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CAN LEADING INDICATORS BE USED TO PREDICT THE DEMAND FOR SEA BORNE DRY BULK ACTIVITY IN THE FAR EAST?

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Abstract

Sea borne dry cargo freight demand has in resent years caused high volatility in earnings for dry bulk shipping companies. Much of this derives from the development in the Far East. In this paper we test if some specific economic indicators can be helpful in forecasting freight demand in this region. We assume that the import of iron ore and coal to Japan and South Korea and iron ore imports to China are good proxies for the overall demand of dry bulk shipping trade. In the empirical test we use a combination of OLS regressions and an ARIMA model to view the forecasting abilities on turning points of series. We further use a six months lag on the explainable variables and a Hodrick-Prescott filter to smooth all series. It becomes evident that the indicators do not have the predictive properties we initially hoped for. We do, however, find some common indicators that show significant t-values in relation to the imports. But, because of our rigid test methods we have some problem with autocorrelation for the OLS analysis.

Acknowledgement

With a combined background of a professional shipping analyst and a graduating student with fresh knowledge about relevant theories we believed we had the best possible basis to write this thesis. Initially we had a clear vision of what we wanted to achieve and with invaluable guidance from professor Øystein Thøgersen we were better able to specify the objectives and to structure the analysis. We also like to thank our academic advisor, Professor Siri Pettersen Strandenes, for her guidance and understanding throughout the process of finalizing this thesis. In addition we like to thank Ph. D. Student George Rabl for reviewing our statistical analysis and for his help with PcWin. Finally, our gratitude goes to Jarle Hammer at Fearnleys Research and Bjørn Bodding at Platou Shipbrokers for invaluable help with finding and supplying data.

The process of completing this thesis has been both rewarding as well as challenging. We believe we have succeeded in dividing the workload between ourselves utilizing our complimentary competence best possible.

Bergen, April 2006

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CONTENTS

1. INTRODUCTION

In traditional economic theory business cycles are usually described as stochastic fluctuations from a determined or a semi – stochastic trend. A leading indicator is normally the aggregate of several macroeconomic time series that separately or put together can give a pre-warning of possible developments and turning points in the economy, often represented by the gross domestic product (GDP) or industrial production (IP). One typical objective of a business cycle analysis is to search for time series that have a high degree of co-movement with the future cyclical behaviour in the macroeconomic activity. As an example, in the 1980s, the Norwegian Central Bank used a leading indicator containing approximately 20 underlying indicators[1] to monitor and forecast the future behaviour of the domestic economy.

Economic growth is normally a necessary precondition for growth in demand for various dry bulk commodities; which again drives seaborne dry bulk demand[2]. Therefore, the freight demand also has a tendency to fluctuate and show a cyclical behaviour. Analogously, we assume that traditional business cycle theory can be used to analyse these time series. For several years now, economic growth in Asia in general and in China, South Korea and Japan in particular, have been the prime drivers of global shipping demand. In this paper we **use import volumes of iron ore and coal to these three economies as a proxy for dry bulk seaborne demand. We then test if there exists any correlation between specific economic indicators and the change in the imports.**

The main seaborne dry bulk commodities are iron ore and coal. Seaborne trade in these two major bulks covers roughly 65% of total dry bulk demand today[3]. Wergeland and Wijnolst and Stopford refer to similar estimates[4]. A majority[5] of these commodities end up in China, Japan and South Korea. Consequently, we find the imports of these commodities to the three countries a good measure of the overall tendency of the market demand. For our analysis we have selected approximately 20 time series that we believe could be possible leading indicators for the reference indicators. We use ordinary least square (OLS) – regression analysis in PcGive to test the forecasting properties of the variables. However, the methods

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[1] Dørum & Lund, 1986
[2] Figure 2-2
[3] Numbers from Clarkson
[4] Wergeland & Wijnolst, 1982 and Stopford, 1996
[5] Discussed further through table 2-5 and 2-6.

used prior to the OLS – test are just as vital and we explain the process as we go along. In addition, an AR(I)MA model is used to compare the result of the OLS analysis. Here, we do an empirical analysis of the models forecasting abilities on the turning points of the observations for each country.

In chapter 2 we describe the various elements of the dry bulk shipping market. This is intended to be an introduction with the purpose of connecting the business cycle theory and the actual shipping market. Chapter 3 covers the model and method of analysis, which is the theory behind the process of handling and analysing the data. The actual process is described in chapter 4, where we analyse the findings for each country separately. Finally, we make some concluding remarks in chapter 5.

2. THE SHIPPING MARKET AND COMMODITY IMPORTS

In order to show the link between the analysis and the actual market situation we find it imperative to include a discussion of the main factors influencing the dry bulk shipping market. In particular we believe this illustrates the complexity of the market and it gives a valid background for the analysis. In the following we first present a simplified supply and demand model before we discuss in more detail the demand side of the dry bulk market and the complications of commodity trade.

2.1 Supply and demand for sea borne trade

As with most other markets, the price (freight rates in dry bulk shipping) is determined by supply and demand. The supply side is a function of the fleet [new deliveries, scrapping, lay-ups, productive life], the fleet productivity [efficiency in ports (congestion), efficiency at sea (vessel speed, ballasting, canal closures etc.)], and the freight rates. The sum of these elements makes up the hockey stick shaped supply curve shown in figure 2-1 below. The demand side for ship transportation is as mentioned a function of the global economic business cycle; the development in the commodities shipped at sea, the average haul, political events and transportation costs. This is discussed further below.

Figure 2-1 Supply and Demand versus freight rates

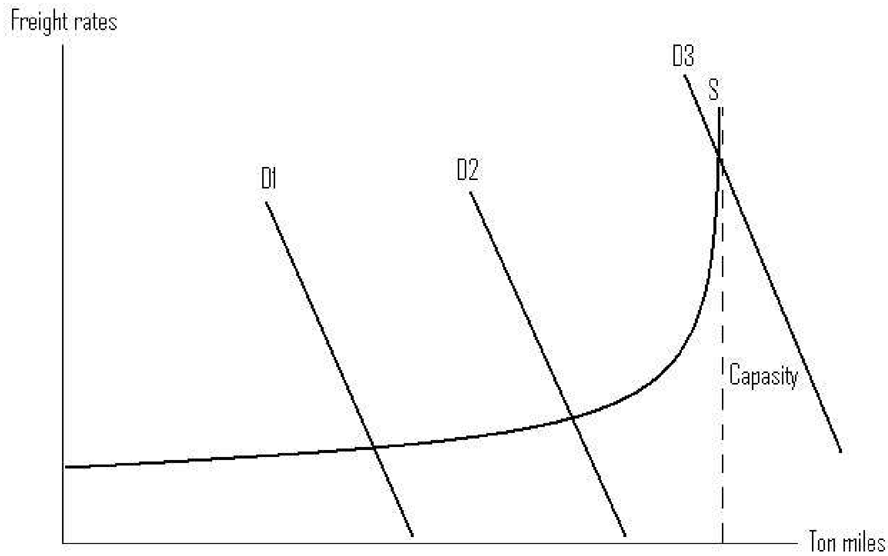


Figure 2-1 illustrates a very simplified supply and demand model for seaborne transportation. It is a short-term model that gives a fair reflection of the dynamics in the seaborne market for transport. In the model the maximum capacity of the fleet (the supply side) is fixed, shown by the vertical dotted line. When freight rates fall below a certain level due to lower demand, the productivity of the fleet starts declining. First of all this takes effect through slow steaming[6]. Later, if the market falls below running costs of a ship some vessels are placed in lay-up. With increased demand, freight rates eventually rise. Vessels in lay-up start trading again and at a certain rate slow steaming ends. This development continuous until the total fleet trades at full capacity[7]. Should demand exceed full capacity it is reasonable to assume that other factors, such as psychology, becomes a part of the function. In such a market shippers may not be able to fix a vessel unless they "pay-up". In effect, at the level of full capacity there is practically no limit to the heights freight rates could go to as the shippers bid up the rates in order to secure a vessel for their cargo. During the fall of 2003 and up until the winter 2004/2005 the dry bulk market traded at full capacity and at rates three times as high as in previous cycles.

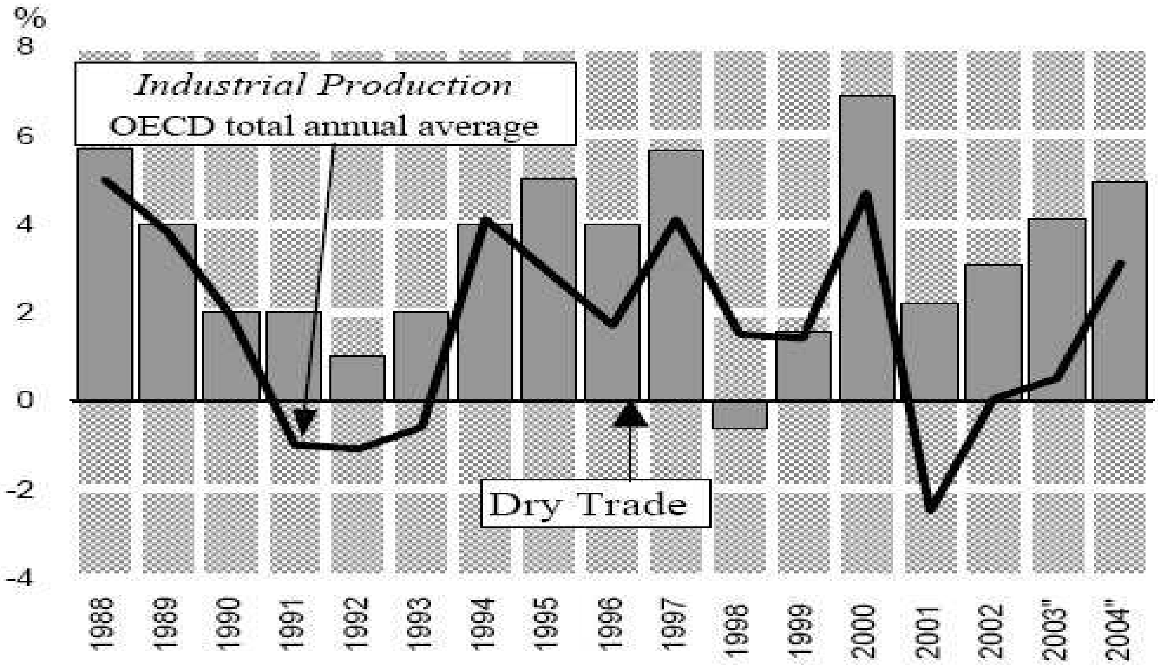
Longer term, new vessels are delivered, the infrastructure in the ports is improved relaxing possible congestion, new trades are developed and the supply curve shifts to the right. Eventually the market finds a new equilibrium, which is to the left of full capacity in the simplified model. Interestingly, there is usually an increased ordering activity at market peaks. Due to the fairly long lead-time between the initial ordering and the physical delivery of a vessel, normally between 24 and 48 months, the physical delivery of these vessels has tended to take place after the demand cycle has turned. On delivery, a combination of weaker demand and stronger supply amplifies the fall in rates, which again helps to explain the historically high volatility in freight rates.

In this paper, we focus on the demand side. Most of the cargoes transported in dry bulk vessels are raw materials or semi finished products used as input into industrial production. In general there are five major factors that influence the demand for ship transportation. The development in the world economy is probably the most important factor. There seems to be a clear relationship between seaborne dry bulk demand and the global business cycle. We can say that without significant growth in the global economy, we are not likely to see strong

[6] When ship owners face low freight rates he/ she will slow down the speed of the ships.
[7] There will always be inefficiencies in the trading due to ballasting and congestion in ports etc. which would limit the utilization of the fleet to some extent.

growth in demand for dry bulk transportation. Both logic and several studies suggest there is such a link[8]. Empirical analysis shows that business cycles have been a major determinant of the short run behaviour of shipping freight rates. Klovland[9] found that peaks in the business cycle have coincided with peaks in commodity prices and shipping rates.

Figure 2-2 OECD Growth / Dry Trade Growth[10]



From figure 2-2 it is relatively clear that dry bulk trade falls when the growth in industrial production is slowing down/contracting and rise when industrial production expands. Economic growth is driven by investments and consumption. Consequently, with positive real economic growth the demand for raw materials and seaborne transport should also improve. This is also the core assumption of our thesis. By looking at leading indicators for imports to the main raw material importing areas, such as China, Japan and South Korea, we hope to find leading indicators for dry bulk demand.

Together with the overall effects from global growth, structural developments in various areas of the world, has a direct influence on the flow of commodities and hence seaborne commodity trades. It is for example positive for dry bulk trade that economies, such as China and Japan, with none or at least insufficient natural resources build up steel and

[8] Klovland 1991 and Stopford 1997
[9] Klovland, Jan Tore, 2003
[10] Clarkson Research Studies

manufacturing industries. This initiates seaborne trade in two ways. First, through imports of raw material to the manufacturing areas and furthermore it usually also generates trades for finished products to the consuming areas.

The sailing distance or average haul influence the time at sea, which is positively correlated with the demand for seaborne transport. The development of iron ore exploration in Brazil in combination with increased steel production in China has had a very positive influence on the average haul for Capesize vessels. The average haul with iron ore from Brazil to China is more than twice as long (about 22 days) compared with the average haul from the iron ore ports in the northern part of Australia (about 10 days). This means that the demand for dry bulk transportation will be twice as high for the former compared with the latter for each additional ton of iron ore shipped.

Political events have always been an important factor for dry bulk demand. The closing of the Suez Canal during the Yom Kippur war in the early 1970s is perhaps the event that has had the largest effect on the shipping market. Due to the closure of the canal vessels that normally sailed through the canal were forced to sail around Africa, which in effect multiplied the sailing distance.

The last major factor is the transport cost. For most commodities transport costs have been relatively marginal compared with the value of the cargo that is shipped but in periods of high freight rates, such as during the very high market seen in 2004 and 2005, it is sometimes less costly to purchase relatively more expensive commodities from nearby suppliers. Therefore, during times of very high or very low freight rates it is not unusual to see some changes in "normal" trading patterns, which again could influence average hauls.

From table 2-1 a. we find that in 2004 more than 21% of world GDP stem from the USA, however, only about 7% of total dry bulk imports went to the USA, as can be seen in table 2-1 b. Adding together the GDP for Japan, China and other Asia, their total contribution to world GDP was no more than 33%, but their share of total dry bulk imports was approximately 62% in 2004 and their share of the total growth in dry bulk imports between 1990 and 2004 was 86%. This underlines what was mentioned above about the uncorrelated relationship between GDP and shipping activity. In fact, even though there is and has been a clear relationship between global economic growth and dry bulk trade it is important to remember that national economic size does not necessarily say very much about a countries direct importance for dry bulk demand.

Table 2-1 a GDP based on PPP in USD billion and as share of the World GDP[11]

	1990		2004 E		2004-1990		Share of
	USD	%	USD	%	USD	%	Growth
JAPAN	2 451	9 %	3 612	7 %	1 160	-2,5 %	4 %
CHINA	1 497	6 %	6 913	13 %	5 416	7,3 %	20 %
OTH ASIA	2 743	10 %	7 130	13 %	4 387	3,0 %	16 %
W. EUROPE	4 843	18 %	8 614	16 %	3 771	-2,2 %	14 %
USA	5 760	22 %	11 175	21 %	5 415	-0,8 %	20 %
FSU/E.EUR	2 974	11 %	3 733	7 %	759	-4,3 %	3 %
L.AMERICA	2 126	8 %	4 034	8 %	1 908	-0,5 %	7 %
AFRICA	915	3 %	1 845	3 %	931	0,0 %	3 %
Others	3 035	12 %	6 015	11 %	2 979	-0,2 %	11 %
Total	**26 344**	**100 %**	**53 070**	**100 %**	**26 726**		**100,0 %**

Table 2-1 b. Seaborne Dry Bulk Imports, (% and million tons)[12]

	1990		2004 E		2004-1990		Share of
	MT	%	MT	%	MT	%	Growth
JAPAN	510	32 %	559	24 %	49	-8 %	7 %
CHINA	64	4 %	396	17 %	332	13 %	45 %
OTH ASIA	239	15 %	489	21 %	250	6 %	34 %
W. EUROPE	542	34 %	583	25 %	40	-9 %	5 %
USA	64	4 %	163	7 %	99	3 %	14 %
FSU/E.EUR	144	9 %	70	3 %	(74)	-6 %	-10 %
L.AMERICA	16	1 %	47	2 %	31	1 %	4 %
AFRICA	16	1 %	23	1 %	7	0 %	1 %
Total	**1595**	**100 %**	**2330**	**100 %**	**735,00**		**100,0 %**

Indirectly, however, through the consumption of finished goods there will be an effect. Demand for bulk carriers is inherently dependent on the level of international commodity trading, which in turn is linked to the state of the world economy in general and in the main importing areas in particular.

Over the last 10-15 years Asia's relative share of dry bulk imports has increased substantially. In the Far East Japan and South Korea have been significant importers of a variety of commodities for a long time. More recently China has developed into the most significant importer of dry bulk commodities. An abundance of low cost labour in combination with investments in modern production facilities has turned developing Asia and China in particular into the "factory of the world". Similar to Japan and South Korea, China must import a large share of the raw materials needed in the industrial production. This

[11] IMF, Global Economic Outlook, September 2004
[12] Clarkson Research Studies.

development in Asia is expected to continue and Asia's direct impact on seaborne demand will probably grow further in the future. Consequently, when analysing dry bulk demand it will be increasingly important to look at economic indicators that reflect the business cycles in the Asian economies discussed above.

