Forecasting and Analyzing World Commodity Prices

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Abstract

This paper develops simple econometric models to analyze and forecast three components of the Bank of Canada commodity price index (BCPI), namely non-energy commodity prices (BCNE), the West Texas Intermediate crude oil price (WTI), and other energy prices. In the paper, we present different methodologies to identify transitory and permanent components of movements in these prices. A structural vector autoregressive (SVAR) model is used for real BCNE prices, a multiple structural-break technique is employed for real crude oil prices, and an error-correction model is constructed for real prices of other energy components. Then we use these transitory and permanent components to develop forecasting models. We assess our models' performance in various aspects, and our main results indicate: (a) for real BCNE prices, most of the short-run variation is attributed to demand shocks, (b) the world economic activity and real U.S. dollar effective exchange rate explain much of the cyclical variation of real BCNE prices, (c) real crude oil prices have two structural breaks over the sample period, and their link with the world economic activity is strongest in the most recent regime, (d) real prices of other energy components are highly correlated with the U.S. economic activity, and they are co-integrated with real crude oil prices, (e) our models outperform benchmark models, namely a VAR model, autoregressive (AR) model and a random walk (RW) model, in terms of out-of-sample forecasting, and (f) a 1% positive shock to world economic activity leads to an approximate 7.2% peak response of world commodity prices.

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1. Introduction

The resource sector has traditionally played an important role in the Canadian economy, especially in the area of foreign trade. Over the past decade, total exports of commodities represent, on average, about forty one per cent of Canada's exports of goods[1] and fifteen per cent of Canada's gross domestic product (GDP). Consequently, changes in world commodity prices have historically been a key determinant of Canada's terms of trade, which in turn have affected the real income of Canadians.

The staff at the Bank of Canada (BOC) have designed the Bank of Canada Commodity Price Index (BCPI) to track the prices paid for key Canadian commodities. The BCPI is a fixed-weighted index of the spot or transaction prices of 23 commodities produced in Canada and sold in world markets.[2] All components of the BCPI are priced in U.S. dollars. The choice of commodities is determined by their importance in Canadian production, subject to limitations imposed by data availability. For the purpose of this paper, we split the BCPI into three subindices: non-energy commodity prices (BCNE), the West Texas Intermediate crude oil price (WTI), and energy prices excluding crude oil.[3] To obtain real commodity prices, we divide by the U.S. GDP deflator.

In this paper, we employ three different empirical approaches to model commodity prices. For real BCNE prices, we use an approach that combines a structural vector autoregressive model (SVAR) with a single equation model. The SVAR is used to give us a historical decomposition of movements in real BCNE prices, and to project the permanent (or long-run) component of prices, while the transitory (or short-run) component of real BCNE prices is forecasted with a single equation model. We find that this approach successfully captures the strong linkage of real BCNE prices with the world economic activity and the real U.S. effective exchange rate in the short run.[4] A 1% positive shock to world economic activity leads to an approximate 6% peak response of real BCNE prices, while the response to the real U.S. dollar effective exchange rate shock is small but

1. This ratio is defined as the share of nominal commodity exports in total nominal exports over the period 1990 to 2001.
2. See Appendix A for a description of the BCPI and its components. The weight of each commodity in the index is based on the average value of Canadian production of the commodity over the 1982-90 period.
3. The other energy price index consists of natural gas prices (80%) and coal prices (20%).
4. The U.S. dollar effective exchange rate is defined as a U.S. export weighted average of the exchange rate of U.S. dollar relative to the currencies of Japan (17.59%), U.K. (8.22%), Mexico (14.52%), Canada (35.40%) and Euro zone (24.27%)

it is statistically significant and exhibits the expected sign.[5] We also find that the variance of the transitory component of real BCNE prices accounts for approximately 60% of total real BCNE price variance. This result is consistent with numerous other studies of commodity prices.[6] In terms of out-of-sample forecasting, our approach outperforms a SVAR model and an autoregressive (AR) model.

Two separate models are used for real crude oil prices and other real energy prices. For real crude oil prices, we use a statistical multiple structural-break approach to identify significant shifts in OPEC behavior. After controlling for these mean shifts, we find a very strong role for world economic activity in the determination of oil prices. We estimate that a 1% positive shock to world economic activity leads to an approximate 12% peak response of real crude oil prices with a lag of two to three quarters. In terms of out-of-sample forecasts, the real oil price model outperforms an AR model and a random walk (RW) model. For real prices of other energy components, we use an error correction representation which exploits the long-run relationship between real energy prices excluding crude oil and real crude oil prices. The U.S. output gap, a proxy for North American economic conditions, is shown to be a key factor explaining the short-run price variations.[7]

To quantify the total peak response of the total BCPI to a 1% positive shock to world economic activity, we take the weighted sum of three component responses, where the weight is determined by the share of each individual component in the composition of the BCPI. In total, we estimate that a 1% positive shock to world economic activity leads to a 7.2% peak response of world commodity prices. This is close to the result reported in Hunt (1995).

The remainder of the paper is organized as follows. Section 2 gives a brief overview of recent literature on commodity prices. In Section 3, we present the methodology as well as results for the real BCNE price model. The methodologies and results for the real crude oil price model are dis-

5. We use the world output gap as a proxy for the overall world economic activity, where the output gap is generated using the Hodrick-Prescott (HP) filter.
6. For example, Borensztein and Reinhart (1994) obtain a similar result.
7. Due to the difficulty and cost associated with transportation of natural gas overseas, natural gas prices can be thought of as determined in North American markets while crude oil prices are more globally determined.

cussed in Section 4. Section 5 presents results for the model of real energy prices excluding crude oil. Section 6 reports the peak response of the BCPI to a shock to world economic activity. Section 7 concludes.

2. Literature Review

This section gives a brief overview of some of the recent economic literature pertaining to price formation in world commodity markets. A common theme in many of these studies has been an attempt to disentangle commodity price movements into a cyclical and a long-term movement. This distinction is important for forecasting commodity prices both in the short-run and long-run.

Various methodologies have been used in order to disentangle the trend movement of world commodity prices from the cycle. Reinhart and Wickham (1994) apply two different approaches, namely the Beveridge and Nelson (1981) technique and the Harvey (1985) approach. The first approach is a pure reduced form time-series technique used for the decomposition of a time-series variable, while the second one is a structural time-series approach using the Kalman filter. Each of these two approaches has its own strengths and weaknesses. The pure mechanical filters can easily split a time series into cyclical and permanent components, but lack economic fundamentals. Although the Kalman filter contains certain economic information, it often does not perform very well in practice if the assumptions of normal distributions for disturbances and the initial state vector are violated. When the normality assumption is dropped, there is no longer a guarantee that the Kalman filter will give the conditional mean of the state vector, i.e. the estimates of the state vector could be conditionally biased.[8] Moreover, it becomes more cumbersome to calculate the likelihood function without the normality assumption.

Following the study of Reinhart and Wickham (1994), Borensztein and Reinhart (1994) adopt a structural model to identify the key fundamentals behind commodity prices, and more importantly to quantify the relative contributions of demand and supply shocks. On the demand side, they find that the real U.S. dollar effective exchange rate and the state of the business cycle in industrial countries are closely linked to the cyclical movement of world commodity prices. On the supply side, strong productivity growth of commodity sectors relative to the rest of the econ-

8. See Harvey (1989) for details.

omy and the increased commodity supply relative to the rest of the economy are the primary causes of the downward trend of commodity prices. Using a variance decomposition, the authors conclude that both types of shocks contribute to the total variation of commodity prices in the near term and around 60% of the variation is caused by demand shocks.

