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Macroeconomic Shocks and Business Cycles in Australia

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A small vector autoregression model is estimated to assess how demand and supply shocks influence Australian output and price behavior. The model is identified by assuming that aggregate demand shocks have transitory effects on output, while aggregate supply shocks have permanent effects. The paper describes how Australian macroeconomic variables respond to demand and supply shocks in the short run and in the long run. It also finds that demand shocks are dominant in determining fluctuations in Australian output at a one-quarter horizon, but supply shocks assume the larger role at longer horizons. Supply shocks also account for most of the fluctuations in the Australian price level.

The recession and sluggish growth that have characterized the U.S. economy beginning in the late 1980s have renewed interest in the processes that govern business cycle behavior. Recent studies by Blanchard and Quah (1989), Shapiro and Watson (1988), Judd and Trehan (1989, 1990), and Gali (1992) have used structural vector autoregression models to provide useful insights on U.S. business cycle behavior.[1]

This paper extends their analyses to examine how demand and supply shocks affect business cycle behavior in Australia. The application to Australia is of interest for at least two reasons. First, previous studies give widely differing estimates on the importance of supply and demand shocks in influencing cyclical behavior. A study of Australia may provide further evidence to help clarify this question. Second, a comparison of the evidence from Australia with the results from previous research may highlight similarities or contrasts in business cycle behavior in small open economies and large, relatively closed economies, like the United States.

The paper focuses on three closely related questions: (i) How do macroeconomic variables respond to demand and supply shocks? (ii) How much of the variance in output and inflation is explained by demand and supply shocks? (iii) How do demand and supply shocks influence cyclical behavior, particularly during recessions? These three questions are addressed by estimating a small vector autoregression model of the Australian economy. Unobservable demand and supply shocks are then identified by assuming that aggregate demand shocks have transitory

[1]As discussed below, these studies identify a structural model by using long-run identifying restrictions. Long-run identifying restrictions are also used by Gerlach and Klock (1990) to study Scandinavian business cycles and Moreno (1992a) to study Japanese business cycles. Other studies using such restrictions address somewhat different questions. Hutchison and Walsh (1992) examine the Japanese evidence on the insulation properties of exchange rate regimes, while Hutchison (1992) investigates whether the vulnerability of the Japanese and U.S. economies to oil shocks declined between the 1970s and the 1980s. Another strand of the literature identifies demand and supply shocks by imposing restrictions on the contemporaneous impact of these shocks (Blanchard 1989, Blanchard and Watson 1986, and Walsh 1987).

effects while aggregate supply shocks have permanent effects on output. One advantage of this approach is that it does not assume that short-run fluctuations are entirely due to temporary demand shocks (as in the traditional approach to macroeconomic modeling) or permanent supply shocks (as in early real business cycle models). Instead, the method estimates the relative importance of aggregate demand and supply shocks at various forecast horizons. A second advantage of this approach is that it avoids the imposition of arbitrary identifying restrictions, thus addressing objections raised by Sims (1980). Finally, the paper relies on economic theory to achieve identification, addressing objections to atheoretical VAR methods cited by Cooley and Leroy (1985) or Bernanke (1986).

The description of the dynamic responses of macroeconomic variables to demand and supply shocks obtained by addressing the first question may provide insights that are relevant to policy analysis. At the same time, answers to the second and third questions can shed light on the relative importance of demand and supply shocks in influencing business cycle activity, a question that has acquired prominence in the 1980s with the growing popularity of real business cycle theory. This paper finds that although supply shocks have a strong influence on Australian business cycle behavior, demand shocks still play a significant role.

The paper is organized as follows. Section I provides some background on the Australian economy. Section II describes the model estimated (which closely resembles that used by Shapiro and Watson (1988)) and the identifying restrictions used. Section III discusses the univariate properties of the data, and how these results are used in VAR estimation. Section IV reports the results of VAR estimation and applies them to answer the three questions posed in this introduction. Section V summarizes the findings of this paper and suggests possible extensions.

I. Background

To provide a context for the analysis of Australian business cycles that follows, Table 1 identifies peak-to-trough dates, their duration, average output growth and inflation rates and deviations of these rates from baseline rates during recessionary periods. The baseline rates are based on two subsamples, because statistical tests reported

Table 1

GDP Growth during Recession and Inflation Characteristics of Australia

Peak-Trough Dates	Quarters of Downturn	GDP		Inflation	
		Compound Annual Growth (%)	Deviation from Baseline[a]	Compound Annual Rate (%)	Deviation from Baseline[a]
Full-sample 1960.Q1–1989.Q4	5.2	3.9	−81.2	6.9	5.2
Sub-sample 1[b] 1960.Q1–1973.Q4	8	5.0	−60.7	3.8	−9.5
1960.Q3–1961.Q3	5	−2.7	−153.8	2.0	−47.3
1964.Q4–1966.Q2	7	2.9	−42.1	3.5	−9.8
1967.Q1–1967.Q4	4	2.9	−42.0	3.6	−7.0
1968.Q4–1972.Q3	16	4.7	−4.8	4.9	26.1
Sub-sample 2[b] 1973.Q4–1989.Q4	7	3.0	−101.7	9.6	19.9
1973.Q4–1975.Q4	9	1.1	−63.8	15.1	56.8
1976.Q4–1977.Q4	5	−0.4	−111.7	9.2	−4.7
1979.Q1–1980.Q1	5	0.2	−93.3	10.6	9.8
1981.Q3–1983.Q2	9	−1.2	−138.1	11.3	17.6

[a]Computed as 100 × (cycle rate − subsample average rate) / subsample average rate.
[b]Period average.

later indicate that there was a break in the trend of both the output and inflation series.[2]

Table 1 indicates that Australia grew at an annual rate of about 4 percent in the last three decades. However, average growth slowed sometime in the early 1970s from 5 percent to around 3 percent. Over this period, Australia experienced eight recessions that on average lasted 7.5 quarters. Output growth fell an average of 81 percent below baseline during recessions. By way of comparison, the U.S. has experienced fewer recessions than Australia over a similar period (five). U.S. recessions on average are shorter (under four quarters) and steeper (output growth on average falls 170 percent below baseline during recessions) than Australia's. While these comparisons should be interpreted with some caution, because they partly reflect differences in how recessions are defined in each economy, they suggest contrasts in the cyclical behavior of Australian and U.S. output.[3]

According to Table 1 Australia's inflation averaged 6.9 percent over the sample period. Inflation rose over the two subsamples from 3.8 percent to 9.6 percent beginning in the mid-1970s. It is also apparent that on average there was no decline in inflation (in relation to baseline) during recessions in the second period.

Three factors are likely to have influenced cyclical output and inflation performance in Australia:

First, Australia meets most of its fossil fuel requirements through domestic production. In 1989, Australia produced 22.5 million metric tons of crude petroleum, about 86 percent of its domestic consumption. In 1989, fuels accounted for 5 percent of total imports, which to some degree were offset by exports.

Second, wage-setting is highly centralized due to the dominant influence of the Australian Council of Trade Unions. Nominal wages historically appear to have been relatively rigid. Australian unions were highly successful in putting upward pressure on wages until 1982. Some researchers argue (Chapman 1990) that wage restraint subsequently resulted from the Prices and Incomes Accord between the government and the unions signed in 1983, but others argue that the econometric evidence on this is weak (Blandy 1990).

Third, monetary policy appears to have played a largely passive role in curbing inflation and focused more on correcting external imbalances. The fiscal policy stance has fluctuated sharply over the sample period, on several occasions countercyclically. During the period of fixed exchange rates in place until December 1983, money growth and inflation are believed to have been influenced by external factors (like oil price shocks), as the rise in inflation in the 1970s mirrors similar increases in inflation in OECD countries. In contrast, after Australia switched to floating in December 1983, inflation on average has exceeded the OECD average. There is a widely held view that the government has sought to curb inflation largely through wage agreements under the Accord (Carmichael 1990, Stevens 1991). Monetary policy played a secondary, or even passive role in curbing inflation, but authorities appeared to favor monetary stimulus and nominal exchange rate depreciation to reduce current account deficits. Under these circumstances, the relationship between monetary policy and business cycle fluctuations would depend on the types of shocks accounting for current account deficits. If current account deficits were due to adverse movements in the terms of trade that would also tend to reduce domestic economic activity, monetary policy would operate countercyclically—that is, it would dampen business cycle fluctuations. However, if current account deficits were due to strong domestic demand stimulus, monetary policy would operate procyclically.

In contrast to the uncertain role of monetary policy in influencing business cycle behavior, fiscal policy appears to have operated countercyclically on a number of occasions. For example, the 1973.Q4–1975.Q4 recession was associated with a sharp increase in government consumption spending and a related rise in public borrowing to around 5 percent of GDP from 1 to 2 percent in the 1960s. The higher rate of borrowing was largely maintained until the early 1980s, when public sector borrowing rose to a peak of 7 percent of GDP at the time of the 1981–1983 recession. Large revenue increases and expenditure reductions subsequently reversed the upward trend in public sector borrowing, so that by 1988 the government was a net lender.

In Section IV, the preceding stylized facts are used to suggest interpretations of estimated responses to shocks in Australia.

[2]The sample is broken at the date closest to the break date reported in Table 3, subject to not splitting recessions across two samples. A similar criterion determines the break dates in the tables describing the cyclical behavior of inflation.

