Australia's Commodity Connection: An Empirical Analysis

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Introduction

Australia is a country endowed with significant natural resources and is consistently among the leading iron ore, coal, gold, copper and wheat exporting countries in the world. Throughout Australia's modern history, international commodity price movements have played a significant role in explaining changes in macroeconomic aggregates; indeed, the Australian dollar has long been considered a "commodity currency". However, in light of recent events, including the end of the mining boom, the scaling-back of domestic manufacturing, the rise of the services economy, and the decline in the price of renewable energies, we hypothesise that Australia's long-standing commodity connection has weakened. Our analysis employs structural VAR techniques to measure the evolution of Australia's commodity connection over the past three decades. In order to measure Australia's commodity connection, we draw on four observed relationships between macroeconomic fluctuations in small commodity-exporting economies and changes in world commodity prices. These effects are the external balance, commodity currency, spending, and Dutch disease effects. By dividing our sample into three sub-periods – pre-boom (1991 Q1 – 2002 Q4), boom (2003 Q1 – 2014 Q4), and post-boom (2015 Q1 – 2019 Q2) – we are able to gauge recent changes to Australia's commodity connection and evaluate our hypothesis on a temporal basis.

Data Description

Summary of Data Sources

To investigate the effect of global commodity prices on the Australian economy, we collected data for 6 variables from 3 different sources.

Data on the commodity price index is sourced from the Reserve Bank of Australia and is calculated as a monthly, unadjusted average. The real trade-weighted exchange rate index is also sourced from the RBA and is calculated as a quarterly average value of the Australian dollar in relation to currencies of Australia's trading partners and is adjusted for consumer price levels. This method is outlined by Ellis L (2001). This data is level and not seasonally adjusted. The data on Australia's current account balance is sourced from the OECD and is a measured as a percentage of total GDP and is calculated quarterly. The other data was retrieved from the Australian Bureau of Statistics. GDP growth is measured as year-ended real GDP growth. The terms of trade index is calculated as a percentage change. Manufacturing output is measured as percentage change in gross value added for all manufacturing sectors. All ABS datasets retrieved were quarterly frequency and seasonally-adjusted by the ABS.

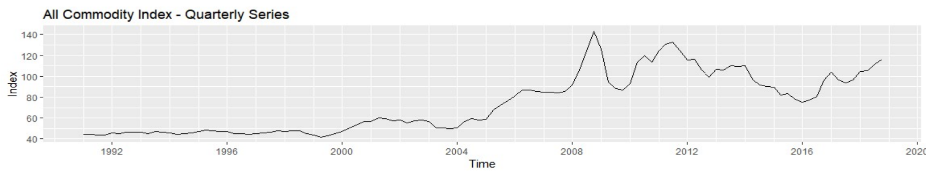
Perhaps the most obvious issues with the data are that the time ranges are not homogenous, and that the frequency of the commodity index is monthly, while the frequency of the other variables is quarterly. Moreover, some variables are in % units, while others are seasonally adjusted. In order to compare data, we require the data to be consistent, which we achieve in the next section.

Stationarity Diagnosis and Data Transformation

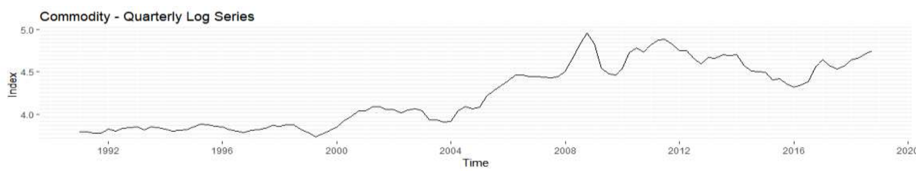
We restricted the scope of the study from the start of 1991 to the second quarter of 2019. This time period allows us to split the data into three sub-periods: pre-boom period (1991Q1 – 2002Q4), boom period (2003Q1 – 2014Q4) and post-boom period (2015Q1 – 2019Q2). We also ensured that the data is consistent by seasonally adjusting series where appropriate. This will be discussed towards the end of this section.

Commodity Index

First, we change the commodity index to a quarterly frequency. We do this by taking an unweighted average of three months to produce a quarterly figure. We take Q1 to be January to March, Q2 to be April to June, Q3 to be July to September, and Q4 to be October to December.



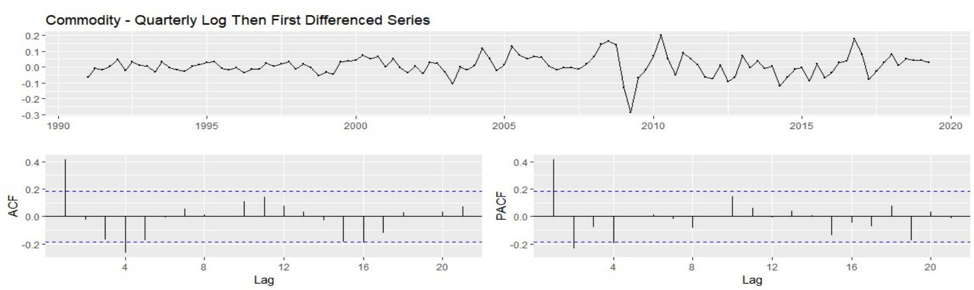
We notice that the volatility is greater in the second half, so we use a log filter to create stationary in variance.



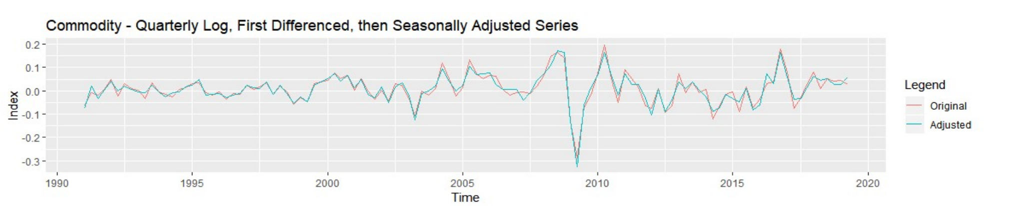
The series is clearly trending. We use a sequence of KPSS tests to decide the number of differences to take, and we end up taking the first difference. The KPSS test was chosen to avoid applying filters unless there is strong evidence in favor of it, and the null hypothesis of stationarity enables us to achieve this.

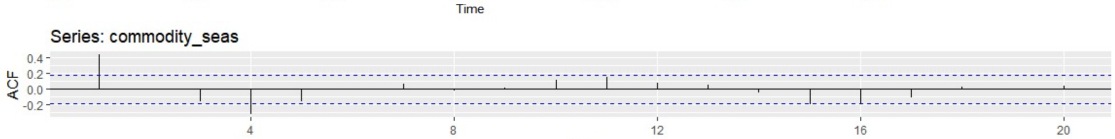
```
ndiffs(lcommodity, test = 'kpss') # Output: Number of rejections in a sequence of KPSS tests

## [1] 1
```

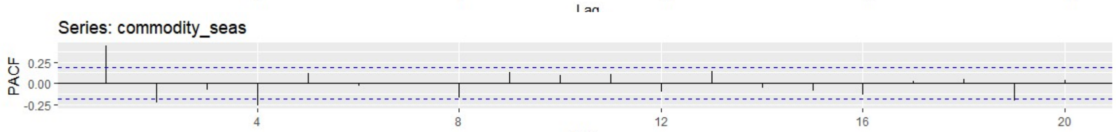
We now verify stationarity in mean and variance, and check for autocorrelations.



The series hovers around 0 and seems mean stationary. The variance seems mostly stationary, except for one brief period around the Great Financial Crisis in 2008-2009. There are statistically significant autocorrelations, at lag 4 (ACF), and lags 2 and 4 (PACF). The pattern of the correlations possibly indicates a cyclic pattern. Since this series is not seasonally adjusted, we apply the X11 method for seasonal adjustment in order to keep all variables consistent.



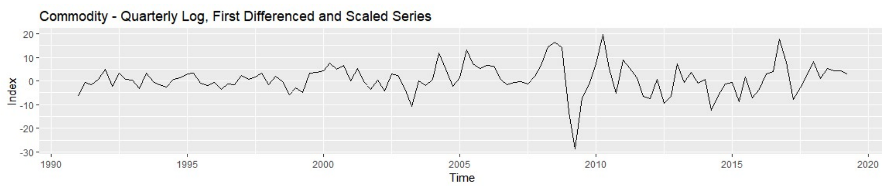




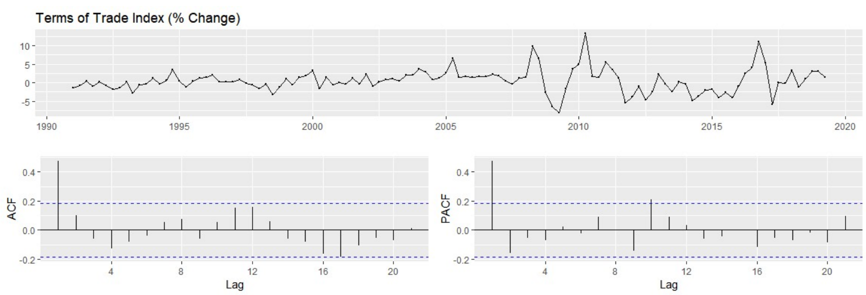
The autocorrelation does not seem to have improved. We use a Ljung-Box Test to test if there is autocorrelation for any of the first 20 lags (5 years). This test assumes no autocorrelation as a null hypothesis.

```
##  Box-Ljung test
## data:  dlcommodity
## X-squared = 52.616, df = 20, p-value = 9.253e-05

##  Box-Ljung test
## data:  commodity_seas
## X-squared = 60.872, df = 20, p-value = 5.215e-06
```

The test rejects the null hypothesis of no autocorrelation in the series before and after seasonal adjustment. Since there is still evidence of autocorrelation, we see no advantage of using seasonal adjustment, and to avoid overfiltering the data, we decide not to use the adjusted series. Finally, we scale the series by a factor of 100, which will result in the final unit being in quarterly percentage growth. This will make this variable interpretable and comparable with the other variables.



