THE LONG-TERM RELATIONS UNDER CLIMATE CHANGE BETWEEN ECONOMIC ACTIVITY AND METAL UTILIZATIONS USING THE FORGETTING FACTOR

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ABSTRACT

In this chapter, we apply an efficient subset of vector error correction model (VECM) using the forgetting factor to examine the cointegration under climate change of the time series of the gross domestic product (GDP) and the industrial production and that of the utilization and consumption of important metals such as copper and steel in some important OECD countries as well as some selected newly industrialized Asian and Latin American countries. Both the long-term and the short-term dynamic relations among these variables are examined and the implications are discussed.

1. INTRODUCTION

Recently, there has been renewed interest among economists in the utilization and consumption of important metals such as copper and steel

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in major world economies (see Penm & Terrell, 2003). It has been well recognized that the consumptions of copper and steel have been closely associated with the general economic activity in a nation. This stems from the belief that a growth in a nation's economic activity stimulates an increase in the demand for consumptions of these important metals. Furthermore, the level of utilization of these metals has often been considered as an indicator of a nation's stages of industrialization and its development of services and technology management.

In recent years, the stability of the relationship between the levels of the metal utilization and that of the general economic activity has received considerable attention. This interest has been primarily in response to a relative slowdown in the growth of the level of utilization of these metals in some consuming countries, despite of their continuing growth in the general economic activity. Several factors may have contributed to a possible change in the relationship between general economic activity and utilization of these important metals. These include the substitution of materials in manufacturing, a more efficient use of metals, and changing consumer preferences.

This chapter tests two hypotheses. The first hypothesis is whether there are stable long-term relationships between the levels of economic activity, and copper and steel consumption, in selected consuming countries all of which are experiencing climate change. The absence of stable long-term relationships would indicate that, over a long period, the levels of copper and steel consumption are less dependent on the level of general economic activity. If stable long-term relationships exist among general economic activity and copper and steel consumption, then, after temporary deviations in the short term, consumption of copper and steel would revert to their traditional long-term relationships with general economic activity.

The second hypothesis is whether the levels of economic activity under climate change lead to a change in the same direction in copper and steel consumption, if comovements in the same direction exist in cointegrating relationships. Such identified "uni-directional" comovements indicate increased/decreased copper and steel consumption from stronger/weaker economic growth. Identification of such long-term relationships and uni-directional comovements, if they exist, would be essential in forecasting consumption of steel and copper.

Powerful computing equipment has had a dramatic impact on mineral resources modeling and simulations and has motivated development of innovative computing-intensive time series approaches to financial services and to trade assessment. Significant advances in powerful computing equipment provide faster computational speed, larger amounts of memory, and more accurate numerical results, than traditional computing. New time series methodology has specified models in a more sophisticated manner, used the data in highly adaptive ways, and facilitated major innovations in development of management in mineral resources and technology management. Against that background, increasingly sophisticated resource industry-oriented approaches to development of resource services and technology management are now of central importance, driven by applications of increasing electronic scale and complexity. As a result, development of these approaches becomes essential, providing resource finance managers with a window of opportunity to make a significant contribution to the frontier of industry-oriented and academic research.

In this chapter, we undertake research in financial resource modeling and data analysis using new and important time series approaches. While trade and environmental investment decisions still operate in an uncertain market, and human judgment can never be fully replaced, quantitative time series analysis has an important role to play in guiding effective decisions and setting trade strategy.

We construct and utilize subset vector error correction model (VECM; see Penm & Terrell, 2003) as a basis for the cointegration test. The unbiased VECM estimation approach is asymptotically equivalent to the maximum likelihood estimation. We also include a forgetting factor in the estimation of the patterned VECMs. The forgetting factor technique is a data weighting process that allows the estimation to place greater weight on more recent observations and less weight on earlier data. In such estimation, the effects on the underlying relationships of slow evolution generated by the causal linkage process will be accounted for.

As to why a subset time series model is used, subset modeling includes full-order models, and researchers use this approach whenever measurements exhibit some periodicity. If the underlying true time series process has a subset structure, the suboptimal full-order specification can give rise to inefficient estimates and inferior projections. Our forgetting factor approach improves the estimated parameter profile, model structure and performance reliability for assessing complex relationships involving slowly evolving long-term effects, such as climate change. These qualities are not found in conventional time series approaches involving only full-order models. Subset modeling is superior to full-order modeling for discovering complex relationships, as has been clearly indicated in Penm and Terrell (2003), Chen, Penm and Terrell (2006), and Penm (2007).

After adopting the hypothesis of long-term cointegration, the VECM shows the short-term dynamic relationships among those variables involved in selected important OECD and selected newly industrialized Asian and Latin American, countries. For the OECD region, a cointegration test is undertaken for the United States, Japan, and the European Union (EU) initial 15-member countries. Argentina, Mexico, and Brazil are involved in the test for the Latin American region for both copper and steel. For the Asian region South Korea, Taiwan and India are included in the test for both copper and steel, and Indonesia is added for the test on steel.

