The Connection Between Commodity Prices and the Consumer Price Index in Canada

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ABSTRACT

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This study examines the relationship between changes in commodity prices and changes in inflation in Canada between 1983 and 2008 by looking at the ability of the Bank of Canada Commodity Price Indices to predict changes in the Consumer Price Index. It is found that indices with energy components lead changes in inflation but only for the latter half of the sample period, 1996-2008. Other suspected leading indicators of inflation, such as the money supply, the foreign exchange rate, the housing index, interest rates, and the price of gold, do not change the relationship or its strength. The positive correlation between commodity prices and inflation is further supported by a decomposition of the mean real returns on portfolios into months in which a four-month moving average of the Bank of Canada Commodity Price Index signals a rising price level and those which do not, the mean real return being substantially higher in the signal-on months.

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1. Introduction

The usefulness of commodity prices as possible leading indicators of inflation has generated, with varying results, considerable interest over the past three decades. An understanding of the relationship between commodity prices and inflation, if one does indeed exist, can be used to improve inflation forecasts for monetary policies pursuing an inflation targeting strategy [Svensson (1999)] and for hedging inflation risk by investors.

Commodity prices are good candidates for inflation prediction because of their markets. Unlike the prices for most goods and services manufactured for consumption, commodity prices are determined in thick, competitive auctions, making them flexible and quick to adjust to changing market conditions. That commodities such as petroleum, metals, and lumber are important inputs throughout the production cycle in the manufacture of countless consumable goods, it is natural to expect changes in their prices to both precede and be positively correlated to changes in overall prices. A surge in demand for final goods, resulting from an expansionary monetary policy, for example, may increase demand for commodities, putting upward pressure on their prices which, in turn, is ultimately reflected in increased prices for consumer and industrial goods. The strength of this relationship, however, will depend on the extent to which the increase in demand for commodities is specific to an industrial sector. The more sector-specific the demand, the less we expect commodity price increases to be reflected in the general prices of final goods and services. Every commodity has some sector-specific or idiosyncratic component in its price fluctuations. For example a flood or other disaster that destroys the supply of a certain type of agricultural product. However, commodities that have good substitutes should experience only short-lived price changes while the market adjusts to supply or demand shocks, resulting in little or no price changes for consumers. But where there are few substitutes for a commodity that is important in the production of many goods and services—oil always the prime example—then a change in price for that commodity would be expected to show up in the form of higher overall prices. In other words, important commodities are a source of systematic or market risk in the language of financial economics.

This study uses vector autoregression (VAR) and Granger-Causality tests to measure the empirical connection between commodity prices and the Consumer Price Index (CPI) in Canada. The period examined is January 1983 to July 2008. Commodity prices are represented by the Bank of Canada Commodity Price Index (BCPI), whose predictive power is examined alone and in combination with other leading indicators of inflation. Sub-indices of the BCPI are then examined to see whether "important" commodities are responsible for any observed relationship.

Cointegration tests do not support a long-term relationship. That is, in the long-run, movements in commodity prices have not been emulated by movements in the CPI. Granger-Causality tests and tests of the VAR coefficients support a significant short-term relationship, but one that is present only when indices contain energy commodities. This is not surprising given Canada's role in the world as a major energy producer. Including additional leading indicators of inflation in the analysis, such as the money supply, the price of gold, the three-month T-bill rate, and the Canadian Housing Index level does not change the relationship or its strength. It is also found that the predictive power of commodity prices is limited to the latter half of the sample period.

The inclusion of commodity futures in a portfolio can have two benefits. First, as is always the case when a less than perfectly correlated asset is added to a portfolio of assets, the risk-reward tradeoff improves. This is the benefit of diversification. However, commodity futures are positively correlated to inflation and negatively correlated to equities [Bodie (1981)] and as such, can help protect a portfolio's purchasing power from unexpected changes in inflation by maintaining the real return of the portfolio. The efficacy of commodity futures is demonstrated by using a signaling strategy that is based on a fourth-month moving average of the Bank of Canada Commodity Price Index containing only energy products designed to detect upward trends in commodity prices signaling rising general prices. In months where the signal was "on" (i.e. rising commodity prices) the real mean monthly return is higher than in months when the signal was "off" (i.e. falling commodity prices).

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 describes the data and methods. Results are presented in section 4 while the discussion of these is in section 5. Section 6 concludes.

2. Background

Interest in commodity prices as predictors of inflation appears to be greatest whenever commodity prices are changing rapidly, but no clear answer has emerged as to their predictive ability. Throughout the late 1980s, amid some sharp declines in commodity prices a few years prior, a flurry of studies were conducted to examine if the decline in commodity prices presaged a slowing of inflation. A connection between the two has a number of practical implications. Analysts have advocated using commodity prices as a guide for monetary policy [Angell (1987), Baker (1987), Johnson (1988)] and the Federal Reserve has examined the usefulness of commodities in stabilizing and predicting inflation [Garner (1988) and Cody and Mills (1991)]. Even Keynes' idea advocating the stabilization of commodity prices [Keynes (1942)] through the creation of a commodity control board was advocated by Reynolds (1982) and Wanniski (1983).

Webb (1988) examined whether commodity prices were predictors of aggregate price change. Similar to the methodology used in this study, Webb employed vector autoregression models and Granger-Causality tests in his analysis. He examined the link between the CPI and two major commodity indices in the United States: the Journal of Commerce Materials Index (JOCI) and the Spot Price Index (SPI). The JOCI is made up of only industrial commodities whereas the SPI, in addition to 13 industrials, also includes 10 foodstuffs. Webb's results are of particular interest because in addition to testing for causality, he also tested, using a small VAR model designed to predict the CPI, the forecasting accuracy of adding commodity price changes to the forecasting mix.

Although Granger-Causality tests indicated statistically significant effects for both commodity indices, the degree of forecast improvement in the CPI was small. Adding the SPI to the mix had no effect on one-month or six-month CPI forecasts and improved only slightly the 12-month forecast. The addition of the JOCI improved forecasts for all horizons up to 12 months, although the improvement again was small. The forecasting period was July 1975 and May 1988.

Bloomberg and Harris (1995) studied the commodity-CPI relationship for the period 1970 to 1994 by looking at a number of commodity indices. The study considered five indices and three key subgroups of commodities, including gold, food, and oil. The indices examined were the JOCI (same as above), the Commodity Research Bureau Index (CRB), both the crude and finished Producers Price Indices (PPI), and two smaller more obscure indices, the National Association of Purchasing Managers price index (NAPM) and the Federal Reserve Bank of Philadelphia prices paid index (PHIL). The CRB index is an equally-weighted average of 23 commodities, including foodstuffs and industrial materials. The crude PPI is divided about evenly into three parts: food, energy, while the finished PPI includes consumer goods, food, capital equipment, and energy. The NAPM index measures the percentage of manufacturing firms reporting higher material prices, plus half the percentage of those firms reporting no change in price. The PHIL index is the percentage of firms in the Philadelphia region reporting no change in prices.

Their findings are noteworthy as they point to a shifting relationship between commodities and the core CPI. The authors employed VAR models to assess the significance of the different indices in predicting the core CPI as well as the direction of these relationships. The results for the entire time period show that three out of the five indices, the JOCI, the CRB, and the finished PPI were significant in predicting inflation, and that all indices were positively related to changes in inflation. However, when the sample was split in two, 1970-1986 and 1987-1994, a perverse break in the commodity-CPI connection was discovered. In the first time period, all indices were significant and positively related to inflation. In the latter period, all indices were still significant, but, with the exception of the JOCI, the other indices were now negatively related to changes in the core CPI. The authors speculate that this may be an example of Goodhart's law. Goodhart (1975) argued that any statistical regularity will tend to collapse once pressure is placed on it for control purposes. According to Bloomberg and Harris (p. no. 30), "if investors believe that monetary authorities are reacting to inflation signals from commodity prices, then the commodity price movements will begin to reflect market expectations of monetary policy rather than independent information on the economy." Therefore, even though rising commodity prices may correctly signal the beginning of rising inflation, very little actual inflation materializes due to offsetting monetary policy. A VAR model estimation, which included a number of monetary policy measures, resulted in a reversal from negative to positive of the signs for the coefficients of the CRB index and both PPIs. However, the signs for the NAPM and PHIL indices remained negative. Their findings suggest that at least some of the weakening in the commodity-

CPI connection in the latter part of the sample stems from monetary policy reaction. Lastly, the VAR analysis of the three commodity subgroups shows that oil and food are significant and positively related to changes in the core CPI for both the full sample and split sample periods. Gold, however, despite its reputation as an inflation hedge, sent unreliable signals in all time frames.

The practical applications and benefits of including commodity prices in monetary policy formulation, if any, were examined more formally in a study by Cody and Mills (1991). Similar to other studies, in the first step, to examine the commodity-CPI connection, the authors employed a VAR model and Granger-Causality tests. Their VAR model included industrial production, the money supply (M2), the federal funds rate, the CRB index, and the CPI over the period 1959 to 1987. Their cointegration tests indicated that all the variables except for the CPI had a unit root in the level of the series that was corrected by differencing each series once. The CPI needed to be differenced two times to achieve stationarity. The VAR and Granger-Causality results confirmed that commodities were significant in predicting changes in inflation and that commodities possessed the two necessary characteristics required for a successful monetary indicator. First, commodity prices responded to lagged changes in monetary policy as measured by the federal funds rate. Second, in addition to commodities being significant in predicting the path of the CPI, they were also significant in predicting the future path of the federal funds rate and industrial production.