2.2 The commodity trade – the dominance of iron ore and coal

Dry bulk commodity demand is relatively complex to analyse with over 40 different commodities or commodity groups involved, each having a range of different factors influencing their overall demand. Traditionally, however, dry bulk demand has been divided into the 5 "major" bulks (iron ore, coal, grain, bauxite/ aluminium and phosphate) in addition to the minor bulks. As inputs to steel production, fluctuations in both the iron ore and coking coal markets are strongly correlated to the steel industry, whilst the remaining major bulks are related to other specific factors. The "minor" bulks are individually small in volume but collectively they make up a significant share of world commodity trades, primarily as input to industrial production.

There are reasons to believe that some commodities have a greater importance than others. The major bulk commodities are listed in table 2-2. In relative terms iron ore and coal are by far the two most important commodity groups when measured in volumes shipped, having a combined share of more than 53% of the total seaborne demand in 2004. This share was 43,3 % in 1985 and 44.5% in 1995.

Table 2-2 The five major bulk commodities shipped by sea (mill. tons)[13]

Commodity	1965	1075	1985	1995	2004
Iron ore	152	292	321	399	605
Coal	59	127	272	403	644
Grain	70	137	181	184	265
Bauxite and alumina	21	41	40	49	54
Phosphate	26	38	43	28	26
Total major dry bulks	328	635	857	1063	1594
Minor dry bulk			512	738	749
Total dry bulk			1369	1801	2343
Iron ore & coal % of total dry bulk			43,3	44,5	53,3

In 2004 the aggregate import of iron ore to Japan, South Korea and China was 384 million tons, approximately 65 % of the world total seaborne trade in iron ore.[14] We believe that by

[13] Data from Clarkson Research Studies

analysing the import statistics for iron ore into Japan, South Korea and China we have found a good proxy for the development of the total iron ore imports to this region. With regards to coal we have only analysed imports to Japan and South Korea due to the fact that good and reliable import data are difficult to find for China. In 2004 Japan imported 38,6% of the world's total seaborne trade of coal. This share has been stable over the last 15 years. South Korea imported 12,2% of the seaborne total the same year. Asia combined imported nearly 60% of all seaborne coal traded in 2004. Europe is another important importing area for coal, receiving more than 30% of the world total in 2004. The remaining imports were spread between several minor importing nations.

Because of their relative importance for dry bulk trade in general we believe imports of iron ore and coal to Japan and South Korea and iron ore to China are good proxies for variations in the overall dry bulk demand. It means that we expect high and low imports of iron ore and coal to these economies to mirror the changes in overall dry bulk demand. In the following we discuss the imports of these commodities in more detail.

In 2003 1,23 billion tons of iron ore was produced in the world. A substantial part of this was processed where it was explored and some was sold to destinations that did not demand seaborne transportation. The main producers by region are listed in table 2-3.

Table 2-3 Iron Ore Production, million tons[15]

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Former U.S.S.R	149,638	165,603	143,824	137,381	132,749	138,599	157,502	151,994	158,725	171,167
South America	201,243	212,344	212,131	220,577	213,471	218,045	239,030	225,293	258,021	280,699
North America	109,612	114,737	114,375	115,623	116,615	107,885	113,279	85,168	94,952	96,524
Asia	318,889	332,693	322,818	341,463	296,517	310,161	302,422	301,476	327,814	369,314
Oceania	131,142	141,637	149,800	160,267	155,579	157,429	170,625	183,075	188,959	214,828
Others	90,045	95,162	90,463	88,042	90,591	84,581	90,079	87,619	89,973	97,776
Total	**1,000,569**	**1,062,176**	**1,033,411**	**1,063,353**	**1,005,522**	**1,016,700**	**1,072,937**	**1,034,625**	**1,118,444**	**1,230,308**

** Others include EU19, other Europe, Africa, Middle East*

The main exporters of iron ore are divided equally between the Pacific and the Atlantic basin. Together the two major exporters Australia and Brazil exported an estimated 405 million tons in 2004, which is 2/3 of the global total. When looking at the growth since 1993 these two producers dominate as well.

[14] Clarksons Research Studies
[15] International Iron and Steel Institute, Steel Statistical Yearbook 2003

The iron ore market has been substantially consolidated over the past few years and three of the major producers (Rio Tinto, BHP Billiton and CVRD) dominate the market place. According to the expansion plans between these three, the importance of Brazil and Australia continues to increase.

In volume terms iron ore is the single most important commodity traded in sea borne dry bulk vessels. In 2004 an estimated 605 million tons were shipped. Table 2-4 illustrates where this growth has taken place. Whilst total growth in the period 1981 through 1989 were 44 million tons and from 1990 through 2000 48 million tons, growth in iron ore trade has accelerated significantly the last five years. From 2000 through 2004 seaborne iron ore trade expanded almost 200 million tons.

Table 2-4 Iron Ore Exports, million tons[16]

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
PACIFIC												
Australia	117	125	137	136	156	145	148	158	157	166	189	201
India	32	31	32	32	32	31	31	32	32	38	55	70
Peru	5	6	6	4	4	4	4	4	4	4	5	5
ATLANTIC												
Brazil	112	125	131	130	140	143	140	160	160	165	184	204
Canada	19	20	20	18	22	22	20	20	18	17	19	19
Sweden	16	15	17	16	18	16	14	16	14	15	16	18
S.Africa	20	20	22	20	22	22	21	22	22	25	26	26
Mauritania	10	10	12	11	12	11	11	11	10	11	11	11
TOTAL	352	380	402	392	431	420	403	452	458	474	521	605

This is also reflected in the development in the import shares over the same period. In 1980 the consolidated iron ore imports to China, South Korea and Taiwan made up only 4.6% of the world total iron ore trade. At the same time imports to Japan and Western Europe contributed 85.3%. In 2004, however, more than 45% of all iron ore imports went to China, South Korea and Taiwan whilst imports to Japan and Europe had fallen to 45%.

Table 2-5 Dry Bulk Sea borne Trade – Iron Ore Imports, % share of total trade[17]

	JAPAN	CHINA	S.KOREA	TAIWAN	W.EUROPE	Others	Total
1980	42,6 %	1,9 %	2,8 %	0,9 %	42,7 %	9,1 %	100,0 %
1989	35,7 %	3,5 %	6,1 %	2,3 %	42,0 %	10,4 %	100,0 %
1998	29,6 %	13,5 %	8,7 %	3,3 %	32,0 %	12,8 %	100,0 %
2004	22,3 %	34,5 %	7,8 %	2,9 %	22,8 %	9,7 %	100,0 %

[16] Clarkson Research Studies
[17] Clarkson Research Studies

Today there are four major iron ore trades. From Tubarao (Brazil) to Rotterdam (Europe), Tubarao to Beilun/ Baoshan (China), from west Australia to Beilun/ Baoshan and from west Australia to Japan. In addition there is a growing trade from India to China.

When it comes to coal, it has many important industrial uses. Most considerably in electricity generation, steel and cement manufacturing and in industrial process heating. More than half of the total world coal production currently provides around 39% of the world's electricity[18]. Many countries are heavily dependent on coal for electricity generation. In 1998 they included Poland (96%), South Africa (90%), Australia (86%), China (81%), India (75%), Czech Republic (74%), Greece (70%), Denmark (59%), and the USA (56%)[19].

The demand for energy is closely related to economic growth and the standards of living. As economic development takes place, households start to switch from traditional sources of energy to modern ones. Often, as in most of the Asian economies, growth has depended on the export of processed raw materials and manufactured goods. Such energy demanding activities involve a rapid growth in energy use. The growth in energy demand relies on a large quantity of coal throughout the world, also beyond our time.

Coal is vital for pig iron and steel production. The two major processes for producing steel are Basic Oxygen Furnaces (BOF) and Electric Arc Furnaces (EAF). In 2003 63.7% of global steel was produced in BOF. In this process coal is used in the blast furnace and it takes about 0.63 tons (630 kg) of coal to produce 1 ton (1000 kg) of steel. In addition, much of the electricity used in steel production, particularly in Asia is generated from coal-fired power stations[20]. Coal is furthermore essential in cement production since a majority of all the cement plants worldwide are coal-fired. Cement is necessary for the construction of almost all large buildings, factories, roads and dams.

[18] World Coal Institute, Coal and Steel Facts – 2005 edition.
[19] World Coal Institute, Coal and Steel Facts – 2005 edition.
[20] World Coal Institute, Coal and Steel Facts – 2005 edition.

Table 2-6. Coal Imports, million tons, average growth rates (%)[21].

	Japan		W.Europe		Korea/Taiwan		Others		Total		Total
	Coking	Steam	Coking	Steam	Coking	Steam	Coking	Steam	Coking	Steam	Coal
1987	74	19	44	64	13	23	9	32	139	138	277
1988	76	28	47	61	16	26	15	42	154	156	310
1989	73	32	48	71	17	25	16	32	154	160	314
1990	74	33	50	86	17	27	12	37	153	183	336
1991	75	37	38	94	20	28	26	42	159	200	359
1992	72	39	38	100	21	33	24	34	154	206	360
1993	73	40	34	81	22	38	26	46	156	206	362
1994	72	45	39	92	22	44	24	36	157	217	374
1995	73	52	39	99	22	51	25	40	160	242	402
1996	73	56	37	101	23	53	32	51	165	261	426
1997	75	58	40	107	25	61	30	56	170	282	452
1998	72	59	44	106	26	64	28	54	169	284	453
1999	73	64	40	110	24	71	26	58	162	302	464
2000	75	70	42	112	26	83	30	75	174	340	514
2001	79	77	40	126	27	90	23	84	168	377	545
2002	79	80	39	123	26	95	25	101	169	399	568
2003	80	88	44	133	27	98	21	122	171	441	612
2004	80	100	48	143	29	111	26	108	182	462	644

Average Annual Growth Rates

2000-04	0.5%	11.2%	1.1%	4.7%	13.0%	12.9%	7.2%	7.7%	1.5%	7.2%	4.9%

As figure 2-6 shows the main importers of coal are Japan, South Korea/Taiwan and Western Europe. Both have experienced stable growth rates for some time now. Other major steel producers such as China and USA have sufficient domestic coal to service their steel industries. As mentioned earlier coal data is not included in the Chinese analysis

[21] Clarksons Reaserach Studies Limited

3. MODEL AND METHOD

Leading indicators are used to predict the future development in business cycles. The term "business cycle" is most often used for fluctuations in GDP. However, we believe that the fluctuations in seaborne dry bulk demand (imports of iron ore and coal to Japan, China and South Korea) have similar properties as that of the fluctuations in GDP. Hence, we also use business cycles to explain fluctuations in shipping demand. The objective of this paper is to find leading indicators for dry bulk demand in the Far East. But before we start the actual analysis it is important to discuss some of the main economic and statistical elements of the business cycle theory and methodology. In this chapter we start by explaining the economic concept of business cycles and the properties of cyclical deviations. The chapter then describes the key statistical elements of the forthcoming analysis in chapter 4. In section 3.1 business cycles and the trend factor in the time series data are defined. The difference between the growth and classical cycles follows in 3.2 and in 3.3 we cover some main elements related to economic indicators. In sections 3.4 through 3.7 we focus on seasonality, irregularity and trend. Finally, in the last section the relevant statistics involved when analysing time series are described.

3.1 Business cycles and trend defined

Although fluctuations in the economy are a well-known fact, the theoretical key concepts of cycles and trends are necessary to discuss. Traditionally, business cycle analysts and macro economists have decomposed macroeconomic time series into cyclical and trend components. The cyclical component captured temporary fluctuations associated with the business cycle, whilst the trend component described long-term economic growth[22]. To define business cycles Arthur Burns and Wesley Mitchell, in their historical "Measuring business cycles" in 1946, wrote the following:

> *"Business cycles can be seen as fluctuations in the aggregate economic activity of nations that organize their work mainly in business enterprises. A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals that merge into expansion phase of the next cycle. This sequence of changes is recurrent but*

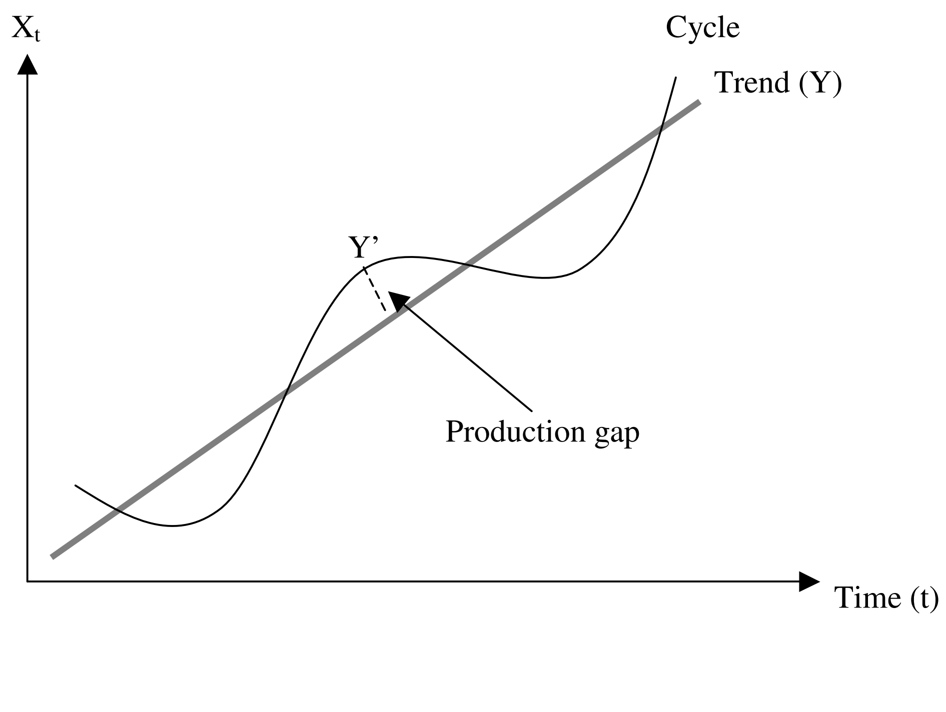
[22] Balke 1991

not periodic. In duration business cycles vary from more than one year to ten or twelve years. They are not divisible into shorter cycles of similar character with amplitudes approximating their own."[23]

From this definition we first of all conclude that business cycles consist of co-movements of several economic activities. Secondly, business cycles are a phenomenon occurring only in decentralized market economies. This means that governments do not intervene comprehensively in the economy. Consequently, the former communist economies of Eastern Europe did not have economic cycles the way we define them in the Western World. Looking to China the government influence has to a great extent been exchanged with a more capitalistic market form. Thirdly, business cycles are characterized by a period of expansion preceding a period of contraction or vice versa. Fourth, business cycles occur repeatedly, although not periodically. Despite the fact that economists initially assumed cycles to be periodical, it is widely accepted in modern business cycle theory today that cycles often have different duration.

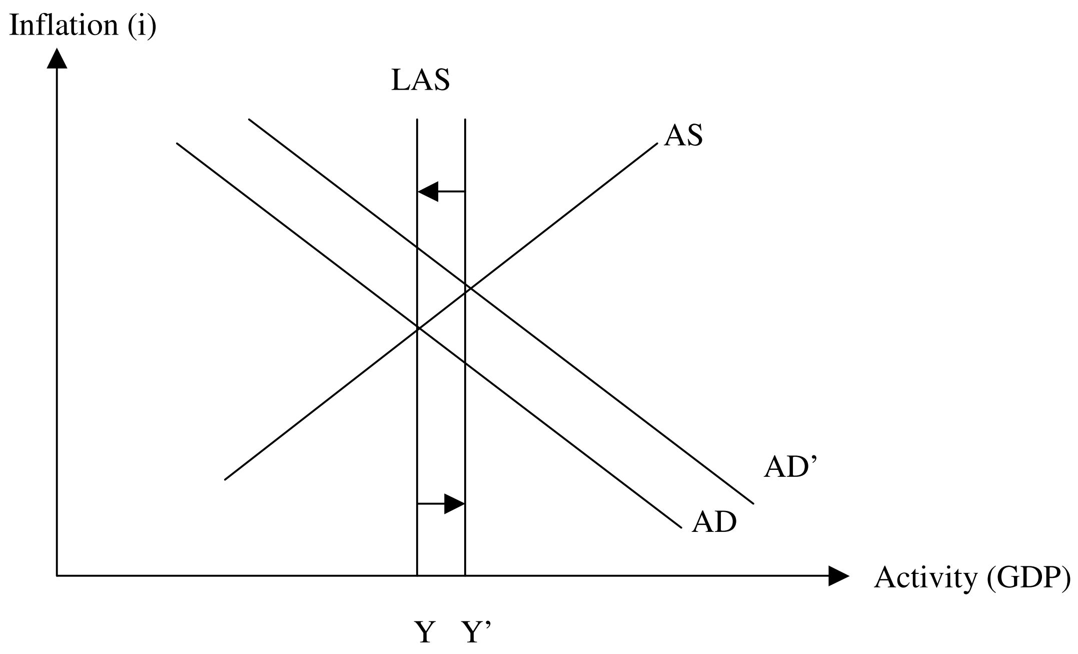
Figure 3-1 Business cycles and aggregate supply and demand.

a.



[23] Burns and Mitchell (1946)

b.



