

Investigating Inflation Transmission by Stages of Processing

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1 Introduction

At the time of the 1973–74 oil price shock, the featured index for the US Bureau of Labor Statistics Producer Price Index program was “All Commodities.” For some time, this index was dominated by effects of oil prices as their effects spread to refined petroleum producers and other producers experiencing higher energy prices. Critics complained that the single summary index gave a very limited picture of what was happening in prices. In 1978, BLS shifted its publication emphasis to a stage of processing (SOP) system. As explained by Gaddie and Zoller (1988):

The basic idea of a stage of process system is that the economy can be subdivided into distinct economic segments which can be arranged sequentially so that the outputs of earlier segments become inputs to subsequent ones, up through final demand. . . . To the extent that such a sequential system of processing stages can be defined, it is possible to trace the transmission of price change through the economy and to develop information on both the timing and magnitude of price pass-throughs to final demand.

The initial SOP system (Popkin, 1974) is based on allocating products or commodities to three stages, Crude, Intermediate, and Finished, based on their degree of fabrication and end use. These will be denoted CSOP, since they are commodity-based. The Finished Goods index, representing goods nearest final consumption, is usually emphasized in press releases. Crude and Intermediate indexes are watched as possible indicators of future movements in Finished Goods.

A second SOP system (Gaddie and Zoller, 1988), denoted ISOP, with data available from June 1985, dovetails with an improved, industry-based sample

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design, introduced gradually over the 1978–85 period. In statistical terms, the redesign represents probability sampling of products made by individual industries under the SIC (Standard Industrial Classification) system. In conceptual terms, the ISOP represents an interindustry flow model for the economy. Using the Bureau of Economic Analysis (BEA) Input/Output tables, transaction flows between producing and consuming industries can be estimated. Four stages, Crude, Primary, Semifinished, and Finished Goods Producers, are derived as weighted averages of component SIC indexes.

Table 1 shows ISOP industry composition and transaction flow. Overall, the Crude stage represents about 10 percent of covered transactions, and the other stages roughly 30 percent each. The CSOP distribution for the three stages Crude, Intermediate, and Finished is roughly 10–50–40. Since these stages are formed by putting together commodities, wherever made, other statistics like those in Table 1 are not available for the CSOP. Following many analysts, we emphasize “core” SOPs, that is, indexes which exclude Food and Energy sectors, each representing about 15 percent of the total. These components are obviously important, but their volatility may mask other relationships in the data. The core PPI is almost entirely manufacturing; in moving from Crude to Finished the shares of Durable and Nondurable roughly reverse with Crude containing about 20 percent Durable and Finished about 80 percent Durable. The current ISOP industry coverage is quite limited. In recent years, many indexes in the service-producing industries have been added, but they are not yet in the existing ISOP.

As a starting point for partitioning industries into stages, we have an input/output table showing transaction flows between producing and consuming industries, a matrix like Table 1C, but with roughly 500 detailed industries. As indicated in the definition, the aim is to order these industries so that for a given row, representing a producing industry, most of the output is to subsequent industries, i.e., to industries to the right of the matrix diagonal. Companies, however, make such a variety of products, and their products are consumed by such a variety of industries, that no ordering produces a purely upper triangular matrix. Gaddie and Zoller’s efforts to maximize “forward flow” and limit “internal flow” (consumption within the stage where produced) and “backward flow” (consumption by previous stages) are rather successful. The flow summary of Table 1D shows that the ISOP achieves a forward flow exceeding 80 percent, while backward flow and internal flow are 6 percent and 11 percent, respectively. A possible shortcoming, however, is that 30 percent of transactions skip one or more stages. For example, roughly 30–40 percent of output of each of the first three stages goes to Final Demand (products for personal consumption or capital investment). Thus, for instance, output from Primary differs considerably from input to Semifinished.

Success in analyzing price transmission among stages and to consumer prices has been limited. Matthey (1990), who makes an extra effort to extend the

Table 1. Composition of SO

A. Transactions (billions of dollars)

	Crude	Primary
Food	39.4	13.8
Energy	138.7	38.5
Core	253.0	54.3
Total	431.1	106.6

B. Industry sector distribution

Industry sector

Mining
Nondurable manufacturing
Durable manufacturing
Total

C. Transaction flows among stages

Producing stages	Consuming stages	
	Crude	Primary
Crude	22	2
Primary	8	1
Semifinished	6	
Finished	2	

We would like to thank Soon Park for his helpful comments.

D. Transaction flow summary

Backward	Internal	Forward
6	11	83

ISOP data available at the BEA website, which explicitly compares the ISOP with the CSOP between output from one stage to the next, and leakage, in the ISOP equivalent to the CSOP. An advantage with the ISOP is that it provides an advantage with the ISOP over the CSOP. Engle (1977), Engle (1986), Blanchard (1986), and many others have fo

Table 1. Composition of SOPs by industry sector (based on 1992 value of shipments)

<i>A. Transactions (billions of dollars)</i>					
	Crude	Primary	Semifinished	Finished	Total
Food	39.4	134.9	200.3	198.7	573.3
Energy	138.7	389.8	0	0	528.5
Core	253.0	543.8	858.4	831.8	2487.0
Total	431.1	1068.5	1058.7	1030.5	3588.8

B. Industry sector distribution within core SOPs

Industry sector	Crude	Primary	Semifinished	Finished
Mining	6	1	0	0
Nondurable manufacturing	75	53	30	22
Durable manufacturing	19	46	70	78
Total	100	100	100	100

C. Transaction flows among ISOP

Producing stages	Consuming stages					Total
	Crude	Primary	Semifinished	Finished	Final demand	
Crude	22	23	9	17	29	100
Primary	8	14	21	20	37	100
Semifinished	6	6	11	34	43	100
Finished	2	2	1	5	90	100

We would like to thank Soon Paik at BLS for this table.

D. Transaction flow summary (%)

Backward	Internal	Forward (1)	Skip
6	11	53	30

ISOP data available at the time, has the only analytic study we have seen which explicitly compares CSOP and ISOP. Pointing out large flow differences between output from one stage and input to the next stage, due to skips and leakage, in the ISOP equations he uses the ISOP input indexes for input prices, an advantage with the ISOP, and finds forecast performance are similar for the two SOPs. Engle (1978), Silver and Wallace (1980), Granger, Robins, and Engle (1986), Blanchard (1987), Boughton and Branson (1991), Clark (1995), and many others have found evidence of price transmission among stages or

evidence that changes in producer prices Granger-cause changes in consumer prices. Boughton and Branson find that producer prices and the CPI are not cointegrated, yet find a weak short-run relationship in which commodity prices help predict future CPI inflation. It is often found that the relationships between PPI and CPI are weak especially in terms of out-of-sample forecast performance.