Cashin, Liang and McDermott (2000) examine the persistence of shocks to commodity prices. They use a median-unbiased estimation procedure proposed by Andrews (1993) instead of a unit root test to check the persistence of shocks. Using IMF data on sixty individual commodity prices, they find that shocks to most commodity prices are long-lasting (reflected by the high value of the half-life of a unit shock), and the variability of the persistence is fairly large. However, they fail to identify and quantify the relative importance of demand and supply factors to the persistence of shocks. Cashin and McDermott (2001) use much longer sample periods and examine whether the long-run behavior of commodity prices has changed. In particular, they look at the trend of most commodity prices, the duration of price booms and slumps, and also the volatility of price movements. They apply various statistical tests and compare the patterns of commodity price movements across different sample periods. The authors come to the conclusion that there has been an apparent downward trend in real commodity prices over the last 140 years because of relative productivity growth in commodity sectors and a structural change in supply conditions.[9] Moreover, the short-term volatility is highly related to the business cycle.

In practice, numerous methodologies have been employed to disentangle transitory and permanent movements in commodity prices. Though convenient to apply, pure time-series filters suffer from a lack of structural economic fundamentals. In contrast, although structural models are constructed based on the economic theory, they are often costly and time-consuming to develop and maintain. For instance, it would be very costly to develop and maintain models for 23 individual components of the BCPI. Therefore, as a compromise, we combine basic time series approaches with simple economic theory to develop econometric models for the three major BOC commodity price indexes.

9. Coletti (1992) examines a small set of non-energy commodities that mainly include industrial materials (e.g. metals, minerals and forest products) over the 1900-91 period. He finds no obvious secular decline in relative prices of those commodities.

3. The real BCNE price model

This section consists of three subsections. The first two parts describe the methodology used to identify and to forecast the transitory and permanent components of real BCNE prices. The last subsection shows the results.

3.1 Identifying the transitory and permanent components of real BCNE prices

We use a SVAR approach to decompose historical BCNE prices into transitory and permanent components. Under this approach, a number of economic restrictions are imposed on the long-run effects of different types of shocks. The main strength of the SVAR methodology is that one does not have to impose a fully specified theoretical structure and the data are allowed to speak. The only assumptions are that the variable of interest (i.e. real BCNE prices) can be decomposed into one or more permanent components and one or more transitory components, and that the transitory shocks are uncorrelated with the permanent shocks. However, the SVAR methodology has its own weakness. Notably, the results are often sensitive to the choice of variables included in the estimation. Also, results can be affected by the number of lags chosen in the reduced form, assumptions on the order of integration of variables, and the presence of co-integrating relationships among variables.

In our model, variable selection is based on economic theory and the findings of previous studies. To capture the information about transitory shifts in real BCNE prices arising from changes in world economic conditions, we use the G7 output gap as a proxy for the world economic activity.[10] The G7 inflation rate,[11] a proxy for the global inflation rate, is added to capture the importance of having a nominal anchor in the model as suggested by the SVAR literature.[12] In light of the empirical studies on world commodity prices in the previous section, we include two additional demand indicators - the real U.S. long-term interest rate as a proxy for the real world interest rate, and the real U.S. dollar effective exchange rate - to identify the cyclical component

10. The G7 output gap is generated using the SVAR methodology for the U.S. (see Lalonde (1998)) and the HP filter for the rest of G7 countries. We take the sum of individual output gaps weighted by each country's share in the composition of the G7 output evaluated at purchasing power parity. We use the term "world output gap" through the rest of the paper.

11. The G7 inflation rate is generated by taking the sum of individual inflation rates weighted by each country's share in the composition of the G7 output evaluated at purchasing power parity. We use the term "global inflation rate" through the rest of the paper.

of real BCNE prices.[13] In addition, we have attempted to include some supply-side determinants of the permanent component of real BCNE prices. However, given the fact that the real BCNE price is an aggregate price index, it is hard to find a proper measure of productivity.[14]

The final SVAR contains the following five variables: real BCNE prices (*Rbcne*), the world output gap (*Wygap*), the global inflation rate ($W\pi$), the real U.S. long term interest rate (*RRus*) and the real U.S. dollar effective exchange rate (*Erus*). We assume that the real U.S. interest rate is stationary in levels.[15] ADF tests show that the world output gap is stationary in levels and the rest of variables are first difference stationary. Furthermore, a Johansen co-integration test shows that there is no co-integrating relationship between *Rbcne*, $W\pi$ and *Erus*. The technical details on the SVAR methodology are presented in Appendix B. We estimate the model over the period of 1972-2001 using quarterly data.[16]

3.2 Forecasting the transitory and permanent component of real BCNE prices

The second step of the approach consists of finding the best way to produce forecasts of both the temporary and permanent components that are both tractable and consistent with projections of the rest of the world economy. We use the SVAR to forecast the permanent component of real BCNE prices. We have also estimated a simple equation to forecast the transitory component of real BCNE prices. This equation captures the link between the transitory component of real BCNE prices and the world output gap as well as the real U.S. effective exchange rate gap.[17] The

12. If monetary policy has a neutral effect across different sectors of the economy, both in the short-run and long run, the presence of the global inflation rate in the model may not be important. However, because monetary policy may not affect all sectors in the same manner in the short-run, it can have a transitory effect on relative prices. Consequently, using real BCNE prices alone may not be sufficient to purge the effects of monetary policy. Out-of-sample forecasting performance of the model including the global inflation rate is slightly better than the one which excludes it. Furthermore, results show that real BCNE prices do react, in the short-run, to a shock affecting the trend inflation rate.
13. Since world commodities are all priced in U.S. dollars, movements in the real U.S. dollar effective exchange rate will affect the demand for commodities by countries other than the U.S. This in turn will affect prices.
14. If the productivity growth only happens in a particular sector, this tends to lower production cost in this sector relative to the rest of the economy. Consequently, this causes lower prices of goods produced in this sector relative to the aggregate level (i.e. lower relative prices).
15. The augmented Dickey-Fuller (ADF) test provides an ambiguous evidence regarding the stationarity of the real U.S. long-term interest rate. However, we assume here that it is stationary. The results are robust to this assumption.
16. We estimate the same model over the sample of 1972-95 and we find that the transitory component of real BCNE prices is almost identical to the one estimated over the full sample period.

equation is defined as:

<u>Regression Equation</u>:

$$Rbcnegap_t = A(L)Rbcnegap_{t-1} + B(L)Wygap_t + C(L)Ergap_t \text{ ,}^{18} \tag{1}$$

where *Rbcnegap* is the transitory component of real BCNE prices (i.e. real BCNE price minus the SVAR estimates of its permanent component), *Wygap* is the world output gap and *Ergap* is the real U.S. dollar effective exchange rate gap. This equation has the advantage of relying on a small number of estimated parameters, which helps to reduce out-of-sample forecasting errors. In addition, it clearly quantifies the impacts of the world output gap and the real U.S. dollar exchange rate gap on the change in the transitory component of real BCNE prices.

3.3 Results of real BCNE price model

This section presents results of the real BCNE price model. First, we use variance decomposition to quantify the relative importance of supply and demand shocks. Second, we discuss the link between the world output gap and the transitory component of real BCNE prices. The last part evaluates the forecasting performance of the model.

3.3.1 The relative importance of supply and demand shocks

Table 1 reports the variance decomposition of real BCNE prices at different time horizons. After the first year (step=4), the transitory shocks (i.e. demand shocks) explain almost 60% of the total variance of real BCNE prices. After two years (step=8), however, the contribution of demand shocks falls dramatically and accounts for only 10% of the total. The model shows a significant contribution of demand shocks to real BCNE prices in the short term, and this is consistent with other studies mentioned earlier. Figure 1 plots the corresponding impulse responses of real BCNE prices to a positive one standard deviation <u>total</u> demand and supply shock. Real BCNE prices exhibit a small hump-shaped response to the total demand shock while the response to the supply shock appears to be more gradual.

17.We use the HP filter to generate the real U.S. dollar exchange rate gap.

18.It is worth noting here that the real U.S. interest rate is excluded in the equation due primarily to its strong collinearity with the world output gap, but it can still indirectly affect the forecast of real BCNE prices via its impact on the forecast of the world output gap.