[3]Peak-to-trough dates for the U.S. are reported by the NBER, which currently tracks the behavior of four series to date recessions: real income, real sales, nonagricultural employment and industrial production. See Hall (1991). No comparable information is available for Australia, so peak-to-trough dates are those reported in OECD (1987). These peak-to-trough dates are based on the estimation of so-called phase-average trend (using the peaks and troughs of sine waves as the turning points of the cycle). It closely approximates a linearly deterministic trend if such a trend is unbroken, or a succession of segmented linear trends. The recession dates selected include what the OECD calls "minor cycles." In the absence of a more extensive dating procedure, the cycles reported in Table 1 are necessarily imprecise and the VAR analysis reported later provides additional information on whether they are reasonable.

II. The Model

Following Shapiro and Watson (1988), consider a standard growth model where shocks to demand are allowed to influence the behavior of output in the short run. In such a model, the log levels of the labor supply n_t^* and technology τ_t^* are governed by:

$$(1) \qquad n_t^* = \delta_n + n_{t-1}^* + \Theta_n(L)\epsilon_{2t}$$

$$(2) \qquad \tau_t^* = \delta_\varepsilon + \tau_{t-1}^* + \Theta_\varepsilon(L)\epsilon_{3t},$$

where ϵ_{2t}, ϵ_{3t} are mutually uncorrelated shocks that influence long-run growth (ϵ_{1t} is defined later), and $\theta_n(L)$, $\theta_\epsilon(L)$ are lag polynomials.[4]

The long-run log level of output is determined by a Cobb-Douglas production function:

$$(3) \qquad y_t^* = \alpha n_t^* + (1-\alpha)k_t^* + \tau_t^*.$$

Impose the theoretical restriction that the steady-state capital-output ratio is constant:

$$(4) \qquad k_t^* = y_t^* + \eta,$$

where η is the constant log capital-output ratio. Substituting (4) into (3) yields

$$(5) \qquad y_t^* = n_t^* + \left(\frac{1}{\alpha}\right)\tau_t^*,$$

where the constant term $\frac{\eta(1-\alpha)}{\alpha}$ is suppressed.

Equations (1) to (5) describe a real business cycle model with very simple dynamics. To close the model, introduce an aggregate demand shock ϵ_{4t} that is serially uncorrelated and uncorrelated with growth shocks ϵ_{2t}, ϵ_{3t}, and that allows the labor input and output to deviate temporarily from their long-run levels. Then we have

$$(6) \qquad n_t = n_t^* + \Xi_n(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}]'$$

and

$$(7) \qquad y_t = y_t^* + \Xi_y(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}]'.$$

It is assumed that labor supply and output are nonstationary. First-differencing to account for such nonstationarity, and substituting (1), (2), and (5) into (6) and (7), yields

$$(8) \qquad \Delta n_t = \Theta_n(L)\epsilon_{2t} + (1-L)\Xi_h(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}]$$

$$(9) \qquad \Delta y_t = \Theta_n(L)\epsilon_{2t} + \alpha^{-1}\Theta_\varepsilon(L)\epsilon_{3t} + (1-L)\Xi_y(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}].$$

In the present case, the model is completed by incorporating the processes governing the price level, p_t,

$$(10) \qquad \Delta p_t = \Xi_p(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}].$$

The specification in equation (10) reflects the assumption that the price level is integrated (the first difference is stationary) and all the shocks have a long-run effect on the price level.

The model is now extended by including an exogenous oil price shock that has an effect on all of the other variables of the model,

$$(11) \qquad \Delta o_t = \Xi_o(L)\epsilon_{1t}.$$

To sum up, the model may be described as follows

$$(12) \qquad \begin{bmatrix} \Delta o_t \\ \Delta n_t \\ \Delta y_t \\ \Delta p_t \end{bmatrix} = B(L) \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \end{bmatrix}.$$

The shocks ϵ_{1t} to ϵ_{4t} respectively correspond to shocks to the oil price, labor supply, technology, and a demand shock.

In equation (12), shocks to the oil price are one source of external supply shocks. However, in a small open economy like Australia, other external disturbances may be important in influencing business cycle behavior. If external effects are important, both the supply and demand shocks in the present model may be interpreted as combinations of domestic and external shocks.

The structural shocks of model (12) can be recovered by first estimating a vector autoregression (VAR) model, and then exploiting the information from the sample variance-covariance matrix to achieve identification. As discussed earlier, one of the key identifying assumptions is that unobservable demand and supply shocks are identified by assuming that aggregate demand shocks have transitory effects while aggregate supply shocks have permanent effects on output. The estimation and identification procedures closely resemble those used by Shapiro and Watson (1988) and are discussed more fully in Appendix A.[5]

[4]These polynomials are assumed to have absolutely summable coefficients and roots outside the unit circle (i.e., the dynamics described by the polynomials are transitory, so the polynomials can be inverted).

[5]Although the model used in this paper is similar to Shapiro and Watson's (1988) model, the application differs in two ways: (i) the labor supply is represented by the labor force, rather than by the total hours worked by all employed persons; (ii) one equation is used to represent shocks to demand, rather than two equations, as in Shapiro and Watson. However, Shapiro and Watson do not separately identify the two demand shocks, but instead use the combined effects of the two shocks in their analysis.

III. DATA ANALYSIS

To estimate the system described by equation (12) I collected quarterly data for the oil price (o), the Australian labor force (n), Australian real GDP (y) and the Australian CPI (p). The data and sources are described in Appendix B. Certain properties of the series included in the model must be checked in order to determine the appropriate specification for estimation purposes. First, it is necessary to determine whether the series are difference- or trend- stationary. This is done by testing the null hypothesis that each series included in the model contains a unit root. If the variables are difference-stationary, it is appropriate to estimate the VAR model by using the first differences of the series. If the variables are trend stationary, the VAR model may be estimated by taking the residuals from a deterministic trend. Second, it is desirable to account for the possibility of breaks in the deterministic trend. The reason is that standard (Dickey-Fuller) tests may fail to reject the unit root null even if the time trend is deterministic, if there is a large one-time shift in the intercept or in the trend.[6] To account for this possibility, I test for breaks in the deterministic trend in each series. If the hypothesis of a trend break cannot be rejected, I test the unit root null against the alternative of a broken deterministic trend. Third, if the variables are difference stationary, it is necessary to establish whether the series in the model share common trends. If they do not, estimation of a VAR model in first differences is appropriate.

Unit Roots

To test for unit roots I apply the Augmented Dickey-Fuller and Phillips-Perron tests for unit roots to the levels and first differences of the series in the system (see Dickey and Fuller 1979, and Schwert 1987). The results of the tests, reported in Table 2, suggest that the labor force and output in Australia, as well as the oil price, are all difference-stationary. The results for the price level are ambiguous. Both tests indicate that the price level is nonstationary. However, when inflation is tested the Phillips test rejects the unit root null, whereas the Augmented Dickey-Fuller test cannot do so. In what follows, I assume that the price level is difference stationary.

The unit root test results should be interpreted with caution. Research has shown that tests for unit roots have low power (that is, they have low ability to reject the unit root null when it is false) against plausible local alternatives. Also, the autoregressive models and unit root test statistics computed for them have been found to be structurally unstable under small perturbations, so that small perturbations in the model lead to large changes in the distribution theory for the statistics (Cavanagh, undated).

Table 2

Tests for Unit Roots

Variable	Log Levels (with constant and trend)		First Differences (with constant)	
	Dickey-Fuller Test	Phillips	Dickey-Fuller Test	Phillips
Labor Force	−1.39	−1.75	−2.85*	−10.32***
Price (CPI)	−2.89	−2.36	−2.06	−7.83***
Real GDP	−1.92	−1.26	−4.39***	−12.34***
Oil	−1.54	−1.85	−3.55**	−6.65***

Note: * Reject null hypothesis (unit root) at 10% level.
** Reject null hypothesis at 5% level.
*** Reject null hypothesis at 1% level.
Seasonally adjusted data from 1960.Q1 to 1989.Q4, except for Labor Force, which is 1966.Q3–1989.Q4.

Trend Breaks

Standard tests for trend breaks assume that the date at which the break occurs is known without using the data series being tested. In practice, the data are used to find the break date, so standard critical values for testing the null hypothesis of no break in the trend cannot be used. To address this problem I follow a strategy similar to that adopted by Christiano (1992) and use a bootstrap methodology to calculate the most likely date for a break. As inspection of the series suggests that trend breaks occurred in the 1970s, I confine my search for breaks to that period. The test results, reported in Table 3, indicate that the null hypothesis of no trend break is rejected for GDP and CPI (the null of no trend break is not rejected for the oil price and the labor force, as these results are not reported here). On this basis, I test the unit root null hypothesis against the alternative of a deterministic trend with a break for GDP and CPI, also relying on bootstrap simulations to find the critical values. As also reported in Table 3, for these two series, the unit root null cannot be rejected against the alternative of a broken deterministic trend.[7]

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[6]See Perron (1989) for the precise conditions.

[7]To construct Table 3, 1000 simulated series were generated using the following bootstrap methodology. The equation $\Delta y = \mu + \beta \Delta y$ was

Table 3

Tests for Break in Trend in the 1970s and for Unit Root Null against Alternative of Broken Deterministic Trend

Variable	Most Likely Break Date	Test for Break (F Statistic)	Test for Unit Root (t Statistic)
Real GDP	1974.Q2	332**	−2.9
		(.03, 64.4)	(.76, −3.5)
Price (CPI)	1974.Q2	523**	−2.0
		(.03, 96.6)	(.92, −3.2)

Note: See Notes to Table 2. Numbers in parentheses are significance levels and expected values.

