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An Import Demand Function for the Australian Economy Using Vector Autoregression Techniques

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Abstract

The recent growth in the Chinese economy appears to have contributed to the recent mining boom in Australia. While Australia's mining industry is an export-oriented industry, the imported capital equipment suggests that there may be a relationship between exports and imports. This paper analyses whether imports are likely to be affected by exports. While this question has received some attention in the literature, this is the first Australian study to investigate this relationship using a Vector Autoregression (VAR) approach. This VAR model thus incorporates lagged values of imports and exports as explanatory variables. To develop this model, data from 1984-2012 was used. The data was tested for stationarity; and these tests conclude that there is a statistically significant cointegrating relationship between imports and exports. Policymakers may benefit from an understanding of this relationship; as such an understanding might assist them in the formulation of future international trade policy for Australia.

Key words: Imports, VAR, VECM

JEL Classification Numbers: C32, F14, F47

1. Introduction

As computers and information technology have become increasingly more sophisticated, macroeconometric models have grown from single equations that focussed on a few variables, to larger models which entail several hundred equations. Prior to the last three decades, macroeconometric models involving autoregressions were univariate autoregressions, namely being: single-equation, single-variable, and linear models. In univariate autoregressions, the current value of a given variable is explained by its own lagged values. Sims (1980) provided a new modelling framework which led to the development of vector autoregressions (VARs). A VAR, while still linear, is an *n*-equation, *n*-variable model unlike its single-equation, single-variable univariate counterpart. Therefore, in the VAR case, each variable is explained by its own lagged values as well as the lagged value of all the other remaining *n-1* variables as well.

Following the work of Sims (1980), structural VARs (SVARs) were developed by researchers where a SVAR is a VAR that is based on economic theory. SVAR models hence utilise an econometric rather than a pure statistical approach. In the Australian context, SVARs have focussed on the Australian macroeconomy as a single whole unit. Australian studies in the last decade include:

Brischetto and Voss (1999) and Dungey and Pagan (2000). In each of these studies the researchers developed a SVAR model of the entire Australian economy. Furthermore, Fry and Pagan (2005) looked at some of the econometric issues in developing such SVARs for modelling the Australian macroeconomy.

By the development of these SVAR models, Brischetto and Voss (1999), Dungey and Pagan (2000), and Fry and Pagan (2005) contributed to the understanding of the overall workings of the entire Australian macroeconomy as a single whole unit. However, the question still remains whether SVAR models can go beyond explaining these overall workings of the entire Australian macroeconomy. Little research has been conducted on utilising SVAR techniques for specific components of the Australian macroeconomy. Furthermore, only a few studies use a SVAR approach to model specific components of Australia’s external, that is, Australia’s overseas sector. Under-researched macroeconomic components for Australia’s external economy using a SVAR approach include: credit market shocks, financial capital flows, exchange rates, export demand, as well as import demand. The question thus remains whether a SVAR approach can model such specific macroeconomic components and their behaviour. More specific SVAR research is needed to provide macroeconomic policymakers with specific and relevant tools for formulating their policies.

This paper utilises a SVAR approach to model one such under-researched Australian macroeconomic component, that is, import demand. While there has been research to date on import demand functions using non-SVAR approaches, previous studies have failed to recognise the time series properties of the modelled data. Thus, there is a case to argue that previous studies may have resulted in statistically biased and statistically inconsistent estimates. Furthermore, to the best of the author’s knowledge, no comprehensive econometric research has been conducted on Australia’s import demand function for almost two decades since Wilkinson’s (1992) study.

The model developed by Wilkinson (1992) and most other Australian SVAR models were developed prior to the Global Financial Crisis (GFC). Thus, these SVAR models, both of the overall Australian macroeconomy as well as those on specific macroeconomic components, need to be revisited. These SVAR models need to be revisited in this post-GFC, post-Eurozone Crisis era to determine whether there has in fact been a structural break in macroeconomic variables. A structural break will thus render the models of even the past decade as out-dated and invalid. Macroeconometricians, in the last two decades, have explored the possibility of structural breaks in their SVAR models in the post-float era. Furthermore, macroeconometricians have also explored the possibility of structural breaks in their SVAR models in the post-inflation targeting era. Therefore, this study is timely as it will also look at whether there is yet a third structural break in this post-GFC, post-Eurozone Crisis era which Australian SVAR models need to take into account. This paper will thus examine if such a structural break has had an impact on Australia’s import demand function.

In this post-GFC, post-Eurozone crisis era, this research makes an important contribution to the policy-making arena as it influences strategic trade policy in this increasingly open and interdependent global economy. Furthermore, in the context of the post-2005 mining boom which is by nature an export-oriented industry, there is a direct feedback into import demand. This feedback is due to the fact that the bulk of the capital equipment that is utilised in the mining industry is in fact imported into Australia. As the mining boom continues into 2012 and beyond, so does the necessitated demand for imported capital equipment which accounts for approximately 25% of Australia’s imports.

Since the export-oriented mining boom fuels the demand for imported capital equipment, this paper models the demand for imports with exports as an explanatory variable. Positive movements in export prices result in larger profits for the mining industry and these profits in turn have a direct impact on the demand for imported capital equipment. While Wilkinson (1992) as well as Dwyer and Kent (1993) incorporated the price of exports in estimating an import demand model for Australia, these studies failed to incorporate aggregate exports explicitly in their estimation of an import demand function. This paper thus applies a more sophisticated approach by identifying a cointegrating relationship for exports within the formulation of an import demand function. Thus, this approach makes the model that is developed in this paper richer and relevant to the current decade.

Identifying a cointegrating relationship within the context of an import demand function will also be valuable research due to the particular nature of the mining industry which imports the capital equipment to fuel their export activities. Thus, apart from the importance of this research to macroeconomic policy-makers, on a microeconomic or industry level, this research would naturally be very useful to specific Australian industries such as: the mining industry, the import-substitutes industry, as well as the import-servicing industry. Furthermore, this research makes an important contribution to the literature by taking SVARs further into the under-researched realm of explaining specific Australian macroeconomic phenomena.

To develop this import demand function for Australia using a SVAR approach, this paper is organised as follows: The next section provides the literature review and develops the conceptual macroeconomic framework in order to build the postulated SVAR. The third section builds the SVAR model in stages; this section then leads to the discussion of the empirical results in the penultimate section. The final section concludes with a summary of findings, explanation of limitations, and suggestions for future research.

2. Literature Review

There has been extensive research into estimating the elasticity of imports for countries other than Australia, due to its significance in formulating trade theory and hence trade policy. In its simplest form, we can aim to estimate the following relationship that is based on the traditional theory of demand, where the demand for an imported product, M^D, depends on its own price as well as real income. Traditionally, the real quantity of imports demanded is generally determined by the ratio of import prices to domestic prices and domestic income, in period *t*:

$$M^D = f(P,Y)$$

As simplistic as the above functional form is, the problem that arises, however, is that economic theory doesn't provide much direction on three counts. Firstly, we need to formulate what the appropriate measure of M^D actually is. Having arrived at the appropriate measure of M^D, the second issue that arises is in the decision of the appropriate functional form of *f(.)*. Thirdly, we need to consider whether lagged values of M^D, P or Y need to be included in the specification. In the absence of theoretical direction, the exact specification of an import demand function has largely become an empirical issue, where there are several studies that explore appropriate specifications.

Due to the nature of the data series, specifications of import demand functions are in log-linear form, and thus the estimated coefficients of variables represent estimated elasticities. Arize and Afifi (1987) look at calculating such elasticities in the import demand function for various developing countries. Arize and Afifi (1987) also look at whether there has been a structural break in this import demand relationship during the period of estimation with respect to the OPEC oil price shocks. Their paper tends to focus on the sign, size and significance of the estimated elasticities.

Arize and Afifi (1987) estimated four different log-linear variations of the import equation. The setup of some of these equations implies a partial adjustment process as they included lagged dependent variables. However, the equations are only valid if the series are themselves stationary. In the absence of stationarity we will experience the problem of spurious regression. In this case, ordinary least squared estimates of any parameters will be inconsistent and inefficient, unless the variables are cointegrated. Furthermore, the data generating process will not represent a valid error correction mechanism. In this paper, the high R^2 for the estimated equations for most of their 30 countries is indicative of this spuriousness.

