# Forecasting Inflation using Commodity Price Aggregates*

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## Abstract

This paper examines the usefulness of commodity price aggregates for forecasting CPI and PPI inflation for five major commodity-exporting countries that have adopted inflation targeting monetary policies. We find that the information contained in commodity prices can be helpful in predicting inflation, and that disaggregating to sub-indexes of commodity prices provides superior forecasts than do aggregates. We also examine the out-of-sample forecasting performance. While we find some variation in the out-of-sample predictions, overall the sub-indexes perform better than do the aggregates. They also mostly outperform the random walk, while on average they are comparable to the AR(1) process. The MIDAS approach, using mixed frequency data, does not generate further improvements in out-of-sample forecasts.

*Keywords:* commodity prices, CPI and PPI inflation forecasts, inflation targeting

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## 1. Introduction

The increase in inflation targeting as part of an objective of monetary policy, together with the volatility of asset prices and periodic stock market bubbles, has raised the issue of the proper response of monetary policy to asset market signals. Early simulations by Fuhrer and Moore (1992) argued against responding to asset market prices, suggesting that their weight in the monetary policy rule is equivalent to targeting the real interest rate and leads to a loss in control of inflation. Bernanke and Gertler (1999, 2001) also argued that monetary policy should not respond to changes in asset prices, except insofar as they reflect inflationary expectations. Several reasons are given for this view, including the difficulty of determining whether a change in an asset price is reflecting fundamentals or is a speculative bubble. In contrast, Cecchetti, Genberg, and Wadhani (2002) argue that targeting monetary policy to misalignments in asset prices may improve macroeconomic performance.[1]

More recently, attention has focused to the more specific role of commodity prices as a significant determinant of current and future inflation. This view is articulated by Federal Reserve Chairman, Ben Bernanke, who has suggested that rising prices for globally traded commodities have been a principal aspect of the more recent inflationary experience.[2]

Both the theoretic basis for this relationship and the empirical evidence are mixed. Regarding the theoretical linkage, there is the issue of causality and simultaneity. Do commodity prices affect inflation, or are both responding to general demand conditions, with commodity prices simply adjusting more rapidly? Overall, the empirical evidence linking commodity prices to inflation forecast is ambiguous, being statistically significant for some periods and insignificant in others; see e.g. Blomberg and Harris (1995), Hooker (2002), Stock and Watson (2003). Part of the difficulty is the volatility of commodity prices, making them difficult to predict. More recently Gospodinov and Ng (2010) obtain some success in using the principal

[1] Much of the debate is summarized by Bean (2003), who in discussing the position of the Bank of England, suggests that the bottom line depends upon assumptions one is making about the underlying stochastic structure of asset prices and the information available to the policymaker.

[2] This view was expressed in a Speech to the Federal Reserve Bank of Boston, June 2008.

components of convenience yields in predicting inflation. However, they also find that using the IMF aggregate commodity index has little power in predicting inflation.

Most of the evidence employs United States, and to some extent, United Kingdom data. In this paper we re-examine this question from the viewpoint of small commodity-exporting countries. The motivation for doing so is three-fold. First, commodity prices have a direct link with the real economy. Given the high commodity production dependency in these countries, world commodity price movements have direct effects on production revenues and export earnings, and therefore output, real wages, and other aspects. That is, it is not just the pure financial asset channel addressed in the previous literature. Second, there is the "commodity currency" phenomenon passing through to the consumer price index (CPI): Previous literature has demonstrated that commodity prices play a key role in driving the currency value of major commodity-exporting countries; see e.g. Amano and van Norden (1993), Chen and Rogoff (2003). These responses tend to be very fast and even contemporaneous. To the extent that exchange rates pass through to consumer prices over time, world commodity price movements may have an effect on domestic inflation. Finally, focusing on small economies eliminates the simultaneity issues identified by Gospodinov and Ng (2010). Given these channels, world commodity price movements may help predict future inflation, of either or both of the CPI or producer price index (PPI).

We should emphasize that our focus is on analyzing the empirical relationships between commodities prices and inflation, rather than developing the theoretical linkages. In doing so, we focus on two aspects. First, we determine the extent to which disaggregation of the commodities index improves the accuracy of the predictions over those obtained from the aggregate. Second, we investigate the extent to which using commodity price data available over mixed frequencies can improve the forecasts of quarterly inflation of the two indexes.

We consider five countries: Australia, Canada, Chile, New Zealand, and South Africa. These are all small open economies, heavily commodity dependent, with all having market-determined floating exchange rates. All five countries are inflation targeters, although they do not necessarily target the same price index. For example, Canada looks at core inflation, while the rest tend to focus on CPI inflation. However, these countries specialize in different types of commodity products, ranging from agricultural, mineral, to energy-related goods. The literature so far has treated these countries' exports as one aggregate basket, without explicit recognition of the distinct trends and cycles the prices of different broad commodity categories follow (see e.g. Cashin, McDermott, and Scott, 1999).

In addition to looking at the aggregate index, we also consider broad categories of sub-indexes. Since agricultural markets and energy markets are likely to be driven by different world shocks, allowing different components to have differential impacts is likely to improve the quality of the predictions. Thus, we consider the basic time series properties of seven commodity sub-indexes for these five countries. The indexes include: Metals, Textiles, Raw Industrials, Foodstuffs, Fats & Oils, Livestock and Energy. We first establish that in general they are highly correlated, confirming the significant co-movement obtained in previous studies.[3] This observed co-movement in commodities prices is often assumed to reflect some common underlying trend, possibly due to reaction to the same global demand conditions, and/or that substitutions across products tend help transmit shocks across product groups (e.g. oil and bio-fuels). Accepting this view, we examine whether they have predictive power for the two economic indicators we consider: CPI inflation, and PPI inflation, respectively.

We should note that, although the Central Banks have their own country-specific commodity price indexes [see e.g. the website of the Bank of Canada and the Reserve Bank of Australia], we prefer to utilize market information that is more readily available to the public (CRB index). There are several reasons for this. First, our interest in this question is motivated not only from the perspective of the policy maker, but also from the standpoint of the public. Specifically, since these indexes are observable on a daily basis they can be used in real time, and enable us to examine the effectiveness of using mixed data frequency forecasts. Moreover,

[3] See e.g. Pindyk and Rotemberg (1980), Deb, Trivedi, and Varangis (1996). Ai, Chatrath, and Song, (2006). However, we do not examine the issue of "excess co-movement" investigated in some of these studies.

these indexes are chosen from markets that are especially sensitive to changes in global economic conditions and as such may serve as early indicators for gauging future economic conditions and likely policy actions.

We find that both the commodity price series and the CPI and PPI contain unit roots, and while the commodity prices do not appear to have any linear trends, both the CPI and PPI series do. We also find evidence of a single cointegrating vector between the commodity price series and the CPI or PPI using the methodology of Johansen (1991).

We first examine in-sample predictability by regressing the two inflation indicators (CPI inflation, and PPI inflation) one quarter ahead on the seven sub-commodities price indexes, plus the error correction term based on the cointegrating relationship for the five countries. We present the results for a first order vector error correction model (VECM(1)) , although as part of our robustness check we also estimated VECM(2)s. The main general finding we obtain is a strong in-sample Granger causality effect from commodity price changes to both CPI and PPI inflation. In all cases, some sub-indexes have predictive content, energy being almost uniformly significant in predicting both CPI and PPI inflation. Lagged inflation is often, but not always, the most important factor. The error correction term is also highly significant in most cases, although its coefficient is small, implying a very gradual adjustment toward the long-run trend.

As part of a robustness check we do several things. First, we explore the effect of currency-denomination, that is whether commodity price movements in the world market priced in US dollars directly has effect, or translating them to domestic currency provides a stronger signal (leaving structural exploration and interpretation to a separate study). Overall, the results remain generally unchanged. Second, we estimate the VECM(1) equations using two alternative aggregate commodity price indexes. Overall, neither aggregate index does well in predicting aggregate CPI inflation, although both perform credibly in predicting PPI inflation, with both measures yielding qualitatively similar results. Thus, our results suggest that the gains from disaggregation are greater in predicting CPI inflation than they are in predicting PPI inflation.

Third, in light of the high correlation among the commodity price sub-indexes, we reduce the dimensionality of the regressors in the VCM by adopting the Least Angle Regressions (LARS) procedure pioneered by Efron et al (2004). This is a computationally efficient stagewise regression procedure that selects the appropriate regressors so as to minimize the prediction error as measured by a $C_p$ statistic. This approach yields results that are generally consistent with the full VECM(1) regressions, confirming the general importance of sub indexes.

After confirming the in-sample predictive ability of commodity prices for inflation, we examine their out-of-sample forecasting performance. In doing so, we compare the predictions using the sub-indexes to those obtained using two benchmark univariate predicting schemes, namely (i) a random walk process and (ii) an AR(1) process, We exclude the Phillips Curve as one of the benchmark inflation forecasting schemes. This is because evidence by Atkeson and Ohanian (2001), and more recently by Stock and Watson (2007), suggests that it is not particularly successful in forecasting inflation, being out-performed by standard autoregressive models.

In evaluating the out-of-sample forecasting performance we employ two classes of models. The first is the conventional out-of-sample prediction parallel to the in-sample prediction where we use quarterly commodity prices to predict quarterly inflation. The second uses mixed-sampling data, the so-called "MIDAS" approach of Ghysels et al (2002). This procedure uses information contained in higher frequency commodity price data (e.g. daily) data to help forecast inflation observed at lower frequencies (e.g. quarterly). While there is some variation in the out-of-sample predictions across the five economies, overall the sub-indexes perform better than do the aggregates. In addition, the sub-indexes mostly outperform the random walk, while on average they are generally comparable to the predictions from the AR(1) process. Finally, overall the MIDAS approach does not generate substantial improvement.

The remainder of the paper proceeds as follows. Section 2 discusses some of the background issues in greater detail, including a discussion of the data. Section 3 describes the in-sample predictive ability of the commodity sub-indexes, while Section 4 considers their out-of-sample forecasting performance. Section 5 concludes.

