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Can Exchange Rates Forecast Commodity Prices? Recent Evidence using Australian Data

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Abstract

Recent papers by Chen et al (2009, 2010) suggest that exchange rates have predictive power over future commodity price movements. We use a Vector Error-Correction model to test this hypothesis using Australian data. We find substantial evidence of in-sample forecasting power but are unable to consistently out-perform naïve benchmarks for out-of-sample forecasts.

Any mistakes are the authors' responsibility.
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Introduction

Commodity prices are known to be fundamental in determining the present value of exchange rates, particularly in commodity currencies such as Australia, New Zealand, South Africa and Canada (see Amano and Norden, 1993; Djoudad et al, 2001; Gruen and Kortian, 1996). Chen and Rogoff (2003) examined this relationship for three commodity currencies: Australia, New Zealand and Canada, and found that the world price of a basket of their major commodity exports was a strong determinant of their real exchange rates.

It is logical to believe that exchange rates would be good forecasters of commodity prices. Campbell and Shiller (1987), Engel and West (2005) and Chen et al (2010) demonstrated the process by which exchange rates are able to predict commodity prices through the forward-looking present value computation of asset prices. As Chen et al (2010) and Harri et al (2009) explain, as commodity prices represent a major part of Australia's domestic production and exports, price movements have significant effects on the exchange rate. Knowing this, when market participants expect a future change in commodity prices they factor in these expectations into the current exchange rate value.

Chen et al (2009; 2010) analysed whether exchange rates could successfully forecast commodity prices, comparing their results to the random-walk benchmark, the AR(1) benchmark, and forecasted futures market prices. They found that exchange rates outperform all three benchmarks as both an in- and out-of-sample predictor of future commodity prices for commodity currency countries. This result has proved robust to the dollarization effect present in price forecasts.

One inconsistency in the exchange rate-commodity price literature is the direction of causality between the series. Chen et al (2009; 2010) argue that the direction of causality runs strongest from exchange rates to commodity prices and thus exchange rates are the forecasting variable, while Akram (2009) argues that the reverse holds true, using commodity prices as the explanatory variable. Both sources have claimed success, and there is no conclusive evidence over which is the superior forecaster.

This article expands on the existing literature on present-value exchange rate models by testing the relationship between exchange rates and commodity prices, as well as analysing whether exchange rates can predict future commodity prices. We find that while our model can out-predict the naïve forecasting models over some benchmarks, this result is not robust to the benchmark used.

Data

This study focuses on the Australian exchange rate, as Australia is what is referred to as a "commodity currency"; this refers to a currency which has a high correlation with movements in world commodity prices. This is a result of the country's reliance on commodity production (Chen et al, 2009).

We use monthly exchange rate data for Australia spanning from the 1983:12 to 2011:5 period. December 1983 is significant as it marks the floating of the Australian dollar. For exchange rate data we shall be using the Trade Weighted Index (denoted TWI) or effective exchange rate in our results. We shall also examine the 2003-2011 forecasting period, which roughly coincides with a notable resource boom. For commodity prices the Reserve Bank of Australia (RBA) index of commodity prices[1] (ICP) is used which employs weightings based upon relative export earnings.

Nonstationarity and Cointegration

One of the most common problems encountered when analysing macroeconomic or financial time series is that the series exhibits nonstationarity. Thus the first step is to determine whether the series are stationary in levels or whether there exists a stochastic trend in the variables. As discussed in Engel and Granger (1987), both of the variables should be integrated of the same order for a cointegrating relationship to exist.

Table 1. Unit Root Test Results

Variable	Dickey-Fuller τ Statistics			
	Levels		First Differences	
	Constant only	Constant with a trend	Constant only	Constant with a trend
ICP	-0.4745	-2.1355	-9.9326***	-9.9956***
TWI	-2.3819	-2.6313	-16.659***	-16.867***

Critical values from MacKinnon (1996). Null hypothesis is variable is nonstationary. *, ** and *** Significant at 10%, 5% and 1% levels respectively.

Table 1 shows τ statistic results of the Augmented Dickey-Fuller unit root test results in both levels and first-differences. As the unit root tests are unable to reject that these series are nonstationary in levels, we use first-differenced data. Having confirmed that both the RBA commodity price index and Trade-weighted Index are I(1) variables, we next test for cointegration between the two series. The existence of a cointegrating relationship will allow us to respecify the VAR in first differences as a Vector Error-correction model[2].