While the Arize and Afifi (1987) paper looks at various developing countries, the paper by Goldstein, Khan and Officer (1980) looks at a host of industrialised countries. This paper formulates a general import demand function in which the prices of imports, tradable goods and non-tradable goods enter as explanatory variables. This function is then tested by utilising new price indices of tradable and non-tradable goods where the price indices are constructed by the authors themselves.

There are a series of key papers that explore import demand functions for the U.S economy. In Hayes and Stone (1983), the authors examine the responses of U.S. trade models to U.S. national income. Murray and Ginman (1976) empirically test traditional import aggregate import demand models using U.S. data, as do Thursby and Thursby (1984). Thursby (1988) furthers this to evaluate the coefficients in mis-specified regressions with an application to import demand.

Goldstein, Khan and Officer (1980) argued for the use of the price of non-tradable goods in a model of import demand. Empirical studies prior to this assumed that the demand for imports is independent of the price of non-tradable goods where in fact both domestic tradable and non-tradable goods are potential competitors with imports in a consumer's budget. In prior studies, consumers were assumed to be making a two-step decision where firstly they allocate their expenditure between all tradable goods and non-tradable goods based on their relative price, and then secondly, consumers allocate their expenditure on tradable goods between imports and domestic tradable goods. In essence, there was an assumption of separability in consumption that allowed consumers to make such a two-step decision process. This assumption had the practical advantage of the need to include only one relative price in the aggregate import equation. However, as consumers make a simultaneous decision between these categories of goods, Goldstein, Khan and Officer (1980) build a general import demand function in which the prices of imports, the prices of tradable goods, as well as the price of non-tradable goods enter the function as explanatory variables.

The contributions by Wilkinson (1992) and Dwyer and Kent (1993) are the most thorough examinations of the import demand function for the Australian economy to date. Both papers follow from Goldstein, Khan and Officer (1980) in including the price of non-tradable goods in the specification of their import demand functions. Dwyer and Kent (1993) explain Australia's import demand in terms of the increased openness of the Australian economy. To test this assertion, the authors proxy the degree of openness by the effective rate of protection and observe its impact on the demand for imports. The authors examine how the degree of the openness of the Australian economy helps determine the demand for aggregate imports, as well as its sub-classifications, being, consumption goods, capital goods and intermediate goods. They find that while reductions in protection do not in fact determine aggregate import demand, they do find that reductions in protection do determine the demand for imported consumption goods, as well as the demand for imported intermediate goods. Consistent with previous studies, the authors look at the demand for imports as an excess demand function. The rationale is that as the more open an economy is, it would not only determine the demand for imports, but it would also influence the supply of domestically produced import-substitutes.

Wilkinson (1992) looks at two main determinants of import demand which are domestic activity and relative prices. The paper also looks at cyclical determinants, such as potential domestic output as this can help determine import demand especially when the economy is operating at close to potential output and thus domestic supply constraints are close to being reached. Wilkinson (1992) shows that there is a positive relationship between the demand for imports and rises in the relative price of domestic goods to imports. The author notes that the influence on imports of the domestic activity variable and the influence on imports of the relative price variable are reinforcing over time. This phenomenon is explained by the fact that when the domestic economy is experiencing strong growth, this will eventuate in rising domestic inflation which will in turn increase the relative price of domestic goods to imports. Monetary policy may be tightened as a response to these inflationary pressures which will then result in an exchange rate appreciation. Such an exchange rate appreciation will reinforce, in the short run, increases in the price of domestically produced goods relative to the price of imports. The paper thus finds that cycles in domestic activity and cycles in relative prices have a high degree of correlation with cycles in imports. Unlike other studies that focus on the relative price of tradable goods, Wilkinson (1992) looks at the relative price of exports and finds that the relative price of exports is indeed a significant determinant of import demand.

In the literature, when models for import demand are explored, most of these studies model imports as a function of domestic prices as well as a variable that captures economic activity. Furthermore, several studies aim to model the cyclical factors of imports as well. In past studies, the ratio of the price of exports to the price of imports has been generally included as an explanatory of import demand. The motivation for this is two-fold: If there is an increase in the prices of exports, Australia will then have a greater capacity to consume imports even if there is no change in the level of production as measured by GDP in constant prices. Furthermore, these changes in export prices could filter out the effects in specific sectors of the economy. In the Australian case, about 50% of Australian imports are intermediate goods, whereas 25% of imports are capital goods. Thus, a change in export prices, if it were to make exportable industries more profitable, would then have a significant effect on the demand for imports.

In prior studies that modelled imports, authors made the assumption that the series being looked at were in fact stationary. This means that each series is assumed to have a constant mean and variance over time. If this assumption holds, we can then be certain that the sample mean and the sample variance are in fact a correct representation of the actual population mean and actual population variance of a particular series. If, however, the series are in fact non-stationary, then the standard statistical and econometric results need to be treated with caution. Even though the coefficient estimates are still consistent, their test-statistics do not in fact have the standard distributions and thus the usual hypothesis tests are no longer valid. Unlike previous studies, Wilkinson (1992) acknowledges the time series properties of the data. Times series data are examined and are found to contain unit-root stationarity. In doing so, this study finds there is strong evidence of a cointegrating relationship between imports, activity and the relative price of imports and exports. These approaches will be discussed in detail in the following section on methodology.

The aforementioned papers by Wilkinson (1992), and Dwyer and Kent (1993), built models of import demand, also known as import demand functions, for the Australian economy. Within the framework of economic theory both papers considered "imports" as the aggregate dollar value of the purchases of overseas goods, services and physical capital by domestic agents. As such, neither paper included the purchases of overseas financial assets such as overseas bonds, shares and derivatives in their definition of imports. This is not surprising, as theoretically, these purchases are referred to as financial capital inflows. Traditionally, financial capital inflows are placed within the framework of financial economics or finance where these authors and the literature in general seem to adhere to this strict de-lineation. "Demand" within the economic framework of import demand in both papers was in fact an *excess* demand function where domestic agents were assumed to be willing and able to purchase overseas products in excess of the domestic supply; primarily due to the fact that domestic supply was insufficient in terms of quantity, quality or both.

In building models of import demand, Wilkinson (1992) and Dwyer and Kent (1993), as well as others in the literature, have aimed to establish a cause-and-effect relationship between specified determinants of imports and the overall dollar value of imports experienced by an economy. The economic literature on import demand postulates and analyses the topic on two broad fronts: Firstly, there are investigations into the appropriate choice of variables that are in fact significant determinants of import demand; and secondly, there are investigations into the appropriate econometric modelling approach. Both branches of literature on import demand functions are based on economic theory as well as econometric methodology. However, it is also the case that a paper may lean more towards economic theory than econometric methodology or vice versa. Both approaches have merit in the literature of import demand as the economic theory supports the establishment of econometric methodology, while the econometric methodology validates the economic theory.

The main contribution that Wilkinson (1992) made to the econometric methodology of import demand functions was that the paper took into account the time-series properties of the data that was being modelled. Prior to this study, most previous studies on import demand did not tend to take the time-series properties of the data into account; specifically, it would have been important to test for the stationarity of the time-series data. In the absence of stationarity, any results of previous studies could have produced coefficient estimates which were biased. While the coefficient estimates would be still consistent in a statistical sense, any statistical test performed on the results of previous studies would be invalid as the test statistics would no longer have the standard distribution if the modelled data were indeed non-stationary. Wilkinson (1992) proved that time-series data used in models of import demand, in fact, has tended to be non-stationary. To overcome this, the paper discussed two possible econometric techniques: these being the econometric technique of differencing, and the econometric technique of cointegration. After an analysis of the relative merits of each technique the author settled on the technique of cointegration to build their model of import demand. The choice of the technique of cointegration over the technique of differencing is commendable as this then retains the long run properties of the time-series which in itself can provide further useful insights into import demand.

On the other hand, the main contribution that the paper by Dwyer and Kent (1993) made to the economic theory of import demand functions was that the paper introduced a new variable into the standard excess demand function. The authors insightfully argued that the openness of the economy was a significant determinant of the level of import demand. Various forms of barriers to trade such as import-tariffs and export-subsidies have effectively shielded the economy from the ability to import overseas products. Since it was difficult to measure the degree of openness of an economy, the authors constructed their own proxy variable which was then incorporated into an excess demand function for imports. The proxy variable that was chosen was the *"effective rate of protection"* where this variable was constructed by looking at how much the domestic economy's government altered the relative price of overseas products via the imposition of import-tariffs and the provision of export-subsidies. This proxy variable that the authors have created provides a useful tool for further investigations beyond the literature of import demand functions, to further their respective fields of study.