The focus of the present paper is on inflation transmission among stages of producer prices and on transmission to consumer prices, and has been undertaken as part of a BLS effort to examine the usefulness of SOPs. The study employs multiple time series methods, and benefits from greater data availability for some of the indexes than the previous studies. Our results show that meaningful relationships exist between processing stages, and that consumer prices are strongly related to CSOP Finished Goods prices.

2 Modeling Inflation Transmission

In this section we describe how vector error correction models (VECM) can be employed to examine the sources of inflation and its transmission. We show how cointegration can be used in a VAR system to identify common stochastic trends subject to permanent changes in inflation rates and how we may investigate the system's responses to permanent shocks.

The data we will analyze are the CSOP which has been generated back to 1947 and the ISOP which starts in June 1985. Thus, our analyses are carried out for 11-year spans, June 1985 through May 1996. All PPI series are core indexes, excluding Food and Energy. CPI series is a core index excluding food, energy, and used cars. All series are monthly, seasonally adjusted, and transformed in logarithms.

In our empirical study the logarithms of all series are characterized as I(1) processes according to the augmented Dickey-Fuller and Phillips-Perron tests. The PPI inflation series in all stages are clearly mean-reverting in both ISOP and CSOP. CPI series display upward trends and their first difference shows rather smoother series than PPI series. In other studies where CPI series is used (e.g. Mehra, 1991), it is often found that the inflation series, the first differences of log prices, are I(1). However, it was not the case in our data.

Consider an SOP system with p stages, and let $X_t = (x_{1t} \dots x_{pt})'$ be the PPI indexes. For example, in the ISOP output index system, $p = 4$ and the elements of X_t are PPI indexes for Crude, Primary, Semifinished, and Finished processors. Let X_t be I(1) and cointegrated with cointegrating rank r ; that is, there exists a $p \times r$ matrix β of rank r ($< p$) such that $\beta' X_t$ is I(0). Then the system can be generated from the VECM

$$\Delta X_t = \mu + \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_k \Delta X_{t-k} + \epsilon_t, \quad (1)$$

where Π and Γ s are $p \times p$, and impact matrix Π should then be chosen for suitable $p \times r$ matrices α .

We estimate the VECM given above, and transform it to a vector moving average

$$\Delta X_t = \mu + C(B)\epsilon_t,$$

where $C(B)$ is a $p \times p$ matrix polynomial. We identify the common factor r as

$$\Delta X_t = \mu + \Gamma(B)\eta_t,$$

where $\Gamma(B) = C(B)\Gamma_0$ and η_t is a $p \times 1$ vector. Partition the structural shock η_t into r common factors $(\eta_{1t}, \dots, \eta_{rt})'$ and η_{it}^2 is $r \times 1$. Let Γ_0 be a $p \times r$ null matrix. Then, η_t can be written:

$$X_t = X_0 + \mu t + Ah_t + \bar{X}_t,$$

where X_0 is initial values at $t=0$, μ is $(p-r) \times 1$ I(1) common factor, \bar{X}_t is $(p-r) \times 1$ I(0) transitory component, deterministic trend, X_t can thus be written as $X_t^P = Ah_t$ and the transitory component \bar{X}_t explained in terms of a small number of common factors which are thus called common factors.

Let η_{it} ($i = 1, \dots, p-r$) be the common factors. $h_{it} = h_{i,t-1} + \eta_{it}$, η_{it}^1 may be called X_t^P , while the remaining $p-r$ elements of A are the long-run multipliers. $A = \lim_{n \rightarrow \infty} \partial X_t / \partial \eta_{t-n}^1$. The limit is zero because $\Gamma^*(B)$ is absolutely summable.

If X_t is cointegrated, i.e., $\beta' X_t$ is I(0), the process X_t^P is not cointegrated. Let β be a $p \times r$ matrix of full rank such that $\beta' X_t$ is I(0) (1995, p. 95). Keeping in mind the above conditions leading to the estimation of the long-run multipliers (impulse responses), we have

Assumption 1. Θ is a $(p-r) \times (p-r)$ matrix.

Assumption 2. The permanent component, i.e., $\Sigma_\eta = E(\eta_t \eta_t')$ is block diagonal.

Assumption 3. The permanent component, i.e., Σ_η is diagonal. ■

where Π and Γ s are $p \times p$, and ϵ_t is a $p \times 1$ vector white noise. The long-run impact matrix Π should then be of rank r and can be expressed as $\Pi = \alpha\beta'$ for suitable $p \times r$ matrices α and β .

We estimate the VECM given by (1) following Johansen (1995), and then transform it to a vector moving average model

$$\Delta X_t = \mu + C(B)\epsilon_t, \quad (2)$$

where $C(B)$ is a $p \times p$ matrix polynomial in the backshift operator B . To identify the common factor h_t we rewrite (2) as

$$\Delta X_t = \mu + \Gamma(B)\eta_t, \quad (3)$$

where $\Gamma(B) = C(B)\Gamma_0$ and $\eta_t = \Gamma_0^{-1}\epsilon_t$ for some nonsingular $p \times p$ matrix Γ_0 . Partition the structural shocks $\eta_t = (\eta_t^1 \eta_t^2)'$ such that η_t^1 consists of η_{it} ($i = 1, \dots, p-r$) and η_t^2 is $r \times 1$. We choose Γ_0 so that $\Gamma(1) = (A \mathbf{0})$ with $\mathbf{0}$ being a $p \times r$ null matrix. Then, using the expansion $\Gamma(B) = \Gamma(1) + \Delta\Gamma^*(B)$, (3) can be written:

$$X_t = X_0 + \mu t + Ah_t + \tilde{X}_t, \quad (4)$$

where X_0 is initial values at $t = 0$, μ is $p \times 1$, A is $p \times (p-r)$, $h_t = \sum_{n=0}^{\infty} \eta_{t-n}^1$ is $(p-r) \times 1$ I(1) common stochastic trends, and $\tilde{X}_t \equiv \Gamma^*(B)\eta_t$ consists of $p \times 1$ I(0) transitory components. Apart from the initial values and the deterministic trend, X_t can thus be decomposed into the permanent component $X_t^P = Ah_t$ and the transitory component $X_t^T = \tilde{X}_t$. The elements of X_t can be explained in terms of a smaller number $(p-r)$ of I(1) variables comprising h_t , which are thus called common factors.

Let η_{it} ($i = 1, \dots, p-r$) be the innovations to each stochastic trend h_{it} , i.e., $h_{it} = h_{i,t-1} + \eta_{it}$. η_{it}^1 may be called the permanent shocks because they construct X_t^P , while the remaining shocks η_{it}^2 may be called the transitory shock. The elements of A are the long-run multipliers of the permanent shock η_{it}^1 , that is, $A = \lim_{n \rightarrow \infty} \partial X_t / \partial \eta_{t-n}^1$. The long-run multiplier of the transitory shock η_{it}^2 is zero because $\Gamma^*(B)$ is absolutely summable.