## 2. Background and Data Descriptions

### 2.1 The Inflation-Commodity Price Linkage in Commodity Currency Economies

As shown in Table A.1, Australia, Canada, Chile, New Zealand, and South Africa produce a variety of primary commodity products, ranging from agricultural and minerals to energy-related goods. Together, these commodities represent between a quarter and well over a half of each of these countries' total export earnings. Our study focuses on these five small commodity-exporting economies because each has a relatively long history of operating under well-functioning open markets, with floating exchange rates and transparent monetary policies. These characteristics allow us to interpret our findings, positive or negative, as reflecting market transmission mechanism, rather than active government management.

Previous studies have documented the strong connection between global commodity price movements and these countries exchange rates, emphasizing structural linkages through the income effect and the terms of trade channel.[4] Empirically, these countries' exchange rates exhibit a strong and robust response to global commodity price fluctuations; their currencies are thus referred to as "commodity currencies".[5] This phenomenon motivates us to determine further, whether the linkage may help predict inflation.[6]

These earlier studies rely mostly on a pre-constructed country-specific index published by either their central banks or other organizations, which are not necessarily available to the public in real time, especially at high frequency.[7] We use indexes that are observable daily,

[4] See discussions in Chen, Rogoff, and Rossi, (2010).
[5] See Chen and Rogoff (2003) and references therein.
[6] If exchange rate pass-through is gradual, one would see predictability from commodity prices to inflation, for example. Note, however, that we do not formally test any specific structural channel.
[7] For example, Australia, Canada and New Zealand all publish these indexes on a monthly basis.

which has the advantage of enabling us to test the extent to which daily information may provide information with respect to quarterly inflation. This issue is addressed in detail in Section 4.2.

As is evident from Table A1, these countries produce a variety of commodity products that have very different production structures (e.g. sheep vs. coal) and face different market conditions within the global economy. This suggests that different types of products have differential impacts on the economy and its inflation response. In addition, because of differences in the degree of co-movements across categories, sub-indexes may imply different weights. We explore this by looking at sub-indexes of world commodity prices, which are representative major products for the world commodity markets, although not necessarily specific to these countries.[8]

## 2.2 Data Descriptions

We use quarterly data between 1983Q1-2010Q4 to test whether the seven commodity sub-indexes discussed below can predict CPI-inflation and PPI-inflation a quarter ahead in the five commodity currency countries. The quarterly price level data we use are from the IMF's International Financial Statistics. These IFS series are seasonally unadjusted, and inflation is measured as the log-difference of the price level, quoted at an annual rate.[9]

The commodity sub-indexes we employ are collected from two different sources and are available at the daily frequency. Six are compiled by the Commodity Research Bureau (CRB), and in addition, we use the S&P GSCI Energy Index from Global Financial Data.[10] Thus the seven sub-indexes we use and their components are as follows:[11]

[8] Over the past few decades, all of these countries experienced major changes in policy regimes and market conditions. These include their adoption of inflation targeting in the 1990s, the establishment of Intercontinental Exchange and the passing of the Commodity Futures Modernization Act of 2000 in the United States, and the subsequent entrance of pension funds and other investors into commodity futures index trading. We therefore pay special attention to the possibility of structural breaks in our analyses.

[9] PPI/WPI is line number: 63…ZF and CPI 64...ZF, except for Chilean where 64A..ZF is used instead as 64...ZF is unavailable. Australia and New Zealand only have quarterly CPI.

[10] The S&P index has a .997 correlation with the Reuter's Energy Index, which ended in 2008.

[11] Since May 1981, the CRB began calculating its index on a daily basis. Twenty-two commodities are combined into an 'All Commodities' grouping, with two major subdivisions (Raw Industrials, and Foodstuffs) and four smaller

- *Foodstuffs*: Hogs, steers, lard, butter, soybean oil, cocoa, corn, Kansas City wheat, Minneapolis wheat, and sugar (40.9%).
- *Raw Industrials*: Hides, tallow, copper scrap, lead scrap, steel scrap, zinc, tin, burlap, cotton, print cloth, wool tops, rosin, and rubber. (59.1%)
- *Livestock and Products*: Hides, hogs, lard, steers, and tallow.
- *Metals*: Copper scrap, lead scrap, steel scrap, tin, and zinc. (On January 2, 2003, the index was changed so that Copper, electrolytic cathodes, was replaced with Copper, scrap #2 wire and Zinc, prime western, was replaced with Zinc, special high grade.)
- *Textiles and Fibers*: Burlap, cotton, print cloth, and wool tops.
- *Fats and Oils*: Butter, cottonseed oil, lard, and tallow.
- *S&P GSCI Energy:* Crude oil (Brent and WTI), natural gas, heating oil, and gasoline, with crude oil accounting for roughly 70% of the index.

From these descriptions we see that there is some overlap in coverage across some of these sun-indexes, as a result of which they are likely to move closely together.

## 2.3. Summary Statistics

Tables 1 and 2 report relevant summary statistics. Unit root tests confirm that these variables are I(1), so we use first differenced log variables.[12] From these tables the following observations can be made:

> **Table 1A:** The mean growth rates, as well as the volatility of the major commodity price sub-indexes vary substantially across the different groups. The coefficients of variations (CV) range between 18.5 for energy to just over 7 for raw industrial material and metals.

groups (Metals, Textiles and Fibers, Livestock and Products, and Fats and Oils). The groupings are non mutually exclusive. *(Source: http://www.crbtrader.com/crbindex/spot_current.asp).*

[12] The Elliott, Rothenberg, and Stock (1996) modified version of the Dickey-Fuller test confirms that the level variables (in logs) are I(1), while the unit root null is strongly rejected for the first-differenced variables.

**Table 1B:** There is strong positive correlation between most commodity sub-index inflation, supporting our earlier observation of "co-movement". Note, however, that price movements of textiles do not seem to be significantly correlated (at least contemporaneously) with those of energy and foodstuffs. We do not explore whether the co-movement is justified by fundamentals or whether it is reflecting herding behavior. However, the amount of correlation present is sufficient to justify reducing the dimensionality of the regressors, which we do using least angle regression techniques discussed in Section 3.3.

**Table 2A:** Both the growth rate of the CPI and PPI, and their respective volatilities, exhibit substantial variation across the five economies.

**Table 2B:** CPI and PPI are highly correlated, as to be expected. The correlation between commodity sub-index inflation is not as strong with either CPI or PPI inflation. For example, no such correlations are significant in the case of either Australia or NZ. Contemporaneous correlations are mostly positive with inflation, but can be negative, such as in the case of Chile. This possibly reflects issues such as the pass-through dynamics from exchange rate, or features of the production structure.

Finally, we note that these are all contemporaneous correlations. In Section 3 below we explore whether elements of these co-movements may be useful in forecasting inflation.

## 2.4. Cointegration

A number of authors have investigated cointegration between some measure of commodity prices and CPI levels; see e.g., Baillie (1989), Kugler (1991), Pecchenino (1992), Furlong and Ingenito (1996), Mahdavi and Zhou (1997) and Belke et al (2009). Early studies using residual-based tests for cointegration typically did not find cointegration whereas later studies using the methodology of Johansen (1991) generally found cointegration. To our knowledge no previous study has considered cointegration between disaggregated commodity price indexes and CPI or PPI prices. We use Johansen's methodology to determine if there are any cointegrating relationships (common trends) among our collection of log price series. The existence of cointegration between consumer/produce prices and commodity prices allows for another channel, through an error correction model, by which commodity prices can be used to predict inflation. Our analysis is based on the VAR(p) model

$$Y_t = \Phi D_t + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \varepsilon_t, \tag{1}$$

where $Y_t$ is an $8 \times 1$ vector with first element either log CPI or log PPI for a given country and remaining elements log commodity prices, $D_t$ contains deterministic terms, and $\varepsilon_t$ satisfies $E[\varepsilon_t] = 0,\ E[\varepsilon_t \varepsilon_s'] = 0$ for $t \neq s$, and $E[\varepsilon_t \varepsilon_s'] = \Sigma$ for $t = s$. For all countries, a VAR(2) is selected by the AIC as the best fitting model. Visual inspection of the price series show consumer and producer prices exhibit clear upward trends whereas the commodity prices do not. Accordingly, we test for cointegration imposing the restriction that the cointegrating relations contain a linear trend.

The results of the cointegration tests are summarized in Tables 3A and 3B. For all countries, the Johansen trace test finds at least one cointegrating vector at the 5% significance level and sometimes two[13]. Given the ordering of the variables in $Y_t$, the first cointegrating vector can be interpreted as a long-run equilibrium relationship between consumer or producer prices and commodity prices. Tables 3A and 3B report the maximum likelihood estimates of the first cointegrating vector for each country normalized on consumer and producer prices, respectively. The cointegrating vectors are somewhat hard to interpret, which could be due to high correlation among some of the commodity price indexes and the presence of a linear trend. Tables 4A and 4B give the estimated error correction (EC) models for CPI and PPI inflation, respectively, based on cointegrated VAR(2) models with a single cointegrating vector. For all countries, the EC term

[13] We also tested for cointegration using just the commodity prices and could not reject the null of no cointegrating vectors at the 1% significance level.

is significant at the 5% level. This result indicates that the deviation from the long-run trend defined by the estimated cointegrating vector has some predictive power for future inflation. However, because the magnitudes of the estimated speed of adjustment coefficients are small, the predictive power of the EC terms is not expected to be large. In the next section, we summarize the in-sample predictive performance of commodity prices for inflation based on EC and other models.

## 3. Can Commodity Prices Predict Inflation?

In this section we explore in-sample predictive regressions using information contained in the commodity price indexes, and controlling for lagged inflation. We exclude other fundamental factors based on alternative structural models of price adjustments, the most common being the output gap variable from the Phillips' curve. Our objective is to determine whether or not information obtained from global commodity markets, which to a large extent are exogenous to these small open economies, is in fact useful in complementing forecast models based on real, structural factors.

