Natural Gas Prices and Industrial Sector Responses: An Experimental Module for STIFS

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By

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Abstract

The Short-Term Integrated Forecasting System (STIFS) generates monthly forecasts of energy demand, supply and prices using some forecast information that is incorporated into STIFS that is generated by other models that do not run in an integrated framework with STIFS. This includes the macroeconomic forecasts and projections for certain energy supply variables. There is no direct feedback between the macroeconomic models projections and STIFS components. Members of the STIFS Team can attempt to coordinate iterations between the two models. However, this is not desirable for two main reasons. First, it suffers from specification problems in the richness and complexity of the dynamic interactions because the feedback is not directly estimated. Second, the iteration process requires staff time and resources that are limited.

This project tests an experimental model for the interaction between natural gas prices, natural gas consumption, and industrial sector activity. Two strategies are followed. The first involves a simple VAR framework capturing the time series dynamics testing for Granger causality and examining impulse response functions and forecast error variance decompositions. In the second approach, energy and economic variables are analyzed in terms of integration, cointegration for a long-run relationship between oil and natural gas prices. **[This latter part of the project is ongoing but is not completed here]** The general to specific modeling methodology is used to develop a data coherent parsimonious representation. Issues related to parameter constancy, encompassing, and forecasting are discussed. The forecasting performance of the two strategies is compared and the potential gain from using the experimental module is discussed.

INTRODUCTION

The Short-Term Integrated Forecasting System (STIFS) generates monthly forecasts of energy demand, supply and prices using some forecast information that is incorporated into STIFS that is generated by other models that do not run in an integrated framework with STIFS. This includes the macroeconomic forecasts and projections for certain energy supply variables. There is no direct feedback between the macroeconomic models projections and STIFS components. Members of the STIFS Team can attempt to coordinate iterations between the two models. However, this is not desirable for two main reasons. First, it suffers from specification problems in the richness and complexity of the dynamic interactions because the feedback is not directly estimated. Second, the iteration process requires staff time and resources that are limited.

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Why an Industrial Response Module (IRM) for STIFS?

The Short-Term Integrated Forecasting System (STIFS) generates monthly forecasts of energy demand, supply and prices using an array of econometric relationships (estimated with monthly data) and numerous accounting identities and other relationships that tie together highly aggregated energy flows and stocks covering major energy sources and economic sectors. STIFS constitutes a major integrated information system in EIA, bringing together energy quantities and prices from various sources within EIA (and from elsewhere) in a consistent, time series format. The energy information is coupled with other economic and non-economic information to form a modeling database from which forecasting equations are estimated, saved and later used to produce monthly projections, analytical reports, and frame policy discussions.

Some forecast information that is incorporated into STIFS is generated by other models that do not run in an integrated framework with STIFS. This information includes the macroeconomic forecasts and projections for certain energy supply variables.

There is no current direct feedback between the macroeconomic model projections and STIFS components. Members of the STIFS Team can attempt to coordinate iterations between the two models. However, this is not desirable for two main reasons. First, it suffers from specification problems in terms of the richness and complexity of the dynamic interactions because the feedback is not directly estimated. Second, the iteration process requires staff time and resources that are limited.

The current EViews® system used to prepare projections for EIA's Short-Term Energy Outlook takes as given macroeconomic drivers from a prepared solution of a large commercial macroeconomic model of the U.S. economy. Neither the particular sensitivities of key industrial drivers to energy price shocks nor the stochastic properties of these key drivers are retrievable from the standard macroeconomic inputs provided to STIFS. These pieces of information are desirable to increase the usefulness of STIFS in the context of scenario or uncertainty analysis without the labor-intensive and costly process of iterating the flow of information into and out of the large macro model.

Purpose for Developing and Testing a Pilot IRM

The development of the IRM will provide a first attempt to address the feedback issue. The objective is to focus on a limited set of STIFS and macroeconomic sectors.
Since 2000 there have been two major natural gas price shocks. The manufacturing sector

has been particularly affected by the high natural gas price increases and volatility.

Six of the most energy consumptive industry groups - chemicals, petroleum refining, primary metals, paper, food processing, and nonmetallic minerals (glass, lime, cement, etc.) - lead the way in natural gas consumption. Among those, the chemical industry is dominant. According to the 1998 Manufacturing Energy Consumption Survey (MECS), the chemical industry used 36 percent of all natural gas consumed by all U.S. manufacturers in 1998 (and in fact, 12 percent of TOTAL U.S. gas consumption for all purposes). Together, the top six industry groups accounted for 84 percent of manufacturing use of natural gas, so most of the aggregate economic effect of natural gas price trends would be evident in those industries.

Beyond the amount of natural gas used, the share of natural gas in total production cost is another key factor in assessing impacts. Natural gas costs represent a large proportion of the cost of doing business for some sectors -- 40 percent for the nitrogen fertilizer industry in 1998. For chemicals as a whole, natural gas costs were 2 to 3 percent of overall costs in that same year.

Higher and more volatile natural gas prices have led industry analysts to use a term – "demand destruction" to refer to the impacts. The term can have several connotations and has different meanings depending on the speaker/writer. The first refers to the loss in natural gas consumption as firms switch or substitute for other fuel sources. The ability to do so depends on end-use of natural gas, the capital stock and the technology available to the first. Conservation is another form of reducing cost per unit of output. This has the aspect of "permanence" to it, because there is little incentive for firms to return to less efficient processes. Third, firms' output will decline in response to higher input costs as they become less competitive domestically and internationally. The IRM is not expected to have the capability to decompose demand destruction into these three elements.

The purpose of this task is to develop a methodology for providing response functions for key industrial output variables in the STIFS model to energy price shocks, particularly those related to natural gas, and to tie the resulting mechanism into the underlying macroeconomic forecast in such a way as to preserve the expected relationships between industrial output and aggregate income. A key output of the task will be new EViews objects and programs that can readily be integrated in the STIFS EViews system.

Methodology

Natural gas price movements and volatility will be analyzed individually and relative to crude oil prices (specifically refiners' acquisition cost of crude oil). Currently, industrial production indexes are used as the macroeconomic drivers in parts of the natural gas consumption and price module(s).

The VAR will be used to evaluate the current STIFS equations for industrial natural gas prices and the forecasting implications of the feedback models.

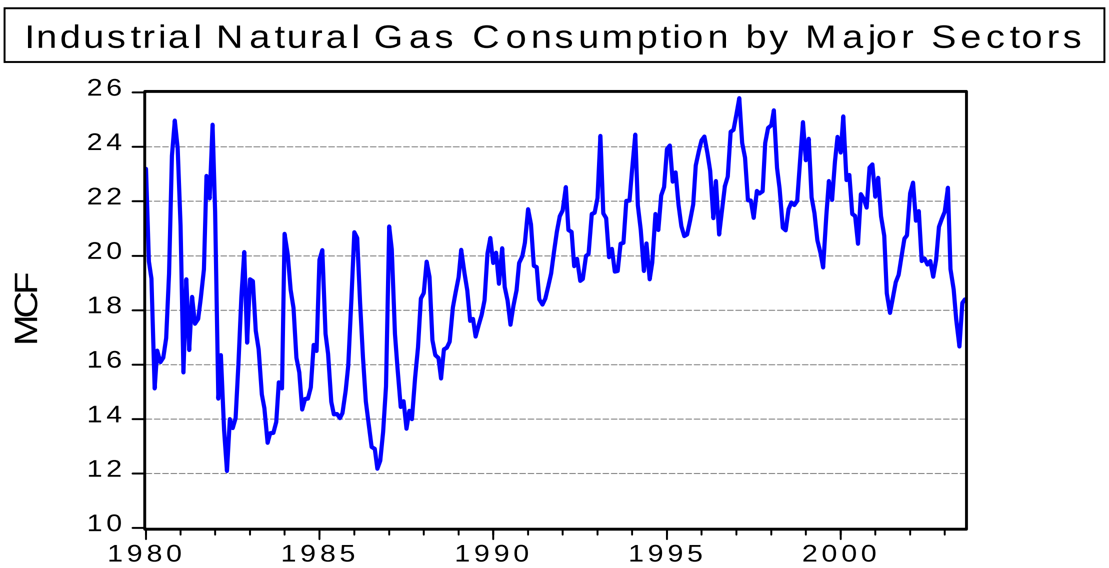
THE DATA

Table 1 provides the variable names, short descriptions and the sources of the data used in the study.

Industrial Natural Gas Consumption

The variable name NGINX is the mnemonic in STIFS for total industrial natural gas demand (including gas used in industrial cogeneration plants) in the United States. The series excludes gas used in oil and gas field operations and at natural gas processing plants. The data series extends from January 1989 through the current period (Figure 1).

Figure 1.



The industrial production index, calculated as the weighted average of the top 6 gas-consuming manufacturing industries (where the weights are year-2000 value added weights used by the Federal Reserve Board), is illustrated in Figure 2.

Figure 2.

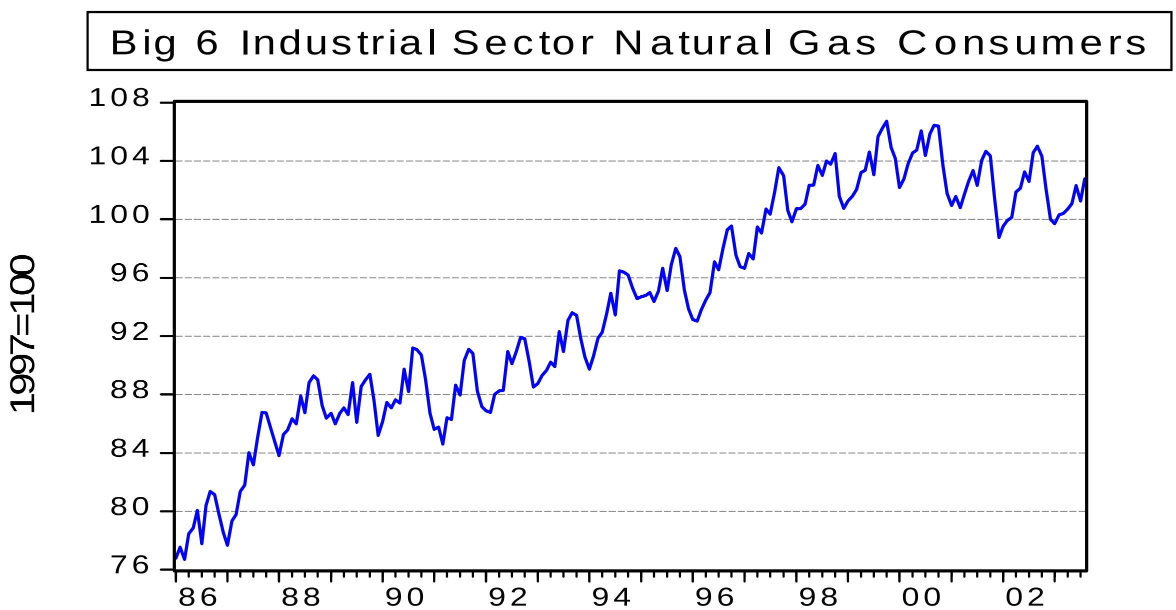
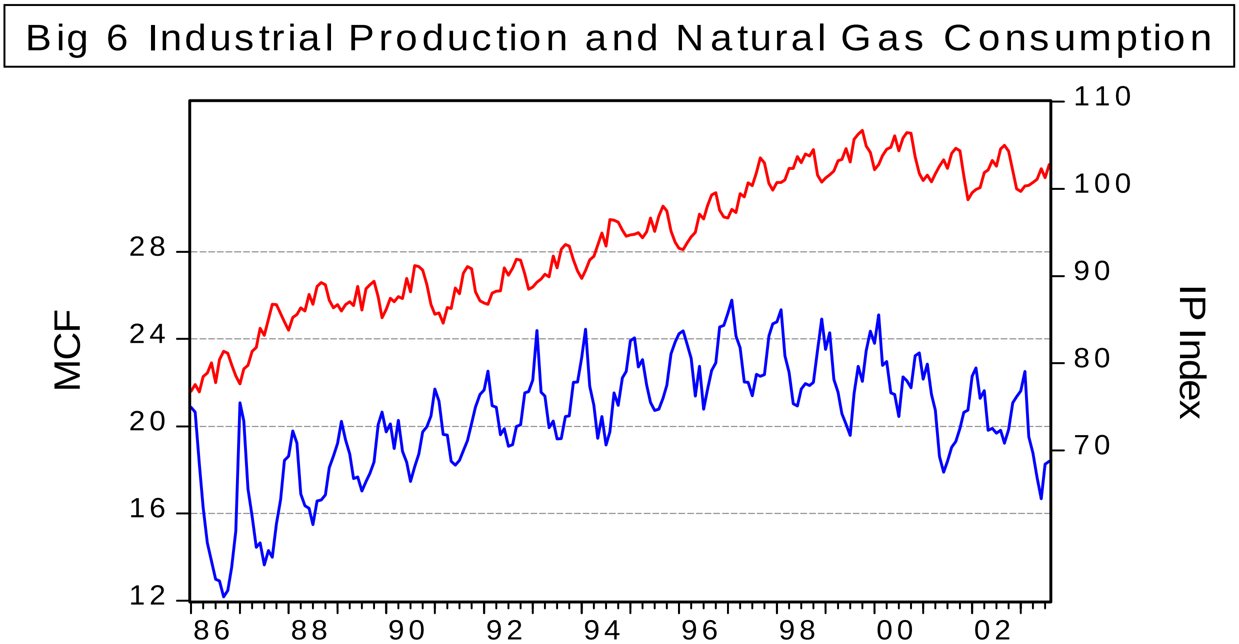


Figure 3 presents monthly industrial natural gas consumption plotted along with the gas-intensive industrial output index.

Figure 3.



Industrial Natural Gas Prices

Hamilton (1996) proposed a "net oil price" measure to capture the impact of oil price shocks based on previous experience. It is calculated as the differential between the maximum realized price in the previous twelve months and the current price. If the current price is higher, the term is equal to zero. Following Mork (1989), Gardner and Joutz (1996) and Balke, Brown, and Yucel (1999) asymmetric effects are incorporated by examining the impact of downward price shocks. A second "net oil price" measure is constructed using the differential when it is negative, otherwise it is zero.

Figure 4 indicates the monthly track for average industrial natural gas prices, in nominal and real dollar terms. The industrial price shown here is based on gas utility deliveries for own account, which represent a relatively small fraction of total industrial sales.

However, we note that this price series exhibits month-to-month changes over time that are consistent with monthly changes in average wellhead prices.

Figure 4.