This research will build upon both these two papers, as mentioned, using recent data; as well as building on these two studies by incorporating recent developments in the literature. Furthermore, this paper aims to postulate further determinants of import demand; as well as further the econometric methodology via modifications to the modelling approach.

3. The Model

In general, an import demand equation can be specified as:

$$M_t \square\square f(Y_t , P_t)$$

Following from Sinha and Sinha (2000) we can specify the long-run import demand function after taking the logarithms of all variables in log-linear form to get:

$$lnM_t \square\square\square\square\square\square\square lnY_t \square\square\square lnRPM_t \square\square\square\square lnRPX_t + u_t$$

In this postulated model of import demand, *M* is the real quantity of aggregate imports and *Y* is real gross domestic product (real GDP). *PM* of Sinha and Sinha (2000) is replaced by *RPM* which is the relative price of imports. Furthermore, *PD*, the domestic price of Sinha and Sinha (2000) is replaced by *RPX* is the relative price of exports. The use of relative prices as the basis for the determinants of imports follows from Wilkinson (1992) and Athukorala and Menon (1995).

This paper takes the real quantities of aggregate imports, *M*, aggregate exports, *X*, (at constant prices) as well as the real GDP, *Y*, (at constant prices) from the Australian Bureau of Statistics (ABS). Furthermore, the relative price of imports, *RPM*, is calculated by dividing the implicit price deflator for imports by the implicit price deflator for GDP. Likewise, the relative price of exports, *RPX*, is calculated by dividing the implicit price deflator for exports is calculated by dividing the implicit price deflator for exports by the implicit price deflator for GDP. The natural logarithm of these variables is then taken, and thus in any estimated equation, the coefficients are then the respective elasticities. The descriptive statistics of these transformed series are presented in the next section.

4. Descriptive Statistics of Variables

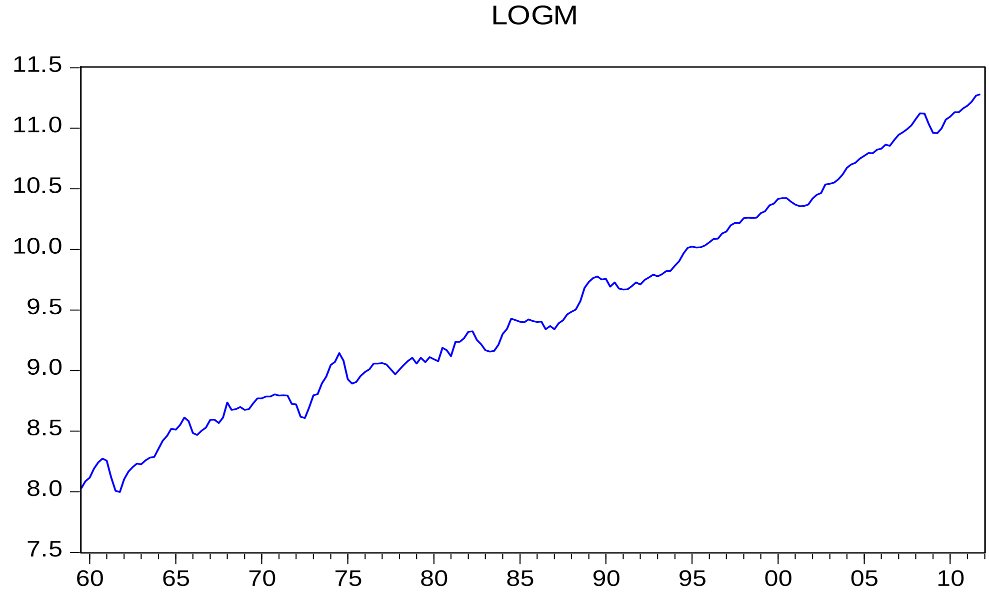
Table-1. Descriptive Statistics

	LOGM	LOGY	LOGRPM	LOGRPX	LOGX
Mean	9.536469	11.88714	0.560102	0.200921	9.839568
Median	9.399182	11.90040	0.628127	0.213320	9.775566
Maximum	11.28096	12.73090	0.872085	0.540122	11.10463
Minimum	7.997999	10.89944	-0.125286	-0.138944	8.257385
Std. Dev.	0.887595	0.519560	0.236893	0.166790	0.838110
Skewness	0.267731	-0.134421	-1.159786	0.068932	-0.052171
Kurtosis	2.002631	1.983734	3.637680	1.939982	1.731073
Jarque-Bera	11.21282	9.669389	50.63665	9.998138	14.18430
Probability	0.003674	0.007949	0.000000	0.006744	0.000832
Sum	2002.659	2496.299	117.6214	42.19343	2066.309
Sum Sq. Dev.	164.6553	56.41807	11.72871	5.814163	146.8074
Observations	210	210	210	210	210

The following section shows the time-series plots of these transformed variables. Both the positive correlation of *logM* with *logY* as well as the negative correlation of *logM* with *logRPM* is in line with the a priori expectation. As per the generic import demand equation, there is a consistent trending relationship with *logM* and *logY* which re-affirms the import demand formulation.

5. Natural Logarithms of Variables

Figure-1. logM for Australia - 1959 - 2012



Shareef and Tran (2008) note from the above that the decreased in the volatility after the mid-1980s can be attributed to the floating of the Australian dollar. They also note that this stability in *logRPM* has been a major contributing factor in stabilising the dependent variable *logM*. Furthermore, they note that this stability has been a major contributing factor to solidifying the long run relationship between *logM* and *logY*. The natural logarithms of the postulated dependent variables are presented in Figures 2 thru 5.