The remainder of this chapter is constructed as follows. In Section 2, we outline warnings about climate change identified in the Stern Review. In Section 3, we discuss Australia's copper, iron ore, and steel exports. In Section 4, we outline the construction of patterned VECM, which demonstrates the ‘‘presence and absence'' restrictions on the coefficients of subset time series systems, including full-order systems. Also, brief descriptions of the forgetting factor techniques used for estimation are given. In Section 5, we briefly describe data sources for testing purposes. We then detail the methodology of cointegration and present the estimation results in Section 6. In Section 7, a summary is given.

2. WARNINGS FROM THE STERN REVIEW

The Stern Review (Stern, 2006) indicates that the potential impact of climate change could create risks of major disruption to economic and social activity and suggests the resulting climate change will produce about US$7 trillion economic and environmental loss. Severe climate change will make world climate conditions harsher and render drought, storms, cyclones, heat waves, floods, and tsunamis more likely to occur in numerous areas of the globe. The direct economic loss from natural disasters is doubling every 10 years. The insurance and reinsurance sector has an inherent exposure to the direct effects of climate change. As suggested in the International Panel on Climate Change (IPCC) 2000 Special Report on Emission Scenarios, weather-related events of all magnitudes resulted in about US$710 billion in insured and uninsured economic losses between 1985 and 1999. Climate change–related risks are increasingly considered for specific ‘‘susceptible'' sectors, such as hydroelectric and mineral projects, and irrigation, agriculture, metal, and tourism sectors. Also, the lost hydropower production would be US$2.75 billion per annum by 2060.

Most recently, scientists have been able to construct evidence of climate change from collected information on temperature, rainfall, and other weather variables from measuring stations all over the world, including the most important metal trade countries of Australia including United States, Japan, the initial 15-member countries of the EU, Korea, Taiwan, India, Brazil, Mexico, Indonesia, and Argentina. Furthermore, earth orbiting satellites and other technological advances have enabled scientists to examine the big picture, collecting many different types of information about the above countries and their climate on a sophisticated scale. The obvious major reported evidence for climate change is that (i) sea level rose about 17.5 centimeters in the last century, though in the past decade the rate of rise nearly doubled; (ii) levels of carbon dioxide have recently been higher than in the past decade; (iii) global surface air temperatures rose about three-quarters of a degree Celsius in the past century; (iv) the top 650 m of oceans has recently shown warming of about 0.18°F; and (v) many species of plants and animals are already responding to global warming, moving to higher elevations.

Scientists have predicted climate change impacts in the long run, which include a general rise in surface temperature; changes in seasonal temperature variation and rainfall patterns; variations in soil moisture and water resources; alteration of agricultural climate zones and crop growth periods; and increases in the incidence of severe weather events such as floods and droughts. Additionally, crop productivity, growth distribution of vegetation, forestry growth patterns, sea levels, and marine production operations are also expected to be negatively impacted, and thus directly threaten one-sixth of the world's population.

Globally, in the absence of policy interventions, the long-run adverse relationship between gross domestic product (GDP) and greenhouse gas (GHG) emissions per head is likely to persist. The Stern Review suggests that global warming could eventually shrink the global economy by 20 percent, although taking immediate action would cost just one percent of global GDP.

Utilizing renewable energy resources and reducing GHG emissions have become an internationally popular and discernible trend. All industrialized and developing countries, including the most important metal trade countries of Australia listed above, have endeavored to save oil, gas, and coal consumption as an approach to improve competition and meet environmental objectives in the long run.

The Kyoto Protocol is an amendment to the United Nations Framework Convention on Climate Change, which was negotiated in Kyoto, Japan, in December 1997. Concern over global warming had prompted the world's governments to negotiate the Kyoto Climate Change Treaty, which requires the world's largest economies to cut their overall emissions of GHG. The protocol assigns mandatory emission limitations for the reduction of GHG emissions to the signatory nations.

Australia is required to cut emissions below 108 percent of 1990 levels by 2008–2012, with further reductions to be negotiated in future. Furthermore, the protocol includes "flexible mechanisms" that allow Australia to meet its GHG emission limitation by purchasing GHG emission reductions from elsewhere. The United States is the world's largest emitter of GHGs. The USA's plans to curb emissions of GHGs must be placed in the context of science and politics. The American Clean Energy and Security Act of 2009 envisages the following cuts in GHG emissions in the energy sector in the United States: Calendar year/Emission allowances (in millions), 2012/4,770; 2015/4,942; 2020/4,873; 2030/3,533; 2035/2,908; 2040/2,284; 2050; and each year thereafter 1,035. Japan is the world's fifth biggest emitter of GHGs (after the United States, China, India, and Russia), and is the only one of the five that is under pressure to meet a GHG emissions limit. For its size, Taiwan is a major emitter of GHGs. The EU accounts for around 10 percent of global emissions. The EU has decided to work as a unit to meet its emissions targets as suggested by Kyoto. South Korea is the world's 10th highest emitter of GHGs and plays a significant role in the global climate change arena. GHG emissions and climate change have become important issues of national discussion with a view to reducing GHG emissions. Taiwan produces more carbon dioxide than most developing nations. Having the natural environment of a subtropical island, Taiwan is very vulnerable to the impacts of climate change and is yet to meet its own GHG reduction targets. India is the world's fourth largest economy and fifth largest GHG emitter. India has a number of policies that contribute to climate mitigation by reducing GHG emissions. In some respects, India's emissions are low compared to those of other major economies. Indonesia is the third largest global emitter of GHGs. The challenge for Indonesia is to create appropriate and effective adaptation and mitigation strategies to meet GHG emission reduction and avoidance targets. Mexico ranks as the 14th largest emitter of GHGs in the world. Mexico has agreed with the World Bank to lead the Latin America and the Caribbean world toward development of lower carbon emissions. Brazil is the world's eighth largest emitter of GHGs. Yet, it has an unusual emissions profile, with 75 percent emissions resulting from unsustainable land use and intensive deforestation, as the Amazon in Brazil comprises one of the world's largest forests and ecosystems. Although Argentina makes only a small contribution to world GHG emissions, it is already experiencing the effects of global warming. More research is being undertaken to understand the precise nature of the impact of global warming on Argentina.