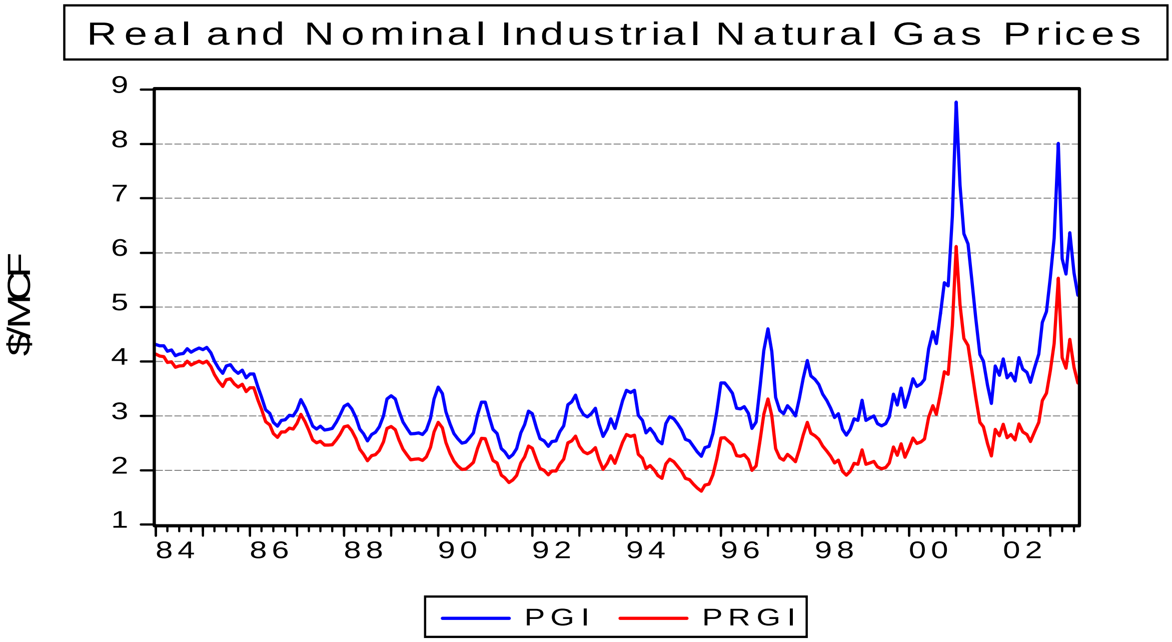


Figure 5 shows actual, maximum and "net price" concepts described above.

Figure 5.

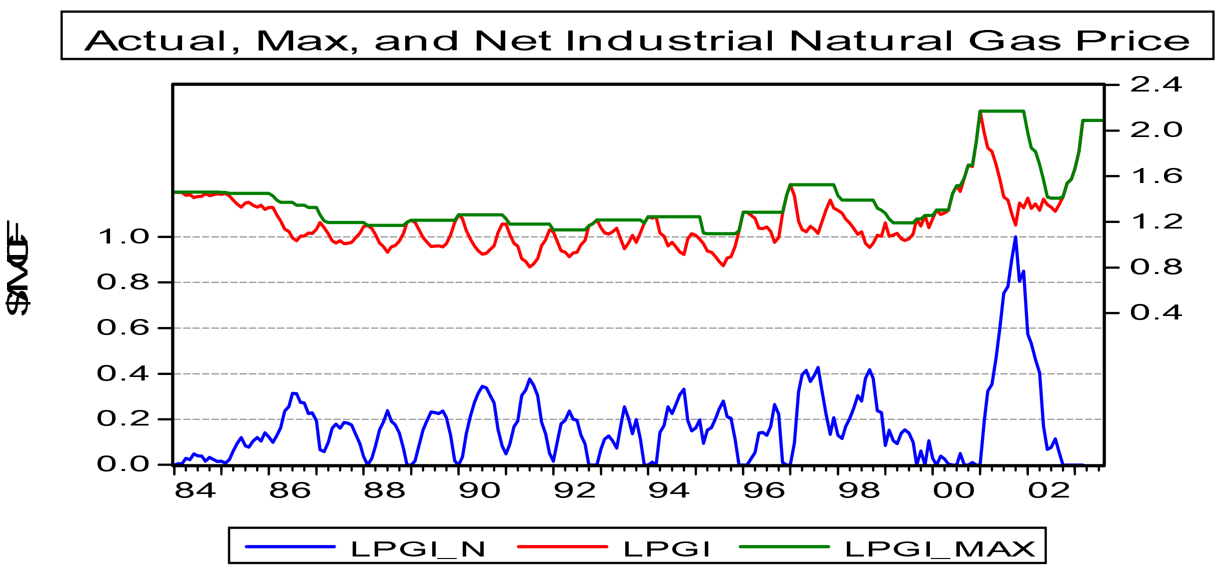
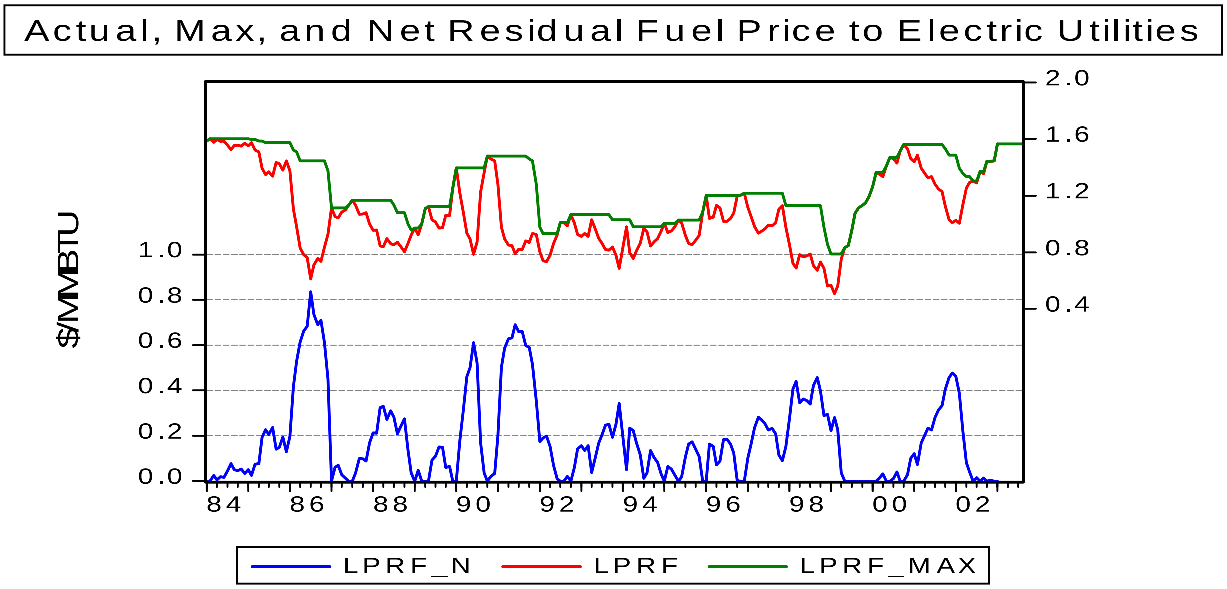


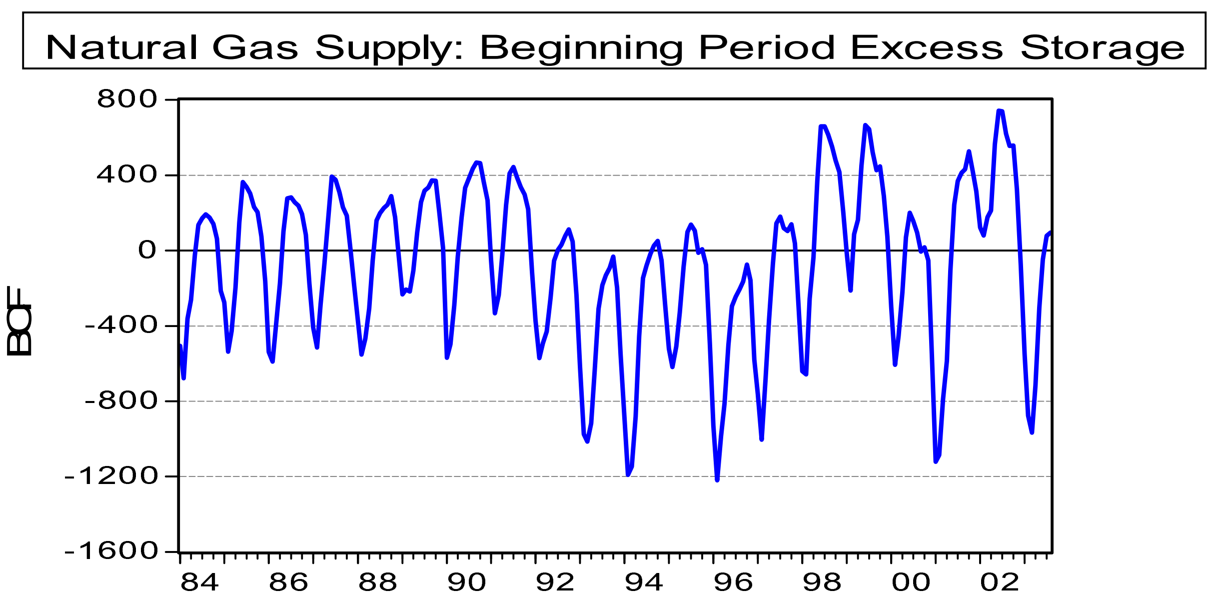
Figure 6 illustrates the "net price" calculation applied to the residual fuel price (delivered to the electric power sector).

Figure 6.



A variable which indicates the relative adequacy of natural gas in underground storage at any point in time (gasvar in STIFS) is the difference between beginning-period working gas storage and the previous 5-year average for the same month (Figure 7).

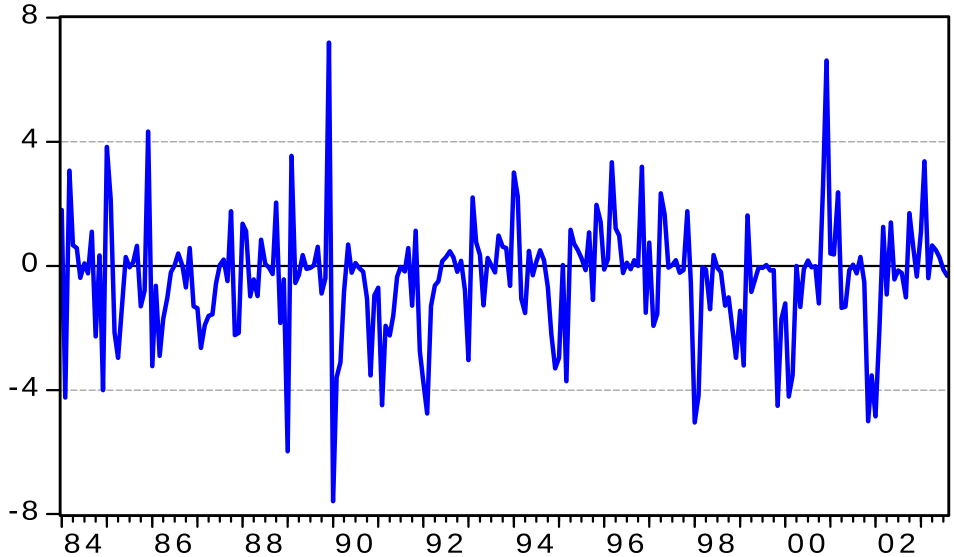
Figure 7.



Another important factor related to natural gas demand and price in the short term is weather, particularly heating degree-days. Deviations from normal heating degree-days (where normal is the trend-adjusted long-term average), expressed on a per-day basis, are presented in Figure 8.

Figure 8.

Deviation of Heating Degree Days from Normal Per Day



MODELING ISSUES AND SPECIFICATION AND EMPIRICAL RESULTS

The research follows the general-to-specific modeling approach advocated by Hendry (1986, 2000, and 2001). The general-to-specific modeling approach is a relatively recent strategy used in econometrics. It attempts to characterize the properties of the sample data in simple parametric relationships which remain reasonably constant over time, account for the findings of previous models, and are interpretable in an economic and financial sense. Rather than using econometrics to illustrate theory, the goal is to "discover" which alternative theoretical views are tenable and test them scientifically.

The approach begins with a general hypothesis about the relevant explanatory variables and dynamic process (i.e. the lag structure of the model). The general hypothesis is considered acceptable to all adversaries. Then the model is narrowed down by testing for simplifications or restrictions on the general model.

The first step involves examining the time series properties of the individual data series. We look at patterns and trends in the data and test for stationarity and the order of integration. Second, we form a Vector Autoregressive Regression (VAR) system. This step involves testing for the appropriate lag length of the system, including residual diagnostic tests and tests for model/system stability. Issues of causality, impulse responses, and forecast error decomposition can be addressed. Third, we examine the system for potential cointegration relationship(s). [**This latter part of the project is ongoing but not completed here]** Data series which are integrated of the same order may be combined to form economically meaningful series which are integrated of lower order. Fourth, we interpret the cointegrating relations and test for weak exogeneity. Based on these results a conditional error correction model of the endogenous variables is specified, further reduction tests are performed and economic hypotheses tested.

A VAR with lag length (or order) p can be expressed as

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + B(L)\, X_t + e_t \qquad (1.1)$$

Where Y is (n * 1) the number of variables
- A_0 is (n * 1) the matrix of intercepts and deterministic variables (n * 1) the intercept plus seasonal dummies and or trend variables
- A_i is (n * n) matrix of coefficients at lag i
- e_t is (n * 1) the vector of error terms with mean 0 and contemporaneous variance covariance matrix Σ
- X is (m * 1) the set of exogenous variables
- B(L) Lag operator for exogenous variables

The econometric modeling techniques will involve issues related to stationarity, integration, cointegration, and conditional volatility. Applied econometricians face the following issues when working with VAR models:

- The choice of variables (energy consumption and supply, energy prices, income, drilling and exploration costs, taxes, and demographic) to answer the problem
- The determination of the lag length to capture the data generating process (DGP).
- The parameterization of the model. Clearly it will be over parameterized. Many coefficients will be effectively zero. For example, variable j has no explanatory power for variable i at lag k.
- The issue of multicollinearity. This makes it difficult to determine the important regressors using individual t-tests. Thus, F-tests or Chi-Square tests can help to detect this problem.
- Model and parameter stability issues are important tests for the robustness of the model, due to changes in market structure, demand, regulatory effects, and technological change.
- Granger Causality is a way to test for overparameterization and understanding the dynamic effects.
- The issues of stationarity, integration, and cointegration are important for model specification and design.
- The degrees of exogeneity: weak, strong, and super, are linked to inference testing, forecasting, and policy analysis.

What have been the contributions of VARs to empirical research and forecasting?

- A simple means to represent the time series dynamics of a set of variables looking at issues like: short-run vs. long-run effects, tests of Granger “Causality”, tests of exogeneity, and cointegration analysis
- A method to study the dynamic response of endogenous variables to shocks using Impulse Response Functions and Structural VARs (See Gamber and Joutz 1993 and 1995)
- A method to examine empirically testable implications from economic theory. For example, can any parameters from a structural model be identified? What restrictions are necessary for identification?
- A simple approach to generate forecasts incorporating theoretical models.
- A method for decomposing time series into economically meaningful components. What is the contribution of different variables to explaining the movement in the series of interest? Forecast error variance decompositions are a

means for answering this question.

Integration and Stationarity Issues

Several features of the data discussed in the previous section need to be considered. Energy and economic data are often characterized by trends of some sort, seasonality, shifts, and structural breaks. The industrial natural gas sector data contains all of these.

The seasonal factors appear to be deterministic as they are relatively constant. Peaks and troughs do not appear to shift during the course of a year. Trends and their specification are important for time series analysis, specification, estimation, and inference. There do appear to be possible changes, breaks and shifts, in the natural gas series. A partial explanation is a result of definitional and measurement issues in the 1980s. (This is not a focus of the current research.) The sample period for the analysis was chosen to begin in January 1989 to avoid these problems and it is appropriate from an industrial market or institutional perspective.