3.3.2 The world output gap and the transitory component of real BCNE prices[19]

Figure 2 plots the evolution of both the world output gap and the transitory component of real BCNE prices over the historical period. There is a strong positive relationship between the two variables. The world output gap tracks most of the important cyclical movements of real BCNE prices since the mid 1970s.

Table 2 reports the parameter estimates of equation (1). The Hausman test fails to reject the null hypothesis of exogeneity of the world output gap, and hence we use instrumental variable estimation (IVE). The instruments used for the estimation are four lags of the world output gap, the transitory component of real BCNE prices, the real U.S. dollar exchange rate gap and the real U.S. long-term interest rate. The standard errors of the estimated parameters are modified using an 8-lag Newey-West correction. We start with eight lags for each regressor, and then remove the most insignificant estimates one by one until all the remaining coefficients are statistically significant at the 5% significance level. All the coefficient estimates have the expected signs and are statistically significant in the final model. The transitory component of real BCNE prices itself is fairly persistent with a root of about 0.71, and both the world output gap and the real U.S. dollar effective exchange rate gap contribute significantly to transitory movements of real BCNE prices. Furthermore, we calculate the relative contributions of a positive one standard deviation shock to each regressor in our model to the total response of the real BCNE transitory component. We find that around 80% of the total response comes from shocks to the world output gap (72%) and the real U.S. dollar exchange rate gap (8%). In other words, only a small fraction (20%) of the response is left unexplained by our model.

Figure 3 plots the real BCNE price versus its permanent component over history. The implied cyclical movements of real BCNE prices are consistent with our expectations. Figures 4 and 5 show the responses of real BCNE prices to a 1% positive shock to the world output gap and the real U.S. dollar effective exchange rate gap respectively. The peak response of real BCNE prices to the world output gap shock is about 6% and occurs almost contemporaneously with the peak of

19. As a robustness checking, we also try the U.S. output gap. We find that models with the world output gap outperform those with the U.S. output gap in most cases. All results for the U.S. output gap model are available upon request.

the world output gap itself. In comparison, the response to a shock to the real U.S. dollar effective exchange rate gap is much smaller, with a peak of about -0.35%, but it exhibits the expected sign.

3.3.3 Out-of-sample forecast of real BCNE prices

World commodity price shocks have a peak impact on the core inflation rate with a lag of two to four quarters in the Canadian economic projection model used at the Bank of Canada. Since monetary policy tends to have its full impact on inflation with a lag of six to eight quarters, the monetary authority will be most interested in forecasts of world commodity prices two to four quarters ahead.

We evaluate our model's out-of-sample forecasting performance by comparing it with forecasts from two benchmark models: VAR model and AR(1) model. Our model forecasts of real BCNE prices combine SVAR forecasts of the permanent component and single equation forecasts of the transitory component. As mentioned earlier, we focus on the forecasting horizon which is of interest to the monetary authority, namely two to four-quarters ahead. According to the RMSE of out-of-sample forecasts from 1992q1 to 2001q4,[20] the combined approach uniformly outperforms the two benchmark models regardless of the forecasting horizons (see Table 3) according to smaller values of RMSE.[21]

Tables 4 to 6 report the *p*-values of the forecast encompassing test statistic, which was originally devised by Chong and Hendry (1986) to compare two competing models based on the out-of-sample forecasting errors. The encompassing test results support the use of the combined approach. The results indicate that we can not reject the null hypothesis of “A encompasses B”, which implies that forecasts from either of two benchmark models (model B) are unlikely to improve the forecasting performance of the combined approach (model A) for any forecasting

20.We use a rolling sample regression to generate out-of-sample forecasts for a given time horizon.

21.The fact that the combined approach outperforms the VAR model could be explained by the following arguments. The choice of the variables included in the SVAR were not made on the basis of their ability to forecast real BCNE prices but on their ability to give information pertinent to the identification of the permanent and transitory components of real BCNE prices. Second, SVAR literature shows that it is important to include a large number of lags in the SVAR in order to identify properly the transitory component of a variable. With a small sample, this strategy is clearly not optimal in terms of out-of-sample forecast performance because it relies on many estimated parameters. The combined model attempts to address those issues.

horizon. On the other hand, we can always reject the null hypothesis of "B encompasses A" at the 5% significance level except for one case when we compare four-quarter ahead forecasts with the RW model. This implies that our combined approach improves the forecasting performance of two benchmark models.

4. The real crude oil price model

This section consists of two subsections. The first part describes the methodology that we use to identify and forecast the transitory and permanent components of real WTI crude oil prices. The second subsection presents results of the model.

4.1 Methodologies

Crude oil prices have experienced a few large permanent shifts over history, most notably in 1979-80 and 1985-86.[22] To test for structural breaks in the data (under the assumption that the time and the number of breaks is unknown), we use the methodology proposed by Bai and Perron (1998) (hereafter BP).[23] The strength of the BP methodology is that we can estimate the time and the number of structural breaks endogenously with allowance for varying parameters across regimes. Given the fact that world oil prices are spot prices, we also allow the model to capture the contemporaneous effect of the world output gap on prices.

4.2 Results of the real crude oil price model

This section is divided into three parts. First, we examine the estimation results for the model of real crude oil prices. Second, we use the estimated model to identify transitory and permanent components of crude oil prices. Third, we evaluate the model's out-of-sample forecasting performance.

4.2.1 Estimation of real WTI crude oil model

We first consider the real WTI crude oil price over the full sample period. An ADF test can-

22. These large movements in price are related to specific developments in the market, particularly with changes in the behaviour of the OPEC cartel.
23. See Appendix C for a brief discussion of the BP methodology.

not reject the presence of a unit root. However, when allowing for structural changes, we can reject the hypothesis that the real WTI crude oil price has a unit root.[24]

Using the procedure proposed by BP, we estimate a single equation model with allowance for up to three structural changes. The sample period is from 1974q2 to 2001q4. In this framework, all the parameters of the model are allowed to shift at the structural break point. At the 5% level, the test is detecting two breaks in 1979q3 and 1985q4.[25] It is interesting to note that the test is capturing the break points matching well the two historical oil price shocks that happened in the late 1970s and the mid-1980s. The first oil shock in the late 1970s began with the Iranian revolution and the accompanying disruption of its petroleum exports. Moreover, the outbreak of the war between Iran and Iraq in 1980 shook the oil market as well. The second oil shock in the mid-1980s was primarily caused by the collapse of the OPEL cartel.[26] The first experiment we do is to use three dummy variables to capture regimes separated by two breaks.

Regression Equation:

$$Rwti_t = D1 * Dumm1 + D2 * Dumm2 + D3 * Dumm3 + C(L)Rwti_{t-1} + DD(L)Wygap_t + E(L)Ergap_t. \qquad (2)$$

Table 7 reports the OLS estimation results of equation (2) without allowing varying coefficients across regimes. We report the model parameter estimates for the two cases with and without the real U.S. dollar exchange rate gap. As seen in Table 7, the results for both cases are almost identical. Real crude oil prices are fairly persistent over the full sample with an AR root of 0.67 (the sum of the two autoregressive coefficients) and the estimated coefficient associated with the lagged world output gap is about 2%. The real U.S. dollar effective exchange rate gap is not statistically significant over the whole sample period.