In a second step, to examine the appropriate policy response to commodity price movements and to identify and separate the "type" of shock to which the Federal Reserve should respond, Cody and Mills employed a structural methodology developed by Bernanke (1986), Blanchard and Watson (1986), and Sims (1986). Identifying the "type" of shock was important because, as previously mentioned, commodities are subject to large market-specific shocks that do not have macroeconomic consequences (i.e. general inflation) to which the Federal Reserve should not respond. Cody and Mills separated the fundamental shocks and calculated, given an objective function and estimates of the fundamental shocks, the optimal policy response. Given this optimal response, they then calculated over a 26 year period (1961-1987) whether a more desirable outcome to inflation would have occurred. The optimal policy is defined as:

$$Loss = wVAR(\Delta CPI) + (1-w)VAR(\Delta IP) \tag{1}$$

where w is the weight applied to inflation stabilization. The policy that minimizes the weighted average of the variances of inflation and industrial production growth is the optimal policy. The policy calls on the Federal Reserve to raise interest rates in response to accelerating commodity prices. The level of increase in interest rates is dependent on the value of the feedback from commodity price changes based on estimations from their VAR model. To allow for various time horizons in the Federal Reserve's objectives, Cody and Mills calculate the variances of the one-, six-, and 12-month growth rates of the CPI and Industrial Production.

Their results show that when w is close to zero (more emphasis is put on output stabilization) there is little difference between the historical and the optimally simulated paths for inflation. However, as the weight of w in the equation increases, the policy calls for significantly greater feedback from commodity prices, thus raising interest rates by greater amounts in response to accelerating commodity prices. As a result, there are significant differences between the historical outcomes and the optimally generated outcomes. The optimal outcomes resulted in lower and less variable rates of inflation. In addition, the effect of higher interest rates on real growth as measured by the change in industrial production was relatively small, suggesting that in the long run, the effect of the policy change on industrial production is neutral.

The role of commodity prices in the design of monetary policy was also studied by Garner (1988) who tested the ability of the Federal Reserve to accurately control a broad commodity price index. In the late 1980s some economists, for example, Geneteski (1982) and Miles (1984) suggested that the Federal Reserve could use conventional policy instruments to control either a broad commodity price index or the price of gold. Their logic behind this argument was that in general, commodities are so closely linked to the general price level that achieving a commodity price target would also control the general inflation rate. Rather than intervening directly in the commodity markets, as monetary authorities did with the gold standard for example, they would instead control commodity markets through the use of conventional monetary policy, for example, through open market operations.

In order for a commodities target strategy to play a role in a monetary policy where the final objective is assumed to be the general price level, Garner argued that (p. 509) "the commodity index should be related dependably to both the general price level and the Federal Reserve's policy instruments. If, instead, commodity prices are to be an informational variable, the only requirement is that the index contain useful information about future movements of the general price level." His results, however, do not support the controllability of a commodity price index. For the adoption of a commodity price target, commodity prices and the general price level should be cointegrated, and his results did not support cointegration. Furthermore, Granger-Causality tests involving a commodity index and a number of monetary policy instruments including the monetary base, the Treasury bill rate, and the exchange rate do not support such a strategy. His variance decompositions also do not support controllability. The error variance for the commodity index was explained mostly by its own innovations or unexpected price movements. The monetary variables never explained a large percentage of the prediction error variance. Garner did find that commodity prices are information variables in that they contain useful information about the future movements of the general price level. Garner analyzed the relationship between three commodity indices, the CRB, the JOCI, and the PPI for crude materials as well as the price of gold and inflation. According to the cointegration results, a long-run connection between these is doubtful. However, with the exception of gold, the Granger-Causality results indicate precedence between commodities and inflation. In addition, his variance decompositions also support the view that commodity prices are useful in predicting the general inflation rate. The inclusion of either three of the indices in the variance decompositions explained about 25 percent of the prediction error variance in the CPI.

Commodity futures, when included in a portfolio can provide a hedge against inflation. Bodie (1981) demonstrated that adding commodity futures to a portfolio containing T-bills, bonds, and stocks can help improve the risk-return tradeoff. Bodie argued that investors should be concerned with the real return of their portfolio rather than the nominal return. With unexpected inflation, the real return or the purchasing power of the portfolio diminishes. As such, a portfolio needs to contain an asset class that is positively correlated to inflation so as to help offset some of the loss in the real return. According to the calculations in the study, the real returns of T-bills, bonds, and stocks are all positively correlated with one another and negatively correlated to inflation. Commodity futures real returns on the other hand are positively correlated with inflation and negatively correlated with the real returns of the three above asset classes. Consequently, when included in a portfolio, commodity futures can provide a hedge against inflation. The analytical framework for the investment strategies Bodie designed was based on the mean variance-analysis of Harry Markowitz, which is consistent with utility maximization. Using the real annual returns of the asset classes mentioned above, Bodie constructed the minimum-variance frontiers for portfolios not containing commodity futures and one containing commodity futures. The frontier containing commodity futures always dominated the one that did not.

3. Data and Methods

3.1.1 Commodity indices and the price index

Commodity prices are represented by monthly observations on the Bank of Canada Commodity Price Index denoted BCPIALL. They are obtained from CANSIM (Statistics Canada) under table 176-0001 and cover the period January 1983 to July 2008. Sub-indices include the BCPI with no energy products denoted BCPINO and the BCPI with only energy products denoted BCPIEN. The index is composed of the three major commodity groups[1] represented by energy, food, and industrials. The BCPI was established in 1973 and is designed to track the price of 23 commodities produced in Canada and sold in world markets. The weight of each commodity in the total index and in the sub-indices is based on the average value of Canadian production of the commodity from 1988 to 1999. The BCPI is used to analyze movements in GDP, industrial production prices, inflation, and the exchange rate[2]. The last major update of the weightings and composition of the index was done in 2000. In addition to the BCPI, this study, in order to better identify the individual commodity or commodity group with the strongest link to inflation, examined both sub-indices of the BCPI as well as oil and gold. Data for the spot prices of oil and gold were obtained from Bloomberg. All data in the study are end-of-month.

Since 1914, The Bank of Canada has been collecting figures for the Consumer Price Index denoted CPI. The CPI, available monthly, is a broad measure of the cost of

[1] A full description of the Index is provided in the appendix.
[2] Todd Hirsch – Research Department, Bank of Canada

living in Canada. The Bank of Canada uses the CPI in determining the payments of the Canada Pension Plan and Old Age Security as well as to make adjustments to monetary policy. The calculations for the CPI are based on a representative shopping basket of about 600 goods and services[3] and the weights reflect typical consumer spending patterns. The current base year for the index is 1992 with a value of 100. Monthly observations for the CPI were obtained from CANSIM under table 326-0020.

3.1.2 Control Variables

In order to better isolate the predictive power of commodities, a number of additional suspected leading indicators of inflation were included in the analysis [see, for example, Watson and Stock (2003)]. These indicators are the Canadian money supply, the Canadian Housing Index, the three-month Government of Canada Treasury Bond yield, and the foreign exchange rate of the Canadian dollar as measured against the US dollar. The potential of these variables as leading indicators of inflation lies in basic macroeconomic concepts. For example, an unanticipated acceleration of the growth in the money supply can affect interest rates and over stimulate aggregate demand, thereby increasing price pressures in the economy [Dwyer and Hafer (1988), Friedman (1992)]. Exchange rate fluctuations can impact prices through their effect on imports and exports [Al-Abri (2005)] and an increase in asset prices such as housing can, mainly through bubbles, impact inflation [Goodhart (2001)]. With the exception of the exchange rate, which was obtained from Bloomberg, monthly observations for the rest of the series were

[3] From the Bank of Canada Facts Sheet.

obtained from CANSIM under the Business Leading Indicators for Canada table with identifier 377-0003.

3.1.3 Other series

Commodity futures are represented by the S&P GSCI, formerly the Goldman Sachs Commodity Index, and denoted SPGSCI. The index, originally developed by Goldman Sachs, is now owned and published by Standard and Poor's[4]. The index is calculated according to a weighted world production basis and is made up of the commodities that are the most active and liquid in the futures market. The respective weight of each commodity in the index is determined by the average quantity of production over the last five years. The composition of the index is reviewed on a monthly basis. Sub-indices of the S&P GSCI used in this study are the energy index denoted by SPGSEN and the gold index denoted by SPGSGC. Contracts are tradable in US dollars through the Chicago Mercantile Exchange. Equities are represented by the S&P/TSX Composite Index and denoted SPTSX. Bonds are represented by the iShares Canadian Bond Index and denoted iXBB. The iXBB fund seeks to replicate the performance of the DEX Universe Bond Index[5].

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[4] http://www2.standardandpoors.com/portal/site/sp/en/us/page.topic/indices_gsci

[5] The DEX Bond Index consists of a broadly diversified selection of investment-grade Government of Canada, provincial, corporate and municipal bonds issued domestically in Canada and denominated in Canadian dollars.