Analysis of the autocorrelation functions and partial autocorrelation functions suggested that there were not seasonal unit roots, but that there might be simple zero order unit roots. The null hypothesis of a unit root is tested using the Augmented Dickey Fuller Test with seasonal dummy variables, represented by:

$$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 y_{t-1} + \sum_{j=1}^{p} \beta_j \Delta y_{t-j} + \sum_{i=1}^{11} \gamma_i d\_mon_{i,t} + \varepsilon_t \qquad (1.2)$$

Table 2 presents the ADF results test for: nominal industrial natural gas prices; the net natural gas price; industrial natural gas consumption, and industrial production. Conditional on the lag length selection to remove serial correlation from the estimated residuals, the null hypothesis is that $\alpha_2 = 0$. Rejection suggests that the series are stationary. There are eight columns in the table. The first gives the maximum lag length for the dependent variable in each test equation. The column headed beta Y_1 presentes the implied lagged value in level form, and the third column, headed sigma, is the standard error of the ADF regression. The next four columns are used for selecting the lag lengh for the regressions: t_DY_lag is the t-statistic associated with the maximum lag in ADF, t-prob is the p-value for the statistic, and F-prob is the significance of the F-test on lags dropped to that point. It appears as though ten lags should be used in each test. We report the I(1) tests which all suggest that all four series are integrated of order one, that is they have a unit root. Testing for I(2) processes was performed, but not reported here.

VAR Model Specification

Two systems with five alternative model specifications are considered. The first system has three equations for the industrial natural gas price, industrial natural gas consumption, and the industrial production index of the six major consuming industries. The second system has four equations; a net industrial natural gas price equation is added to the first three equations. Five alternative exogenous variable groupings were considered in each VAR system. The most general model included twelve lags of the endogenous variables, eleven seasonal dummy variables for January through November, three event dummy variable for unseasonable weather, and five exogenous variables. The five models are:

1. No seasonal and event dummies and exogenous variables
2. No event dummies and exogenous variables
3. No exogenous variables
4. No event dummies
5. Include seasonal and event dummies and exogenous variables

The fifth model is considered the most general one and the other four impose restriction on it.

The general form of the vector autoregressive (VAR) system that captures the extent of feedback between the industrial sectors and (industrial) natural gas prices is:

$$\begin{bmatrix} ngicuus_t \\ pgi\_n_t \\ nginx_t \\ gbig6_t \end{bmatrix} = A(L)\begin{bmatrix} ngicuus_{t-1} \\ pgi\_n_{t-1} \\ nginx_{t-1} \\ gbig6_{t-1} \end{bmatrix} + D\begin{bmatrix} Dmon_{t,p} \\ Dmon_{t,net} \\ Dmon_{t,c} \\ Dmon_{t,y} \end{bmatrix} + C\begin{bmatrix} D\_Hand_t \\ D\_9402_t \\ D\_9602_t \end{bmatrix} + B\begin{bmatrix} x_{t,1} \\ x_{t,2} \\ x_{t,3} \\ x_{t,4} \\ x_{t,5} \end{bmatrix} + \begin{bmatrix} e_{t,p} \\ e_{t,net} \\ e_{t,c} \\ e_{t,y} \end{bmatrix} \quad (1.3)$$

where

- ngicuus(p) – nominal price of natural gas to industry deflated by the producer price index for non-energy and food products, $/MCF (1982-84=0).
- pgi_n(net) - Hamilton “net price” of industrial natural gas, the difference between the highest monthly price in the last three years and the current price.
- nginx(c) - natural gas demand by industry including CHP, BCFD.
- gbig6(y) - is the industrial production index for the six largest industrial sectors consuming 80% of that sector’s natural gas.

A(L) is a matrix polynomial lag operator where each matrix is 4x4

$$A(L) = A_1 L^1 + A_2 L^2 + A_3 L^3 + A_4 L^4 + A_5 L^5 + A_6 L^6 + A_{12} L^{12}$$

D is a 4x12 matrix of a constant and coefficients for 11 monthly dummy variables in each equation with December as the constant.

C is a 4x3 matrix of coefficients for the three extreme events. This matrix can be expanded later to include more events.

B is 4x5 matrix for the vector, x, of exogenous variables.

The vector ~ is the vector of white noise residual terms which may be contemporaneously correlated. The symbols (p, net, c, and y) represent the price, “net price”, consumption, and industrial production respectively.

Initial Model Selection

Table 3.a and Table 3.b present the results of the zero restrictions used for both systems. There are five columns in each table with the model number in the first column. Columns two through five contain the Log Likelihood, AIC, SC, and HQ statistics respectively.

Model 4 appears to be the most parsimonious representation in both systems, except by the HQ statistic in the four variable model. Below each table is another form of reduction test in finite samples. A sequence of F-tests is compared against alternative models. Again, model 4's specification appears to be appropriate. The p-value associated with reducing from model 5 to model 4, removing the event dummies, is 0.80 and 0.24 in the three variable and four variable VARs, respectively.

VAR Model Lag Length Selection

A primary benefit of VAR models is that they can capture the dynamics of the system. The seasonal nature of the data and sample size suggests that twelve lags may be an appropriate starting point. The selection criteria for the appropriate lag length of the unrestricted VAR model follow the asymptotic χ^2 test(s) suggested by Sims (1980). The maximum possible lag length considered was twelve, the number of months in a year. Each model included eleven dummy monthly dummy variables and the constant. The chi-squared statistic used was:

$$\chi^2_r \sim (\tilde{T} - c)[\log\det\tilde{\Sigma}_r - \log\det\Sigma_u] \qquad (1.4)$$

where det Σ_r and det Σ_u are the determinants of the restricted and unrestricted covariance matrices of residuals respectively. The number of observations is T, and c is a correction for the number of variables in the unrestricted model. The adjustment is used to improve the small sample properties of the statistic. This is calculated as the number of estimated coefficients in all equations. If there are n variables (equations), p lags of each variable, and an intercept, we have c = n^2 * p+ n coefficients. In our comparison the test statistic is distributed as χ^2_r with n*n(u-r) degrees of freedom where u is the maximum number of lags and r is the restricted lag length. The difference between u and r represents the number of zero restrictions imposed on the lags for each variable in the system.

In finite samples, the likelihood ratio approach is not as appealing since it relies on asymptotic theory. In addition, this test applies only in the case where one model is a restricted version of the other. The Bayesian Scwhartz Criterion (BSC), the Akaike Information Criterion (AIC), and the Hannan-Quinn Criterion are used as alternative criterion. They rely on information similar to the Chi-Squared tests and are derived as follows:

$$
\begin{aligned}
AIC &= \log(\text{ Det } \hat{\Sigma}\ ) + 2 * c * T^{-1} \\
BSC &= \log(\text{ Det } \hat{\Sigma}\ ) + c * \log(T) * T^{-1} \\
HC &= \log(\text{ Det } \hat{\Sigma}\ ) + 2 * c * \log(\ \log(T)\ ) * T^{-1}
\end{aligned}
\qquad (1.5)
$$

Intuitively, the log determinant will decline as the number of regressors increases, just as in a single equation ordinary least squares regression. It is similar to the residual sum of squares or estimated variance. The second term on the right hand side acts as a penalty for including additional regressors; it increases the statistic. We calculate these statistics for each lag length and choose the lag length based on the model(s) with the minimum value for the statistics. The three tests do not always agree as to the optimal lag lengths. The AIC is biased towards selecting more lags than is actually needed, but this is not necessarily bad.

Tables 4, 5, and 6 (4-variable model) and 7,8 and 9 (3-variable model) were used in the lag length selection process. Model 4 for both systems was estimated with twelve lags of the dependent variables. In the four variable system with 176 observations, 48 degrees of freedom are used up for these parameter estimates alone. The model is more than likely over parameterized. An alternative model with the first six lags of each variable and lag twelve was considered. The estimation results for these models are shown in Tables 10-13. Tables 4 and 7 present the Lagrange multiplier test for serial correlation through lag 12 in both systems. It appears as though there is no serial correlation in the residuals beyond two to three lags. These results at important lags may be dominated by the over-parameterization of other lags. Similar results are obtained in Tables 5 and 8. The AIC, SC, and HQ statistics are minimized at 3,1, and 2 lags, respectively, in both the four variable and three variable VAR systems. Tables 6 and 9 report the Wald Lag Exclusion tests in the VARS where lags seven through eleven have been omitted. The rows in the table report the contribution of the lagged terms at given lags in each equation. For example, in the four equation system at lag 1 the lag values do not provide explanatory power for the LNGICUUS equation, but do for the other three variables: LPGI_N, LNGINX, and LGBIG6. The last column in each row is a joint test for explanatory power of all the variables at a particular lag across all equations. In the four equation VAR, zero restriction on the lagged values provide explanatory power at lag six and twelve. The respective p-values for the Wald tests are 0.068 and 0.001. In the three equation system, the same values are 0.35 and 0.026 respectively.

VAR Model Residual Diagnostics

Residual diagnostic tests examine the estimates for normality and serial correlation. Tables 14 and 15 contain test results for skewness, kurtosis, and the Jarque-Bera test. In both systems, there does not appear to be a problem with skewness. However, there does appear to be a problem with excess kurtosis. The equations for industrial consumption and production have outliers that give a sharp peak to the estimated residual distribution. This leads to rejection of the Jarque-Bera test for normality in these equations and the systems as a whole. We could model the outliers using dummy variables, but have chosen not too.

VAR Model Stability

Natural gas markets have experienced periods of “excess” supply or “gluts” and tightness, and increases in price volatility. Any or all of these events could have contributed to a “structural” break in the data generating process between natural gas prices, industrial consumption, and industrial output.

The textbook approach to model constancy assumes that modeler knows the date of a possible structural break in the sample. He/she fits the model over the full sample and for the two "halves" of the sample. The full sample implicitly imposes the same model structure throughout and can be considered a restricted model. This is evaluated against the unrestricted model comprised of the two "halves" using an F-test. We take an agnostic view on the possibility of structural breaks over the 1989-2003 sample.

Model constancy of the VAR system is evaluated using recursive estimation techniques. Suppose the original model has T observations. The technique begins by estimating the model over the first s<T observations in the sample and then fitting the model using s+1, s+2, ..., up to T observations. At this point there are a number of tests for evaluating model (and parameter) constancy. They are often best presented in graphical form, because of the large number of statistics which are calculated.

A familiar statistical presentation is the 1-step ahead residuals plus the standard error bound used to search for outliers. The 1-step residuals are given by $\hat{e}_t = y_t - x_{t'}\hat{\beta}_t$ and plotted with the current estimate of +/-2$\hat{\sigma}_t$ on either side of zero. When $\hat{e}_t$ is outside the band it can be interpreted as an outlier. Standardized innovations are another way to illustrate the presence of outliers.

We report two types of recursive Chow tests. The first is the 1-step Chow test. This looks at the sequence of one period ahead predictions from the recursive estimation for period s to T. The tests are F(1,t-k-1) under the null hypothesis of parameter constancy. The statistic is calculated as:

$$\frac{(RSS_t - RSS_{t-1})(t-k-1)}{RSS_{t-1}} \sim F(1,t-k-1) \text{ where } t = s, s+1, \ldots, T \qquad (1.6)$$

The test assumes that the dependent variables, y_t, are approximately normally distributed.

The *N-down test or Break-Point Chow test* plots the test statistic over the sample scaled by either the 5% or 1% critical value and can be interpreted as a forecast stability test. The model is estimated for the first s observations. A forecast is constructed from period s+1 through T and the F-test is calculated. The null hypothesis is that the estimated model and forecast will explain or predict the full sample the same as model for the full sample. The number of periods in the forecasts goes down from T-s+1 to 1 as the model is estimated and forecasts are performed recursively. Recursive estimation permits construction of Chow tests over the full sample and lets the data do the talking. The

Break-Point Chow test is calculated as:

$$\frac{(RSS_T - RSS_{t-1})(t-k-1)}{(RSS_{t-1})(T-s+1)} \sim F(T-s+1, t-k-1) \ \ where\, t = s, s+1, \ldots, T \qquad (1.7)$$

The results of the 1-step ahead Chow tests and the Break-point Chow test are presented graphically in Figures 9 and 10 respectively. At each observation the normalized test statistic calculated as the ratio of the statistic to the appropriate critical value at 1%. The sequence of tests is plotted. When the normalized value exceeds unity, this indicates a rejection of the null hypothesis of no structural break.

The estimation sample begins in January 1989 and the model is fit through December 1994 before the recursive analysis begins. The graphs for the four-equation VAR system are provided; there is little difference with the three equation VAR system. (They are available upon request.) By construction the equations for the industrial natural gas price and the “net” natural gas price are going to be unstable. In the figures, the test statistics are normalized by the critical values. Thus, when the lines exceed unity it represents a rejection of the null hypothesis of insignificant errors or model stability. A single graph is shown for each equation and the fifth graph is for the system as a whole.

Figure 9. 1 Step-Ahead Chow Test Results

(4-Variable model)

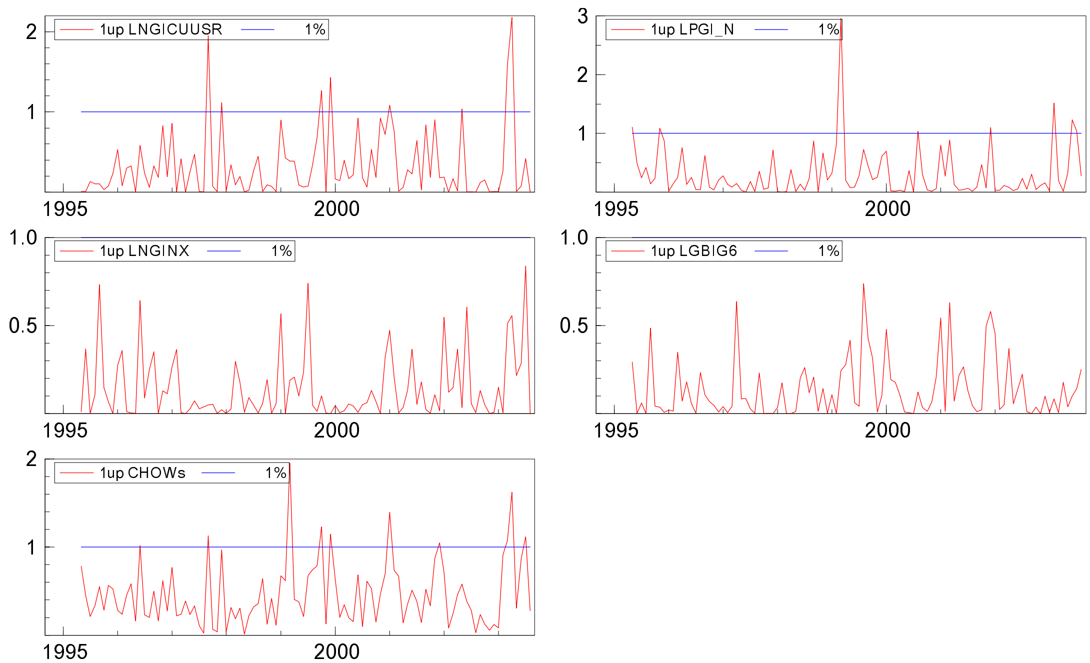
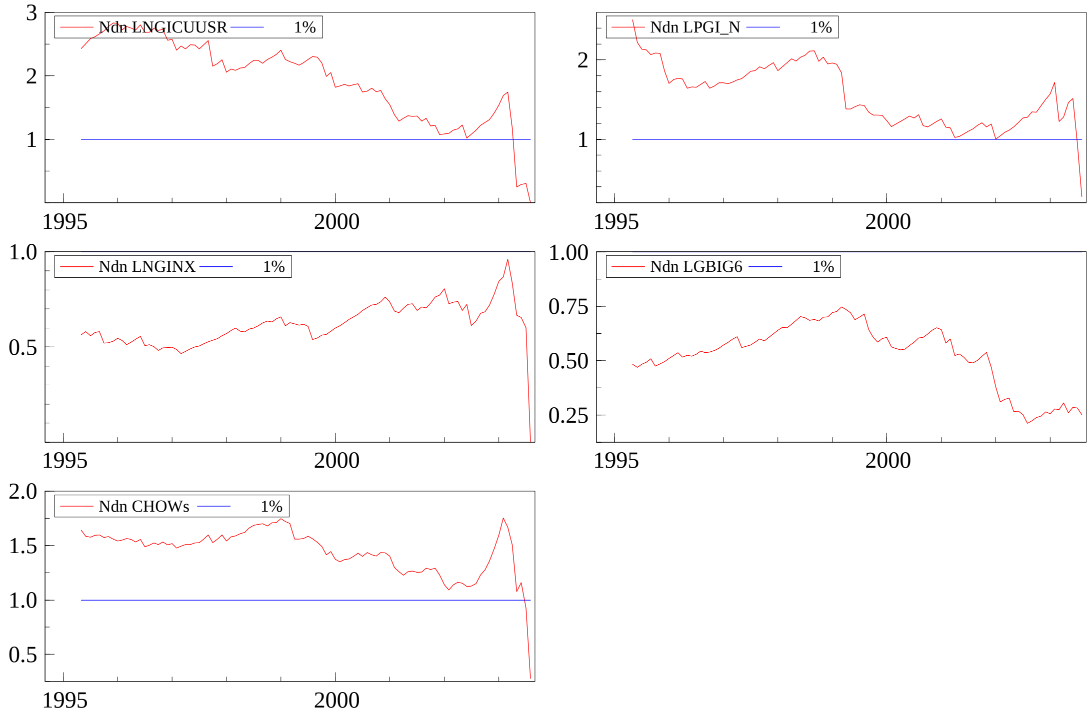