If X_t is cointegrated, i.e., $\beta'X_t$ is I(0), then $\beta'X_t^P = 0$ so $\beta'A = 0$ (because the process X_t^P is not cointegrated). Thus let $A = \beta_{\perp}\Theta$ where β_{\perp} is a $p \times (p-r)$ matrix of full rank such that $\beta'\beta_{\perp} = 0$. β_{\perp} may be estimated following Johansen (1995, p. 95). Keeping in mind our prices application, we make several assumptions leading to the estimation of the long-run multipliers A and the short-run multipliers (impulse responses) of the permanent shocks η_{it}^1 .

Assumption 1. Θ is a $(p-r) \times (p-r)$ lower triangular matrix of full rank. ■

Assumption 2. The permanent shocks and the transitory shocks are uncorrelated, i.e., $\Sigma_{\eta} = E(\eta_t\eta_t')$ is block diagonal. ■

Assumption 3. The permanent shocks η_{it}^1 are uncorrelated, i.e., $\Sigma_{\eta^1} = E(\eta_{it}^1\eta_{it}^1')$ is diagonal. ■

Under Assumptions 1 and 2 we have

$$C(1)\Sigma_\epsilon C(1)' = \Gamma(1)\Sigma_\eta\Gamma(1)' = A\Sigma_{\eta_1}A' = \hat{\beta}_\perp\Theta\Sigma_{\eta_1}\Theta'\hat{\beta}_\perp', \tag{5}$$

where Σ_ϵ is $\text{cov}(\hat{\epsilon})$. Pre- and post-multiplying this by $\bar{\beta}_\perp = \hat{\beta}_\perp(\hat{\beta}_\perp'\hat{\beta}_\perp)^{-1}$ yields:

$$\Theta\Sigma_{\eta_1}\Theta' = \bar{\beta}_\perp' C(1)\Sigma_\epsilon C(1)' \bar{\beta}_\perp. \tag{6}$$

Under Assumption 3, Θ and Σ_{η_1} can be estimated from a Choleski decomposition of (6) either by normalizing the diagonal elements of Θ or by standardizing the permanent shocks with $\Sigma_{\eta_1} = I_{(p-r)}$.

When there is one common factor ($p - r = 1$), the permanent shock η_{1t} may be easily attached with some structural meaning. When there are more than one permanent shocks ($p - r > 1$), it may be hard to give η_{it} ($i = 1, \dots, p - r$) structural interpretation unless some additional a priori structural information is provided on the long-run multiplier A or on β_\perp . Let $\beta_\perp = \bar{A}Q$ and $\Pi = Q\Theta$ so that $A = \beta_\perp\Theta = \bar{A}Q\Theta = \bar{A}\Pi$. Then we can obtain:

$$\Pi\Sigma_{\eta_1}\Pi' = \bar{A}' C(1)\Sigma_\epsilon C(1)' \bar{A}, \tag{7}$$

where $\bar{A} = \bar{A}(\bar{A}'\bar{A})^{-1}$. Having derived this expression, King *et al.* (1991, p. 831) impose structural information obtained from economic theory onto \bar{A} and assume Π is lower triangular, that requires Q be lower triangular (which we will also assume). To estimate Π and Σ_{η_1} from the Choleski decomposition of (7) the diagonal element of Π is normalized (i.e., $\pi_{ii} = 1$).

If an SOP system is effective, it will contain information on the size and direction of inflation transmission. Forward flow corresponds to supply shocks, and backward flow to demand shocks. Recall that in the ISOP only 6 percent of shipment flows are backward flow, so the stages do contain directionality in terms of supply and demand. We assume that permanent inflation shocks are supply-driven and demand-driven effects are transitory:

Assumption 4. Let $\bar{A} = (I_p - c(\beta'c)^{-1}\beta')c_\perp$ where $c = (\mathbf{0} \ I_r)'$ is $p \times r$ and $c_\perp = (I_{p-r} \ \mathbf{0})'$ is $p \times (p - r)$. Q is a $(p - r) \times (p - r)$ lower triangular matrix of full rank. ■

For the expression of \bar{A} , see Johansen (1995, p. 48). Under Assumptions 1 and 4, $\Pi = Q\Theta$ is lower triangular, which makes the first $(p - r)$ rows of $\beta_\perp = \bar{A}Q$ lower triangular. This means that only forward shock propagation has a long-run effect. The price indexes in the later stages include the permanent components of the previous stages (x_{i+1}^P contains x_i^P , $i = 1, 2, \dots, p - 1$), but not vice versa. It should be noted that no such an assumption is imposed for the transitory components.

With the normalization $\beta = (-\phi \ I_r)'$ where ϕ is $r \times (p - r)$, $\bar{A} = (I_{p-r} \ \phi)'$. Then the permanent component $X_t^P = Ah_t = \bar{A}\Pi h_t$ is partitioned to $X_t^{1P} = \Pi h_t$ and $X_t^{2P} = \phi\Pi h_t$. In this representation of a cointegrated system, the first

$(p - r)$ elements (X_t^1) are co-integrated. The remaining r elements (X_t^2) can be expressed as $\Delta X_t^2 = u_t^2$ and $X_t^2 = \phi X_t^1 + \dots$. This process with full rank spectral density has been used by Phillips (1995).

Assumption 4 may be tested. This test has not yet been available. Testing for Granger-causality between the values of the F -statistics to the permanent component x_j for ISOP and CSOP are significant at the 0.050 (say), indicate the presence of inflation transmission from x_i to x_j . Values above the diagonal in the matrix of the Granger causality tests indicate that the Granger causality tests where feedback exists from x_j to x_i . The results are consistent with Assumption 4 (inflation transmission).

ISOP		
$x_j \setminus x_i$	x_1	x_2
x_1		.000
x_2	.000	
x_3	.015	.010
x_4	.769	.243

Because Assumption 4 is not testable in the long run. The full causality matrix based on the spectral decomposition of the long-run matrix in extent or direction at low frequencies. The definition provided by Ho and Phillips (1995) for testing Granger-causality at low frequencies. The error correction coefficients are significant. The results of testing $H_0 : \alpha < \alpha_c$ above Granger causality rejection.

The representation $A = \beta_\perp\Theta$ is used in Assumption 4. Future work will explore the application or use the general representation.

