Does Commodity Price Index predict Canadian Inflation?

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Abstract

I statistically evaluate the usefulness of the Bank of Canada Commodity Price Index (BCPI) for a leading indicator of inflation in Canada. Using monthly observations between January 1972 and March 2010 for a bivariate vector autoregressive (VAR) model, I find an important role of the BCPI for predicting Canadian inflation, but not vice versa.

Keywords: Commodity Price Index, Inflation, Leading Indicator, Generalize Impulse-Response Function, Granger Causality, Diebold-Mariano-West Statistics

JEL Classification: E31, E37
I. Introduction

This paper statistically evaluates the effectiveness of the Bank of Canada Commodity Price Index (BCPI) as an early indicator for Canadian inflation.\textsuperscript{1} It is known that commodity prices are quite flexible while final goods prices tend to be sticky in the short-run. Given close linkages between commodity prices and final goods prices, then, commodity price inflation may provide useful information for predicting overall inflation in near future.

For this purpose, I employ a bivariate vector autoregressive (VAR) model of the BCPI and Canadian Consumer Price Index (CPI) with monthly observations that span from January 1972 to March 2010. My empirical results provide strong evidence of the BCPI as a useful leading indicator for inflation, but not vice versa. I illustrate that the BCPI continues to Granger cause the CPI by recursive and 20 year moving window methods. The Diebold-Mariano-West (DMW) statistics implies that the BCPI has a statistically significant out-of-sample predictive power for the CPI. Similar evidence is reported by the generalized impulse-response function analysis.

The rest of the present paper is organized as follows. Section II discusses some connections between commodity prices and final goods prices. In Section III, I present my empirical model. Section IV reports my empirical results. Concluding remarks follow in the last section.

II. Commodity Prices as Leading Indicators for Inflation

It is well-known that prices of final goods and services tend to be “sticky” in presence of menu costs or other market frictions (see Romer, 2005, for textbook explanations on price-stickiness). On the contrary, most commodities such as gold and crude oil are highly tradable across countries, and their prices are normally determined in competitive and flexible-price markets. Given that, commodity prices may serve as leading indicators of final good prices or aggregate prices such as the consumer price index if there’s a close connection between commodity prices and

\textsuperscript{1} The Bank of Canada Commodity Price Index (BCPI) is a chain Fisher price index of the US$ prices of 24 commodities produced in Canada and sold in world markets. Detailed explanations are available at the following webpage (http://www.bankofcanada.ca/en/rates/commod.html).
final goods prices. The current literature identifies at least the following three linkages (see Blomberg & Harris, 1995; Cheung, 2009).

First, commodities such as food and energy are important inputs to final good productions. When there’s commodity price inflation, final goods prices may respond only gradually (price-stickiness) in the short-run. However, firms in final goods sectors should eventually raise their prices. Put differently, commodity price inflation will be passed through to final goods price inflation.

Second, unusually high demand for final goods may generate inflationary pressures in both commodity markets and final goods markets. Since price adjustments in final goods sectors tend to be sluggish, while commodity prices are not, final goods prices will respond to demand pressures only slowly gaining ground on commodity prices.

Third, a certain commodities such as precious metals have been popular as an inflation hedge. When commodity prices increase, the market may interpret it as a forewarning signal of an overall inflationary pressure. Forward looking firms, then, may incorporate such inflation expectations into their price adjustment, causing actual inflation. That is, inflation may arise as a self-fulfilling process.

III. The Empirical Model

Let $cpi_t$ and $cmp_t$ be the consumer price index (CPI) and the commodity price index (CMP), expressed in natural logarithms. I propose the following bivariate VAR($p$) model for these variables with deterministic trends.

$$x_t = Ad_t + B(L)x_{t-1} + Cu_t,$$

where

$$x_t = \begin{bmatrix} cpi_t \\ cmp_t \end{bmatrix}, \quad d_t = \begin{bmatrix} 1 \end{bmatrix}.$$

2 Firms’ forward looking behavior typically arises in the Neo Keynesian macroeconomic model where firms have an opportunity to optimize their prices with a constant probability (Calvo pricing) in each period. See Galí (2008) for a textbook explanation.
and $A$ is the coefficients matrix for the deterministic terms, $B(L)$ denotes the lag polynomial matrix, $u_t$ is a vector of structural shocks, and $C$ is a matrix that describes the contemporaneous structural relationships among $cpi_t$ and $cmp_t$.