Figure 10. Recursive N-Step Down Break Test Results

(4-Variable model)



The 1-step Chow graphs show only a few rejections for the price and net price equations out of 104 tests. These occur in 1997, 1999, 2000, and 2003.

The N-step down tests have a similar but stronger pattern. The equation estimates for the industrial natural gas price and the "net" natural gas price show rejections up until the last few months. The models appear unstable, because of the tremendous instability in the natural gas price series in the last year but also in 2000. This is driven by the price movements and heights which had previously not been realized. If the recursive tests were performed on shorter samples, the models would have appeared (more) stable. There are no rejections for the natural gas consumption equation and industrial production equation. The graph for the system as a whole shows the same rejection pattern as the price equations.

Impulse Responses

A VAR representation, even in finite form, has an infinite VMA, vector moving average representation. This important feature is used to trace out the impact of a shock to the jth variable to the ith variable in the system h periods ahead or the impulse response. The accumulated impulses are calculated to construct long-run multipliers.

The VAR as estimated here is a reduced form or primitive system. The contemporaneous innovation terms, e_{it}, are correlated. Thus, the shocks are a combination of terms and have common component(s) which cannot be associated with a specific variable. Knowing the autoregressive coefficient matrices and the variance covariance matrix of the estimated innovations is not sufficient to identify the system. Calculation and interpretation of the impulse responses would be subject to the ordering of the equations and not unique.

The Choleski decomposition offers one possible identification approach to transforming the innovations so that they are uncorrelated. This imposes a “structure” on the system, which comes from economic theory and industry knowledge. The uncorrelated or structural shocks, ε_t, can be derived from a transformation G to the innovations so that they are uncorrelated.

$$\begin{array}{c} {}_{t,p} \\ {}_{t,net} \\ {}_{t,c} \\ {}_{t,y} \end{array} \qquad G \begin{array}{c} e_{t,p} \\ e_{t,net} \\ e_{t,c} \\ e_{t,y} \end{array} \quad \sim \ (0, \quad)$$

$$\begin{array}{ccccc} 1 & g_{12} & 0 & 0 & e_{t,p} \\ 0 & 1 & 0 & 0 & e_{t,net} \\ g_{31} & g_{32} & 1 & & e_{t,c} \\ g_{41} & g_{42} & g_{43} & 1 & e_{t,y} \end{array} \qquad (1.8)$$

The transformed innovations, ε_t , retain the mean zero property, but the variance-covariance matrix is diagonal. The specification in the four variable VAR system is based on a general assumption that prices are more flexible than real measures like consumption and industrial production. The net price measure captures the impact of the current price shock to previous maximum prices. Innovations to consumption and industrial activity do not have a contemporaneous impact on either the net price or price level. This feeds into the shock to the current price level. The “structural” net price shock has a contemporaneous impact, g_{12} , on the current level shock. There is no contemporaneous impact of innovations to the current price level from current consumption, and industrial activity. The net price and price level innovations do impact consumption and economic activity. The specification in the three variable VAR system uses the same ordering except that the net price measure and innovations are not in the model.

(1.9)

$$\begin{matrix} t,p \\ t,c \\ t,y \end{matrix} \qquad G \begin{matrix} e_{t,p} \\ e_{t,c} \\ e_{t,y} \end{matrix} \quad \sim (0, \quad)$$

$$\begin{matrix} 1 & 0 & 0 \\ g_{21} & 1 & 0 \\ g_{31} & g_{32} & 1 \end{matrix} \quad \begin{matrix} e_{t,p} \\ e_{t,c} \\ e_{t,y} \end{matrix}$$

Figure 11 and 12 show the cumulative impulse responses with two standard error bounds. The Standard errors for the impulse responses are calculated using 1000 repetitions in a Monte Carlo procedure. There are three rows and four columns for the four variable VAR system and three rows and three columns for the three variable VAR system. Impulse responses for the net oil price measure are not computed. The rows show the responses for a particular variable through twelve periods from the “structural” shocks of each variable. The columns provide the impulse responses from a particular variable on the variables in the system.

The “net” oil price measure has significant effects on the industrial price series and industrial production. The price response (in Figure ZZ first row and first column)is negative and consistent with the notion that there has been a shock to the previous maximum experienced so prices should begin to moderate. The revelation of a shock to the “net” price has a negative impact on industrial production. This could be interpreted as a signal to the economy of a forthcoming recession. The impact of price shocks on the industrial price does have permanent and significant impacts on industrial gas price level.

Figure 11. Accumulated Response to Cholesky One s.d. Innovations (4-Variable model)

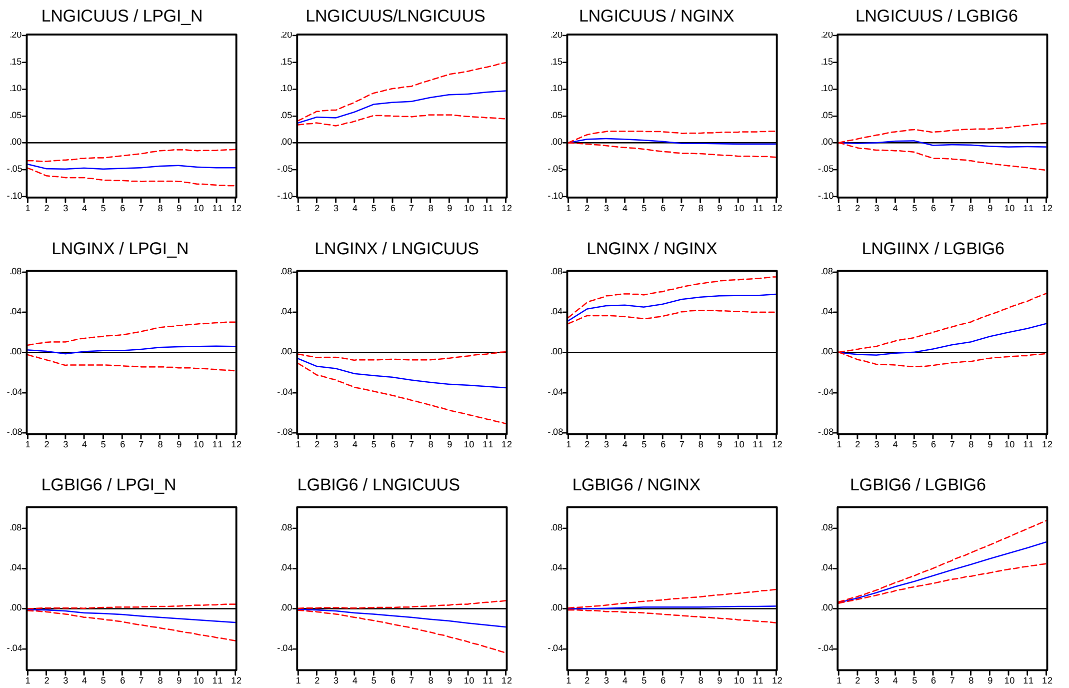
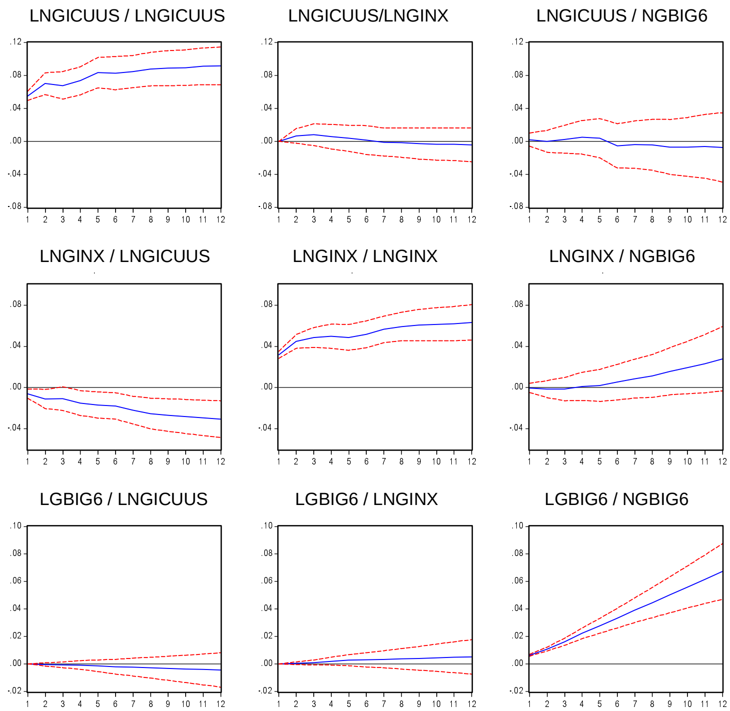


Figure 12. Accumulated Response to Cholesky One s.d. Innovations (3-Variable model)



(This result occurs for all three own innovation shocks and is consistent with the non-stationary properties of the data.) In addition, this shock to appears to reduce industrial consumption and industrial activity. The former occurs right away, while the later takes 6-12 months to occur and is not as statistically significant. There may be a minor 1-2 month positive impact of industrial natural gas consumption shocks on the industrial price level. The impact of this innovation on industrial activity is indistinguishable from zero. Industrial production innovations do not appear to have an impact on industrial natural gas prices. There is a positive and permanent impact on industrial natural gas consumption which is consistent with theory. An explanation for this is that prices are strongly determined by other market factors like petroleum prices, and non-market factors such as weather.

The impulse responses in the three variable VAR model are similar to the four variable model. The main difference is in the strength and significance of the industrial price shocks. Consumption does not appear to decline by as much, but appears to be more significant. The impact on industrial activity is less significant.

Forecast Error Variance Decompositions

Tables 16 and 17 show the forecast error variance decompositions for the 4-variable system and the three variable system. In the four variable system the orthogonalized innovations are ordered as the net-price shock, the current natural gas price level shock, industrial natural gas consumption, and the industrial production index. The three variable system is the same except there is no net-price shock. The decomposition for the net price variable is not presented as this is a created variable.

Ninety-five percent of the forecast error variance for the natural gas price level is explained by itself or the net price measure. Initially, the net price explains slightly over half, but falls to forty-three percent after one year. The own price shocks share of the variance moves in a mirror image to the net price. Consumption shocks explain ninety-five percent of the forecast error in the first month and decline to about two-thirds by twelve months. The natural gas price shock and production index explain sixteen percent and thirteen percent by the end of a year respectively. Industrial production shocks also explain about ninety five percent of their forecast error variance initially, but decline to only eight-three percent after a year. The contributions of the price level, net price, and natural gas consumption shocks are eight, five, and four percent respectively by twelve months ahead. However these three estimates are imprecise.

The decomposition of the forecast error variance in the three variable system for the natural gas price is similar to the four variable system. Over ninety-five percent is explained by the price measure over the twelve month period. Short-run shocks to consumption of natural gas and industrial production do not have a strong influence for forecast errors for prices. Industrial consumption own shocks are major factors in its own forecast errors in the first three months. After a year industrial production and natural gas price level shocks contribute about twelve percent and nine percent respectively to the forecast error variance for consumption. Industrial production forecast shocks explain over ninety percent of the forecast error variance through twelve months. The difference between the four variable system and the three variable system, despite the imprecision is that including the net price measure in the model appears to inject price effects on industrial activity.

Granger "Causality" Testing

Table 18 presents the Granger Causality tests for the 4-variable model. Each of the 4 variables appears to have explanatory power for one or more of the other variables at the 10% level in the system. It is not clear how to interpret the causal relationship from the real variables to the net price. Lagged values of the natural gas price have very high power for explaining the net price, but do not appear to preceed consumption or industrial consumption. The net price term does help to explain industrial production albeit at only 7%. Both lagged values of industrial consumption and the production index appear to explain both price measures, but not each other. There may some imprecision in the later result. The p-value for industrial production on consumption is 13% and neither price measure appears to “cause” consumption. However, all three variables do at the 5% level.

Table 19 presents the Granger Causality tests for the 3-variable model. Each of the 3 variables appears to have explanatory power for one of the other variables at the 10% level in the system. Lagged values of the natural gas price have marginal power explaining the industrial consumption at just above the 5% level. Both lagged values of industrial consumption and the production index appear to explain the industrial natural gas price measure at 6% and less than 1% respectively. But they do not appear to help explain each other. The p-value for industrial production on consumption is 20%. Jointly the lagged price measure and industrial production index have a p-value of just under 8%. Industrial production does not appear to “cause” the natural gas price level or industrial consumption.

Model Simulation

The four variable model was simulated over the period January 1998 through August 2003. The dynamic stochastic solution was solved for in Eviews 4.1. The values for the exogenous variables were used. Figure X presents graphs of the “forecast” and actual levels for each series. Figure XX presents graphs of the percent deviation of the "forecasted" values from the actuals. Discontinuities in the net natural gas price graph reflect ratios where the denominator was zero, the natural gas price was at a new high.