Tables 8 to 10 report the BP procedure results for three regimes with allowance for varying coefficients. As seen, the estimate of the lagged world output gap changes considerably across

24. The sum of AR coefficients is 0.58 and the *t*-statistic is -5.3, which compares to a 2.5% critical value of -5.3 (see Zivot *et al (1992)*).
25. The test statistics for the sup$F(1|0)$ and sup$F(2|1)$ are 30.7 and 27.4, respectively. This compares to the 5% critical values of 20.1 and 22.1.
26. From 1982 to 1985, OPEC attempted to set production quotas low enough to stabilize prices. These attempts met with repeated failure as various members of OPEC would produce beyond their quotas. During most of this period, Saudi Arabia acted as the swing producer cutting its production to stem the free falling prices. In the late 1985, Saudi Arabia stopped doing that and increased its production, and this eventually caused the collapse of OPEC and oil price plunge in 1986.

regimes. Although it is not statistically significant in the first regime, the estimate has the correct sign. In the second regime, it exhibits the wrong sign, but it is statistically insignificant. In contrast, its magnitude increases substantially in the most recent regime with a value of about 6%, which is almost three times the average value over the entire sample as reported in Table 7.[27]

Furthermore, since WTI crude oil prices are spot prices, we would expect crude oil prices to respond immediately to the world output gap shock. The Hausman test indicates that the null hypothesis of exogeneity of the world output gap is rejected at 5% level of significance. This implies that applying the OLS to the BP procedure cannot produce consistent estimates, and we should instead use the IVE. The instruments used are four lags of all explanatory variables in the model. However, given the small number of observations in the first two regimes, applying IVE to the BP procedure tends to give us very biased results.[28] Hence, we use IVE to re-estimate equation (2) with an additional variable for world inventories of crude oil only for the third regime, which has a relatively sufficient number of observations.[29] Table 11 reports the IVE estimates of all the parameters. The world output gap remains statistically significant at the 5% level of significance, and the estimated coefficient associated with the world output gap is around 4.5%. In the preferred model, we also add the change in crude oil inventories. The third lag of the change in crude oil inventories is statistically significant and exhibits the expected sign.[30]

4.2.2 The transitory and permanent components of real crude oil prices

Given the nature of the model, the permanent component consists of three different means caused by two structural breaks. Figure 6 plots the world output gap versus the transitory component of real WTI crude oil prices across the three regimes. The closest link between the two variables appears in the most recent regime. Figure 7 shows that a 1% positive shock to the world output gap leads to an approximate 12% peak response of real WTI crude oil prices with a lag of two to three quarters.

27. However, the real U.S. dollar effective exchange rate gap is not statistically significant, and excluding it increases the magnitude and improves the significance of the estimated elasticity of real crude oil price with respect to the world output gap.
28. The bias problem becomes severe in a small sample. See Davidson and Mackinnon (1993) for details.
29. As Tables 8 to 10 have shown that the strongest link between the world output gap and real crude oil prices is in the third regime, we are more interested in the IVE estimates for this regime.
30. Because only the third lag of the change of crude oil inventory enters our model, we do not need a model to forecast this variable in order to forecast real oil prices over very short time horizons.

4.2.3 Out-of-sample forecast of the real crude oil price model

We use the estimated single equation model from Table 11 to forecast real crude oil prices. We compare the two- to four-step ahead forecasting performance of our model with two benchmark models from 1992q1 to 2001q4. Table 12 compares the RMSE of two to four-step ahead out-of-sample forecasts of our model with two benchmark models: AR(1) model and RW model. It is evident that regardless of the forecasting horizons concerned, our model uniformly outperforms the other two as reflected by smaller values of RMSE.

We have also estimated an alternative specification excluding the oil inventory measure. We find models excluding the inventory measure always perform worse than those including it. Furthermore, for near-term forecasting (two quarters ahead), they are even worse than naive forecasts using a RW model. Our results are strong in the sense that the first several periods' out-of-sample forecasts may be severely biased given a much smaller number of observations in the initial estimations (1986q1 to 1991q1) compared to the whole sample period.

Tables 13 to 15 report the *p*-values of forecast encompassing test statistics. The test results again support the use of our model. The results show that we cannot reject the null hypothesis of "A encompasses B", which implies that it is impossible to improve the forecasting capability of our model (model A) with the help of forecasts from either of two benchmark models (model B) for any forecast horizon. On the other hand, we can always reject the null hypothesis of "B encompasses A" at the 10% significance level, which implies that our model can provide useful information to improve the forecasting performance of two benchmark models.

5. The model of real prices of energy excluding crude oil

Using the Johansen co-integration test, we find a co-integrating relationship between real crude oil prices and real prices of energy excluding crude oil. The Hausman test shows that real crude oil prices are weakly exogenous in the model. Therefore, we use an error-correction specification. Instead of using the world output gap as a measure of real economic activity, we use the U.S. output gap in this model given that the markets for energy components other than crude oil are concentrated in North America.

<u>Regression equation</u>:

$$DRener_t = G(L)DRener_{t-1} + H(L)USygap_t + \alpha(Rener_{t-1} + \beta Rwti_{t-1} + constant). \qquad (3)$$

Table 16 reports the parameter estimates of equation (3). Several points are worth mentioning. First, the U.S. output gap is strongly correlated with short-term price movements. Second, the speed of adjustment coefficient (α) is relatively small (about 14% of the gap between real prices of other energy components and the long-run trend is adjusted each quarter), but it is highly significant at the 1% level. Third, the estimated co-integrating relationship indicates that the long-run elasticity of real prices of other energy components with respect to real crude oil prices is close to one.

6. Response of the BCPI to a shock to world economic activity

Finally, we calculate the total peak response of the total BCPI to a positive shock to the world output gap by taking the weighted sum of responses of the three subindices to the same shock. The weight is determined by the share of each price subindex in the BCPI. We have calculated a value of about 7.2% for the peak response of the BCPI to an average 1% shock to the world output gap.[31]

7. Conclusion

To summarize, the variance decomposition shows that about 60% of the total variation in real BCNE prices is attributable to demand shocks. This is consistent with the studies in the literature for other commodity price indexes. We also found a very close link between the world output gap and transitory movements in real BCNE prices. For real WTI crude oil prices, a multiple structural-break test indicates two structural breaks over the sample period. We used the exogenous mean shifts of real WTI crude oil prices across three different regimes as a measure of the permanent component of real crude oil prices. The respective forecasting model shows the strongest link between the cyclical component of real WTI crude oil prices and the world output gap occurs in the most recent regime. For real energy prices excluding crude oil, an error correction model was

31. Hunt (1995) finds that a 1% positive shock to the world output gap averaged over six quarters leads to about an 8% peak response of the BCPI.

adopted. The co-integrating relationship between real prices of other energy components and real crude oil prices is used to identify the permanent component of the former.

In terms of the forecasting performance, we compared two- to four-step ahead forecasts of our models with benchmark models: SVAR model, AR(1) model and RW model. The tests showed that our models uniformly outperform the baseline models,

All results suggest that we can provide better short-term forecasts of world commodity prices relative to benchmark models. A potential avenue for future work is to put more effort into developing the supply side of the model, and to explore key supply indicators such as productivity growth in commodity producing sectors that can reasonably explain the long-term behavior of world commodity prices. The models with richer structures can be further developed in future research in order to better analyze and forecast the commodity prices both in the short-run and long-run. In addition, for the real WTI crude oil price model, the regime switching approach such as the Markov- switching method can be used to forecast future structural breaks of prices.

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Table 1: Variance decomposition of real BCNE prices

Step	Supply shock	Demand shock
1	29%	71%
4	41%	59%
8	89%	11%
16	90%	10%
∞	100%	0%

Table 2: Forecasting equation of the transitory component real BCNE prices (R*bcnegap*)
(IVE estimation of equation (1))

Variable	Coefficient
$Rbcnegap_{t-1}$	0.711 (15.79)
$Wygap_t$	0.059 (7.34)
$Wygap_{t-1}$	-0.041 (-5.24)
$Ergap_t$	-0.002 (-2.54)

Note: *t*-statistics are in parentheses.