Cointegration

While the preceding tests suggest that the model variables are nonstationary when considered individually, it is possible that these variables share a common nonstationary trend. In this case, a stationary linear combination of the variables may be found, and the variables are said to be *cointegrated*. When variables are cointegrated, estimating a VAR model where the series are expressed in first differences, as proposed above, would be inappropriate. One reason is that first-differencing would remove important information about the behavior of the variables contained in the common trend.[8]

A number of tests for cointegration have been developed in the literature. I use the method proposed by Johansen (1988) and applied by Johansen and Juselius (1990). Table 4 reports the results of the Johansen's trace and maximum eigenvalue tests. Based on the critical values reported by Johansen and Juselius (Table A.2) both tests fail to reject the null hypothesis that there is no cointegration. In what follows, I assume that the series in the model are not cointegrated and that estimation of the VAR model in first differences is appropriate.

To sum up, conventional tests suggest that all the series included in the model are difference stationary. There is evidence of a break in the deterministic trend in GDP and in the CPI, but the unit root null still cannot be rejected for these two series when this break is taken into account. Furthermore, a statistical test cannot reject the null hypothesis that there is no stationary linear combination of the variables in the model.

In view of the preceding results, the data are transformed as follows. The first differences of o, n, y and p were taken to obtain stationary representations. The differenced series Δo_t, Δn_t were demeaned by subtracting the respective sample means. To account for breaks in the trend rates

Table 4

Johansen Test for Cointegration

H_0: $r \leq$	0	1	2	3
Trace	44.5	22.1	9.8	2.2
95 % critical value	48.4	31.3	17.8	8.1
H_0: $r =$	0	1	2	3
Maximum eigenvalue	22.4	12.3	7.5	2.2
95% critical value	27.3	21.3	14.6	8.1

Note: Critical values are from Table A.2 of Johansen and Juselius (1990) which assumes that the nonstationary processes contain linear trends.

estimated. Disturbances were randomly drawn from the residuals of this equation with replacement and used to generate 1000 simulated series. The first sample observation was used as the starting value. To test for a trend break, equation $y_t = \alpha_0 + \alpha_1 d_t^b + \alpha_2 t + \alpha_3 sdum_t^b$ was then re-estimated using each of the 1000 artificial series for $b = bdat + 5$ to $b = ldat$. The maximum F statistic for b between 1970:Q1 and 1979:Q4 for each of the 1000 artificial series was selected. These 1000 maximum F-statistics were then ranked in ascending order. The 1 percent critical value was then given by the F statistic with rank 990 (1 percent of the set of maximum F statistics exceed this F-value), the 5 percent critical value by the statistic with rank 950, and so on. The expected value is given by the statistic with rank 500.

To test the unit root null against the alternative of a broken deterministic trend, the equation $\Delta y_t = \beta_0 + \beta_1 d_t^b + \beta_2 t + \beta_3 d_t^b + \beta_4 y_{t-1} + \beta_5 \Delta y_{t-1} + \beta_6 \Delta y_{t-2}$ was reestimated using each of the 1000 artificial series used to generate Table 3. For each series, the date b was set to correspond to the peak of the F statistic computed by the equation used to find the most likely trend break in Table 3. To find critical values, the 1000 t-statistics testing the null were collected, and critical values were constructed in a manner analogous to Table 3.

[8]Engle and Granger (1987) show that the appropriate model if the variables are cointegrated is an error correction model, rather than a VAR in first differences. Another way of looking at this problem is to note that a VAR made up of first-differenced variables that are cointegrated involves "overdifferencing." As in the univariate case of "overdifferencing," the vector ARMA system of variables expressed in first differences will contain noninvertible MA terms that cannot be represented by a VAR.

of growth and inflation, the differenced series Δy, Δp were demeaned by subtracting the appropriate subsample means, where the subsamples were defined by the break dates identified using the bootstrap simulation procedure (1974.Q2 in both cases). The demeaned series were used to estimate a VAR model. (A similar procedure of subtracting subsample means is used by Blanchard and Quah. However, they pick the break date without using a statistical test.)

IV. Model Estimation Results

The VAR model was estimated over 1966.Q3–1989.Q4 (no earlier data are available for the Australian labor force). Using the identifying restrictions discussed in Appendix A, a structural moving average representation (as in equation (12)) was obtained. This moving average representation allows us to address the three questions posed in the introduction to this paper.

Impulse Responses

The first question posed in the introduction, concerning the qualitative responses to supply and demand shocks, can be addressed by reference to Charts C.1 to C.4 in Appendix C, which illustrate the effects of one standard deviation shocks to the levels of the variables. (By construction, shocks to the domestic variables have no effect on the oil price, so the response of the oil price to Australian variables is not illustrated.) The impulse responses are illustrated for horizons up to 12 quarters to focus on the short-run dynamics. In general, the impulse responses are close to the long-run values at these horizons. Also, the one standard error bands around the impulse responses in a number of cases widen sharply at long forecast horizons, as might be expected for nonstationary series.[9] For these reasons, the loss of information from truncating the impulse response horizons is not very great.

An important test of the plausibility of the model and identifying procedure adopted in this paper is whether the responses to supply and demand shocks conform to the predictions of theory. We would expect

- positive shocks to the oil price to reduce output and increase the price level in the long-run;
- positive shocks to labor supply and technology to increase output and reduce the price level in the long-run;
- positive shocks to demand to increase labor and output temporarily (as a result of the identifying restrictions) and the price level permanently;

The charts indicate that the responses to shocks in the model broadly conform to these expectations, although the standard error bands are in some cases quite wide, particularly at horizons exceeding four quarters.

The charts also reveal some interesting dynamics: for example, GDP rises sharply in response to technology shock, overshoots its long-run level slightly at about 10 quarters before settling to close to its long-run level of around ¾ percent above the pre-shock level. This long-run level is achieved at around 20 quarters and is not shown in the chart. (The CPI declines with similar, but smoother, dynamics.) In contrast, Blanchard and Quah (1989), Shapiro and Watson (1988) and Moreno (1992a) indicate a more pronounced overshooting in the output response to technology shocks in the U.S. and Japan respectively. However, these comparisons should be interpreted with caution because the standard errors in all these models appear to be quite large.

In addition, some of the impulse response results appear to be broadly consistent with the characteristics of the Australian economy discussed in Section I:

Australia does not appear to be vulnerable to oil price shocks in the very short run, which is consistent with its status as oil producer and exporter. The impulse responses indicate that Australian GDP *rises* temporarily in response to oil price shocks, followed by a long-run decline. This suggests that an oil price increase initially stimulates the economy through Australia's oil sector, but the stimulus is reversed as the effects of a higher oil price spread to the rest of the economy.

The effects of demand shocks on output die out quickly, which is consistent with an active countercyclical policy The charts indicate that the effects of a positive shock to GDP are fully reversed within one year, which appears to be relatively fast. In contrast, Blanchard and Quah (1989) find that the effects of a demand shock on U.S. output take about six years to be fully reversed. Moreno (1992a) estimates that in Japan, the effects of a demand shock on output are fully reversed after two years. The rapid reversal of demand shocks suggests that the countercyclical effects of fiscal policy and (to the extent applicable) of monetary policy were quite important in Australia (recall discussion in Section I). However, it is important to stress that the

[9] These standard error bands are obtained by using a Monte Carlo simulation procedure with 300 replications to construct pseudo-impulse responses and the first and second moments of these impulses. The pseudo-impulse responses are generated by using draws from the Normal and Wishart distributions to modify the variance covariance matrix and the moving average coefficients of the structural innovations. See Doan (1990). In the charts, a two-standard-error band tends to disguise the short-run dynamics in the impulse responses, so a one-standard-error band is shown instead.

rapid reversal in the effects of demand shocks on output is only an indicator of the possible effects of countercyclical policy, and that other explanations for this rapid reversal may be offered. In the model estimated in this paper, demand shocks reflect the combined effects of private and public demand, and there is no way of separating these two effects.

Australia appears to have a relatively flat short-run Phillips curve, which is consistent with apparent rigidities in the labor market. To assess the Phillips curve tradeoff, I computed the ratio of cumulative GDP growth per unit of cumulative inflation in response to a one-standard-deviation shock to demand.

A shock to demand yields its greatest output growth stimulus per unit of inflation in the first quarter, about 208 percent. The cumulative output gain subsequently tapers off smoothly to 147.50 percent in the second quarter, 100 percent in the third quarter, and to 48 percent in the fourth quarter. The cumulative output gain is negative and small at eight and twenty quarters, and is zero at forty quarters. To provide a benchmark, these results may be compared to estimates obtained from a similar model for Japan (Moreno 1992a) where labor markets appear to be more flexible than in Australia. In Japan, the corresponding cumulative increases in output growth per unit of inflation are 93 percent at one quarter, 43 percent at four quarters, 3 percent at eight quarters, and close to zero at twenty quarters. Thus, Australia appears to have a relatively favorable output-inflation tradeoff in the very short run.