### 3.1 In-Sample Predictive Regressions: VECM

We begin by considering whether information contained in the current commodity sub-indexes can help predict inflation rates one quarter ahead. We do so by employing the standard in-sample linear predictive regression equation, as below, for each of the five countries:

$$\pi_{t+1} = c + \alpha EC_t + \rho \pi_t + \sum_i \psi_i dlP_t^i + \varepsilon_{t+1} \tag{2}$$

where $\pi$ denotes either the CPI-inflation rate ($\pi^{CPI}$) or the PPI inflation rate ($\pi^{PPI}$), $EC_t$ is the error-correction term from the cointegrated VAR(2) with a restricted trend, and $dlP^i$ are the changes in the logarithms of the seven price indexes of world commodity aggregates, all expressed as annual rates. We note that eq. (2) is based on a VECM(1) and that we present results below based on this specification. But the general results are robust to a variety of specifications, including VECM(2), VAR(1), VAR(2) where the EC term is omitted, and other predictive specifications with different lag lengths (see ONLINE appendix).

The basic results are reported in Tables 4A-B. All standard error estimates are corrected for heteroskedasticity and serial correlation. In addition to individual coefficient estimates, the tables report the adjusted $R^2$ with and without the inclusion of the lagged inflation term. In addition, we conducted Wald tests for the joint significance of the 7 indexes and the p-values (available in an Appendix available on line) are consistently below 10%.

Turning first to the CPI inflation estimates in Table 4A, a number of results are worth highlighting. First, the difference between the $R^2$, with and without lagged inflation, suggests that a significant amount of the explanatory power is coming from the autoregressive structure, with the one exception being Chile. Nevertheless, the sub-indexes are still important. Indeed, each sub-index is significant for at least one country, and Energy is significant (at least at the 10% level) for all five.

In terms of the individual countries, Australian CPI inflation depends on four indexes (Livestock, Energy, Foodstuffs, and Fats and oils), while in addition to these four indexes, Chilean CPI inflation also depends upon Textiles. South Africa also depends upon five sub-indexes (Livestock, Energy, Raw Industrials, Textiles, and Metals). In contrast, the only sub-index weakly significant for Canada is Energy, while for New Zealand Textiles is also significant.

With respect to the PPI inflation results presented in Table 4B, we see some differences in the patterns. First, the adjusted $R^2$ are uniformly lower than for CPI, with generally less explanatory power being due to the autoregressive component, the exception to this again being Chile. Again, energy is the overall most significant sub-index. In addition, PPI inflation is dependent upon fewer sub-indexes than is CPI, this reflecting the specialization of production. In the case of Chile, New Zealand, and South Africa, Energy is the only significant sub-index, while in the case of Australia Fats and Oils is also marginally significant. Canadian PPI inflation, in contrast, depends upon foodstuffs and Livestock.

We have also estimated the same regressions using a VECM(2) specification. These results are available on request from the authors. The results are generally similar, although inevitably there are some differences. In the case of CPI inflation, the adjusted $R^2$ exhibits the same overall pattern as for the VECM(1) case. Contemporaneous energy remains uniformly significant across the five economies, while in the case of Canada, lagged energy is significant as well. All sub-indexes are significant for at least one country. South Africa, which for the VECM(1) specification had five significant sub-indexes, now has only two (Livestock and Energy), while in contrast, Australia now finds six sub-indexes to be significant, and a similar case applies to Canada. A similar pattern applies to the PPI. In the case of Australia, all 7 of the sub-indexes are significant in some form (either contemporaneous or lag), resulting in an increase in the $R^2$ from 0.46 to 0.57. In contrast, no sub-index is significant for South Africa.

Given that these regressors are highly correlated, we view the results here as showing evidence that commodity indexes are collectively useful for predicting inflation. This dynamic connection is consistent with theories of price rigidity and gradual exchange rate pass-through. Clearly, different specifications are appropriate for the different economies.

### 3.2. Alternative Predictors: Home-Currency-Based Sub-Indexes & Aggregate Indexes

Given the nature of the results summarized in Table 4, it is necessary to undertake some robustness checks. First, we recall that the sub-indexes summarized in Table 4 measure the changes expressed in US dollars. Tables 5A and 5B report the analogous equations in the case where the sub-indexes for the commodity prices have been converted into domestic currency. This has been done by using the end-of-period spot market exchange rate. Comparing Tables 5 with Tables 4, the picture is pretty much the same. There are small switches, the most significant being that New Zealand has a lot more significant sub-indexes in with the sub-indexes measures in the home currency than when they are measured in US dollars.

As a second robustness check, we consider using an aggregate index of commodity prices to predict inflation. To examine this question we modify the basic equation (2) to

$$\pi_{t+1} = c + \alpha EC_t^{Agg} + \rho\pi_t + \psi dlP_t^{Agg} + \varepsilon_{t+1} \tag{3}$$

where $dlP_t^{Agg}$ is the change in the log aggregate index and $EC_t^{Agg}$ is the error correction term from the cointegration model for CPI and PPI and the aggregate index. We employ two such aggregate measures. The first is an aggregate spot series (from CRB), which we denote by $dlP_t^{Agg-Spot}$. The other is called Reuters-Jefferies/CRB index, which by incorporating some information on futures prices is, not pure spot. We denote this by $dlP_t^{Agg-CRB}$. The estimates of (3) for CPI and PPI inflation, corresponding to these two aggregate indexes are reported in Tables 6A-D.

Looking first at the results for the CPI inflation, we see that the results are clearly inferior to those using the sub-indexes. In no case is $dlP_t^{Agg-Spot}$ significant, while $dlP_t^{Agg-CRB}$ is significant only in the case of Australia and Canada. In contrast, both aggregate indexes perform much better in explaining the PPI inflation, being highly significant in all cases, except for Chile, where they are significant at the 10% level.

Overall, we view these results as confirming that there are substantial gains to be made from using sub-indexes to forecast CPI inflation. With regard to PPI inflation, the gains are less dramatic, but still worthwhile. Not only are there marginal improvements in explanatory power, but also some insights into structural differences.

### 3.3. Least Angle Regressions

As stated earlier, we choose to use the seven sub- indexes that are observable directly by the market, some of which cover overlapping product sets. As a way to select a parsimonious and efficient set of predictors for inflation, we next employ the least angle regressions (LARS) due to Efron, Hastie, Johnstone, and Tibshirani (2004). Similar to Lasso and forward-stagewise regressions, LARS as a model-selection algorithm is relatively fast and easy to implement, balancing goodness-of-fit and parsimony; see Efron et al. (2004) for a full description of the algorithm and its relation to other alternatives. The LARS procedure provides a natural way to judge the relative importance of the variables for explaining inflation that is superior to the traditional stepwise regression.

LARS starts by setting the coefficients on all predictors to zero, and adds in variables step-by-step based on their correlation with the residuals of the previous model. To select the shrinkage level (the number of variables to include), the LARS procedure computes an estimate of the prediction error, $C_p$. While there are other alternatives such as the cross-validation approach, the minimized $C_p$ criterion is computationally simple, and can deliver generally good properties; see Madigan and Ridgeway (2004). As a robustness test, we include the seven sub-indexes into LARS, together with lagged inflation and also the error-correction term, and see if any of these sub-indexes are selected to be included in the specifications producing the minimum $C_p$.

Tables 7A and 7B show the LARS results for CPI- and PPI-inflation.[14] We report regression specifications chosen by the minimized $C_p$ statistics and we report the $R^2$'s for the regression after the inclusion of the particular variable. For example, we see that in the CPI regression for Australia, the first variable selected is lagged CPI inflation, $\pi_t^{CPI}$, since it has the smallest $R^2$ (0.10) amongst the reported numbers. The next variable entering is EC, followed by Energy, Livestock, and Metal, producing a final $R^2$ of 0.438. Regressions that include additional variables that currently have no reported coefficients deliver larger $C_p$ statistics, hence are not selected. For CPI inflation, lagged inflation is consistently selected first (with the exception of Chile) followed by the EC term. However, for PPI inflation, lagged inflation is not the first variable selected (the one with the lowest $R^2$) for Australia and Canada. In all cases, at least one, and up to six, commodity sub-indexes are selected in addition to lagged inflation and the EC term. The incremental R-squares from the sub-indexes are often non- negligible either.

[14] We used both the R package lars and Stata to run the LARS regressions reported here.

Energy remains the most important sub-index in explaining CPI inflation, being significant in all countries except for New Zealand, where textiles continues to be important. Likewise, several sub-indexes continue to be important in explaining CPI inflation in Canada, Chile, and South Africa. The importance of Energy in explaining PPI inflation is again confirmed in Table 7B.

We take these results as additional confirmation that world commodity price sub-indexes have predictive content for subsequent CPI and PPI inflation a quarter later.

## 4. Out-of-Sample Forecasts

This section analyzes the extent to which the commodity sub-indexes can help forecast inflation rates out-of-sample. We compare the forecast performances of the various commodity price-based models with two time-series benchmarks: the random walk (RW) and the AR(1) specifications, both of which are commonly used in the literature; see Atkeson and Ohanion (2001) and Stock and Watson (2007). Given the prevalence of parameter instability found in the general inflation forecast literature, we adopt the rolling out-of-sample scheme (rather than a recursive one) as it is more robust to the presence of time-varying parameters and requires no explicit assumption as to the nature of the time variation in the data. We use a rolling window with size equal to 68 quarters to estimate the model parameters and generate one-quarter ahead forecasts recursively (what we call "model forecasts"), yielding 40 forecasts.[15] (The results are very similar with other reasonable window sizes).