Table 3: Out-of-sample forecasts of real BCNE prices

(forecasting period: 1992q1 - 2001q4)

Forecasting horizon	**SVAR**	**AR(1) model**	**Combined approach**
	RMSE	RMSE	RMSE
2	0.0633	0.0649	0.0530
3	0.0737	0.0671	0.0564
4	0.0815	0.0748	0.0640

Table 4: Forecast encompassing tests (2-step ahead forecasts)

(*p-value*)

Encompassing tests for A= the combined approach and B= the benchmark models		
Null hypothesis	**Combined approach vs AR(1) model**	**Combined approach vs random walk model**
A encompasses B	0.288	0.994
B encompasses A	0.009	0.015

Table 5: Forecast encompassing tests (3-step ahead forecasts)

(*p-value*)

Encompassing tests for A= the combined approach and B= the benchmark models		
Null hypothesis	**Combined approach vs AR(1) model**	**Combined approach vs random walk model**
A encompasses B	0.685	0.597
B encompasses A	0.008	0.039

Table 6: Forecast encompassing tests (4-step ahead forecasts)
(*p-value*)

Encompassing tests for A= the combined approach and B= the benchmark models		
Null hypothesis	**Combined approach vs AR(1) model**	**Combined approach vs random walk**
A encompasses B	0.727	0.781
B encompasses A	0.025	0.061

Table 7: The real crude oil price model (full sample: 1974Q2-2001Q4)
(OLS estimation of equation (2) with three dummy variables)

Variable	Model 1 (with real U.S. dollar exchange rate gap)	Model 2 (without real U.S. dollar exchange rate gap)
Dumm1	1.013 (6.00)	0.976 (5.81)
Dumm2	1.188 (6.04)	1.144 (5.85)
Dumm3	0.927 (5.94)	0.898 (5.76)
$Rwti_{t-1}$	0.912 (9.57)	0.935 (9.88)
$Rwti_{t-2}$	-0.245 (-2.77)	-0.255 (-2.89)
$Wygap_{t-1}$	0.017 (1.69)	0.023 (2.42)
$Ergap_{t-2}$	-0.005 (-1.48)	-
$\bar{R}^2$	0.85	0.83

Note: *t*-statistics are in parentheses.

Table 8: The real crude oil price model (Regime 1: 1974q2 - 1979q3)

Variable	Coefficient
Dumm1	1.986 (17.15)
$Rwti_{t-1}$	0.170 (1.97)
$Rwti_{t-2}$	0.170 (2.10)
$Wygap_{t-1}$	0.007 (1.41)
$Ergap_{t-2}$	-0.186 (-1.23)
$\bar{R}^2$	0.92

Note: *t*-statistics are in parentheses.

Table 9: The real crude oil price model (Regime 2: 1979q4 - 1985q4)

Variable	Coefficient
Dumm2	1.048 (5.50)
$Rwti_{t-1}$	0.868 (7.34)
$Rwti_{t-2}$	-0.165 (-1.61)
$Wygap_{t-1}$	-0.007 (-0.74)
$Ergap_{t-2}$	-0.778 (-1.89)
$\bar{R}^2$	0.92

Note: *t*-statistics are in parentheses.

Table 10: The real crude oil price model (Regime 3: 1986q1 - 2001q4)

Variable	Coefficient
Dumm2	1.103 (4.01)
$Rwti_{t-1}$	0.873 (8.96)
$Rwti_{t-2}$	-0.261 (-3.74)
$Wygap_{t-1}$	0.055 (2.64)
$Ergap_{t-2}$	-0.390 (0.61)
$\bar{R}^2$	0.92

Note: *t*-statistics are in parentheses.

Table 11: The Real crude oil price model (Regime 3: 1986q1 - 2001q4)
(IVE estimation of regime 3 with contemporaneous world output gap and oil inventories)

Variable	Coefficient
Dumm3	1.071 (3.98)
$Rwti_{t-1}$	0.965 (11.31)
$Rwti_{t-2}$	-0.344 (-3.26)
$Wygap_{t}$	0.045 (3.07)
$Inventory_{t-3}$	-0.035 (-4.34)

Note: *t*-statistics are in parentheses.

Table 12: The real crude oil price model: RMSE of out-of-sample forecasts (1992q1 - 2001q4)

Forecasting horizon (quarters)	Our model	Random Walk	AR(1) model
2	0.134	0.176	0.208
3	0.170	0.225	0.239
4	0.202	0.276	0.246

Table 13: Forecast encompassing tests (2-step ahead forecasts)

(*p-value*)

Encompassing tests for A= our model and B= the benchmark models		
Null hypothesis	**Our model vs AR(1) model**	**Our model vs random walk model**
A encompasses B	0.157	0.499
B encompasses A	0.016	0.033

Table 14: Forecast encompassing tests (3-step ahead forecasts)

(*p-value*)

Encompassing tests for A= our model and B= the benchmark models		
Null hypothesis	**Our model vs AR(1) model**	**Our model vs random walk model**
A encompasses B	0.356	0.654
B encompasses A	0.041	0.086

Table 15: Forecast encompassing tests (4-step ahead forecasts)

(*p-value*)

Encompassing tests for A= our model and B= the benchmark models		
Null hypothesis	**Our model vs AR(1) model**	**Our model vs random walk model**
A encompasses B	0.660	0.411
B encompasses A	0.046	0.077

Table 16: Equation of the first difference of real energy prices excluding crude oil (IVE estimation of equation (3): 1974q2 - 2001q4)

Variables	**Coefficient**
$DRener_{t-1}$	0.492 (3.80)*
$DRener_{t-2}$	-0.327 (-2.12)
$DRener_{t-3}$	0.262 (2.09)
$USygap_t$	0.013 (2.94)
α	-0.135 (-3.36)
β	-1.139 (-2.14)
constant	-1.051 (-2.24)
$\bar{R}^2$	0.31

Note: t-statistics are in parentheses.