Variance Decompositions and the Importance of Supply Shocks

The impulse response functions illustrate the qualitative responses of the variables in the system to shocks to supply and demand. To indicate the relative importance of these shocks requires a variance decomposition. In order do this, consider the n-step ahead forecast of a variable based on information at time t. The variance of the error associated with such a forecast can be attributed to unforecastable shocks (or innovations) to each of the variables comprising the system that occur between $t+1$ to $t+n$.

Table 5 reports the variance decompositions of the structural forecast errors of the variables in levels, at horizons up to forty quarters (10 years).

By construction, the variance in the forecast error of the oil price is attributable entirely to shocks to the oil price and is not reported. It is also apparent that shocks to the labor supply are the main determinants of the variance of the forecast error of the labor force at all horizons. This result would probably differ if a variable that is more sensitive to changes in demand in the short-run were used.

We can use the variance decompositions for GDP to assess the empirical importance of demand and supply shocks, which is the second question posed in the introduction. Demand shocks are most important in the very short run, accounting for 64 percent of the forecast error one-quarter ahead. However, supply shocks soon assume the dominant role: They account for 74 percent of the forecast error variance at eight quarters and 95 percent at forty quarters. Supply shocks are in turn dominated by shocks to technology.

Three points are worth highlighting. First, the variance decomposition estimates are relatively imprecise, so the results of the point estimates should be viewed with some caution. For example, at the one-quarter horizon for demand shocks, the 95 percent confidence band ranges from a low of 27 percent to a high of 89 percent.[10] However, the estimates in Table 5 do not appear to be less precise than estimates reported by Blanchard and Quah (1989) or Shapiro and Watson (1988), or the estimates in Sims's (1980) study (see Runkle (1987)).

Second, in their study of the U.S. economy, Shapiro and Watson (1988) found that shocks to labor supply were large at short horizons (in the neighborhood of 40 percent or higher). This is surprising because theory and empirical studies of the U.S. economy suggest an important role for permanent shocks to labor supply at long forecast horizons, but not at short ones. In the case of Australia, the contribution of labor supply shocks to the variance of the forecast error is small. It ranges from 4.5 percent at one quarter to 13 percent at eight quarters and down to 5 percent at forty quarters. One possible explanation for the relatively small contribution of the labor supply is that the

[10]The empirical 95 percent confidence band was constructed by using a bootstrap simulation procedure with 300 replications to generate pseudo-variance decompositions, as was done for the impulse responses. However, instead of constructing a symmetric one-standard-error band based on the normal approximation, I define the 95 percent band as follows. The lower bound is that value such that 2.5 percent of the pseudo-variance decomposition values are lower. The upper bound is that value such that 2.5 percent of such values are higher. One advantage of this approach is that it excludes values below 0 or above 100 and thus reflects the constraint that the variance decompositions must sum to 100. The empirical distribution found in this manner is skewed, as the point estimate of the variance decomposition in a number of cases is close to the upper or lower boundary of the 95 percent band. A similar bootstrap procedure is used by Blanchard and Quah (1989) to report asymmetric empirical one-standard-error bands. Shapiro and Watson (1988) report one-standard-error bands that appear to be based on the normal approximation. The normal approximation does not take into account the constraints on the values of the variance decompositions, so the lower bound of the standard error band may be negative, and the upper bound may exceed 100. See Runkle (1987) for a discussion of some of these issues.

Table 5

Variance Decompositions

Quarters Ahead	Proportion of Variance Explained by Shock to: Aggregate Supply				Aggregate Demand
	Oil Price	Labor Supply	Technology	Total	
Labor Force					
1	0.7 (0.0,12.8)	87.2 (48.0,96.3)	11.7 (0.2,37.6)	99.6	0.4 (0.0,20.7)
4	1.8 (0.7,14.7)	83.4 (47.9,87.3)	13.7 (6.2,30.9)	98.9	1.1 (0.4,15.9)
8	1.2 (0.9,14.2)	88.8 (58.9,90.4)	7.2 (3.6,21.2)	97.2	2.8 (1.6,15.2)
12	0.8 (0.9,12.9)	92.7 (58.2,92.9)	4.7 (2.6,23.1)	98.2	1.8 (1.1,16.7)
20	0.6 (0.7,12.5)	95.4 (44.8,95.7)	2.9 (1.7,26.2)	98.9	1.1 (0.7,22.0)
40	0.4 (0.5,16.1)	97.5 (6.1,97.7)	1.5 (0.9,49.6)	99.4	0.5 (0.3,43.5)
GDP					
1	2.2 (0.0,19.8)	4.5 (0.1,16.1)	29.6 (3.2,61.7)	36.3	63.6 (26.7,89.4)
4	1.9 (0.7,20.1)	10.0 (1.3,29.7)	39.6 (16.9,60.1)	51.5	48.5 (24.3,66.3)
8	2.2 (1.9,26.6)	12.9 (2.6,37.9)	58.4 (26.8,69.0)	73.5	26.5 (12.7,43.7)
12	3.7 (2.2,32.4)	9.7 (2.1,36.0)	69.7 (26.9,76.1)	83.1	16.9 (7.5,42.7)
20	5.7 (2.0,42.4)	6.8 (1.6,32.0)	77.1 (23.4,81.1)	89.6	10.4 (4.0,47.9)
40	6.6 (1.2,49.0)	5.0 (0.7,33.0)	83.0 (18.8,88.5)	94.6	5.4 (1.7,47.5)
CPI					
1	0.6 (0.0,14.3)	11.6 (1.0,26.8)	62.5 (45.9,73.3)	74.7	25.4 (16.4,33.5)
4	1.5 (0.1,19.8)	15.2 (1.2,36.7)	61.4 (37.4,77.2)	78.1	21.8 (7.3,39.9)
8	5.7 (0.2,37.4)	6.3 (1.0,29.1)	60.4 (30.8,78.7)	72.4	27.6 (7.3,51.1)
12	9.2 (0.3,46.6)	3.3 (0.6,23.9)	58.0 (24.5,78.3)	70.5	29.4 (5.9,52.3)
20	12.2 (0.2,54.6)	1.8 (0.4,27.5)	55.4 (19.8,76.4)	69.4	30.6 (4.9,57.1)
40	13.6 (0.1,61.1)	0.8 (0.2,28.1)	54.4 (17.0,77.5)	68.7	31.2 (4.5,60.2)

Note: Empirical 95 percent confidence bands are in parentheses.

proxy used for this variable, the labor force, varies relatively little. If total employment—which varies somewhat more than the labor force—is used instead of the labor force in the model, labor supply shocks are larger but still small. They account for 2 percent of the variance of the forecast error at one quarter, 28 percent at eight quarters and 29 percent at forty quarters.[11]

Third, oil price shocks play a limited role, accounting for about 2 percent of the variance of the forecast error up to eight quarters, rising to under 7 percent at forty quarters. This is somewhat below the short-run results for the U.S. obtained by Shapiro and Watson (1988) but similar to their long-run results.

Supply shocks are the most important factor influencing the short-run behavior of the price level in Australia. Supply shocks account for 75 percent of the variance of the one-quarter-ahead forecast error of Australia's CPI, rising to 78 percent at four quarters, and then falling gradually to 69 percent at forty quarters. Technology shocks are the main source of supply shocks at all horizons. Shocks to labor supply have a stronger influence at short horizons (fewer than twenty quarters), accounting for up to 15 percent. Oil price shocks have a larger influence at longer horizons (twenty to forty quarters), accounting for about 12 to 14 percent. The oil price has a stronger influence on the price level than on GDP.

To sum up, both demand and supply shocks have an important effect on output throughout the Australian business cycle. Demand shocks are dominant in the very short-run, but their importance tapers off quickly as the forecast horizon is extended. In contrast, supply shocks have a dominant influence on the price level at all forecast horizons.

Evidence from Other Studies

The preceding results may be compared to Shapiro and Watson's (1988) results for the U.S. using a similar model. The contribution of supply shocks to output in the U.S. is 72 percent at a quarter's horizon and 80 percent at eight quarters, which is larger than the 36 percent and 74 percent found for Australia in Table 5. However, supply shocks explain 12 percent or less of the variance of the U.S. price level at horizons up to eight quarters, much lower than the 78 percent found for Australia over similar horizons.[12]

The results of a study of Scandinavian business cycles by Gerlach and Klock (1990), which covers Denmark, Norway and Sweden, are closer to those reported here. Gerlach and Klock estimate a bivariate model of output and price for each economy using annual data for the period 1950–1988, and impose the identifying restrictions proposed by Blanchard and Quah (1989). In general, they find that the contribution of supply shocks to output for all three countries at a year's horizon is large, ranging from 50 to 75 percent. The contribution to inflation in two of the three countries is also large, ranging from 66 percent to 83 percent.[13]

Patterns of Cyclical Behavior

Further insights on cyclical behavior can be gained by examining the pattern of shocks to output during cyclical downturns, which is the third question posed in the introduction. For this purpose, Chart 1 reports the eight-step ahead forecast error in output growth and the cumulative contributions of demand and supply shocks to this error in Australia. Australia's VAR sample begins in 1966.Q3 (the starting date for the labor force series) and data points are used up in setting an eight-quarter forecast horizon. As a result, Chart 1 begins in 1970 and only five of the eight recessions reported in Table 1 are included.

The description of recessions offered in Chart 1 differs from that offered in Table 1. In Table 1, the severity of recessions is measured in terms of deviations from a baseline rate of growth. In Chart 1, the severity of recessions is assessed by examining how unforecastable innovations make output growth deviate from what was anticipated given the information available eight quarters before.