The Johansen cointegration technique, progenited by Johansen (1988) and Johansen and Juselius (1990), is used where the method is based upon the equilibrium properties of an estimated Vector Error Correction Model (VEC). Given the sensitivity of the Johansen cointegration results to the lag length selected, we must first determine an optimal lag length which balances the trade-off between the increased accuracy of more parameters with the loss in parsimony. Based on the Akaike Information Criterion (AIC), we use seven lags in levels (six in differences).

Tests based upon both trace and maximum eigenvalue statistics are reported in Table 2 where estimates are normalized on commodity prices. Both statistics indicate the rejection of the null of no cointegration.

[1] The RBA index of commodity prices serves includes 21 commodities weighted by relative export earnings.
[2] We note that the finding of cointegration is also of interest on an academic level, given the rarity of finding empirically established cointegrating relations.

Table 2. Johansen Cointegration Test Results

Model	Coint Coef	Adjust Coef		Test Result		
		ΔRBA_ICP	ΔTWI	Rank	Trace	Max Eig
(ICP | TWI)	1 -2.6079*	-0.0160	0.0211	1	23.90 ***	22.30 ***
	(0.610)	(0.0046)	(0.0051)			

Significant at 5% significance level using critical values from MacKinnon, Haug and Michelis (1999). Null hypothesis of no cointegrating vectors *(r = 0)* rejected against the alternative of at most one cointegrating vector.

VEC Estimation

Having established cointegration a VEC model is estimated using OLS. The equilibrium equation is $v_{t-1} = ICP_{t-1} - 2.6079_{t-1} + 106.546$ and the model is

$$\Delta Z_t = \delta + \lambda v_{t-1} + \Gamma_1 Z_{t-1} + \cdots \Gamma_6 Z_{t-6} + \varepsilon_t$$

where ΔZ_t is a 2×1 vector of fitted values, δ contains 2×1 intercepts, λ consists of two speed-of-adjustment parameters, each Γ_i is a 2×2 matrix of estimated coefficients and ε_t is an error term. Estimated parameters are given in Table 3 with t-statistics in parenthesis.

Table 3 Parameter Estimates from VEC Model

Parameter		ΔTWI		ΔICP	
λ		.021023		-.016022	
		[4.14330]		[-3.49019]	
$\Gamma_{\Delta TWI}/\Gamma_{\Delta ICP}$	$t-1$	0.034281	-0.069129	-0.083145	0.497719
		[0.58002]	[-1.04711]	[-1.56006]	[8.36042]
$\Gamma_{\Delta TWI}/\Gamma_{\Delta ICP}$	$t-2$	0.043228	0.027060	0.165918	-0.083863
		[0.72445]	[0.36927]	[3.08355]	[-1.26910]
$\Gamma_{\Delta TWI}/\Gamma_{\Delta ICP}$	$t-3$	-0.025415	-0.061023	0.090351	0.083675
		[-0.41752]	[-0.84220]	[1.64602]	[1.28066]
$\Gamma_{\Delta TWI}/\Gamma_{\Delta ICP}$	$t-4$	-0.127563	-0.107271	0.195525	0.265505
		[-2.08958]	[-1.47709]	[3.55184]	[4.05428]
$\Gamma_{\Delta TWI}/\Gamma_{\Delta ICP}$	$t-5$	-0.056475	-0.012052	0.141451	-0.015653
		[-0.90784]	[-0.16396]	[2.52160]	[-0.23615]
$\Gamma_{\Delta TWI}/\Gamma_{\Delta ICP}$	$t-6$	-0.038214	-0.119032	0.034408	-0.068967
		[-0.60783]	[-1.90012]	[0.60692]	[-1.22089]

Table 3 displays the results of the estimated six-lag VEC model The adjustment coefficients for both equations prove significant at a 1 per cent level. We conclude that both exchange rates and commodity prices adjust significantly to short-run deviations from equilibrium. We note that while the *ICP* equation has the expected negative sign, *TWI* takes on an unexpected positive value. This is possibly caused by the omission of an important variable or the existence of a near-unit root in one or more of the series. Most of the individual coefficients are significant at a 1 percent level (for the *ICP* equation) with commodity price lag 2,3,5,6 and exchange rate lag 3 and 6 being exceptions.