So far in this section we have discussed the assumptions, we can also test the assumptions. The first $(p - r)$ columns of the permanent shocks η_t^1 , and the remaining r columns respond to the permanent components of the first $(p - r)$ columns of $\Gamma(1)$ of x_{it} ($i = 1, \dots, p$) to each

$(p-r)$ elements (X_t^1) are considered as common factors because the remaining r elements (X_t^2) can be expressed as a linear combination of X_t^1 ; that is, $\Delta X_t^1 = u_t^1$ and $X_t^2 = \phi X_t^1 + u_t^2$ where $u_t = (u_t^1 \ u_t^2)'$ is a stationary stochastic process with full rank spectral density matrix. This triangular representation has been used by Phillips (1991) and Stock and Watson (1993).

Assumption 4 may be tested using β_{\perp} but it is not so simple and the test has not yet been available. Instead, we check the validity of Assumption 4 by testing for Granger-causality between x_i and x_j ($i, j = 1, \dots, p, i \neq j$). The p -values of the F -statistics to test the hypothesis that x_i does not Granger-cause x_j for ISOP and CSOP are shown below. The significant p -values, smaller than 0.050 (say), indicate the presence of Granger-causality and suggest the inflation transmission from x_i and x_j . The p -value matrices with insignificant p -values above the diagonal would be consistent with Assumption 4. For ISOP, the Granger causality tests generally support Assumption 4 except for one case where feedback exists from Primary (x_2) to Crude (x_1). For CSOP the test results are consistent with Assumption 4 for all cases (with one marginal exception).

ISOP					CSOP			
$x_j \setminus x_i$	x_1	x_2	x_3	x_4	$x_j \setminus x_i$	x_1	x_2	x_3
x_1		.000	.983	.868	x_1		.115	.079
x_2	.000		.185	.975	x_2	.054		.154
x_3	.015	.010		.754	x_3	.032	.002	
x_4	.769	.243	.002					

Because Assumption 4 is about permanent shocks, we also focus on causality in the *long* run. The full causal relationship can be decomposed by frequency based on the spectral decomposition of the series. Causality may be different in extent or direction at low frequencies than at other frequencies. Using the definition provided by Hosoya (1991), Granger and Lin (1995) show that Granger-causality at low frequencies in a cointegrated system depend on the error correction coefficients α . In Tables 2 and 3 discussed in the next section, the results of testing $H_0: \alpha_i = 0$ ($i = 1, \dots, p$) are entirely consistent with the above Granger causality results.

The representation $A = \beta_{\perp} \Theta$ admits more general forms than those adopted in Assumption 4. Future work could adopt other forms fitting a particular application or use the general form for testing assumptions such as Assumption 4.

So far in this section we have discussed the long-run multipliers A . Under the assumptions, we can also determine short-run multipliers of the permanent shocks. The first $(p-r)$ columns of $\Gamma(B)$ show how the series ΔX_t respond to the permanent shocks η_t^1 , and their accumulated sums show how the series X_t respond to the permanent shocks η_t^1 . See King *et al.* (1991) for estimation of the first $(p-r)$ columns of $\Gamma(B)$. Denoted by ${}_i R_j(n) = \partial x_{it} / \partial \eta_{j,t-n}$ is the response of x_{it} ($i = 1, \dots, p$) to each permanent shock $\eta_{j,t-n}$ that occurred n periods ago

($j = 1, \dots, p - r, n = 0, 1, \dots$). It may be noted that the ij th element of A is $\lim_{n \rightarrow \infty} R_j(n)$.

Since the VECM can be used for forecasting, we also compute the fraction of the h step ahead forecast error variance of $\Delta x_{i,t+h}$ ($i = 1, \dots, p$) attributed to each permanent shock η_{jt} ($j = 1, \dots, p - r$), which is given by:

$$\omega_{ij,h} = \sum_{n=0}^{h-1} (\gamma_{ij,n}^2 \Sigma_{\eta}^{jj}) / \text{MSE}_i(h),$$

where $\gamma_{ij,n}$ is the ij th element of Γ_n with Γ_n being defined from $\Gamma(B) = \sum_{n=0}^{\infty} \Gamma_n B^n$, Σ_{η}^{jj} is the j th diagonal element of Σ_{η} , and $\text{MSE}_i(h)$ is the i th diagonal element of the mean squared error matrix of the optimal h step ahead forecast of ΔX_t , $\text{MSE}(h) = \sum_{n=0}^{h-1} \Gamma_n \Sigma_{\eta} \Gamma_n' = \sum_{n=0}^{h-1} C_n \Sigma_{\epsilon} C_n'$. The estimated $\omega_{ij,h}$ provides information about the relative importance of permanent shocks in h step ahead forecasts of ΔX_t .

3 Inflation Transmission among SOPs

3.1 ISOP

We have analyzed and found positive results based on the reduced form model (2) and with respect to the shocks ϵ_t , allowing backward transmission, as found between the Primary and Crude stages. Here, however, we apply the structural model (3) with Assumptions 1–4, both for comparison with CSOP and for the appeal of the simplified generating mechanism with the common factor representation (4).

Table 2 reports the results of testing for cointegration (Panel A), testing for restrictions on α and β , testing for residual autocorrelations in each equation in the system (Panel B), the ML estimates of \bar{A} , Π , and A (Panel C), and variance decompositions with simulated standard errors computed using 300 replications in parentheses (Panel D). The lag length $k = 5$ in the VECM is chosen using the Akaike and Schwarz information criteria (AIC and SIC) as well as the battery of residual diagnostics. The ISOP series $X_t = (x_{1t} x_{2t} x_{3t} x_{4t})'$ are cointegrated with three common stochastic trends.

In Panel B, following Johansen (1995), we test for weak exogeneity and for long-run exclusion. The tests for long-run exclusion are based on the hypothesis that a subset of the variables in X_t does not enter the cointegration space, which, if not rejected, implies that the variables in question can be omitted from the long-run relations between the ISOPs. The hypothesis is $H_0 : \beta_i = 0$ for each $i = 1, 2, 3, 4$. The results show that all of them are significant. Similar tests have been performed on the rows of α , corresponding to tests for weak exogeneity and also for Granger-causality in the long run. They can be formulated as $H_0 : \alpha_i = 0$ for each $i = 1, 2, 3, 4$, that the i th component in X_t is not

A. Testing for cointegrating rank (with $k = 5$ lags)

H_0	trace	λ_{\max}
$r = 0$	64.65***	46.21***
$r = 1$	18.44	13.11
$r = 2$	5.33	4.28
$r = 3$	1.06	1.06

*** denotes significance at 1% level.

B. Testing for $H_0 : \alpha_i = 0$ and $H_0 :$

ith equation	$H_0 : \alpha_i = 0$
$i = 1$.00013
$i = 2$.42919
$i = 3$.00006
$i = 4$.03046