Terms of Trade

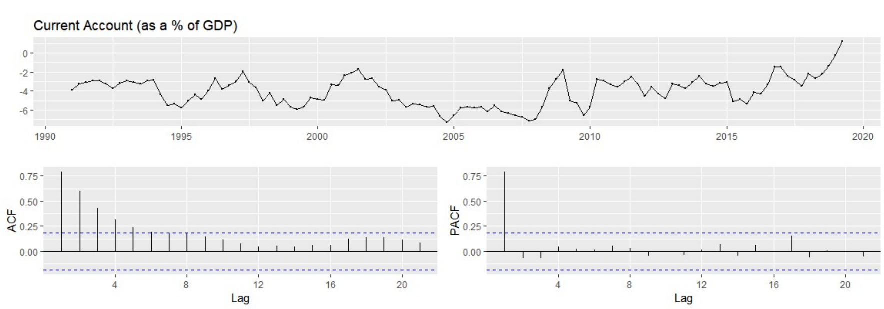


The series seems stationary in mean as it hovers around zero, and mostly seems stationary in variance. While there are some statistically significant autocorrelations, these may be spurious due to the number of lags tested. There is a slight cyclic pattern visible in the ACF, which does not pass statistical significance. However, as the data was seasonally adjusted by the ABS, we are not able to perform any further adjustments to remove autocorrelation. To confirm stationarity, we run a KPSS test to see if we can reject the assumption of stationarity.

```
ur.kpss(termsoftrade_ts)
## # KPSS Unit Root / Cointegration Test #
## The value of the test statistic is: 0.1142
```

The p-value is insignificant at the 5% level, which indicates insufficient evidence in favor of non-stationarity.

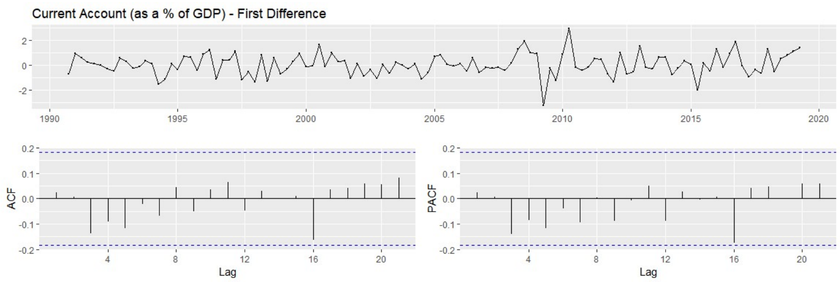
Current Account



The series seems stationary in variance only. There are 6 significant autocorrelations and visually, the series does not seem to consistently hover around a single horizontal line. We used a KPSS test to see if any differencing is required to achieve stationarity.

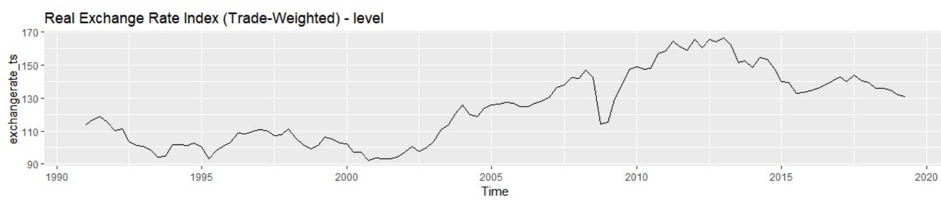
```
# KPSS
ndiffs(window(currentaccountpc_raw, start=1991, end=c(2019,2)), test = 'kpss')

## [1] 1
```

The test indicates that the first difference must be taken to achieve stationarity. After first differencing, we check for stationarity.



The series now seems to be mean and variance stationary and has no significant autocorrelations.

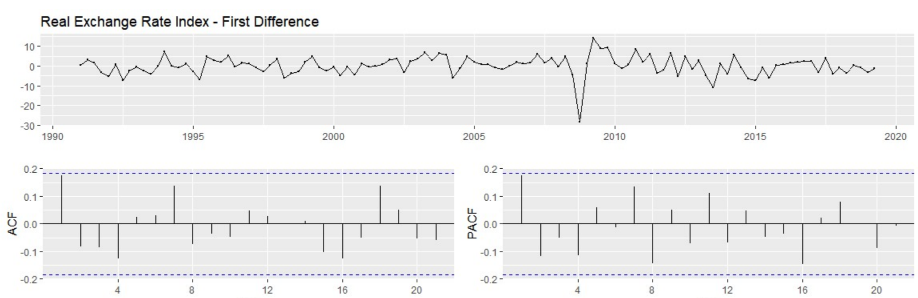
Real Exchange Rate



There is clear non-stationarity in the mean, but the variance looks possibly stationary. We use a series of KPSS tests to figure out the number of differences to take to achieve stationarity.

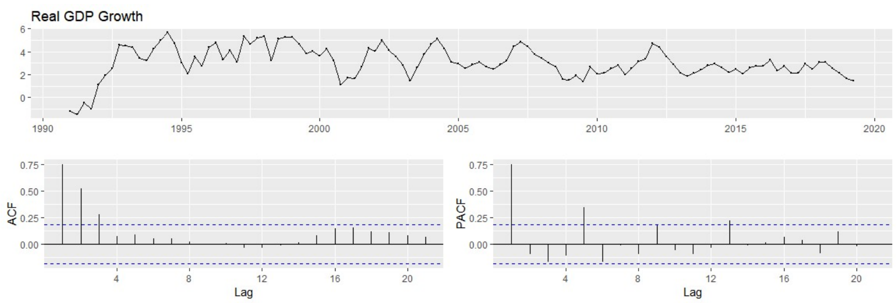
```
ndiffs(exchangerate_ts, test = 'kpss')

## [1] 1
```

The KPSS test shows we can assume stationarity after one difference, and so we take the series' first difference.



We now have a mean and variance stationary series, which does not have any statistically significant autocorrelations at the 5% level.

Real GDP Growth

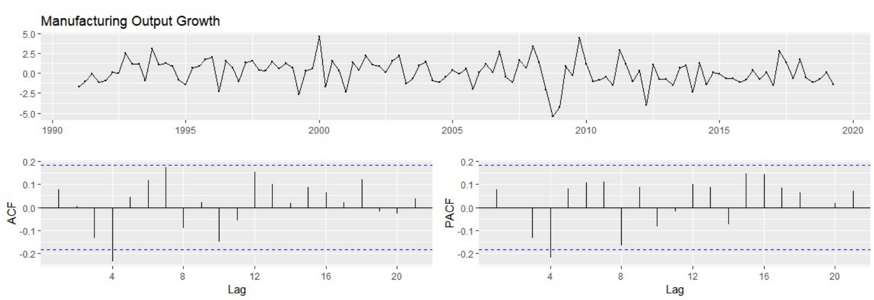


The series hovers around a horizontal line and seems mostly stationary in variance, although this is difficult to confirm visually. The decaying pattern for lags 1 to 3 in the ACF indicates a short-term memory and there is a slight, statistically insignificant sinusoidal pattern which may indicate cycles. We can confirm stationarity with a KPSS test.

```
ur.kpss(output_ts)
## # KPSS Unit Root / Cointegration Test #
## The value of the test statistic is: 0.2996
```

The test statistic indicates that there is insufficient evidence for non-stationarity.

Manufacturing Output Growth



The series hovers around a horizontal line and seems stationary in variance. There is only one statistically significant autocorrelation at lag 4 in the ACF and PACF, and multiple other lags are close to statistical significance. We can confirm stationarity with a KPSS test. It is also worth testing for autocorrelation with a Ljung-Box test, as the one statistically significant result may be spurious.

```
ur.kpss(manufacturing_ts)
## # KPSS Unit Root / Cointegration Test #
## The value of the test statistic is: 0.4295

Box.test(manufacturing_ts, lag=20, type='Ljung-Box')

##  Box-Ljung test
## data:  manufacturing_ts
## X-squared = 27.862, df = 20, p-value = 0.1127
```

The tests show that there is insufficient evidence for non-stationary, and insufficient evidence for autocorrelation.

Additional Comments: Seasonal adjustment and cyclic patterns.