One explanation of business cycles, and maybe the easiest one, is that they are reactions from stochastic shocks or impulses, for instance on aggregate demand[24]. Although the effects of such shocks normally would fade away, new and additional shocks continuously have an impact on the cycle movements. Figure 3-1 illustrates how a positive shock in aggregate demand can influence the economy. In figure 3-1 a. the vertical axis may show production or GDP, which in our case is seaborne dry bulk demand mirrored by imports of iron ore and coal. The horizontal axis shows time. A shock in demand shifts the aggregate demand line from AD to AD' in 3-1 b. To match the demand increase, production is increased from Y to Y'. The effect is an expanding economic activity leading to a positive production gap. The expansion is illustrated as growth in the cycle towards a peak point Y' above the trend line in figure a. The trend, which is relatively more rigid (and for this model equal to the potential production Y), is shown as a simple regression line. For the shipping market a positive shock in demand can in the same way increase aggregate imports and thus the demand for seaborne trade.

In the 1920s, Warren Persons presented another theory that time series can be divided into four components: a trend component, a cycle component, a seasonal component, and an

[24] Burns and Mitchell (1946)

irregular factor. With a basis in a business cycle time series, for instance GDP (Y), it is possible to simplify and describe this as an equation:

$$Y_t^{unadjusted} = C_t * T_t * SES_t * E_t \tag{1}$$

From equation (1) we see that the unadjusted GDP contains several factors. C is the cyclical component that over time deviates from trend. T is the trend factor describing the long-term economic growth trajectory, which may be considered deterministic or stochastic. SES is the seasonal component. Seasonal fluctuations are common in most markets and therefore an explanatory factor in an economic expansion. Finally, there are some aspects of the economic development, which are neither predictive nor explainable. These are considered irregular components marked as E in the formula. By taking the logarithm of the equation we can redefine the formula:

$$\ln Y_t^{unadjusted} = \ln C_t * \ln T_t * \ln SES_t * \ln E_t \tag{2}$$

This can also be written as:

$$\equiv y_t^{unadjusted} = c_t + \tau_t + ses_t + \varepsilon_t \tag{3}$$

In equation (3) the formula is on a logarithm form and therefore it is easier to illustrate the equation graphically. By assuming $\varepsilon = 0$ and seasonally adjust equation (3) we can subtract the elements of stochastic irregularity and seasonally deviation, respectively. This is a simple description of the method used in our analysis and is further discussed later in this chapter. The formula now only contains the cyclical component and the trend elements as equation (4) illustrate:

$$y_t = c_t + \tau_t \tag{4}$$

Not all movements in a time series describe a business cycle. There are certain requirements that must be fulfilled in order for movements to be defined as a cycle. The most important are duration and amplitude. For a deviation to be defined as business cycles it must first of all last for a minimum duration of time. In addition, a movement must be of certain strength or amplitude to count as a cyclical move.

The NBER (the National Bureau of Economic Research) for instance, evaluates several key indicators in their analysis. NBER defines a recession (contraction) as a significant decline in the total output, income, employment and trade; lasting at least six months, and confirmed by a widespread contractions in several sectors in the U.S. economy[25]. Another definition of a cycle is often described as the "two-quarter-rule", which in short states that two consecutive quarters of contraction in the economy is defined to be a recession.

Two alternative theories are based on statistical methods. The Bry-Broschan method tries to mimic the NBER dates using an algorithm. It roughly parallels the traditional sequence of first identifying major cyclical movements, then delineating the neighbourhoods of their maximum and minimum, and finally narrowing the search for turning points to specific dates. In contrast to the NBER dates, this procedure relies on individual series, because a comprehensive analysis with the use of different statistical tools can lead to a loss of consistency over time[26]. The Bry-Broschan method requires a cycle to be at least 15 months.

Romer's rule, on the other hand calculates the production loss from the last absolute turning point. From this rule we can find a "cut-off point" and date the turning point based on empirical evidence.

A business cycle typically fluctuates around a growing trend drawn as an average of the deviations of the cycles. The trend can often be seen as the steady state in the growth theory of Solow[27]. Steady state is based on the belief that productivity only can be improved by an increase in technology; that is, the effectiveness of labour (or the economy) grows at some constant rate. Thus, the trend changes according to the change in technology. Innovation and improved skills in engineering and research contribute to deviations in the semi-stochastic trend.

[25] www.nber.org/cycles.html
[26] Christoffersen, P.F. (1990), Dating the turning points of Nordic business cycles, mimeo, McGill University.
[27] Kydland & Prescott, 1990 p. 8

Traditionally the trend has been considered deterministic and a result of the rigid long-term economic growth rate. If we take a closer look at the time series y_t represented by equation (4) a deterministic trend would have a constant growth (μt) and could therefore be drawn as a regular and straight regression:

$$\tau_t = \tau_0 + \mu t \qquad (5)$$

The change in or growth of the trend (τ_t) is equal to the constant (μ). Thus, the growth in the economy is decided by the growth in capital, labour, and technology.

Recent research, however, has postulated that a trend has more of a stochastic character. Whether trends are deterministic or stochastic has important implications for the nature of fluctuations in economic time series and can lead to quite different characterizations of the cycles. It is of no surprise that stochastic trends are much more difficult to predict than deterministic. By redefining equation (5) we can find a new formula to illustrate the stochastic trend approach:

$$\tau_t = \mu + \tau_{t-1} + \varepsilon_t \qquad (6)$$

In equation (6) the trend is a random walk with a draft ($\mu \neq 0$) or an average growth rate and ε_t is a random variable. What separates it from equation (5) is the implication of a shock.

Whilst for a stochastic trend a shock will be permanent, a shock to the deterministic trend will only be temporary. When forecasting the business cycle, having a stochastic trend, it is almost impossible to separate the trend from the more volatile cycle component. Shocks make a permanent impact on the trend and the standard deviation continuously increases as the forecast horizon is extended[28].

In our case with the demand side of the shipping market, the assumption that the stochastic regularity is zero and that the seasonal fluctuation is possible to separate may help us in making a model for predicting the business cycles with leading indicators. We use this theory,

[28] Balke 1991

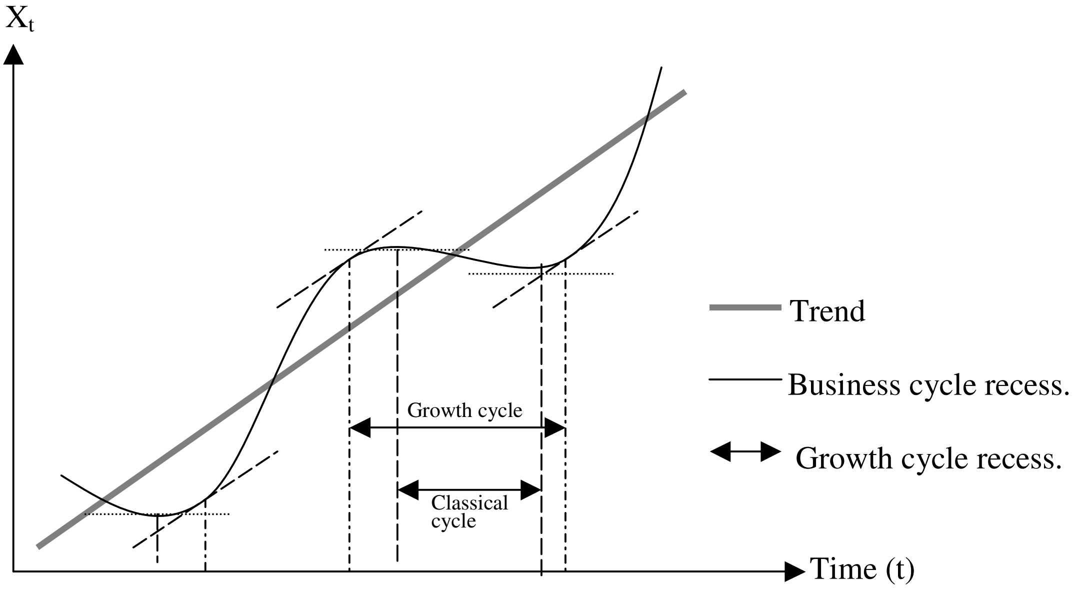
most often used for GDP measures, analogously on the import to Japan, South Korea and China.

3.2 Growth and classical cycle theory.

As already mentioned the cycles typically deviate around a trend. In order to fully understand this concept we find it necessary to discuss the two main ideas of a cycle. Peaks and troughs in a business cycle are usually called turning points where a period of contraction turns into a new period of expansion or a period of expansion turns into a subsequent period of contraction. In a recession the cycle eventually hit a trough and in an expansion it hits a peak. However, economists have different opinions on how to define these points in the business cycles.

Generally economists distinguish between the growth cycle theory and the classical cycle theory. While the growth cycle theory is predominantly used in Europe, the U. S. Chamber of Commerce and the NBER favours the classic cycle theory[29]. The difference between the two is illustrated in figure 3-2 and has primarily to do with how to measure the peaks and troughs.

Figure 3-2 Growth and classical cycles.



Classical turning points ....

Growth cycle turning points – – – –

[29] Romer, 1994

The classical cycle theory measures the cycles as absolute peaks and troughs, i.e. turning points take place when growth is equal to zero. Thus, periods of expansion in the classical cycles tend to have a longer duration than the periods of contractions. The growth cycles, however, measure the turning points relative to the trend and consequently the duration of recessions and expansions tend to be more similar. An additional effect of the latter is that the production gaps are larger than for the classical cycles. A production gap is the difference between the actual production and the potential economic activity and is often used by Central Banks to monitor and control the economy so that the growth in activity does not divert too much from trend.

3.3 Leading, lagging, and coinciding indicators

To understand and monitor economic activity and in effect the business cycle, economists use macroeconomic and microeconomic indicators. Economic indicators are quantitative statistics of various activities in an economy that when organized in individual time series or grouped together give information about the economy and the business cycle. Some indicators are able to say something about where in the business cycle we are, will be, or have been. Indicators may be a single time series or consist of several time series. The latter would typically be an indicator index. Due to the statistical quality of some time series it is sometimes possible to use them to project and confirm turning points in growth cycles. The composite indicators are normally divided into three components: leading indicators, coincident indicators, and lagging indicators. Coincident indicators signal turning points at approximately the same time as the real business cycle turns. They are therefore described as the contemporary economic picture. Some examples include employment, personal income, and industrial production. Lagging indicators, on the other hand, typically confirm a turning point after the actual economic event. Typically corporate profit is an example of a lagging indicator for a country's economy. A leading indicator, more importantly, is used to forecast turning points in the business cycle in advance. This indicator should be able to anticipate turning points because it has a causal or reporting lead[30]. Typically a leading indicator is correlated with the actual business cycles, but some months in advance. Such could for instance be bond yield and stock prices.

[30] Niemira Klein, Forecasting financial and economic cycles, 1994 p. 168

The theory of leading indicators has two distinct parts: a stochastic foundation and an economic component. The economic component has been developed around a loosely formulated expectation theory of the business cycles. Because of this the study of leading indicators is usually supported by empirical studies and empirical evidence.

Statistical mathematics is used to identify indicators. By comparing quantitative statistics in the real economy, the correlation between various time series is found. A correlation number close to one indicates that a time series is highly pro cyclical; a number close to minus one indicates that a series is counter cyclical. A number close to zero, however, means that a series does not vary with the cycle in any systematic way, thus the series is uncorrelated. Equation 10 describes the characteristics needed to identify a leading indicator[31]:

$$corr\left(X_{t-n}, C_t\right) \neq 0 \qquad (7)$$

The equation shows that for a series X to be a leading indicator of the cyclical component C it must correlate with the actual cyclical movement of C at time t-n months in advance. The correlation must also be significantly different from 0.

To find good leading indicators is difficult and sometimes quite time consuming. The amount of potential indicators is large and the selection of indicators requires some judgement and knowledge of data sources, which is at the core of econometric research. However, some useful screening rules exist[32]:

1. Search for leading indicators based on a causal relationship – they are most likely to be robust over numerous cycles.
2. Look for data with the highest frequency – use monthly instead of quarterly.
3. Look for series with the longest history.

However one must be aware of the potential pitfalls involved when using these screening rules. Especially selecting the data with the highest frequency may add more noise to the time series. Moreover, a long time series has the possibility of change in character over time, so the

[31] Kydland and Prescott, 1996
[32] Niemira Klein, Forecasting financial and economic cycles, 1994 p. 170

data could loose its reliability. This is typically for the time series for China, which has seen a totally different economic situation in the last five to ten years compared with the relatively more closed economy that existed before this time.

3.4 Seasonal adjustments

If a time series is observed at monthly or quarterly intervals (or even on a weekly or daily basis), it may exhibit seasonality. Seasonal patterns are defined as recurrent inter-year fluctuations and the objective of all seasonal adjustment methods is to smooth out those patterns. Smoothing might be done before making a forecast or simply in order to make the time series easier to analyse and interpret[33]. Seasonal adjustment techniques are basically ad hoc methods of computing seasonal indices and then using those indices to deseasonalize the series by removing the seasonal variations. In some cases, however, obstacles may occur during the elimination process. One example is holidays, which typically are not fixed on a particular date. In the Western World Easter is a good example of this. To make seasonal adjustments on the time series we want to eliminate the SES_t in equation (1):

$$Y_t^{unadjusted} = C_t * T_t * E_t \qquad (8)$$

In equation (8) the seasonal component is subtracted. On the other hand, not all time series have seasonal patterns. Good examples of this may be interest rates and inflation rates[34]. In our case we use X11 and X12 in the statistical program PcGive to find these variations and also base our adjustments on these two models. Most methods of adjusting time series for seasonal fluctuations are usually based on similar rules. We have explained the Pindyck & Rubinfeld method in the appendix.

3.5 The irregular component

The last component in a time series is the irregular or noise component (E_t). This factor is often neglected as a component, since it lacks importance over time because it is seen as an error that given sufficient time averages out to zero and therefore becomes insignificant[35]. The irregular component should, however, not be overlooked but used. The fact that each of the

[33] Pindyck & Rubinfeld, 1991 p 417
[34] Jeffrey M. Wooldridge, Introduction to Econometrics – A modern approach, 2003
[35] Forecasting financial and economic cycles by Niemira and Klein, 1994, p 158

four components in a series in some way has impact on one another makes the irregular component no less important. Although the decomposing of factors is often fruitful, it is important not to go to the extreme and overemphasize the segregation of the components. Because of the assumptions under the OLS regression method presented below, the error component is set to zero.

3.6 Separation of trend and cycles

Despite the interdependence between the components, it is often fruitful to separate the trend component from the other components and to smooth the time series before evaluating the indicators. There are numerous methods of smoothing a time series. The Kalman filter is a recursive method based on the information available at time t, and the system matrices at t, that calculates the optimal estimator for a vector at t[36]. This is, however, a complex procedure, which we do not discuss further. Several other smoothing techniques, however, are based on the Kernel function, which is a weighting function used in nonparametric function estimation. One such smoothing technique is the Epanechnikov kernel smoother, also known as the np – filter. Another is the natural cubic spline filter, otherwise known as the sp – filter. However, one of the most commonly used methods today is the Hodrick – Prescott – filter (HP – filter). The two economists presented this filter theory in the early 1980's, and since then this filter technique has received a broad recognition amongst economists. By using the information inherent in the time series the method estimates the production gap. The production gap may be defined as the difference between the actual production and the potential production. Hodrick and Prescott consider the potential production, or the long time aggregate supply, to be the trend. The actual production and the temporary state, on the other hand, is the equivalent of the deviating business cycle, which could destabilize the economy. Consider a time series y_t, which consist of a cyclical component c_t and a trend component τ_t like in equation (4). The Hodrick and Prescott theory put emphasis on the variance between the cycle c and the trend τ. The theory is based on equation 12 below. The first term is the difference between actual and trend. If the activity is based on for instance GDP this is considered the production gap for a country. The second term is the variance of the trend. This is weighted by λ (lambda). The lambda parameter thus determines the smoothness of the trend putting a relative weight on smoothness in the minimising problem. When λ is small, i.e. close to zero, the second term in equation 9 becomes negligible. By minimizing the remaining first term,

[36] Forecasting, structural time series models and the Kalman filter, Andrew C. Harvey, Cambridge University Press 1989.

trend τ_t is set equal to the actual activity y_t; hence there is no smoothing. If λ on the other hand goes towards infinity, the second term is weighted. To minimize the equation, τ_t is set so that the variation in trend is small, thus the production gap is often large. In effect, the choice of λ is determined by ones preference of smoothing.

$$\min\left\{\sum_{t=1}^{T}(y_t-\tau_t)^2+\lambda\sum_{t=2}^{T-1}[(\tau_{t+1}-\tau_t)-(\tau_t-\tau_{t-1})]^2\right\} \quad (9)$$

The choice of λ is also related to the data available. For quarterly data the λ value is often set at $\lambda = 1600$ and for annual data $\lambda = 100$. For monthly data, however, it is common to use $\lambda = 14400$[37]. The essence of the HP –filter method is the minimization problem in equation (9). Given the value of λ used in the formula, the filter calculates the value of τ_t, which minimizes the cyclical component.

The method is well known throughout the economic society and there are various software programs available making the necessary calculations. Moreover, a study done by Bonenkamp et al. with economic time series of Netherlands economy shows that the HP –filter does not require a trend process that is stable over time like the linear filtering[38]. Despite all the advantages with the method, there are also some disadvantages. First, the theory assumes that the trend is the same as the potential production without any theoretical support. Secondly, the fact that the filter is based on the observations from t-1 and t+1 it has an "end-point problem". At the beginning and at the end of a time series no further observations exist, so that more weight must be put on contemporaneous observations. Another, and closely related, problem is that newly published data often is revised or corrected after some time, also known as real time problem. The results of a filtering process may therefore be unreliable. This is however an issue for all filters, which is used to smooth time series. A fourth disadvantage is the problem concerning a long lasting negative production gap. For instance in Japan, which is one of the economies we look at, growth has in recent years been very low. This might impact the trend by decreasing the trend estimate; thereby it could give the impression that there has been no recession. Thus, long lasting cycles may result in unrealistic results. Finally, equation (9) puts the same weight on both negative and positive

[37] Kydland and Prescott (1996)

[38] Measuring business cycles in the Netherlands 1815-1913: A comparison of business cycle dating methods, by Jan Bonenkamp, Jan Jacobs and Gerard H. Kuper.

divergence from trend. Therefore, it postulates that expansions and recessions have equal length in time. However, that is necessarily not a correct assumption.