C. Estimation of the long run multi

$$\bar{A} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1.08 & -2.77 & 2.19 \end{bmatrix} \quad \Pi =$$

D. Fractions of forecast error variance

h	η_1			
	$i = 1$	$i = 2$	$i = 3$	$i = 4$
1	.805 (.047)	.487 (.085)	.051 (.058)	.000 (.022)
2	.818 (.060)	.708 (.073)	.453 (.105)	.025 (.059)
12	.861 (.060)	.770 (.064)	.452 (.084)	.300 (.083)
60	.848 (.058)	.774 (.061)	.451 (.084)	.305 (.085)

Monte Carlo standard errors are in

Table 2. ISOP

A. Testing for cointegrating rank (with $k = 5$ lags)

H_0	trace	λ_{max}
$r = 0$	64.65***	46.21***
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$r = 2$	5.33	4.28
$r = 3$	1.06	1.06

*** denotes significance at 1% level.

B. Testing for $H_0 : \alpha_i = 0$ and $H_0 : \beta_i = 0$, and residual diagnostics (p-values)

ith equation	$H_0 : \alpha_i = 0$	$H_0 : \beta_i = 0$	Ljung-Box tests for ε_i
$i = 1$.00013	.00000	.86
$i = 2$.42919	.00000	.65
$i = 3$.00006	.00379	.93
$i = 4$.03046	.04109	.87

C. Estimation of the long run multiplier

$$\bar{A} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1.08 & -2.77 & 2.19 \end{bmatrix} \quad \Pi = \begin{pmatrix} 1 & 0 & 0 \\ .42 & 1 & 0 \\ -.002 & 1.76 & 1 \end{pmatrix} \quad A = \begin{bmatrix} 1 & 0 & 0 \\ .42 & 1 & 0 \\ -.002 & 1.76 & 1 \\ .08 & 1.10 & 2.19 \end{bmatrix}$$

D. Fractions of forecast error variance, $\omega_{ij,h}$, for Δx_{t+h} attributed to η_j

h	η_1				η_2				η_3			
	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 1$	$i = 2$	$i = 3$	$i = 4$
1	.805 (.047)	.487 (.085)	.051 (.058)	.000 (.022)	.014 (.026)	.265 (.079)	.581 (.161)	.161 (.171)	.040 (.030)	.017 (.042)	.218 (.168)	.749 (.172)
2	.818 (.060)	.708 (.073)	.453 (.105)	.025 (.059)	.043 (.028)	.106 (.040)	.258 (.082)	.150 (.157)	.040 (.032)	.011 (.019)	.093 (.078)	.695 (.162)
12	.861 (.060)	.770 (.064)	.452 (.084)	.300 (.083)	.035 (.035)	.069 (.028)	.241 (.072)	.155 (.094)	.068 (.030)	.058 (.024)	.137 (.058)	.454 (.113)
60	.848 (.058)	.774 (.061)	.451 (.084)	.305 (.085)	.038 (.035)	.066 (.027)	.241 (.073)	.155 (.091)	.082 (.034)	.065 (.026)	.140 (.057)	.452 (.112)

Monte Carlo standard errors are in brackets.

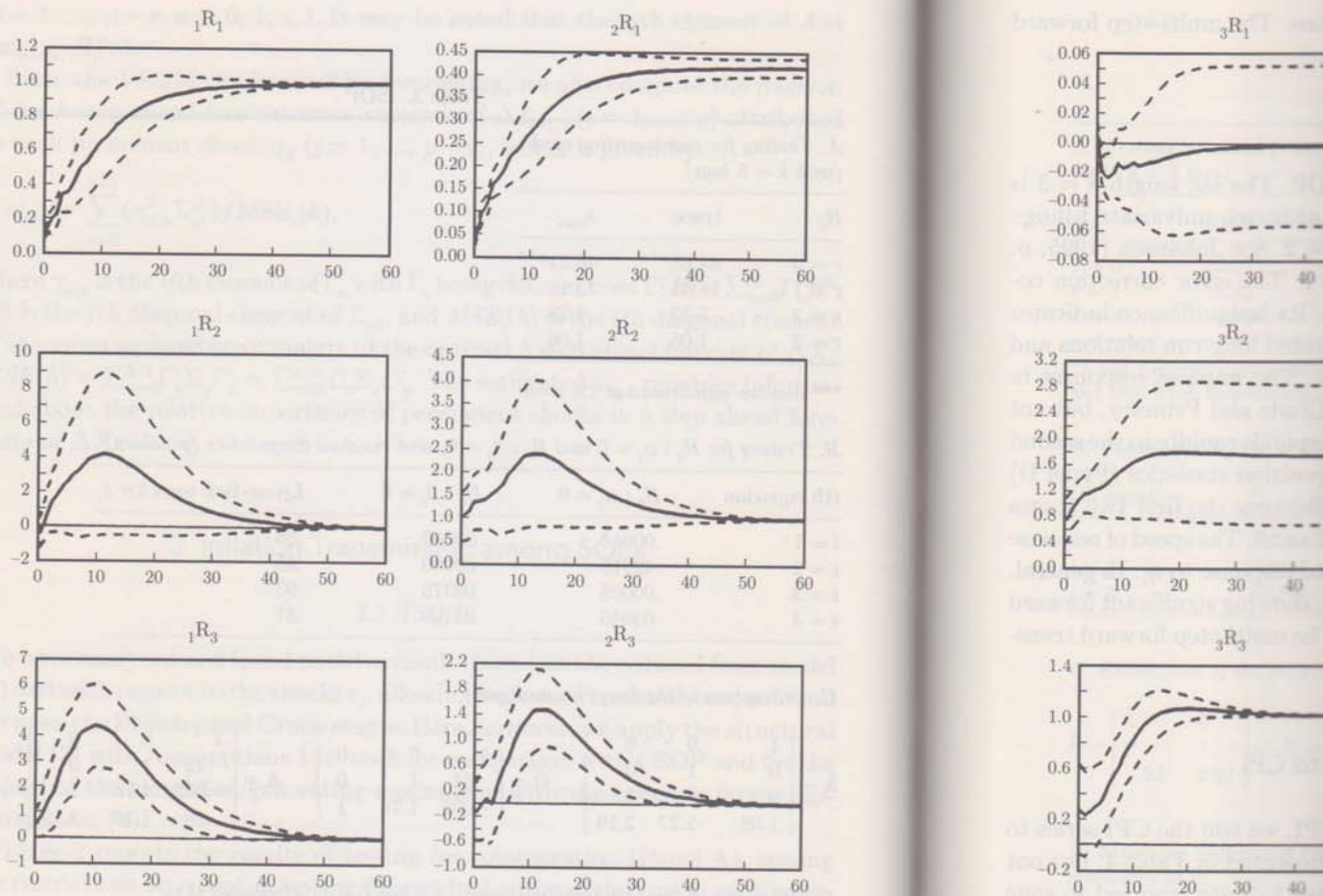


Figure 1. ISOP: Responses (iR_j) of variable x_i to shock η_j

adjusting toward the estimated long-run relations. If not rejected it implies that the variable in question itself takes the role of a common trend in the system. No rejection of $H_0: \alpha_2 = 0$ indicates that there is some backward inflation flow from Primary to Crude, consistent with the Granger-causality tests in the previous section.