Much of the data seasonally adjusted by the ABS relies on the X11 method. To keep our other variables consistent, we tested the X11 method to see if we could remove any seasonality that showed in the autocorrelation plots. However, this adjustment was not successful in removing seasonality. There was still evidence of autocorrelation in both our adjusted data and the ABS-adjusted data, which was shown in the seasonal adjustment of the commodity index.

Summary of Final Transformations

Let x_t be the original series and y_t be the final series.

Commodity Price Index: $y_t = \log(q_t) - \log(q_{t-1})$, where q_t is calculated as an unweighted average of values for three months (Jan-Feb-Mar/Apr-May-Jun/Jul-Aug-Sep/Oct-Nov-Dec).

Real exchange rate: $y_t = x_t - x_{t-1}$

Current Account: $y_t = x_t - x_{t-1}$

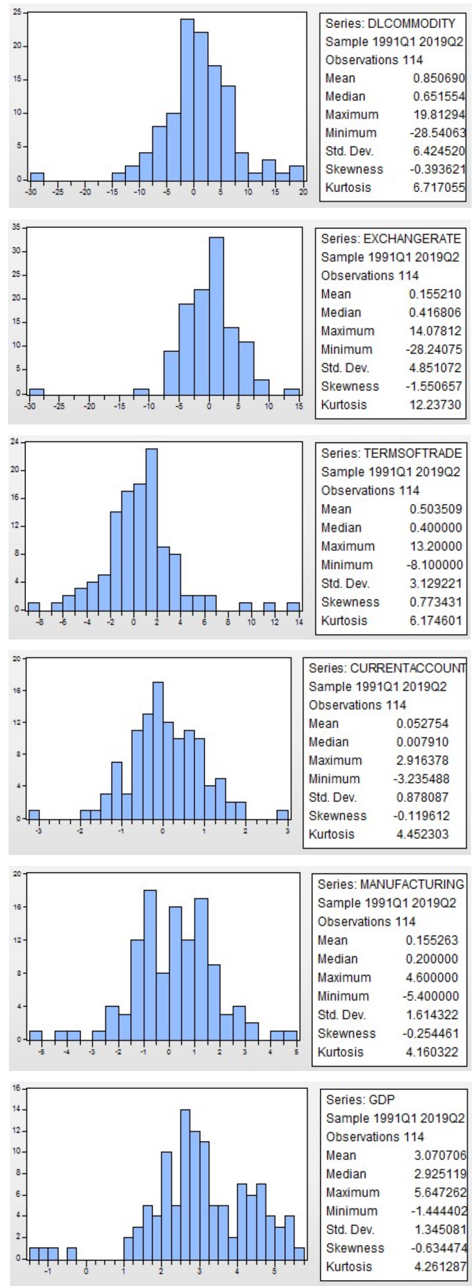
Real GDP growth, terms of trade, and manufacturing output were kept in their original series.

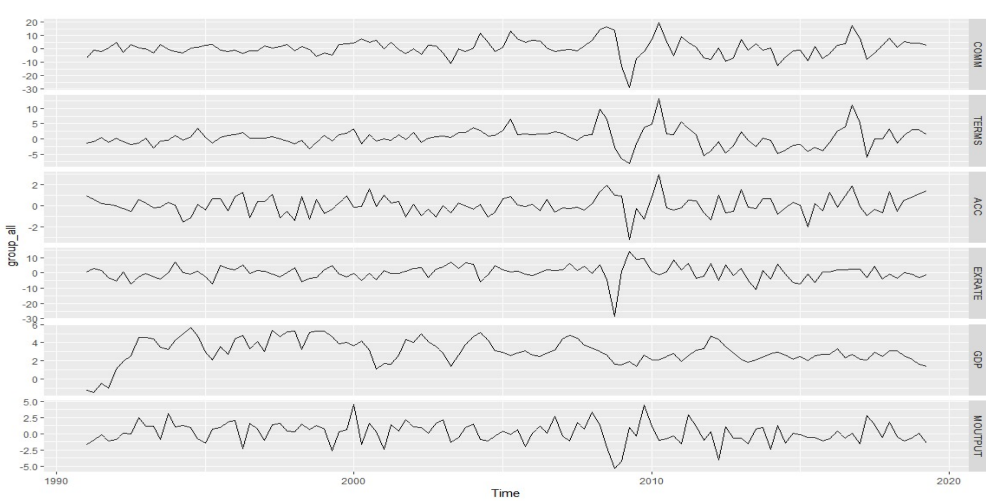
Descriptive statistics and Discussion of Variables

The histogram shows the distribution of the transformed variables. Descriptive statistics were calculated for each variable and are displayed next to the histogram. Overall, the mean quarterly growth ranged between 0-6%, typical of economic data. Manufacturing output had the lowest mean growth at 0.16% per quarter, while business investment had the highest mean growth at 5.35%. The difference in volatility across variables was also notable. Investment and commodity price growth had a standard deviation of 9.51% and 6.42% respectively, which far exceeded 1.61% for manufacturing output growth.

The time series are all mostly stationary in mean and variance. However, our data shows extreme volatility from 2007 to 2010. This is likely due to the Great Financial Crisis, which may reasonably be expected to negatively affect the reliability of interpretations.

Finally, we acknowledge that the consistency of our data is still an issue, since current account data does not have a unit of percentage growth, but only level growth.





Empirical Methodology

In this section, we lay out the building blocks of our unifying empirical framework which allows for identification of the effects of world commodity prices on Australian macroeconomic variables over time.
Our approach combines two strands of literature. The first is related to observed relationships between macroeconomic fluctuations in small commodity-exporting economies and changes in world commodity prices. We draw on four effects – external balance, commodity currency, spending, and Dutch disease effects – as indicators of Australia's commodity connection, and measure the evolution of these effects over three sub-periods; pre-boom

(1991 Q1 – 2002 Q4), boom (2003 Q1 – 2014 Q4), and post-boom (2015 Q1 – 2019 Q2). These dynamic measurements are dependent on the second strand of literature related to vector autoregression (VAR) and structural vector autoregression (SVAR) models.

VARs are a convenient starting set of models that allow us to analyse endogenous variables relevant to each of the four effects without imposing restrictions motivated by economic theory.

Let:

- $\mathbf{y}_t$ be a $N \times 1$ vector of N relevant variables.
- Φ_0 be a $N \times 1$ vector of intercepts.
- Φ_i be a $N \times N$ matrix of parameters for time $i = 1,2,\dots,p$.
- $\mathbf{u}_t$ be a $N \times 1$ vector of shocks.

Then our VAR model takes the form $\mathbf{y}_t = \Phi_0 + \Phi_1\mathbf{y}_{t-1} + \cdots + \Phi_p\mathbf{y}_{t-p} + \mathbf{u}_t$. We assume that $\mathbb{E}[\mathbf{u}_t] = \mathbf{0}$ and has a positive-definite covariance matrix $\Omega = \mathbb{E}[\mathbf{u}_t\mathbf{u}_t^T]$. It is also assumed that the shocks are serially uncorrelated, so $\mathbb{E}\left[\mathbf{u}_t\mathbf{u}_{t-k}^T\right] = 0$. The VAR model also requires that all variables are the same order of integration. In the previous section, some variables were found to be non-stationary, but stationarity was achieved by filters. This allowed us to create a VAR in differences (Ashley & Verbrugge, 2009).

The VAR model selection process involved optimal lag tests based on likelihood-based methods. We used the AIC, SC and HQ statistics to decide the optimal number of lags, p, and the best fit model. To resolve contradictory results of the test, we placed greatest weight on the lag length recommended by the HQ statistic. Our reasoning is as follows. SC and HQ statistics are consistent in as much as when the sample size goes to infinity, they will choose the correct lag structure. The AIC statistic is an inconsistent procedure in that if the sample size goes to infinity, it doesn't necessarily converge to the true lag structure. In small samples, such as ours, SC tends to be too conservative; that is, choose lag lengths that are too short. Thus, we focus mainly on the HQ statistic.

VAR models contain multiple parameters that make it difficult to identify the important explanatory variables. One strategy is to perform a Granger causality test – a joint test on the lags of each variable in each equation of the VAR. Granger causality indicates whether lagged values of a variable have additional predictive power on a response variable. However, Granger causality is limited by the fact that it is only a statistical tool, and it is not always clear whether it has any epistemic utility. We perform Granger causality tests by performing chi-square tests applied to each equation of our VARs separately. The null hypothesis assumes no Granger causality, and tests are performed at the 5% significance level. Granger causality allows us to identify the relative importance of (lagged) variables in a VAR. However, except for very simple VAR models based on 1 lag, Granger causality tests do not necessarily reveal the direction of causality. Therefore, we compute impulse responses to observe how the variables in a VAR model react to a shock.