3. AUSTRALIA'S COPPER, IRON ORE, AND STEEL EXPORTS

The substantial risks in insurance markets and their increasing complexity clearly require a better understanding of impacts of climate change on energy, mineral and metal resources, and energy commodity price movements, such that the resultant strategy for adaptation to climate change by the insurance industry can be managed more effectively. Specifically, one of the biggest challenges to a modern natural disaster insurance manager is that of setting out an array of reactive and proactive options across time for reducing overall losses to the community. Not only does our approach have the potential to reduce insurers' exposure, and in so doing limit the level of claims to encourage managers to adopt disaster mitigation measures, but it also could enable a more selective risk exposure of insurance items, so that good risks are rewarded and poor risks are penalized.

Mineral and metal energy resources play an important role in Australia's economy. The Australian Bureau of Agricultural and Resource Economics (ABARE) 2008 annual report indicates that since 2000, mineral and metal energy resources directly contribute about five percent of GDP annually in Australia, representing about AU$50 billion in 2008. Around two-thirds of Australian mineral and energy production has been exported since 2000. Each of these energy commodities, in particular copper, iron ore, and steel, recorded substantial increases in both export prices and volumes in that period.

Many experts believe that the most cost-effective way to reduce GHG emissions is through increased energy efficiency. Copper could play a significant role in making the nations of the world more energy efficient. Among the engineering metals, copper is the best conductor of heat and electricity. By using copper instead of less energy efficient materials, more of the electricity generated can be used to reap benefits from the products we use. The increased electrical efficiency reduces electrical demand, which in turn reduces the consumption of fossil fuels. Reduced fossil fuel consumption means reduced emissions of GHGs, which in turn reduces society's impact on climate change. About 70 percent of all copper consumption is used to benefit from copper's enhanced thermal and electrical energy efficiency properties.

The price of copper is also an important factor for most copper supply and export countries, including Australia. Before the end of 2003, the world market price of copper was relatively stable. Since 2004, the price began to move upwards considerably. In 2000, Australia ranked as one of the top five largest producers in the world of mined copper. In 2007, ABARE indicated that Australia's copper exports reached the level of nearly AU$7 billion.

The value of world exports of iron and steel increased by 203 percent over the period 1985 through 2002, reaching nearly US$144 billion, and the share in world commodities exports rose by about half a percent, reaching almost 11 percent in 2002. Australia has become one of the world's largest export countries for iron ore and steel. In 2007, ABARE indicated that Australia's iron ore and steel exports reached nearly AU$11 billion.

The climate change challenge has induced changes in the production, distribution, and consumption patterns of metal energy resources, in particular steel. During the steelmaking process that is based on processing iron ore or scrap, GHG emissions occur at many stages. However, through major advances in technology in the steel industry in North America, Western Europe and Japan have reduced energy consumption per unit of production by about 50 percent in the past decade. The most promising approach to limit GHG emissions is recycling. This approach exhibits the lowest CO_2 substitution cost and avoids drastic revisions of steel-making practices. Other promising approaches include smelting reduction and increased use of natural gas, plant biomass, electricity, or hydrogen vectors in more innovative ways to achieve a reduction in CO_2 emissions. In the OECD countries overall, direct process-related emissions from iron and steel production account for about 2.4 percent of total GHG emissions. Furthermore, iron ore and steel exports that form one of Australia's largest mineral earners are expected to increase. This is because Australia's iron ore industry has undergone a renewed investment growth following the emergence of new ore types, rising production and generally improved exchange rates of the Australian dollar against the US dollar.

To improve understanding of trade complexity in the energy metal resource industries in conditions of climate change, it is crucial to utilize sophisticated time series decision support approaches to identify energy metal consumption patterns, which focus on the short-term dynamics and the long-term relationship between the consuming sectors and the economic activities. The research outcomes will provide a better understanding of the nature of such complexity problems in the energy metal trade and have direct application in solving those practical problems that are of both regional and global concern.

4. METHODOLOGY

4.1. The Forgetting Factor

The use of forgetting factor in time series analysis has attracted considerable interest in recent years. For example, Penm and Terrell (2003) utilize a forgetting factor in subset autoregressive modeling of the spot aluminum and nickel prices on the London Metal Exchange. The use of the forgetting factor technique to estimation and simulation of financial market variables has been reported by Brailsford, Penm, and Terrell (2002).