Figure 1: Impulse response of real BCNE prices

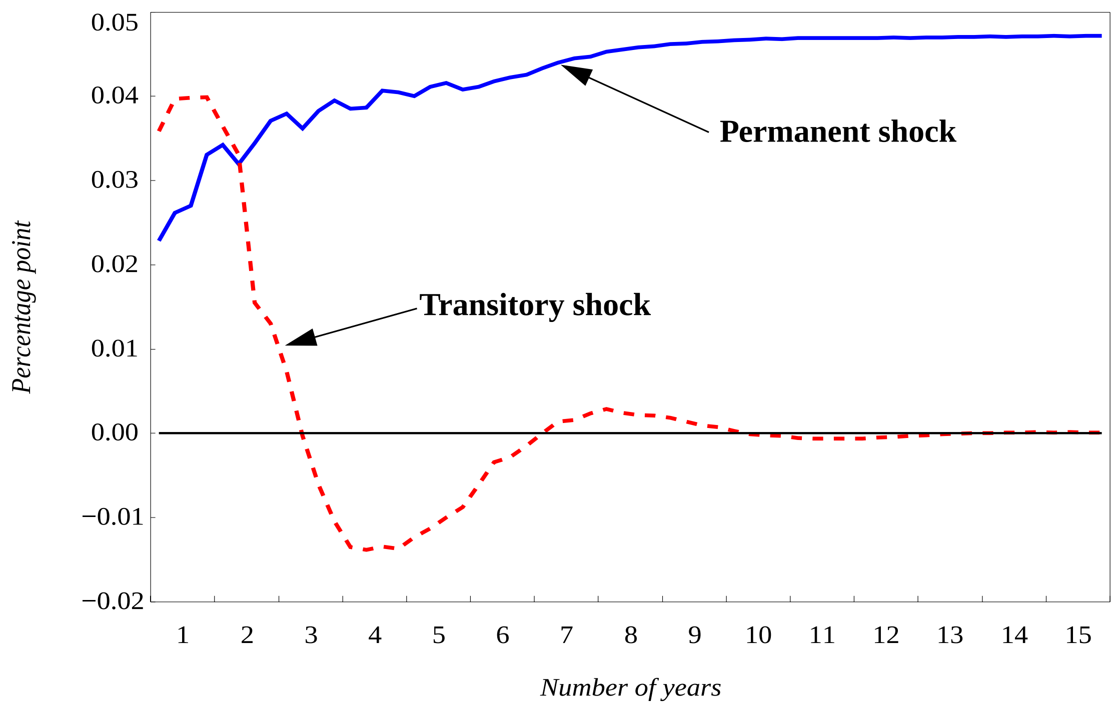


Figure 2: The world out put gap and the transitory component of real BCNE prices

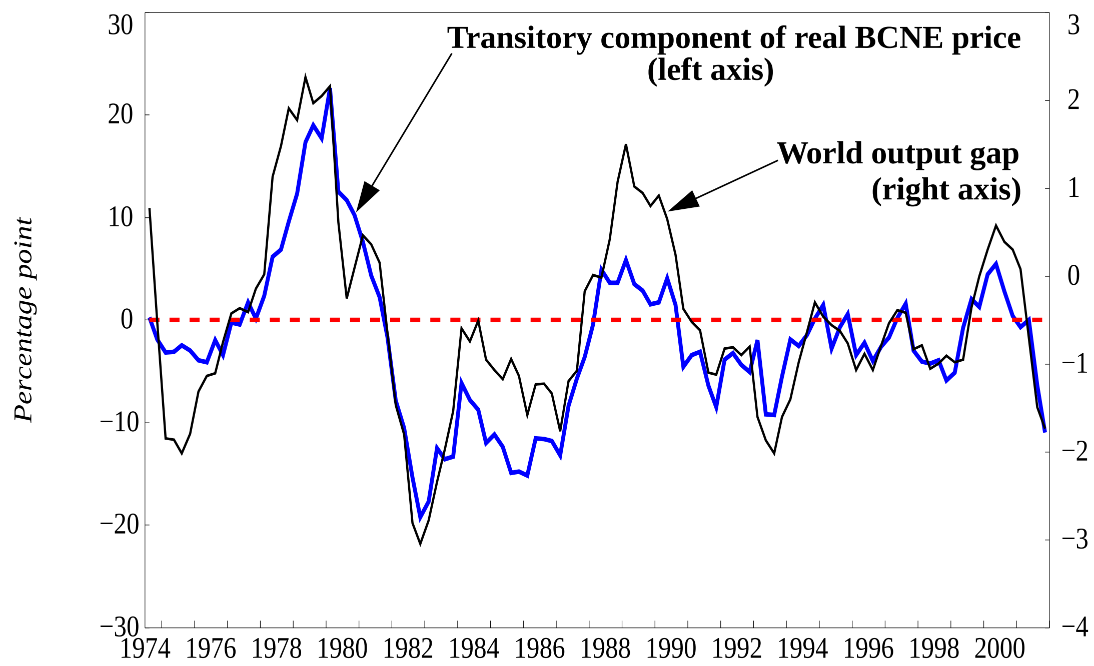


Figure 3: The real BCNE price and its permanent component

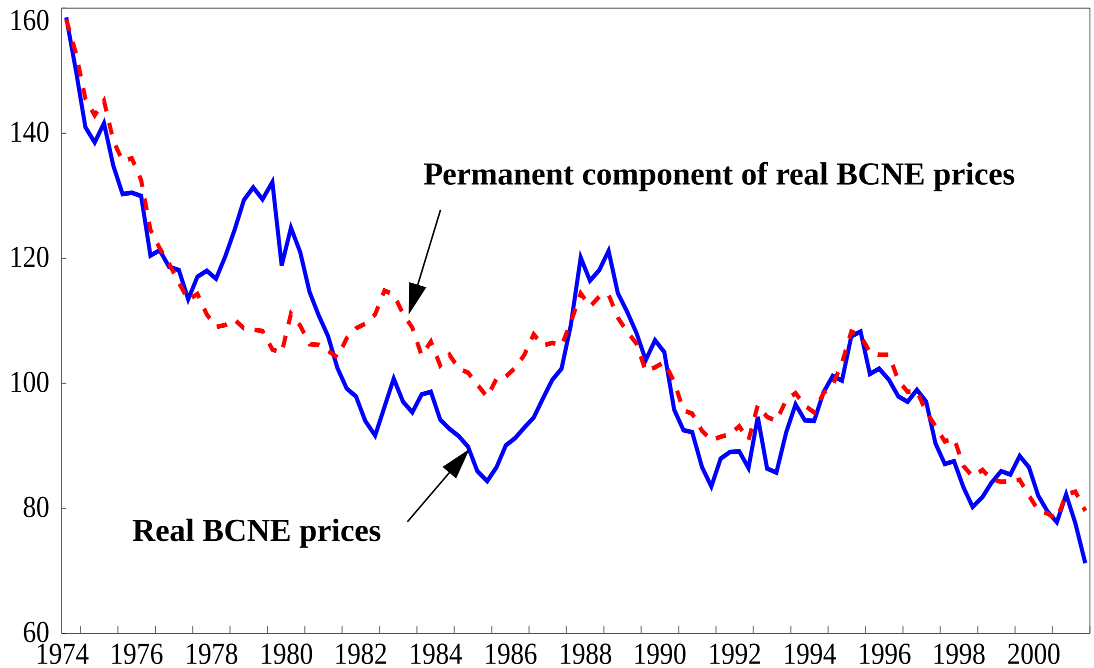


Figure 4: Simulation of a one percentage point positive shock to world output gap

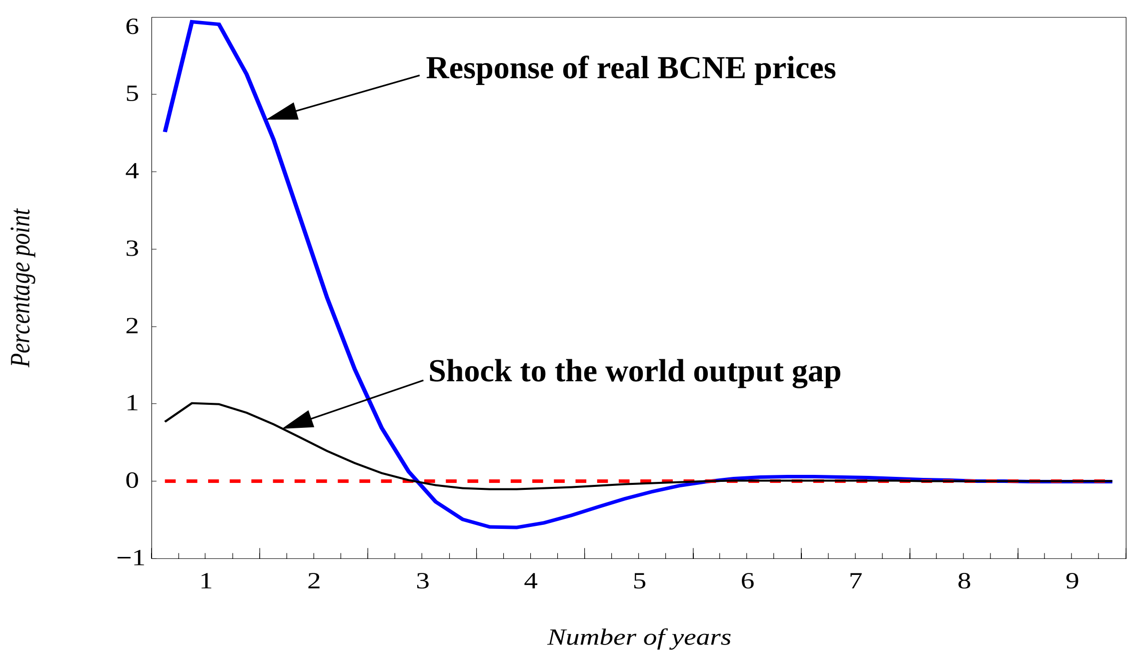


Figure 5: Simulation of a one percentage point positive shock to the real U.S. dollar effective exchange rate gap