For each of CPI- and PPI- inflation in the five countries, we compare the forecast errors from the commodity-price-based models against those from the two time-series benchmark models, RW and AR(1), which we specify in the form

[15] Given that the rolling forecast procedure is quite standard in the literature, we do not describe it here but refer interested readers to Clark and McCracken (2001), Clark and West (2006, 2007) for a theoretical exposition, and Engel, Mark, West (2007), and Chen, Rogoff, and Rossi (2010) for applications. There are no rigorous guidelines for how best to select window size and our choice of 68, while reasonable and generally within the conventional size, given the sample size, is nevertheless arbitrary. We have experimented with different window sizes ranging from 60-82 and our results not very different.

| | | |
|---|---|---|
| RW | $E_t(\pi_{t+1}) = \pi_t$ | (4a) |
| AR(1) | $E_t(\pi_{t+1}) = c + \rho\pi_t$ | (4b) |

In doing so, we employ two forms of the model. The first type is the out-of-sample specification, parallel to the in-sample analyses we have conducted in the earlier sections; i.e. matched frequency predictors are used. These include the following (as designated in Table 8)

| | | |
|---|---|---|
| AR + Agg Index: | $E_t(\pi_{t+1}) = c + \rho\pi_t + \psi dlP_t^{Agg-Spot}$ | (5a) |
| Agg Index: | $E_t(\pi_{t+1}) = c + \psi dlP_t^{Agg-Spot}$ | (5b) |
| SubIndex: | $E_t(\pi_{t+1}) = c + \sum_i \psi_i dlP_t^i$ | (5c) |

In addition, we also explore the forecast combination, consisting of the simple average of the 7 univariate forecasts: $E_t(\pi_{t+1}^i) = c_i + \psi_i dlP_t^i$ for each *i*, together with the AR. We denote this by FC: AR+7 SubIndexes in Table 8.[16]

The second group of model-based forecasts use mixed-sampling data ("MIDAS" of Ghysels et al, 2002 and Andreaou et al, 2010a). Mixed frequency sampling models aim to extract information content from high frequency indicators to help forecast target variables observed at lower frequency.[17] We use the OLS-based generalized autoregressive distributed lag (GADL) model developed in Chen and Tsay (2011) to examine whether daily information in commodity price aggregates may help forecast quarterly inflation.[18] The basic motivation and setup of GADL merges the pioneering work on NLS-MIDAS by Ghysels et al. (2002) and the classic work of Almon (1965) of approximating distributed lag (ADL) coefficients with simple

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[16] Note that we have not included the EC terms from the rolling forecasts. The main reason for this is that the EC term always has a tiny coefficient, indicating very gradual adjustment, and it not likely to play a significaint role in the next quarter forecast.
[17] The chapter in Oxford Handbook on Economic Forecasting by Andreou et al. (2010b) provides a good survey on how these models have been used extensively to forecast various macroeconomic indicators as well as financial series.
[18] GADL is a simpler method to run the so-called "MIDAS" regressions pioneered by Ghysels et al (2002). See Chen and Tsay (2011) for a detailed comparisons and discussion.

low-order polynomials. GADL inherits the ease of estimation from the ADL literature and it delivers estimates for the "aggregate impact" parameters relevant in the NLS-MIDAS literature.

We run the following GADL forecast equations (again, for rolling window size = 68)

$$E_t(\pi_{t+1}^{CPI}) = c + \sum_i \psi_i W_i(L^{1/m}, \theta_i) dlP_t^{i,(m)} \text{ for selected i from 7 sub-indexes} \tag{6}$$

where $W_i(L^{1/m}, \theta_i) = \sum_{k=1}^{K} b_i(k;\theta_i) L^{(k-1)/m}$

Here $m$ and $dlP_t^{i,(m)}$ denote higher sampling frequency (in our case daily) and observations, which we index with $k = 1$ to $K$. We present results based on three choices of $K = 14, 34, 54$, indicating using data of a few weeks, over a month, to almost the full quarter. $L^{1/m}$ is the lag operator in frequency-m space, and $b_i(k;\theta_i)$ is the weight on each of the $K$ lagged daily commodity price change. As in Chen and Tsay (2011), we parameterize these weighting coefficients with a ($K \times n$) Vandermonde matrix, as in the traditional ADL literature of Almon (1965), where $n-1$ denotes the degree of the polynominal which the lagged coefficients are assumed to satisfy. The estimation dimension of eq (6) above is thus reduced from *1+iK* to *1+in*. We choose n = 3 in our forecast analyses below. Given our small sample size in the rolling estimation procedures (window size = 68), we note that using all 7 indexes would still stretch the degrees of freedom. We thus do multi-variate GADL regressions involving only the sub-indexes for livestock, energy, foodstuffs and fats & oils, as these were typically the most statistically significant indexes in the VECM(1) equations for each country . These equations are run with and without the AR and are denoted in Table 8 by AR+GADL-MIDAS and GADL-MIDAS, respectively.

We then complement these results by doing Forecast Combination; that is taking a simple average of 7 univariate forecasts

$$E_t(\pi_{t+1}^{i}) = c_i + \psi_i W_i(L^{1/m}, \theta_i) dlP_t^{i,(m)} \tag{7}$$

for each *i* and AR, which we denote by FC: AR +7 GADL-MIDAS.

We find that in terms of RMSEs, models based on commodity price indexes produce mostly smaller RMSEs than does the RW, the notable exception being in forecasting CPI inflation for Chile and South Africa. But they seldom produce significantly smaller RMSEs than does the AR(1) model, a result that is consistent with forecasting inflation in the US, for example. The fact that it is easy to forecast better than RW, but hard to forecast better than AR is not surprising, given that we already observe that the additional predictive power of the sub-indexes in-sample regressions are not very large. However, we should note that we have more than a 10% improvement for forecasting Australian CPI over AR, and a 5% improvement in a couple other cases. Overall, the introduction of mixed-frequency data does not lead to significant improvement over the conventional approach, except in the case of South Africa, when it is still outperformed by the AR forecasts.

In summary, we see that overall, world commodity markets do have differential impacts on the key price variables in these five commodity exporting economies. For both CPI and PPI inflation rates, however, commodity indexes, whether the specific selected individual ones or their collective main principal components, can help provide better forecast for inflation rates a quarter ahead. We certainly could explore alternatives that may improve the forecast performance further, such as by looking more specifically into possible structural breaks and incorporating this information into the forecast model, or by combining these forecast equations using market-based indicators with structural variables such as the output gap or unemployment rates from the Phillips' curve.

## 5. Conclusions

With central banks increasingly basing their monetary policies on some form of Taylor rule in which the nominal interest rate is adjusted in response to some measure of inflationary pressures, the question is raised to what degree should the response incorporate changes in asset prices. The consensus view seems to be that these prices should be taken into account only to the extent that they reflect underlying inflationary expectations, and therefore may be reasonable predictors of future inflation. Starting from this viewpoint, this paper has examined the information contained in sub-indexes of commodity prices, using data for five small commodity-dependent economies. The motivation for this choice is that commodity prices are asset prices, which such economies can take as exogenously given, thereby avoiding issues involving simultaneity which would naturally arise in large economies such as the United States. In addition, by influencing the choice of production techniques and consumption choices, commodity prices have a direct link to the real economy.[19]

The overall message of this paper is the following. Our empirical estimates do suggest that the information contained in commodity prices can be helpful in predicting both CPI and PPI inflation. We find this to be encouraging, since the objective of monetary policy is usually directed toward targeting inflation. Moreover, since different countries are specialized in different commodity groups, the prices of which although co-moving also follow different dynamic paths, our findings suggest that disaggregating to sub-indexes is helpful as well.

Having established that the sub-indexes of commodity prices do indeed contain information that may be useful in predicting inflation and that therefore may form an appropriate component of monetary policy the natural next step is to add commodity prices to the monetary policy rule itself. One can then introduce this augmented policy rule into a complete calibrated structural model of a small open economy and examine the extent to which this additional information does in fact improve the effectiveness of monetary policy in terms of enhancing macroeconomic performance and promoting price stability.

[19] The most widely studied aspect of this element involves the role of oil/energy as an intermediate input, on which an extensive literature exists.

**Table 1**

**A. Summary Statistics for Quarterly Changes in Commodity Sub-Indexes ( $dlP_t^i$ )**

1983Q1-2010Q4 ; Annual Rate

| | $dlP_t^{Livestock}$ | $dlP_t^{Energy}$ | $dlP_t^{Foodstuff}$ | $dlP_t^{Raw\ Ind.}$ | $dlP_t^{Textiles}$ | $dlP_t^{Metal}$ | $dlP_t^{Fats\,\&\,Oils}$ |
|---|---|---|---|---|---|---|---|
| Mean | 2.43 | 3.97 | 2.22 | 3.30 | 1.85 | 5.57 | 2.81 |
| St. Dev | 35.0 | 73.5 | 26.3 | 23.5 | 19.0 | 40.3 | 45.3 |

**B. Bi-variate Correlations for Quarterly Changes in Commodity Sub-Indexes ( $dlP_t^i$ )**

| $i$ = | $dlP_t^{Livestock}$ | $dlP_t^{Energy}$ | $dlP_t^{Foodstuff}$ | $dlP_t^{Raw\ Ind.}$ | $dlP_t^{Textiles}$ | $dlP_t^{Metal}$ | $dlP_t^{Fats\,\&\,Oils}$ |
|---|---|---|---|---|---|---|---|
| $dlP_t^{Livestock}$ | 1.00 | | | | | | |
| | (---) | | | | | | |
| $dlP_t^{Energy}$ | 0.47 | 1.00 | | | | | |
| | (0.00) | (---) | | | | | |
| $dlP_t^{Foodstuff}$ | 0.66 | 0.26 | 1.00 | | | | |
| | (0.00) | (0.01) | (---) | | | | |
| $dlP_t^{Raw\ Ind.}$ | 0.66 | 0.46 | 0.50 | 1.00 | | | |
| | (0.00) | (0.00) | (0.00) | (---) | | | |
| $dlP_t^{Textiles}$ | 0.27 | 0.16 | 0.21 | 0.59 | 1.00 | | |
| | (0.01) | (0.09) | (0.03) | (0.00) | (---) | | |
| $dlP_t^{Metal}$ | 0.51 | 0.42 | 0.47 | 0.91 | 0.34 | 1.00 | |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (---) | |
| $dlP_t^{Fats\,\&\,Oils}$ | 0.80 | 0.31 | 0.79 | 0.58 | 0.21 | 0.48 | 1.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.02) | (0.00) | (---) |

Note: Sample period: 1983Q1 - 2010Q4 (n = 112). Numbers in the parentheses are the p-values for the null hypothesis that the correlation is zero.