Consider a vector autoregressive (VAR) model of the following form:

$$z(t) + \sum_{\tau=1}^{q} \mathbf{A}_\tau z(t-\tau) = \boldsymbol{\varepsilon}(t) \qquad (1)$$

where $z(t)$ is a $k \times 1$ vector of wide-sense stationary series. $\boldsymbol{\varepsilon}(t)$ is a $k \times 1$ vector of independent and identically distributed random process with $E\{\boldsymbol{\varepsilon}(t)\} = 0$ and $E\{\boldsymbol{\varepsilon}(t)\boldsymbol{\varepsilon}'(t-\tau)\} = \Omega$ if $\tau = 0$ and $= 0$ if $\tau > 0$. $\mathbf{A}_\tau$, $\tau = 1, \ldots, q$ are $k \times k$ matrices of coefficients. The observations $z(t)[t = 1, \ldots, T\}$ are available.

Let $\boldsymbol{\lambda}(t) = \left[\lambda_1(t) \ldots \; \ldots \lambda_n(t)\right]$ denotes a $1 \times k$ vector associated with time t. Following O'Neill, Penm, and Penm (2007), a strategy for determining the value of the forgetting factor $\boldsymbol{\lambda}(t)$ is as follows.

$$\boldsymbol{\lambda}_i(t) = \boldsymbol{\lambda}^{\eta-t+1} \text{ if } 1 \le t \le \eta \text{ and } = 1 \text{ if } \eta < t \le T \text{ for } i = 1, \ldots, n \qquad (2)$$

Eq. (2) means that "forgetting" of the past occurs from time η. No forgetting is involved from time η+1 to time T. If $\boldsymbol{\lambda} = 1$ for every t, then we obtain the ordinary least squares solution. If $0 < \boldsymbol{\lambda} < 1$, the past is weighted down geometrically from time η. In theory, the value of $\boldsymbol{\lambda}$ could be different between $\boldsymbol{\lambda}_i(t)$ (a so-called variable forgetting factor). For simplicity, we only consider the fixed forgetting factor case in which the value of $\boldsymbol{\lambda}$ is constant for $\boldsymbol{\lambda}_i(t)$.

This means that the coefficients in Eq. (1) are estimated to minimize,

$$\sum_{t=1}^{T} \boldsymbol{\lambda}(t) \left[z(t) - \sum_{\tau=1}^{q} \mathbf{A}_\tau y(t-\tau)\right] \left[z(t) - \sum_{\tau=1}^{q} \mathbf{A}_\tau z(t-\tau)\right]' \qquad (3)$$

One important issue relating to the use of the forgetting factor in estimation is how to determine the value of $\boldsymbol{\lambda}$ in applications. The conventional method is based on arbitrary or personal choices. Penm and Terrell (2003) propose to determine the value of $\boldsymbol{\lambda}$ using the bootstrap. In this study, their recommended method is adopted for the determination of the value of $\boldsymbol{\lambda}$. While Brailsford et al. (2002) also propose a procedure to determine the value of dynamic forgetting factor for nonstationary systems, we have focused on the use of a fixed forgetting factor in this study, because applications of a fixed forgetting factor to forex market movements is likely to be more predictable.

4.2. VECM for an I*(1) System*

In constructing VECM for an $I(1)$ system, from Eq. (1) we have

$$A^q(L) = I + \sum_{\tau=1}^{q} \mathbf{A}_\tau L^\tau$$

where L denotes the lag operator, and $Lz(t) = z(t-1)$. It is assumed that the roots of $|A^q(L)| = 0$ lie outside or on the unit circle to ensure that $z(t)$ can contain $I(1)$ variables.

Of note, $z(t)$ is integrated of order d, $I(d)$, if it contains at least one element that must be differenced d times before it becomes $I(0)$. Furthermore, $z(t)$ is cointegrated with the cointegrating vector, $\boldsymbol{\beta}$, of order g, if $\boldsymbol{\beta}'z(t)$ is integrated of order $(d\text{–}g)$, where $z(t)$ has to contain at least two $I(d)$ variables.

Following Penm and Terrell (2003), the equivalent VECM for Eq. (1) can then be expressed as follows:

$$A^q(1)z(t-1) + A^{q-1}(L)\Delta z(t) = \boldsymbol{\varepsilon}(t) \tag{4}$$

where $z(t)$ contains variables of the types $I(0)$ and $I(1)$. Note that 'Δ' represents the difference, $\Delta z(t) = z(t) - z(t-1)$ and $\boldsymbol{\varepsilon}(t)$ is stationary. Eq. (4) can be rewritten as follows:

$$\mathbf{A}^* z(t-1) + A^{q-1}(L)\Delta z(t) = \boldsymbol{\varepsilon}(t) \tag{5}$$

where $\mathbf{A}^* = A^q(1)$ and $\mathbf{A}^* z(t-1)$ is stationary, and the first term in Eq. (5) is the error correction term. The term $A^{q-1}(L)\Delta z(t)$ is the VAR part of the VECM.