3.7 Evaluating the indicators.

Indicators need to be re-evaluated after some time to confirm that the causality and the quality of the leading indicator are still relevant. In the case of insignificance the method is ether to substitute the indicator or perhaps increase or decrease the lag time. The frequency of such re-evaluations is based on the context of what to project. In our case with import as the dependent indicator, evaluation may be required relatively often. The factors affecting this time series are many, so the capabilities of both the import and the independent indicators may alter during time.

3.8 Statistical theory

Time series have characteristics that differ from regular cross-sectional data. Among other things it comes with a temporal ordering. This means that we for example know that December 1975 immediately precedes January of 1976. Moreover, whilst the past may affect the future, the future cannot affect the past. When analysing time series data statistical tools are of vital importance. In our analysis we use the ordinary least square (OLS) regression to find the relationship between the reference indicator and the leading indicators.

3.8.1 OLS regression

We use ordinary least squared (OLS) regression when estimating and testing the model empirically with actual figures. The OLS regression analysis is a method for estimating the parameters of a linear regression model. The ordinary least squares estimates are obtained by minimizing the sum of squared residuals $\left(Y_t - \hat{Y}_t\right)^2$. Y is the actual occurrence, while the $\hat{Y}$ is the estimated figures[39]. For several periods the model can be written as:

True model: $$Y_{t+k} = \alpha + \sum_{i=1}^{N} \beta_i x_{it} + \varepsilon_t \qquad (10\text{-a})$$

Estimated model: $$\hat{Y}_{t+k} = \hat{\alpha} + \sum_{i=1}^{N} \hat{\beta}_i x_{it} + \varepsilon \qquad (10\text{-b})$$

[39] Wooldridge 2003, p. 799

In equation 10-a Y is the real dependent variable at time t + k, and in our case Y is the measure for fluctuations in the dependent variable at time t and t + k, whilst X is the independent variable explaining the Y. β is the true effect of the independent variable x_i on the dependent variable. Finally the ε is the error or disturbance and the indescribable factor in the regression. For this procedure there are several important assumptions. For the estimated model $\hat{\alpha}$ and $\hat{\beta}$ is the estimated fixed coefficient and the estimated effect of x_i on Y, respectively.

In the following we only make a quick presentation of the assumptions[40] for OLS regression and do not discuss in depth the different issues concerning each of them since this would exceed the scope of this paper:

A1. Linear in parameters

The stochastic process $\{(x_{t1}, xt2, \ldots, x_{tk}, y_t): t = 1, 2, \ldots, n\}$ follows the linear model

$$y_t = \beta_0 + \beta_1 x_{t1} + \ldots + \beta_k x_{tk} + \varepsilon_t \qquad (11)$$

where $\{\varepsilon_t$: t=0 1, 2, …, n} is the sequence of the error. n is the number of observations (time periods). Being too rigid about this assumption could however be dangerous in some situations. A non – linear model could also be the case, but then we cannot use an OLS model.

A2. Zero conditional mean

For each t, the average expected value of the error ε_t, given the explanatory variables for all time periods, is zero:

$$E(\varepsilon_t|X) = 0, t = 1, 2, \ldots, n. \qquad (12)$$

Assuming the error term to be normally distributed, one can also denote this assumption as $\varepsilon_t \sim N(0, \sigma^2_t)$. This implies that no relevant variables have been omitted. If some relevant variable is omitted, the results ($\hat{\beta}$'s) are biased.

[40] Wooldridge 2004, p. 316 - 322

A3. No perfect co-linearity

In the sample, and therefore in the underlying time series process, no independent variable is constant or a perfect linear combination of others. Although this assumption allows some correlation, it rules out perfect correlation between the explanatory variables.

A4. Homoscedasticity

Conditional on X, the variance of ε_t is the same as for all t:

$$Var(\varepsilon_t|X) = Var(\varepsilon_t) = \sigma^2, t = 1,2, \ldots, n. \quad (13)$$

As the assumption states, the OLS-regression analysis anticipates that there is a constant variance in the error term. The alternative is heteroscedasticity in which the variance changes through the series. Variables that lead to this type of variance are typically interest rates, inflation rates, exchange rates, and stock prices. In the case of the interest rates the increase in the deviations originates from changes in The Federal Reserves monetary policy targets[41]. There has been developed several statistical methods for measuring and testing time series for heteroscedasticity. One example is White's test (1980), which was explicitly intended to test for forms of heteroskedsticity that invalidate the usual OLS standard errors and statistics. Alternatively the program also contains a second estimator, the "Jack-knife" (McKinnan and White) method. These two estimators provide consistent estimates of the regression coefficient's standard errors even if the residuals are heteroscedastic in an unknown way.

A5. No serial correlation (auto correlation)

Conditional on X, the errors in two different time periods are uncorrelated:

$$Corr(\varepsilon_t, \varepsilon_s|X) = 0, \text{ for all } t \neq s, \text{ or}$$
$$Corr(\varepsilon_t, \varepsilon_s) = 0, \text{ for all } t \neq s. \quad (14)$$

[41] Bails and Peppers, Business Fluctuations, 1993 p. 261

When checking for auto correlation we use a Durbin and Watson (DW) method. The method is presented in the appendix.

Perhaps the most important and most relevant assumption is that the error terms, ε_t, from equation 12, corresponding to different observations are randomly distributed and unrelated to each other.

3.8.2 ARMA modelling

In some cases the OLS - regression model does not have the properties that is necessary for a forecasting model. One problem in particular is to quantify the accuracy or uncertainty of the forecasting analysis. As an alternative the models of the Box-Jenkins (B/J) methodology can help with this problem. The ARMA (or ARIMA[42]) model we use is a univariate Box-Jenkins. While the OLS captures the influence of independent variables on the dependent variable, the ARMA model develops a forecasting model that is based solely on the current and past observations in the time series of the dependent variable.

As for the OLS model (Assumption 2), the expected value of the residual component in the AR(I)MA model is zero. The model further intuitively assumes the data to be stationary without any seasonally fluctuations.

In chapter 4 we use the AR(I)MA model as a supplement to the OLS to see if the two models give similar results for the empirical test.

[42] The letter I stands for integrated and suggests that the model uses data that has been differenced to obtain stationarity.

4. ANALYSIS AND RESULTS

Reference is made to the description of dry bulk demand in chapter 2 where we propose that dry bulk seaborne demand is a function of international trade in raw materials, and where the importance of iron ore and coal was highlighted. Because of their relative importance for seaborne demand, we believe imports of iron ore and coal to Japan and South Korea, and imports of iron ore to China, are good proxies for fluctuations in the overall dry bulk demand in this region. I.e. high (low) imports of iron ore and coal to these economies should mirror changes in overall dry bulk demand. However, due to the volatility in imports it is important to use correct tools when analysing the data. In this chapter we use the business cycle theory and statistical methodology described in chapter 3 in an attempt to make a model capable of forecasting the short-term dry bulk demand outlook. We use a standard ordinary least squared (OLS) model to test various business indicators believed to have significant leading capabilities, six months in advance, for coal and iron ore imports into Japan and South Korea, which again should give an indication of likely changes in overall dry bulk demand. For China we only use imports of iron ore as the dependent variable. China is a net exporter of coal and in effect sufficient. Finally, we review the results by comparing the OLS forecast with an ARIMA model.

4.1 The composite leading indicator

When deciding on the business indicators and independent variables to be tested in the analysis we applied the simple checklist in chapter 3.3. As a starting point we considered some of the components making up the OECD composite leading indicator (CLI). This is an indicator that was developed during the 1980's by the Statistical Directory of OECD to forecast the economic activity in the various economies within the OECD area[43]. From this, we selected some other components also believed to be relevant for imports to the Far East, and thus for the dry bulk demand in the region. In addition, we have selected some indicators for the US economy, such as the Purchasing Manager's Index (PMI) released monthly by the Institute for Supply Management. We have also looked at some financial indicators such as long-term interest rates and some local currencies against the USD. From this, we ended up with a list of eleven main categories of time series:

[43] OECD Composite leading indicators, 2001

- **Construction activity** –construction is one of the main end-users of steel. Higher construction activity leads to more steel production and higher demand for iron ore and coal. This category includes both private and government projects for the countries.
- **Investments** – say something about future expectations about changes in industrial production and the manufacturing activity in an economy. Increased investment activity indicates optimism for the future and in effect an increased industrial activity level, which again would be positive for the demand for steel and several other dry bulk commodities such as iron ore, coal, cement, but to mention a few.
- **Industrial production (IP) and manufacturing** – is central for the economic development in a country. Industrial production is usually cyclical and the demand for raw material fluctuates with it. Constructions will typically be included here, so we have used IP time series excluding construction activity.
- **Exports** – give signals about the demand picture for the manufacturing products produced in an economy. China, South Korea and Japan are very dependent on exports and a large share of their manufacturing production ends up in the export markets. In effect, higher exports leads to more industrial production and consequently increased demand for raw material in these economies.
- **Purchasing Managers Index (PMI)** – is a US diffusion index giving signals about purchasing managers' intentions with regards to purchasing activity in the future. This index has good leading qualities on Industrial production and GDP in USA. USA is a very important purchaser of goods produced in China, Japan and South Korea. A positive PMI (above 50) indicates expansion in the economy, which again is positive for US production and in effect exports from China, Japan and South Korea.
- **OECD CLI** – is one of the most influential leading indicators. As described previously, it is designed by OECD to give leading indications of the economic activity in the OECD area. We have used a total-index version including all the member economies for our analysis in order to grasp a wider based development in the whole OECD area.
- **Commodity prices** – say something about the short-term supply and demand balance in various commodity markets. We have used the index compiled by the Commodity Research Bureau (CBR). This is a commodity spot price index covering 22 basic commodities whose markets are presumed to be among the first to be influenced by

changes in economic conditions. Over time higher prices for these commodities could be a reflection of increased demand, which again should be positive for the activity level in general, and for seaborne dry bulk trade in particular.

- **Stock prices for raw material producers and/or steel companies** - should in an efficient market be a good indicator of the expectation in the market. In theory new information related to a certain company will immediately be reflected in the price of the company's equity. Higher equity prices could therefore reflect expectations of higher demand for a company's products and thus more shipping demand.
- **Raw material inventories** – "in house" stocks of raw materials are most likely counter cyclical to the demand for a commodity. Decreasing inventories should then suggest increased future demand in response to increased production and consumption of a product. Low inventories of coal and iron ore in Japan, South Korea and China could be an indication of increased future imports.
- **Interest rates** – say something about the expected activity level. Historically declining short-term rates has been a precursor for a positive turnaround in the economy whilst increasing short-term interest rates have signalled the opposite. High bond yields have reflected expectations of a higher activity level and inflation whilst low bond yields have been a more negative signal.
- **Exchange rates** – are vital for the terms of trade. Most commodities are priced in US dollars. Traditionally it has been stated that a weak US dollar is good for shipping demand. The reasoning has been that a weaker US dollar reduces the price of commodities measured in local currencies and therefore has a positive effect on the demand for commodities. We look at the development in USD/KRW and USD/JPY to see if this generally accepted rule of thumb has empirical evidence to support it. Initially we wanted to do the same for Chinese Yuan, but the exchange rate development against USD would be of no use to us since this currency has been fixed to the dollar since 1997. We use the USD as the benchmark since this is the currency for freight rates.

In our effort to gather relevant and efficient time series we ran into obstacles. First of all, some of the suggested time series were not easily available. Second, several of the suggested time series had only a limited history obtainable. China in particular has very limited reliable data available. Moreover, the longer-term data from China has occasionally over the last decade been substantially altered. Therefore, there risk of drawing wrong conclusions from the material could not be ruled out. Consequently, we use data covering a shorter interval of years for this country. Japan, on the other hand, has well documented economic time series dating back to the 1960's and for South Korea we have found reliable data starting in the 1980s. We are more confident using this material. The variables for each country can be found in the appendix. Our main base of data was the Thompson Datastream, accessible through Norwegian School of Economics and Business Administrations computers. Also, we received some time series from the research departments of Clarkson in London, Platou Shipbrokers and Fearnleys in Oslo.

4.2 Analysis by country

The analysis is done in a standard version of the statistical program GiveWin2.00 with PcGive 10.0 and X12Arima modules. PcGive is used as a tool to make all the necessary models and calculations for the analysis, while the X12Arima is used to detect and smooth seasonal fluctuations. GiveWin was chosen because it is relatively easy to use and it adapts several worksheet programs such as Excel. We first transferred the data series from Datastream to Excel to modify it before carrying the data forward to GiveWin. We also used Minitab for our analysis of autocorrelation and partial autocorrelation to test for stationarity and finding the right ARIMA model, respectfully.

In order to keep the number of indicators as low as possible we wanted to see if there was an option to eliminate any of the series. The reason for this is that we sought to make the model as simple as possible. By making a correlation matrix with all the time series against each other we are able to locate any large correlations existing between the series. If there is a high positive or negative correlation between two or more variables, we can subtract one or more of the indicators since they have almost the same relationship to the dependent variable as the other. The most correlated series are listed in the appendix for each country.

Much of the data material is initially unadjusted and may therefore contain both seasonal fluctuations (ses) and noise (ε). Over time, however, ε is assumed to equal 0 as discussed in chapter 3.8. As described, if there are seasonal fluctuations present in the time series we would like to subtract these elements. The data was first run through Minitab and X12Arima. The latter uses an F – test to identify significant evidence of seasonality. The auto correlation test is also a useful tool when looking for seasonal patterns. However, some series are already adjusted and others do not have seasonal patterns. The problem in this case, might be that important information disappears. For instance the interest rate and exchange rate do not have these fluctuations and need not be adjusted[44].

After deseasonalising the relevant data both the dependent and independent variables should most likely be a function of a trend component and a cyclical factor, as equation 4 in chapter 3.1 indicates:

$$y_t = c_t + \tau_t \qquad (4)$$

Our objective is to analyse the cyclical deviations and we therefore want to separate the two. Besides, both the OLS regression analysis and the AR(I)MA model assume stationarity. This is of course not always so. In fact, several of the time series we use for this analysis have an increasing trend, easily explained for instance by the increased activity in the economic environment during the last decade. By the presence of trend there is a wide consent that differencing is a useful tool to de-trend the time series[45]. In order to establish the existence of stationary data the auto correlation[46] function is used in Minitab.

Eventually, when the time series are adjusted it is sometimes beneficial to smooth the time series to make the turning points more transparent. However, other times smoothing may obliterate the analytic quality of the series. As already mentioned, the most common method is the Hodrick – Prescott (HP) – filter, although the NP - filter or SP – filter may be used as well. We base our estimates fully on the HP-method both because of the fact that it is simple to exercise and because of its popularity in the economic society. When smoothing, we use a $\lambda = 2000$ to display the business cycles well enough. With λ smaller then 2000 the cycles will be too volatile and with $\lambda = 14400$, like Kydland and Prescott propose to use for data on a monthly basis[47], the deviations would be too difficult to observe.

To catch the leading quality of the independent variables we lag these time series by six months as explained earlier. The reason for this exact time lag is that according to our

[44] Wooldridge 2000, p. 340
[45] Business fluctuations, Dale G. Bails & Larry C. Peppers, 1993.
[46] This is often also called serial correlation.
[47] Kydland & Precott, 1991 p. 9

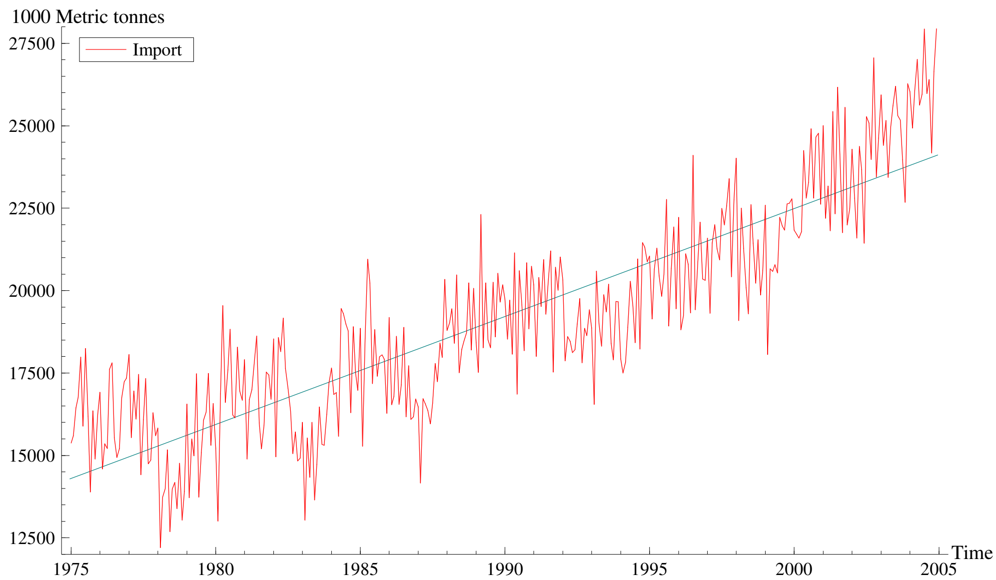
indicators we think this is a good fit. Although it would of course be fruitful to test for different lags as well, we have to set some restrictions on the depth of the paper and the magnitude of work involved.