From Panel D, it is observed that the first permanent shock η_1 , the permanent shock to the Crude processor, explains a significant portion of the inflation fluctuations in all stages, the amount declining through the stages, but increasing in the long run (as the forecast horizon h increases) with faster speed in earlier stages. The second permanent shock η_2 , which is another permanent shock to Primary processor, accounts for substantial variations in Primary and Semifinished processors. Its role declines for the longer forecast

horizons. The third permanent shock η_3 , the permanent shock to the Finished processor, explains a significant portion of the inflation fluctuations in the Finished processor, but not in the other two processors. The transmission from Semifinished to Finished processor is significant, but the transmission from Semifinished to Primary processor is not significant.

Turning to Figure 1, which shows the impulse responses of the three variables to the three shocks, along with the two standard deviations, it is observed that the first shock and the third shock on Finished processor appear significant. In the other two processors, the responses are not significant. However, the long-run effects are significant in all three processors, implying that there are permanent transmissions throughout the system.

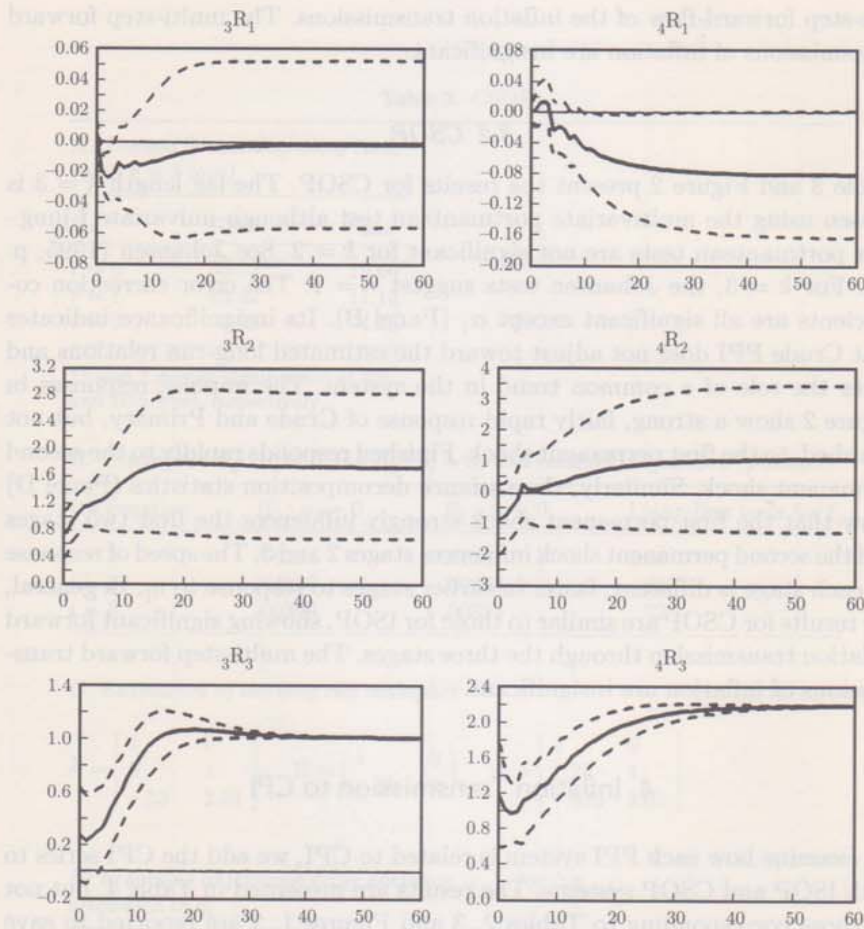


Figure 1. (cont.)

horizons. The third permanent shock η_3 that arrives at the third stage of processing to the Semifinished processor shows very significant inflation transmission from Semifinished to Finished stages.

Turning to Figure 1, which graphs the dynamic responses to the three shocks along with the two standard deviation confidence bands computed by Monte Carlo simulation using 300 replications (dashed lines), we see significant long-run effects of the first shock on Primary, the second shock on Semifinished, and the third shock on Finished. None of the other effects in the forward direction appear significant. In the backward direction, some of the short-run effects are substantial, implying that demand shocks matter in the short run. However, the long-run effects are zero by construction. ISOP captures the inflation transmissions throughout the economic segments fairly well with significant

one-step forward-flow of the inflation transmissions. The multi-step forward transmissions of inflation are insignificant.

3.2 CSOP

Table 3 and Figure 2 present the results for CSOP. The lag length $k = 3$ is chosen using the multivariate portmanteau test although univariate Ljung-Box portmanteau tests are not significant for $k = 2$. See Johansen (1995, p. 22). For $k = 3$, the Johansen tests suggest $r = 1$. The error correction coefficients are all significant except α_1 (Panel B). Its insignificance indicates that Crude PPI does not adjust toward the estimated long-run relations and takes the role of a common trend in the system. The impulse responses in Figure 2 show a strong, fairly rapid response of Crude and Primary, but not Finished, to the first permanent shock. Finished responds rapidly to the second permanent shock. Similarly, the variance decomposition statistics (Panel D) show that the first permanent shock strongly influences the first two stages and the second permanent shock influences stages 2 and 3. The speed of response by each stage is different, faster in earlier stages to response to η_1 . In general, the results for CSOP are similar to those for ISOP, showing significant forward inflation transmission through the three stages. The multi-step forward transmissions of inflation are insignificant.

4 Inflation Transmission to CPI

To examine how each PPI system is related to CPI, we add the CPI series to both ISOP and CSOP systems. The results are presented in Table 4, but not all those corresponding to Tables 2, 3 and Figures 1, 2 are reported to save space. Overall, the results give support to Popkin's original notions of stages. Later stages respond to earlier stages, and the CPI responds to PPI. The CPI responds to the shocks to the PPI systems, most strongly to the last permanent shock, more when CSOP is used than when ISOP is used. CSOP Finished relates more closely to the CPI than ISOP Finished. The latter pair has slightly inferior cointegration test statistics. In Panel A, it is shown that when CPI is added to the CSOP the rank of cointegration increases from $r = 1$ to $r = 2$, and thus adding CPI to CSOP does not increase the dimension of the common factors or the number of the permanent shocks. This is not the case for ISOP. Although Panel B shows that both ISOP and CSOP Granger-cause CPI, Panel C shows that only CSOP Granger-causes CPI in the long run. The CPI series adjusts to correct the deviations from the cointegrating relationship only with CSOP. The entire ISOP system relates less strongly to the CPI than the CSOP does.