**Table 2A: Country-Specific Quarterly Inflation Rates**

1983Q1-2010Q3; Annual Rate

| | Australia | Canada | Chile | New Zealand | S. Africa |
|---|---|---|---|---|---|
| $\pi_t^{CPI}$ | | | | | |
| Mean | 3.81 | 2.62 | 9.74 | 3.96 | 8.80 |
| Std. Dev. | 3.15 | 2.37 | 9.07 | 4.79 | 6.30 |
| $\pi_t^{PPI}$ | | | | | |
| Mean | 3.21 | 1.88 | 10.29 | 3.62 | 8.65 |
| Std. Dev. | 6.30 | 4.91 | 14.00 | 5.60 | 6.43 |

**Table 2B: Correlations b/w Inflations, & World Commodity Sub-Index Inflation ( $dlP_t^i$ )**

| | Australia | | Canada | | Chile | | New Zealand | | South Africa | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\pi_t^{CPI}$ | $\pi_t^{PPI}$ | $\pi_t^{CPI}$ | $\pi_t^{PPI}$ | $\pi_t^{CPI}$ | $\pi_t^{PPI}$ | $\pi_t^{CPI}$ | $\pi_t^{PPI}$ | $\pi_t^{CPI}$ | $\pi_t^{PPI}$ |
| $\pi_t^{CPI}$ | 1 | | 1 | | 1 | | 1 | | 1 | |
| | (--) | | (--) | | (--) | | (--) | | (--) | |
| $\pi_t^{PPI}$ | **0.52** | 1 | **0.43** | 1 | **0.69** | 1 | **0.56** | 1 | **0.61** | 1 |
| | **(0.00)** | (--) | **(0.00)** | (--) | **(0.00)** | (--) | **(0.00)** | (--) | **(0.00)** | (--) |
| $dlP_t^{Livestock}$ | 0.07 | 0.13 | **0.33** | **0.36** | -0.15 | **-0.19** | 0.02 | 0.07 | -0.06 | **0.28** |
| | (0.49) | (0.17) | **(0.00)** | **(0.00)** | (0.11) | **(0.04)** | (0.88) | (0.44) | (0.55) | **(0.00)** |
| $dlP_t^{Energy}$ | -0.03 | 0.12 | 0.11 | **0.18** | -0.14 | -0.12 | 0.07 | 0.06 | -0.12 | 0.06 |
| | (0.79) | (0.22) | (0.26) | **(0.06)** | (0.15) | (0.22) | (0.46) | (0.50) | (0.22) | (0.55) |
| $dlP_t^{Foodstuff}$ | 0.03 | 0.05 | **0.23** | **0.23** | -0.14 | **-0.23** | -0.09 | -0.06 | -0.10 | **0.17** |
| | (0.76) | (0.57) | **(0.02)** | **(0.01)** | (0.14) | **(0.02)** | (0.37) | (0.55) | (0.30) | **(0.07)** |
| $dlP_t^{Raw\ Ind.}$ | 0.07 | 0.06 | **0.16** | **0.19** | **-0.20** | **-0.33** | 0.07 | -0.08 | -0.13 | 0.05 |
| | (0.41) | (0.55) | **(0.10)** | **(0.05)** | **(0.03)** | **(0.00)** | (0.47) | (0.38) | (0.18) | (0.62) |
| $dlP_t^{Textiles}$ | 0.06 | -0.06 | 0.02 | 0.00 | -0.08 | **-0.18** | 0.11 | -0.06 | -0.11 | -0.03 |
| | (0.53) | (0.54) | (0.81) | (0.99) | (0.38) | **(0.06)** | (0.24) | (0.50) | (0.24) | (0.76) |
| $dlP_t^{Metal}$ | 0.02 | 0.04 | 0.09 | 0.12 | **-0.21** | **-0.34** | 0.03 | -0.13 | -0.16 | -0.04 |
| | (0.84) | (0.65) | (0.34) | (0.21) | **(0.03)** | **(0.00)** | (0.79) | (0.16) | (0.10) | (0.69) |
| $dlP_t^{Fats\ \&\ Oils}$ | 0.01 | 0.05 | **0.26** | **0.29** | -0.14 | -0.14 | 0.00 | 0.02 | -0.03 | **0.21** |
| | (0.92) | (0.61) | **(0.01)** | **(0.00)** | (0.16) | (0.14) | (0.97) | (0.81) | (0.77) | **(0.03)** |

Note: Sample period: 1983Q1 - 2010Q3 (n = 106).

Numbers in the parentheses are the p-values for the null hypothesis that the correlation is zero

**Table 3A: Estimated Cointegrating Vectors Normalized on CPI**

$lP_t^{CPI} = c_0 + \delta t + \sum_i \beta_i lP_t^i + u_t$ where i = 7 sub-indexes

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| Livestock | 0.26085*** | -0.02093 | -1.91712 | 0.87306*** | 0.96557 |
| | [0.01314] | [0.05042] | [2.76336] | [0.05448] | [3.85130] |
| Energy | -0.16071*** | -0.12966*** | -0.58787*** | -0.44426*** | -2.33432*** |
| | [0.00095] | [0.00387] | [0.21061] | [0.00368] | [0.27391] |
| Foodstuff | 0.85634*** | 1.39900*** | -7.25076** | 1.26488*** | 12.70466*** |
| | [0.01611] | [0.06254] | [3.32373] | [0.06445] | [4.80335] |
| Raw & Ind. | -0.28024** | -0.65414 | 14.31955 | -2.44757*** | -19.43091 |
| | [0.14576] | [0.56077] | [30.88649] | [0.62729] | [42.52758] |
| Textile | 0.20611*** | 0.45098*** | -6.67029 | -1.13707*** | 8.41397 |
| | [0.03648] | [0.14023] | [7.77199] | [0.15081] | [10.69072] |
| Metal | 0.20884*** | 0.29183*** | -6.22778 | 1.16592*** | 8.42829 |
| | [0.02524] | [0.09683] | [5.33723] | [0.10756] | [7.33754] |
| Fats & Oils | -0.84544 *** | -1.03705*** | 4.60023*** | -1.20971*** | -7.18311*** |
| | [0.00640] | [0.02460] | [1.32439] | [0.02589] | [1.91056] |
| Trend | 0.00864*** | 0.00629*** | 0.08010*** | 0.00940*** | 0.02115*** |
| | [0.00000] | [0.00000] | [0.00003] | [0.00000] | [0.00003] |

Note: The cointegrating vectors are maximum likelihood estimates normalized on CPI from cointegrated VAR(2) models with one cointegrating vector. Values in brackets represent standard errors. Asterisks indicate significance at 1% (***), 5% (**), and 10% (*) level. A constant term is included in the estimation (results not reported).

**Table 3B: Estimated Cointegrating Vectors Normalized on PPI**

$lP_t^{PPI} = c_0 + \delta t + \sum_i \beta_i lP_t^i + u_t$ where $i$ = 7 sub-indexes

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| Livestock | 0.28341*** | -1.53592 | 0.57883 | 0.34929*** | 0.35367*** |
| | [0.01011] | [2.01176] | [0.73933] | [0.02993] | [0.06281] |
| Energy | -0.03745*** | -1.17432*** | -0.64296*** | -0.30259*** | -0.38450*** |
| | [0.00077] | [0.14843] | [0.05899] | [0.00208] | [0.00438] |
| Foodstuff | 0.42448*** | 11.91247*** | 5.28977*** | 1.44455*** | 1.52614*** |
| | [0.01374] | [2.71508] | [0.91378] | [0.04129] | [0.07590] |
| Raw & Ind. | 0.95069*** | -9.11147 | -3.16565 | -0.85446** | -0.29420 |
| | [0.10997] | [23.35852] | [8.16229] | [0.33061] | [0.68315] |
| Textile | -0.40556*** | 5.02833 | 1.78755 | 0.34574*** | 0.25305 |
| | [0.02780] | [5.90188] | [2.04919] | [0.08137] | [0.17048] |
| Metal | -0.21982*** | 3.54654 | 1.32810 | 0.49114*** | 0.21800* |
| | [0.01895] | [3.99762] | [1.40954] | [0.05714] | [0.11855] |
| Fats & Oils | -0.68962*** | -6.52501*** | -3.95921*** | -1.15754*** | -1.33948*** |
| | [0.00501] | [1.07091] | [0.35968] | [0.01581] | [0.02990] |
| Trend | 0.00588*** | 0.01535*** | 0.02284*** | 0.00920*** | 0.02311*** |
| | [0.00000] | [0.00001] | [0.00001] | [0.00000] | [0.00000] |

Note: The cointegrating vectors are maximum likelihood estimates normalized on PPI from cointegrated VAR(2) models with one cointegrating vector. Values in brackets represent standard errors. Asterisks indicate significance at 1% (***), 5% (**), and 10% (*) level. A constant term is included in the estimation (results not reported).