Real estate is represented by the Scotia Capital REIT Index and denoted SCREIT. A REIT is a closed-end investment fund that owns real estate. It serves to securitize the underlying real estate investments and allows investors to trade shares of these. A REIT provides a liquid method for investors to trade and participate in the real estate market which is otherwise illiquid. Previous work supports the idea that real estate assets provide a hedge against inflation. Fama and Schwert (1977) find that changes in returns on residential real estate are positively correlated to changes in inflation. Hartzell, Hekman, and Miles (1987) find that a diversified portfolio of commercial real estate provided a complete hedge against inflation over the 1973-1983 period. Consequently, REITs, which are simply financial claims on these underlying assets, should perform well in an inflationary environment. Although the literature on this is mixed, there is some evidence to support the view that REITs can provide at least a partial hedge against inflation due to their positive correlation with inflation. Park, Mullineaux, and Chew (1990) find that REITs can provide a partial hedge against anticipated inflation. Chatrath and Liang (1998) find some evidence that REITs provide a long-run hedge against inflation.

3.2 Unit Roots and Cointegration

Economic forecasting models are typically time-series models, and as such are based on the idea that the data are generated by a stochastic process and that this stochastic process can be characterized in a manner that will permit forecasting. Characterization requires the data to be stationary. But, according to Nelson and Plosser (1982), most economic time series are non-stationary. A non-stationary series is one whose mean is time-varying or which does not, as a minimal requirement, exhibit reversion to a long-run level, and is a series whose variance is non-finite and evolving. In other words, the stochastic process that generates non-stationary series changes over time.

An example of such non-stationary data would be the GDP. The GDP will typically grow over time; therefore it lacks a constant long-run mean. This is especially true if the interval between two periods is large. Using standard OLS on non-stationary data greatly increases the chances of getting spurious regression results because the requirement of constant error variance is violated. Any inference tests drawn on these estimates will be invalid. Determining if a series is stationary requires testing for the presence of a unit root.

Consider, for example, the first order autoregressive model below:

$$y_t = \theta y_{t-1} + e_t \tag{2}$$

where e_t is a white noise error process (an independently normally distributed random variable with zero mean). This series has a unit root if the autoregressive parameter θ is equal to one. In such a case, to try to achieve stationarity, y_{t-1} needs to be subtracted from both sides. The result is:

$$y_t - y_{t-1} = y_{t-1} - y_{t-1} + e_t \tag{3}$$

$$\Delta y_t = e_t \tag{4}$$

Since e_t is a white noise process as defined above, Δy_t is a stationary series. In most cases, differencing a series once is enough to achieve stationarity. Furthermore, the number of times a series needs to be differenced in order to achieve stationarity is called the order of homogeneity. A series that needs to be differenced only once is said to be first-order homogeneous, denoted I(1). If a series has a unit root, it should be used in differenced form.

Although there are several tests designed to test for the presence of a unit root, the most popular is that proposed by Fuller (1979) known as the Augmented Dickey Fuller test (ADF). It involves estimating the coefficients in the following regression:

$$\Delta y_t = \alpha_0 + \alpha_1 T + \beta y_{t-1} + \sum_{i=1}^{I} \delta_1 \Delta y_{t-i} + \varepsilon_t \tag{5}$$

where y is the series being tested for the presence of a unit root, T is a time trend, ε_t is a white noise error term, and i is the lag order. Depending on the nature of the series being tested, this test can also be performed without a time trend factor.

Under the null hypothesis that series y does have a unit root, the β coefficient must equal zero. The logic behind this condition is that if the stochastic process that generated the series y is changing and cannot be characterized, then there should be no correlation between y_t and y_{t-1}. In other words, in a non-stationary series, y_{t-1} will provide no useful information in forecasting y_t. A standard t-test is used to determine if β is statistically different from zero; however, critical values are non-standard; the critical values used are taken from Mackinnon (1991). In order to ensure that the seasonal effects in the variables are captured, 12 lags [see for example Bloomberg and Harris (1995)] were used for the ADF test above, as well as for all subsequent tests in this paper.

The ADF test can also be used to test for cointegration. If two series share the same number of unit roots (i.e. the number of times each series needs to be differenced to achieve stationarity) they are more likely to be cointegrated. Two non-stationary time series are cointegrated when a linear long-term relationship is discovered in the levels of the series. This implies that even though two series are non-stationary, their evolution over time is such that the stochastic processes that generated them are similar. As such, there may exist a linear combination of the two that is stationary. Of course, cointegration between two variables is more likely to exist when there is some logical link or relationship between them; for example, the GDP and the money supply are related and might therefore be expected to be cointegrated. If two variables are cointegrated differencing is not required.

The theory of cointegration is due to Engle and Granger (1987) who recommend a two-step procedure to test for it. Cointegration tests will focus on the residuals, generated in a first step, of the cointegrating regression below:

$$CPI_t = a + b\ CI + u_t \tag{6}$$

where *CPI* is the general price level, *CI* is the Commodity Price Index in question and u_t is the residual that will be tested in step 2. To test u_t, in step two, Engle and Granger recommend estimating the auxiliary regression below (eq. 7), generated from the saved residuals of equation 6, and then use the ADF test from above to see if the residuals are cointegrated.

$$\Delta u_t = a_0 + a_1 T + b_0 u_{t-1} + \sum_{i=1}^{12} b_i \Delta u_{t-i} + e_t \tag{7}$$

In equation 7, u is the series being tested for cointegration. Specifically, the second step tests the null hypothesis that the residuals u from the cointegrating regression are not stationary. If the residuals are stationary (i.e. if b_0 is significantly different from zero) then the null hypothesis of non-stationarity is rejected and we can conclude that the CPI and the commodity index in question are cointegrated.

3.3 Granger-Causality Tests

If changes in commodity prices can help predict changes in the general price level, then changes in commodity prices need to precede changes in the general price level. In other words, the changes in commodity prices need to "cause or lead" the changes in the CPI and not the other way around. This is known as precedence, and is based on the idea that a cause cannot come after the effect. According to Granger (1969), one variable is said to "Granger-Cause" another if the lagged values of one add statistically significant predictive power to another series' own lagged values for one-step ahead forecasts. However, the Granger-Causality model can predict for only one period ahead in a bivariate (two variable) environment. The use of a Granger-Causality relationship in a forecasting context is therefore relatively limited when forecasting beyond one period is required. However, according to Dufour and Renault (1998), the importance of the Granger test cannot be understated since it has been shown that no causality for one period ahead in a bivariate system implies no causality at, or up to, any future horizon.

To test if variable x Granger-Causes variable y the two following regressions must be estimated:

Unrestricted Regression:

$$y_t = \sum_{i=1}^{k} \alpha_i y_{t-i} + \sum_{i=1}^{k} \beta_i x_{t-i} + \varepsilon_t \tag{8}$$

Restricted Regression:

$$y_t = \sum_{i=1}^{k} \alpha_i y_{t-i} + \varepsilon_t \tag{9}$$

where y is the inflation variable and x is the commodity index in question. The sum of squared residuals from these regressions will be used to calculate an F statistic in order to test the $\beta_{i's}$. If the $\beta_{i's}$ are statistically different than zero, the null hypothesis that "x does not Granger-Cause y" can be rejected. Next, the same regressions must be run again but this time switching x and y places (i.e. the dependent variable becomes the independent and vice versa) to test the hypothesis that "y does not Granger-Cause x". In order to be able to conclude that "x does Granger-Cause y" the null hypothesis that "x does not Granger-Cause y" must be rejected and the hypothesis that "y does not Granger-Cause x" must be accepted.