Figure-2. logY for Australia - 1959 - 2012

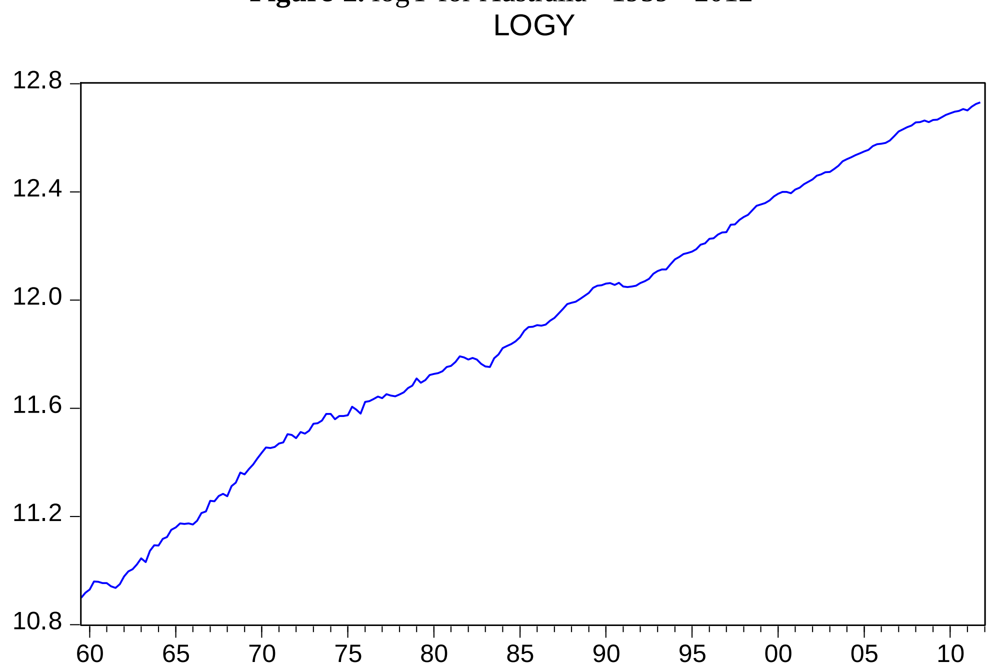


Figure-3. logRPM for Australia - 1959 - 2012

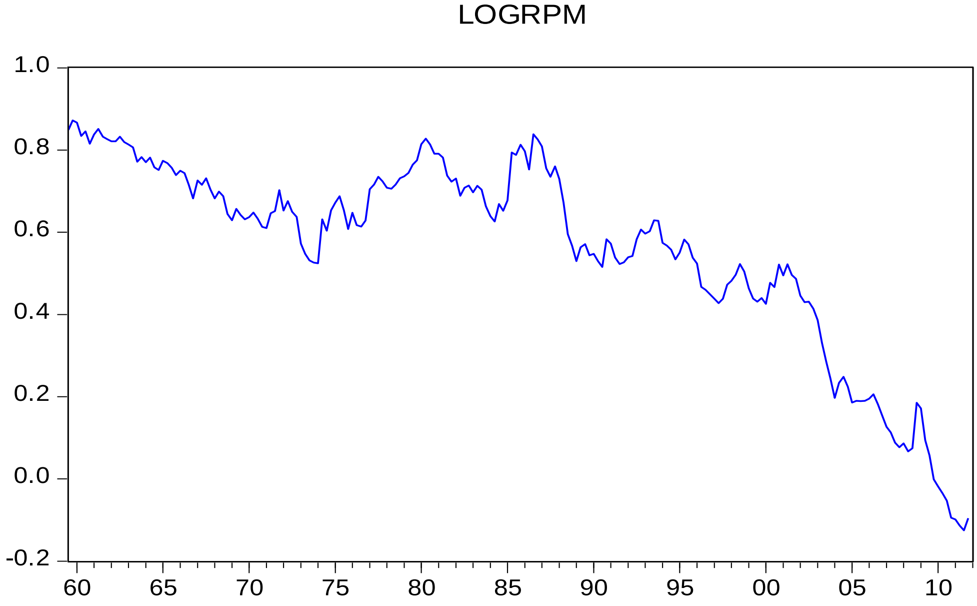


Figure-4. logRPX for Australia - 1959 - 2012

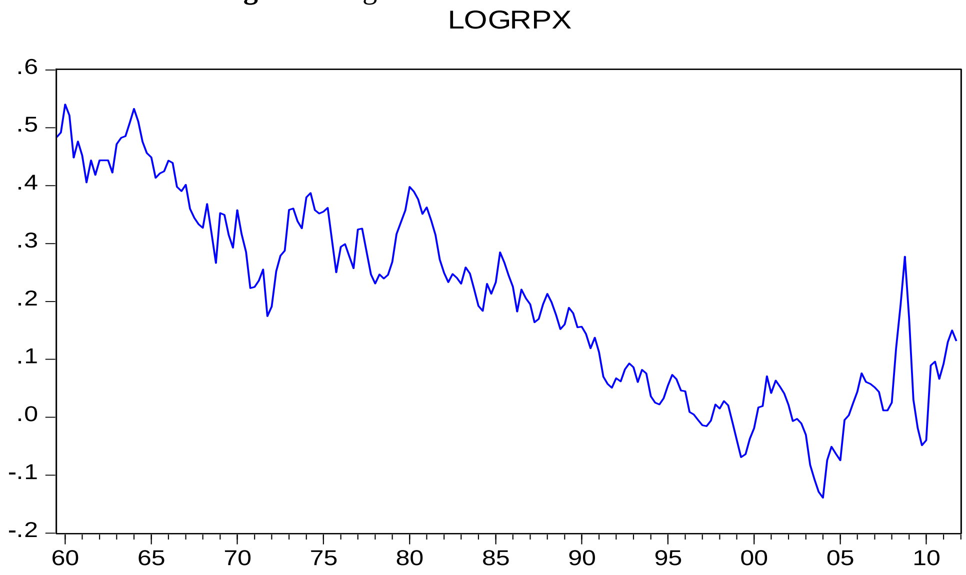
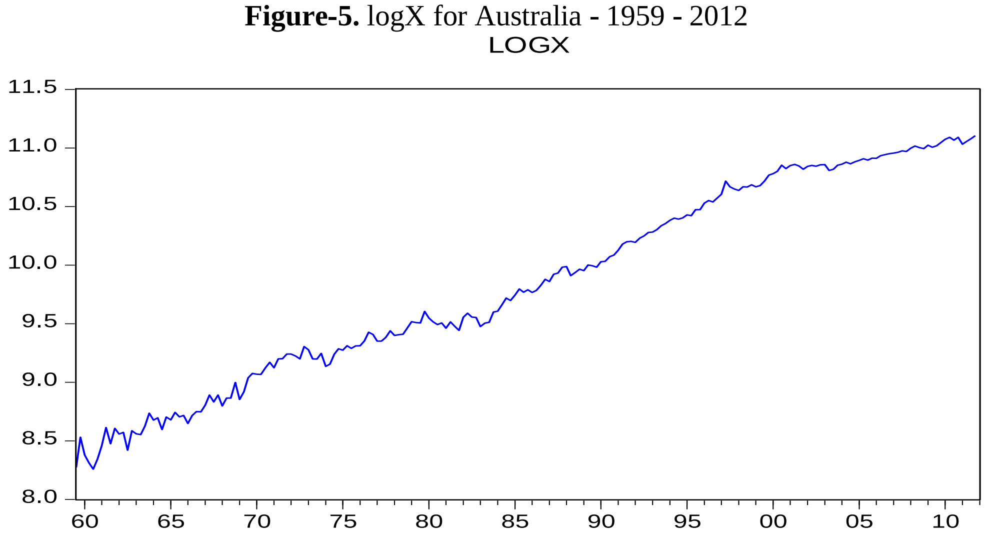


Figure-5. logX for Australia - 1959 - 2012



6. Methodology

As in any market, the equilibrium quantity of imports is the outcome of the equilibrium derived when the demand and supply of importable products meet. The demand for importable products can be satisfied from two sources: the foreign supply of imports, as well as the domestic supply of import-substitutes.

However, as Leamer and Stern (1970) note, the determinants of the demand for imports are far less complicated than the determinants of supply of imports. The common avenue that is taken in the literature to overcome the difficulty in identifying import supply functions is to assume an infinite elasticity of supply for imports. In other words, the equilibrium quantity of imports is a pure response to a change in import demand as discussed in Murray and Ginman (1976). While it is perceivable that there is indeed an infinite elasticity of overseas supply, especially for a small open economy such as Australia, this is unlikely the scenario for the domestic supply of import-substitutes. We thus, treat the price of imports as exogenous to our import demand model. Thus, presuming that there is a domestic supply of import-substitutes, import demand functions are in essence, excess demand functions.

In the traditional model of import demand, the excess demand function of imports is a function of real income and the price of imports, P_m , relative to the price of domestic goods, P_y:

$$M^D = (\frac{P_m}{P_y}, \frac{Y}{P_y})$$

This functional form of import demand is a very restricted model, as it only differentiates between the prices of imports and that of all domestically produced goods. Agents however allocate their budgets between imports and three categories of domestically produced goods, namely, import-substitutes, exportable goods, and non-traded goods. Hall, Jankovic and Pitchford (1989) show that the price of each type of good can be integrated into a model of import demand. According to the above functional form, Goldstein, Khan and Officer (1980) argued that consumers are viewed implicitly as engaging in a two-step decision process, and that there is separability in consumption. As mentioned in the section on the literature review, this paper will follow from Goldstein, Khan and Office (1980), Wilkinson (1992) and Dwyer and Kent (1993) in including the price of non-tradable goods in the specification of an import demand function. The purpose of this paper is to formulate a general import function in which the prices of imports, tradable goods as well as non-tradable goods enter as explanatory variables.

It must be noted that we implicitly assume that imports, M_t , is in fact the same as the quantity demanded, $M^d{}_t$. In effect, we are assuming that either importing firms satisfy their experienced demand right on schedule, or at least manage to correct any disequilibrium within a twelve month period. Thus, at a very basic level, the demand for imports is modelled as simply a function of prices and income. It has been asserted in the literature that agents' utility functions are a function of imports, tradable goods and non-tradable goods which they aim to maximise subject to their budget constraint. This gives us the theoretical functional form of:

$$M^D = f(P_m, P_t, P_{nt}, Y)$$

where the variables are defined as: P_m: price of imports, P_t : price of tradable goods, P_{nt} : price of non-tradable goods, and Y : a measure of domestic economic activity.

Based on the standard theory of demand, one would expect that the partial derivatives of imports with respect to the above three prices would satisfy the conditions:

$$\frac{\partial M^D}{\partial P_m} < 0 \ ; \ \frac{\partial M^D}{\partial P_{nt}} > 0 \ ; \ \frac{\partial M^D}{\partial P_t} > 0$$

The actual variable that is chosen to represent economic activity needs some careful consideration. An economic activity variable that measures income is appropriate if imports are primarily intermediate products that are sold to other enterprises to transform into finished products.