**Table 4A: VECM(1) Coefficient Estimates: CPI-Inflation**

$$\pi_{t+1}^{CPI} = c + \alpha EC_t + \rho \pi_t^{CPI} + \sum_i \psi_i dlP_t^i + \varepsilon_{t+1}$$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t$ | -0.04466*** | -0.01629** | 0.01380*** | -0.04192*** | -0.00442*** |
| | [0.01069] | [0.00661] | [0.00156] | [0.00875] | [0.00112] |
| $\pi_t^{CPI}$ | 0.49639*** | 0.25939*** | -0.07413 | 0.61895 *** | 0.54380*** |
| | [0.07520] | [0.09565] | [0.09705] | [0.06945] | [0.07291] |
| $dlP_t^{Livestock}$ | -0.03709*** | 0.00121 | -0.07612** | -0.01483 | -0.04057** |
| | [0.01375] | [0.01290] | [0.03150] | [0.02029] | [0.02033] |
| $dlP_t^{Energy}$ | 0.01935*** | 0.00614* | 0.03283*** | 0.01089* | 0.01955*** |
| | [0.00390] | [0.00353] | [0.00843] | [0.00589] | [0.00574] |
| $dlP_t^{Foodstuff}$ | -0.03214** | 0.01269 | -0.06792* | -0.02348 | 0.01648 |
| | [0.01606] | [0.01525] | [0.03573] | [0.02269] | [0.02369] |
| $dlP_t^{Raw\ Ind.}$ | -0.05035 | 0.03494 | 0.14643 | 0.08279 | 0.17068** |
| | [0.04794] | [0.04445] | [0.10991] | [0.06862] | [0.07131] |
| $dlP_t^{Textiles}$ | 0.00408 | -0.01470 | -0.08285* | -0.11052 *** | -0.05616* |
| | [0.02176] | [0.02033] | [0.04990] | [0.03175] | [0.03284] |
| $dlP_t^{Metal}$ | 0.02478 | -0.01421 | -0.08042 | -0.03264 | -0.07852** |
| | [0.02101] | [0.01952] | [0.04866] | [0.03026] | [0.03147] |
| $dlP_t^{Fats\,\&\,Oils}$ | 0.04056*** | -0.00862 | 0.06849*** | 0.01954 | -0.00135 |
| | [0.01190] | [0.01105] | [0.02507] | [0.01628] | [0.01684] |
| Constant | 0.00302*** | 0.00341 *** | 0.00319 | 0.00202* | 0.00444** |
| | [0.00093] | [0.00095] | [0.00212] | [0.00112] | [0.00189] |
| N obs. | 110 | 110 | 110 | 110 | 110 |
| Adj. $R^2$ | 0.79 | 0.64 | 0.85 | 0.73 | 0.89 |
| Adj. $R^2$ w/o $\pi_t^{CPI}$ | 0.19 | 0.09 | 0.64 | 0.11 | 0.25 |

Note: The error-correction term: $EC_t = lP_t^{CPI} - \sum_i \beta_i lP_t^i - \delta t - c_0$ and $i$ = 7 sub-indexes, is computed based on the cointegration relation reported in Table 3A. We note that each VECM regression includes all sub-indexes and is run using a restricted trend, as chosen based on Johansen-Juselius (1990) test for cointegration. Values in brackets represent standard errors. Asterisks indicate significance at 1% (***), 5% (**), and 10% (*) level.

**Table 4B: VECM(1) Coefficient Estimates: PPI-Inflation**

$$\pi_{t+1}^{PPI} = c + \alpha EC_t + \rho \pi_t^{PPI} + \sum_i \psi_i dlP_t^i + \varepsilon_{t+1}$$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t$ | -0.09684*** | 0.00155 | -0.01858** | -0.01423 | -0.04024** |
| | [0.03277] | [0.00195] | [0.00920] | [0.01689] | [0.01370] |
| $\pi_t^{PPI}$ | 0.17709** | 0.20667** | 0.47222*** | 0.54095 *** | 0.45016 *** |
| | [0.08487] | [0.10092] | [0.08930] | [0.09325] | [0.08741] |
| $dlP_t^{Livestock}$ | -0.01652 | -0.05522** | 0.09327 | 0.00535 | -0.02455 |
| | [0.03205] | [0.02546] | [0.06910] | [0.02733] | [0.03207] |
| $dlP_t^{Energy}$ | 0.02568*** | 0.01110 | 0.04884** | 0.01865** | 0.02232** |
| | [0.00852] | [0.00695] | [0.01923] | [0.00760] | [0.00925] |
| $dlP_t^{Foodstuff}$ | -0.03123 | 0.09272*** | 0.01133 | 0.04061 | 0.02856 |
| | [0.03676] | [0.03089] | [0.08304] | [0.03163] | [0.03681] |
| $dlP_t^{Raw\ Ind.}$ | -0.11653 | 0.12392 | 0.01762 | -0.11443 | 0.09124 |
| | [0.11250] | [0.08751] | [0.23853] | [0.09182] | [0.10944] |
| $dlP_t^{Textiles}$ | -0.00027 | -0.02087 | -0.07677 | 0.01650 | -0.04273 |
| | [0.05000] | [0.04014] | [0.10924] | [0.04235] | [0.05013] |
| $dlP_t^{Metal}$ | 0.07039 | -0.02616 | -0.01923 | 0.05377 | -0.03304 |
| | [0.04821] | [0.03843] | [0.10497] | [0.04056] | [0.04846] |
| $dlP_t^{Fats\,\&\,Oils}$ | 0.04824* | -0.01734 | -0.01298 | 0.00683 | 0.00676 |
| | [0.02763] | [0.02144] | [0.05936] | [0.02265] | [0.02705] |
| Constant | 0.00430*** | 0.00351 *** | 0.00745 * | 0.00393*** | 0.00744*** |
| | [0.00156] | [0.00125] | [0.00434] | [0.00142] | [0.00271] |
| N obs. | 110 | 110 | 110 | 110 | 110 |
| Adj. $R^2$ | 0.46 | 0.38 | 0.57 | 0.58 | 0.77 |
| Adj. $R^2$ w/o $\pi_t^{PPI}$ | 0.24 | 0.20 | 0.09 | 0.11 | 0.12 |

Note: The error-correction term: $EC_t = lP_t^{PPI} - \sum_i \beta_i lP_t^i - \delta t - c_0$ and $i$ = 7 sub-indexes, is computed based on the cointegration relation reported in Table 3B. We note that each VECM regression includes all sub-indexes and is run using a restricted trend, as chosen based on Johansen-Juselius (1990) test for cointegration. Values in brackets represent standard errors. Asterisks indicate significance at 1% (***), 5% (**), and 10% (*) level.

**Table 5A: VECM(1) Estimates with Home Currency Sub-Indexes: CPI-Inflation**

$$\pi_{t+1}^{CPI} = c + \alpha EC_t^{HC} + \rho \pi_t^{CPI} + \sum_i \psi_i dlP_t^{i,HC} + \varepsilon_{t+1}$$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t^{HC}$ | -0.05320*** | -0.00270*** | 0.01247*** | -0.03696*** | -0.00624*** |
| | [0.01092] | [0.00088] | [0.00140] | [0.00797] | [0.00139] |
| $\pi_t^{CPI}$ | 0.39824*** | 0.23002** | -0.09085 | 0.56882*** | 0.50382*** |
| | [0.07792] | [0.09693] | [0.09640] | [0.07204] | [0.07242] |
| $dlP_t^{Livestock,HC}$ | -0.03698*** | 0.00520 | -0.06655** | -0.01528 | -0.04237** |
| | [0.01324] | [0.01274] | [0.03121] | [0.02050] | [0.02008] |
| $dlP_t^{Energy,HC}$ | 0.01891*** | 0.00608* | 0.02986*** | 0.01002* | 0.02154*** |
| | [0.00370] | [0.00346] | [0.00837] | [0.00591] | [0.00566] |
| $dlP_t^{Foodstuff,HC}$ | -0.01606 | 0.00500 | -0.03433 | 0.01161 | 0.00853 |
| | [0.01342] | [0.01428] | [0.03032] | [0.02006] | [0.01979] |
| $dlP_t^{Raw\ Ind.,HC}$ | 0.00797 | 0.03722 | 0.19736* | 0.17751 ** | 0.15855** |
| | [0.04590] | [0.04336] | [0.10216] | [0.06934] | [0.06844] |
| $dlP_t^{Textiles,HC}$ | -0.00080 | -0.02259 | -0.06248 | -0.10890*** | -0.06132* |
| | [0.02113] | [0.02037] | [0.05237] | [0.03222] | [0.03173] |
| $dlP_t^{Metal,HC}$ | -0.00354 | -0.01567 | -0.10797** | -0.07617** | -0.07547** |
| | [0.02027] | [0.01913] | [0.04564] | [0.03077] | [0.03045] |
| $dlP_t^{Fats\,\&\,Oils,HC}$ | 0.03306*** | -0.00687 | 0.04820** | 0.00195 | 0.00256 |
| | [0.01079] | [0.01058] | [0.02329] | [0.01532] | [0.01566] |
| Constant | 0.00303*** | 0.00304*** | -0.00316 | 0.00208* | 0.00292 |
| | [0.00090] | [0.00097] | [0.00242] | [0.00113] | [0.00199] |
| N obs. | 110 | 110 | 110 | 110 | 110 |
| Adj. $R^2$ | 0.80 | 0.65 | 0.85 | 0.72 | 0.90 |
| Adj. $R^2$ w/o $\pi_t^{CPI}$ | 0.28 | -0.02 | 0.67 | 0.01 | 0.21 |

Note: The error-correction term: $EC_t^{HC} = lP_t^{CPI} - \sum_i \beta_i lP_t^{i,HC} - \delta t - c_0$ and $i$ = 7 sub-indexes, is computed based on the cointegration relations parallel to those reported in Table 3A but using sub-indexes in home currencies. We note that each VECM regression includes all sub-indexes and is run using a restricted trend, as chosen based on Johansen-Juselius (1990) test for cointegration. Values in brackets represent standard errors. Asterisks indicate significance at 1% (***), 5% (**), and 10% (*) level.