Consider a bivariate commodity currency effect VAR with $p = 2$ lag:

$$commodit\ \ _t = \phi_{10} + \phi_{11}commodity_{t-1} + \phi_{12}commodity_{t-2} + \phi_{13}RER_{t-1} + \phi_{14}RER_{t-2} + u_{1t}$$
$$RER_t = \phi_{20} + \phi_{21}commodity_{t-1} + \phi_{22}commodity_{t-2} + \phi_{23}RER_{t-1} + \phi_{24}RER_{t-2} + u_{2t}$$

A problem with this VAR is that a shock in one variable is difficult to interpret, as the disturbances in each equation are not independent of each other. Consider a commodity price shock in period t represented by an increase in u_{1t}. In period $t + 1$, the second equation in our system becomes

$$RER_{t+1} = \phi_{20} + \phi_{21}commodity_t + \phi_{22}commodity_{t-1} + \phi_{23}RER_t + \phi_{24}RER_{t-1} + u_{2t+1}$$

The real exchange rate in period $t + 1$ is partially determined by $commodity_t$, which is partially determined by u_{1t}. Since RER_{t+1} is also determined by its error term, u_{2t+1}, u_{1t} is correlated with u_{2t+1}.
A solution to this is to write the model as a recursive system so the VAR becomes a structural VAR, or SVAR. The SVAR approach allows us to use economic theory to transform the reduced-form VAR model into a system of structural equations. The crucial difference between the atheoretical and structural VAR is that the latter yields impulse responses and variance decompositions that can be given structural interpretations.

Consider a bivariate commodity currency effect structural VAR with $p = 2$ lags

$$commodity_t = a_0 + a_1 commodit_{t-1} + a_2 commodity_{t-2} + a_3 RER_{t-1} + a_4 RER_{t-2} + v_{1t}$$
$$RER_t = b_0 + b_1 commodity_{t-1} + b_2 commodity_{t-2} + b_3 RER_{t-1} + b_4 RER_{t-2} + b_5 + commodit_t + v_{2t}$$

where the disturbances v_{1t} and v_{2t} are now independent.

$commodity_t$ now features in the second equation, while RER_t does not appear in the first equation. The recursive ordering in this system is

$$commodit_t \text{ to } RER_t.$$

This ordering is not arbitrary; rather, it is motivated by economic theory. A key assumption underlying our dynamic analysis of all four effects is that fluctuations in world commodity prices are exogenously determined, so as to avoid reverse causality problems. This implies that Australian domestic factors have no effect on global commodity prices and that Australia's exports of commodities do not comprise a significant fraction of total world commodity supply. This 'price taker' assumption allows us to order global commodity prices first in our structural VAR models and estimate dynamic effects such that domestic structural shocks have no contemporaneous effect on global commodity prices. We assume that global commodity price shocks have their origin in global shocks exogenous to Australia, such as global demand shocks, unexpected disruptions of commodity supply, wars, natural disasters in major commodity-producing countries, unexpected changes in precautionary demand for commodities in fear of future supply shortages, and speculative trading. Directed by our 'price-taker' assumption, we discuss the economic theory drawn on to transform the reduced-form VAR models into structural equations for each effect.

A. *External balance effect SVAR*

The external balance effect is observed when trade and current account balances in small commodity-exporting economies are usually positively correlated with their terms of trade (i.e. the ratio of export and import prices) and the world prices of exported commodities in real terms. When real commodity prices increase, the revenue from exports exceeds the cost of imports, leading to an accumulation of foreign assets (or to a reduction of foreign debt). Thus, we assign the external balance effect SVAR the following recursive ordering.

$$commodity_t \text{ to } ToT_t \text{ to } CAB_t$$

B. *Commodity currency effect SVAR*

The commodity currency effect implies the real exchange rates of small commodity-exporting economies are strongly correlated with prices of their exported commodities. In particular, rising commodity prices result in appreciation of the real exchange rate. This effect is well documented. For example, Cashin, Cespedes and Sahay (2004) find a long run cointegrating relationship between the real exchange rates and real prices of exported commodities for 19 out of 58 commodity-exporting economies, while Chen and Rogoff (2003) report similar findings for a few developed resource-rich economies. Thus, we construct the commodity currency effect SVAR according to the following ordering.

$$commodit_t \text{ to } RER_t$$

C. *Spending effect SVAR*

The spending effect occurs when windfall income gains from commodity exports are partially spent inside small commodity-exporting economies, driving up domestic demand. For example, Spatafora and Warner (1999) find in general a strong positive effect of the terms of trade shocks on all aggregate domestic spending components: consumption, investment and government expenditures. Accordingly, we assign the spending effect SVAR the following recursive ordering.

$$commodit_t \text{ to } ToT_t \text{ to } GDP_t$$

where GDP encompasses consumption, investment and government expenditures.

D. Dutch disease effect SVAR

The Dutch disease effect captures a negative relationship between an increase in export revenues from primary commodities and a decline in the output of the non-commodity tradable sector, mainly manufacturing. The underlying mechanism goes as follows: an increase in primary commodities exports appreciates the real exchange rate, making non-commodity exports more expensive; as a result, the manufacturing sector becomes less competitive and its output declines. Thus, we construct the Dutch disease effect SVAR according to the following ordering.

$$commodity_t \text{ to } RER_t \text{ to } manufacturing_t$$

Empirical Results

This section presents the main empirical results obtained from our dynamic structural VAR models for each of the four effects.

A. External balance effect

Figure A1 shows optimal lag length test results based on trial two-lag external balance effect VARs for the three sub-periods.

Figure A1: Optimal Lag Length Test

VAR Lag Order Selection Criteria
Endogenous variables: PRB_COMMODITY PRB_TERMS_OF_TRADE PRB_CUR
Exogenous variables: C
Date: 09/24/19 Time: 22:31
Sample: 1 48
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-217.1267	NA*	12.09429*	11.00633*	11.13300*	11.05213*
1	-208.6350	15.28501	12.43022	11.03175	11.53841	11.21494
2	-200.5736	13.30131	13.14404	11.07868	11.96534	11.39927
3	-197.8639	4.064511	18.39431	11.39320	12.65986	11.85118
4	-189.9908	10.62864	20.27273	11.44954	13.09620	12.04492
5	-175.9267	16.87703	16.85412	11.19633	13.22299	11.92911
6	-171.3051	4.852641	23.35167	11.41525	13.82191	12.28542
7	-159.3401	10.76851	23.65705	11.26700	14.05366	12.27457
8	-149.7507	7.192009	29.16348	11.23754	14.40419	12.38250

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: B_COMMODITY B_TERMS_OF_TRADE B_CURRENT_AC
Exogenous variables: C
Date: 09/25/19 Time: 14:13
Sample: 1 48
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-274.6744	NA	214.8888	13.88372	14.01039	13.92952
1	-253.0024	39.00962*	114.2628*	13.25012*	13.75678*	13.43331*
2	-244.2485	14.44402	116.7122	13.26242	14.14908	13.58301
3	-242.5719	2.514825	171.9908	13.62860	14.89525	14.08658
4	-234.0656	11.48344	183.6471	13.65328	15.29994	14.24866
5	-229.4327	5.559589	244.6663	13.87163	15.89829	14.60441
6	-222.5590	7.217379	302.8876	13.97795	16.38460	14.84812
7	-214.7981	6.984752	378.6313	14.03991	16.82656	15.04747
8	-204.6497	7.611314	453.8947	13.98249	17.14913	15.12745

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: POB_COMMODITY POB_TERMS_OF_TRADE POB_CUR
Exogenous variables: C
Date: 09/24/19 Time: 22:47
Sample: 1 48
Included observations: 15

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-88.09984	NA*	37.84913*	12.14665*	12.28826*	12.14514*
1	-84.40720	5.415865	79.86148	12.85429	13.42073	12.84826
2	-80.91452	3.725532	202.3045	13.58860	14.57987	13.57804
3	-73.26575	5.099179	438.5392	13.76877	15.18487	13.75368

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

The AIC, SC and HQ statistics all select 0 lags for the pre-boom and post-boom VARs, suggesting that there is no external balance effect in the pre- and post-boom periods. All three statistics select 1 lag for the boom VAR, and the re-estimated boom VAR with 1 lag is shown below in figure A2.

Figure A2: VAR Estimates (Boom Period)

Vector Autoregression Estimates
Date: 09/24/19 Time: 22:36
Sample (adjusted): 2 48
Included observations: 47 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	B_COMMOD	B_TERMS_O	B_CURRENT
B_COMMODITY(-1)	0.180090	-0.066906	0.038695
	(0.20019)	(0.09728)	(0.02797)
	[0.89960]	[-0.68777]	[1.38358]
B_TERMS_OF_TRADE(	1.715573	0.928498	0.085487
	(0.38364)	(0.18643)	(0.05360)
	[4.47180]	[4.98048]	[1.59500]
B_CURRENT_ACCOUN	-4.234516	-1.926876	-0.409205
	(1.40371)	(0.68212)	(0.19611)
	[-3.01666]	[-2.82483]	[-2.08666]
C	-0.638620	0.130107	-0.063645
	(0.94630)	(0.45985)	(0.13220)
	[-0.67486]	[0.28294]	[-0.48142]

As the lag structure is $p = 1$, the t-statistics presented in the VAR output can be used to test for Granger causality, and the sign of the parameter estimate can be used to identify causal direction. The t-statistic to test that terms of trade Granger causes the global commodity price index is 4.47180, which is greater than 2 in magnitude. We conclude that the estimated positive effect (1.715573) of terms of trade on the global commodity price index is statistically significant and suggests Granger causality from terms of trade to the global commodity price index. Since the point estimate is positive, this result suggests that increases in Australia's terms of trade predict an increase in global commodity prices. The t-statistic to test that the current account balance Granger causes the global commodity price index is -3.01666, the absolute value of which is also greater than 2. Thus, the estimated negative effect (-4.234516) of the current account balance on the global commodity price index is statistically significant and suggests that there is Granger causality from the current account balance to the global commodity price index. Since the point estimate is negative, this result suggests that increases in Australia's current account balance predict a decrease in global commodity prices. These two results are surprising, given our assumption that global commodity prices are exogenous to Australian macroeconomic variables.