It is apparent that the first recession indicated in the chart (which actually begins in 1968.Q4, according to Table 1) is not considered a recession by the VAR model:

[11]Shapiro and Watson (1988) use total hours worked by all workers, which varies even more at business cycle frequencies. Judd and Trehan (1989) point out that total hours appears to contain a very strong demand component, so using it as a proxy for labor supply can result in implausible dynamic responses to shocks.

[12]Previous studies on the relative importance of supply shocks based on U.S. data reveal that the estimates are very sensitive to assumptions about trend behavior, such as whether the series are trend or difference stationary, or whether there are breaks in the mean rate of drift of output. For this reason, the present study has attempted to ensure that the assumptions about trend behavior are reasonable, by testing for unit roots, trend breaks and cointegration. Also, the comparison with the U.S. is based on a study which makes very similar assumptions to those adopted in this paper.

[13]In *Denmark* at a year's horizon, supply shocks account for around 50 percent of the variance of output and around two-thirds of the variance of inflation. At a five-year horizon, the proportion rises to 75 percent for output and to 35 percent for inflation. In *Norway* supply shocks account for around 98 percent of the variance of output at all horizons, but for just over 10 percent of the variance of inflation. Finally, in *Sweden* at a year's horizon, supply shocks account for 60 percent of the variance of output and 83 percent of the variance of inflation. At a five-year horizon the proportion rises to 95 percent for output and falls to 80 percent for inflation.

The forecast errors tend to be positive rather than negative.[14] For the remaining four recessions, the forecast errors are consistently negative, as expected. The discussion that follows focuses on these last four recessions.

The following features of Australian recessions stand out. First, negative supply and demand shocks have been a feature of the four recessions discussed here. Second, the recessions of 1973.Q4–1975.Q4 and of 1981.Q3–1983.Q2 were more severe than the two intervening recessions (1976.Q4–1977.Q4 and 1979.Q1–1980.Q1). The two more severe recessions were associated with larger adverse supply shocks.

Chart 2 illustrates the eight-step ahead forecast error for inflation in Australia as well as the cumulative contributions of supply and demand shocks to the forecast error. It is apparent that recessionary episodes in Australia have been associated with adverse supply shocks that have contributed to temporary increases in inflation. With the exception of the 1982 recession, these inflationary pressures were reinforced by shocks to demand.

V. *Summary and Conclusions*

This paper has estimated a small structural vector autoregression model to assess the determinants of business cycle behavior in Australia. The model sheds light on the dynamic responses of Australian macroeconomic variables to demand and supply shocks. In the model, shocks to technology raise output and lower the price level, while shocks to demand temporarily raise output and permanently raise the price level. These responses conform to intuition and theoretical expectations.

The empirical results also shed light on the relative importance of demand and supply shocks in influencing output and inflation behavior in Australia. Demand shocks are dominant in determining fluctuations in Australian output at a one quarter horizon, but supply shocks assume the larger role at longer horizons. Supply shocks also account for most of the fluctuations in the Australian price level. In contrast, research by Shapiro and Watson (1988), using a similar model, finds that supply shocks play a larger short-run role in influencing U.S. output and a very small role in influencing the U.S. price level. The empirical results also indicate that supply shocks in Australia are dominated by shocks to technology, with shocks to the labor supply or to the oil price playing a smaller role.

[14]For this episode, the VAR results appears to conform more closely to the views of informed observers than does Table 1. In private correspondence, Glenn Stevens of the Reserve Bank of Australia indicates that 1968 is generally not regarded as a recession year in Australia.

CHART 1
Components of Output Growth Forecast Error (8 steps)

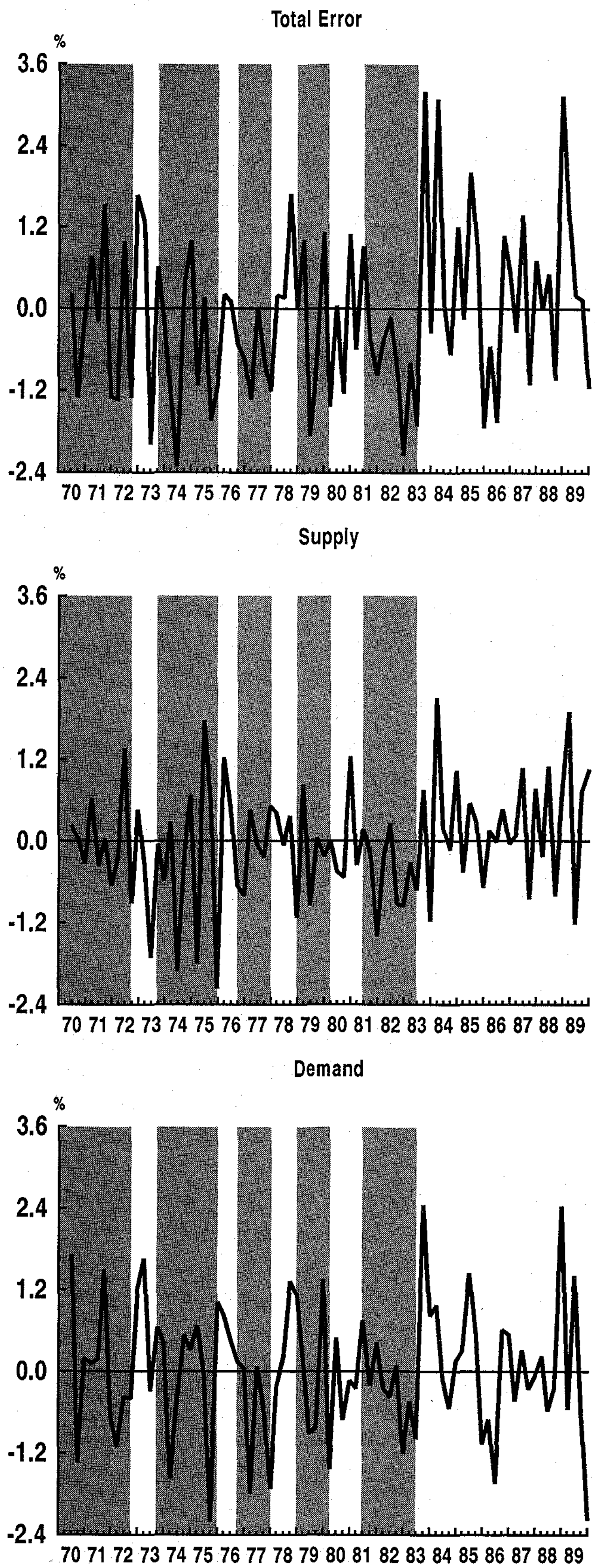
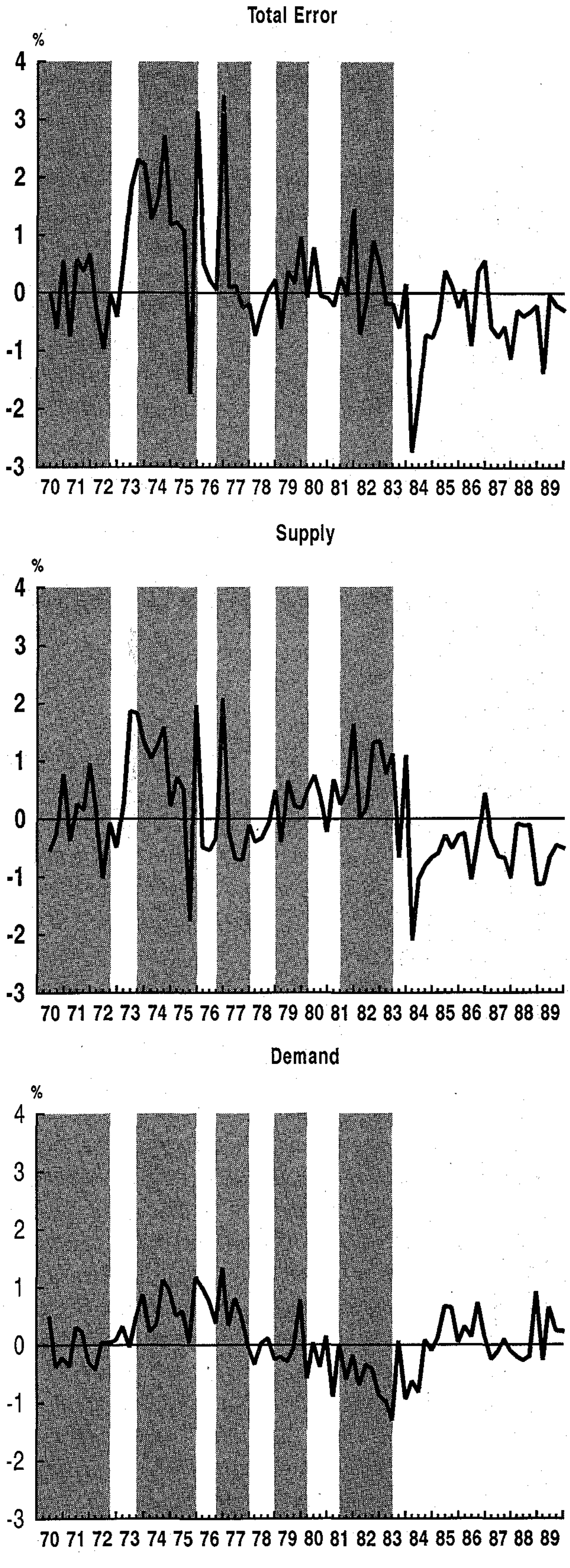


CHART 2

Components of Inflation Forecast Error (8 steps)



The present paper has used a model that has certain appealing theoretical features and has the further advantage of being directly comparable to Shapiro and Watson's (1988) model of the U.S. However, future research can extend the model in several ways. First, demand shocks identified in this paper reflect the combined impact of private and government actions, and can therefore only provide indirect insights on the possible role of government policy in influencing business cycle fluctuations. A larger model that explicitly identifies monetary and fiscal policy shocks could be used to analyze the role of government policy in Australia more directly. Second, other variables, such as wages and hours worked, may be introduced to capture the effects of labor markets more fully. Third, the model could be extended to assess the impact of external shocks in addition to the oil price. Aside from clarifying the relative importance of external and domestic shocks, such an extension could potentially shed light on a number of interesting questions, such as the insulation properties of alternative exchange rate regimes.[15]

[15]Moreno (1992b) assesses insulation under alternative exchange rate regimes in Korea and Taiwan.