Because $y(t)$ is cointegrated of order 1, the long-term impact matrix, $\mathbf{A}^*$, must be singular. As a result, $\mathbf{A}^* = \boldsymbol{\alpha\beta}'$ and $\boldsymbol{\beta}'z(t-1)$ is stationary, where the rank of $\mathbf{A}^*$ is r $(0 < r < s)$, and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}'$ are matrices of dimensions $s \times r$ and $r \times 2s$, respectively. The columns of $\boldsymbol{\beta}$ are the cointegrating vectors and the rows of $\boldsymbol{\alpha}$ are the loading vectors.

Penm and Terrell (2003) demonstrate that a system that involves both cointegrated and stationary series can be characterized by sparse patterned VECM that includes full-order models. This patterned VECM can be used for estimation of such a cointegrated system. The development course of the climate change is a long-term slowly evolving underlying process, and the effects of climate change will be exhibited in the detected long-term cointegrating relations.

Our search algorithm originally proposed by Penm and Terrell (2003) to select the optimal sparse VECM and the associated patterned $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ is briefly described below.

1. To begin this algorithm, we first identify the optimal sparse patterned VECM using model selection criteria.
2. After the optimal sparse patterned VECM is identified, the rank of the long-term impact matrix is then computed using the singular value decomposition method so that the number of cointegrating vectors in the system will be known.
3. A tree-pruning algorithm that avoids evaluating all candidates is then implemented for the search of all acceptable sparse patterns of the loading and cointegrating vectors.
4. The identified candidates of the sparse patterned cointegrating vectors are estimated by the method based on a triangular VECM representation proposed in Penm and Terrell (2003).
5. The estimation of the associated candidates for the sparse patterned loading vectors is carried out by the Yule–Walker estimation method with linear restrictions.
6. The optimal sparse patterned $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are finally selected by model selection criteria.

Furthermore, for copper consumption, the VECM of Eq. (5) can be rewritten as follows:

$$\begin{bmatrix} \Pi(L) & \Gamma(L) \\ \Phi(L) & \Theta(L) \end{bmatrix} \begin{bmatrix} \Delta C_t \\ \Delta E_t \end{bmatrix} + \begin{bmatrix} \alpha_1 \beta_1 \\ \alpha_2 \beta_1 \end{bmatrix} \begin{bmatrix} 1 & \frac{\beta_2}{\beta_1} \end{bmatrix} \begin{bmatrix} C_{t-1} \\ E_{t-1} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \end{bmatrix}$$

where

$$y(t) = \begin{bmatrix} C_t \\ E_t \end{bmatrix}; \ \boldsymbol{\varepsilon}(t) = \begin{bmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \end{bmatrix}; \ A^{q-1}(L) = \begin{bmatrix} \Pi(L) & \Gamma(L) \\ \Phi(L) & \Theta(L) \end{bmatrix}$$
$$\boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix}; \ \boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} \tag{6}$$

Eq. (6) can then be described as follows:

$$\begin{cases} [\Pi(L)\ \Gamma(L)]\begin{bmatrix} dC_t \\ dE_t \end{bmatrix} + \delta_1 \begin{bmatrix} C_{t-1} \\ \mu E_{t-1} \end{bmatrix} = \varepsilon_t^1 & (7) \\ [\Phi(L)\ \Theta(L)]\begin{bmatrix} dC_t \\ dE_t \end{bmatrix} + \delta_2 \begin{bmatrix} C_{t-1} \\ \mu E_{t-1} \end{bmatrix} = \varepsilon_t^2 & (8) \end{cases}$$

where $\delta_1 = \boldsymbol{\alpha}_1\boldsymbol{\beta}_1$; $\delta_2 = \boldsymbol{\alpha}_2\boldsymbol{\beta}_1$ and $\mu = \boldsymbol{\beta}_2/\boldsymbol{\beta}_1$.

For steel consumption, Eq. (6) becomes

$$\begin{cases} [\Pi(L)\ \Gamma(L)]\begin{bmatrix} dS_t \\ dE_t \end{bmatrix} + \delta_1 \begin{bmatrix} S_{t-1} \\ \mu E_{t-1} \end{bmatrix} = \varepsilon_t^1 & (9) \\ [\Phi(L)\ \Theta(L)]\begin{bmatrix} dS_t \\ dE_t \end{bmatrix} + \delta_2 \begin{bmatrix} S_{t-1} \\ \mu E_{t-1} \end{bmatrix} = \varepsilon_t^2 & (10) \end{cases}$$

where C and S denote copper and steel consumptions, respectively, and E denotes GDP. $\Pi(0) = 0; \Gamma(0) = 0; \Phi(0) = I;\ \Theta(0) = I$.

5. DATA SOURCES

In this chapter, refined copper consumption was used to approximate copper consumption in each country investigated. Apparent consumption of finished steel was used in the estimation for OECD countries, while apparent consumption of crude steel was used in the estimation for developing countries. Both GDP and industrial production were used to approximate the level of general economic activity.