Figure 13. Forecast Simulation Levels

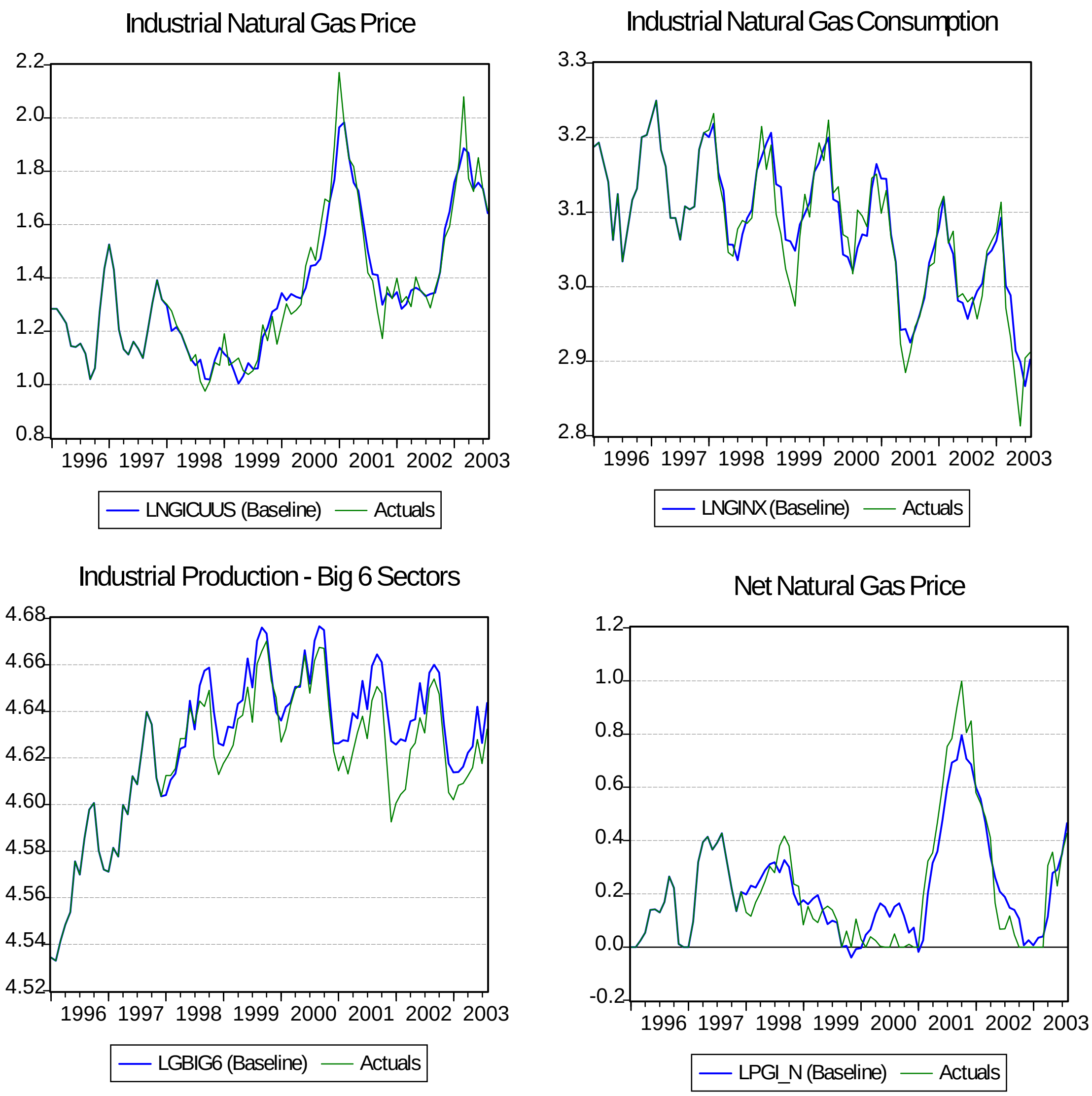
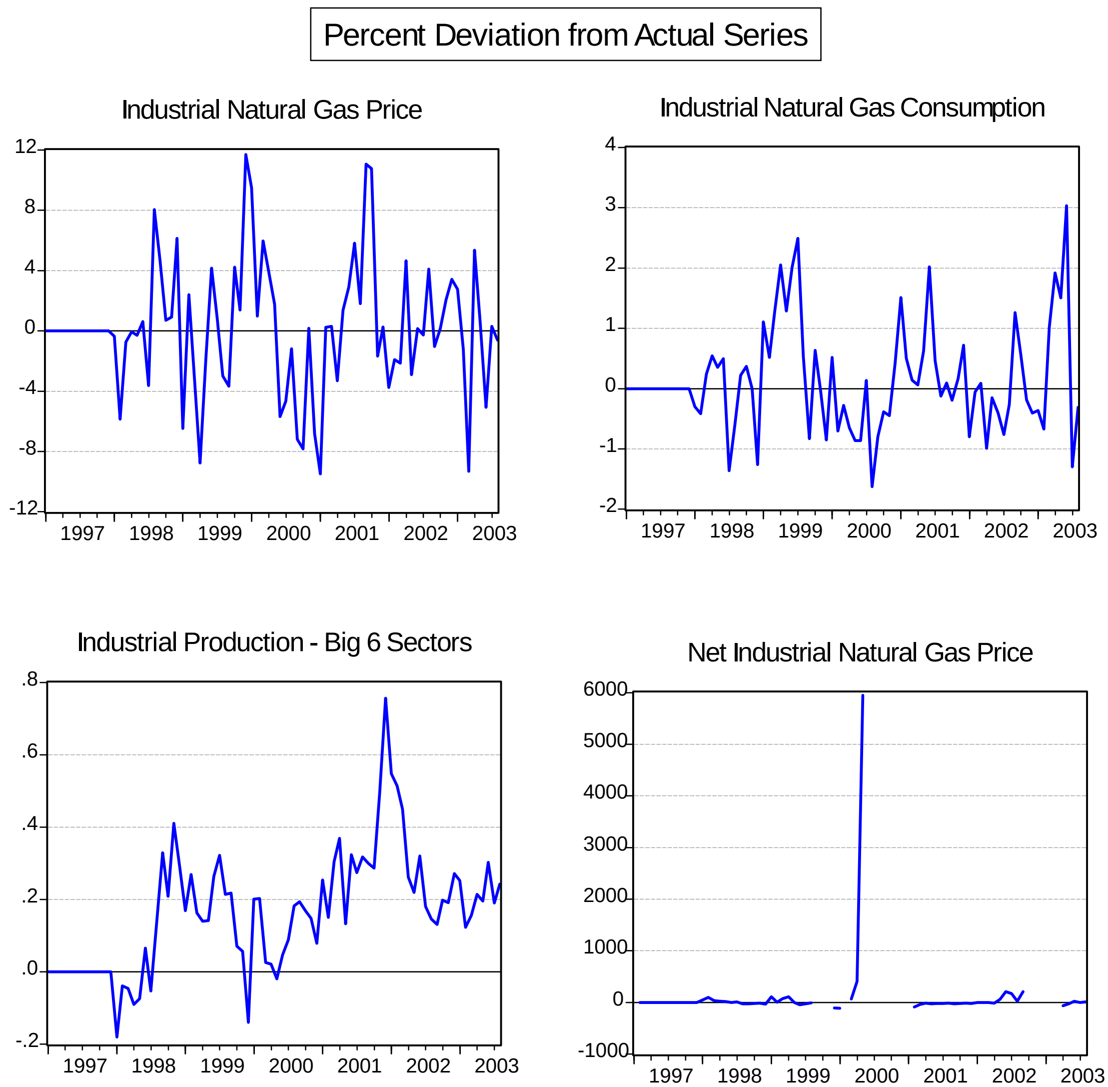


Figure 14. Forecast Simulation Percent Deviation from Actual



CONCLUSIONS

QUESTIONS FOR THE COMMITTEE

Does the VAR approach to modeling relationships between the variables (industrial natural gas price, industrial natural gas consumption, industrial production) appear fruitful?

Would you recommend another approach?

What do you think are the strengths and weaknesses of the approach?

How can the current model be improved?

Should VAR models for other sectors and fuels be considered? Which ones?

What do you think of the “net” price variable?

Are there other “net” price variables that you think should be considered? Are their better types of shock variables?

Is modeling the natural gas consumption of the BIG 6 industrial sectors appropriate?

They are currently weighted by value-added in 2000. Are there other weighting schemes which should be considered like natural gas consumption weights?

REFERENCES

Table 1 Variable Definitions

Name	Description and Units	Source
NGICUUS	nominal price of natural gas to industry, $/MCF.	
NGICUUSR	real price of natural gas to industry deflated by the producer price index for non-energy and food products, $/MCF, WPIINUS (1982-84=0).	
PGI_N	Net Industrial Natural Gas Price Measure, the difference between the highest monthly price in the last three years and the current price.	
NGINX	Natural gas demand: industrial sector (Incl CHP), BCFD, NSA	
GBIG6	Weighted Industrial Production Index for six largest natural gas consuming 2-digit sectors, consuming 80% of that sector's natural gas. Weights by value-added in 2000 0.0994*g331+0.2760*g311+0.1176*g322+0.3544*g325+0.0838*g327+0.06886*g324, NSA, 1997=100	Federal Reserve Board
NGSPRFTC	the lagged relative price of, ngspuus, to the lagged rftcuus, converted to MCF. The spot price, (in DMMB) is divided by 1.03 and the fuel price (in $/G) is divided by 6.287.	
RFTCEUS	price of retail residual fuel price, $/MMBTU	
NGSPUUS	spot natural gas, $/TCF	
RFEUDUS	the price of residual fuel oil to electric utilities, ($/MMBTU)	
x(4)	the deviation of heating degree days from normal, (ZGHDPUS-ZGHNPUS). They are population weighted and divided by the number of days in the month, ZSAJQUS.	
ZWHDPUS	Monthly population weighted degree days	
ZWHNPUS	Monthly population weighted normal heating degree-days. Normal = trend-adjusted 1971-2000 average.	
x(5)	Interaction term between cold weather monthly dummy variables and deviations of heating degree days from normal. The monthly variables are October through April.	
ZSAJQUS	The number of days per month	
GASVAR	deviation of natural gas from normal storage levels (BCFD)	
D_HAND	Dummy variable for Hurricane Andrew which caused production shutdowns in September and October 1992.	
D_9402	Dummy variable for February 1994 as a result of cold weather, ice storms, and transmission problems.	
D_9602	Dummy variable for February 1996 for expectations of cold weather and low inventories leading to panic in the spot price market.	

Table 2 Augmented Dickey-Fuller Tests

sample is 1987 (2) - 2003 (8)

LNGICUUSR: ADF tests (T=199, Constant+Trend+Seasonals; 5%=-3.43 1%=-4.01)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
12	-2.480	0.91413	0.06819	-0.9607	0.3380	-5.250	
11	-2.736	0.90729	0.06817	0.1887	0.8506	-5.254	0.3380
10	-2.764	0.90860	0.06799	3.782	0.0002	-5.264	0.6201
9	-2.086	0.92947	0.07051	-1.048	0.2961	-5.196	0.0022
8	-2.317	0.92295	0.07053	-0.02822	0.9775	-5.200	0.0034
7	-2.373	0.92278	0.07033	-0.8551	0.3936	-5.210	0.0076
6	-2.613	0.91692	0.07028	1.351	0.1784	-5.216	0.0112
5	-2.375	0.92603	0.07044	-0.4690	0.6396	-5.215	0.0105
4	-2.626	0.92184	0.07029	1.361	0.1753	-5.224	0.0171
3	-2.383	0.93058	0.07045	1.115	0.2663	-5.224	0.0153
2	-2.204	0.93703	0.07050	-1.096	0.2743	-5.227	0.0166
1	-2.541	0.92949	0.07054	1.134	0.2582	-5.231	0.0180
0	-2.351	0.93620	0.07059			-5.234	0.0189

LPGI_N: ADF tests (T=199, Constant+Trend+Seasonals; 5%=-3.43 1%=-4.01)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
12	-3.616*	0.77512	0.05189	1.725	0.0863	-5.796	
11	-3.269	0.80216	0.05219	0.9763	0.3303	-5.789	0.0863
10	-3.126	0.81642	0.05218	2.116	0.0358	-5.793	0.1425
9	-2.703	0.84361	0.05269	-0.2356	0.8140	-5.778	0.0404
8	-2.863	0.84016	0.05255	1.280	0.2023	-5.788	0.0790
7	-2.624	0.85776	0.05264	-0.6851	0.4942	-5.789	0.0753
6	-2.919	0.84780	0.05257	1.188	0.2364	-5.796	0.1055
5	-2.681	0.86680	0.05263	-0.06527	0.9480	-5.798	0.1040
4	-2.883	0.86569	0.05248	1.584	0.1148	-5.808	0.1542
3	-2.504	0.88867	0.05270	0.2134	0.8312	-5.805	0.1089
2	-2.586	0.89180	0.05256	0.2234	0.8235	-5.815	0.1521
1	-2.691	0.89516	0.05243	2.767	0.0062	-5.824	0.2030
0	-1.768	0.93482	0.05336			-5.794	0.0391

LNGINX: ADF tests (T=199, Constant+Trend+Seasonals; 5%=-3.43 1%=-4.01)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
12	-0.07121	0.99809	0.02888	0.4462	0.6560	-6.968	
11	-0.01693	0.99955	0.02881	0.2902	0.7720	-6.977	0.6560
10	0.01415	1.0004	0.02874	-2.701	0.0076	-6.986	0.8682
9	-0.2360	0.99371	0.02925	-0.01246	0.9901	-6.956	0.0610
8	-0.2378	0.99369	0.02917	-3.713	0.0003	-6.966	0.1167
7	-0.5016	0.98627	0.03020	-1.013	0.3124	-6.901	0.0010
6	-0.5709	0.98441	0.03020	-2.634	0.0092	-6.905	0.0015
5	-0.7732	0.97861	0.03069	-0.4872	0.6267	-6.877	0.0002
4	-0.8209	0.97742	0.03063	-2.528	0.0123	-6.886	0.0004
3	-1.072	0.97025	0.03108	-1.430	0.1546	-6.861	0.0001
2	-1.243	0.96564	0.03117	-2.699	0.0076	-6.860	0.0001
1	-1.698	0.95296	0.03169	-3.323	0.0011	-6.831	0.0000
0	-2.345	0.93461	0.03254			-6.783	0.0000

LGBIG6: ADF tests (T=199, Constant+Trend+Seasonals; 5%=-3.43 1%=-4.01)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
12	-2.114	0.94987	0.006324	0.4178	0.6766	-10.01	
11	-2.078	0.95156	0.006309	-0.5501	0.5830	-10.01	0.6766
10	-2.219	0.94923	0.006296	2.812	0.0055	-10.02	0.7886
9	-1.802	0.95841	0.006418	0.9372	0.3500	-9.989	0.0431
8	-1.671	0.96197	0.006416	-0.9338	0.3517	-9.994	0.0603
7	-1.869	0.95816	0.006414	0.4676	0.6407	-9.999	0.0776
6	-1.823	0.95974	0.006400	0.2439	0.8076	-10.01	0.1181
5	-1.812	0.96038	0.006383	0.1993	0.8423	-10.02	0.1750
4	-1.807	0.96100	0.006366	0.1105	0.9121	-10.03	0.2437
3	-1.817	0.96137	0.006349	2.845	0.0049	-10.04	0.3225
2	-1.439	0.96908	0.006471	-0.2632	0.7927	-10.00	0.0536
1	-1.496	0.96827	0.006454	-3.594	0.0004	-10.01	0.0771
0	-2.039	0.95596	0.006659			-9.956	0.0025

beta Y_1 is the implied lagged value in level form, sigma is the standard error of the ADF regression, t_DY_lag is the t-statistic associated with the maximum lag in ADF, t-prob is the p-value for the statistic, and F-prob is the significance of the F-test on lags dropped to that point. * is a rejection of the null for a unit root.