Appendix A
Identifying VARS

Moving Average Representation[1]

To motivate the general approach to setting up and identifying VAR models, consider a $k \times 1$ vector of endogenous variables z, with a structural moving average representation given by:

$$z_t = B(L)\epsilon_t \tag{A.1}$$

where

$B(L) = B_0 + B_1L + B_2L^2 + \ldots$ is a $k \times k$ matrix of polynomials in the lag operator L

ϵ_t is a $k \times 1$ vector of white noise disturbance terms

$\epsilon_t \sim (0, \Sigma_\epsilon)$ and Σ_ϵ is diagonal (that is, the structural shocks are mutually orthogonal)

In order to estimate the response of the elements of z_t to innovations in the elements of the mutually orthogonal structural disturbances contained in ϵ_t, a procedure is needed to identify these structural disturbances. The conventional approach is to estimate the VAR representation of z_t:

$$H(L)z_t = u_t, \tag{A.2}$$

where

$H(0) = I$ (that is, no contemporaneous variables enter on the right hand side of the VAR equations)

$u_t \sim (0, \Sigma_u)$, where Σ_u is not a diagonal matrix (that is, the residuals are not mutually orthogonal)

If we invert the VAR representation, we obtain,

$$z_t = D(L)u_t; D(L) = H(L)^{-1}. \tag{A.3}$$

By decomposing the elements of (A.3) using the matrix $B(0)$ (the matrix that defines the contemporaneous structural relations) between the variables, we can recover (A.1):

$$D(L)u_t = D(L)B(0)B(0)^{-1}u_t = B(L)\epsilon_t \tag{A.4}$$

so we can write

$$D(L) = B(L)B(0)^{-1} \tag{A.5}$$

and

$$u_t = B(0)\epsilon_t \tag{A.6}$$

[1]This section draws heavily on the lucid discussion in Hutchison and Walsh (1992).

Equation (A.6) indicates that an estimate of $B(0)$ is needed in order to recover the mutually orthogonal structural disturbances ϵ_t from the estimated VAR residuals u_t.

To motivate the conditions such an estimate must fulfill, note that (A.6) also implies that the diagonal covariance matrix of structural disturbances Σ_ϵ is related to the covariance matrix of the VAR residuals, Σ_u, by

$$\Sigma_\epsilon = B(0)^{-1}\Sigma_u B(0)'^{-1}. \tag{A.7}$$

Equation (A.7) suggests that two conditions must be satisfied in order to identify $B(0)$. First, the number of parameters to be estimated must not exceed the number of unique elements in the sample covariance matrix Σ_u. Specifically, there are k^2 unknown elements in $B(0)$, and the matrix Σ_u contains $k(k+1)/2$ unique elements. A necessary condition for identification is that $k^2 - k(k+1)/2 = k(k-1)/2$ additional restrictions be imposed. We can think of this as an order condition.

Second, the system of nonlinear equations resulting from (A.7) must have at least one solution. This may fail if identifying restrictions are imposed in a manner that prevents equating elements on both sides of the equation. Bernanke (1986) suggests that this can be thought of as a rank condition.

Identification

A number of approaches to identification of a VAR system have been adopted in the literature. The earliest approach, pioneered by Sims (1980), assumes that $B(0)$ is lower triangular. This imposes restrictions on the contemporaneous correlations of shocks to variables that are equivalent to assuming that the economy described by the vector z_t has a recursive structure. Under such a structure, the first variable is unaffected by shocks to the remaining variables, the second variable is affected by shocks to the first two variables, but is unaffected by shocks to the remaining variables, and so on. (The last variable is affected by shocks to all variables.

The main disadvantage of Sims's approach is that it is not easily reconciled with economic theory. Two alternative approaches have been adopted to address this problem. First, a number of authors (Bernanke 1986, Sims 1986, Walsh 1987, Blanchard 1989) have imposed zero restrictions on $B(0)$ to achieve identification. Such contemporaneous restrictions are explicitly motivated by theory and do not necessarily assume a recursive structure.

Second, other researchers (Blanchard and Quah 1989, Shapiro and Watson 1988, Judd and Trehan 1989, 1990, Hutchison, Walsh 1992 and Moreno 1992a) have achieved identification by imposing zero restrictions on the long-run multipliers $B(1)$, in a manner that permits the estimation of

B(0). Such restrictions are motivated by the idea that certain disturbances have no long-run impact on certain elements of z.

Setting $L=1$, (A.4) implies that

$$B(0) = D(1)^{-1}B(1) = H(1)B(1) \quad \text{(A.4}'\text{)}$$

where $D(1)$ is the matrix of long-run multipliers estimated from the VAR and $H(1)$ is the matrix of sums of coefficients obtained from the estimated VAR. Restrictions on $B(1)$, along with the restrictions implied by (A.6), can be used to obtain an estimate of $B(0)$. For higher order VARs, higher order polynomials are involved in finding a solution, so numerical techniques are needed to estimate $B(0)$. One such technique is applied by Hutchison and Walsh (1992).

Estimation

A simple method for recovering the structural disturbances is applied by Shapiro and Watson (1988) in a recent study of the U.S. economy. Shapiro and Watson estimate a system that yields the structural disturbances directly from the VAR representation, that is,

$$C(L)z_t = \epsilon_t, \quad \text{(A.8)}$$

where $C(L) = B(L)^{-1}$, and $B(L)$ is found in (A.1) or (12) in the text.

The structural disturbances are recovered directly from (A.8) as follows. First, $C(0) \neq I$ so contemporaneous values of z_t are now allowed to enter on the right hand side of some of the equations. To obtain consistent estimates, these equations are estimated using two-stage least squares, with the exogenous and the predetermined (lagged) variables as instruments.

Second, the dynamic restrictions on the long-run multipliers (zeros on $B(1)$) are reflected in restrictions on the sums of coefficients of the appropriate variables (that is, as zeros on the corresponding elements of $C(1)$).

Third, Shapiro and Watson ensure that the estimated residuals are mutually orthogonal by estimating each equation in (A.8) sequentially and including the residuals from previous equations in the estimate of the current equation. Thus, the residual in the first equation is used in estimating the second equation, the residuals of the first two equations are used in estimating the third equation, and so on.

Another way to ensure that the appropriate residuals are mutually orthogonal is to estimate each equation in (A.8) without including residuals from the other equations and then use the Choleski decomposition of the covariance matrix to obtain the moving average representation. Although the Choleski decomposition is used, the system is not in this case recursive, because the contemporaneous values of z_t have been included in estimation. (Thus, the critique of atheoretical recursive methods of VAR identification does not apply here.)

This paper uses Shapiro and Watson's (1988) estimation technique to recover structural shocks from a VAR system but relies on the Choleski decomposition to recover orthogonal shocks.

To achieve identification, I impose the following restrictions: First, the oil price depends only on its own lagged values and is completely unaffected by other variables in the model. Second, the labor force can be affected by other variables in the short run; however, the long-run impact of these other variables is zero (in particular, there are no wealth effects on the labor supply). Third, the level of GDP is permanently affected by shocks to the oil price, the labor supply, and technology (supply shocks). Shocks to demand have temporary effects on GDP. No restrictions (except the lag length) are imposed on the effects of the variables of the system on the price level. Given such restrictions, the long-run multipliers in equation (12) in the text satisfy[2]:

$$B(1) = \begin{bmatrix} b(1)_{11} & 0 & 0 & 0 \\ 0 & b(1)_{22} & 0 & 0 \\ b(1)_{31} & b(1)_{32} & b(1)_{33} & 0 \\ b(1)_{41} & b(1)_{42} & b(1)_{43} & b(1)_{44} \end{bmatrix} \quad \text{(A.9)}$$

The zeros in the first and second rows reflect the restriction that oil prices and the labor supply are unaffected by other variables in the long run. The zero in the third row reflects the restriction that the demand shock, ϵ_{4t} in equation (12) of the text, has only temporary effects on output. In a 4-equation system, the variance covariance matrix contains 10 unique elements, but there are 16 unknown parameters. Six additional restrictions are needed to identify the system. In equation (A.9), there are seven restrictions, implying that the system is overidentified.