Data for refined copper consumption were obtained from the World Bureau of Metal Statistics. Data for apparent consumption of crude steel are published by the International Iron and Steel Institute (IISI), while those for finished steel consumption came from Datastream. The macroeconomic data, GDP and industrial production, were obtained from the International Monetary Fund. The sample periods used, subject to data availability, in the estimation are presented in Table 1.

Table 1. Data Samples Subject to Data Availability.

Country	Series	Sample Period[a]
The United States	Copper	1982(1)–2005(4)
	Steel	1986(2)–2005(4)
Japan	Copper	1982(1)–2005(4)
	Steel	1986(2)–2005(4)
The EU countries	Copper	1982 (1)–2005(4)
	Steel	1986(2)–2005(4)
South Korea	Copper	1982(1)–2005(4)
	Steel[b]	1967–2005
Taiwan	Copper[b]	1967–2005
	Steel[b]	1959–2005
India	Copper[b]	1967–2005
Indonesia	Steel[b]	1972–2005
Mexico	Copper	
	(a) GDP	1981(1)–2005(4)
	(b) Industrial production	1982(1)–2005(4)
	Steel[b]	1967–2005
Argentina	Copper[b]	1969–2005
	Steel[b]	1969–2005
Brazil	Copper[b]	1969–2005
	Steel[b]	1969–2005

[a]Quarterly GDP data are seasonally adjusted except for South Korea and Mexico.
[b]Annual data.

6. MODELING RESULTS

In this chapter, cointegration theory was utilized to test for the existence of long-term relationships between general economic activity and copper and steel consumption in major consuming countries. Following Engle and Granger (1987), a set of variables is said to be cointegrated, if the individual variables are nonstationary, such as copper and steel consumption and the level of general economic activity, but a linear combination of these variables becomes stationary. In other words, the test for cointegration shows whether random shocks to the relationships between these variables tend to dissipate over time or whether the shocks have a permanent effect on their relationships whereby copper and steel consumption and the level of general economic activity tend to drift apart from each other in an independent manner. Evidence that cointegration exists among a set of variables provides strong support for the presence of long-term relationships among them.

Table 2. VECM Indicating Relationships between Copper Consumption and General Economic Activity.

Eq. (7) for copper consumption: $\Pi(L)\Delta C_t + \Gamma(L)\Delta E_t + \delta_1 C_{t-1} + \mu E_{t-1} = \varepsilon_t^1$.

A fixed forgetting factor with the value 0.99 applies to all observations. Variables are in logarithms. C denotes copper consumption, E gross domestic product, g deseasonalized E, and P industrial production. General economic activity is indicated by either E or P as proxies.. D_i, $i = 1, 2, 3$ are seasonal dummies, d is first difference, and $|t - statistics|$ are shown in brackets. For simplicity, ε_t^1 is not displayed below.

The United States

$$\Delta C_t = \underset{(4.73)}{2.1558} - \underset{(1.36)}{0.1135}\Delta C_{t-2} + \underset{(4.47)}{0.3665}\Delta C_{t-4} + \underset{(2.82)}{3.4135}\Delta E_{t-1} - \underset{(2.15)}{0.5772}(C_{t-1} - \underset{(6.31)}{0.5563}\, E_{t-1})$$

$$\Delta C_t = \underset{(5.07)}{2.2561} + \underset{(4.12)}{0.3261}\Delta C_{t-4} + \underset{(2.78)}{2.14721}\Delta P_t + \underset{(1.79)}{1.3735}P_{t-3} - \underset{(7.11)}{0.6786}(C_{t-1} - \underset{(4.44)}{0.6443}P_{t-1})$$

where P_t denotes industrial production, and replaces E_t in Eq. (7).

Japan

$$\Delta C_t = \underset{(5.89)}{2.993} + \underset{(1.81)}{0.157}\Delta C_{t-2} + \underset{(2.94)}{0.257}\Delta C_{t-4} + \underset{(1.62)}{2.055}\Delta E_t - \underset{(6.84)}{0.742}(C_{t-1} - \underset{(4.48)}{0.401}\, E_{t-1})$$

$$\Delta C_t = \underset{(3.36)}{1.597} - \underset{(5.68)}{0.577}\Delta C_{t-1} + \underset{(2.88)}{2.111}\Delta P_t - \underset{(3.58)}{0.415}(C_{t-1} - \underset{(2.51)}{0.471}P_{t-1})$$

The European Union countries

$$\Delta C_t = \underset{(2.06)}{1.968} - \underset{(3.07)}{0.543}\Delta C_{t-1} - \underset{(4.31)}{0.578}\Delta C_{t-2} - \underset{(5.17)}{0.493}C_{t-3} + \underset{(2.73)}{4.391}\Delta E_{t-1} - \underset{(2.28)}{0.472}\,(C_{t-1} - \underset{(2.22)}{0.537}E_{t-1})$$

$$\Delta C_t = \underset{(1.62)}{1.419} - \underset{(2.98)}{0.585}\Delta C_{t-1} - \underset{(4.33)}{0.636}\Delta C_{t-2} - \underset{(5.53)}{0.533}\Delta C_{t-3} + \underset{(2.02)}{1.877}\Delta P_{t-1} + \underset{(1.93)}{1.787}\Delta P_{t-2} - \underset{(2.25)}{0.499}(C_{t-1} - \underset{(2.11)}{0.831}P_{t-1})$$