**Table 5B: VECM(1) Estimates with Home Currency Sub-Indexes: PPI-Inflation**

$$\pi_{t+1}^{PPI} = c + \alpha EC_t^{HC} + \rho \pi_t^{PPI} + \sum_i \psi_i dlP_t^{i,HC} + \varepsilon_{t+1}$$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t^{HC}$ | -0.10959*** | -0.00008 | -0.00279 | -0.03737** | -0.03192 *** |
| | [0.02377] | [0.00982] | [0.00210] | [0.01665] | [0.00929] |
| $\pi_t^{PPI}$ | 0.02449 | 0.24424** | 0.45796*** | 0.56939*** | 0.44386*** |
| | [0.08733] | [0.10310] | [0.08656] | [0.08418] | [0.08719] |
| $dlP_t^{Livestock,HC}$ | -0.01732 | -0.05167** | 0.11296 | -0.00818 | -0.02564 |
| | [0.02983] | [0.02549] | [0.07048] | [0.02636] | [0.03203] |
| $dlP_t^{Energy,HC}$ | 0.02114*** | 0.01259* | 0.04722** | 0.02339*** | 0.02564*** |
| | [0.00792] | [0.00702] | [0.01966] | [0.00729] | [0.00916] |
| $dlP_t^{Foodstuff,HC}$ | 0.01835 | 0.07230** | 0.00071 | 0.03628 | 0.01070 |
| | [0.02973] | [0.02897] | [0.07030] | [0.02568] | [0.03077] |
| $dlP_t^{Raw\ Ind.,HC}$ | -0.11172 | 0.09671 | -0.01232 | -0.05507 | 0.10139 |
| | [0.10184] | [0.08665] | [0.23928] | [0.08962] | [0.10636] |
| $dlP_t^{Textiles,HC}$ | 0.02315 | -0.02925 | -0.07864 | -0.00713 | -0.06687 |
| | [0.04758] | [0.04058] | [0.12291] | [0.04115] | [0.04999] |
| $dlP_t^{Metal,HC}$ | 0.06346 | -0.01405 | -0.00784 | 0.02442 | -0.03926 |
| | [0.04371] | [0.03830] | [0.10577] | [0.04028] | [0.04777] |
| $dlP_t^{Fats\&Oils,HC}$ | 0.02314 | -0.01001 | -0.02323 | 0.01487 | 0.01109 |
| | [0.02270] | [0.02101] | [0.05299] | [0.01981] | [0.02466] |
| Constant | 0.00203 | 0.00326*** | 0.00831* | 0.00335** | 0.00386 |
| | [0.00161] | [0.00120] | [0.00463] | [0.00135] | [0.00307] |
| N obs. | 110 | 110 | 110 | 110 | 110 |
| Adj. $R^2$ | 0.52 | 0.37 | 0.56 | 0.60 | 0.77 |
| Adj. $R^2$ w/o $\pi_t^{PPI}$ | 0.27 | 0.32 | 0.06 | 0.18 | 0.03 |

Note: The error-correction term: $EC_t^{HC} = lP_t^{PPI} - \sum_i \beta_i lP_t^{i,HC} - \delta t - c_0$ and $i$ = 7 sub-indexes, is computed based on the cointegration relations parallel to those reported in Table 3B but using sub-indexes in home currencies. We note that each VECM regression includes all sub-indexes and is run using a restricted trend, as chosen based on Johansen-Juselius (1990) test for cointegration. Values in brackets represent standard errors. Asterisks indicate significance at 1% (***), 5% (**), and 10% (*) level.

**Table 6A: CPI-Inflation VECM(1) Estimations using Aggregate Spot Index**

$$\pi_{t+1}^{CPI} = c + \alpha EC_t^{Agg-Spot} + \rho\pi_t^{CPI} + \psi dlP_t^{Agg-Spot} + \varepsilon_{t+1}$$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t^{Agg-Spot}$ | -0.00936*** | -0.00802*** | -0.02132*** | -0.01527*** | -0.00810*** |
| | [0.002] | [0.001] | [0.003] | [0.003] | [0.001] |
| $\pi_t^{CPI}$ | 0.40254*** | 0.19808** | 0.08406 | 0.47913*** | 0.41450*** |
| | [0.087] | [0.096] | [0.097] | [0.080] | [0.075] |
| $dlP_t^{Agg-Spot}$ | 0.01086 | 0.01437 | -0.00984 | -0.00382 | 0.00836 |
| | [0.012] | [0.010] | [0.029] | [0.016] | [0.016] |
| N obs. | 110 | 110 | 110 | 110 | 110 |
| Adj. $R^2$ | 0.73 | 0.62 | 0.80 | 0.68 | 0.89 |
| Adj. $R^2$ w/o $\pi_t^{CPI}$ | 0.21 | 0.17 | 0.55 | 0.26 | 0.41 |

**Table 6B. CPI-Inflation VECM(1) Estimations using Aggregate CRB Index**

$$\pi_{t+1}^{CPI} = c + \alpha EC_t^{Agg-CRB} + \rho\pi_t^{CPI} + \psi dlP_t^{Agg-CRB} + \varepsilon_{t+1}$$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t^{Agg-CRB}$ | -0.00945*** | -0.00991*** | -0.02019*** | -0.01453*** | -0.00750*** |
| | [0.002] | [0.001] | [0.002] | [0.003] | [0.001] |
| $\pi_t^{CPI}$ | 0.36915*** | 0.13958 | 0.11679 | 0.46547*** | 0.43754*** |
| | [0.088] | [0.097] | [0.094] | [0.080] | [0.074] |
| $dlP_t^{Agg-CRB}$ | 0.01415* | 0.01511** | 0.00999 | 0.00731 | 0.01397 |
| | [0.009] | [0.007] | [0.021] | [0.012] | [0.011] |
| N obs. | 110 | 110 | 110 | 110 | 110 |
| Adj. $R^2$ | 0.74 | 0.64 | 0.79 | 0.68 | 0.89 |
| Adj. $R^2$ w/o $\pi_t^{CPI}$ | 0.23 | 0.19 | 0.55 | 0.26 | 0.41 |

Note: The error-correction terms: $EC_t^{Agg-Spot}$ or $EC_t^{Agg-CRB}$, are computed based on the cointegration relations between log-CPI level and the respective aggregate indexes; they are estimated without trend or constant. Model specification is chosen based on Johansen-Juselius (1990) test for cointegration. Values in brackets represent standard errors. Asterisks indicate significance at 1% (***), 5% (**), and 10% (*) level.

**Table 6C: PPI-Inflation VECM(1) Estimations using Aggregate Spot Index**

$$\pi_{t+1}^{PPI} = c + \alpha EC_t^{Agg-Spot} + \rho \pi_t^{PPI} + \psi dlP_t^{Agg-Spot} + \varepsilon_{t+1}$$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t^{Agg-Spot}$ | -0.01901*** | -0.00269*** | -0.01496*** | -0.01255*** | -0.00680*** |
| | [0.004] | [0.001] | [0.003] | [0.003] | [0.001] |
| $\pi_t^{PPI}$ | 0.16034* | 0.18876** | 0.32309*** | 0.43911*** | 0.33171*** |
| | [0.088] | [0.089] | [0.096] | [0.080] | [0.086] |
| $dlP_t^{Agg-Spot}$ | 0.09503*** | 0.08518*** | 0.10871* | 0.05841*** | 0.07639*** |
| | [0.026] | [0.021] | [0.058] | [0.021] | [0.024] |
| N obs. | 110 | 110 | 110 | 110 | 110 |
| Adj. $R^2$ | 0.38 | 0.32 | 0.56 | 0.56 | 0.77 |
| Adj. $R^2$ w/o $\pi_t^{PPI}$ | 0.14 | 0.23 | 0.16 | 0.08 | 0.21 |

**Table 6D. PPI-Inflation VECM(1) Estimations using Aggregate CRB Index**

$$\pi_{t+1}^{PPI} = c + \alpha EC_t^{Agg-CRB} + \rho \pi_t^{PPI} + \psi dlP_t^{Agg-CRB} + \varepsilon_{t+1}$$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t^{Agg-CRB}$ | -0.02457*** | -0.01258*** | -0.01747*** | -0.01567*** | -0.00639*** |
| | [0.004] | [0.003] | [0.003] | [0.003] | [0.001] |
| $\pi_t^{PPI}$ | 0.06482 | 0.14998* | 0.29158*** | 0.38346*** | 0.33723*** |
| | [0.089] | [0.087] | [0.093] | [0.080] | [0.086] |
| $dlP_t^{Agg-CRB}$ | 0.07457*** | 0.06955*** | 0.07796* | 0.04624*** | 0.05928*** |
| | [0.018] | [0.015] | [0.041] | [0.015] | [0.018] |
| N obs. | 110 | 110 | 110 | 110 | 110 |
| Adj. $R^2$ | 0.43 | 0.37 | 0.57 | 0.58 | 0.77 |
| Adj. $R^2$ w/o $\pi_t^{PPI}$ | 0.18 | 0.28 | 0.16 | 0.12 | 0.22 |

Note: The error-correction terms: $EC_t^{Agg-Spot}$ or $EC_t^{Agg-CRB}$, are computed based on the cointegration relations between log-PPI level and the respective aggregate indexes; they are estimated without trend or constant. Model specification is chosen based on Johansen-Juselius (1990) test for cointegration. Values in brackets represent standard errors. Asterisks indicate significance at 1% (***), 5% (**), and 10% (*) level.

**Table 7A. Least Angle Regressions: Coefficient Values Based on Minimum Cp Statistics**

CPI: $\pi_{t+1}^{CPI} = c + \alpha EC_t + \rho \pi_t^{CPI} + \sum_i \psi_i dlP_t^i + + \varepsilon_{t+1}$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t$ | -0.0348 | -0.0135 | 0.0128 | -0.0292 | -0.0037 |
| | *(0.276)* | *(0.078)* | *(0.539)* | *(0.400)* | *(0.499)* |
| $\pi_t^{CPI}$ | 0.3995 | 0.2383 | | 0.5299 | 0.5999 |
| | *(0.100)* | *(0.043)* | | *(0.259)* | *(0.382)* |
| $dlP_t^{Livestock}$ | -0.0173 | | -0.0362 | | -0.0216 |
| | *(0.419)* | | *(0.627)* | | *(0.529)* |
| $dlP_t^{Energy}$ | 0.0093 | 0.004 | 0.0370 | | 0.0110 |
| | *(0.359)* | *(0.124)* | *(0.621)* | | *(0.510)* |
| $dlP_t^{Foodstuff}$ | | 0.0235 | 0.0219 | | 0.0541 |
| | | *(0.141)* | *(0.660)* | | *(0.550)* |
| $dlP_t^{Raw\ Ind.}$ | | | -0.0274 | | |
| | | | *(0.652)* | | |
| $dlP_t^{Textiles}$ | | | | -0.0489 | 0.0091 |
| | | | | *(0.510)* | *(0.574)* |
| $dlP_t^{Metal}$ | 0.0027 | | | | -.0074 |
| | *(0.438)* | | | | *(0.559)* |
| $dlP_t^{Fats\,\&\,Oils}$ | | -0.0151 | | | -0.0248 |
| | | *(0.197)* | | | *(0.520)* |

Note: The table reports coefficient estimates for regressors chosen based on the minimum Cp statistic under least angle regressions. Numbers in the parentheses represent the $R^2$ when the particular regressor is added. EC is the error-correction series used in Table 4A.