A criterion for usefulness of time series models is forecast performance.

A. Testing for cointegrating rank (with $k = 3$ lags)

H_0	trace	
$r = 0$	35.02**	19
$r = 1$	15.42	11
$r = 2$	4.29	4

** and * denote significance at 5% and 10% level, respectively.

B. Testing for $H_0 : \alpha_i = 0$ and $H_1 : \alpha_i \neq 0$

i th equation	$H_0 : \alpha_i = 0$
$i = 1$.76284
$i = 2$.04836
$i = 3$.00399

C. Estimation of the long run matrix

$$\bar{A} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -.53 & 2.01 \end{bmatrix} \quad \Pi = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$$

D. Fractions of forecast error variance attributed to η_j

h	η_1		
	$i = 1$	$i = 2$	$i = 3$
1	.923 (.038)	.007 (.024)	.000 (.014)
2	.902 (.033)	.002 (.028)	.000 (.019)
12	.893 (.031)	.331 (.075)	.102 (.042)
60	.889 (.030)	.429 (.076)	.103 (.042)

Monte Carlo standard errors are in parentheses.

Table 3. CSOP

A. Testing for cointegrating rank (with $k = 3$ lags)

H_0	trace	λ_{\max}
$r = 0$	35.02**	19.60*
$r = 1$	15.42	11.13
$r = 2$	4.29	4.29

** and * denote significance at 5% and 10% level, respectively.

B. Testing for $H_0 : \alpha_i = 0$ and $H_0 : \beta_i = 0$, and residual diagnostics (p -values)

ith equation	$H_0 : \alpha_i = 0$	$H_0 : \beta_i = 0$	Ljung-Box tests for $\hat{\varepsilon}_i$
$i = 1$.76284	.01102	1.00
$i = 2$.04836	.00283	.96
$i = 3$.00399	.00332	.72

C. Estimation of the long run multiplier

$$\bar{A} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -.53 & 2.01 \end{bmatrix} \quad \Pi = \begin{pmatrix} 1 & 0 \\ .24 & 1 \end{pmatrix} \quad A = \begin{bmatrix} 1 & 0 \\ .24 & 1 \\ -.039 & 2.01 \end{bmatrix}$$

D. Fractions of forecast error variance, $\omega_{ij,h}$, for $\Delta x_{i,t+h}$ attributed to η_j

h	η_1			η_2		
	$i = 1$	$i = 2$	$i = 3$	$i = 1$	$i = 2$	$i = 3$
1	.923 (.038)	.007 (.024)	.000 (.016)	.068 (.037)	.682 (.051)	.410 (.074)
2	.902 (.033)	.002 (.028)	.000 (.019)	.059 (.027)	.697 (.049)	.386 (.071)
12	.893 (.031)	.331 (.075)	.102 (.042)	.059 (.024)	.488 (.071)	.369 (.060)
60	.889 (.030)	.429 (.076)	.103 (.042)	.062 (.023)	.412 (.069)	.369 (.060)

Monte Carlo standard errors are in brackets.

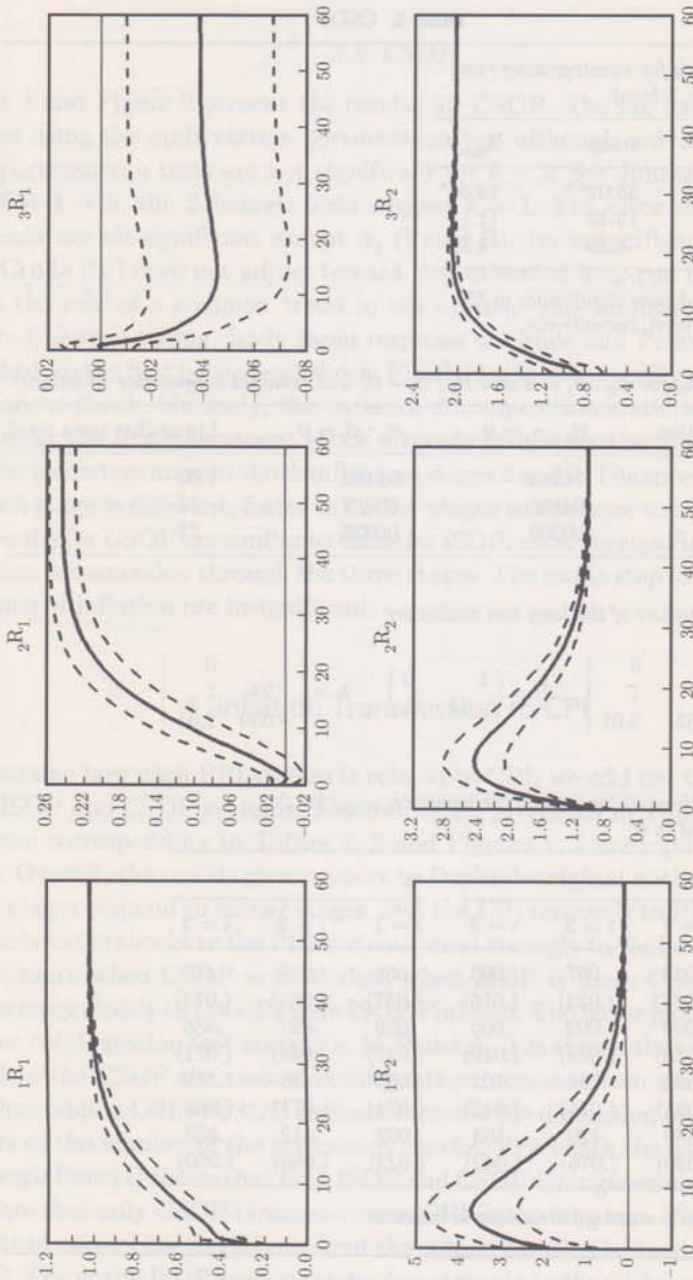


Figure 2. CSOP: Responses (R_{ij}) of variable x_i to shock η_j

Table 4. Fo

A. Testing for cointegrating rank

H_0	ISOP + CPI (k)
$r = 0$	79.03**
$r = 1$	36.28
$r = 2$	19.34
$r = 3$	8.17
$r = 4$	3.80