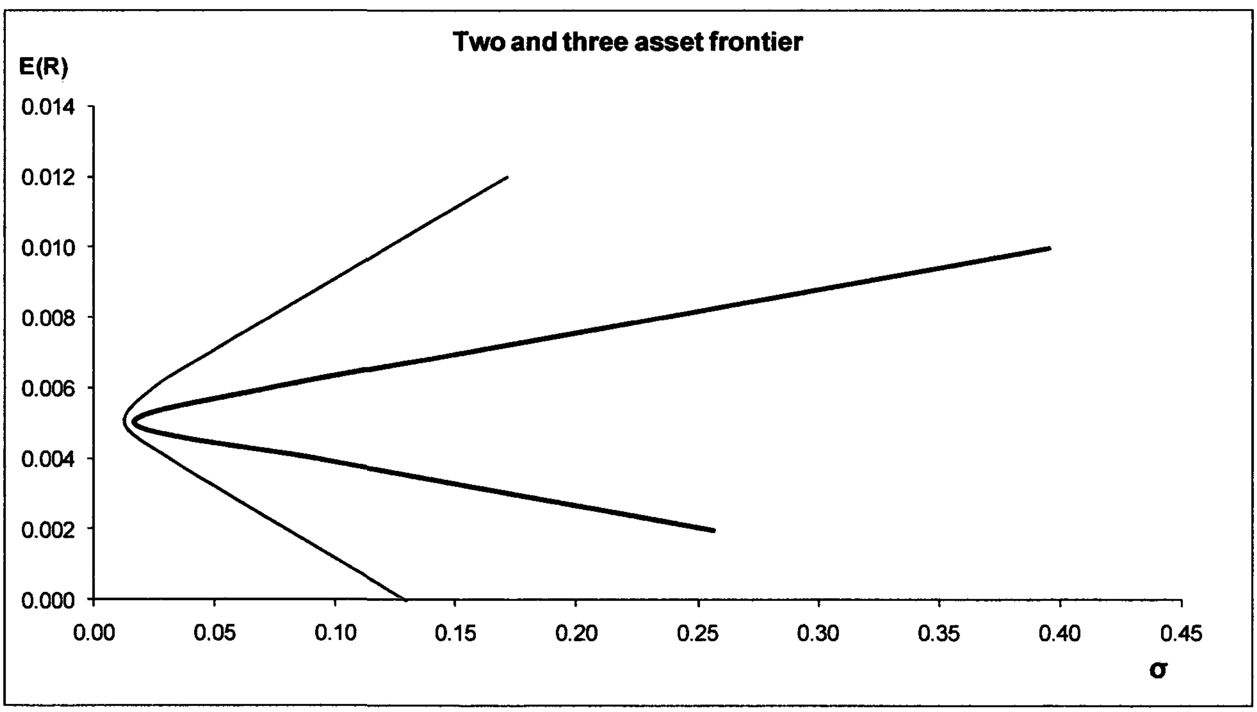
3.4 Vector Autoregression

Vector autoregression (VAR) provides a convenient framework for examining the dynamic relationships that are encountered when dealing with economic time series. These models were introduced as an alternative to simultaneous equation models through the work of Sims (1980). Unlike a simultaneous equation model, a VAR model is not a structural model in the sense that it does not require one to distinguish between the endogenous and exogenous variables. The need to make the distinction in simultaneous equations models was heavily criticized by Sims. In a VAR model all that is necessary is a specification of the variables that are believed to interact with each other and the largest number of lags that are required to capture their interaction. The estimation of each equation is then carried out by OLS. Despite their simplicity, VAR models have been found to provide forecasts of macroeconomic variables that are often competitive with forecasts from those larger models [Lupletti and Webb (1986)]. In a VAR model, it is assumed that each variable specified can be best explained by using past values of both itself and all other variables specified. Furthermore, as opposed to a Granger-Causality forecast which is limited to only one period, VAR forecasts can extend beyond one period.

3.5 Portfolio Hedging Strategy

Portfolio theory tells us that, due to diversification, the addition of a less than perfectly correlated asset to an existing portfolio of assets will always increase the efficiency of the portfolio (i.e. the risk-reward tradeoff improves) [Markowitz (1952)]. In other words, a more diversified portfolio will be more efficient than a less diversified portfolio. In addition, a three asset frontier will always envelope a two asset frontier, a four asset frontier will always envelope a three asset frontier, and so on. This result can be observed visually in Figure 1 below.

Figure 1



The envelope frontier is made up of three assets: the S&P TSX, the ishares XBB index fund, and the S&P GSCI. The interior frontier is made up of two assets: the S&P TSX and the ishares XBB index fund. Data are 92 monthly observations from December 2000 to July 2008.

With this said, one aspect of this study is to analyze the performance of a portfolio when the additional asset is an inflation hedge, for example a commodity index or REITs. To demonstrate the efficacy of adding such an asset, a signaling strategy is devised that permits the calculation of separate mean real returns for "signal-on" and "signal-off" months (explained in detail below). This decomposition of returns is designed to illustrate the correlation between commodity prices and inflation and is based on a four-month moving average of the BCPI containing only energy commodities. If commodity prices are good signals of a rise in the general price level, then mean real returns should be higher in signal-on months. The four-month time period was arbitrarily selected and 92 monthly observations were used form December 2000 to July 2008.

By averaging a number of observations, a moving average provides a simple method for smoothing data and removing many outlying data points. It is also an effective way of revealing any trends in the data [James (1968)]. The moving average employed in this study is a simple one and can be summarized by the model MA (m, r), where m is the number of months and r is a filter band. A filter band provides a threshold around the MA that the current index price must cross before a signal is said to be detected. Filter bands of 0% and 10% are used in this study. As such, a $MA_t(4, 0.1)$ is the four-month moving average at time t with a 10% filter band (r). At time t, a moving average is calculated as:

$$ma_t(m) = \frac{1}{m}\sum_{i=0}^{m} x_{t-1} \qquad (10)$$

where *m*, as mentioned above, is the number of months, and x_t is the closing price at time *t* of the BCPIEN. When the current month closing price of the BCPIEN is more than 10% above the four-month moving average, for example $(P_5 > (1+r)\text{xMA}_{1-4})$, this is interpreted as an upward trend signaling rising general prices. These months are referred to as "signal-on" months. When this is not the case, the month is a "signal off" month, for example $(P_5 \leq (1+r)\text{xMA}_{1-4})$. The addition of any less than perfectly correlated asset to a portfolio of assets will move the frontier leftward and upward; in other words, the extra asset should always be held. Consequently, the decomposition of mean real returns based on moving-average signals should not be viewed as a trading strategy or a forecasting tool in the sense that it signals to an investor when they should alternate between holding and not holding the hedging asset. Rather, it is a device to illustrate the importance of including a hedging asset in the portfolio generally. To accomplish this, four three-asset portfolio frontiers comprised of the SPTSX, the iXBB, and a hedging asset are created. The hedging asset is one of the SPGSCI, the SPGSEN, the SPGSGC, or the SCREIT. Three portfolios on each frontier are selected, and the mean real return is calculated for the signal-on and signal-off months. The risk levels selected for each portfolio correspond to the risk of each asset in the portfolio. Consequently, a total of 12 efficient portfolios will be formed (four frontiers x three portfolios).

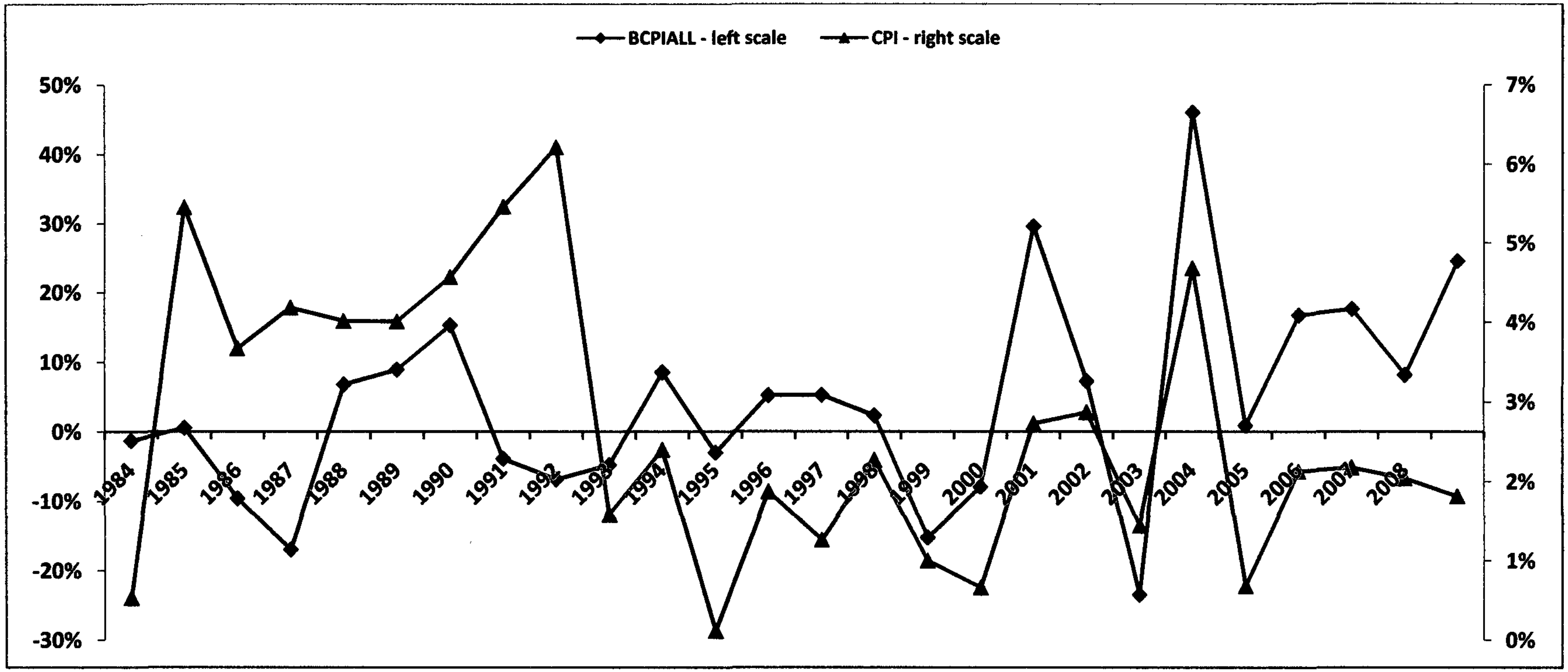
4. Results

4.1 Visual analysis

Figure 2 plots changes in the BCPIALL and changes in the CPI over the past 26 years. In order to assume causality, we are looking for peaks and troughs in the BCPIALL to precede peaks and troughs in the CPI. For the most part, the path of these two variables underscores the reason that many inflation hawks will often point to commodities as precursors to inflation. With the exception of 1983 and 1984 and 1989 to 1992, most of the turning points in the inflation cycle were predated by turning points in the BCPIALL. The link between the BCPIALL and the CPI appears especially strong between 1997 and 2007 and serves to illustrate why commodities are often cited as being leading indicators of inflation. Although these results are impressionistic and informal, they point to a short-run connection between commodities and general price levels. A stable long-run connection, however, seems less likely based on the observations in Figure 3 because the trends appear to drift apart on several occasions. The CPI, between 1983 and 2008 displays an almost steady upward trend whereas the BCPI during the same time period has been much more erratic and volatile. In many instances, according to the BCPI, commodity prices suffered from deflation. Consequently, during the 26 year period, movements in the BCPI were not emulated by movements in the CPI.