Choosing an economic activity variable that measures expenditure is appropriate if the overwhelming nature of imports is finished goods.

We assume no money illusion, that is, we assume that the import demand function is homogeneous of degree zero with respect to income and with respect to prices. Thus the import demand function can be normalised by any one of these prices, such as the price of non-tradable goods which then yields:

$$M^D = \left(\frac{P_m}{P_{nt}}, \frac{P_t}{P_{nt}}, \frac{Y}{P_{nt}}\right)$$

However, in this paper, as it specifically aims to look at how the mining boom, that is an export industry, is impacting on Australian import demand, will thus replace P_t with P_x:

$$M^D = \left(\frac{P_m}{P_{nt}}, \frac{P_x}{P_{nt}}, \frac{Y}{P_{nt}}\right)$$

The above functional form is consistent with that utilised by Wilkinson (1992). Furthermore, this approach which explicitly includes the price of exports will be needed as this paper aims to examine the cointegrating relationships between imports and exports in formulating the import demand function. This cointegrating technique will be discussed further in the following section that details my proposed specific approach.

This paper will examine a multivariable model that models imports as a function of real GDP, *Y*, the relative price of imports, *RPM*, as well as the relative price of exports, *RPX*. The developed model, follows from Sinha and Sinha (2000). This model takes all the variables in log-linear form, and thus the long-run import demand function can be written as follows:

lnM_t □□□□□□□lnY_t □□□$lnRPM_t$ □□□□$lnRPX_t + u$

In this postulated model of import demand, *M* is the real quantity of aggregate imports and *Y* is real gross domestic product (real GDP). *PM* of Sinha and Sinha (2000) is replaced by *RPM* which is the relative price of imports. Furthermore, *PD*, the domestic price of Sinha and Sinha (2000) is replaced by *RPX* is the relative price of exports. The use of relative prices as the basis for the determinants of imports follows from Wilkinson (1992) and Athukorala and Menon (1995).

7. A VAR Approach

A structural VAR is a VAR that uses economic theory to form the contemporaneous links among the variables. Thus, structural VARs require economic assumptions to help identify the model, and this allows the correlations to have a causal interpretation. This need not involve the entire VAR where every single causal link is identified; a structural VAR could only involve a single specific equation whose causal link is identified. Once we have these, we now have the variables that allow these contemporaneous links to be estimated using regression analysis.

Suppose we treat each variable symmetrically. Thus, we let the time series of imports, M_t , be affected by current and past values of another series such as exports, X_t , where both variables have been transformed into logs. Treating the variables symmetrically would imply that the time series, X_t , is affected by current and past values of the series, M_t . An example of such a bi-variate system is provided below:

$M_t = b_{10} – b_{12}X_t + \gamma_{11}M_{t-1}+\gamma_{12}X_{t-1} + \varepsilon_{mt}$

$X_t = b_{20} – b_{21}M_t + \gamma_{21}M_{t-1}+\gamma_{22}X_{t-1} + \varepsilon_{xt}$

It is assumed that:

- M_t and X_t are stationary
- ε_{mt} and ε_{xt} are white-noise disturbances
- ε_{mt} and ε_{xt} have standard deviations of σ_m and σ_x respectively

- ε_{mt} and ε_{xt} are uncorrelated.

These assumptions, if all fulfilled in the initial round of modelling, would be an econometricians dream come true. In reality, various econometric techniques would need to be utilised to transform the raw data sets to fulfil the assumptions stated above for the transformed set of variables.

Returning to the aforementioned equations, we would call this a first-order VAR as the longest lag length in the above model is one. Furthermore, there is feedback in this structure, since imports, M_t , and exports, X_t , are allowed to affect each other. In a VAR modelling context, ε_{mt} and ε_{xt} can be treated as shocks, or impulses, in M_t and X_t respectively. Once we have estimated and identified the model, the next step will be to establish the impulse responses and the variance decompositions. An impulse response function gives the response of one variable to a shock in another variable that is in the system. A variance decomposition is a way to attribute the variances of a given variable to the other variables in the model.

In several earlier studies that modelled import demand authors assumed that the data series that were being modelled exhibitted stationarity. If the variables that are being modelled are in fact non-stationary, then conventional econometric results need to be carefully interpreted. While the coefficients that have been estimated are consistent, the test statistics will have non-standard distributions. If the series are stationary, it is said to not have a unit root, and then we have need to have two additional assumptions which are that the errors are homoscedastic and there is no autocorrelation. If these assumptions are satisfied, then our Ordinary Least Squares estimators of the coefficients are consistent. Furthermore, the Ordinary Least Squares estimates of the standard errors are correct. This means under the null hypothesis that the coefficients are zero, the estimated coefficients divided by their standard deviations are asymptotically normal, and therefore, the standard *F*-statistics have an *F*-distribution.

If the series is not stationary, that is, it has a unit root, for example,
$M_t = M_{t-1} + \varepsilon^x{}_t$, then the coefficient divided by the standard deviation of at least one variable in the model will not be normally distributed. There are two solutions to this: One solution is to build a VAR model in first differences, where the differenced variables exhibit stationarity. Another solution is to use the technique of cointegration.

If the series imports, M_t, and exports, X_t, are non-stationary, that is, they have unit roots, M_t and x_t are said to be cointegrated if, e.g., $M_t - \delta X_t$ does not have a unit root $(\delta \neq 0)$. In other words, a linear differencing of the two variables is in fact stationary. If the variables are not conitegrated then the only solution would be is to estimate a VAR model in first differences. If the variables are in fact conitegrated, then we estimated a VAR model in the conitegrated differences. This is technically known as a Vector Error Correction Mechanism, (VECM).

When estimating a cointegrating relationship, what we are doing is that we are estimating the long-run steady state relationship between the variables being examined, that is, exports and imports in the example above. Economic theory can then be used to explain why these variables do in fact have this long-run steady state relationship.

8. Data Collection

As the data that is examined is macroeconomic in nature, all data series are readily and freely available from Australian government databases available online. These are namely the Australian Bureau of Statistics[1] and The Reserve Bank of Australia[2]. It goes without saying that this paper will solely be looking at quantitative data and the issues of qualitative data will neither be experienced nor be discussed here. The data sets will be time series data sets, where a variable that is measured has data collected at regular, usually quarterly, frequencies. Most macroeconomic series go back to September 1959. The postulated models will be developed for the period 1984Q4 to 2012Q1, however, for robustness tests of the long-run relationships this paper will examine the entire data set that is available from the ABS. As the data sets are macroeconomic in nature, the general tendency is for macroeconomic series to be reported at least on a quarterly basis.

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[1] http://www.abs.gov.au/AUSSTATS/abs@.nsf/web+pages/statistics?opendocument#from-banner=GT

[2] http://www.rba.gov.au/statistics/index.html

The above-mentioned sample for the data set is on the grounds of structural breaks identified in economic theory. A structural break is if there is a shock to the economy, where the variables being examined then begin to follow an econometrically significant different underlying pattern than they did previously. One possibility is that the data set may need to be reduced to data since December 1983 when the Australian Dollar was first floated. Another possibility is that the data set may need to be reduced to data since January 1993 when the Reserve Bank of Australia first introduced inflation targeting as an explicit objective of monetary policy. These are recognised structural breaks in the respective data sets of the exchange rate and the inflation rate. Furthermore, due to the topical nature of the study, I am interested in looking at whether there has been a structural break in the post-Global Financial Crisis, post-Eurozone Debt Crisis era. However, the data set for the post-GFC, post-Eurozone Debt Crisis era is relatively small, seeing that the GFC only began in latter half of 2008.

In trying to fulfil the modelling assumptions and objectives that were discussed earlier in this paper, various transformations to the data will be required. Some of these transformations, some purists would argue, result in the loss of valuable information that is inherent in the raw and underlying data series. However, as an econometrician, one has to weigh the marginal cost of losing such information with the marginal benefit of being able to further the scope of the data set after such transformations.

9. VAR Estimation

Before estimating the vector error correction mechanism (VECM), we need to specify the relevant order of lags (p) for the VAR model. This is done using Information Criterion, in particular the Akaike Information Criterion (AIC). Based on the Information Criterion presented below, a VAR with a lag order of 3 is decided, as this is what minimised the AIC.