The other two notable parameter estimates in this VAR are the coefficients on the global commodity price index in the terms of trade and current account equations. Both of these estimates have t-statistics with absolute values less than 2, suggesting no Granger causality from the global commodity price index to terms of trade and no Granger causality from the global commodity price index to Australia's current account. The first result is surprising given Australia's terms of trade nearly doubled during the mining. This result seems to indicate that global commodity prices may not have been as influential to Australia's terms of trade uptick as expected. The second result is not as surprising, given that Australia's current account balance hovered around a horizontal line for most of the mining boom period.

A SVAR was estimated and the impulse responses are given in figure A3. The most notable result is that a positive global commodity price shock during the mining boom decreases all of the variables in the system, which is inconsistent with economic theory, as an increase in the price of a significant proportion of Australia's exports should automatically lead to an increase in terms of trade, and, holding government's saving and spending decisions fixed, an improvement in Australia's current account balance.

Figure A3: Impulse Response

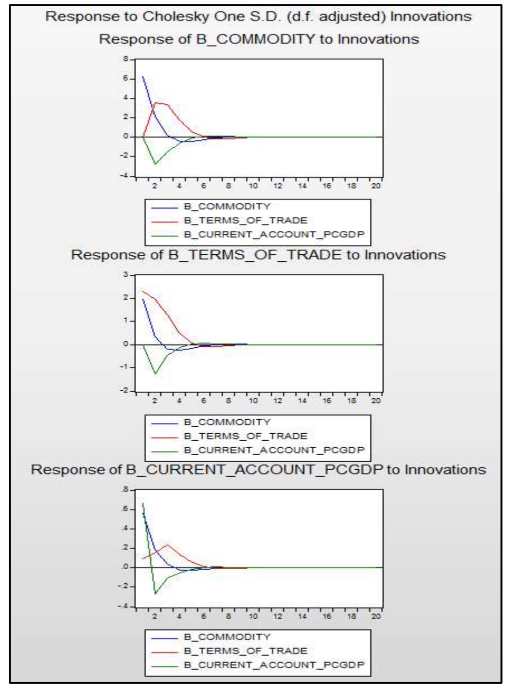


Figure A4 shows the variance decompositions (%) for the first 4 quarters (1 year) and figure A5 shows the variance decompositions (%) for the variables over 20 quarters. Notably, just under 50% of volatility in the global commodity price index in the intermediate- to long-run is due to external factors, with the biggest effects coming from terms of trade. Also of note is that the majority of variance in the current account balance comes from the current account balance itself and the global commodity price index, with terms of trade contributing less than 20% in the long run.

Figure A5: 5-year Variance Decomposition

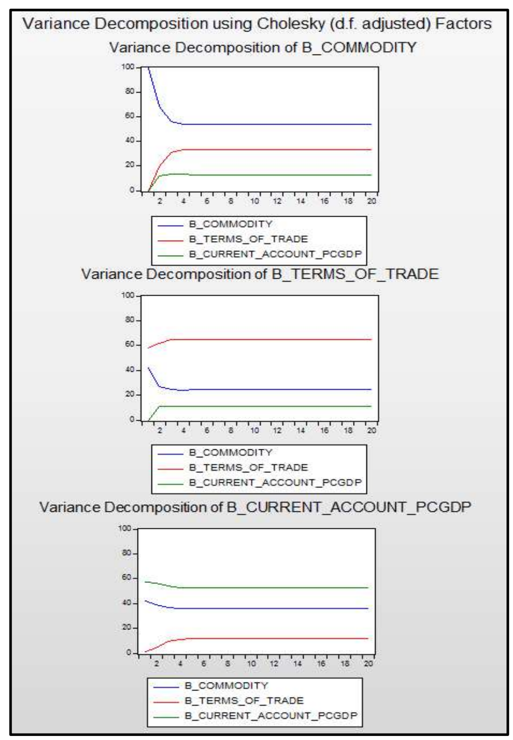


Figure A4: 1-year Variance Decomposition

Period	S.E.	B_COMMOD	B_TERMS_	B_CURREN
Variance Decomposition of B_COMMODITY:				
1	6.237577	100.0000	0.000000	0.000000
2	7.980981	68.11448	19.71909	12.16642
3	8.781901	56.29966	30.59520	13.10513
4	8.991198	53.94586	33.05018	13.00395
Variance Decomposition of B_TERMS_OF_TRADE:				
1	3.031090	42.26717	57.73283	0.000000
2	3.835785	27.11496	61.97901	10.90603
3	4.073035	24.25243	64.73467	11.01290
4	4.113246	24.16001	64.93992	10.90007
Variance Decomposition of B_CURRENT_ACCOUNT_PCGDP:				
1	0.871420	41.86995	1.216922	56.91313
2	0.942675	39.38867	3.833064	56.77827
3	0.979088	36.65205	9.543940	53.80401
4	0.990834	35.84505	11.29529	52.85966

Cholesky Ordering: B_COMMODITY B_TERMS_OF_TRADE B_CURRENT_ACCOUNT_PCGDP

Based on these results, there is no evidence that Australia's current account balance was positively correlated with national terms of trade and world prices of exported commodities in the pre-boom and post-boom periods. Moreover, these results actually suggest a negative external balance effect during the mining boom; casting considerable doubt over the strength of Australia's commodity connection. A possible economic explanation for this is that during the boom, the cost of imports also increased, offsetting export revenues and preventing the accumulation of foreign assets and the reduction of foreign debt.

B. Commodity currency effect

Figure B1 shows optimal lag length test results based on trial two-lag external balance effect VARs for the three sub-periods.

Figure B1: Optimal Lag Test Criteria

VAR Lag Order Selection Criteria
Endogenous variables: PRB_COMMODITY PRB_R_EXCHANGE_RATE
Exogenous variables: C
Date: 09/24/19 Time: 21:39
Sample: 1 48
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-198.5093	NA*	77.45766*	10.02546*	10.10991*	10.05600*
1	-195.5740	5.430260	81.73736	10.07870	10.33203	10.17030
2	-191.9417	6.356570	83.42594	10.09708	10.51930	10.24975
3	-190.5364	2.318750	95.42546	10.22682	10.81793	10.44055
4	-186.2729	6.608365	94.96975	10.21365	10.97364	10.48844
5	-185.0307	1.801189	110.4808	10.35154	11.28042	10.68739
6	-182.7769	3.042610	122.9777	10.43885	11.53662	10.83577
7	-180.6103	2.708343	138.6114	10.53051	11.79717	10.98850
8	-173.9436	7.666615	126.0328	10.39718	11.83273	10.91623

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: B_COMMODITY B_R_EXCHANGE_RATE
Exogenous variables: C
Date: 09/24/19 Time: 21:44
Sample: 1 48
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-271.5883	NA	2991.960	13.67942	13.76386	13.70995
1	-257.6345	25.81469	1819.893	13.18172	13.43505*	13.27332
2	-250.6809	12.16870*	1573.284*	13.03405*	13.45627	13.18671*
3	-248.2567	3.999976	1710.190	13.11283	13.70394	13.32656
4	-244.3786	6.010962	1735.141	13.11893	13.87893	13.39372
5	-240.8333	5.140694	1798.975	13.14167	14.07055	13.47752
6	-238.9306	2.568712	2037.921	13.24653	14.34430	13.64345
7	-235.1200	4.763194	2115.745	13.25600	14.52266	13.71399
8	-228.7435	7.332958	1951.858	13.13718	14.57272	13.65623

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: POB_COMMODITY POB_R_EXCHANGE_RATE
Exogenous variables: C
Date: 09/24/19 Time: 22:01
Sample: 1 18
Included observations: 15

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-82.80940	NA*	279.3769*	11.30792*	11.40233*	11.30691*
1	-81.14235	2.667284	385.3513	11.61898	11.90220	11.61596
2	-78.95061	2.922311	511.4697	11.86008	12.33212	11.85505
3	-78.66245	0.307369	930.5490	12.35499	13.01584	12.34795

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

As with the external balance effect, the AIC, SC and HQ statistics all select 0 lags for the pre-boom and post-boom commodity currency VARs, suggesting that there is no connection between global commodity prices and the Australian exchange rate in the pre- and post-boom periods. Both the AIC and HQ statistics select 2 lags for the boom VAR, and the boom VAR with 2 lags is shown below in figure B2.

The VAR in figure B2 contains too many parameter estimates for us to identify the importance of each variable. Thus, we perform Granger causality tests. Figure B3 shows that the Australian real exchange rate Granger causes the global commodity price index, and the global commodity price index Granger causes the Australian real exchange rate. Thus, there is bidirectional Granger causality (feedback). Since the "All" category is less than 0.05 for both Granger causality tests, both variables are endogenous. While Granger causality from commodity prices to the real exchange rate is in line with economic theory, and provides support for the notion that the Australian dollar is a 'commodity currency', Granger causality from the real exchange rate to the global commodity price index runs counter to our assumption that global commodity prices are exogenous to Australian macroeconomic variables.