Figure 2

Short-run link between commodities and the CPI



The left scale is the annual percentage change in commodities as represented by the Bank of Canada Commodity Price Index. The right scale is the annual percentage change in the Canadian Consumer Price Index. Data are 26 annual observations from 1983 to 2008.

Figure 3

Long-run price link between commodities and the CPI

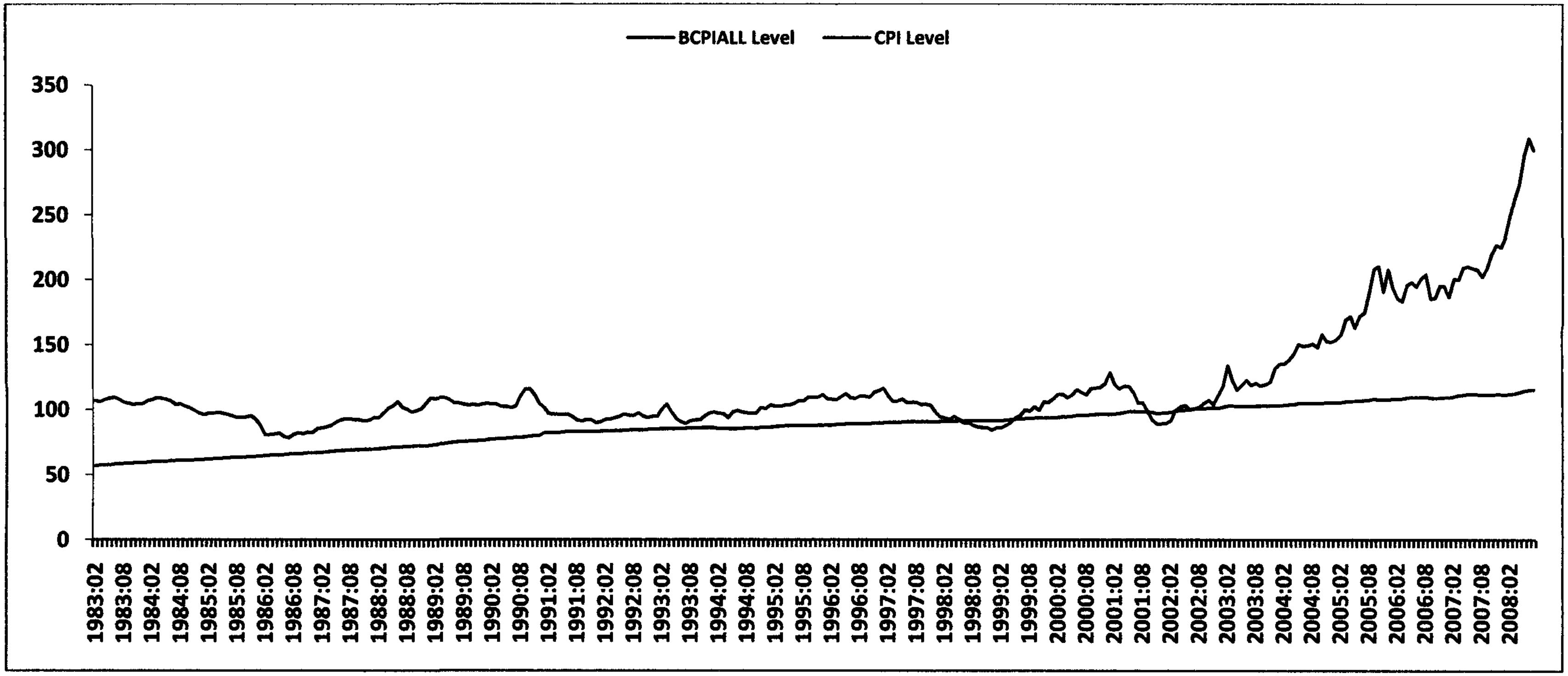


Figure 3 shows the price level for both commodities, as represented by the Bank of Canada Commodity Price Index, and the Canadian Consumer Price Index. Data are 306 monthly observations from February 1983 to July 2008.

4.2 Unit Roots Tests

Table 1 reports the test statistics for the null hypotheses that there is a unit root in either the levels or first differences of each of the series. From these results the presence of a unit root cannot be rejected in the level of any of the series. However, differencing each series once is enough to achieve stationarity. Therefore, it can be concluded that all of the series have a single unit root.

Table 1
Unit Root Test Statistics

Variable	**Level**	**1st difference**
BCPIALL	-0.44	-4.94*
BCPIEN	-1.33	-5.86*
BCPINO	-2.01	-3.49*
CPI	-2.14	-3.55*
FX	-0.84	-3.99*
Gold	0.08	-3.66*
Oil	-1.11	-4.68*
Housing Index	-2.22	-5.64*
Money Supply	-1.93	-4.25*
Three-month T-bill	-1.39	-4.80*

Presented are t-statistics for the null hypothesis of presence of a unit root in the levels or first difference of the series. Based on Augmented Dickey-Fuller tests with 12 autoregressive terms. Critical values for the 5% test are -3.43 and come from Mackinnon (1991). * indicates significant at the 5% level. Variables were entered as natural logs of the series except for the three-month T-bill rate which is not in log form.

Table 2a

Bivariate Cointegration Test Statistics

Dependant (y_i)	**Independent (x_i)**	**Test Statistic**
CPI	BCPIALL	-2.26
CPI	Gold	-1.72
CPI	Oil	-2.71
CPI	BCPIEN	-2.84
CPI	BCPINO	-2.24

t-statistics for the null hypothesis that y_i and x_i are not cointegrated.
None of the above combinations were significant at either the 5% or 10% levels

Table 2b

Multivariate Cointegration Test Statistics

Dependant (y_i)	**Independent (x_i)**	**Test Statistic**
CPI	BCPIALL, FX, Money Supply, T-bill, Housing Index	-3.12
CPI	BCPIEN, FX, Money Supply, T-bill, Housing Index	-2.97
CPI	BCPINO, FX, Money Supply, T-bill, Housing Index	-2.55

t-statistics for the null hypothesis that y_i and x_i's are not cointegrated. None of the above combinations were significant at either the 5% or 10% levels

Tables 2a and 2b present the test statistics for the null hypotheses that the CPI is not cointegrated with the other economic variables in the sample. In both the bivariate and multivariate environments the null hypothesis of no cointegration is not rejected at either the 5% or 10% levels of significance. The absence of support for cointegration implies there likely does not exist a linear long-term relationship between the economic variables in question in line with Figure 3. However, there may very well still exist a short-run relationship between inflation, commodities, and the other four variables in question which can be discovered by employing Granger Causality tests and a multivariate vector autoregression model (VAR).

Table 3

Granger Causality Test Statistics

y_i	x_i	**Dependent (y_i)**	**Dependent (x_i)**
CPI	BCPIALL	1.9* (0.03)	1.45 (0.14)
CPI	Gold	0.68 (0.77)	1.18 (0.29)
CPI	Oil	2.15* (0.02)	1.21 (0.28)
CPI	BCPIEN	2.05* (0.02)	1.66** (0.08)
CPI	BCPINO	0.31 (0.99)	1.15 (0.33)

Notes: * indicates significant at the 5 percent level ** indicates significant at the 10 percent level
Columns 3 and 4 show F values and P-values. P-values are in parentheses. We are testing two hypotheses:
1-Null hypothesis is: x_i does not Granger-Cause y_i
2-Null hypothesis is: y_i does not Granger-Cause x_i

4.3 Granger Causality Tests

The Granger test statistics in TABLE 3 above confirm that the BCPIALL and the price of oil may be said to "Granger-Cause" or precede changes in the CPI. However, results are somewhat mixed for the BCPIEN, because when the BCPIEN is the independent variable the CPI is significant, albeit only at the 10% level. In order to conclude that "BCPIEN does Granger-Cause the CPI" one must be able to reject the null hypothesis that "the BCPIEN does not cause the CPI" and to accept the hypothesis that "the CPI does not Granger-Cause the BCPIEN". The change in the price of gold was not significant in preceding the change in inflation. This is somewhat surprising since gold has typically been regarded as an inflation hedge. It might be hypothesized that perhaps the use of other hedging tools such as financial futures has diminished the demand for gold in this respect. Lastly, the BCPINO fails all significance tests.

4.4 Vector Autoregression

The Granger tests above are encouraging as they confirm that commodities in Canada are generally useful in predicting the CPI. However, the Granger tests alone are not enough to establish concretely the predictive usefulness of commodities, as they are limited to only one time period ahead. Furthermore, the Granger tests are done in a bivariate environment. There may be additional macroeconomic variables which add explanatory value in forecasting the inflation rate and which therefore must be examined. Adding additional variables to the CPI equations could change the predictive abilities of the BCPI indices. In order to examine these possibilities, vector autoregression models are employed.