Table-2. VAR Estimates

VAR Lag Order Selection Criteria
Endogenous variables: LOGM LOGRPX LOGRPM LOGY
Exogenous variables: C
Sample: 1984Q3 2012Q1
Included observations: 110

Lag	LogL	LR	FPE	AIC	SC	HQ
0	424.2840	NA	5.64e-09	-7.641527	-7.543328	-7.601697
1	1145.172	1376.241	1.53e-14	-20.45768	-19.96668*	-20.25853*
2	1168.358	42.57694	1.35e-14	-20.58832	-19.70453	-20.22985
3	1186.629	32.22351*	1.30e-14*	-20.62961*	-19.35302	-20.11182
4	1192.391	9.743804	1.57e-14	-20.44348	-18.77409	-19.76636
5	1200.872	13.72338	1.82e-14	-20.30676	-18.24458	-19.47033
6	1208.381	11.60518	2.15e-14	-20.15239	-17.69740	-19.15663
7	1217.070	12.79592	2.50e-14	-20.01945	-17.17167	-18.86438
8	1231.984	20.87959	2.61e-14	-19.99971	-16.75913	-18.68531

* 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

9.1. Vector Error Correction Estimates

Here the approach of Hendry (1979), Dutta and Ahmed (1999) and Shareef and Tran (2008) is followed. Here, a general-to-specific approach is used to estimate the Error Correction Model for import demand. Based on the AIC in the previous section, initially 3 lags of the explanatory variables are included and 1 lag of the error correction term. After this, the insignificant variables can be iteratively. This gives us the following general form for the ECM which follows from Shareef and Tran (2008):

$$\Delta \ln M_t = \beta_0 + \sum_{i=1}^{3} \beta_{1i} \Delta \ln M_{t-i} + \sum_{i=1}^{3} \beta_{2i} \Delta \ln Y_{t-i} + \sum_{i=1}^{3} \beta_{3i} \Delta \ln RPM_{t-i} + \sum_{i=1}^{3} \beta_{4i} \Delta \ln RPX_{t-i} + \beta_5 EC_{t-1} + \varepsilon_t$$

where EC_{t-1} is the error-correction term lagged one period. Based on the output in the following table, the following equation of the ECM best fits the data:

$$\Delta \ln M_t = -0.005 + 0.365 \Delta \ln M_{t-2} + 1.112 \Delta \ln Y_{t-1} - 0.260 \Delta \ln RPX_{t-2} - 0.333 EC_{t-1}$$

$$\Delta \ln Y_t = 0.026 EC_{t-1}$$

$$\Delta \ln RPM_t = 0.334 EC_{t-1}$$

$$\Delta \ln RPX_t = 0.135 EC_{t-1}$$

Table-3. VECM Estimates

Vector Error Correction Estimates				
Sample (adjusted): 1984Q3 2011Q4				
Included observations: 110 after adjustments				
Standard errors in ( ) & t-statistics in [ ]				
Cointegrating Eq:	**CointEq1**			
LOGM(-1)	1.000000			
LOGRPX(-1)	-0.094117			
	(0.09314)			
	[-1.01050]			
LOGRPM(-1)	0.542508			
	(0.07981)			
	[6.79727]			
LOGY(-1)	-1.773696			
	(0.07755)			
	[-22.8715]			
C	11.36439			
Error Correction:	D(LOGM)	D(LOGRPX)	D(LOGRPM)	D(LOGY)
CointEq1	-0.333630	0.134658	0.333711	0.026371
	(0.07748)	(0.10063)	(0.10423)	(0.02174)
	[-4.30603]	[1.33819]	[3.20172]	[1.21320]
D(LOGM(-1))	0.117375	0.194508	-0.077491	-0.013925
	(0.11053)	(0.14355)	(0.14869)	(0.03101)
	[1.06190]	[1.35494]	[-0.52114]	[-0.44904]
D(LOGM(-2))	0.364669	0.175481	-0.089963	0.010448
	(0.10427)	(0.13542)	(0.14027)	(0.02925)
	[3.49735]	[1.29582]	[-0.64137]	[0.35716]
D(LOGM(-3))	0.025411	0.036647	0.061757	0.012487
	(0.10452)	(0.13575)	(0.14061)	(0.02932)
	[0.24311]	[0.26996]	[0.43921]	[0.42583]
D(LOGRPX(-1))	-0.181143	0.374521	0.178990	0.004832
	(0.10606)	(0.13774)	(0.14267)	(0.02975)
	[-1.70796]	[2.71899]	[1.25454]	[0.16241]
D(LOGRPX(-2))	-0.260048	0.003058	0.109182	-0.023521
	(0.10934)	(0.14201)	(0.14709)	(0.03068)
	[-2.37830]	[0.02153]	[0.74227]	[-0.76676]
D(LOGRPX(-3))	0.074077	-0.123372	-0.047473	-0.004072
	(0.09916)	(0.12878)	(0.13339)	(0.02782)
	[0.74708]	[-0.95802]	[-0.35591]	[-0.14637]
D(LOGRPM(-1))	0.068515	-0.314908	-0.167807	-0.007105
	(0.12133)	(0.15757)	(0.16321)	(0.03404)

	[0.56471]	[-1.99849]	[-1.02814]	[-0.20873]
D(LOGRPM(-2))	0.084635	-0.123105	-0.211148	-0.036766
	(0.12030)	(0.15624)	(0.16183)	(0.03375)
	[0.70353]	[-0.78792]	[-1.30473]	[-1.08936]
D(LOGRPM(-3))	-0.021290	0.119120	0.051278	0.028881
	(0.11758)	(0.15271)	(0.15818)	(0.03299)
	[-0.18106]	[0.78005]	[0.32418]	[0.87550]
D(LOGY(-1))	1.112647	-0.080935	-0.211227	0.163642
	(0.36611)	(0.47548)	(0.49250)	(0.10271)
	[3.03915]	[-0.17022]	[-0.42889]	[1.59323]
D(LOGY(-2))	0.153842	-0.062347	0.371595	0.129393
	(0.37358)	(0.48519)	(0.50256)	(0.10481)
	[0.41180]	[-0.12850]	[0.73941]	[1.23456]
D(LOGY(-3))	0.443509	-0.457060	-0.723462	-0.134300
	(0.37118)	(0.48207)	(0.49933)	(0.10414)
	[1.19486]	[-0.94812]	[-1.44887]	[-1.28967]
C	-0.004972	-0.005053	-0.002194	0.006592
	(0.00493)	(0.00640)	(0.00663)	(0.00138)
	[-1.00830]	[-0.78907]	[-0.33079]	[4.76520]
R-squared	0.506364	0.336161	0.219424	0.139281
Adj. R-squared	0.439518	0.246266	0.113722	0.022726
Sum sq. resids	0.051657	0.087132	0.093482	0.004066
S.E. equation	0.023197	0.030127	0.031205	0.006508
F-statistic	7.575026	3.739488	2.075859	1.194976
Log likelihood	265.4155	236.6615	232.7925	405.2253
Akaike AIC	-4.571190	-4.048391	-3.978045	-7.113188
Schwarz SC	-4.227493	-3.704694	-3.634348	-6.769490
Mean dependent	0.017615	-0.000472	-0.006557	0.008187
S.D. dependent	0.030985	0.034701	0.033147	0.006583
Determinant resid covariance (dof adj.)		9.67E-15		
Determinant resid covariance		5.61E-15		
Log likelihood		1180.470		
Akaike information criterion		-20.37219		
Schwarz criterion		-18.89920		

The long run relationship is thus:

$$\log M_t = -11.364 + 1.774 \log Y_t - 0.543 \log RPM_t + 0.094 \log RPX_t + u_t$$

9.2. Structural VAR Estimates

Sims (1980) provided a new modelling framework which led to the development of vector autoregressions (VARs). A VAR, while still linear, is an *n*-equation, *n*-variable model unlike its single-equation, single-variable univariate counterpart. Therefore, in the VAR case, each variable is explained by its own lagged values as well as the lagged value of all the other remaining *n-1* variables as well. Expressed in its structural form gives us:

$$Az_t = B_1 z_{t-1} + B_2 z_{t-2} + B_3 z_{t-3} + B_4 z_{t-4} + u_t$$

$$Euu' = \Sigma_u = \begin{bmatrix} \sigma^2 u_1 & 0 & 0 & 0 \\ 0 & \sigma^2 u_2 & 0 & 0 \\ 0 & 0 & \sigma^2 u_3 & 0 \\ 0 & 0 & 0 & \sigma^2 u_4 \end{bmatrix}$$