Table 3.a Specification Selection from Alternative VAR Models with Net Price Sample 1989.01 – 2003.08

Model	Log Likelihood	AIC	Schwartz	HQ
1	1475.6556	-15.451	-13.361	-14.603
2	1605.8456	-16.430	-13.548	-15.261
3	1612.5548	-16.370	-13.272	-15.113
4	1646.5670	-16.666	-13.423	-15.350
5	1672.9467	-16.602	-12.783	-15.503

Model Reduction via F-test

MODEL(5) --> MODEL(4): F(32,444)= 1.1753 [0.2382]
MODEL(5) --> MODEL(3): F(40,456)= 2.2661 [0.0000]**
MODEL(5) --> MODEL(2): F(52,466)= 1.9536 [0.0002]**
MODEL(4) --> MODEL(1): F(96,477)= 3.7888 [0.0000]**

MODEL(4) --> MODEL(3): F(8,256) = 6.8220 [0.0000]**
MODEL(4) --> MODEL(2): F(20,425)= 3.1852 [0.0000]**
MODEL(4) --> MODEL(1): F(64,503)= 5.0520 [0.0000]**

MODEL(3) --> MODEL(2): F(12,344)= 0.83868 [0.6104]
MODEL(3) --> MODEL(1): F(56,507)= 4.4594 [0.0000]**

MODEL(2) --> MODEL(1): F(44,510)= 5.4807 [0.0000]**

The five models are:

1) No seasonal and event dummies and exogenous variables
2) No event dummies and exogenous variables
3) No exogenous variables
4) No event dummies
5) Include seasonal and event dummies and exogenous variables

The fifth model is considered the most general one and the other four impose restriction on it.

Table 3.b Specification Selection from Alternative VAR Models without Net Price

Sample 1989.01 – 2003.08

Model	Log Likelihood	AIC	Schwartz	HQ
1	1342.6584	-14.257	-12.672	-13.615
2	1473.2713	-15.242	-12.864	-14.277
3	1478.5957	-15.166	-12.572	-14.114
4	1517.8231	-15.521	-14.410	-12.783
5	1522.9502	-15.443	-12.488	-14.244

Model Reduction via F-test

MODEL(5) --> MODEL(4): F(12,349)= 0.64854 [0.8001]
MODEL(5) --> MODEL(3): F(20,438)=   3.6005 [0.0000]**
MODEL(5) --> MODEL(2): F(32,488)=   2.5246 [0.0000]**
MODEL(5) --> MODEL(1): F(76,522)=   4.6889 [0.0000]**

MODEL(4) --> MODEL(3): F(8,270) =   8.4265 [0.0000]**
MODEL(4) --> MODEL(2): F(20,448)=   3.6998 [0.0000]**
MODEL(4) --> MODEL(1): F(64,530)=   5.4962 [0.0000]**

MODEL(3) --> MODEL(2): F(12,362)= 0.69928 [0.7524]
MODEL(3) --> MODEL(1): F(56,535)=   4.6585 [0.0000]**

MODEL(2) --> MODEL(1): F(44,537)=   5.7906 [0.0000]**

The five models are:

1) No seasonal and event dummies and exogenous variables
2) No event dummies and exogenous variables
3) No exogenous variables
4) No event dummies
5) Include seasonal and event dummies and exogenous variables

The fifth model is considered the most general one and the other four impose restriction on it.

Table 4 VAR Residual Serial Correlation LM Tests – 4-variable Model

VAR Residual Serial Correlation LM Tests
H0: no serial correlation at lag order h
Date: 03/17/04 Time: 11:20
Sample: 1989:01 2003:08
Included observations: 176

Lags	LM-Stat	Prob
1	31.39807	0.0120
2	27.79299	0.0335
3	15.76848	0.4692
4	22.91516	0.1160
5	20.40675	0.2025
6	15.84146	0.4641
7	19.22812	0.2570
8	19.63372	0.2372
9	27.39964	0.0372
10	20.91918	0.1816
11	23.10515	0.1110
12	14.56703	0.5565
13	15.96538	0.4554

Probs from chi-square with 16 df.

VAR Residual Serial Correlation LM Tests
H0: no serial correlation at lag order h
Date: 03/17/04 Time: 11:20
Sample: 1989:01 2003:08
Included observations: 176

Lags	LM-Stat	Prob
1	31.39807	0.0120
2	27.79299	0.0335
3	15.76848	0.4692
4	22.91516	0.1160
5	20.40675	0.2025
6	15.84146	0.4641

Probs from chi-square with 16 df.

Table 5 VAR Lag Order Selection Criteria – 4-variable Model

```
==========================================================================
VAR Lag Order Selection Criteria
Endogenous variables: LNGICUUS LPGI_N LNGINX LGBIG6
Exogenous variables:  D_SDUM GASVAR (LNGSPUUS(-1)/1.03)/(LRFTCUUS(-
1)/6.287) LRFEUDUS(-1)(
Date: 03/17/04   Time: 11:20
Sample: 1989:01 2003:08
Included observations: 176
==========================================================================
  Lag    LogL        LR       FPE       AIC        SC         HQ
==========================================================================
   0    414.9680    NA      2.18E-07  -3.988273  -2.835370  -3.520661
   1    638.322   2168.673  2.41E-13  -17.70821  -16.26708* -17.12369
   2   1666.619   48.87676  2.10E-13  -17.84795  -16.11859  -17.14653*
   3   1683.195   27.87764  2.09E-13* -17.85449* -15.83691  -17.03617
   4   1697.975   24.18582  2.13E-13  -17.84063  -15.53482  -16.90540
   5   1710.113   19.31002  2.25E-13  -17.79674  -15.20271  -16.74461
   6   1726.091   24.69390  2.27E-13  -17.79649  -14.91424  -16.62746
   7   1737.091   16.49861  2.42E-13  -17.73967  -14.56918  -16.45373
   8   1744.581   10.89518  2.71E-13  -17.64297  -14.18426  -16.24013
   9   1764.430   27.96874  2.63E-13  -17.68670  -13.93977  -16.16696
   10  1780.312   21.65814  2.69E-13  -17.68537  -13.65021  -16.04873
   11  1800.372   26.44253  2.62E-13  -17.73150  -13.40812  -15.97796
   12  1826.468   33.21300* 2.40E-13  -17.84623  -13.23462  -15.97578
   13  1839.125   15.53289  2.57E-13  -17.80823  -12.90840  -15.82088
==========================================================================
 * indicates lag order selected by the criterion
 LR: sequential modified LR test statistic (each test at 5% level)
 FPE: Final prediction error
 AIC: Akaike information criterion
 SC: Schwarz information criterion
 HQ: Hannan-Quinn information criterion
```

Table 6 VAR Lag Exclusion Wald Tests – 4-variable Model

VAR Lag Exclusion Wald Tests
Date: 03/17/04 Time: 11:20
Sample: 1989:01 2003:08
Included observations: 176

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	LNGICUUS	LPGI_N	LNGINX	LGBIG6	Joint
Lag 1	5.270330	64.65935	35.49432	74.77634	285.7763
	[0.260667]	[3.04E-13]	[3.68E-07]	[2.22E-15]	[0.000000]
Lag 2	2.047120	1.865048	7.109933	10.93084	23.17889
	[0.727092]	[0.760562]	[0.130192]	[0.027352]	[0.109035]
Lag 3	3.947669	2.316255	10.08036	2.489416	16.30239
	[0.413134]	[0.677811]	[0.039096]	[0.646532]	[0.432063]
Lag 4	1.472194	0.852193	1.591576	14.38032	20.00502
	[0.831555]	[0.931317]	[0.810305]	[0.006175]	[0.219995]
Lag 5	4.794720	6.198192	0.926794	5.059021	18.62108
	[0.309016]	[0.184828]	[0.920686]	[0.281295]	[0.288802]
Lag 6	5.153824	7.345143	0.642838	4.319195	25.08342
	[0.271875]	[0.118735]	[0.958187]	[0.364528]	[0.068368]
Lag 12	14.99228	16.55351	15.58120	1.883287	38.32953
	[0.004717]	[0.002360]	[0.003636]	[0.757215]	[0.001358]
df	4	4	4	4	16

Table 7 VAR Residual Serial Correlation LM Tests – 3-variable Model

VAR Residual Serial Correlation LM Tests
H0: no serial correlation at lag order h
Date: 03/17/04 Time: 11:33
Sample: 1989:01 2003:08
Included observations: 176

Lags	LM-Stat	Prob
1	25.58759	0.0024
2	15.32495	0.0824
3	8.403164	0.4941
4	3.360731	0.9483
5	7.150594	0.6214
6	3.291020	0.9516
7	6.122042	0.7276
8	8.944652	0.4424
9	10.34945	0.3229
10	7.257987	0.6103
11	5.552807	0.7837
12	7.863126	0.5480
13	19.32661	0.0226

Probs from chi-square with 9 df.

VAR Residual Serial Correlation LM Tests
H0: no serial correlation at lag order h
Date: 03/17/04 Time: 11:33
Sample: 1989:01 2003:08
Included observations: 176

Lags	LM-Stat	Prob
1	25.58759	0.0024
2	15.32495	0.0824
3	8.403164	0.4941
4	3.360731	0.9483
5	7.150594	0.6214
6	3.291020	0.9516

Probs from chi-square with 9 df.

Table 8 VAR Lag Order Selection Criteria – 3-variable Model

VAR Lag Order Selection Criteria
Endogenous variables: LNGICUUS LNGINX LGBIG6
Exogenous variables: D_SDUM GASVAR (LNGSPUUS(-1)/1.03)/(LRFTCUUS(-1)/6.287) LRFEUDUS(-1)(
Date: 03/17/04 Time: 11:33
Sample: 1989:01 2003:08
Included observations: 176

Lag	LogL	LR	FPE	AIC	SC	HQ
0	336.7440	NA	7.55E-06	-3.281182	-2.416505	-2.930473
1	1299.724	1718.045	1.48E-10	-14.12187	-13.09506*	-13.70540
2	1317.669	31.40273	1.34E-10	-14.22351	-13.03458	-13.74129*
3	1330.250	21.58727	1.29E-10*	-14.26420*	-12.91314	-13.71622
4	1336.728	10.89522	1.33E-10	-14.23554	-12.72236	-13.62180
5	1340.208	5.733706	1.42E-10	-14.17281	-12.49750	-13.49331
6	1345.924	9.224497	1.48E-10	-14.13550	-12.29806	-13.39025
7	1348.999	4.857553	1.59E-10	-14.06818	-12.06861	-13.25716
8	1350.599	2.471871	1.74E-10	-13.98408	-11.82238	-13.10731
9	1359.210	13.01442	1.76E-10	-13.97966	-11.65584	-13.03713
10	1362.882	5.424074	1.88E-10	-13.91911	-11.43316	-12.91082
11	1373.092	14.73586	1.87E-10	-13.93287	-11.28479	-12.85882
12	1385.133	16.96660*	1.82E-10	-13.96742	-11.15722	-12.82762
13	1391.689	9.014742	1.89E-10	-13.93965	-10.96732	-12.73409

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 9. VAR Lag Exclusion Wald Tests – 3-variable Model

VAR Lag Exclusion Wald Tests
Date: 03/17/04 Time: 11:33
Sample: 1989:01 2003:08
Included observations: 176

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	LNGICUUS	LNGINX	LGBIG6	Joint
Lag 1	7.378234	30.97330	73.43093	116.8882
	[0.060771]	[8.61E-07]	[7.77E-16]	[0.000000]
Lag 2	3.384349	2.672137	9.408560	14.50934
	[0.336074]	[0.444983]	[0.024324]	[0.105326]
Lag 3	2.191392	9.177107	2.136779	11.98391
	[0.533646]	[0.027027]	[0.544508]	[0.214218]
Lag 4	2.172937	1.925789	6.618795	11.54303
	[0.537299]	[0.587951]	[0.085093]	[0.240313]
Lag 5	4.190698	0.710040	0.335169	5.441438
	[0.241595]	[0.870840]	[0.953284]	[0.794256]
Lag 6	6.618718	1.101272	2.243517	9.905260
	[0.085096]	[0.776767]	[0.523428]	[0.358209]
Lag 12	6.415887	13.97250	0.618776	18.89453
	[0.093039]	[0.002943]	[0.892121]	[0.026105]
df	3	3	3	9

Table 10 VAR Model 4 Estimates – 4-variable Model

Vector Autoregression Estimates
Date: 03/17/04 Time: 11:19
Sample: 1989:01 2003:08
Included observations: 176
Standard errors in ( ) & t-statistics in [ ]

	LNGICUUS	LPGI_N	LNGINX	LGBIG6
LNGICUUS(-1)	0.287897	0.744002	-0.129315	-0.000272
	(0.13736)	(0.12256)	(0.06148)	(0.01477)
	[2.09596]	[6.07027]	[-2.10331]	[-0.01838]
LNGICUUS(-2)	-0.144766	-0.097603	0.190289	-0.014991
	(0.17842)	(0.15920)	(0.07986)	(0.01919)
	[-0.81138]	[-0.61307]	[2.38276]	[-0.78134]
LNGICUUS(-3)	0.354016	-0.229617	-0.138990	0.000209
	(0.18121)	(0.16170)	(0.08111)	(0.01949)
	[1.95359]	[-1.42005]	[-1.71357]	[0.01074]
LNGICUUS(-4)	0.019742	0.068920	0.061742	0.039021
	(0.18319)	(0.16347)	(0.08200)	(0.01970)
	[0.10776]	[0.42162]	[0.75297]	[1.98086]
LNGICUUS(-5)	-0.162058	-0.095696	-0.005212	-0.043685
	(0.18308)	(0.16336)	(0.08195)	(0.01969)
	[-0.88518]	[-0.58579]	[-0.06360]	[-2.21899]
LNGICUUS(-6)	0.011517	0.229775	-0.024301	0.020543
	(0.13179)	(0.11760)	(0.05899)	(0.01417)
	[0.08738]	[1.95388]	[-0.41195]	[1.44953]
LNGICUUS(-12)	-0.098526	0.032786	0.010449	0.003024
	(0.07152)	(0.06382)	(0.03201)	(0.00769)
	[-1.37755]	[0.51373]	[0.32639]	[0.39317]
LPGI_N(-1)	0.105696	0.940494	-0.173931	0.003039
	(0.13759)	(0.12277)	(0.06158)	(0.01480)
	[0.76820]	[7.66060]	[-2.82425]	[0.20542]
LPGI_N(-2)	-0.096189	-0.108337	0.176760	-0.023913
	(0.19698)	(0.17577)	(0.08817)	(0.02118)
	[-0.48832]	[-0.61637]	[2.00479]	[-1.12893]
LPGI_N(-3)	0.331026	-0.179966	-0.037264	-0.010962
	(0.19961)	(0.17811)	(0.08935)	(0.02146)
	[1.65835]	[-1.01040]	[-0.41708]	[-0.51071]
LPGI_N(-4)	-0.108473	0.142557	0.032840	0.060972
	(0.20323)	(0.18134)	(0.09096)	(0.02185)
	[-0.53375]	[0.78613]	[0.36102]	[2.79005]
LPGI_N(-5)	-0.073425	-0.196914	0.002894	-0.042782
	(0.20478)	(0.18272)	(0.09166)	(0.02202)

Table 10 VAR Model 4 Estimates – 4-variable Model (cont.)