After deciding the method to be used we make the analysis for each individual economy separately. First we examine Japan before testing the same properties in South Korea and China.

4.2.1 Japan.

Figure 4-1 shows the aggregate monthly imports of iron ore and coal to Japan in the period from January 1975 to January 2005. The horizontal axis indicates time, while the vertical axis measures million tons of aggregate iron ore and coal imported. It seems initially as if the imports during this period have had an increasing trend. The straight line shows the deterministic regression line through the time series deviations. The imports saw two serious troughs during the 80s. The 1990s had a weaker overall growth rate compared to the rest of the series. The time series plot does not seem to indicate any direct influence of the Asian crisis in 1996-97, unlike the imports to South Korea and China analysed later. Finally, over the last few years imports has picked up.

Figure 4-1 Aggregate iron ore and coal import to Japan.



For the rest of the Japanese analysis we use monthly data stretching from 1984 through 2004. To make use of the OLS and ARIMA models we have to make some adjustments in the material. Both the OLS regression analysis and the ARIMA model assume stationarity. After a quick glance at figure 4-1, this assumption seems violated. On the other hand, this may not necessarily be so. To test for stationarity we use a correlogram[48] of the time series in Minitab shown in figure A-1 in the appendix. As can be seen from the plot in this figure, the autocorrelation function (ACF) for Japan is diminishing. However, the diminishing serial correlation does not decrease fast enough. Therefore, we conclude that the import of iron ore and coal to Japan is not stationary but contains a trend element (τ). To eliminate trend from time series, and to achieve stationarity, some level of differencing is required. The correlogram gives some indication of the appropriate level of differencing. Although the determination of an appropriate number of differencing is subjective, it is beneficial to use as low a number of differences as possible. The reason for this is that for every step of differencing one month of data is lost in the time series. To eliminate the trend factor in the case of Japanese imports we primarily difference with one lag (D1), hence {(t-1)-t}. The new ACF plot is displayed in figure A-2 in the appendix.

Figure A-2 shows the ACF plot for the Japanese imports after differencing the time series. Although clearly stationary, it shows patterns of seasonal variations. A typical indication of this is the bars exceeding the dotted line. In addition, a test in X12Arima in PcGive also shows evident signs of seasonality. We therefore use X12Arima to deseasonalise the time series.

When testing the co-movements of the independent variables we first initiate a correlation test between these variables. The results of this test, shown in the appendix, indicate that several of the time series are highly correlated[49]. The most significant correlation exists between industrial production (IP) and investments, above 0.96, which is extremely high. Despite the fact that we could eliminate one of these series in addition to others, we proceed with the same amount of indicators. The reason for this is that when we subtract one of these indicators the result of the OLS-test becomes weaker.

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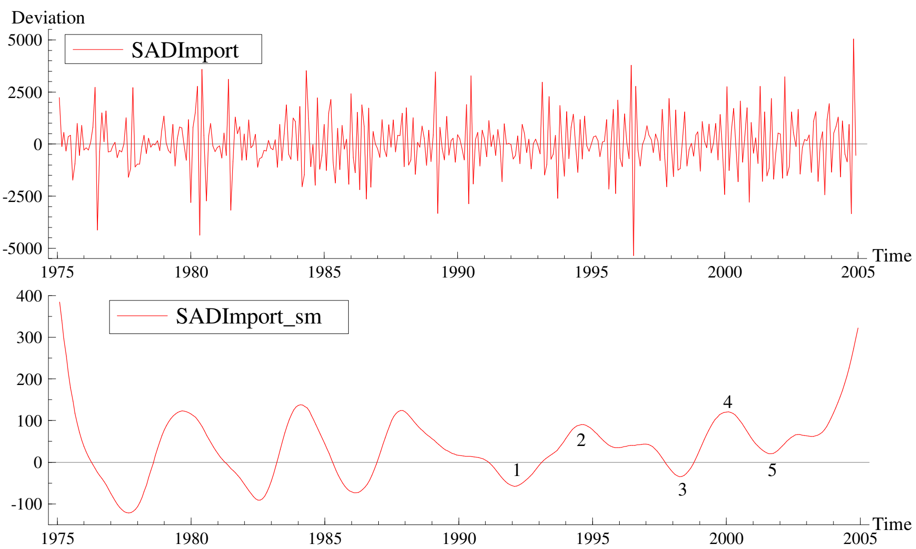
48 Bails & Peppers p. 455

49 In the table are only significant correlated series.

We then test for trend and seasonal deviation in each of the time series based on the ACF and X12Arima in the same way as for the imports above. In table A-1 in the appendix we list the test results for each of the indicators. An X means that there is presence of either trend or seasonality and a 0 means absence of the same properties. Several time series have one of the two properties and others contain both trend and seasonality. Because of this we differentiate the series with one lag to eliminate trend and deseasonalise the data containing seasonal variation for those series containing these qualities.

To observe the effects of the HP – filter on the data, we use both smoothed and original series. The result of this is listed in the appendix. Figure 4-2 shows the differentiated, seasonally adjusted, and un-smoothed data of the import at the top and the corresponding smoothed series at the bottom. Since the series are differentiated, the figure only shows the deviations and not the real values on the vertical axis.

Figure 4-2 Smoothed and un-smoothed differentiated import for Japan



As figure 4-2 displays, the smoothed import has fewer and far more apparent turning points and it may therefore be easier to test empirically how the OLS regression can forecast these. The OLS modelling tests on the unsmoothed and smoothed time series are presented in the appendix as EQ(1) and EQ(2), respectfully. An "SA" indicates that the series is seasonally adjusted; a D means that it is differentiated; a "sm" means that the data is smoothed and a 6 indicates that it is lagged by six months. "Constant" is the constant of the OLS regression. While the OLS test for un-smoothed data shows no significant indicators since they all are within the interval -2 to 2, the examination of the smoothed data has several strong t – values. For the latter test, shown in table EQ(2), there are several strong indicators. One reason for this may be the high volatility of the unsmoothed data and the less fluctuating series for the smoothed data, var(SADImport) and var(SADImport_sm), respectively.

The estimated sample for both tests is 1987(7) to 2004(12), which means July 1984 through December 2004. The reason for starting in July is that some of the data is differentiated by one month and all is lagged by six. The number of variables is 20 and the total amount of observations is 246 for both tests. The log-likelihood is far lower for the unsmoothed data than is the case for the smoothed variables. The mean for the smoothed data is higher than for the unsmoothed. The reason for this may be the previously discussed end – problem of the HP – filter.

What is immediately evident is the significance of the construction activity. Both the private sector (SAGover_sm_6) and the public sector (SAGover_sm_6) have positive t-values, 17.8 and 6.39 respectively. The positive t-values mean they are pro – cyclical. Thus an increase (decrease) in this variable should indicate an increase (decrease) in imports. In reality this seems natural. Large amounts of steel and iron, which is produced out of iron ore and coal, are used for construction in Japan. An increased activity in the construction market increases the demand for steel and iron and therefore also the demand for iron ore and coal. Furthermore, domestic investments (DInvestm_sm_6) have a t-value of 3.48, which specify a pro – cyclical relation to the imports of iron ore and coal to Japan.

To analyse the industrial production and manufacturing activity we inserted time series for industrial production (DIP_sm_6), freight transport (DTransp_sm_6), unemployment rate (DUnempl_sm_6) and domestic vessel transport (SAVessel_sm_6). While the series for transport show no or low significance, the unemployment rate and total industrial production show an opposite correlation of what we initially thought. Unemployment is usually counter – cyclical, which should give a negative t-value. We find the value of 3.47 not to be according to economic theory. Moreover, industrial production is expected to be pro – cyclical, but has a value of -5.37. Thus we conclude that industrial production and manufacturing activity in Japan cannot be used as a leading indicator six months in advance for the imports of iron ore and coal and thus seaborne dry bulk demand.

According to economic theory exports is thought to be pro – cyclical. A trough in exports should then indicate a future recovery in exports and in the industrial activity in general, paving the way for more imports of raw material and other inputs to production. The question is if this can be seen six months in advance. The OLS model shows that exports of iron and steel (SAExIS_sm_6) and total exports to Europe (SAEuro_sm_6) both have positive significant t-values. However, the exports to China (SAChina_sm_6) and the US (SAUSA_sm_6) have negative significant t-values. This inconsistency may be a result of different exposure to the six month lag.

Although the stock price of the dominant Japanese steel producer Nippon (Nippon_sm_6) shows an unexpected negative t-value, the iron ore resource company BHP Billiton (DBHP_sm_6) has a highly significant and pro – cyclical t-value of 17.5. The latter should indicate that an increase in the BHP Billiton stock price indicates an increase in iron ore and coal imports to Japan six months after and therefore an increased activity in dry bulk shipping.

According to the results the inventories of steel and other raw materials (SAInvent_sm_6) have a negative correlation with the iron ore and coal imports with a t-value of -15.2. This confirms the theory that increased inventory typically is a precursor for lower demand (imports).

The t-value for the JPY relative to the USD is also significant at 9.58 and a partial R^2 of 29%. Thus, a weaker (stronger) USD versus the JPY indicates an increase (decrease) in imports, which confirms the general belief in the shipping market that a weaker USD often means a better shipping market.

The test also indicates that the indexes PMI (PMI_sm_6) and CLI (DCLI_sm_6) are not significantly correlated to imports. This shows the less direct importance of USA and OECD on seaborne demand relative to the emerging economies in Asia in particular. More surprisingly, however, is that the CRB index (CRB_sm_6) only has a marginally positive t-value. The same goes for Japanese interest rates (DInterest_sm_6) with a small negative value.

The coefficients, which are tabled in the first column in EQ(1) and EQ(2), show how a change in the independent variable affects the dependent variable. To see the obstacle we compare the OLS results from EQ(1) and EQ(2). For instance for the IP, in the first table the coefficient is positive, but it turns negative after the smoothing and lagging of the independent variables. This may be a result of our choice of lag and that another lag would be preferable. Also for other variables, such as interest rate, this was a problem.

By the use of a 5% significance level both the tests with un-smoothed and smoothed data contains serial correlation. The first test gives a positive autocorrelation (DW = 3.08) and the latter a very strong negative (DW = 0.0845)[50]. This indicates that the assumption 2 from chapter 3 is violated. The credibility of the test is therefore not so high. On the other hand, the R^2 for the smoothed data is high, which correlates to the t-values. This means that the explanation properties of the independent variables are high. R^2 adjusted is however a value that "punishes" tests with large numbers of independent variables. Therefore eliminating some of these variables on basis of the correlation test may alter this value.

To test the prediction properties of the model empirically on the turning points we isolate the different turning points between 1990 and 2004 in figure 4-2. Using the theory presented in chapter 3 we find five turning points, which are all marked in the lower part of the figure:

1. Trough turning point in February 1992.
2. Peak turning point in July/ August 1994.
3. Trough turning point in April 1998.
4. Peak turning point in January/ February 2000.
5. Trough turning point in July/ August 2001.

As can be seen from figure 4-2 there is also other turning points in earlier years, but we chose to use more recent data. We forecast these periods based on the OLS regression method and by ARIMA before testing them empirically with the actual events. The forecasts are done in PcGive for each of the five turning points.

[50] The autocorrelation theory is briefly explained in the appendix.

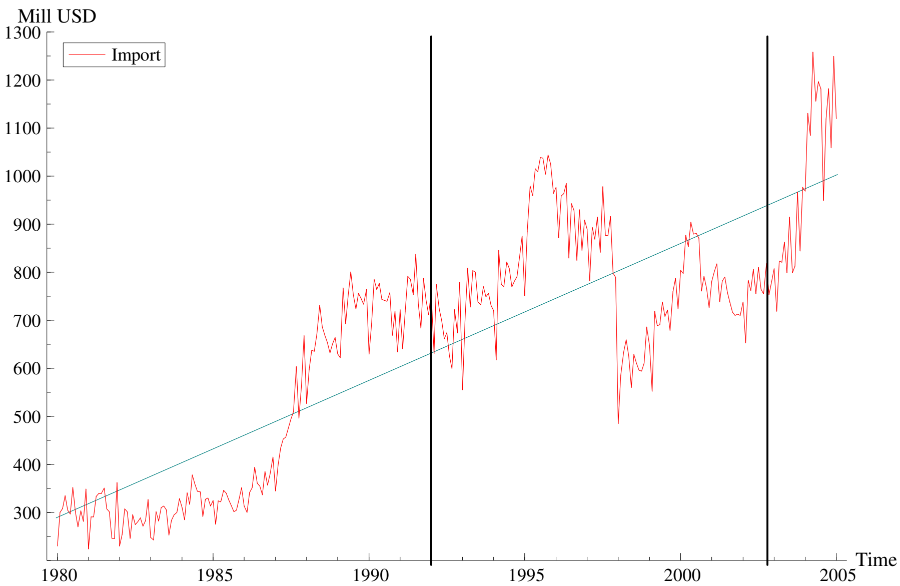
Figures A-3 through A-7 in the appendix are graphically displaying the results of the forecast models OLS (scattered line) and the ARIMA (blue line) and the actual smoothed imports in red. Since the data is differentiated the vertical axis shows the deviations, while the horizontal axis is indicating time. Figure A-3 shows the OLS forecast and the ARIMA forecast during the period of 1991 – 92 where we spotted the first turning point in the selected interval. Both forecasts starts in 1991 – 8 (August) and are based on deseasonalised, differentiated and smoothed (λ=2000) data. The turning point is estimated to 1992 – 2 (February). As can be seen from the graph the OLS forecast does not predict this. The ARIMA forecast on the other hand shows a turning point in 1991 – 9, but which is far too early compared to the actual plot. The next breaking point in the time series of iron ore and coal imports is between July and August in 1994, which is shown in figure A-4. Instead of breaking of in the mid 1994 the OLS predicts an increase of import through the whole year. The ARIMA forecast shows a turning point in the month immediately after the forecast is initiated and therefore does not predict correctly. Figure A-5 is displaying the forecast results from the OLS regression and ARIMA forecast done for the period 1997 – 98. In this period we see a trough in April 1998. Both the estimates are missing the turning point. The fourth turning point we found during the period between 1990 and 2004 was a peak in the early months of 2000. The smoothed blue line (SADImport_sm) of the bottom graph of figure A-6 shows this turning point. The OLS forecast, which starts in July 1999, is however too early in the prediction of this peak. According to the prediction the peak is in August, approximately three to four months in advance. Since the estimated time series is differenced (D = 1) and lagged by six months this could indicate that the model may have a leading capability with earlier lags. The final turning point in this period for the Japanese import of iron ore and coal was the trough at the end of July and at the start of August 2001.This is shown in figure A-7, where the smoothed data is displayed in the bottom graph and the un-smoothed on top. The smoothed forecast model indicates a turning point in March 2001. Comparing this estimate with the one done for the peak in January 2000 they both seem to be early with the prediction. For the last approximation this could mean that the indicator may be a fitted leading indicator for the import with a larger lead time.

The first three tests gave the impression of a model not capable of predicting the turning points, whilst the two last assessments gave a different reading. If the lag had been somewhat larger the model could at these two turning points have given a better fit with reality.

4.2.2 South Korea

South Korea has during the last few decades been one of the major importers of dry bulk commodities. It is situated on a peninsula bordering to North Korea, which is a very closed economy with limited trade with others. This makes South Korea dependent on seaborne trade and after the industrialisation South Korea became a significant factor for dry bulk demand. Figure 4-3 exhibits the historical development in imports of industrial raw materials from 1980 to 2005. The imports are measured in millions of dollars (vertical axis) per month (horizontal axis) and contain data for all the raw materials imported to the country excluding food and liquid materials. We have not been able to separate the time series for iron ore and coal from these data. However we believe the data have similar cyclical properties as the data initially searched for, because a significant portion of the data in fact is the imports of iron ore and coal[51]. Therefore, we believe this time series to be a good proxy of the turning points facing the total imports of iron ore and coal.

Figure 4-3 Imports of inedible and non-fluid crude materials into South Korea



South Korean production and exports increased towards the end of the 1980's. This also had an impact on the imports of commodities. Through the last years of that decade and throughout most of the 1990's imports were relatively high compared with previous years. The Asian crisis in 1997 and 1998 had a significantly negative influence on the economy putting it into recession. As a result imports fell during this period. But the country's economy

[51] Fearnleys research department estimates around 55%

soon recovered and imports improved with it, before dropping at the beginning of this decade. Since the end of 2004 demand has been high and it has contributed substantially to the strong shipping market.

Because of the difference in volume imported during the last 25 years or so we believe it is constructive to divide the time series into three separate periods, as shown in figure 4-3, and analyse them separately. Alternatively we could have used dummy variables. We have chosen to use one period from 1991 through 2004 for our analysis.