Figure B2: VAR Estimates (Boom Period)

Vector Autoregression Estimates
Date: 09/24/19 Time: 21:43
Sample (adjusted): 3 48
Included observations: 46 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	B_COMMOD	B_R_EXCHA
B_COMMODITY(-1)	0.529207	-0.153249
	(0.14385)	(0.15363)
	[3.67878]	[-0.99751]
B_COMMODITY(-2)	0.122309	-0.216360
	(0.15121)	(0.16149)
	[0.80884]	[-1.33974]
B_R_EXCHANGE_RATE	0.597931	-0.026000
	(0.16063)	(0.17155)
	[3.72244]	[-0.15156]
B_R_EXCHANGE_RATE	0.628656	-0.289724
	(0.18763)	(0.20038)
	[3.35052]	[-1.44584]
C	-0.837730	1.570210
	(0.91130)	(0.97325)
	[-0.91926]	[1.61336]

Figure B3: Granger Causality

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 09/24/19 Time: 21:45
Sample: 1 48
Included observations: 46

Dependent variable: B_COMMODITY

Excluded	Chi-sq	df	Prob.
B_R_EXCHANGE_RA	30.62454	2	0.0000
All	30.62454	2	0.0000

Dependent variable: B_R_EXCHANGE_RATE

Excluded	Chi-sq	df	Prob.
B_COMMODITY	6.359028	2	0.0416
All	6.359028	2	0.0416

We compute impulse responses to understand the dynamic properties of the boom commodity currency VAR. The impulse responses are given in figure B4. Notably, a positive shock in global commodity prices raises the real exchange rate, as predicted by the commodity currency premise. Unexpectedly, however, global commodity prices increase in response to a positive shock in the Australian real exchange rate, which is, again, counter to our assumption that Australia is a price taker in this context and cannot affect global commodity prices.

Figure B4: Impulse Response

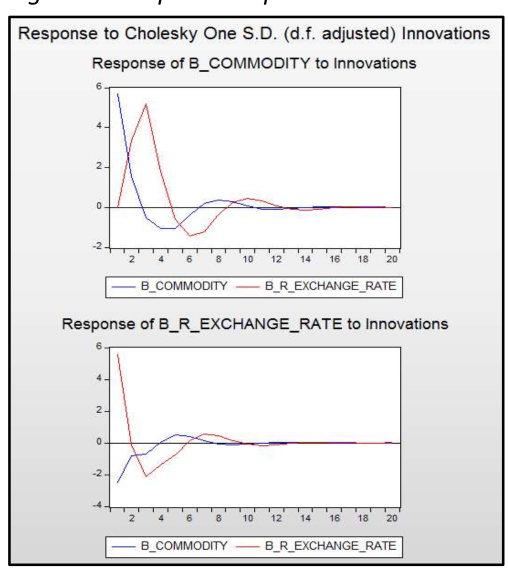


Figure B5: 1-year Variance Decomposition

Variance Decomposition of B_COMMODITY:

Period	S.E.	B_COMMODI	B_R_EXCHA
1	5.695461	100.0000	0.000000
2	6.769698	75.91640	24.08360
3	8.531416	48.18790	51.81210
4	8.777502	46.92138	53.07862

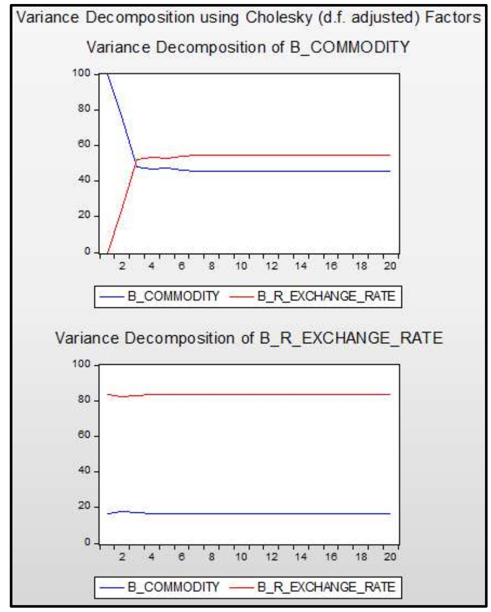
Variance Decomposition of B_R_EXCHANGE_RATE:

Period	S.E.	B_COMMODI	B_R_EXCHA
1	6.082621	16.55975	83.44025
2	6.137815	17.99827	82.00173
3	6.532866	17.13326	82.86674
4	6.684023	16.36711	83.63289

Cholesky Ordering: B_COMMODITY B_R_EXCHANGE_R

Figure B5 shows the variance decompositions (%) for the first 4 quarters (1 year), and figure B6 shows the variance decompositions (%) for the mining boom variables over 20 quarters (5 years). Perhaps most surprisingly, in the long-run, around half of the variance in the global commodity price index is due to Australia's real exchange rate; a counter-prediction of our model which orders global commodity prices first in the structural VAR so as not to be affected by shocks in the real exchange rate. The variance of the real exchange rate is maintained in both the long- and short-run, in spite of a shock in global commodity prices.

Figure B6: 5-year Variance Decomposition



Based on these results, there is no evidence that the Australian dollar was a commodity currency before and after the mining boom, and only weak evidence that the AUD was correlated with global commodity prices during the boom. Possible economic explanations for this is that during the boom, interest rates restricted currency-driven movements in the AUD, and that the Great Financial Crisis in 2008-2009 saw a brief slowdown in industrial expansion, and a decline in demand for Australia's commodities. The lack of a commodity connection post-boom also provides tentative support for our hypothesis that the structure of the Australian economy has diversified in recent years, with transitions underway toward the services and renewable energy sectors.

C. Spending effect

Figure C1 shows optimal lag length test results based on trial two-lag external balance effect VARs for the three sub-periods.

Figure C1: Optimal Lag Length Criteria

VAR Lag Order Selection Criteria
Endogenous variables: PRB_COMMODITY PRB_TERMS_OF_TRADE PRB_R_G
Exogenous variables: C
Date: 09/25/19 Time: 21:26
Sample: 1 48
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-227.2582	NA	20.07167	11.51291	11.63958*	11.55871*
1	-216.0879	20.10647	18.04335	11.40440	11.91106	11.58759
2	-203.9113	20.09150	15.53122	11.24556	12.13222	11.56615
3	-197.3275	9.875683	17.90749	11.36637	12.63303	11.82436
4	-188.8722	11.41462	19.16995	11.39361	13.04027	11.98899
5	-172.7700	19.32266*	14.39328	11.03850	13.06515	11.77127
6	-163.2654	9.979844	15.62203	11.01327	13.41992	11.88344
7	-147.8048	13.91449	13.28848*	10.69024*	13.47689	11.69781
8	-139.9937	5.858324	17.90475	10.74969	13.91633	11.89465

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: B_COMMODITY B_TERMS_OF_TRADE B_R_GDP
Exogenous variables: C
Date: 09/25/19 Time: 21:27
Sample: 1 48
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-285.0821	NA	361.5873	14.40410	14.53077	14.44990
1	-248.0443	66.66790*	89.17477*	13.00222*	13.50888*	13.18541*
2	-241.8950	10.14636	103.7559	13.14475	14.03141	13.46534
3	-240.1710	2.586095	152.5350	13.50855	14.77521	13.96653
4	-233.6946	8.743149	180.2712	13.63473	15.28139	14.23011
5	-227.7862	7.090040	225.3314	13.78931	15.81597	14.52208
6	-222.4350	5.618747	301.0163	13.97175	16.37840	14.84192
7	-205.7328	15.03198	240.6388	13.58664	16.37329	14.59421
8	-198.3986	5.500631	332.0587	13.66993	16.83658	14.81489

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: POB_COMMODITY POB_TERMS_OF_TRADE POB_R_G
Exogenous variables: C
Date: 09/25/19 Time: 21:31
Sample: 1 48
Included observations: 15

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-84.76215	NA*	24.25403*	11.70162	11.84323*	11.70011
1	-77.65358	10.42590	32.45358	11.95381	12.52025	11.94778
2	-70.05117	8.109239	47.52840	12.14016	13.13143	12.12960
3	-56.13039	9.280521	44.64464	11.48405*	12.90015	11.46897*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Due to a limited sample size and the propensity of the statistics to opt for a conservative (i.e. longer) lag length, we interpret the pre-boom and post-boom optimal lag length test as suggesting 0 lags for the post-boom VAR. This implies that there is no spending effect pre- and post-boom. The AIC, SC and HQ statistics all select 1 lag for the boom VAR, and the re-estimated boom VAR with 1 lag is shown in figure C2.