South Korea

$$g_t = E_t - \underset{(94.35)}{10.503} + \underset{(2.61)}{0.414}D_1 + \underset{(1.77)}{0.283}D_2 + \underset{(1.47)}{0.236}D_3$$

$$\Delta C_t = \underset{(3.41)}{1.958} - \underset{(3.53)}{0.553}\Delta C_{t-1} - \underset{(2.82)}{0.391}\Delta C_{t-2} - \underset{(2.07)}{0.266}\Delta C_{t-3} - \underset{(3.23)}{0.499}\,(C_{t-1} - \underset{(2.77)}{1.374}g_{t-1})$$

$$\Delta C_t = -\underset{(1.91)}{0.739} - \underset{(1.92)}{0.368}\Delta C_{t-1} - \underset{(1.95)}{0.636}\Delta C_{t-2} - \underset{(1.83)}{0.672}\Delta C_{t-3} - \underset{(4.15)}{0.766}(C_{t-1} - \underset{(3.61)}{1.1791}\, P_{t-1})$$

Taiwan

$$\Delta C_t = \underset{(5.18)}{28.553} - \underset{(5.32)}{1.152}\,(C_{t-1} - \underset{(5.12)}{1.697}E_{t-1})$$

India

$$\Delta C_t = -\underset{(1.86)}{1.199} + \underset{(3.88)}{0.497}\Delta C_{t-2} + \underset{(3.15)}{3.018}\Delta E_{t-1} - \underset{(4.88)}{0.596}(C_{t-1} - \underset{(3.78)}{0.753}E_{t-1})$$

$$\Delta C_t = \underset{(2.78)}{1.151} + \underset{(2.71)}{0.336}\Delta C_{t-2} + \underset{(2.95)}{2.915}\Delta P_t - \underset{(4.93)}{0.647}\,(C_{t-1} - \underset{(4.22)}{0.635}P_{t-1})$$

Argentina

$$\Delta C_t = -\underset{(3.68)}{11.325} + \underset{(1.87)}{0.324}\Delta C_{t-1} + \underset{(2.61)}{2.186}\Delta E_t - \underset{(1.88)}{1.989}\Delta E_{t-1} - \underset{(3.93)}{0.749}\,(C_{t-1} - \underset{(3.91)}{1.696}\, E_{t-1})$$

Mexico

$$g_t = E_t - \underset{(29.87)}{6.437} + \underset{(1.77)}{0.047}D_1 + \underset{(1.58)}{0.018}D_2 + \underset{(2.35)}{0.063}D_3$$

$$\Delta C_t = \underset{(4.47)}{1.761} - \underset{(4.53)}{0.531}\,(C_{t-1} - \underset{(2.05)}{1.659}g_{t-1})$$

$$\Delta C_t = -\underset{(1.70)}{1.833} + \underset{(1.99)}{1.542}\Delta P_t - \underset{(4.92)}{0.615}\,(C_{t-1} - \underset{(2.53)}{1.388}P_{t-1})$$

Table 3. VECM Indicates Relationships between Steel Consumption and General Economic Activity.

Eq. (9) for steel consumption: $\Pi(L)\Delta S_t + \Gamma(L)\Delta E_t + \delta_1 S_{t-1} + \mu E_{t-1} = \varepsilon_t^1$.

A fixed forgetting factor with the value 0.99 applies to all observations. Variables are in logarithms. S denotes steel consumption. E gross domestic product, g deseasonalised E, and P industrial production. General economic activity is indicated by either E or P as proxies.. D_i, $i = 1, 2, 3$ are seasonal dummies, d is first difference, and $|t - statistics|$ are shown in brackets. For simplicity, ε_t^1 is not displayed below.

The United States

$$\Delta S_t = \underset{(1.93)}{1.133} - \underset{(2.21)}{0.241}\Delta S_{t-2} + \underset{(3.56)}{3.315}\Delta E_t + \underset{(3.15)}{3.032}\Delta E_{t-1} - \underset{(2.31)}{0.185}(S_{t-1} - \underset{(2.15)}{0.782}E_{t-1})$$

Japan

$$\Delta S_t = \underset{(3.31)}{1.818} + \underset{(2.05)}{0.221}\Delta S_{t-2} - \underset{(1.72)}{0.203}\Delta S_{t-3} - \underset{(2.28)}{0.267}\Delta S_{t-4} + \underset{(2.18)}{1.791}\Delta E_t + \underset{(3.51)}{1.720}\Delta E_{t-2} - \underset{(3.97)}{0.295}(S_{t-1} - \underset{(3.93)}{0.773}E_{t-1})$$

$$\Delta S_t = \underset{(1.71)}{0.717} - \underset{(2.82)}{0.315}\Delta S_{t-1} - \underset{(2.52)}{0.231}\Delta S_{t-3} - \underset{(2.38)}{0.257}\Delta S_{t-4} + \underset{(2.80)}{0.950}\Delta E_t + \underset{(3.12)}{1.982}\Delta E_{t-1} - \underset{(3.20)}{0.177}(S_{t-1} - \underset{(3.07)}{1.138}P_{t-1})$$