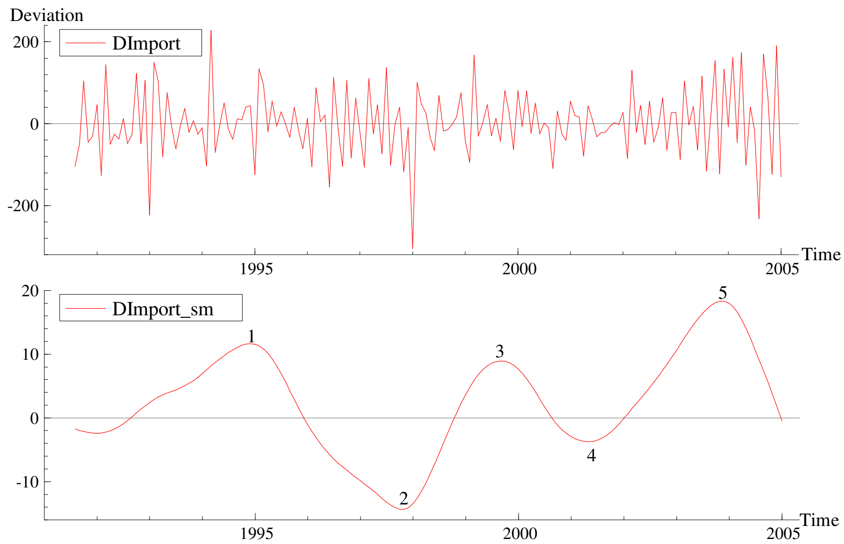
When analysing the data we use the same approach as for the Japanese imports. First we test the time series for stationarity. The test is done in Minitab and the correlogram is shown in figure A-8 in the appendix. The ACF plot for South Korean imports has almost the same properties as those for Japan. This clearly indicates a trend pattern in the import. To eliminate the presence of trend in the time series we differentiate it by 1st order. Figure A-9 shows the differentiated data in a correlogram. Although initially from the ACF plot it seems as if there are seasonal elements in the series, seasonally tests by X12Arima in PcGive indicate an alternative conclusion. Therefore, we do not seasonally adjust the South Korean imports.

The same method is used for the independent variables as well. When the seasonality tests are different from ACF in the X12Arima test we trust our analysis on the X12Arima model, because we find this test more credible and of better quality.

When treating the independent variables we first take a look at the correlation between them to see if they have similar deviation properties. The six most correlated series are listed in a matrix in the appendix. Some variables are quite correlated, which gives us a reason for erasing one or more of the variables from the test. For instance investments and industrial production have a fairly high correlation with a value of about 0,8. Export to USA also had a high correlation with some of the production and manufacturing indicators, at levels around 0.7. Nevertheless we decided to use all of the original variables despite some high correlations because when eliminating some of the independent variables we lose some of the significant t-values and the Durbin – Watson value moves closer to 0.

The results of the analysis for trend and seasonal deviations are listed in table A-2. An X means that there is presence of a property and a 0 means no presence. Most strikingly, perhaps, is that almost all the variables have a trend, but relatively few contained seasonality. This could indicate that the series are already adjusted without informing about it. To make the statistics useful for our analysis of the import we differentiated the variables with trend elements and deseasonalised those series with seasonal deviations. In the upper part of figure 4-4 we present the unsmoothed deviations of South Korean imports. The lower half displays the smoothed series with the numbered turning points. The horizontal axis for both graphs is indicating time.

Figure 4-4 Smoothed and un-smoothed import for South Korea



Next we lag the independent series by six months so that we can test their ability to predict the import to South Korea.

As is relatively apparent from figure 4-4, the turning points are more transparent in the smoothed graph on the bottom than in the un-smoothed graph at the top. However, in order to see the difference using the OLS regression analysis, we test for both smoothed and un-smoothed import. The results of the tests are listed in the appendix under EQ(1) and EQ(2), respectively. The test shows some of the same pattern as for the OLS test on the Japanese numbers. While there are several significant variables in the smoothed statistics, only one variable of the un-smoothed material is significant. For the analysis of South Korean imports we use 162 observations stretching from August 1991 through January 2005. This is the test interval after the series are differentiated and lagged by six. Totally 22 parameters or variables are used including a constant for the OLS regression. The variance of unsmoothed imports, var(DImport), is naturally much higher than that of the smoothed imports, var(DImports_sm).

As is the case for the Japanese analysis the log-likelihood is lower for the unsmoothed series than for the smoothed variables. The test of the unsmoothed data does not reveal any significant variables. We therefore concentrate on table EQ(2) in the appendix.

Japanese construction activity, both private and public, showed some highly significant t-values. Consequently, we initially expected to see the same results for the South Korean construction time series. However, while governmental construction activity (SAGover_sm_6) has a disappointing significant counter-cyclical t-value, construction iron and steel consumption (DConstrISC_sm_6) is not significant in the OLS regression analysis. Private construction (DPrivate_sm_6), on the other hand, is significantly pro-cyclical, but much lower than expected with a t-value of 2.19.

Moreover, neither industrial production nor manufacturing activity variables give the expected results. Freight transport on land (DTransp_sm_6) is not significant, unemployment (Unempl_sm_6) is pro-cyclical and industrial production (SADIP_sm_6) is unfavourably counter-cyclical.

Reviewing the export time series we see that exports of iron ore and steel products (SADExpISProd_sm_6) and total exports to China (DChina_sm_6) are both significant and pro-cyclical. Meanwhile exports to Europe's 15 largest economies (DEURO15_sm_6) and exports to the US (SAUSA_sm_6) are significant, but unexpectedly counter-cyclical.

The US PMI in the Japanese analysis was not significant. Compared to the South Korean imports, on the other hand, PMI (PMI_sm_6) has a t-value of 5.13. This could indicate that an increased purchasing activity in the US is a pre-warning of an increase in the South Korean shipping demand. The additional ISM-index (SAISM_sm_6) is not significant with a t-value below 2.

Although the commodity price index (CRB_sm_6) was not significant referring to the Japanese imports, it is highly significant and pro-cyclical in this test. An increase (decrease) in this commodity spot price index may indicate an increase (decrease) in the South Korean imports. The CLI reading is not significant for this economy.

As to the stock price of Nippon Steel (Nippon_sm_g) and BHP (DBHP_sm_6), neither has the expected pro-cyclical t-values.

Producers inventories ((SADInvent_sm_6) is counter-cyclical with a t-value of -4.11, confirming the results from the Japanese analysis and our assumption that large inventories indicates a slower demand for imports six months later.
Interest rate (DInterest_sm_6) has a t-value of 4.16 and thus pro-cyclical in relation to imports.

Finally, the value of the Korean Won (KRW) exchange rate (DExchge_sm_6) is counter-cyclical with a t-value of -4.59. This means that a depreciation of the KRW versus the USD (a higher USD/KRW exchange rate) indicates decreased imports and in effect lower shipping demand.

As with the Japanese figures South Korea also faces autocorrelation according to Durbin – Watson. The test for the un-smoothed material has a DW = 2.84 and therefore a negative correlation with a $\hat{\rho}$ = -0.42. For the smoothed figures the $\hat{\rho}$ = 0.89, which indicates a positive autocorrelation (DW = 0.207). In conclusion neither of the two tests gives any strong incentives to use the model for forecasting. Nevertheless, we test the model empirically in the following.

In order to measure the predictive capabilities of the independent variables we tested if they could point out the turning points of imports. From the smoothed material we found five turning points in the import time series:

1. Peak turning point in December 1994.
2. Trough turning point in October 1997.
3. Peak turning point in September 1999.
4. Trough turning point in April/ May 2001.
5. Peak turning point in November 2003.

These peaks and troughs are displayed in figure 4-4 above. In addition to the OLS regression we also used an ARIMA model to compare the results. The first turning point in imports was in December 1994. Figure A-10 in the appendix displays the results of the empirical test.

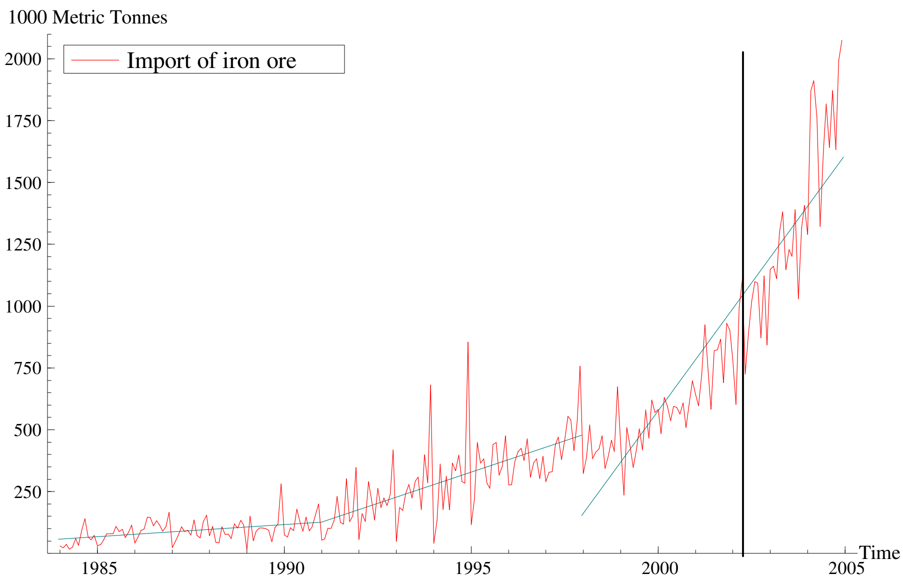
Horizontally the graph shows the time and vertically the deviation. The lagged OLS model is not able to project the turning point in the end of 1994. Neither does the ARIMA model, even though the latter indicates a peak one month into the forecasting period. The ARIMA model shows the same pattern in all five empirical tests. It suggests a turning point in the series one month into every period. The OLS model also fails to project the turning points in real imports. The breaks in 1997, 1999 and 2001 are illustrated in figures A-11, A-12 and A-13, respectively. The last turning point, in late 2003, is shown in figure A-14. Compared with the other tests, this result was the closest we came to a positive outcome for our model. At this turning point the OLS model projects a peak four months before the actual imports turned. The reason for this may be that the model uses more data than the first four tests and therefore have a better basis for the forecast. Another explanation might be that the turning points are making a pattern, which the model recognises. Alternatively the close projection may be the result of a pure stochastic chance and should therefore not be used at all.

4.2.3 China

China was until recently a small participant in international trade. However, after becoming a member of the World Trade Organization (WTO) the Chinese were forced to open up their markets for international competition and in effect more trade. Today the Chinese economy is one of the main driving forces behind the strong growth in international trade. In order to keep industrial production and economic growth at a high level the country must import a lot of the raw materials needed. The main means of transporting these commodities is deap sea using dry bulk vessels of various sizes. This is the background for our use of imports as a proxy for seaborne transportation demand. China has historically been well equipped with coal and has therefore been an exporter of this commodity. However, more recently China has become a net importer of coal. However, since this is not of a very large magnitude, we have chosen not to include imports of coal into the time series.

Figure 4-5 below shows the total imports of iron ore to China in the period between 1984 through 2004. The horizontal axis indicates time and the vertical axis shows imports in 10000 metric tonnes. The figure shows that imports grew moderately throughout the 1980's, increasing somewhat in the 1990's. Towards the end of the 1990's and up until today both growth and the volatility has increased substantially. From the start of the new millennium Chinese production of pig iron and steel accelerated further, which triggered a similar growth in iron ore imports. Because of these extreme variations between periods in the Chinese economy, we have decided only to use the most recent observations. Thus, we analyse the time series in the interval 1997 – 2004.

Figure 4-5 Imports of iron ore to China



Due to the increase throughout the 90's and the acceleration in growth after 1999, we find reason to believe that imports of iron ore to China contains a trend. To test for this we used a similar approach as described previously. Figure A-15 in the appendix is a correlogram of the Chinese imports from which we conclude that there is evidence of a trend. To eliminate this we first differentiate the import time series. Then, we test the independent variables giving the results listed in table A-3 in the appendix. Nearly all of the time series show signs of trend. Only the indexes and "government projects started" did not contain a trend factor. This seems reasonable since China in the later years have had an enormous growth in its industrial production and in the consumer market.

We also test the dependent and the independent variables for seasonal variations. For this analysis we first use a correlogram, which was compared with a test in X12Arima. An X behind the variable in table A-3 shows that a series has seasonal variations and a 0 indicates no seasonality. Except for the export to Japan and Europe and the ISM, new construction started and FDI had seasonal variation. In addition the unemployment rate also showed sign of the same variations.

In addition we test the Chinese variables for correlation with each other. The nine most correlated series are listed first in the appendix for China. As seen before the export time series are highly correlated. As the correlation table in the appendix shows the industrial production is well correlated to the export variables. However, testing without the IP data does not alter the results significantly. On the contrary, according to the DW, the problem with autocorrelation increased by eliminating these variables.

The next step is to lag the independent variables six months before using the HP-filter to smooth the time series. The end-point problem with the HP-filter is a complication in this case. The reason for this is the extreme shifts seen in the Chinese economy over the last few years, and in effect the likelihood of poor quality of real time data.

Figure 4-6 Smoothed and un-smoothed differentiated imports to China

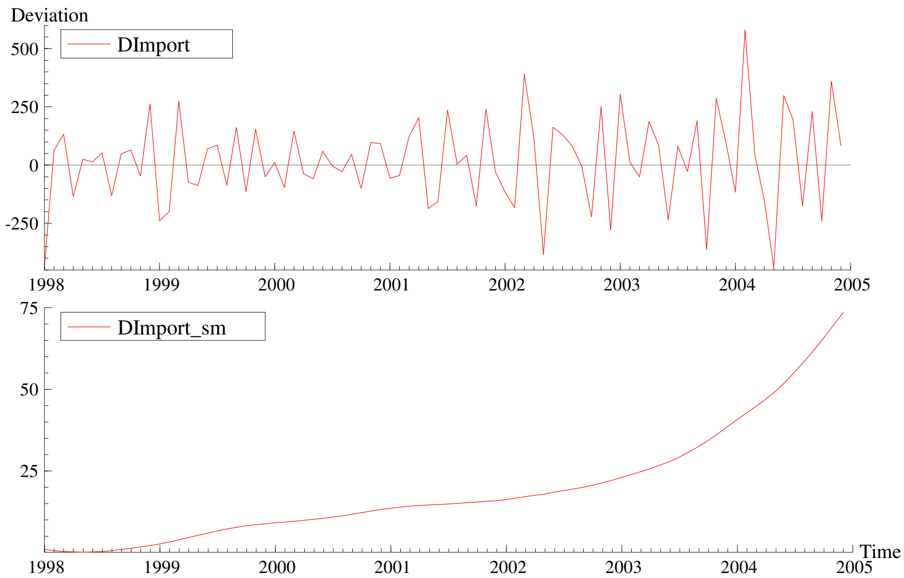


Figure 4-6, top schedule, shows the original differentiated time series of imports of iron ore to China, while the lower schedule shows the smoothed imports of the same data for our chosen time interval. As with the previous analysis on Japan and South Korea, in figure 4-6 the deviation from the mean value is indicated on the vertical axis and time on the horizontal axis. Because of the extreme growth in the Chinese economy in recent years, there have not been any detectable turning points. This is especially critical for the later empirical test.

The test results of both the unsmoothed and smoothed data are listed in EQ(1) and EQ(2) in the appendix, respectively. Unfortunately, 12 observations are dropped since the last six months of both “governmental projects started” and “newly started constructions” are missing data for the last part of 2004. This is reported in the appendix on top of each test results, but should not have an immediate effect on the results. The total number of observations is 72, which we believe to be sufficient for an OLS analysis. The number of variables is 20, including a constant in the regression. Compared with the smoothed variables, variation of the unsmoothed variables is much higher. Some of the variables used in the two previous tests are not available in the Chinese data and in order to compensate we have decided to use some substitutes in this case.

The OLS test on the unsmoothed data show one significant variable. Industrial output of steel (DIPSteel_6) has a t-value of 2.24, which is the only significant unsmoothed variable of all three tests.

As is the case for the Japanese and South Korean analysis, the test on Chinese smoothed time series produce several significant t-values. Construction activity in the public sector (Gov_sm_6) is significant and pro-cyclical with a t-value of 10.8. Total new construction started (SANCons_sm_6), on the other hand, has a surprising t-value of -2.91. The difference in cyclical movement may be due to a different exposure to the lag. In addition, the time series are not composed with the same figures, which give the data different characters.

Initially we thought foreign direct investments (SADFDI_sm_6) would have a positive t-value. Although these investments have been substantial over the last decade and has boosted the activity in construction and industrially production, this variable is insignificant when related to imports with a six months lag. For production and manufacturing activity we use four variables. While the t-value for the industrial index (IndIndex_sm_6) is insignificant, unemployment is unexpectedly pro-cyclical. Industrial output of steel show a positive t-value in the unsmoothed test. This is not the case when smoothed. Then it has a t-value of -6.54. Industrial production, contrary to the findings for Japan and South Korea, is significant and pro-cyclical.

With a six months lag the variable steel and iron export (DExStIr_sm_6) is not significant and exports to Japan (SADJapan_sm_6) is surprisingly counter-cyclical. Exports to Europe

(SADEuro_sm_6) and the US (DUSA_sm_6) indicate an expected pro-cyclical behaviour with t-values of 3.54 and 15.9, respectively.

All of the consumer indexes ISM (SAISM_sm_6), PMI (PMI_sm_6) and CLI (DCLI_sm_6) were thought to be pro-cyclical in reference to the imports of iron ore six month in advance. Although the ISM and the CLI both have positive t-values, the PMI show an opposite cyclical character.

The commodity price index CRB (CRB_sm_6) has a t-value of 7.87. Thus an increase (decrease) in this variable may indicate a future increase (decrease) in the imports and thus in shipping demand.

Stock prices of important companies in the steel and iron ore markets was initially also thought to be pro-cyclical to changes in imports when lagged by six months. While the price of BHP Billiton (DBHP_sm_6) shows a convincing t-value of 17.2, the listed price of Nippon Steel (Nippon_sm_6) is significant, but counter-cyclical.