A VAR of lag length p (VAR(p)) can be written as:

$$z_t = A^{-1}B_1z_{t-1} + A^{-1}B_2z_{t-2} + A^{-1}B_3z_{t-3} + A^{-1}B_4z_{t-4} + A^{-1}u_t$$

The vector z_t contains the discussed variables, which are ordered according to economic theory in anticipation of the Cholesky decomposition as:

$$z_t = \begin{bmatrix} RPX_t \\ Y_t \\ RPM_t \\ M_t \end{bmatrix}$$

The error terms of the equations will be correlated across equations. This means that the structural parameters from the residuals of the equations cannot be identified. First, we estimate the reduced form of the equations and we recover the structural shocks, u_t. Once this is done, we compute the Cholesky decomposition of the variance-covariance matrix of the residuals. In general, for each symmetric, positive definite matrix X, the Cholesky decomposition is an upper triangular matrix U such that:

$$X = U'U$$

Then:

$$z_t = A^{-1}B_1z_{t-1} + A^{-1}B_2z_{t-2} + A^{-1}B_3z_{t-3} + A^{-1}B_4z_{t-4} + A^{-1}u_t$$
$$z_t = A^{-1}B_1z_{t-1} + A^{-1}B_2z_{t-2} + A^{-1}B_3z_{t-3} + A^{-1}B_4z_{t-4} + e_t$$

In order to identify the model, based on the proposed ordering of the variables: *RPX*, *Y*, *RPM* and *M*, the following restrictions are imposed on the A matrix:

$$A = \begin{bmatrix} . & 0 & 0 & 0 \\ . & . & 0 & 0 \\ . & . & . & 0 \\ . & . & . & . \end{bmatrix}$$

Since the number of restrictions is in line with the number of equations in the model, the following statistical output confirms that convergence is achieved after 7 iterations and the model is just identified. This gives us the A^{-1} matrix for the Cholesky decomposition as:

$$A^{-1} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -C_2 & 1 & 0 & 0 \\ -C_4 & -C_5 & 1 & 0 \\ -C_7 & -C_8 & -C_9 & 1 \end{bmatrix}$$

Thus, through the Cholesky decomposition of Σ_e we can obtain a matrix, B, where the main diagonal has the standard deviation of all the structural shocks:

$$Ae = Bu$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ C_2 & 1 & 0 & 0 \\ C_4 & C_5 & 1 & 0 \\ C_7 & C_8 & C_9 & 1 \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix} = \begin{bmatrix} C_1 & 0 & 0 & 0 \\ 0 & C_3 & 0 & 0 \\ 0 & 0 & C_6 & 0 \\ 0 & 0 & 0 & C_{10} \end{bmatrix} \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0.028 & 1 & 0 & 0 \\ -0.632 & -0.083 & 1 & 0 \\ -0.145 & -0.857 & 0.363 & 1 \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix} = \begin{bmatrix} 0.029 & 0 & 0 & 0 \\ 0 & 0.006 & 0 & 0 \\ 0 & 0 & 0.023 & 0 \\ 0 & 0 & 0 & 0.021 \end{bmatrix} \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{bmatrix}$$

Extracting the structural VAR estimates presented in the next section, gives us the orthogonalised shocks. The decomposition of the above gives us:

$e_{1t} = C_1 u_{1t}$
$e_{1t} = 0.029 u_{1t}$

$-C_2 e_{1t} + e_{2t} = C_3 u_{2t}$
$e_{2t} = C_2 e_{1t} + C_3 u_{2t}$
$e_{2t} = 0.028 e_{1t} + 0.006 u_{2t}$

$-C_4 e_{1t} – C_5 e_{2t} + e_{3t} = C_6 u_{3t}$
$e_{3t} = C_4 e_{1t} + C_5 e_{2t} + C_6 u_{3t}$
$e_{3t} = -0.632 e_{1t} - 0.083 e_{2t} + 0.023 u_{3t}$

$-C_7 e_{1t} – C_8 e_{2t} – C_9 e_{3t} + e_{4t} = C_{10} u_{4t}$
$e_{4t} = C_7 e_{1t} + C_8 e_{2t} + C_9 e_{3t} + C_{10} u_{4t}$
$e_{4t} = -0.145 e_{1t} - 0.857 e_{2t} + 0.363 e_{3t} + 0.021 u_{4t}$

These orthogonalised shocks help us analyse the impulse response functions that are presented in the following section.

Table-4. SVAR Estimates

Structural VAR Estimates				
Sample (adjusted): 1984Q3 2011Q4				
Included observations: 110 after adjustments				
Estimation method: method of scoring (analytic derivatives)				
Convergence achieved after 7 iterations				
Structural VAR is just-identified				
Model: Ae = Bu where E[uu']=I				
Restriction Type: short-run text form				
@e1 = C(1)*@u1				
@e2 = C(2)*@e1 + C(3)*@u2				
@e3 = C(4)*@e1 + C(5)*@e2 + C(6)*@u3				
@e4 = C(7)*@e1 + C(8)*@e2 + C(9)*@e3 + C(10)*@u4				
where				
@e1 represents LOGRPX residuals				
@e2 represents LOGY residuals				
@e3 represents LOGRPM residuals				
@e4 represents LOGM residuals				
	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	-0.028070	0.021332	-1.315846	0.1882
C(4)	0.632169	0.078173	8.086835	0.0000
C(5)	0.082545	0.346677	0.238104	0.8118
C(7)	0.145136	0.087303	1.662443	0.0964
C(8)	0.856894	0.306687	2.794036	0.0052
C(9)	-0.363183	0.084326	-4.306889	0.0000
C(1)	0.028877	0.001947	14.83240	0.0000
C(3)	0.006461	0.000436	14.83240	0.0000
C(6)	0.023492	0.001584	14.83240	0.0000
C(10)	0.020776	0.001401	14.83240	0.0000
Log likelihood	1158.960			
Estimated A matrix:				
1.000000	0.000000	0.000000	0.000000	

0.028070	1.000000	0.000000	0.000000
-0.632169	-0.082545	1.000000	0.000000
-0.145136	-0.856894	0.363183	1.000000
Estimated B matrix:			
0.028877	0.000000	0.000000	0.000000
0.000000	0.006461	0.000000	0.000000
0.000000	0.000000	0.023492	0.000000
0.000000	0.000000	0.000000	0.020776

9.3. Impulse Response Functions

For VAR models, what we are interested in are the impulse response functions. These functions trace out how a variable reacts over time to a one-unit or one-standard deviation increase in the value in one of the error terms of the VAR. By shocking one error while the others are held constant implies that the errors must be uncorrelated across equations. In essence, recursive and structural VARs are needed when calculating impulse response functions (IRFs).

The first step is that if we know A and Σ_u , we can begin from:

$z_t = A^{-1}B_1z_{t-1} + A^{-1}B_2z_{t-2} + A^{-1}B_3z_{t-3} + A^{-1}B_4z_{t-4} + A^{-1}u_t$

$z_t = A^{-1}B_1z_{t-1} + A^{-1}B_2z_{t-2} + A^{-1}B_3z_{t-3} + A^{-1}B_4z_{t-4} + e_t$