	[-0.35856]	[-1.07767]	[0.03158]	[-1.94285]
LPGI_N(-6)	-0.004763	0.109936	-0.007020	0.006597
	(0.14173)	(0.12647)	(0.06344)	(0.01524)
	[-0.03360]	[0.86929]	[-0.11066]	[0.43287]
LPGI_N(-12)	0.073573	-0.045359	-0.016278	0.003592
	(0.03573)	(0.03188)	(0.01599)	(0.00384)
	[2.05937]	[-1.42286]	[-1.01795]	[0.93488]
LNGINX(-1)	0.201483	-0.108195	0.420108	0.006009
	(0.19562)	(0.17456)	(0.08756)	(0.02104)
	[1.02995]	[-0.61983]	[4.79786]	[0.28565]
LNGINX(-2)	-0.195245	0.182893	0.046376	-0.003170
	(0.21783)	(0.19437)	(0.09750)	(0.02342)
	[-0.89634]	[0.94097]	[0.47565]	[-0.13534]
LNGINX(-3)	-0.015049	-0.077879	0.104828	0.024400
	(0.22274)	(0.19875)	(0.09970)	(0.02395)
	[-0.06756]	[-0.39185]	[1.05146]	[1.01874]
LNGINX(-4)	0.002234	0.019978	0.024278	-0.023239
	(0.21823)	(0.19473)	(0.09768)	(0.02347)
	[0.01024]	[0.10260]	[0.24854]	[-0.99030]
LNGINX(-5)	-0.042128	-0.119468	0.087621	-0.014810
	(0.21692)	(0.19356)	(0.09709)	(0.02333)
	[-0.19421]	[-0.61723]	[0.90245]	[-0.63491]
LNGINX(-6)	0.101346	-0.072345	-0.004898	0.020340
	(0.19020)	(0.16972)	(0.08513)	(0.02045)
	[0.53284]	[-0.42627]	[-0.05753]	[0.99448]
LNGINX(-12)	-0.419928	0.496882	0.200590	0.007475
	(0.15115)	(0.13488)	(0.06766)	(0.01625)
	[-2.77814]	[3.68400]	[2.96480]	[0.45991]
LGBIG6(-1)	-0.202540	0.074533	-0.285934	0.702550
	(0.76504)	(0.68264)	(0.34243)	(0.08227)
	[-0.26475]	[0.10918]	[-0.83501]	[8.54001]
LGBIG6(-2)	0.792735	-0.645274	0.568402	0.284152
	(0.92929)	(0.82921)	(0.41595)	(0.09993)
	[0.85306]	[-0.77818]	[1.36651]	[2.84356]
LGBIG6(-3)	0.051056	-0.348207	0.383378	0.066576
	(0.92426)	(0.82472)	(0.41370)	(0.09939)
	[0.05524]	[-0.42221]	[0.92671]	[0.66986]
LGBIG6(-4)	-0.360190	0.041935	-0.353259	-0.172181
	(0.91125)	(0.81311)	(0.40788)	(0.09799)
	[-0.39527]	[0.05157]	[-0.86609]	[-1.75715]
LGBIG6(-5)	-1.638171	1.574120	-0.003206	0.004452

Table 10 VAR Model 4 Estimates – 4-variable Model (cont.)

	(0.89376)	(0.79750)	(0.40005)	(0.09611)
	[-1.83290]	[1.97381]	[-0.00802]	[0.04632]
LGBIG6(-6)	1.741810	-0.939555	0.206487	0.057740
	(0.78645)	(0.70175)	(0.35202)	(0.08457)
	[2.21477]	[-1.33886]	[0.58658]	[0.68276]
LGBIG6(-12)	-0.036252	-0.064098	-0.423171	0.040753
	(0.40704)	(0.36320)	(0.18219)	(0.04377)
	[-0.08906]	[-0.17648]	[-2.32266]	[0.93108]
D_JAN	0.126452	-0.103603	0.010359	0.015432
	(0.04283)	(0.03821)	(0.01917)	(0.00461)
	[2.95273]	[-2.71119]	[0.54040]	[3.35097]
D_FEB	0.069101	-0.091028	0.032387	0.023024
	(0.04740)	(0.04230)	(0.02122)	(0.00510)
	[1.45778]	[-2.15211]	[1.52645]	[4.51698]
D_MAR	-0.005711	-0.020717	-0.049405	0.023733
	(0.05322)	(0.04749)	(0.02382)	(0.00572)
	[-0.10730]	[-0.43623]	[-2.07388]	[4.14684]
D_APR	-0.077436	0.040126	-0.023078	0.027852
	(0.05550)	(0.04953)	(0.02484)	(0.00597)
	[-1.39512]	[0.81019]	[-0.92892]	[4.66652]
D_MAY	-0.136495	0.110981	-0.073138	0.025592
	(0.05858)	(0.05227)	(0.02622)	(0.00630)
	[-2.33005]	[2.12317]	[-2.78932]	[4.06264]
D_JUN	-0.114032	0.102069	-0.029495	0.044057
	(0.06446)	(0.05751)	(0.02885)	(0.00693)
	[-1.76917]	[1.77469]	[-1.02234]	[6.35648]
D_JUL	-0.145142	0.135995	-0.041745	0.015624
	(0.07049)	(0.06290)	(0.03155)	(0.00758)
	[-2.05908]	[2.16218]	[-1.32311]	[2.06124]
D_AUG	-0.147739	0.123219	-0.000750	0.039345
	(0.06053)	(0.05401)	(0.02709)	(0.00651)
	[-2.44083]	[2.28142]	[-0.02768]	[6.04489]
D_SEP	-0.094972	0.093653	0.013841	0.034050
	(0.06295)	(0.05617)	(0.02818)	(0.00677)
	[-1.50862]	[1.66722]	[0.49119]	[5.02991]
D_OCT	-0.084950	0.072979	0.021403	0.024897
	(0.05364)	(0.04787)	(0.02401)	(0.00577)
	[-1.58363]	[1.52467]	[0.89141]	[4.31617]
D_NOV	0.045905	-0.052810	0.027995	-0.000861
	(0.04654)	(0.04152)	(0.02083)	(0.00500)
	[0.98643]	[-1.27177]	[1.34399]	[-0.17198]

Table 10 VAR Model 4 Estimates – 4-variable Model (cont.)

GASVAR	-2.57E-05	1.43E-05	-1.12E-05	-3.62E-06
	(2.3E-05)	(2.0E-05)	(1.0E-05)	(2.5E-06)
	[-1.12144]	[0.69975]	[-1.09279]	[-1.46700]
(LNGSPUUS(-1)/1.0	0.229781UUS	-0.1971637)	-0.015937	0.000652
	(0.02638)	(0.02353)	(0.01181)	(0.00284)
	[8.71204]	[-8.37757]	[-1.34991]	[0.22979]
LRFEUDUS(-1)	0.122034	-0.080275	0.021330	-0.005302
	(0.03244)	(0.02894)	(0.01452)	(0.00349)
	[3.76241]	[-2.77365]	[1.46923]	[-1.52024]
(ZGHDPUS-ZGHNPUS)	0.007998	-0.005333	0.001057	0.001170
	(0.01247)	(0.01112)	(0.00558)	(0.00134)
	[0.64154]	[-0.47943]	[0.18936]	[0.87281]
((ZGHDPUS-ZGHNPUS	-0.004989)*(	0.005551OV+	0.002602AN+	-0.002115AR+D_APR)
	(0.01290)	(0.01151)	(0.00577)	(0.00139)
	[-0.38670]	[0.48220]	[0.45065]	[-1.52446]
R-squared	0.963781	0.942207	0.944071	0.993703
Adj. R-squared	0.951982	0.923381	0.925851	0.991652
Sum sq. resids	0.427287	0.340208	0.085606	0.004941
S.E. equation	0.056895	0.050767	0.025466	0.006118
F-statistic	81.68578	50.04688	51.81672	484.4450
Log likelihood	280.0957	300.1508	421.5733	672.5700
Akaike AIC	-2.682906	-2.910804	-4.290606	-7.142841
Schwarz SC	-1.890285	-2.118183	-3.497985	-6.350220
Mean dependent	1.198498	0.191695	3.049033	4.564978
S.D. dependent	0.259640	0.183407	0.093522	0.066961

Determinant Residual Covaria	8.59E-14
Log Likelihood (d.f. adjuste	1648.564
Akaike Information Criteria	-16.73368
Schwarz Criteria	-13.56320

Table 11. Residual Covariance Matrix and Residual Correlation Matrix – 4-variable Model

Residual Covariance Matrix

	LNGICUUS	LPGI_N	LNGINX	LGBIG6
LNGICUUS	0.003237	-0.002093	-0.000298	1.19E-05
LPGI_N	-0.002093	0.002577	8.77E-05	-4.58E-05
LNGINX	-0.000298	8.77E-05	0.000649	2.37E-05
LGBIG6	1.19E-05	-4.58E-05	2.37E-05	3.74E-05

Residual Correlation Matrix

	LNGICUUS	LPGI_N	LNGINX	LGBIG6
LNGICUUS	1.000000	-0.724639	-0.205955	0.034305
LPGI_N	-0.724639	1.000000	0.067869	-0.147444
LNGINX	-0.205955	0.067869	1.000000	0.152363
LGBIG6	0.034305	-0.147444	0.152363	1.000000

Table 12 VAR Model 4 Estimates – 3-variable Model

Vector Autoregression Estimates
Date: 03/17/04 Time: 11:33
Sample: 1989:01 2003:08
Included observations: 176
Standard errors in ( ) & t-statistics in [ ]

	LNGICUUS	LNGINX	LGBIG6
LNGICUUS(-1)	0.273367	-0.014864	-0.002008
	(0.10617)	(0.04735)	(0.01148)
	[2.57476]	[-0.31392]	[-0.17489]
LNGICUUS(-2)	-0.116986	0.044866	0.000356
	(0.09354)	(0.04171)	(0.01011)
	[-1.25067]	[1.07556]	[0.03523]
LNGICUUS(-3)	0.127767	-0.103248	0.004244
	(0.09498)	(0.04236)	(0.01027)
	[1.34526]	[-2.43766]	[0.41325]
LNGICUUS(-4)	0.131427	0.047361	-0.005870
	(0.09714)	(0.04332)	(0.01050)
	[1.35298]	[1.09327]	[-0.55888]
LNGICUUS(-5)	-0.109748	-0.006394	-0.005719
	(0.09936)	(0.04431)	(0.01074)
	[-1.10455]	[-0.14430]	[-0.53234]
LNGICUUS(-6)	0.080073	-0.035292	0.008059
	(0.07667)	(0.03419)	(0.00829)
	[1.04444]	[-1.03225]	[0.97210]
LNGICUUS(-12)	-0.022562	0.029290	-0.000105
	(0.03984)	(0.01777)	(0.00431)
	[-0.56636]	[1.64864]	[-0.02428]
LNGINX(-1)	0.245431	0.459438	0.013588
	(0.19075)	(0.08507)	(0.02063)
	[1.28667]	[5.40091]	[0.65877]
LNGINX(-2)	-0.235751	0.023319	0.000890
	(0.21851)	(0.09745)	(0.02363)
	[-1.07890]	[0.23930]	[0.03768]
LNGINX(-3)	-0.076772	0.115495	0.016812
	(0.22355)	(0.09969)	(0.02417)
	[-0.34342]	[1.15849]	[0.69550]
LNGINX(-4)	0.004582	0.034346	-0.024428
	(0.21926)	(0.09778)	(0.02371)
	[0.02090]	[0.35125]	[-1.03032]
LNGINX(-5)	-0.013000	0.075493	-0.007529
	(0.21935)	(0.09782)	(0.02372)

Table 12 VAR Model 4 Estimates – 3-variable Model (cont.)

	[-0.05926]	[0.77173]	[-0.31742]
LNGINX(-6)	0.084283	0.001369	0.017236
	(0.19245)	(0.08582)	(0.02081)
	[0.43795]	[0.01595]	[0.82824]
LNGINX(-12)	-0.344889	0.187180	-0.002210
	(0.13974)	(0.06232)	(0.01511)
	[-2.46811]	[3.00364]	[-0.14627]
LGBIG6(-1)	-0.374625	-0.153760	0.676567
	(0.73859)	(0.32938)	(0.07987)
	[-0.50722]	[-0.46681]	[8.47133]
LGBIG6(-2)	1.024924	0.468911	0.296977
	(0.89884)	(0.40085)	(0.09719)
	[1.14028]	[1.16980]	[3.05552]
LGBIG6(-3)	-0.207756	0.341637	0.119909
	(0.91966)	(0.41013)	(0.09944)
	[-0.22591]	[0.83300]	[1.20579]
LGBIG6(-4)	-0.562040	-0.360435	-0.221223
	(0.90461)	(0.40342)	(0.09782)
	[-0.62130]	[-0.89344]	[-2.26157]
LGBIG6(-5)	-1.501972	0.070735	0.002698
	(0.90115)	(0.40188)	(0.09744)
	[-1.66672]	[0.17601]	[0.02769]
LGBIG6(-6)	1.848446	0.034942	0.078845
	(0.78583)	(0.35045)	(0.08497)
	[2.35222]	[0.09971]	[0.92788]
LGBIG6(-12)	0.086181	-0.319208	0.032678
	(0.38705)	(0.17261)	(0.04185)
	[0.22266]	[-1.84931]	[0.78078]
D_JAN	0.127624	0.003192	0.016252
	(0.04244)	(0.01893)	(0.00459)
	[3.00698]	[0.16866]	[3.54120]
D_FEB	0.060128	0.028736	0.025855
	(0.04657)	(0.02077)	(0.00504)
	[1.29114]	[1.38368]	[5.13437]
D_MAR	-0.005397	-0.057179	0.024360
	(0.05359)	(0.02390)	(0.00580)
	[-0.10071]	[-2.39240]	[4.20363]
D_APR	-0.070200	-0.029669	0.029076
	(0.05575)	(0.02486)	(0.00603)
	[-1.25911]	[-1.19327]	[4.82297]
D_MAY	-0.119669	-0.085314	0.026356

Table 12 VAR Model 4 Estimates – 3-variable Model (cont.)