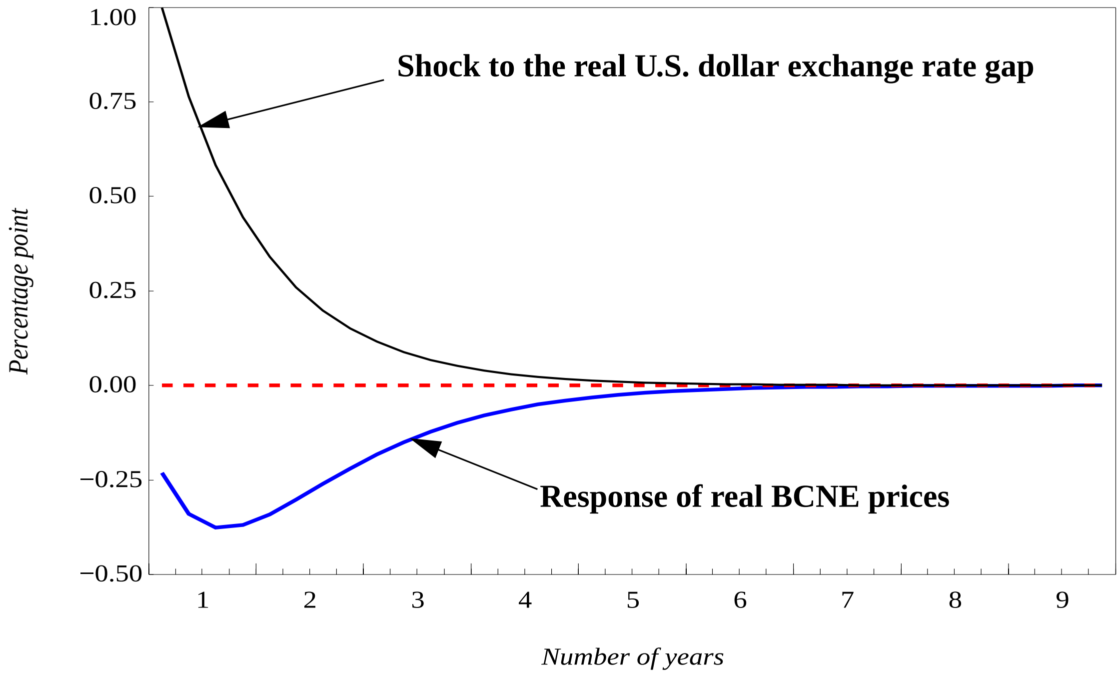


Figure 6: The world output gap and the transitory component of real WTI crude oil prices (in per cent)

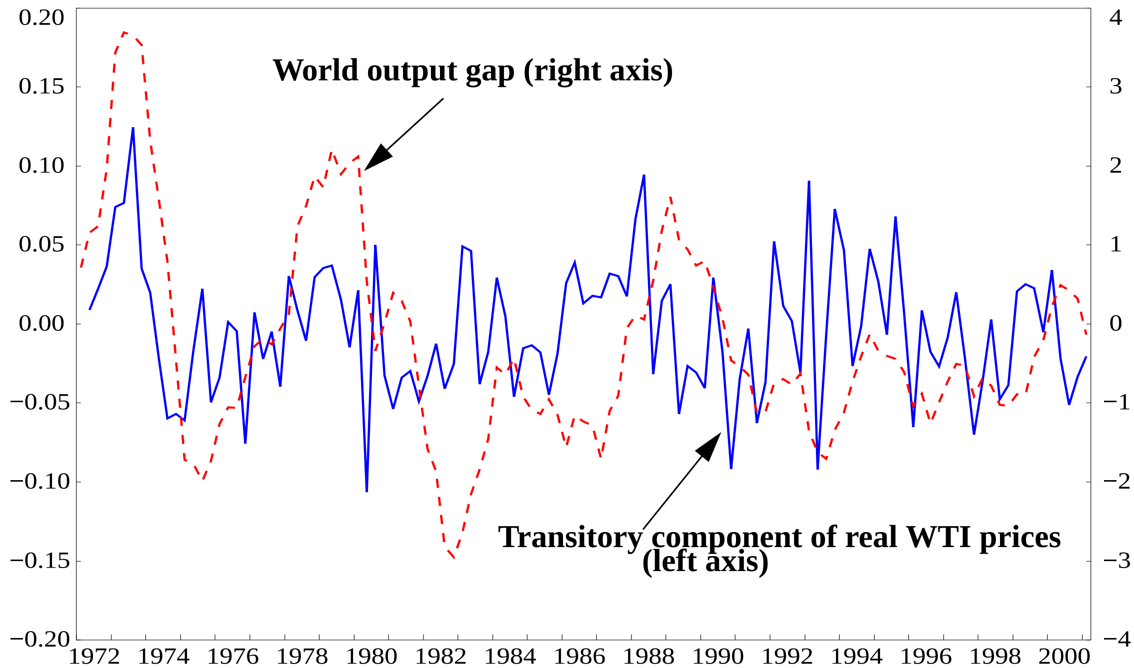
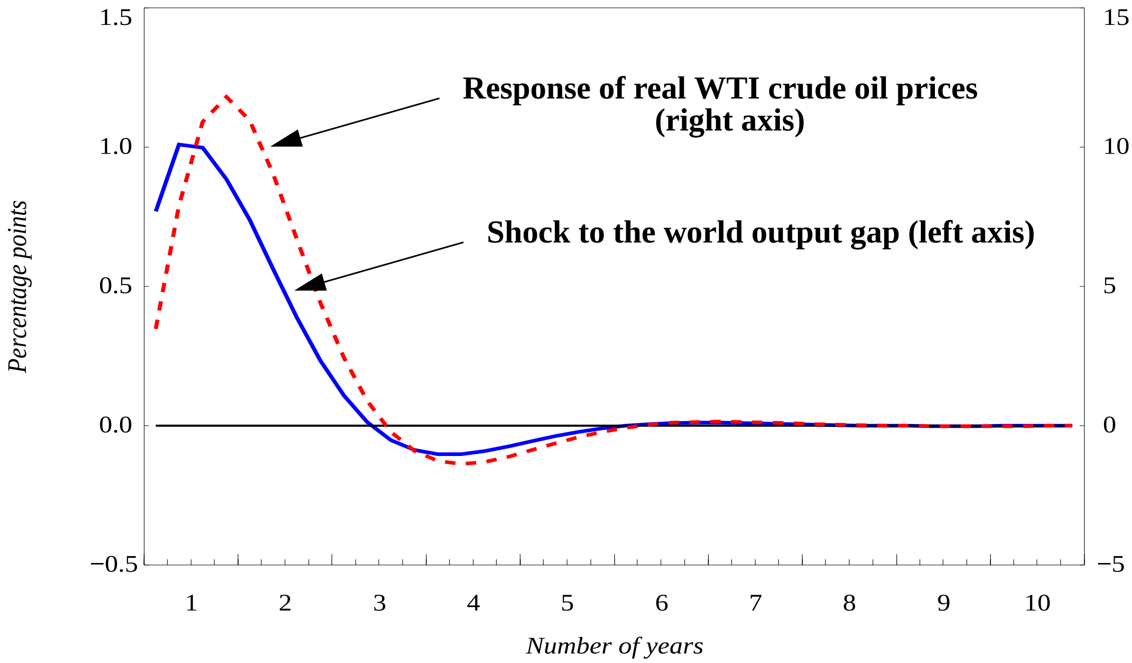


Figure 7: Simulation of a one per cent positive shock to the world output gap (Regime 3)



Appendix A: Weights of Commodities and Sub-Indexes in the BCPI

Item	Weight
Total BCPI	**100.0**
1.0 Energy	**34.9**
Crude Oil	21.7
Natural Gas	10.4
Coal	2.7
2.0 Total BCPI excluding Energy	**65.1**
2.1 Food	18.8
2.1.1 Grains and Oilseeds	8.8
Barley	1.2
Canola	1.3
Corn	0.8
Wheat	5.5
2.1.2 Livestock	9.2
Cattle	6.1
Hogs	3.2
2.1.3 Fish	0.7
Cod	0.04
Lobster	0.34
Salmon	0.36
2.2 Industrial Materials	46.3
2.2.1 Metals	14.4
Gold	2.8
Silver	0.6
Aluminum	3.0
Copper	2.9
Nickel	2.4
Zinc	2.7
2.2.2 Minerals	2.3
Potash	1.3
Sulphur	1.0
2.2.3 Forest Products	29.6
Lumber	9.0
Newsprint	8.3
Pulp	12.3