Finally, Chinese interest rate (DIntrest_sm_6), which has been rather stable in recent years, returns an unsignificant t-value. Therefore, we do not believe this to be a good leading indicator for the future imports of iron ore to China.

Another aspect is the test for serial correlation of the smoothed figures. This test is presented in the appendix and shows a DW = 1.85. The DW – value is close to 2, which indicates no autocorrelation. This may contribute to the credibility of the test.

To examine the forecast abilities of the OLS and ARIMA models there must be turning points present. Reviewing the lower schedule of figure 4-10 the absence of peaks and troughs in the imports series is clear. Theoretically a decrease of the λ – value should make the time series more volatile. This is however not the case for the Chinese imports observations. Even with λ equal to 200 and 500 did not reveal any obvious peaks or troughs. Alternatively we could use a larger set of observations, say 1990 – 2004, but the change of the Chinese economy alters the character of the observations. This was the initial reason for only using the interval between 1997 and 2004 in the first place. Therefore we have to base the empirical conclusion without testing the Chinese observations.

4.3 Suggestions for later papers within the same frame.

In order to set parameters and boundaries for this paper we made some assumptions from the beginning. By doing this we also excluded elements which could be of interest to analyse. Below we list some suggested possible subjects for further analysis:

- Test for other lags
- Test without a constant
- Test with other periods or using dummy variables.
- Using other values for λ's, lower or no smoothing at all.
- Differentiating all variables.

5. CONCLUDING REMARKS

The initial objective of this paper was to locate well known economic indicators and test their leading capabilities on the seaborne dry bulk demand in the Far East. The reason for choosing this geographical area as the objective of our analysis is the regions increasing importance for seaborne dry bulk trade. A model capable of forecasting the demand could thus be of great value for ship-owners and ship operators exposed to carrying dry bulk commodities.

We assume that imports of iron ore and coal to Japan and South Korea and iron ore to China are good proxies for the overall seaborne dry bulk demand in this area. Strong industrialization combined with a shortage of key raw materials make these countries very dependent on imports. Furthermore their geographical position, relative to the sourcing of the material, makes deep sea vessels the most efficient and very often the only means of transportation. This means that seaborne freight demand should be closely correlated to imports of key commodities into these economies..

In order to limit the scope of the analysis, we had to make several assumptions both in the selection of our indicators and throughout the analysis. The World shipping market is a very complex market to analyse since it is influenced by a vast number of different variables. As mentioned in chapter two, there are five main factors driving the demand side of seaborne trade. These factors, however, are also affected by "sub-factors", which makes the choice of indicators less obvious. We singled out and located approximately 20 of the most important and well used indicators for each country and tested their properties.

In the analysis we were looking for leading indicators that were shared by all three countries and that could give an indication of the demand for iron ore and coal. Our findings, however, show only small signs of the correlation we were trying to establish. Initially with the unsmoothed observations only few of the independent variables showed any t-values of significance. In addition, the occurrence of positive autocorrelation was apparent for all three countries. When using the HP-filter technique and smoothing the time series, however, some of the indicators showed significant t-values. One of the most important independent variables was construction activity.

Perhaps the the most valuable result of this study is the gained knowledge about the difficulties involved when trying to make a model for projecting seaborne demand. The complexity of this market makes it very challenging to create a model that takes into account all the important elements. As to the findings, it is therefore fair to say that they have been reasonably disappointing compared to the initial objectives of the study.

It is relatively clear that the un-smoothed model is incapable of predicting the turning points. Few, if any, independent variables show any t-values of significance and the occurrence of positive autocorrelation is apparent for all three countries. When using HP-filter technique, however, we find some common indicators with significant t-values. The most apparent indicators seem to be the construction variables. Although there are some tests in which the variables have negative t-values, we believe that different lags may lead to pro-cyclical behaviour. The same may be the fact for the exports variables. According to the test results the inventory variables for both Japan and South Korea are pro-cyclical. The consumer indexes, on the other hand, seem to have diversified properties and no constant conclusion may be drawn from these t-values. However, the commodity price index is pro-cyclical for both South Korean and Chinese imports. An increase of this index may indicate increased imports in the Far East. But, even though the tests have some positive results, the OLS regression is showing some signs of serial correlation. This confirms the fact that the models are not suitable as a composite leading indicator for the imports in this region with a six months lag.

Finally, the empirical tests are not giving us any higher expectations for the OLS analysis in this case. Neither the ARIMA method nor the OLS with the same lag are showing any evidence of fitting into the actual plot.

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APPENDIX

I. Methods of seasonal adjustment

There are several accepted methods to seasonally adjust time series. One method postulated by Pindyck and Rubinfeld, and widely used, is based on the assumption of equation (1). The first step is to isolate the cyclical and the trend components using a 12 months moving average. The irregular component is then eliminated as much as possible by averaging the sum of SES and E for each corresponding month in the time series, i.e. January for each year, February for each year, and so on. From this process one ends up with an index value for each month and the sum of the twelve monthly indexes should be approximately 12. In the analysis each monthly value is multiplied by the corresponding index values and the seasonal deviations are subtracted. Another alternative is the statistical method of using seasonal dummy variables in the regression equation to point out seasonality where 1 is the value for seasonal deviation and 0 for no variation.

II. Durbin and Watson (DW) method

When testing the time series for serial correlation we use the method of Durbin and Watson, which by far is the most common diagnostic for detecting autocorrelation. The statistic is used to test for first order serial correlation in the errors of a time series regression model under the classical linear model assumptions. DW is based on the OLS residuals and can be written as:

$$DW = \frac{\sum_{t=2}^{n}\left(\hat{u}_t - \hat{u}_{t-1}\right)^2}{\sum_{t=1}^{n}\hat{u}_t^2} \qquad (16)$$

Equation 16 can be simplified to[52]:

$$DW \approx 2(1-\hat{\rho}) \qquad (17)$$

This approximation is very close even with small samples of data. The tests based on DW and the t-tests based on $\hat{\rho}$ are conceptually the same. Equation 17 indicates that if $\hat{\rho}$ runs towards 0, DW will be closer to 2. If $\hat{\rho}$ is closer to 1, DW runs towards 0, and if $\hat{\rho}$ is closing

[52] Wooldridge 2003, pg. 398 and Baltagi 1999, pg. 119

in on -1, DW goes towards 4. No serial correlation thus gives a $\hat{\rho}$ = 0 and we can therefore test for H_0; $\hat{\rho}$ = 0. For positive autocorrelation the test will be H_1; $\hat{\rho}$ < 0 and negative autocorrelation is a H_1-test for $\hat{\rho}$ > 0. This would give the interval of $DW_L < DW < DW_U$ from which one determine if the data contain serial correlation.

III. Japan

The time series representing the eleven main categories for Japan are:

- Iron ore and coal import
- Construction activity

1. New buildings started in the private sector
2. New building started by the government
3. Total transportation on land

- Investments

4. Net investments mining and manufacturing

- Production and manufacturing activity

5. Unemployment
6. Industrial production excluded construction
7. Produced and exported vessels

- Export

8. Export of steel and iron
9. Export to China
10. Export to Euro 15
11. Export to USA

- PMI

12. PMI
13. ISM

- CLI - OECD

14. CLI

- Commodity prices on steel

15. CRB - index

- Stock prices

16. Nippon Steel stock prices

17. BHP (iron ore mining) stock prices

- Inventories

18. Raw materials – steel and other metals

- Interest rate

19. 10 year Government Bond rate in Japan

- Exchange rate

20. Yen vs. USD

Results:

Correlation matrix:

	Transp	Investm	Unempl	IP	China
Transp	1.0000	0.88263	0.42054	0.93880	0.51986
Investm	0.88263	1.0000	0.20687	0.96148	0.32316
Unempl	0.42054	0.20687	1.0000	0.36552	0.84037
IP	0.93880	0.96148	0.36552	1.0000	0.49461
China	0.51986	0.32316	0.84037	0.49461	1.0000
EURO15	0.78655	0.76446	0.54236	0.82532	0.59382
USA	0.88492	0.75463	0.62947	0.85202	0.67214
CLI	0.83257	0.70470	0.81670	0.81781	0.79811
BHP	0.83783	0.62826	0.75108	0.76277	0.83869

	EURO15	USA	CLI	BHP
Transp	0.78655	0.88492	0.83257	0.83783
Investm	0.76446	0.75463	0.70470	0.62826
Unempl	0.54236	0.62947	0.81670	0.75108
IP	0.82532	0.85202	0.81781	0.76277
China	0.59382	0.67214	0.79811	0.83869
EURO15	1.0000	0.80129	0.84438	0.71615
USA	0.80129	1.0000	0.89801	0.85477
CLI	0.84438	0.89801	1.0000	0.91769
BHP	0.71615	0.85477	0.91769	1.0000

Table A-1 Test for trend and seasonal deviations for Japanese data

Indicator	Trend	Seasonal
Import	X	X
Private building started	0	0
Govern building started	0	X
Transport	X	0
Investments	X	0
Unemployment rate	X	0
IP	X	0
Produced vessels	0	X
Export of iron & steel	0	X
Export China	X	X
Export Europe	X	X
Export USA	X	X
ISM	0	X
PMI	0	0
CLI	X	0
CRB	0	0
Nippon	0	0
BHP	X	0
Inventory	0	X
Interest rate (10 year bond)	X	0
Exchange rate (USD)	X	0

X = positive result and 0 = negative result

<u>EQ(1) Modelling SADImport by OLS-CS (using Japan4.xls) - **not smoohed**</u>

The estimation sample is: 1984 (7) to 2004 (12)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	3000.55	5042.	0.595	0.552	0.0016
Private_6	-1.54193	11.95	-0.129	0.897	0.0001
SAGover_6	2.66821	3.780	0.706	0.481	0.0022
DTransp_6	33.7795	70.13	0.482	0.631	0.0010
DInvestm_6	-61.0545	39.78	-1.53	0.126	0.0104
DUnempl_6	-1464.48	1014.	-1.44	0.150	0.0092
DIP_6	176.675	111.0	1.59	0.113	0.0111
SAVessel_6	-0.0245144	0.4951	-0.0495	0.961	0.0000
SAEx I&S_6	-0.205053	0.4612	-0.445	0.657	0.0009
SAChina_6	0.0912657	0.1825	0.500	0.618	0.0011
SAEURO15_6	-0.00107259	0.001439	-0.745	0.457	0.0025
SAUSA_6	0.00254898	0.09638	0.0264	0.979	0.0000
SAISM_6	-10.0617	27.95	-0.360	0.719	0.0006
PMI_6	-5.76008	28.91	-0.199	0.842	0.0002
DCLI_6	-398.698	312.3	-1.28	0.203	0.0072
CRB_6	-1.63945	5.967	-0.275	0.784	0.0003
Nippon_6	-0.0917533	0.8194	-0.112	0.911	0.0001
DBHP_6	287.575	216.3	1.33	0.185	0.0078
SAInventory_6	-0.000143545	0.0003027	-0.474	0.636	0.0010
DItr rate_6	69.4903	327.8	0.212	0.832	0.0002
DExchange_6	17.6094	23.78	0.741	0.460	0.0024

Sigma	1401.76	RSS	442107575
R^2	0.0448938	F(20,225) =	0.5288 [0.953]
log-likelihood	-2120.47	DW	3.08
no. of observations	246	no. of parameters	21
mean(SADImport)	32.3732	var(SADImport)	1.88166e+006

<u>EQ(2) Modelling SADImport_sm by OLS-CS (using Japan4_sm2000.xls) - **smoothed**</u>

The estimation sample is: 1984 (7) to 2004 (12)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	719.995	165.5	4.35	0.000	0.0772
Private_sm_6	5.29843	0.2976	17.8	0.000	0.5838
SAGover_sm_6	2.23713	0.3500	6.39	0.000	0.1531
DTransp_sm_6	54.7161	22.15	2.47	0.014	0.0263
DInvestm_sm_6	35.3191	10.15	3.48	0.001	0.0508
DUnempl_sm_6	671.711	193.7	3.47	0.001	0.0505
DIP_sm_6	-119.186	22.19	-5.37	0.000	0.1132
SAVessel_sm_6	0.0536836	0.05971	0.899	0.370	0.0036
SAExIS_sm_6	0.144367	0.02370	6.09	0.000	0.1411
SAChina_sm_6	-0.0472745	0.009729	-4.86	0.000	0.0946
SAEuro_sm_6	0.000522866	4.214e-005	12.4	0.000	0.4052
SAUSA_sm_6	-0.0253173	0.002304	-11.0	0.000	0.3482
PMI_sm_6	1.69747	1.200	1.41	0.158	0.0088
DCLI_sm_6	-49.1673	39.37	-1.25	0.213	0.0069
CRB_sm_6	0.260400	0.3299	0.789	0.431	0.0027
Nippon_sm_6	-0.0655347	0.02328	-2.82	0.005	0.0339
DBHP_sm_6	668.493	38.13	17.5	0.000	0.5763
SAInvent_sm_6	-0.000262334	1.724e-005	-15.2	0.000	0.5062
DInterest_sm_6	-48.3501	56.43	-0.857	0.392	0.0032
DExchge_sm_6	21.7463	2.269	9.58	0.000	0.2890

Sigma	5.93406	RSS	7958.14766
R^2	0.991904	F(19,226) =	1457 [0.000]**
log-likelihood	-776.683	DW	0.0845
no. of observations	246	no. of parameters	20
mean(SADImport_sm)	42.1508	var(SADImport_sm)	3996.04