	(0.05767)	(0.02572)	(0.00624)
	[-2.07512]	[-3.31728]	[4.22652]
D_JUN	-0.097035	-0.041265	0.044590
	(0.06375)	(0.02843)	(0.00689)
	[-1.52216]	[-1.45150]	[6.46864]
D_JUL	-0.121911	-0.054568	0.016892
	(0.06936)	(0.03093)	(0.00750)
	[-1.75754]	[-1.76402]	[2.25215]
D_AUG	-0.129213	-0.012117	0.040805
	(0.05983)	(0.02668)	(0.00647)
	[-2.15956]	[-0.45411]	[6.30696]
D_SEP	-0.068003	-0.002869	0.034453
	(0.06152)	(0.02743)	(0.00665)
	[-1.10544]	[-0.10458]	[5.17932]
D_OCT	-0.062770	0.006301	0.026705
	(0.05189)	(0.02314)	(0.00561)
	[-1.20958]	[0.27226]	[4.75907]
D_NOV	0.054702	0.017055	-0.000537
	(0.04604)	(0.02053)	(0.00498)
	[1.18810]	[0.83063]	[-0.10787]
GASVAR	-2.51E-05	-9.49E-06	-2.60E-06
	(2.2E-05)	(9.7E-06)	(2.3E-06)
	[-1.15970]	[-0.98193]	[-1.10744]
(LNGSPUUS(-1)/1.0	0.218352UUS-0.0149167)		0.002096
	(0.02516)	(0.01122)	(0.00272)
	[8.67942]	[-1.32954]	[0.77041]
LRFEUDUS(-1)	0.127404	0.020053	-0.006051
	(0.03274)	(0.01460)	(0.00354)
	[3.89144]	[1.37345]	[-1.70913]
(ZGHDPUS-ZGHNPUS)	0.010049	0.000481	0.001003
	(0.01248)	(0.00557)	(0.00135)
	[0.80526]	[0.08635]	[0.74364]
((ZGHDPUS-ZGHNPUS-0.006277)*(	0.002839OV+-0.002004AN+D_FEB+D_M		
	(0.01289)	(0.00575)	(0.00139)
	[-0.48676]	[0.49369]	[-1.43691]
R-squared	0.960590	0.939589	0.993072
Adj. R-squared	0.950383	0.923943	0.991277
Sum sq. resids	0.464932	0.092466	0.005436
S.E. equation	0.057835	0.025792	0.006254
F-statistic	94.11177	60.05272	553.4372
Log likelihood	272.6655	414.7899	664.1596
Akaike AIC	-2.678017	-4.293067	-7.126813
Schwarz SC	-2.011495	-3.626545	-6.460291

Table 12 VAR Model 4 Estimates – 3-variable Model (cont.)

Mean dependent	1.198498	3.049033	4.564978
S.D. dependent	0.259640	0.093522	0.066961

Determinant Residual Covaria	8.16E-11
Log Likelihood (d.f. adjuste	1294.964
Akaike Information Criteria	-13.45413
Schwarz Criteria	-11.45457

Table 13 Residual Covariance Matrix and Residual Correlation Matrix – 3-variable Model

Residual Covariance Matrix

	LNGICUUS	LNGINX	LGBIG6
LNGICUUS	0.003345	-0.000312	9.30E-06
LNGINX	-0.000312	0.000665	2.06E-05
LGBIG6	9.30E-06	2.06E-05	3.91E-05

Residual Correlation Matrix

	LNGICUUS	LNGINX	LGBIG6
LNGICUUS	1.000000	-0.209370	0.025716
LNGINX	-0.209370	1.000000	0.127941
LGBIG6	0.025716	0.127941	1.000000

Table 14 VAR Residual Normality Tests – 4-variable Model

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
H0: residuals are multivariate normal
Date: 03/17/04 Time: 11:20
Sample: 1989:01 2003:08
Included observations: 176

Component	Skewness	Chi-sq	df	Prob.
1	0.136160	0.543830	1	0.4608
2	-0.090889	0.242316	1	0.6225
3	0.107840	0.341129	1	0.5592
4	0.044076	0.056986	1	0.8113
Joint		1.184261	4	0.8807

Component	Kurtosis	Chi-sq	df	Prob.
1	2.706974	0.629673	1	0.4275
2	2.627047	1.020024	1	0.3125
3	1.846095	9.764309	1	0.0018
4	1.848915	9.716634	1	0.0018
Joint		21.13064	4	0.0003

Component	Jarque-Bera	df	Prob.
1	1.173503	2	0.5561
2	1.262340	2	0.5320
3	10.10544	2	0.0064
4	9.773620	2	0.0075
Joint	22.31490	8	0.0044

Table 15 VAR Residual Normality Tests – 3-variable Model

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
H0: residuals are multivariate normal
Date: 03/17/04 Time: 11:33
Sample: 1989:01 2003:08
Included observations: 176

Component	Skewness	Chi-sq	df	Prob.
1	0.122927	0.443254	1	0.5056
2	0.093147	0.254509	1	0.6139
3	-0.001845	9.99E-05	1	0.9920
Joint		0.697863	3	0.8737

Component	Kurtosis	Chi-sq	df	Prob.
1	2.972848	0.005406	1	0.9414
2	2.038016	6.786367	1	0.0092
3	1.981236	7.611122	1	0.0058
Joint		14.40290	3	0.0024

Component	Jarque-Bera	df	Prob.
1	0.448661	2	0.7991
2	7.040876	2	0.0296
3	7.611222	2	0.0222
Joint	15.10076	6	0.0195

Table 16 Forecast Error Variance Decomposition– 4-variable Model

Accumulated Response of LNGICUUS to Cholesky (d.f. adjusted) One S.D. Innovations
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Variance Decomposition

Variance Decomposition of LNGICUUS:

Period	S.E.	LNGICUUS	LPGI_N	LNGINX	LGBIG6
1	0.056895	47.48981	52.51019	0.000000	0.000000
		(5.15201)	(5.15201)	(0.00000)	(0.00000)
2	0.058330	48.27076	51.00714	0.679370	0.042732
		(5.39924)	(5.41679)	(1.63272)	(0.82944)
3	0.058432	48.10515	50.83175	0.715138	0.347967
		(5.37982)	(5.34985)	(1.82084)	(1.36956)
4	0.060178	50.45118	48.07494	0.707163	0.766714
		(5.53839)	(5.43560)	(1.99055)	(1.80815)
5	0.062305	53.66571	44.90191	0.665675	0.766699
		(5.88288)	(5.59733)	(2.08205)	(1.88103)
6	0.063220	52.72743	43.99587	0.659477	2.617216
		(5.87343)	(5.59345)	(2.19998)	(2.45390)
7	0.063353	52.62825	43.87896	0.709927	2.782861
		(5.82457)	(5.52575)	(2.24148)	(2.52092)
8	0.063908	53.28807	43.27494	0.698409	2.738579
		(5.93138)	(5.56973)	(2.29607)	(2.53317)
9	0.064239	53.62137	42.84445	0.799314	2.734862
		(5.98532)	(5.65561)	(2.34534)	(2.57913)
10	0.064384	53.42614	42.98891	0.795739	2.789218
		(6.03269)	(5.67330)	(2.38778)	(2.64054)
11	0.064569	53.46140	42.81164	0.796779	2.930182
		(6.15356)	(5.75426)	(2.41768)	(2.76735)
12	0.064690	53.52450	42.65829	0.836984	2.980223
		(6.25453)	(5.84753)	(2.45288)	(2.89672)

Variance Decomposition of LNGINX:

Period	S.E.	LNGICUUS	LPGI_N	LNGINX	LGBIG6
1	0.025466	5.175461	0.460625	94.36391	0.000000
		(3.18390)	(1.31564)	(3.46207)	(0.00000)
2	0.028535	10.70294	1.143457	87.79773	0.355879
		(5.32970)	(2.02391)	(5.36546)	(1.08097)
3	0.029318	10.92888	1.743545	86.71040	0.617176
		(5.62424)	(2.40905)	(5.86538)	(1.35871)
4	0.030862	13.65918	2.273187	81.82410	2.243526
		(6.11734)	(2.44565)	(6.48772)	(2.44245)
5	0.031406	13.95292	2.195142	80.80724	3.044698
		(6.39356)	(2.50484)	(6.79742)	(3.05949)
6	0.032325	13.96075	2.144964	79.73188	4.162403
		(6.59987)	(2.48022)	(7.15951)	(3.76976)
7	0.033356	14.44442	2.019650	77.84041	5.695524
		(6.85629)	(2.43977)	(7.54841)	(4.35195)
8	0.034111	15.37175	2.213262	75.61729	6.797702
		(7.39319)	(2.52762)	(7.98120)	(4.94405)
9	0.034933	15.48773	2.111017	73.18139	9.219864

Table 16 Forecast Error Variance Decomposition – 4-variable Model (cont.)

		(7.76537)	(2.48450)	(8.49868)	(5.88049)
10	0.035502	15.55951	2.048614	71.76576	10.62612
		(8.15700)	(2.47953)	(8.94351)	(6.60581)
11	0.036048	15.80479	1.999634	70.31397	11.88161
		(8.58035)	(2.46069)	(9.40412)	(7.33417)
12	0.036711	16.09753	1.956545	68.50036	13.44557
		(9.08310)	(2.42459)	(9.87381)	(8.12237)

Variance Decomposition of LGBIG6:

Period	S.E.	LNGICUUS	LPGI_N	LNGINX	LGBIG6
1	0.006118	1.108014	2.173979	2.030553	94.68745
		(1.71028)	(2.24977)	(2.25780)	(3.60181)
2	0.007481	1.184114	1.828749	2.393418	94.59372
		(2.21720)	(2.46628)	(2.87555)	(4.29693)
3	0.008962	2.220173	2.897503	2.378810	92.50351
		(3.06784)	(3.28216)	(3.12830)	(5.29093)
4	0.010598	4.542468	4.959113	3.478528	87.01989
		(4.22593)	(4.34734)	(4.04407)	(6.97011)
5	0.011401	4.822637	4.457173	3.441369	87.27882
		(4.80965)	(4.25132)	(4.44076)	(7.47867)
6	0.012184	5.661782	4.334024	3.099243	86.90495
		(5.55601)	(4.33589)	(4.45552)	(8.10825)
7	0.012972	5.838266	4.632218	3.290663	86.23885
		(5.85853)	(4.62128)	(4.77594)	(8.72004)
8	0.013555	6.177866	4.749761	3.383178	85.68919
		(6.33086)	(4.80101)	(5.04431)	(9.33102)
9	0.014105	6.568133	4.835848	3.617084	84.97893
		(6.82983)	(4.92153)	(5.34463)	(9.98340)
10	0.014687	7.309755	4.789435	3.850270	84.05054
		(7.50367)	(4.93052)	(5.59941)	(10.6891)
11	0.015158	7.612971	4.841800	3.969519	83.57571
		(8.05004)	(4.99085)	(5.80123)	(11.2908)
12	0.015583	8.039772	4.845988	4.130304	82.98394
		(8.69460)	(5.00323)	(6.02420)	(11.9464)

Cholesky Ordering: LPGI_N LNGICUUS LNGINX LGBIG6
Standard Errors: Monte Carlo (1000 repetitions)

Table 17 Forecast Error Variance Decomposition– 3-variable Model

Accumulated Response to Cholesky (d.f. adjusted) One S.D. Innovations
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Variance Decomposition

Variance Decomposition of LNGICUUS:

Period	S.E.	LNGICUUS	LNGINX	LGBIG6
1	0.057835	100.0000	0.000000	0.000000
		(0.00000)	(0.00000)	(0.00000)
2	0.059939	98.89096	0.959201	0.149834
		(1.92624)	(1.74818)	(0.94286)
3	0.060115	98.44672	0.981278	0.571999
		(2.50856)	(1.96157)	(1.57239)
4	0.060661	97.80122	1.344585	0.854192
		(2.98330)	(2.34670)	(1.95148)
5	0.061480	97.82485	1.329310	0.845842
		(3.10672)	(2.40529)	(2.11530)
6	0.062273	95.44628	1.321417	3.232302
		(3.87552)	(2.45135)	(3.16048)
7	0.062384	95.27811	1.322299	3.399594
		(3.95924)	(2.53727)	(3.24262)
8	0.062467	95.26395	1.318795	3.417252
		(4.04580)	(2.61615)	(3.28767)
9	0.062484	95.22490	1.335799	3.439302
		(4.11157)	(2.66051)	(3.34203)
10	0.062532	95.08378	1.364020	3.552202
		(4.21032)	(2.68854)	(3.41873)
11	0.062625	94.90318	1.393777	3.703041
		(4.31869)	(2.71634)	(3.50705)
12	0.062627	94.89772	1.396827	3.705449
		(4.38186)	(2.74526)	(3.55448)

Variance Decomposition of LNGINX:

Period	S.E.	LNGICUUS	LNGINX	LGBIG6
1	0.025792	4.383600	95.61640	0.000000
		(3.16991)	(3.16991)	(0.00000)
2	0.028438	5.006378	94.88149	0.112136
		(4.17252)	(4.23495)	(0.86158)
3	0.029138	4.843088	94.64404	0.512871
		(3.97496)	(4.24076)	(1.49580)
4	0.030704	7.689274	90.12447	2.186253
		(4.52740)	(4.99034)	(2.59601)
5	0.031324	7.884667	89.24637	2.868962
		(4.64338)	(5.27084)	(3.22541)
6	0.032172	7.533281	88.56162	3.905099
		(4.53742)	(5.59537)	(4.08024)
7	0.033148	8.345063	86.54397	5.110964
		(4.70635)	(6.06885)	(4.72220)
8	0.033775	9.307385	84.65260	6.040019
		(5.05025)	(6.57656)	(5.33749)
9	0.034452	9.198521	82.64655	8.154925

Table 17 Forecast Error Variance Decomposition– 3-variable Model (cont.)

		(5.02710)	(7.13382)	(6.24376)
10	0.034958	9.251518	81.48261	9.265873
		(5.09686)	(7.58295)	(6.97348)
11	0.035432	9.397141	80.22703	10.37583
		(5.20393)	(8.04760)	(7.68441)
12	0.036003	9.322856	78.57578	12.10136
		(5.23730)	(8.58796)	(8.47594)

Variance Decomposition of LGBIG6:

Period	S.E.	LNGICUUS	LNGINX	LGBIG6
1	0.006254	0.066132	1.859055	98.07481
		(0.95770)	(2.13692)	(2.29780)
2	0.007584	0.056286	2.734236	97.20948
		(1.53408)	(2.90059)	(3.27697)
3	0.008965	0.045653	3.306685	96.64766
		(1.60239)	(3.66721)	(3.98312)
4	0.010468	0.047263	4.762711	95.19003
		(1.59353)	(4.66940)	(4.90352)
5	0.011268	0.099779	4.929649	94.97057
		(1.80678)	(5.18544)	(5.46912)
6	0.012004	0.247418	4.742382	95.01020
		(1.90277)	(5.41635)	(5.74599)
7	0.012749	0.229202	5.107096	94.66370
		(1.87020)	(5.77243)	(6.06028)
8	0.013289	0.229839	5.405538	94.36462
		(1.92823)	(6.15904)	(6.44865)
9	0.013830	0.244212	5.711616	94.04417
		(1.96403)	(6.50416)	(6.79659)
10	0.014388	0.257035	6.085096	93.65787
		(1.98858)	(6.85510)	(7.13775)
11	0.014865	0.260440	6.333732	93.40583
		(2.04566)	(7.17184)	(7.46440)
12	0.015314	0.271367	6.595151	93.13348
		(2.09680)	(7.49410)	(7.79960)

Cholesky Ordering: LNGICUUS LNGINX LGBIG6
Standard Errors: Monte Carlo (1000 repetitions)

Table 18: Granger "Causality" Tests: 4 Variable Model

Sample 1989.01 2003.08 (176 observations)

		Dependent Variable			
		LNGICUUS	Net Price	LNGINX	LGBIG6
Exclusion Restrictions p-values	LNGICUUS	--	0.00	0.347	0.324
	Net Price	0.113	--	0.158	0.067
	LNGINX	0.049	0.013	--	0.728
	LGBIG6	0.002	0.005	0.130	--
	All	0.000	0.00	0.044	0.5934

Table 19: Granger "Causality" Tests: 3 –Variable Model

Sample 1989.01 2003.08 (176 observations)

		Dependent Variable		
		LNGICUUS	LNGINX	LGBIG6
Exclusion Restrictions p-values	LNGICUUS	--	0.054	0.973
	LNGINX	0.063	--	0.844
	LGBIG6	0.002	0.201	--
	All	0.000	0.078	0.979