Appendix B: The Blanchard-Quah (1989) decomposition and the link between the structural form and the reduced form of the model

The shocks and the variables in the SVAR for real BCNE prices can be defined as follows:

$$\varepsilon_t = \begin{bmatrix} \varepsilon_s \\ \varepsilon_{d1} \\ \varepsilon_{d2} \\ \varepsilon_{d3} \\ \varepsilon_{d4} \end{bmatrix} \text{ and } Z_t = \begin{bmatrix} \Delta Rbcne \\ Wgap \\ \Delta W\pi \\ RRus \\ \Delta Erus \end{bmatrix}, \tag{1}$$

where ε_s is the only type of shock that will have a permanent effect on real BCNE prices and the other four shocks are restricted to have only transitory effects on real BCNE prices. Given that we are only interested in the decomposition of real BCNE prices into a permanent component and a <u>total</u> transitory component, we treat four transitory shocks as a single aggregate demand shock term.

The moving average representation of the structural model is defined as follow:

$$Z_t = \Gamma(0)\varepsilon_t + \Gamma_1\varepsilon_{t-1} + \Gamma_2\varepsilon_{t-2} + \dots = \Gamma(L)\varepsilon_t, \tag{2}$$

and the corresponding long-run effect matrix of the structural shocks is:

$$\Gamma(1) = \Gamma(0) + \Gamma_1 + \Gamma_2 + \dots + \Gamma_\infty , \tag{3}$$

where, $E(\varepsilon_t \varepsilon_t) = I$. The diagonal elements are normalized to 1's only for the purpose of simplification.

In order to identify the structural model, we first estimate the reduced form of the model (i.e. VAR):

$$Z_t = \sum_{i=1}^{p} \Pi_i Z_{t-i} + e_t, \tag{4}$$

where p is the number of lags[32] and e_t is the vector of the reduced form shocks, where $E(e_t e_t) = \Sigma$.

Given that the stochastic process is stationary, the moving average representation of equation (4) is defined by the following relationship:

$$Z_t = e_t + C_1 e_{t-1} + C_2 e_{t-2} + \ldots = C(L)\, e_t\,, \tag{5}$$

and the long-run effect matrix of the reduced-form shocks is:

$$C(1) = 1 + C_1 + C_2 + \ldots + C_\infty\,. \tag{6}$$

Given equations (2) and (5), the reduced-form residuals are linked to the structural residuals in the following way:

$$e_t = \Gamma(0)\varepsilon_t\,. \tag{7}$$

Consequently,

$$E(e_t\, e_t) = \Gamma(0)\Gamma(0)' \quad \text{because } E(\varepsilon_t\, \varepsilon_t) = I. \tag{8}$$

In addition, the long-run effect matrix of the reduced-form shocks, $C(1)$, is linked to the equivalent matrix of the structural shocks ($\Gamma(1)$) and,

$$\Gamma(1) = C(1)\Gamma(0). \tag{9}$$

In order to identify the structural model, we need to impose a sufficient number of restrictions on the system of equations formed by equations (8) and (9). The fifty elements of the structural form matrices Γ(0) and Γ(1) are unknown and the elements of C(1) and $E(e_t e_t)$ are known from the estimation of the reduced form model. Given that Σ is a symmetric matrix, equations (8) and (9) contain forty different relations. Therefore, we have to impose ten restrictions on the elements of Γ(0) and Γ(1). The Blanchard and Quah decomposition consists of imposing restrictions on the long-run effect matrix of the structural shocks. (i.e. Γ(1)) instead of imposing a predetermined

32. The reduced-form model includes eight lags. We have estimated a model which includes six lags, and results are almost identical.

structure on the variables by the restrictions on the $\Gamma(0)$ matrix. We achieve this by imposing that $\Gamma(1)$ is triangular. Given these restrictions, the system of equations formed by equations (8) and (9) is solvable, and therefore the structural model is identified. The following equation shows the restrictions imposed on the long-run effect matrix of the structural shocks with, for presentation purposes, the shocks of the structural model on the horizontal axis and the variables of the model, in levels, on the vertical axis:

$$\begin{array}{cc} & \begin{bmatrix} \varepsilon_s & \varepsilon_{d1} & \varepsilon_{d2} & \varepsilon_{d3} & \varepsilon_{d4} \end{bmatrix} \\ \begin{bmatrix} Rbcne \\ \int Wygap \\ W\pi \\ \int RRus \\ Erus \end{bmatrix} & \begin{bmatrix} r_{11} & 0 & 0 & 0 & 0 \\ r_{21} & r_{22} & 0 & 0 & 0 \\ r_{31} & r_{32} & r_{33} & 0 & 0 \\ r_{41} & r_{42} & r_{43} & r_{44} & 0 \\ r_{51} & r_{52} & r_{53} & r_{54} & r_{55} \end{bmatrix} = \Gamma(1) \end{array} \tag{10}$$

Therefore, we impose that ε_s is the only type of shock that has a permanent effect on real BCNE prices. This gives four restrictions. The other six restrictions are just required to decompose the total transitory component into its four subcomponents. Consequently, they are irrelevant for decomposing real BCNE prices into a permanent and a total transitory component. In other words, results concerning the decomposition of real BCNE prices are unaffected by the assumption regarding the ordering of the four last variables. This simply reflects the fact that, in the long-run, the model is recursive from top to bottom.

Appendix C: Technical details on Bai and Perron (1995) methodology

We consider a multiple linear regression with m breaks (m+1 regimes). The equation of real crude oil prices is specified in a compact matrix notation as:

$$Y = X\beta + \varepsilon$$

where Y is the observed dependent variable at time t, X is the matrix of covariates, which is partitioned according to the break points T_B, β is the corresponding vector of coefficients, and ε is the disturbance term. The break points $(T_1,...,T_m)$ are explicitly treated as unknown. The purpose is therefore to estimate the regression coefficients and the break points simultaneously when T observations of Y and X are available. The estimation method considered is based on the least squares principle. For each m-partition *(T1,...,Tm)*, the associated least squares estimates of β is obtained by minimizing the sum of squared residuals, denoted here as ST. The estimated coefficients and break points are such that

$$(T_1, \ldots, T_m) = \arg min_{\{T_1, \ldots, T_m\}} S_T(T_1, \ldots, T_m)$$

where the minimization is taken over all partitions $(T_1,...,T_m)$, so the break-point estimators are global minimizers of the objective function.

BP proposed a test based on the supremum of the F-statistic, which is called the sup$F$ test, to detect the multiple breaks. This test is labelled as the sup$F(l+1|l)$. The method amounts to the application of $l+1$ tests of the null hypothesis of no structural change versus the alternative hypothesis of l changes. The test is applied to each segment containing the observation T_{m-1} to T_m with $m = 1,...,l+1$. We reject the null hypothesis in favour of a model with $l+1$ breaks if the overall minimal value of squared residuals is sufficiently smaller than the sum of squared residuals from the l-break model. The break date is selected as the one associated with this overall minimum. The asymptotic distribution of the test statistic depends on the selected minimal length of the segments which is a function of a trimming parameter.[33] To apply the test, we use a trimming of fifteen per cent. Hence, given our sample period of 1974-2001, no more than six breaks are allowed while each regime must have at least sixteen observations.

33.We need to trim the sample by some fraction since the test statistic diverges to infinity, (see Andrews (1993a) for details). For this reason, we cannot test for the presence of a structural break in the first/last four years of the sample or the one very close to another break point.