The three multivariate VAR models in this section include as explanatory variables one of the three commodity indices, lagged values of the CPI, the FX rate, the three-month T-bill rate, and the housing index. The dependent variable is the CPI index. In addition to the commodity indices, the additional predictor variables included in the VAR models were selected because they have been deemed in the literature as good candidates for leading indicators. Webb (1988), in addition to using a commodity index in his multivariate VAR model, also used the foreign exchange rate, the money supply, the 90-day Treasury bill rate, and the capacity utilization rate in manufacturing. Cody and Mills (1989) used the money supply, the federal funds rate, and the industrial production rate in their VAR model. The logic for including a housing index variable in the models is that this is a proxy for the strength of the housing market in Canada: stronger housing demand tends to drive up housing prices, which in turn may drive up consumer spending (the wealth effect), which can ultimately affect inflation.

Table 4 below presents the results of the first three VAR models. Results include P-values and the signs of the sums of the coefficients in the VAR models for the full sample period (1983-2008). The results confirm the Granger-causality tests results for all three commodity indices. The VAR models that include either the BCPIALL or the BCPIEN are significant with P-values of 0.06. However, the BCPINO fails any significance test with a P-value of 0.92. It seems that the energy component of the commodities index plays a major role in predicting inflation. Furthermore, commodity indices appear to be good stand-alone indicators of future inflation since the additional macroeconomic variables in the analysis do little to change or improve the predictive abilities of the BCPIALL and BCPIEN indices. In other words, since none of the new variables introduced here are significant, any predictive ability attributed to commodities in a bivariate Granger test environment really is due to commodity indices with energy commodities and not any other macroeconomic variable. Lastly, lagged values of the CPI are significant in predicting future inflation. As expected, the signs of the commodity indices are positive in the two significant cases which imply a positive relationship between commodity price changes and general price inflation. Oddly enough, the BCPINO has a negative sign on the coefficient; however with a P-value of 0.92 this variable is not significant.

Table 4

CPI Equation Results

Index Specification	BCPIALL		BCPIEN		BCPINO	
Variable	**Sign**	**P-Value**	**Sign**	**P-Value**	**Sign**	**P-Value**
Commodity Index	+	0.06	+	0.06	-	0.92
CPI (lagged)	+	0.00	+	0.01	+	0.02
FX	+	0.54	+	0.52	-	0.37
Money Supply	-	0.87	-	0.81	-	0.87
Three-month T-bill	+	0.90	+	0.89	+	0.73
Housing Index	-	0.54	-	0.58	-	0.53

VAR models are estimated from 1983 to 2008. Presented are p-values and the sign of the sum of the coefficients. Coefficient values are reported in appendix II. Explanatory Variables: Commodity Index (either one of the BCPIALL, BCPIEN, or BCPINO), CPI (lagged), FX, Money Supply, three-month T-bill, Housing Index. Dependent Variable: CPI. Variables are entered as first differences of natural logs except for three-month T-bill which is not in log form.

4.5 Sub-period

Splitting the sample into two time periods allows testing for consistency in the results as well as detecting any structural changes that may have occurred from one period to the next. The sample was split into two time periods running from 1983 to 1995 and from 1996 to 2008. These results are reported in Table 5 below, where a possible structural shift can be seen to have occurred. The BCPIALL and the BCPIEN indices are still significant but are only so in the latter time periods. As expected, the sign for these indices continues to be positive, thus still indicating a positive correlation between commodities and inflation. Test statistics from the VAR model containing the BCPINO mimic those from the full sample period. As such, the commodity index that does not include energy products continues to be a weak predictor of future inflation. The formal results in this section confirm the structural change in the commodity-CPI connection that is somewhat apparent when examining the evolution of these variables over the last 26 years in Figure 3 on page 28. Inflation has been rising steadily over the entire sample period whereas the prices of commodities as measured by the BCPIALL have been rising only in the latter half. During the first time period, commodity prices were quite erratic and alternated frequently from rising in price to falling in price. On a visual basis at least, it appears unlikely that during the first half of the sample period commodity price increases were responsible for the increase in the general price level. Contrary to earlier tests results, the relationship between lagged values of the CPI and current CPI has changed in one instance. The lagged CPI continues to be significant in forecasting current inflation but is now negatively related to inflation in the latter period, when the

BCPIALL is the explanatory variable in the equation. In similar fashion to the full sample test results, the additional macroeconomic variables examined here add little predictive value, as they continue to be insignificant as shown by the statistical tests.

Table 5

Sub-Period VAR Results

Index Specification	BCPIALL				BCPIEN				BCPINO			
Time Period	1983-1995		1996-2008		1983-1995		1996-2008		1983-1995		1996-2008	
Variable	**Sign**	**P-Value**	**Sign**	**P-Value**	**Sign**	**P-Value**	**Sign**	**P-Value**	**Sign**	**P-Value**	**Sign**	**P-Value**
Commodity Index	+	0.85	+	0.00	+	0.19	+	0.00	-	0.57	+	0.20
CPI (lagged)	+	0.02	-	0.04	+	0.00	+	0.02	+	0.00	+	0.43
FX	-	0.83	+	0.48	+	0.47	+	0.59	-	0.69	+	0.31
Money Supply	-	0.35	+	0.88	-	0.26	+	0.93	-	0.24	+	0.88
Three-month T-bill	+	0.85	-	0.92	+	0.55	-	0.97	+	0.59	-	0.28
Housing Index	+	0.29	-	0.30	+	0.22	-	0.58	+	0.10	-	0.33

VAR models are estimated between 1983 & 1995 and 1996 & 2008. Presented are P-values and the sign of the sum of the coefficients. Coefficient values are reported in appendix II. Explanatory Variables: Commodity Index (either one of the BCPIALL, BCPIEN, or BCPINO), CPI (lagged), FX, Money Supply, three-month T-bill, Housing Index. Dependent Variable: CPI. Variables are entered as first differences of natural logs except for the three-month T-bill which is not in log form.

4.6 Commodity specific VAR

The results thus far indicate that the energy component of the commodity index is a determining factor in the link between commodities and the CPI. At any given point, the energy component of the BCPIALL is about 33 percent of the index, and oil represents approximately 70 percent of that. Grouping a number of commodities in the index can blur the predictive power of an individual commodity like oil. To examine better the importance of oil as a leading indicator, oil will be subjected to the same tests as above. Using only oil as a predictive variable is of course a very narrow definition of a commodity; however, Canada is a vast producer and exporter of oil and as such, Canada will therefore see oil representing a disproportionate amount of the economy. Consequently, strong oil prices should impact the inflation rate in two ways: First, the Canadian economy should perform well thus increasing inflationary pressures, and second, higher oil prices should increase production costs which will be partly passed through to the consumer in the form of higher prices hence driving up the inflation rate.

TABLE 6 below presents the test statistics for oil. The results are consistent with earlier VAR models containing either the BCPIALL or BCPIEN. For the full sample period, oil with a P-value of 0.02 and a positive sign has a positive and significant relationship with the CPI. In contrast, when the sample is split into two time periods oil is only significant in the latter period. These statistics mirror the previous statistics and demonstrate that oil is indeed highly responsible for the strength in the commodity-CPI connection. As we expected, the sign for the oil coefficient is positive in all three cases.

Table 6

Commodity specific VAR

Time Period	1983-2008		1983-1995		1996-2008	
Variable	**Sign**	**P-Value**	**Sign**	**P-Value**	**Sign**	**P-Value**
Oil	+	0.02	+	0.22	+	0.00
CPI (lagged)	+	0.00	+	0.02	-	0.25
FX	+	0.49	+	0.63	+	0.48
Money Supply	-	0.74	-	0.31	+	0.69
Three-month T-bill	+	0.75	+	0.44	-	0.96
Housing Index	+	0.78	+	0.19	-	0.29

VAR models are estimated between 1983 & 2008, 1983 & 1995, and 1996 & 2008. Presented are P-values and the sign of the sum of the coefficients. Coefficient values are reported in appendix II. Explanatory Variables: Oil, CPI (lagged), FX, Money Supply, three-month T-bill, Housing Index. Dependent Variable: CPI. Variables are entered as first differences of logs except for the three-month T-bill which is not in log form.

4.7 Portfolio Hedging

Tables 7 to 10 below present the portfolio hedging results. Columns 1 and 2 in each indicate the assets held and the weights of these respectively in each of the portfolios. Each of the rows in the tables represent a different three asset portfolio. Column 3 specifies the monthly standard deviation calculated from nominal monthly returns. Column 4 indicates the expected nominal return, which equals the actual nominal return because weights are rebalanced every month to reflect efficient weights. Column 5 is the real return calculated conventionally as:

$$(1+r)=\frac{(1+R)}{(1+i)} \tag{11}$$

where r is the real return, R is the nominal return, and i is the inflation rate. The last four columns present the mean real monthly returns for signal-off and signal-on months for both a zero percent and a ten percent filter band.