As stated, there is conflicting evidence regarding the direction of causality between commodity prices and exchange rates. We test for causality using the Granger Causality/Block Exogeneity Wald test. If cointegration exists, then causality can be examined utilising the Wald test (Granger, 1988)

Table 4. VEC Granger Causality/Block Exogeneity Wald Tests

Excluded Variable	Chi-Sq	df	Prob.
D(TWI)	36.35421*	6	0.0000*
D(ICP)	16.58671**	6	0.0109**

Note. Asterisks rejection at the 1% (*), 5% (**), and 10% (***) significance levels respectively, indicating evidence of Granger-causality.

Table 5 reports the results of the Wald test from exchange rates to commodity prices and vice versa. The Granger Causality results show the direction of causality runs most strongly from exchange rates to commodity prices. These findings conclude that that the exchange rate does have significant in-sample forecasting power over a broad index of commodity prices, and are consistent with the results in Chen et al (2009; 2010).

Out-of-Sample Forecasting

We compare our VEC(6) out-of-sample forecasts against two benchmarks; the random-walk model as dictated by its importance in exchange rate literature and the AR(1) model as used by Chen et al (2009; 2010). In order to test the predictive power of our VEC(6) model we employ several forecast comparison tests popular in forecasting literature. These include the ENC-NEW forecast encompassing test (Clark and McCracken, 2001), an alternative by Diebold and Mariano (1995), the MSFE test from McCracken (1999) and the ENC-T test (Harvey et al, 1998).

For out-of-sample forecasting we use a fixed forecasting scheme as used by Pagan and Schwert (1990). The data sample is split into two periods, the in-sample observations R and the out-of-sample forecasts P. We estimate the coefficients $\mathbf{\Gamma}_i$ using the data range 1 to R, then use these estimates in forming all P of the model's forecasts. Data realized succeeding period R are used to assist future forecasts.

Table 5 reports the results of our forecast tests for the period 1994:1 to 2011:5. The model parameters are estimated from 1983:12 to 1993:12 with in-sample observations of R = 121 used to estimate the parameters. We forecast commodity prices from 1994:01 to 2011:05, with out-of-sample predictions P = 209.

Table 5. Out-of-Sample Forecasts – 1994:2011

	DM	ENC-NEW	MSE-F	ENC-T
AR(1)	1.556110*	86.75378***	99.3547***	2.81757***
RW	1.877067**	178.9971***	192.572***	3.42423***

Note. Positive values imply that the VECM(6) produces forecasts superior to the benchmark models at at 1% (*), 5% (**), and 10% (***) significance levels, respectively. Critical values are taken from Clark and McCracken (2000), McCracken (1999) and the Student's t-distribution.

We reject the null that the VECM contains excess parameters against both the AR(1) and random-walk benchmarks. The null hypothesis of equal forecast accuracy is rejected at a 1 percent level using the ENC-NEW, ENC-T and MSE-F forecast tests against both the AR(1) and random-walk benchmarks, whereas the DM test rejects at a 10 percent level against the AR(1) benchmark and 5 percent against the random-walk. These tests overall conclude that the VEC(6) model can best the out-of-sample forecasts of the naïve benchmarks over the 1994 partition period.

Table 6. Out-of-Sample Forecasts– 2003:2011

	DM	ENC-NEW	MSE-F	ENC-T
AR(1)	1.841795	-6.16067	-16.7062	-1.91984
RW	-0.89461	6.19082*	6.277286*	1.480604***

The results for the forecasting tests over the 2003:2011 period are reported in Table 6.

Comparing our model's forecasts to the no-change model, we reject the null hypothesis at a 1 per cent level with the ENC-NEW and MSE-F tests, whereas we only reject at a 10 percent level with the ENC-T test and are unable to reject with the DM test. Overall, these results show that our VEC(6) model still out-forecasts the random-walk benchmark over the 2003:2011 period.

These results do not hold when the forecasting model is compared to the AR(1) model however; we are unable to reject the null hypothesis that the benchmark nests our model for any of the tests. It is concluded that our model does not contain any additional information over the AR(1) benchmark over the 2003:2011 period. The model's forecasting power is sensitive to the time period selected.

Conclusion

This paper examined whether information contained in the Australian exchange rate can produce accurate forecasts of future commodity price movements. We found that there exists a significant long-run equilibrating relationship to which the Australian exchange rate and broad index of commodity prices gravitate. We examined the direction of causality and found that causality runs stronger from exchange rates to commodity prices.

Finally, we examined the in-sample and out-of-sample forecasting results of our Vector Error-correction model across a variety of benchmarks, and while we found evidence of strong in-sample forecasting power, our out-of-sample results proved far less robust.

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