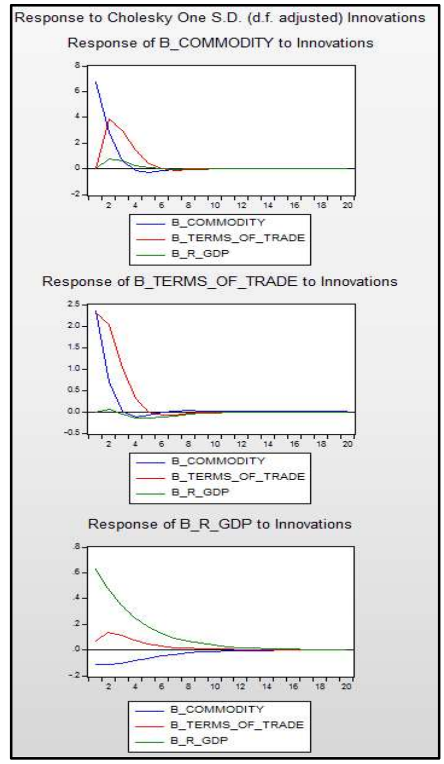
Figure C2: VAR Estimate (Boom Period)

Vector Autoregression Estimates
Date: 09/25/19 Time: 21:28
Sample (adjusted): 2 48
Included observations: 47 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	B_COMMOD	B_TERMS_O	B_R_GDP
B_COMMODITY(-1)	-0.132915 (0.18797) [-0.70711]	-0.205200 (0.09180) [-2.23537]	-0.015477 (0.01797) [-0.86137]
B_TERMS_OF_TRADE(	1.626872 (0.41400) [3.92966]	0.882694 (0.20218) [4.36587]	0.034881 (0.03957) [0.88144]
B_R_GDP(-1)	1.264582 (1.06020) [1.19277]	0.100212 (0.51776) [0.19355]	0.754720 (0.10134) [7.44724]
C	-4.147866 (3.30813) [-1.25384]	-0.056308 (1.61556) [-0.03485]	0.696337 (0.31622) [2.20209]

As the lag structure is $p = 1$, the t-statistics presented in the boom period VAR output can be used to test for Granger causality, and a separate Granger causality test need not be performed. Moreover, as the lag structure is $p = 1$, it is straightforward to identify not only the causal patterns, but also the sign of the causal patterns. The t-statistic to test that terms of trade Granger cause the global commodity price index is 3.92966. As the absolute value of this t-statistic is greater than 2, the estimated positive effect (1.626872) of terms of trade on the global commodity price index is statistically significant and suggests that there is Granger causality from terms of trade to the global commodity price index. Since the point estimate is positive, this result suggests that increases in the terms of trade predict an increase in global commodity prices. The significant t-statistic for the effect of global commodity prices on terms of trade indicates bidirectional Granger causality between terms of trade and the global commodity price index. Notably, real GDP is not Granger caused by any other variable in this system, casting doubt on the spending effect.

Figure C3: Impulse Response



The impulse responses are given in figure C3. The most notable result is that a positive global commodity price shock during the mining boom increases real GDP growth, which provides some evidence that Australia did indeed experience a spending effect during the mining boom. However, this result is weakened by the result that a positive commodity price shock decreases Australia's terms of trade. Interestingly, a positive shock in Australia's terms of trade leads to a short-term increase in real GDP growth, as predicted by the spending effect theory, but gives way to a decrease in real GDP growth in the long run. Perhaps this is a sign of capital overutilization leading to inflation that induces higher interest rates and a contraction in the long-run.

Figure C4: 1-year Variance Decomposition

Variance Decomposition of B_COMMODITY:

Period	S.E.	B_COMMOD	B_TERMS_	B_R_GDP
1	6.755122	100.0000	0.000000	0.000000
2	8.297220	77.58322	21.49156	0.925225
3	8.858845	68.51717	30.21378	1.269057
4	8.977761	66.75357	31.92418	1.322247

Variance Decomposition of B_TERMS_OF_TRADE:

Period	S.E.	B_COMMOD	B_TERMS_	B_R_GDP
1	3.298937	51.02913	48.97087	0.000000
2	3.941374	38.74686	61.22740	0.025749
3	4.074039	36.26664	63.68742	0.045942
4	4.089704	36.07080	63.76460	0.164602

Variance Decomposition of B_R_GDP:

Period	S.E.	B_COMMOD	B_TERMS_	B_R_GDP
1	0.645706	3.232545	1.235436	95.53202
2	0.821004	3.793467	3.455684	92.75085
3	0.905226	4.399005	4.413384	91.18761
4	0.946640	4.845585	4.668665	90.48575

Cholesky Ordering: B_COMMODITY B_TERMS_OF_TRADE B_R_GDP

Figure C4 shows the variance decompositions (%) for the first 4 quarters (1 year). Given its dependence on itself over the first year, real GDP growth might be exogenous. 95.53% of real GDP growth forecast variance in the first period is due to own shocks, with 3.23% from the global commodity price index, and 1.24% from terms of trade. After 1 year, 90.46% of real GDP growth forecast variance is due to own shocks, with 4.85% from the global commodity price index, and 4.67% from the current account balance.

Figure C5: Variance Decomposition

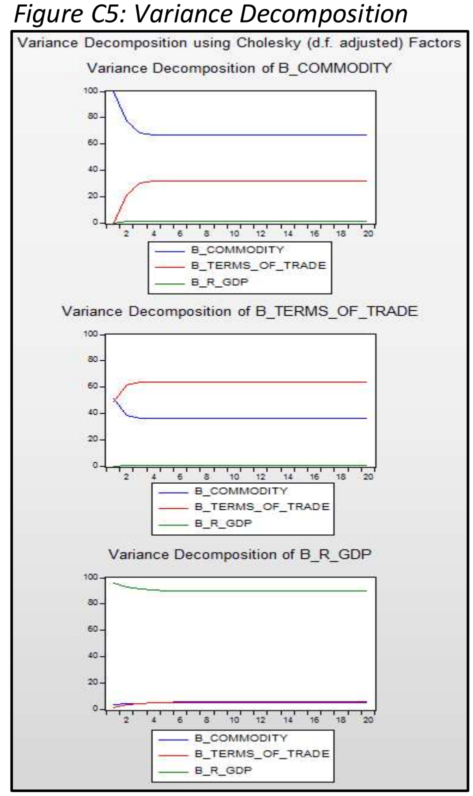


Figure C5 shows the variance decompositions (%) for the variables over 20 quarters, and provides further evidence that real GDP growth is exogenous, as around 90% of real GDP growth variance is explained by itself in the long-run. In the short and long-run, the global commodity price index and terms of trade have hardly any effect on real GDP growth variance.

Figure C6: Granger Causality

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 09/25/19 Time: 22:07
Sample: 1 48
Included observations: 47

Dependent variable: B_COMMODITY

Excluded	Chi-sq	df	Prob.
B_TERMS_OF_TRADE	15.44224	1	0.0001
B_R_GDP	1.422708	1	0.2330
All	16.60434	2	0.0002

Dependent variable: B_TERMS_OF_TRADE

Excluded	Chi-sq	df	Prob.
B_COMMODITY	4.996878	1	0.0254
B_R_GDP	0.037461	1	0.8465
All	5.003924	2	0.0819

Dependent variable: B_R_GDP

Excluded	Chi-sq	df	Prob.
B_COMMODITY	0.741950	1	0.3890
B_TERMS_OF_TRADE	0.776930	1	0.3781
All	0.849109	2	0.6541

Indeed, by running a Granger causality test, as seen in figure C6, we observe that real GDP growth is exogenous to this system as the p-value for "ALL" in the real GDP growth block is 0.6541 which is greater than 0.05, leading us to not reject the null hypothesis that real GDP growth is exogenous in this system.
Based on these results, there is no evidence of a spending effect pre- or post-boom, and weak / borderline-zero evidence of a spending effect during the boom given findings of exogeneity and contradictory impulse responses.

D. Dutch disease effect

Figure D1 shows optimal lag length test results based on trial two-lag external balance effect VARs for the three sub-periods.

Figure D1: Optimal Lag Length Criteria

VAR Lag Order Selection Criteria
Endogenous variables: PRB_COMMODITY PRB_R_EXCHANGE_RATE PRB_MA
Exogenous variables: C
Date: 09/25/19 Time: 09:16
Sample: 1 48
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-269.2247	NA*	163.6344*	13.61123*	13.73790*	13.65703*
1	-264.5951	8.333188	204.0037	13.82976	14.33642	14.01295
2	-258.7812	9.593007	241.3744	13.98906	14.87572	14.30965
3	-254.6592	6.182978	314.7588	14.23296	15.49962	14.69095
4	-244.5666	13.62499	310.4633	14.17833	15.82499	14.77371
5	-238.9439	6.747285	393.6480	14.34719	16.37385	15.07997
6	-236.1260	2.958755	596.8796	14.65630	17.06295	15.52647
7	-226.6090	8.565316	683.4185	14.63045	17.41710	15.63802
8	-212.5795	10.52211	674.7597	14.37898	17.54563	15.52394

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: B_COMMODITY B_R_EXCHANGE_RATE B_MANUFACT
Exogenous variables: C
Date: 09/25/19 Time: 09:19
Sample: 1 48
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-347.1837	NA	8067.371	17.50918	17.63585	17.55498
1	-328.4490	33.72237	4968.292	17.02245	17.52911*	17.20564*
2	-317.9994	17.24189	4662.270*	16.94997	17.83663	17.27056
3	-311.6345	9.547345	5434.754	17.08172	18.34838	17.53971
4	-305.8668	7.786301	6654.685	17.24334	18.89000	17.83872
5	-298.6715	8.634403	7799.680	17.33358	19.36023	18.06635
6	-295.1117	3.737850	11395.76	17.60558	20.01224	18.47575
7	-288.9286	5.564755	15414.85	17.74643	20.53308	18.75399
8	-259.7730	21.86671*	7144.007	16.73865*	19.90530	17.88361