Assuming invertibility, (1) can be rewritten as the following infinite order vector moving average representation.\(^3\)

$$\hat{x}_t = D(L)Cu_t = \sum_{s=0}^{\infty} D_s Cu_{t-s}$$  \hspace{1cm} (2)

Where $\hat{x}_t$ is a vector of demeaned and detrended variables, $D(L) = (I - B(L))^{-1}$, $D_0 = I$, and $D(L)C$ is the moving average polynomials matrix that provides impulse-response functions.

It is also well-known that the orthogonalized impulse-response function (OIRF) by Sims (1980) may yield very different results depending on the order of the variables in $\hat{x}_t$. Therefore, I employ the generalized impulse-response function (GIRF) analysis by Pesaran & Shin (1998), which is ordering free.\(^4\) The scaled $n$-period ahead GIRF is,

$$GIRF_j(n) = \sigma_{jj}^{-1/2} D_n \Sigma e_j, \ j = 1, 2$$  \hspace{1cm} (3)

where $\Sigma$ denotes the least squares variance-covariance matrix, $\sigma_{jj}$ is the $j^{th}$ diagonal element of $\Sigma$, and $e_j$ is a $2 \times 1$ selection vector with 1 as its $j^{th}$ element and zero elsewhere.

Lastly, I investigate whether $cmp_t$ has added predictive out-of-sample forecasting power for $cpi_t$ by the conventional Diebold-Mariano-West (DMW) statistics (Diebold & Mariano, 1995; West, 1996).

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\(^3\) The system is invertible and thus can be represented as a moving average process when all eigenvalues of the companion matrix of (1) are less than one in norm. See any time-series econometrics textbook such as Hamilton (1994) for details.

\(^4\) Kim (2009) illustrates that the GIRF may yield misleading response functions under certain circumstances.
Let $cpi_{t+1|t}^u$ and $cpi_{t+1|t}^r$ are the one-period ahead out-of-sample forecast from a unrestricted (use both variables) and a restricted (use its lagged variables only) model. Define the following loss differential function.

$$d_t = L(ε_{t+1|t}^u) - L(ε_{t+1|t}^r),$$

where $L(ε_{t+1|t}^j) = (cpi_{t+1} - cpi_{t-1|t})^2, j = u, r$. Then the DMW statistic is defined by,

$$DMW = \frac{\bar{d}}{\sqrt{Avar(\bar{d})}},$$

where $\bar{d}$ is the sample mean loss differential function and $Avar(\bar{d})$ denotes its asymptotic variance. The test statistic is asymptotically normally distributed under the null hypothesis of equal predictive power.

### IV. Empirical Results

I use monthly observations of the Bank of Canada Commodity Price Index (BCPI) and Canada Consumer Price Index (CPI), all expressed in natural logarithms. The sample period is January 1972 to March 2010. All data is obtained from DataStream. I choose $p = 3$, the number of lag order, by the Bayesian Information Criteria with a maximum 12 lag-length. Stationarity of the system is confirmed, because all eigenvalues of the companion matrix for (1) are less than 1 in norm.

I first implement the Granger causality test, an $F$ test, with the null hypothesis of no Granger causality. Results are reported in Table 1. $cmp_t$ Granger causes $cpi_t$ at any significance level, while $cpi_t$ fails to Granger cause $cmp_t$ even at the 30% significance level. This implies that $cmp_t$ helps predict $cpi_t$, but not vice versa. Therefore, $cmp_t$ seems to be a useful variable to predict changes of $cpi_t$ in Canada.

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5 Following Andrews & Monahan (1992), I use the quadratic spectral kernel with automatic bandwidth selection for my analysis.
Recently, some authors claim that the empirical link between commodity prices and inflation dramatically has changed (see Furlong & Ingenito, 1996, for example). To evaluate the validity of such claims, I implement the Granger causality tests using a recursive method starting from January 1992. The bottom panel of Figure 1 shows the same strong evidence of one-way Granger causality from \( cmp_t \) to \( cpi_t \) at any significance level, but not the other way with an exception of short periods of time from in mid 2000s. This implies that such a “disconnect” phenomenon exists only temporarily.