The optimal weights of the hedging assets are positive in all 12 of the portfolios. This highlights the importance of holding these hedging assets in the portfolio. In addition, the portfolio weights of all three commodity indices move in similar fashion. That is, they increase in conjunction with the portfolio standard deviation. The weights for the SPGSCI range from 10.41% to 99.5% whereas the weights of the SPGSEN range from 6.83% to 98.96%. The weights for the SPGSGC lie between 18.41% and 99.52%. Similarly, the optimal weights for the SCREIT range from 18.84% and 121.46% and also increase with a rising standard deviation. The mean real monthly returns for the SPGSCI and SPGSEN are larger for signal-on months than for signal-off months for both filter band levels. Signal-on month mean real returns for portfolios containing the SPGSCI, with a standard deviation of 3.83%, were 1.56% and 2.32% for 0% and 10% filter bands respectively while signal-off month mean real returns at the same risk level were -1.17% and -0.23% for 0% and 10% filter bands respectively. Signal-on month mean real returns for portfolios holding the SPGSEN were slightly better than the above mean real returns for portfolios holding the SPGSCI. At the same risk level of 3.83%, signal-on month mean real returns for portfolios holding the SPGSEN were 1.61% and 2.63% for 0% and

10% filter band levels respectively while signal-off month mean real returns were -1.24% and -0.34% for 0% and 10% filter band levels respectively. Efficacy results for portfolios containing the SPGSGC as the hedging asset varied depending on whether a filter band was used or not. At the 3.83% risk level, signal-on and signal-off mean real returns were 0.91% and 0.23% respectively for a 0% filter band. With a 10% filter band however, the mean real return for signal-on months was 0.61% versus 0.64% for signal-off months. Separate tests on the SPGSGC (not shown) using a 5% filter band produced higher mean real returns during signal-on months than during signal-off months. Although either three of these commodity futures index would have provided a hedge against inflation, the most efficient hedge is provided from the SPGSEN. The portfolios with SCREIT were the worst performers. In no case did the mean real returns in signal-on months surpass the mean real returns in signal-off months. At a 3.83% risk level, mean real returns were -0.16% and -0.88% for signal-on months at 0% and 10% filter bands respectively and 1.3% and 0.93% for signal-off months at 0% and 10% filter bands respectively. Similar to portfolios holding the SPGSCG, performance was best with a 0% filter band.

With regards to the results of the portfolios that included a commodity futures index, they illustrate that the average gain in mean real return over a portfolio with fewer assets is best explained by the moving average signal. This, in turn, supports the positive correlation of commodity prices and general price inflation. As such, including commodity futures in the asset mix of a portfolio can help maintain the purchasing power of a portfolio from unexpected changes in inflation.

Table 7 - Portfolio Weights

Portfolio	Efficient Weights	$\sigma_{nominal}$	$E(R_{nominal})$	r_{real}	r_{real} SigOff filter 0%	r_{real} SigOn filter 0%	r_{real}SigOff filter 10%	r_{real} SigOn filter 10%
SPTSX iXBB SPGSCI	0.0405616 0.8553354 0.1041030	0.0133110	0.0054094	0.0034469	0.0007219	0.0052800	0.0021969	0.0067967
SPTSX iXBB SPGSCI	-0.4387867 0.8565475 0.5822393	0.0382829	0.0066249	0.0046174	-0.0117080	0.0155999	-0.0023292	0.0232343
SPTSX iXBB SPGSCI	-0.8526122 0.8575938 0.9950183	0.0636509	0.0077674	0.0056279	-0.0224388	0.0245091	-0.0062367	0.0374250

Three portfolios were selected that have the same risk as the three assets (S&P TSX-ishares XBB index bond fund-S&P Goldman-Sachs Commodity Index) held individually. Expected nominal return $E(R_{nominal})$ will equal actual nominal return because weights are rebalanced every month to efficient weights. The last four columns decompose the real return into means attributable to signal-off and signal-on months for a 0% and 10% filter band. Data are 92 monthly observations from December 2000 to July 2008.

Table 8 - Portfolio Weights

Portfolio	Efficient Weights	$\sigma_{nominal}$	$E(R_{nominal})$	r_{real}	r_{real} SigOff filter 0%	r_{real} SigOn filter 0%	r_{real}SigOff filter 10%	r_{real} SigOn filter 10%
SPTSX iXBB SPGSEN	0.0580178 0.8736611 0.0683211	0.0133110	0.0053960	0.0034343	0.0008923	0.0051443	0.0021395	0.0069043
SPTSX iXBB SPGSEN	-0.3646538 0.9430955 0.4215583	0.0382829	0.0066810	0.0046730	-0.0123629	0.0161335	-0.0033949	0.0262949
SPTSX iXBB SPGSEN	-1.0443300 1.0547994 0.9895807	0.0859121	0.0087475	0.0066649	-0.0336779	0.0338045	-0.0122945	0.0574758

Three portfolios were selected that have the same risk as the three assets (S&P TSX-ishares XBB index bond fund-S&P Goldman-Sachs Commodity Energy Only Index) held individually. Expected nominal return $E(R_{nominal})$ will equal actual nominal return because weights are rebalanced every month to efficient weights. The last four columns decompose the real return into means attributable to signal-off and signal-on months for a 0% and 10% filter band. Data are 92 monthly observations from December 2000 to July 2008.

Table 9 – Portfolio Weights

Portfolio	Efficient Weights	$\sigma_{nominal}$	$E(R_{nominal})$	r_{real}	r_{real} SigOff filter 0%	r_{real} SigOn filter 0%	r_{real}SigOff filter 10%	r_{real} SigOn filter 10%
SPTSX iXBB SPGSGC	0.0954063 0.7204508 0.1841428	0.0133110	0.0058148	0.0038557	0.0031715	0.0043160	0.0038570	0.0038523
SPTSX iXBB SPGSGC	-0.0997534 0.2282032 0.8715502	0.0382829	0.0083215	0.0063389	0.0022689	0.0090769	0.0064304	0.0060936
SPTSX iXBB SPGSGC	-0.1348465 0.1396886 0.9951579	0.0434667	0.0087723	0.0067854	0.0021065	0.0099330	0.0068932	0.0064966

Three portfolios were selected that have the same risk as the three assets (S&P TSX-ishares XBB index bond fund-S&P Goldman-Sachs Gold Index) held individually. Expected nominal return $E(R_{nominal})$ will equal actual nominal return because weights are rebalanced every month to efficient weights. The last four columns decompose the real return into means attributable to signal-off and signal-on months for a 0% and 10% filter band. Data are 92 monthly observations from December 2000 to July 2008.

Table 10 Portfolio Weights

Portfolio	Efficient Weights	$\sigma_{nominal}$	$E(R_{nominal})$	r_{real}	r_{real} SigOff filter 0%	r_{real} SigOn filter 0%	r_{real}SigOff filter 10%	r_{real} SigOn filter 10%
SPTSX iXBB SCREIT	0.0092594 0.8023706 0.1883700	0.0133110	0.0053296	0.0033778	0.0049901	0.0022932	0.0041688	0.0012579
SPTSX iXBB SCREIT	-0.5416148 0.5363029 1.0053119	0.0324683	0.0061118	0.0041640	0.0115614	-0.0008125	0.0082468	-0.0067779
SPTSX iXBB SCREIT	-0.6827436 0.4681388 1.2146048	0.0382829	0.0063122	0.0043654	0.0132449	-0.0016081	0.0092915	-0.0088365

Three portfolios were selected that have the same risk as the three assets (S&P TSX-ishares XBB index bond fund-Scotia Capital REIT Index) held individually. Expected nominal return $E(R_{nominal})$ will equal actual nominal return because weights are rebalanced every month to efficient weights. The last four columns decompose the real return into means attributable to signal-off and signal-on months for a 0% and 10% filter band. Data are 92 monthly observations from December 2000 to July 2008.

5. Discussion

The results presented, both from the Granger tests as well as the VAR models, are encouraging. The Granger results support precedence and causality (i.e. direction of causality) between commodities and the CPI, and the VAR models, particularly the split-sample ones, point to a short-run and positive correlation between commodity prices and inflation. In addition, the signaling strategy, based on a four-month moving average of the BCPIEN, designed to detect upward commodity price trends signaling rising general prices, supports the theory of positive correlation between commodity prices and inflation by showing that the mean real returns for signal-on months are higher than the mean real returns for signal-off months. Therefore, by including commodities in a portfolio, an investor cannot only improve the risk return trade-off but also shield the portfolio from some of the purchasing power loss attributable to unexpected inflation. Between December 2000 and July 2008 the most efficient hedge against inflation was provided by the SPGSEN. This concurs with the VAR test results which support a positive and significant relationship between the BCPIEN and the CPI.

Our analysis clearly shows that the oil component of the BCPI is a major factor in the correlation between commodity prices and the general price level in Canada. Commodity indices containing energy products have become much more reliable indicators of inflation in the latter half of the sample period (1996-2008) versus the earlier one (1983-1995). This structural shift is similar to the one discovered by Bloomberg and Harris (1995)[6]. In their analysis, commodities were good predictors of

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[6] See background section for full details

inflation in the first time period (1970-1986) but lost most of their predictive abilities in the second time period (1987-1994). Their findings were partly explained by offsetting monetary policy The implications of these ongoing structural shifts are that over the long-term, commodities are not good predictors of inflation. Consequently, monetary policy that considers commodity prices must adjust for this ongoing change and diminish the feedback importance of commodities during times of a weak commodity-CPI connection. Similarly, portfolio weights must be rebalanced to reflect changing correlations among commodities and the CPI, to the other portfolio holdings. In times of strong economic growth and rising commodity prices, such as the one we experienced between the early 2000s and the summer of 2008, the commodity-CPI connection is expected to be positive and significant. This is likely even more true in commodity rich countries like Canada. Consequently, in such times, commodities should be viewed as strong information variables and leading indicators of inflation.