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: POB_COMMODITY POB_R_EXCHANGE_RATE POB_MA
Exogenous variables: C
Date: 09/25/19 Time: 09:29
Sample: 1 48
Included observations: 15

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-106.5935	NA	445.6038*	14.61247	14.75408*	14.61096
1	-104.5756	2.959617	1175.456	15.54341	16.10985	15.53738
2	-87.67323	18.02918*	498.1668	14.48976	15.48103	14.47920
3	-75.30652	8.244471	575.6798	14.04087*	15.45697	14.02578*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

The AIC, SC and HQ statistics all select 0 lags for the pre-boom VAR, suggesting that there is no Dutch disease effect in the pre-boom period. Due to a limited sample size and the propensity of the statistics to opt for a conservative (i.e. longer) lag length, we interpret the post-boom optimal lag length test as suggesting 0 lags for the post-boom VAR. This implies that there is also no Dutch disease effect post-boom. Both the SC and HQ statistics select 1 lag for the boom VAR, and the re-estimated boom VAR with 1 lag is shown in figure D2.

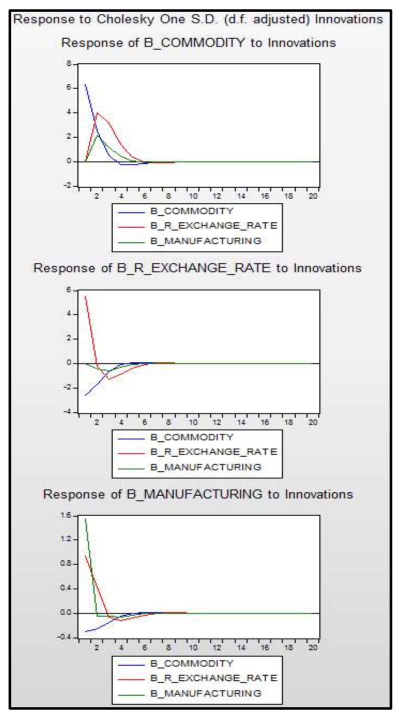
Figure D2: VAR Estimates (Boom period)

Vector Autoregression Estimates
Date: 09/25/19 Time: 09:20
Sample (adjusted): 2 48
Included observations: 47 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	B_COMMOD	B_R_EXCHA	B_MANUFA
B_COMMODITY(-1)	0.669521	-0.287873	-0.008433
	(0.12873)	(0.12499)	(0.03745)
	[5.20097]	[-2.30314]	[-0.22519]
B_R_EXCHANGE_RATE	0.486598	0.011918	0.082243
	(0.20692)	(0.20091)	(0.06020)
	[2.35165]	[0.05932]	[1.36626]
B_MANUFACTURING(-1)	1.389555	-0.299185	-0.030906
	(0.60388)	(0.58634)	(0.17568)
	[2.30105]	[-0.51026]	[-0.17592]
C	-0.103190	1.166449	-0.205551
	(0.98403)	(0.95546)	(0.28627)
	[-0.10486]	[1.22083]	[-0.71803]

As the lag structure is $p = 1$, we use the test statistics to directly infer the presence and direction of Granger causality. The t-statistic to test that the real exchange rate Granger causes the global commodity price index is 2.35165. As the absolute value of this t-statistic is greater than 2, the estimated positive effect (0.486598) of the real exchange rate on the global commodity price index is statistically significant and suggests that there is Granger causality from the real exchange rate to the global commodity price index. Since the point estimate is positive, this result suggests that increases in the Australian dollar predict an increase in global commodity prices. The significant t-statistic for the effect of global commodity prices on the real exchange rate indicates bidirectional Granger causality between the real exchange rate and the global commodity price index; echoing the surprising result from the commodity currency effect results. There is also suggestion that manufacturing Granger causes global commodity prices; another counter-prediction to our model that assumes global commodity prices as exogenous to Australian macroeconomic forces. Notably, manufacturing is not Granger caused by any of the included variables, casting doubt on the Dutch disease effect during the mining boom.

Figure D3: Impulse Response



The impulse responses are given in figure D3. The Dutch disease effect describes a phenomenon where rising real commodity prices, via an appreciation of the real exchange rate, lead to a fall in competitiveness and thus to a decrease in the output of the non-commodity tradable sectors, most notable among which is manufacturing, in small commodity-exporting economies. Our results show that a positive global commodity price shock during the mining boom decreases the real exchange rate and increases manufacturing. This is the opposite prediction of the Dutch disease effect.

Figure D4: 1-year Variance Decomposition

Variance Decomposition of B_COMMODITY:				
Period	S.E.	B_COMMOD	B_R_EXCH	B_MANUFA
1	6.317356	100.0000	0.000000	0.000000
2	8.174954	69.23007	23.78259	6.987331
3	8.851618	59.32932	33.01231	7.658375
4	8.973937	57.78953	34.56322	7.647257
Variance Decomposition of B_R_EXCHANGE_RATE:				
Period	S.E.	B_COMMOD	B_R_EXCH	B_MANUFA
1	6.133880	18.66249	81.33751	0.000000
2	6.401864	24.69085	74.78095	0.528198
3	6.590849	24.32383	74.31211	1.364058
4	6.661213	23.83317	74.59640	1.570433
Variance Decomposition of B_MANUFACTURING:				
Period	S.E.	B_COMMOD	B_R_EXCH	B_MANUFA
1	1.837825	2.689454	25.70907	71.60148
2	1.905287	4.391804	28.92384	66.68436
3	1.913692	5.034270	28.78322	66.18251
4	1.919736	5.081866	29.05893	65.85921
Cholesky Ordering: B_COMMODITY B_R_EXCHANGE_RATE B_MANUFACTURING				

Figure D5: 5-year Variance Decomposition

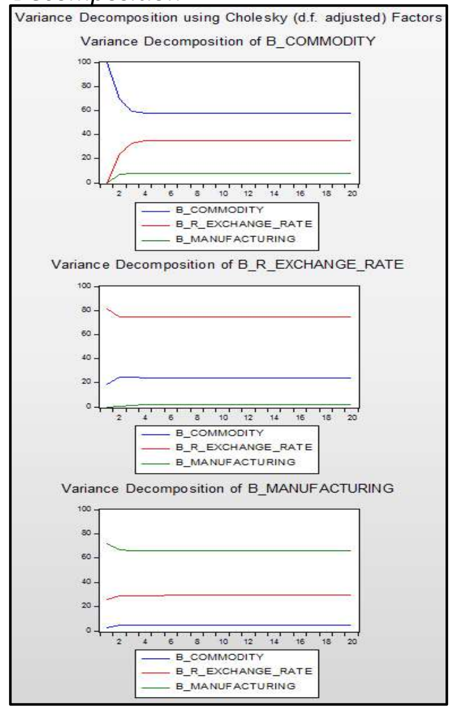


Figure D4 shows the variance decompositions (%) for the first 4 quarters (1 year) and figure D5 shows the variance decompositions (%) for the variables over 20 quarters. Notably, just under 60% of volatility in the global commodity price index in the intermediate- to long-run is due to external factors, with the biggest effects coming from real exchange rate. Also of note is that the majority of variance in manufacturing comes from manufacturing itself and the real exchange rate, with the global commodity price index contributing less than 10% in the long run.

Based on these results, there is no evidence that Australia has, over the past 30 years, been subject to a Dutch disease effect. This adds further weight to the significance of Australia's transitions away from natural resources and towards services-based output driven increasingly by renewable energy sources.

Conclusions and Implications

In this paper we have analysed the dynamic effects that characterise Australia's connection to global commodity price changes. Drawing on structural VAR techniques, we find no evidence of an external balance effect, commodity currency effect, spending effect, or Dutch disease effect during the pre-boom and post-boom periods. Moreover, our mixed boom-period results, including a negative external balance effect, a weak commodity currency effect, a weak / borderline-zero spending effect, and no Dutch disease effect, provide only weak evidence of Australia's commodity connection during the mining boom. Our analysis is conducted with full consciousness of its limited data set and the statistical inaccuracies that may have arisen throughout testing. We also acknowledge the possibility of a structural break during the Great Financial Crisis, which may have dampened the positive results of our boom-period effects. Taking our findings at face value, our hypothesis that Australia's commodity connection has weakened in recent years is confirmed. Indeed, we are led to believe that this weakening can be explained by the end of the mining boom, and transitions to services- and renewable-energy-based domestic output. Future studies might integrate our findings with results measuring Australia's progress towards those transitions. This might be captured by a dynamic spillover index, for example, that measures changes in the variability of Australian macroeconomic variables in response to non-commodity shocks versus commodity shocks over time. However, perhaps more interestingly, our analysis suggests that Australian macroeconomic variables were not tightly linked to global commodity price movements during the mining boom, contrary to common belief, and that the Australian dollar's reputation as a "commodity currency", at least over the past 30 years, may have been unmerited.

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