<table>
<thead>
<tr>
<th>( cmp_t \rightarrow cpi_t )</th>
<th>( cpi_t \rightarrow cmp_t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.3265*</td>
<td>1.0497</td>
</tr>
<tr>
<td>0.0000</td>
<td>0.3703</td>
</tr>
</tbody>
</table>

Note: The null hypothesis is no granger-causality. Superscript * denotes a rejection at the 5% significance level.

Figure 1. Granger Causality Test: A Recursive Method
Next, I obtain the point estimates for my reduced-form VAR system $B(L)$ and associated standard errors. Results are reported in Table 2. I use 5,000 nonparametric bootstrap simulations to get the standard errors. Interestingly, all coefficients of lagged $cmp_t$ in $cpi_t$ equation are statistically significant at the 5% significance level, whereas no coefficients of lagged $cpi_t$ in $cmp_t$ equation is significant. These findings provide added evidence of substantial role of $cmp_t$ for predicting CPI-based inflation in Canada.

I now use these estimates to obtain one-period ahead out-of-sample forecasts of $cpi_t$ from an unrestricted model (full VAR system) and from a restricted model that uses only lagged values of $cpi_t$. Figure 2 reports predictions errors and cumulative sum of squared residuals of predictions by both models. An eyeball metric clearly shows gains from using the full system. However, the DMW statistic, reported in Table 3 provides rigorous statistic evidence. The DMW statistic rejects the null of equal predictive power at any significance level as expected. This implies that $cmp_t$ is an important leading indicator of $cpi_t$ in the future.

### Table 2. Coefficient Estimates

<table>
<thead>
<tr>
<th></th>
<th>$cpi_t$</th>
<th>$cmp_t$</th>
</tr>
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<tbody>
<tr>
<td>$cpi_{t-1}$</td>
<td>1.2162 (0.0465)*</td>
<td>0.1735 (0.3792)</td>
</tr>
<tr>
<td>$cpi_{t-2}$</td>
<td>0.0498 (0.0739)</td>
<td>-0.2993 (0.5942)</td>
</tr>
<tr>
<td>$cpi_{t-3}$</td>
<td>-0.2684 (0.0462)*</td>
<td>0.1106 (0.3719)</td>
</tr>
<tr>
<td>$cmp_{t-1}$</td>
<td>0.0261 (0.0060)*</td>
<td>1.2396 (0.0478)*</td>
</tr>
<tr>
<td>$cmp_{t-2}$</td>
<td>-0.0389 (0.0096)*</td>
<td>-0.1852 (0.0748)*</td>
</tr>
<tr>
<td>$cmp_{t-3}$</td>
<td>0.0148 (0.0063)*</td>
<td>-0.0723 (0.0483)</td>
</tr>
</tbody>
</table>

Note: Standard errors are reported in parenthesis. Standard errors were obtained by 5,000 nonparametric bootstrap simulations. The number of lags is 3 and chosen by the Bayesian Information Criteria.

### Table 3. Diebold-Mariano-West Statistics

<table>
<thead>
<tr>
<th>DMW</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3.469</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

Note: The DMW statistic is asymptotically normally distributed. The null hypothesis is the equal predictive power.
Lastly, I provide the GIRF estimates in Figure 3. I use 5,000 bootstrap simulations to construct 95% nonparametric confidence intervals from the empirical distribution. It should be noted that $cpi_t$ responds positively to a (one standard deviation) $cmp_t$ shock on impact and stays significantly positive for over a long period of time. On the contrary, $cmp_t$ responds to a $cpi_t$ positively only for a short-period of time and the longer-horizon responses become insignificant at the 5% level.\textsuperscript{6} Similar estimates for a sub-sample (January 1972 to December 2001) are reported in Figure 4, which provides an additional evidence of no substantial change in the empirical link between the two variables.

\textsuperscript{6} Acharya \textit{et al.} (2010) report similar results for the US inflation and the CRB index.
Figure 3. Generalized Impulse Response Function Estimates

Note: 95% confidence bands (dashed lines) were obtained by taking 2.5 and 97.5 percentile responses from 5,000 bootstrap simulations.
V. Concluding Remarks

The present paper evaluates a causal relationship (in Granger causality sense) between commodity price inflation and CPI-based inflation. Using monthly observations from January 1972 to March 2010 for a bivariate VAR model, I find strong evidence for a one-way relationship between them. This implies that the commodity prices serve as a useful early indicator of inflation in Canada.
References