To impose the identifying restrictions discussed previously, the following equations are estimated:

$$\Delta o_t = \sum_{i=1}^{l} \Delta h_{11,i} o_{t-i} + u_{1t} \quad \text{(A.10)}$$

[2]For a matrix of polynomials in the lag operator $B(L) = B_0 + B_1L + B_2L^2 + \ldots$, the matrix of long-run multipliers is found by setting $L=1$. This yields $B(1) = B_0 + B_1 + B_2 + \ldots$ or the sum of the moving average coefficients.

$$\text{(A.11)}\quad \Delta n_t = \sum_{i=0}^{l-1} \Delta^2 h_{21,\,i} o_{t-i} + \sum_{i=1}^{l} h_{22,\,i} \Delta n_{t-i} + \sum_{i=0}^{l-1} h_{23,\,i} \Delta^2 y_{t-i} + \sum_{i=0}^{l-1} h_{24,\,i} \Delta^2 p_{t-i} + u_{2t}$$

$$\text{(A.12)}\quad \Delta y_t = \sum_{i=0}^{l} h_{31,\,i} \Delta o_{t-i} \quad \sum_{i=1}^{l} \Delta h_{32,\,i} n_{t-i} + \sum_{i=1}^{l} h_{33,\,i} \Delta y_{t-i} + \sum_{i=0}^{l-1} h_{34,\,i} \Delta^2 p_{t-i} + u_{3t}$$

$$\text{(A.13)}\quad \Delta p_t = \sum_{i=0}^{l} h_{41,\,i} \Delta o_{t-i} + \sum_{i=1}^{l} \Delta h_{42,\,i} n_{t-i} + \sum_{i=1}^{l} h_{43,\,i} \Delta y_{t-i} + \sum_{i=1}^{l} h_{44,\,i} \Delta p_{t-i} + u_{4t}$$

where it is assumed that o, n, y and p are difference stationary, and a lag length of five is used in all equations. Using this lag length yields Q statistics that do not reject white noise at the 5 percent marginal significance level in all equations.

Equations (A.10) and (A.13) are estimated by OLS. Equations (A.11) and (A.12) are estimated by two-stage least squares, with the contemporaneous value of the oil price and the lagged values of all variables as instruments. In equations (A.11) and (A.12), the restriction that certain variables have zero effects in the long run is imposed by expressing these variables in second differences and setting the maximum number of lags to four for these equations.

The system (A.10) to (A.13) incorporates several of the restrictions implied by (A.9). However, the system does not exactly correspond to (A.8) because the variance covariance matrix of the system (A.10) to (A.13) is not diagonal. That is, the unadjusted residuals u_{1t}, u_{2t}, u_{3t}, u_{4t}, are correlated and are not (necessarily) the same as the uncorrelated structural disturbances in (A.8) or in the moving average representation of (12) in the text. To identify the three supply disturbances ϵ_{1t}, ϵ_{2t}, ϵ_{3t}, and the demand disturbance ϵ_{4t} in equation (12) in the text, I select a lower-triangular matrix G such that $G^{-1}\Sigma_u G'^{-1} = I$, where Σ_u is the variance-covariance matrix of the system (A.10) to (A.13). With such a matrix G, it is possible to define $\epsilon_t = u_t G^{-1}$ and $E\epsilon_t\epsilon_t' = I$.

In typical applications, the use of a lower-triangular matrix G, also known as the Choleski factorization, yields a recursive system of mutually orthogonal disturbances of the type proposed by Sims (1980). In the early VAR literature, this was the sole basis for identification. Since many theoretical models do not imply a recursive economic structure, it is difficult to rely on this approach alone to distinguish between demand and supply shocks.[3]

In the present case, however, the Choleski decomposition is only *one* element of the identification procedure, designed to extract mutually orthogonal disturbances. Identification also depends on the specification of the VAR equations, which incorporate the restrictions proposed by Blanchard and Quah and satisfy (A.9) (the Choleski factorization alone cannot guarantee that equation (A.9) will be satisfied). It may also be noted that since contemporaneous values of the explanatory variables are included in the VAR model, the resulting structure of the economy is *not* recursive.

Appendix B
Data Description and Sources

Australia, quarterly

Real Gross Domestic Product. Millions of 1984–85 Australian dollars (A$), seasonally adjusted.
Source: OECD *Main Economic Indicators.*

Consumer Price Index. 1985 = 100.
Source: *International Financial Statistics*, International Monetary Fund.

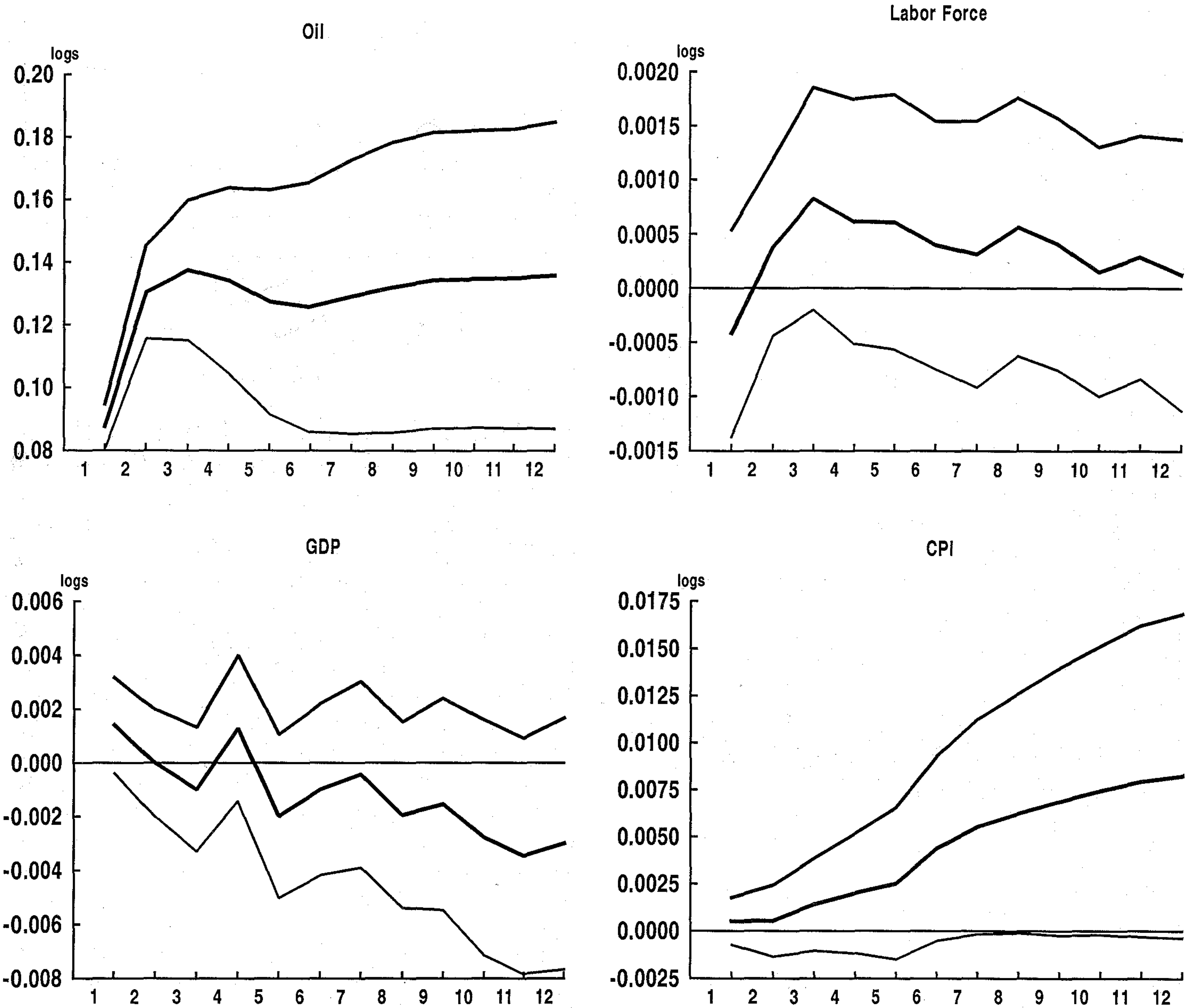
Labor Force. Total labor force, thousands of persons.
Source: Reserve Bank of Australia, *Australia Reserve Bulletin.*

International

Oil. Crude petroleum component of U.S. PPI, 1982 = 100, quarterly average of monthly data.
Source: Citibase.