Although there are several possible factors that contributed to the structural change in the commodity-CPI connection witnessed in Canada between the two periods, the most dominant factor is likely the tremendous price appreciation of commodities in comparison to other asset classes which took place throughout most of the second time period of 1996 to 2008. Consequently, the higher cost of commodities on a global basis caused the commodity component of the input and production process to represent a disproportionate piece of the overall financial cost. This is in contrast to the late 1980s and early 1990s where depressed commodity prices had only a marginal impact on production costs. This was especially true in more advanced service oriented economies.

Some key probable reasons behind the commodity price appreciation are:

The global increase in demand for natural resources resulting from exceptional global economic growth; an increase in non-idiosyncratic supply shocks; increased use of commodity indices as hedging tools against inflation; depreciation of the US dollar;

Demand for commodities, oil not the least, from emerging markets like India and China, is at unprecedented levels. These countries have seen their economies explode over the past decade with double-digit growth in many cases. According to IMF research, these economies have accounted for virtually all of the demand growth in commodities over the past few years, reflecting the greater commodity intensity of their economies when compared with advanced economies[7]. Obviously, the growth of these production oriented economies was partly the result of strong economic growth in most of the western world that demanded more and more commodity based goods from these production based economies. The other part of the commodity demand from emerging markets came from their pressing need to fuel their own economic development (i.e. urban development). Now herein lays some of the logic behind the commodity-CPI connection theory. An increase in demand for final goods will put upward demand

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[7] http://www.imf.org/external/pubs/ft/survey/so/2008/res032008a.htm

pressure on goods being used as inputs (i.e. commodities) in the production process, ultimately driving up the prices of both commodities and final goods. This relationship between global economic growth and commodities has become even more evident since the Fall of 2008 which saw a worldwide recession decimate commodity prices. For example, oil prices dropped almost 80% between August 2008 and December 2008. Furthermore, at the same time many Central Banks have became concerned with deflation. This being said, the disproportionate run-up in commodity prices, when compared to other asset classes, witnessed during the past decade, prior to the global meltdown, is likely one of the contributing causes behind the structural changes we have seen in the commodity-CPI connection in Canada during the 1996 to 2008 time period.

The relationship between commodity prices and general prices depends on what is the underlying driver causing the change in price for a given commodity. If the increase in the price of a commodity is caused by an idiosyncratic shock (specific to that commodity alone) and there are many substitute commodities that can be used, then the overall effect on inflation should be marginal. However, if the opposite occurs and prices are inelastic, then the effect on inflation should be more noticeable. In the current context, it is more likely that the latter is occurring. That is, increased demand from emerging markets is creating non-idiosyncratic pressures, resulting in higher prices for most commodities. Furthermore, commodities with few substitutes, such as oil saw their prices increase the most. Oil prices increased five-fold between 2000 and 2008. Therefore, even though a long-run relationship between commodities and inflation is an unlikely one, these types of tight supply markets can create strong relationships with the CPI in the short-run.

A traditional role for many commodities has been that of a hedging instrument. However, during the 1980s and most of the 1990s many commodities experienced very poor returns causing them to be less than attractive investment and hedging vehicles. An investor who used commodity futures to hedge against inflation during the 1983 to 1995 time period would not have fared very well as commodities failed to match the changes in the CPI. However, as mentioned repeatedly, the performance of commodities changed in the early 2000s.With renewed investor interest and demand in commodities, prices began to surge. With substantially stronger returns, commodities were able to once again provide a more reliable hedge against inflation.

Lastly, most commodities, including oil are traded in US dollars. This means that revenues and profits of foreign commodity producers are largely determined by the strength of the US dollar vs. their respective home currencies. Since late 2002 the US dollar has been weakening against most major currencies in the world, including Canada's. This being the case, commodity prices have likely increased to offset the revenue losses resulting from a falling US currency.

6. Conclusion

This study examined the ability of the Bank of Canada Commodity Price Index to predict changes in the Consumer Price Index. Granger-Causality tests and vector autoregression results indicate a strong relationship between energy commodities and the general price level in Canada. However, split-sample results indicate a structural change has taken place in this relationship. From 1996 to 2008 commodities were good stand-alone indicators of inflation; however prior period results between 1983 and 1995 indicate that they were not.

The theory of correlation between commodity prices and inflation is further supported by positive results of the signaling strategy based on a four-month moving average of the Bank of Canada Commodity Index containing only energy products. The mean real returns were stronger during signal-on months than they were during signal-off moths for portfolios containing either the SPGSCI or the SPGSEN commodity futures index. Portfolios holding the SPGSGC had mixed results depending on the level of filter band used. Results for portfolios containing a REIT index as the hedging asset however did not perform as well. Signal-on months had lower mean real returns than signal-off months.

Not surprisingly, commodity-specific tests reveal that oil has been a strong predictor of inflation in Canada. Given Canada's role as a major oil producing nation, its economy is inherently tied to the price of oil. The Canadian dollar is often referred to as a petrocurrency; having witnessed the downward spiral of the Canadian dollar over the last six months along with the collapse of oil prices, it is obvious that this is still a very relevant term for the dollar. The Canadian dollar has lost value in almost perfect harmony with the fall of oil prices, albeit on a smaller scale. As such, a point for further research can be to examine how the relationship between commodities and more specifically oil and the CPI has changed in the context of the Canadian economy given the unprecedented decline of oil prices, and all commodities, coupled with the increased volatility of these markets over the last six months.

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Appendix I

Below is the composition and weights of commodities in the BCPI and the sub-indices.

Item	Weight %	Item	Weight %
Total BCPI	***100***		
1.0 BCPI Energy Only	***33.93***		
Crude Oil	21.4	Lobster	0.49
Natural Gas	10.69	Salmon	0.35
Coal	1.84	**2.2 Industrial**	**49.32**
2.0 BCPI Excluding Energy	***66.07***	**2.2.1 Metals**	**14.3**
2.1 Food	**16.77**	Gold	2.3
2.11 Grains and Oilseeds	**5.86**	Silver	0.32
Barley	0.65	Aluminum	5.02
Canola	1.25	Copper	2.04
Corn	0.54	Nickel	2.39
Wheat	3.42	Zinc	2.23
2.1.2 Livestock	**9.67**	**2.2.2 Minerals**	**1.66**
Cattle	7.87	Potash	1.66
Hogs	1.8	**2.2.3 Forest Products**	**33.36**
2.1.3 Fish	**1.24**	Lumber	13.58
Crab	0.25	Newsprint	7.7
Shrimp	0.15	Pulp	12.08

Appendix II

CPI Equation Results – Full Sample Period

Index Specification	BCPIALL	BCPIEN	BCPINO
Variable	Sum of coefficient, *b*	Sum of coefficient, *b*	Sum of coefficient, *b*
Commodity Index	0.0241	0.0161	-0.0094
CPI (lagged)	0.4660	0.4247	0.3249
FX	0.0332	0.0305	-0.0171
Money Supply	-0.0536	-0.0606	-0.0810
Three-month T-bill	0.0007	0.0006	0.0006
Housing Index	-0.0089	-0.0094	-0.0096

VAR models are estimated from 1983 to 2008. Presented are the sums of the coefficients. Explanatory Variables: Commodity Index (either one of the BCPIALL, BCPIEN, or BCPINO), CPI (lagged), FX, Money Supply, three-month T-bill, Housing Index. Dependent Variable: CPI. Variables are entered as first differences of natural logs except for three-month T-bill which is not in log form.

Sub-Period VAR Results

Index Specification	BCPIALL		BCPIEN		BCPINO	
Time Period	1983-1995	1996-2008	1983-1995	1996-2008	1983-1995	1996-2008
Variable	Sum of coefficient, *b*		Sum of coefficient, *b*		Sum of coefficient, *b*	
Commodity Index	0.0325	0.0945	0.0282	0.0457	-0.0474	0.0229
CPI (lagged)	0.5859	-0.9259	0.5867	1.1479	0.3487	0.0847
FX	-0.0005	0.1006	0.0181	0.0376	-0.0983	0.0055
Money Supply	-0.1095	0.0220	-0.1139	0.0358	-0.0801	0.0047
Three-month T-bill	0.0007	-0.0015	0.0007	-0.0011	0.0009	-0.0028
Housing Index	0.0119	-0.0083	0.0231	-0.0116	0.0049	-0.0853

VAR models are estimated between 1983 & 1995 and 1996 & 2008. Presented are the sums of the coefficients. Explanatory Variables: Commodity Index (either one of the BCPIALL, BCPIEN, or BCPINO), CPI (lagged), FX, Money Supply, three-month T-bill, Housing Index. Dependent Variable: CPI. Variables are entered as first differences of natural logs except for the three-month T-bill which is not in log form.

Commodity specific VAR

Time Period	1983-2008	1983-1995	1996-2008
Variable	Sum of coefficient, *b*	Sum of coefficient, *b*	Sum of coefficient, *b*
Oil	0.0227	0.0196	0.0401
CPI (lagged)	0.4614	0.5551	-0.7133
FX	0.0546	0.0172	0.0477
Money Supply	-0.0546	-0.1342	0.0280
Three-month T-bill	0.0005	0.0006	-0.000
Housing Index	-0.0102	0.0206	-0.004

VAR models are estimated between 1983 & 2008, 1983 & 1995, and 1996 & 2008. Presented are the sums of the coefficients. Explanatory Variables: Oil, CPI (lagged), FX, Money Supply, three-month T-bill, Housing Index. Dependent Variable: CPI. Variables are entered as first differences of logs except for the three-month T-bill which is not in log form.