Now, we are able to calculate the IRF's to a unit shock of u once we know A^{-1}. We begin by assuming that the system has been in steady state for a while, and then the system is shocked. We then choose one variable at a time, for example, the logged relative price of imports, *logRPM*, and then we observe the responses to the first variable, when a shock hits at time 0:

$$u_0 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

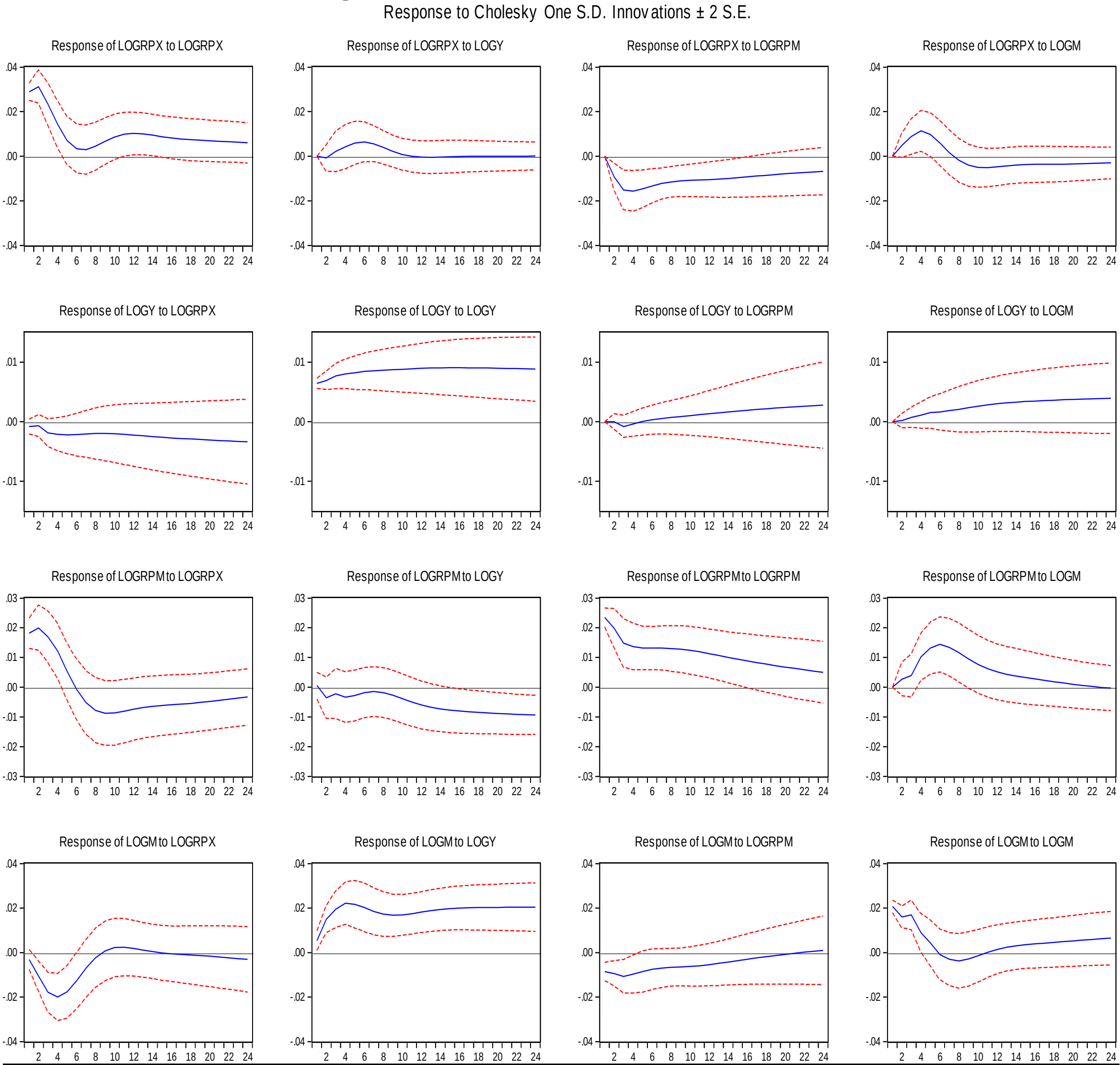
$$z_0 = A^{-1}u_0$$

For every s > 0,

$$z_s = A^{-1}Bz_{s-1}$$

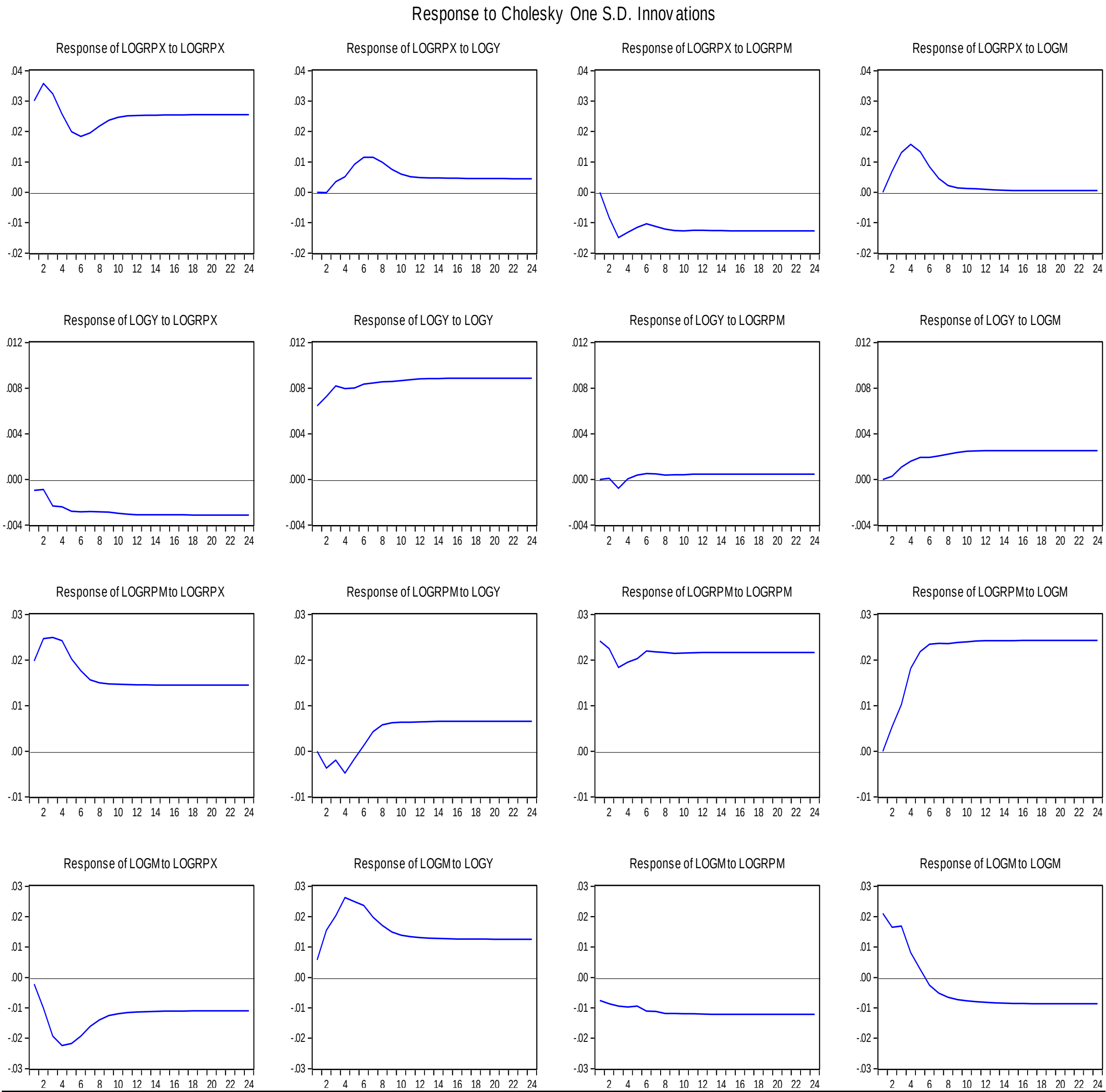
More than the VAR or VECM output themselves, IRFs are more informative in displaying the behaviour of z in response to shocks to the vector u. The impulse responses over 24 quarters of the VAR Model to Cholesky one standard deviation innovations is presented below. All of the IRFs are in line with a priori expecations as can be seen below.

Figure-6. IRFs for the VAR Model



The impulse responses over 24 quarters of the VECM to Cholesky one standard deviation innovations is presented below. As with the case for the VAR Model, all IRFs are in line with a priori expectations which is illustrated below.

Figure-7. IRFs for the VECM



10.Conclusion

This paper utilises a VAR approach to estimate the aggregate import demand function for Australia over the period 1984Q3 – 2012Q1. To the author's knowledge this is the first study on the Australian import demand function that examines both the short run and long dynamics of a postulated demand function. This study adds to the body of knowledge on import demand functions for Australia via the presented impulse response functions of both a vector autoregressive model and a vector error correction model for import demand. The impulse response functions for the VAR and VECM are in line with a priori expectations. Furthermore, the impulse response functions indicate that both system reach stability after 12 quarters, or 3 years. Policymakers may benefit from an understanding of this relationship; as such an understanding might assist them in the formulation of future international trade policy for Australia.

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