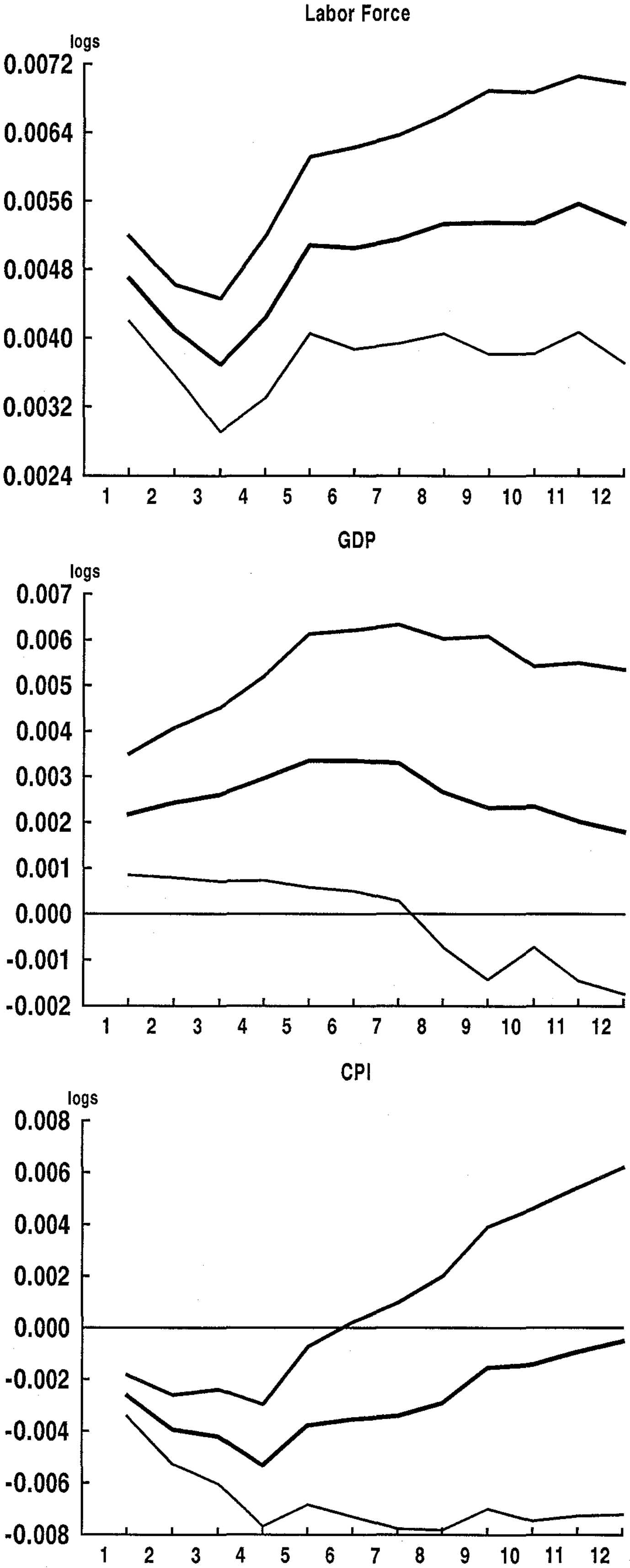
[3]However, a recursive structure may suffice if detailed knowledge of the economy is not required. For example, Moreno (1992b) uses a Choleski factorization to identify mutually orthogonal domestic and external shocks, and to measure the vulnerability of an economy to these external shocks under alternative exchange rate regimes.

CHART C.1
RESPONSE TO OIL PRICE SHOCK



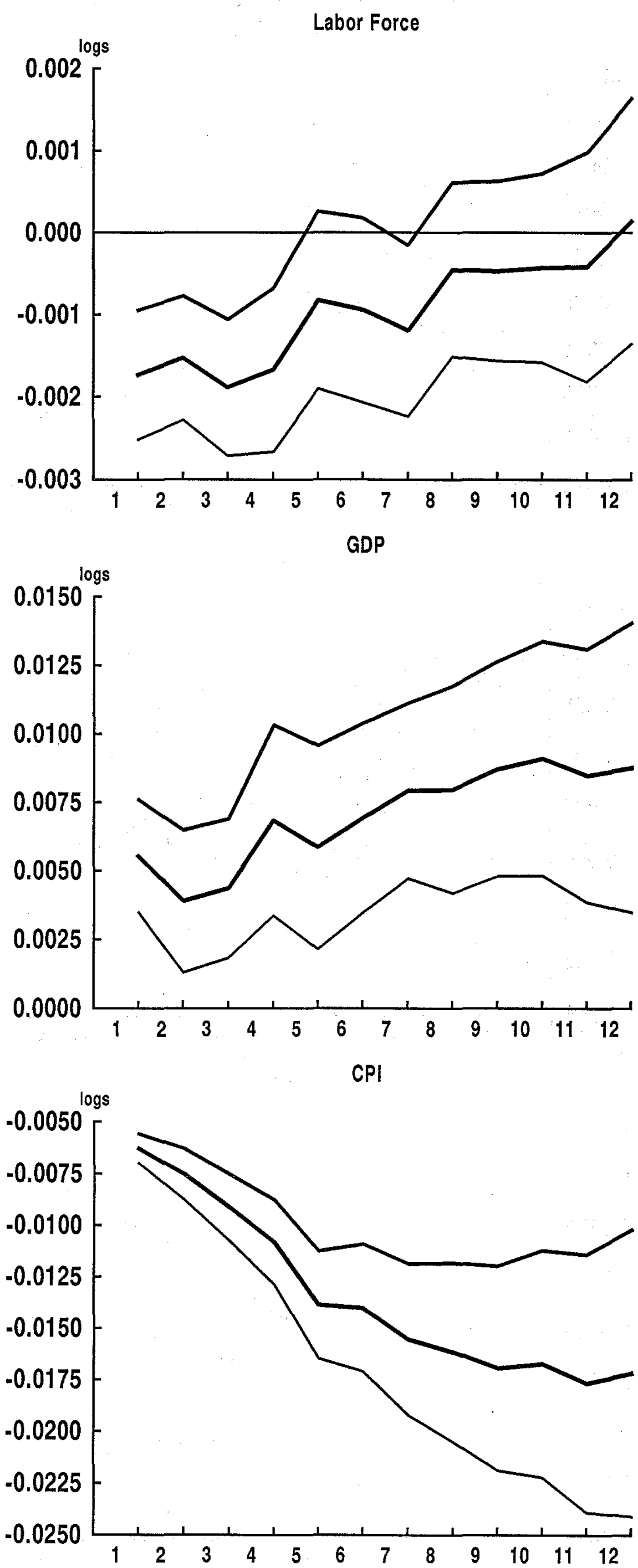
NOTE: Shock is one standard deviation.

CHART C.2
RESPONSE TO LABOR SUPPLY SHOCK



NOTE: Shock is one standard deviation.

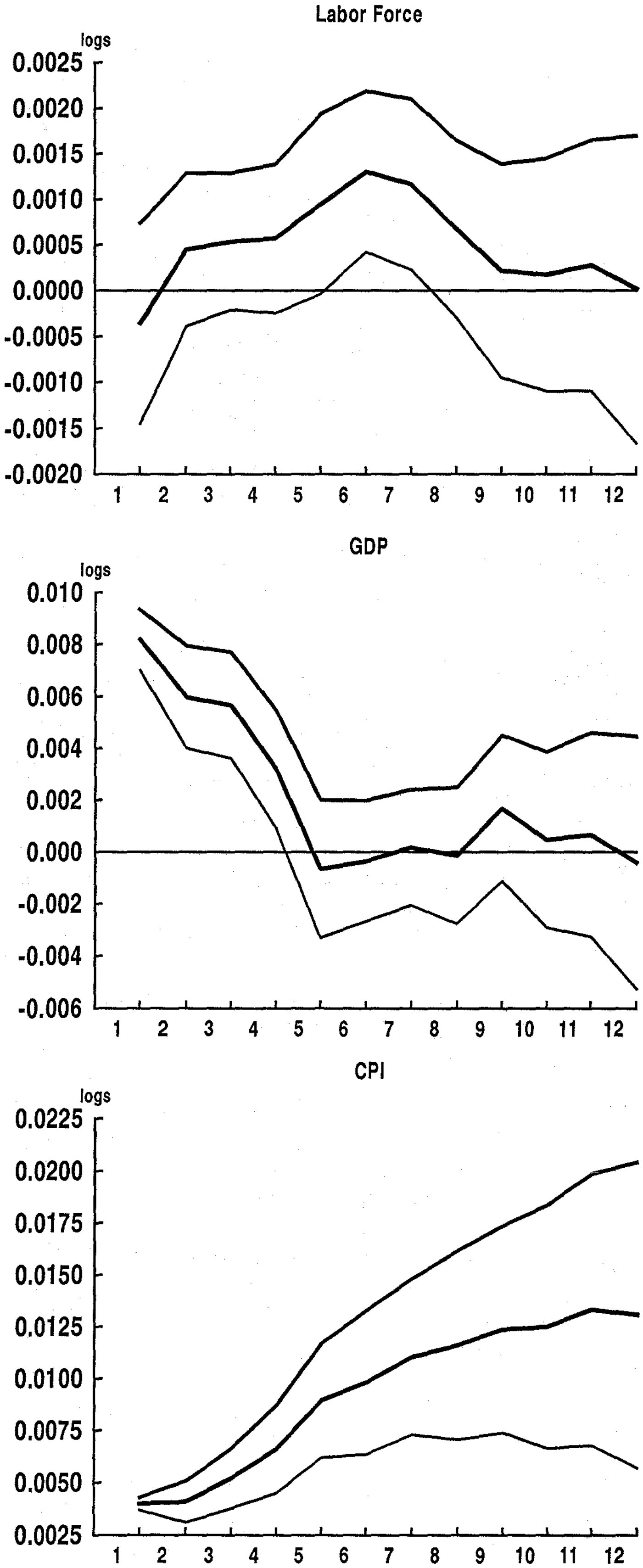
CHART C.3
RESPONSE TO TECHNOLOGY SHOCK



NOTE: Shock is one standard deviation.

CHART C.4

RESPONSE TO DEMAND SHOCK



NOTE: Shock is one standard deviation.

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