**Table 7B. Least Angle Regressions: Coefficient Values Based on Minimum Cp Statistics**

PPI: $\pi_{t+1}^{PPI} = c + \alpha EC_t + \rho \pi_t^{PPI} + \sum_i \psi_i dlP_t^i + + \varepsilon_{t+1}$

| | Australia | Canada | Chile | New Zealand | South Africa |
|---|---|---|---|---|---|
| $EC_t$ | -0.0760 | 0.0016 | -0.0083 | | -0.0262 |
| | *(0.053)* | *(0.238)* | *(0.195)* | | *(0.217)* |
| $\pi_t^{PPI}$ | 0.0846 | 0.1979 | 0.3868 | 0.4444 | 0.3455 |
| | *(0.277)* | *(0.108)* | *(0.111)* | *(0.172)* | *(0.108)* |
| $dlP_t^{Livestock}$ | | -0.0374 | 0.0393 | | |
| | | *(0.278)* | *(0.297)* | | |
| $dlP_t^{Energy}$ | 0.0214 | 0.0123 | 0.0308 | 0.0129 | 0.0034 |
| | *(0.026)* | *(0.127)* | *(0.130)* | *(0.205)* | *(0.311)* |
| $dlP_t^{Foodstuff}$ | | 0.0580 | | 0.0368 | 0.0244 |
| | | *(0.018)* | | *(0.363)* | *(0.279)* |
| $dlP_t^{Raw\ Ind.}$ | | 0.0669 | | | |
| | | *(0.076)* | | | |
| $dlP_t^{Textiles}$ | -0.0340 | | | | |
| | (0.308) | | | | |
| $dlP_t^{Metal}$ | 0.0323 | -0.0058 | | | |
| | *(0.234)* | *(0.191)* | | | |
| $dlP_t^{Fats\ \&\ Oils}$ | | | | | |

Note: The table reports coefficient estimates for regressors chosen based on the minimum Cp statistic under least angle regressions. Numbers in the parentheses represent the $R^2$ when the particular regressor is added. EC is the error-correction series used in Table 4B.

**Table 8: Root Mean Square Errors for Out-of-Sample Forecasts**

**A. Australia**

| | CPI | | | PPI | | |
|---|---|---|---|---|---|---|
| **I. Benchmarks** | | | | | | |
| RW | 0.0088 | | | 0.0225 | | |
| AR(1) | 0.0073 | | | 0.0183 | | |
| **II. Matched Frequency Models** | | | | | | |
| AR+ Agg Index | 0.0074 | | | 0.0191 | | |
| Agg Index | 0.0064 | | | 0.0196 | | |
| SubIndex | 0.0064 | | | 0.0191 | | |
| FC: AR+7 SubIndexes | 0.0063 | | | 0.0183 | | |
| **III. Mixed Frequency GADL Models** | | | | | | |
| Aggregation K | 14 | 34 | 54 | 14 | 34 | 54 |
| AR +GADL-MIDAS | 0.0086 | 0.0086 | 0.0087 | 0.0180 | 0.0198 | 0.0197 |
| GADL-MIDAS | 0.0070 | 0.0073 | 0.0070 | 0.0182 | 0.0196 | 0.0195 |
| FC: AR+7 GADL-MIDAS | 0.0063 | 0.0062 | 0.0061 | 0.0183 | 0.0185 | 0.0185 |

**B. Canada**

| | CPI | | | PPI | | |
|---|---|---|---|---|---|---|
| **I. Benchmarks** | | | | | | |
| RW | 0.0094 | | | 0.0215 | | |
| AR(1) | 0.0072 | | | 0.0174 | | |
| **II. Matched Frequency Models** | | | | | | |
| AR+ Agg Index | 0.0074 | | | 0.0182 | | |
| Agg Index | 0.0071 | | | 0.0182 | | |
| SubIndex | 0.0074 | | | 0.0175 | | |
| FC: AR+7 SubIndexes | 0.0069 | | | 0.0170 | | |
| **III. Mixed Frequency GADL Models** | | | | | | |
| Aggregation K | 14 | 34 | 54 | 14 | 34 | 54 |
| AR +GADL-MIDAS | 0.0080 | 0.0083 | 0.0082 | 0.0189 | 0.0198 | 0.0189 |
| GADL-MIDAS | 0.0074 | 0.0076 | 0.0076 | 0.0174 | 0.0185 | 0.0178 |
| FC: AR+7 GADL-MIDAS | 0.0068 | 0.0069 | 0.0069 | 0.0170 | 0.0173 | 0.0172 |

Note: Aggregation parameter K is relevant only for Window size = 68 (# of forecasts = 40), GADL-MIDAS polynomial n = 3.

**C. Chile**

| | CPI | | | PPI | | |
|---|---|---|---|---|---|---|
| **I. Benchmarks** | | | | | | |
| RW | | 0.0104 | | | 0.0440 | |
| AR(1) | | 0.0113 | | | 0.0363 | |
| **II. Matched Frequency Models** | | | | | | |
| AR+ Agg Index | | 0.0117 | | | 0.0375 | |
| Agg Index | | 0.0190 | | | 0.0378 | |
| SubIndex | | 0.0174 | | | 0.0340 | |
| FC: AR+7 SubIndexes | | 0.0167 | | | 0.0348 | |
| **III. Mixed Frequency GADL Models** | | | | | | |
| Aggregation K | 14 | 34 | 54 | 14 | 34 | 54 |
| AR +GADL-MIDAS | 0.0116 | 0.0112 | 0.0123 | 0.0406 | 0.0375 | 0.0406 |
| GADL-MIDAS | 0.0173 | 0.0183 | 0.0162 | 0.0404 | 0.0385 | 0.0394 |
| FC: AR+7 GADL-MIDAS | 0.0164 | 0.0164 | 0.0161 | 0.0367 | 0.0361 | 0.0359 |

**D. New Zealand**

| | CPI | | | PPI | | |
|---|---|---|---|---|---|---|
| **I. Benchmarks** | | | | | | |
| RW | | 0.0068 | | | 0.0195 | |
| AR(1) | | 0.0054 | | | 0.0169 | |
| **II. Matched Frequency Models** | | | | | | |
| AR+ Agg Index | | 0.0058 | | | 0.0178 | |
| Agg Index | | 0.0067 | | | 0.0184 | |
| SubIndex | | 0.0065 | | | 0.0176 | |
| FC: AR+7 SubIndexes | | 0.0057 | | | 0.0171 | |
| **III. Mixed Frequency GADL Models** | | | | | | |
| Aggregation K | 14 | 34 | 54 | 14 | 34 | 54 |
| AR +GADL-MIDAS | 0.0059 | 0.0069 | 0.0065 | 0.0177 | 0.0174 | 0.0176 |
| GADL-MIDAS | 0.0062 | 0.0060 | 0.0054 | 0.0171 | 0.0164 | 0.0167 |
| FC: AR+7 GADL-MIDAS | 0.0054 | 0.0054 | 0.0053 | 0.0171 | 0.0169 | 0.0167 |

**E. South Africa**

| | CPI | | | PPI | | |
|---|---|---|---|---|---|---|
| | | **I. Benchmarks** | | | | |
| RW | | 0.0100 | | | 0.0251 | |
| AR(1) | | 0.0093 | | | 0.0211 | |
| | | **II. Matched Frequency Models** | | | | |
| AR+ Agg Index | | 0.0097 | | | 0.0224 | |
| Agg Index | | 0.0137 | | | 0.0237 | |
| SubIndex | | 0.0129 | | | 0.0225 | |
| FC: AR+7 SubIndexes | | 0.0123 | | | 0.0217 | |
| | | **III. Mixed Frequency GADL Models** | | | | |
| Aggregation K | 14 | 34 | 54 | 14 | 34 | 54 |
| AR +GADL-MIDAS | 0.0095 | 0.0102 | 0.0107 | 0.0224 | 0.0218 | 0.0222 |
| GADL-MIDAS | 0.0114 | 0.0126 | 0.0120 | 0.0219 | 0.0224 | 0.0221 |
| FC: AR+7 GADL-MIDAS | 0.0117 | 0.0119 | 0.0117 | 0.0216 | 0.0217 | 0.0215 |

**Table A.1. Representative Major Commodity Exports by Country**

| Australia | Canada | New Zealand | Chile | South Africa |
|---|---|---|---|---|
| Coking coal | Crude Oil | Lamb | Copper | Gold |
| Steaming coal | Lumber | Wholemeal MP | Lumber | Platinum |
| Gold | Pulp | Beef | | Coal |
| Iron ore | Nat. Gas | Aluminum | | |
| Wheat | Beef | Cheese | | |
| Aluminum | Newsprint | Wool | | |
| Beef | Aluminum | Casein | | |
| Alumina | Wheat | Fish | | |
| LNG | Nickel | Butter | | |
| Wool | Gold | Sawn Timber | | |
| Cotton | Zinc | Kiwi | | |
| Copper | Copper | Skim MP | | |
| Nickel | Coal | Logs | | |
| Sugar | Hogs | Apples | | |
| Barley | Potash | Pulp | | |
| Zinc | Fish | Skins | | |
| Canola | Canola | | | |
| Lead | Corn | | | |
| Rice | Silver | | | |

Source: Reserve Bank of Australia, Statistics Canada, Reserve Bank of New Zealand , and authors' calculations

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