The European Union countries

$$\Delta S_t = \underset{(3.83)}{2.187} - \underset{(2.12)}{0.201}\Delta S_{t-2} - \underset{(2.15)}{0.171}\Delta S_{t-3} + \underset{(5.08)}{0.468}\Delta S_{t-4} + \underset{(2.31)}{4.062}\Delta E_t + \underset{(1.52)}{2.722}\Delta E_{t-1} - \underset{(4.85)}{0.411}(S_{t-1} - \underset{(3.32)}{1.028}E_{t-1})$$

$$\Delta S_t = \underset{(2.51)}{1.337} - \underset{(2.28)}{0.191}\Delta S_{t-2} - \underset{(2.51)}{0.185}\Delta S_{t-3} + \underset{(5.03)}{0.447}\Delta S_{t-4} + \underset{(2.37)}{2.3521}\Delta P_t - \underset{(4.41)}{0.443}(S_{t-1} - \underset{(3.57)}{1.558}P_{t-1})$$

South Korea

$$\Delta S_t = -\underset{(1.48)}{1.291} - \underset{(3.31)}{0.315}\Delta S_{t-2} + \underset{(3.82)}{2.327}\Delta E_t - \underset{(2.71)}{0.208}(S_{t-1} - \underset{(2.22)}{1.332}E_{t-1})$$

$$\Delta S_t = \underset{(3.31)}{2.237} - \underset{(3.38)}{0.335}\Delta S_{t-2} + \underset{(3.37)}{1.048}\Delta P_t - \underset{(3.07)}{0.391}(S_{t-1} - \underset{(2.73)}{0.947}P_{t-1})$$

Taiwan

$$\Delta S_t = -\underset{(2.77)}{3.238} + \underset{(1.78)}{2.065}\Delta E_t - \underset{(2.63)}{0.323}(S_{t-1} - \underset{(2.68)}{1.258}E_{t-1})$$

India

$$\Delta S_t = \underset{(2.88)}{0.277} + \underset{(2.77)}{0.383}\Delta S_{t-3} + \underset{(1.98)}{0.968}\Delta E_{t-1} - \underset{(4.13)}{0.573}(S_{t-1} - \underset{(4.08)}{1.097}E_{t-1})$$

$$\Delta S_t = \underset{(4.17)}{4.642} + \underset{(1.29)}{0.201}\Delta S_{t-1} + \underset{(1.83)}{0.293}\Delta S_{t-2} + \underset{(2.77)}{0.418}\Delta S_{t-3} + \underset{(2.78)}{1.347}\Delta P_t - \underset{(4.23)}{0.793}(S_{t-1} - \underset{(4.52)}{0.878}P_{t-1})$$

Indonesia

$$\Delta S_t = -\underset{(2.07)}{2.712} + \underset{(2.08)}{3.535}\Delta E_t - \underset{(2.33)}{0.487}(S_{t-1} - \underset{(2.38)}{1.118}E_{t-1})$$

Mexico

$$\Delta S_t = \underset{(1.78)}{0.357} + \underset{(6.75)}{3.012}\Delta E_t - \underset{(4.21)}{0.447}(S_{t-1} - \underset{(4.42)}{1.255}E_{t-1})$$

$$\Delta S_t = \underset{(3.55)}{1.633} + \underset{(6.91)}{2.327}\Delta P_t - \underset{(3.93)}{0.427}(S_{t-1} - \underset{(4.08)}{1.128}P_{t-1})$$

Brazil

$$\Delta S_t = \underset{(2.58)}{1.572} + \underset{(3.22)}{1.691}\Delta E_t + \underset{(3.71)}{1.739}\Delta E_{t-1} - \underset{(3.68)}{0.422}(S_{t-1} - \underset{(3.73)}{1.193}E_{t-1})$$

In the course of applying VECM to test the cointegrating relationships, all variables are log transformed. Unit root tests indicate that all transformed series are *I*(1). We apply a fixed forgetting factor with the value 0.99 to the stochastic system involved. We then conduct the search procedures proposed indicated in Section 4 to obtain the optimal sparse patterned VECM. The optimal VECM is utilized to test for the existence of cointegrating relationships between copper and steel consumption and general economic activity in major consuming countries. The estimated sparse patterned VECM are presented in Tables 2 and 3.

It is noteworthy that, in addition to general economic activity, many other factors, such as own price and prices of substitutes and complements, could also significantly affect copper and steel consumption, especially in the short term. These factors should also be incorporated when forecasting.

7. SUMMARY

The results of this study generally support the view that long-term cointegrating relationships and uni-directional comovements exist between copper and steel consumption and general economic activity in selected consuming countries. As the development course of climate change is a long-term slowly evolving but underlying process, the effects of weather shocks caused by climate change are exhibited in the detected long-term cointegrating relations. The linking sign between metal consumption and economic activities detected in all cointegrating relationships is consistent with the hypothesis that "uni-directional" comovements exist in major consuming countries experiencing conditions of climate change.

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