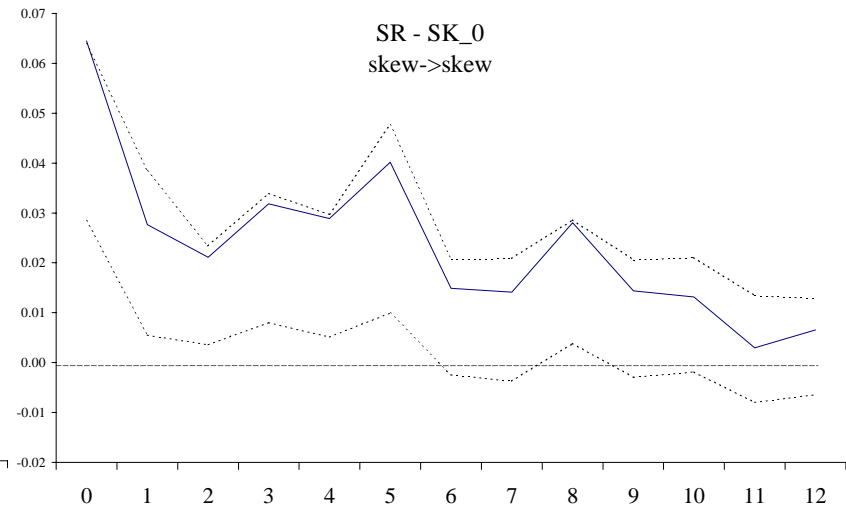
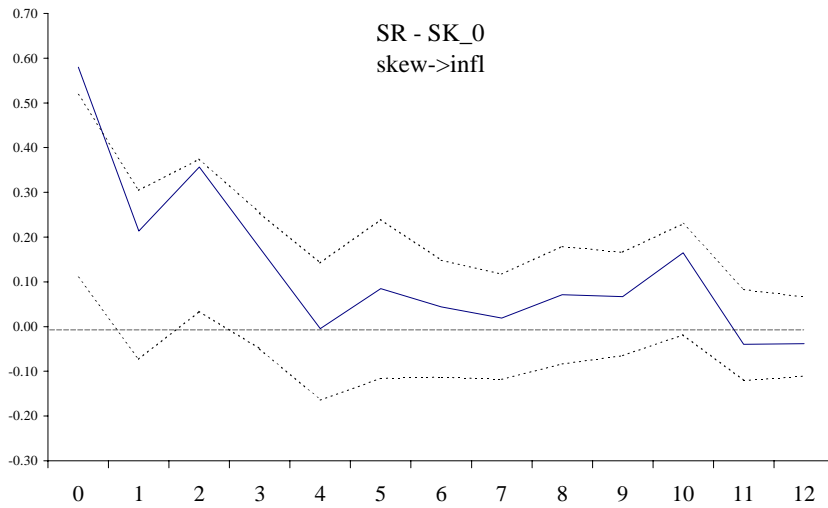
Note: Dashed lines are 90 percent Runkle (1987) confidence bands.
Horizontal axis: months following shock

Figure VIIa
Impulse Response Functions
(Pooled Data)



Note: Dashed lines are 90 percent Runkle (1987) confidence bands.
Horizontal axis: months following shock

Figure VIIb
 Impulse Response Functions
 (Pooled Data)



Note: Dashed lines are 90 percent Runkle (1987) confidence bands.
 Horizontal axis: months following shock