B. In-sample Granger causality test

H_0 : ISOP \nrightarrow CPI

p -values of F -test 0.013

H_0 : SOP \nrightarrow CPI (SOP does not Granger cause CPI)

C. In-sample long-run Granger causality test

ISOP + CPI

p -value .463

H_0 : CPI is weakly exogenous for ISOP

D. Out-of-sample forecast for CPI

Model 1: Univariate AR(7) for CPI
 Model 2: ISOP + CPI with $r = 1$
 Model 3: CSOP + CPI with $r = 1$
 Model 4: CSOP + CPI with $r = 2$

E. Comparing MSEs by Granger causality test (p -values are reported)

A \ B	Model 1	Model 2
Model 1		.988
Model 2	.012**	
Model 3	.121	.854
Model 4	.199	.909

H_0 : Models A and B have the same MSE

H_1 : MSE of Model A is larger than Model B

Table 4. Forecasting CPI using the SOP systems

A. Testing for cointegrating rank (Johansen trace test)

H_0	ISOP + CPI ($k = 5$)	CSOP + CPI ($k = 3$)
$r = 0$	79.03**	60.98***
$r = 1$	36.28	37.25**
$r = 2$	19.34	21.53**
$r = 3$	8.17	6.87
$r = 4$	3.80	N/A

B. In-sample Granger causality test for CPI

	H_0 : ISOP \nrightarrow CPI	H_0 : CSOP \nrightarrow CPI
p -values of F -test	0.013	0.039

H_0 : SOP \nrightarrow CPI (SOP does not Granger-cause CPI)

C. In-sample long-run Granger causality test for CPI; H_0 : $\alpha_i = 0$ in the CPI equation

	ISOP + CPI	CSOP + CPI ($r = 3$)	CSOP + CPI ($r = 2$)	CSOP + CPI ($r = 3$)
p -value	.463	.011	.037	.014

H_0 : CPI is weakly exogenous for each SOP system augmented with CPI.

D. Out-of-sample forecast for CPI inflation

	MSE	RMSE	MAE
Model 1: Univariate AR(7) for CPI	.00000279	.00167	.00133
Model 2: ISOP + CPI with $r = 1$ and $k = 5$.00000371	.00193	.00156
Model 3: CSOP + CPI with $r = 1$ and $k = 3$.00000321	.00179	.00147
Model 4: CSOP + CPI with $r = 2$ and $k = 3$.00000309	.00176	.00144

E. Comparing MSEs by Granger-Newbold test
(p -values are reported)

A \ B	Model 1	Model 2	Model 3	Model 4
Model 1		.988	.879	.801
Model 2	.012**		.146	.091*
Model 3	.121	.854		.130
Model 4	.199	.909	.870	

H_0 : Models A and B have the same MSEs.

H_1 : MSE of Model A is larger than MSE of Model B.

Figure 2. CSOP: Responses (R_t) of variable x_t to shock η_t

Ashley, Granger, and Schmalensee (1980) argue that a sound and natural approach to Granger-causality must rely primarily on the out-of-sample forecasting performance of models relating the series of interest. Our evaluation of CPI forecasts using the SOPs in terms of out-of-sample forecasting performance proceeds as follows. The VECMs are estimated for ISOP plus CPI (with $p = 5$, $k = 5$ and $r = 1$) and CSOP plus CPI (with $p = 4$, $k = 3$ and $r = 1, 2$) using the observations until five years before May 1996, to have post-sample of 60 months. Based on the estimated models, one-step-ahead forecasts are generated for those post-samples, resulting in 60 pairs of forecast errors to evaluate. For each of the SOP augmented with CPI, we calculated the mean squared errors (MSE), root mean square errors (RMSE), and the mean absolute errors (MAE), which are reported in Panel D.

For the quadratic loss (MSE), we use the tests of Granger and Newbold (1977, GN henceforth), Meese and Rogoff (1988), Diebold and Mariano (1995), the sign test, and the Wilcoxon signed-rank test to investigate whether the loss-differences are significant. See Diebold and Mariano (1995) for an exposition of the tests in detail. In Panel E, the probability values (p -values) of the one-sided tests of GN are reported. To save space, we only report for GN tests, but all the other tests give similar results (available on request). Since the CPI has grown fairly slowly and steadily over most of the last decade, great differences cannot be expected. Still, Model 4 for CSOP has a smaller loss than ISOP (Model 2), achieving significance at the 10 percent level. The forecast evaluation seems to favor the CSOP over the ISOP system in terms of forecasting the CPI. However, both CSOP and ISOP have larger losses than the univariate AR(7) model for CPI (Model 1). Model 2 with ISOP plus CPI is significantly inferior to the univariate model (Model 1) almost at the 1 percent level.

These forecast results are somewhat disappointing, but have been seen before. For example, Clark (1995) shows producer price inflation Granger-causes consumer price inflation in-sample but fails to improve out-of-sample forecasts of consumer price inflation. It is widely recognized that price variability or volatility decreases through the stages of production and in consumer prices. Producers and retailers often attempt to avoid inflicting their customers with too many price fluctuations. The rather steady, low rate of inflation in the CPI in the study period may explain the lack of forecasting power. Still, overall, our results show inflation transmission from the earlier, more volatile stages to the later, more stable stages.

5 Conclusions

Using vector error correction models, the sources of inflation and its transmission in terms of direction, speed, and magnitude are examined for stages

of processing. Both ISOP and CSOP show inflation transmission among stages; CSOP shows a stronger transmission. By a small amount, CSOP outperforms ISOP.

The ISOP system has been compared with other industry-based forecasting systems. The “output” price indexes discussed in this paper are related to stages beyond Consumer Price Index like CSOP Finished, relates

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of processing. Both ISOP and CSOP give strong evidence of forward inflation transmission among stages; connections to the CPI are stronger with CSOP. By a small amount, CSOP outperforms ISOP in forecasting the CPI.

The ISOP system has conceptual and analytic advantages, e.g., it can be studied with other industry-based variables, such as wages. In addition to the "output" price indexes discussed in this article, this system includes "input" indexes to stages beyond Crude and an index to Final Demand. This last index, like CSOP Finished, relates closely to the CPI.

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P in the An I(2) A

There has recently been discussion between so called common CPI and the WPI (see Jeon, 1996; Gallo, Mar for this interest is the to inflationary signals, and hence could act as

Econometrically, the Granger and Jeon (1999) (1995) and Gallo *et al.* four commodity price US inflation. Some of rates, others relationships a relationship between index in differences. This discussed and tested conclusion is that price level the order of integration of all price variables all

This paper illustrates Granger (1981, 1986) are ally be integrated, but first appreciated in Gr (1991) and Johansen

This paper has benefited from Niels Haldrup and Massimiliano Research Council is grateful