Figure A-1 ACF plot for Japanese import of iron ore and coal

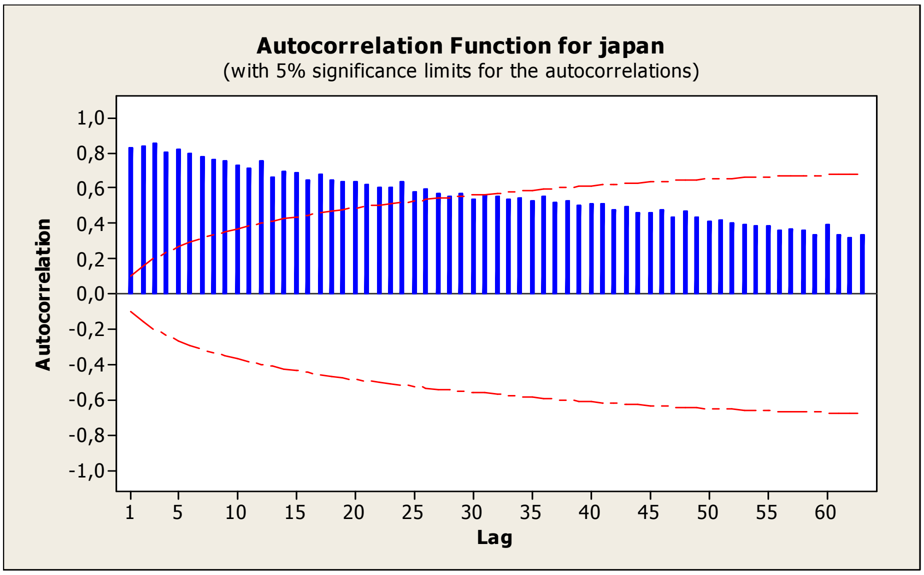


Figure A-2 ACF plot for differentiated Japanese import of iron ore and coal

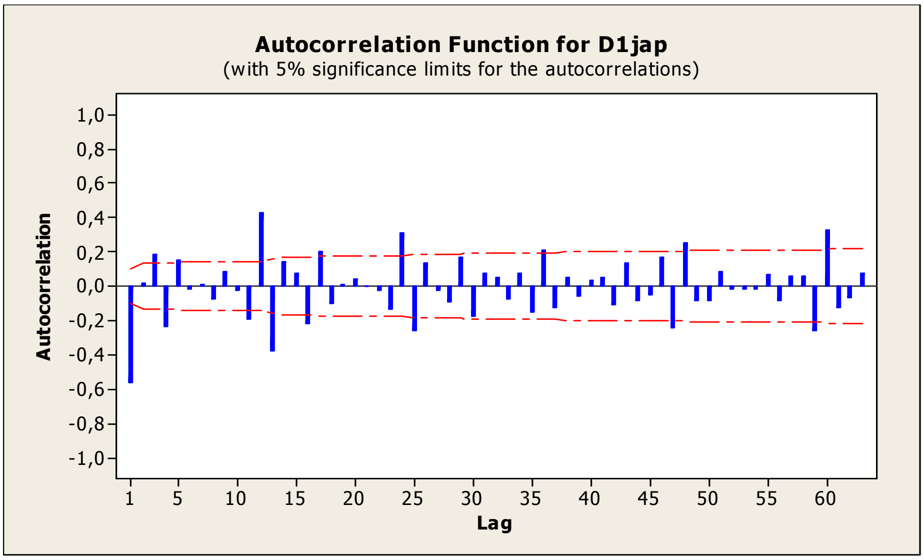


Figure A-3 Forecast of Japanese import of the turning point in start of 1992

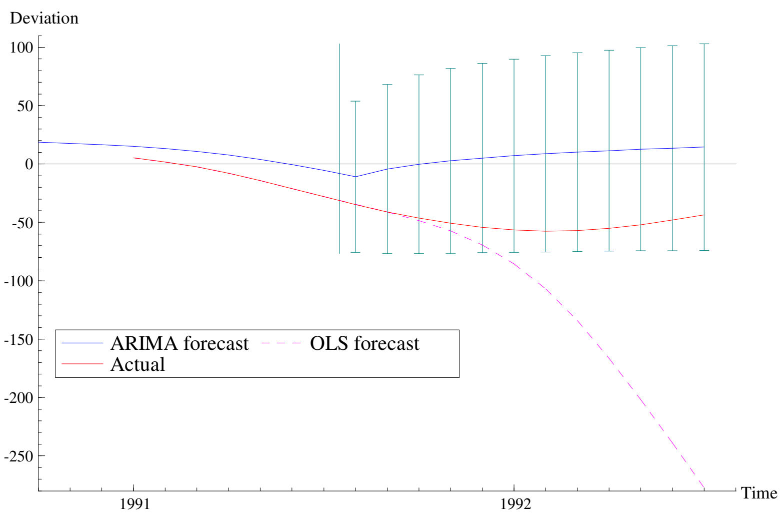


Figure A-4 Forecast of Japanese import of the turning point in mid 1994

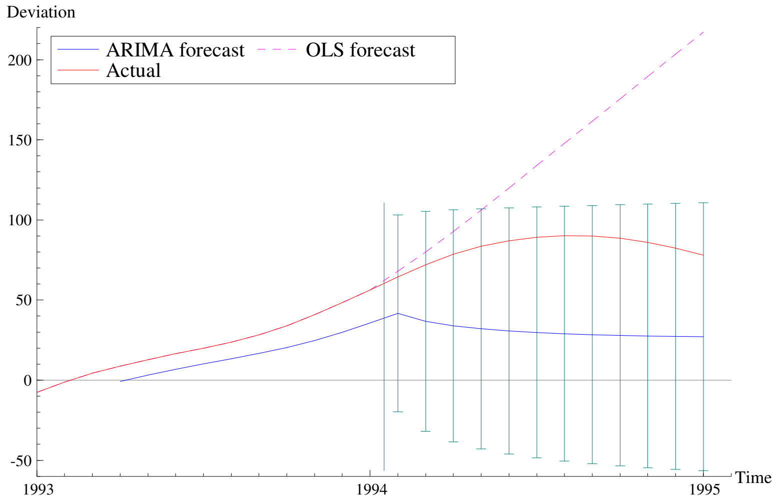


Figure A-5 Forecast of Japanese import of the turning point in April 1998

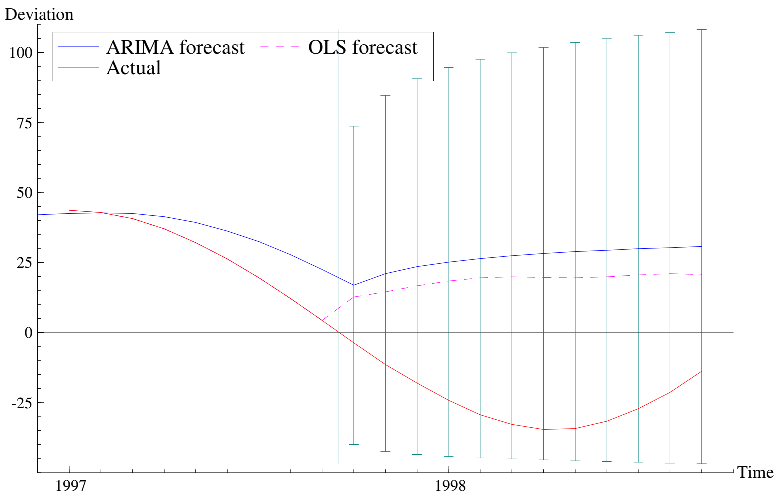


Figure A-6 Forecast of Japanese import of the turning point in start of 2000

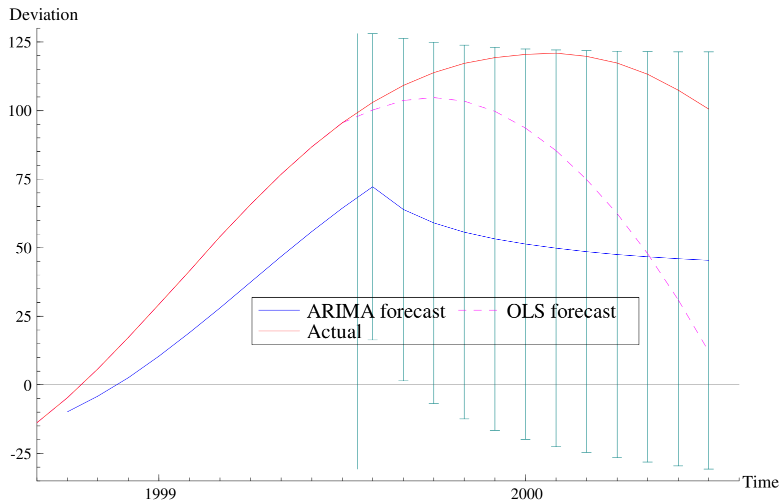
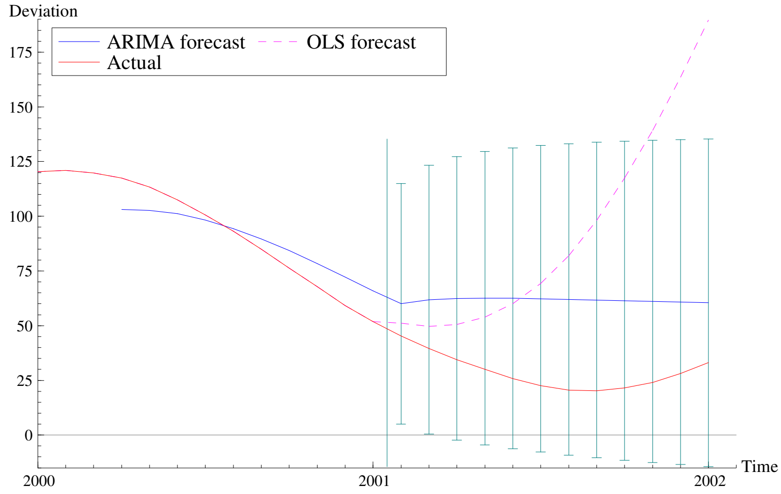


Figure A-7 Forecast of Japanese import of the turning point in July/ August of 2001



IV. South Korea

The time series representing the eleven main categories for South Korea are:

- Import of inedible and non – fluid materials
- Construction activity

1. Private construction orders
2. Government construction orders
3. Steel and iron consumption in construction
4. Freight Transport

- Investments

5. Net direct investments
6. Investments index - IP

- Production and manufacturing activity

7. Unemployment
8. Industrial production excluded construction

- Export

9. Export of machinery and transport equipment
10. Export to China
11. Export to Euro 15
12. Export to USA

- PMI

13. PMI
14. ISM

- CLI – OECD

15. CLI

- Commodity prices on steel

16. CRB – index

- Stock prices

17. Nippon Steel stock prices
18. BHP (iron ore mining) stock prices

- Inventories

19. Producers inventories

- Interest rate

20. 10 year Government Bond rate in South Korea

- Exchange rate

21. Won vs. USD

Results:

<u>Correlation matrix:</u>

	DprodInv	Unempl	DIP	DexStIrPr	DChina
DprodInv	1.0000	0.030419	0.80655	0.64502	0.65702
Unempl	0.030419	1.0000	0.025660	-0.030170	-0.024157
DIP	0.80655	0.025660	1.0000	0.58778	0.67478
DexStIrPr	0.64502	-0.030170	0.58778	1.0000	0.56836
Dchina	0.65702	-0.024157	0.67478	0.56836	1.0000
DUSA	0.73483	0.0061882	0.70760	0.74748	0.63422

	DUSA
DprodInv	0.73483
Unempl	0.0061882
DIP	0.70760
DexStIrPr	0.74748
Dchina	0.63422
DUSA	1.0000

Table A-2 Test for trend and seasonal deviations for South Korean data

Indicator	Trend	Seasonal
Import	X	0
Private construction orders	X	0
Govern construction started	0	X
Steel and Iron consumption construction	X	0
Freight transport	X	0
Net direct investments	0	0
Production investments	X	0
Unemployment rate	0	0
IP	X	X
Export of iron & steel products	X	X
Export China	X	0
Export Europe	X	0
Export USA	X	X
ISM	0	X
PMI	0	0
CLI	X	0
CRB	0	0
Nippon	0	0
BHP	X	0
Inventory	X	X
Interest rate (10 year bond)	X	0
Exchange rate (USD)	X	0

EQ(1) Modelling DImport by OLS-CS (using ForecastKorea.xls) - **not smoothed**

The estimation sample is: 1991 (8) to 2005 (1)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	-20.4759	181.9	-0.113	0.911	0.0001
DPrivate_6	1.94858e-006	7.542e-006	0.258	0.797	0.0005
SAGover_6	-0.000134768	9.256e-005	-1.46	0.148	0.0149
DConstrISCons_6	-1.16943e-005	9.777e-005	-0.120	0.905	0.0001
DTransp_6	-11.1849	7.703	-1.45	0.149	0.0148
Dir investm_6	-0.00608636	0.02013	-0.302	0.763	0.0007
DProdInv_6	0.916632	1.724	0.532	0.596	0.0020
Unempl_6	-5.09402	6.284	-0.811	0.419	0.0047
SADIP_6	5.45959	3.356	1.63	0.106	0.0186
SADExpISProd_6	0.00510835	0.02123	0.241	0.810	0.0004
DChina_6	-0.000138722	6.833e-005	-2.03	0.044	0.0286
DEURO15_6	0.0432482	0.04531	0.955	0.341	0.0065
SADUSA_6	-4.26317e-005	6.025e-005	-0.708	0.480	0.0036
SAISM_6	-0.282077	2.075	-0.136	0.892	0.0001
PMI_6	1.71713	1.966	0.874	0.384	0.0054
DCLI_6	-18.4449	19.00	-0.971	0.333	0.0067
CRB_6	0.149852	0.4081	0.367	0.714	0.0010
Nippon_6	-0.142140	0.1036	-1.37	0.172	0.0133
DBHP_6	-0.0327534	13.93	-0.00235	0.998	0.0000
SADProdInvent_6	-9.55110	5.797	-1.65	0.102	0.0190
DInterest_6	14.2362	13.77	1.03	0.303	0.0076
DExchge_6	-0.0715357	0.2102	-0.340	0.734	0.0008

Sigma	84.1708	RSS	991861.922
R^2	0.0998586	F(21,140) =	0.7396 [0.786]
log-likelihood	-936.167	DW	2.84
no. of observations	162	no. of parameters	22
mean(DImport)	1.73765	var(DImport)	6801.83

EQ(2) Modelling DImport_sm by OLS-CS (using ForecastKorea.xls) - **smoothed**

The estimation sample is: 1991 (8) to 2005 (1)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	-82.0866	18.09	-4.54	0.000	0.1282
DPrivate_sm_6	4.33118e-005	1.975e-005	2.19	0.030	0.0332
SAGover_sm_6	-0.000173443	2.052e-005	-8.45	0.000	0.3379
DConstrISC_sm_6	0.000171955	0.0002920	0.589	0.557	0.0025
DTransp_sm_6	-8.74269	4.604	-1.90	0.060	0.0251
DirInvestm_sm_6	-0.0259870	0.003987	-6.52	0.000	0.2328
DProdInv_sm_6	7.55160	3.358	2.25	0.026	0.0349
Unempl_sm_6	6.51453	1.084	6.01	0.000	0.2051
SADIP_sm_6	-24.8456	4.742	-5.24	0.000	0.1639
SADExpISProd_sm_6	0.133320	0.03077	4.33	0.000	0.1182
DChina_sm_6	0.000187440	3.178e-005	5.90	0.000	0.1990
DEURO15_sm_6	-0.312189	0.07489	-4.17	0.000	0.1104
SAUSA_sm_6	-0.000336162	7.025e-005	-4.79	0.000	0.1406
SAISM_sm_6	-0.0108861	0.3214	-0.034	0.973	0.0000
PMI_sm_6	0.723313	0.1411	5.13	0.000	0.1580
DCLI_sm_6	10.8491	9.609	1.13	0.261	0.0090
CRB_sm_6	0.431447	0.03822	11.3	0.000	0.4764
Nippon_sm_6	-0.0893183	0.01108	-8.06	0.000	0.3169
DBHP_sm_6	-11.1432	4.808	-2.32	0.022	0.0370
SADPrInvent_sm_6	-5.47974	1.334	-4.11	0.000	0.1076
DInterest_sm_6	23.8231	5.730	4.16	0.000	0.1099
DExchge_sm_6	-0.601306	0.1310	-4.59	0.000	0.1308

Sigma	0.290952	RSS	11.8514219
R^2	0.998869	F(21,140) =	5889 [0.000]**
log-likelihood	-18.041	DW	0.207
no. of observations	162	no. of parameters	22
mean(DImport_sm)	2.42479	var(DImport_sm)	64.6966

Figure A-8 ACF plot for South Korean import of crude materials

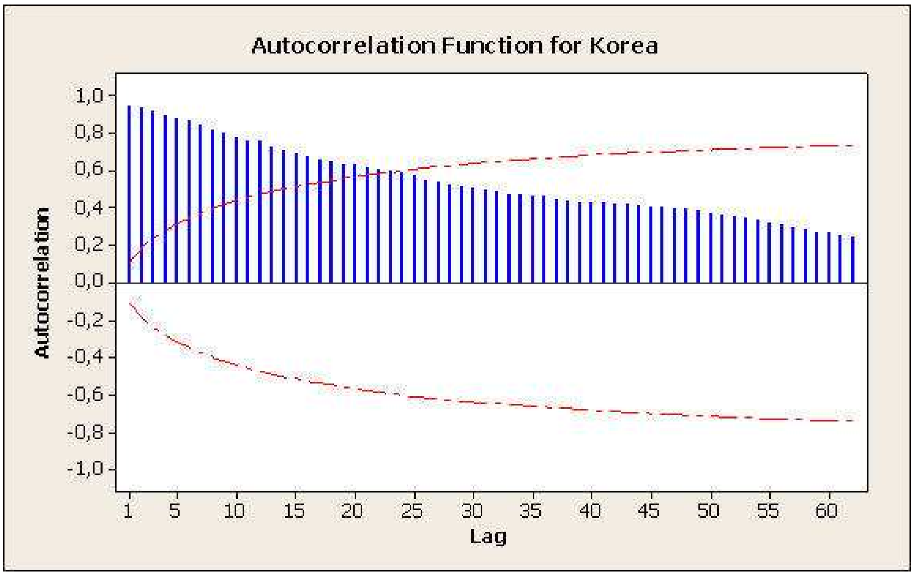


Figure 4-9 ACF plot for differentiated South Korean import crude materials

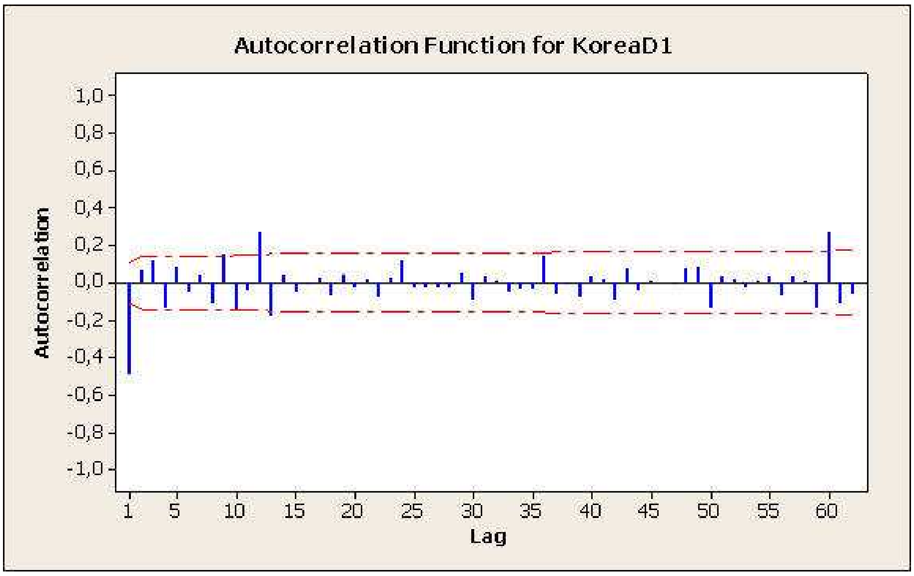


Figure A-10 Forecast of South Korean import of the turning point in December 1994

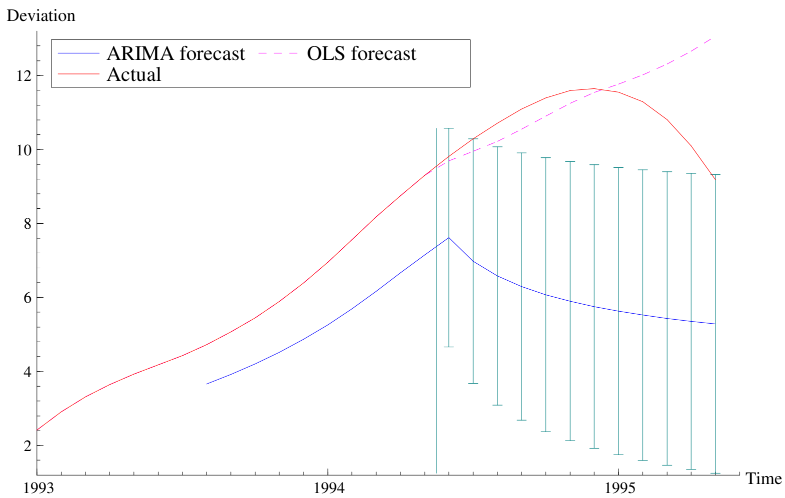


Figure A-11 Forecast of South Korean import of the turning point in October 1997

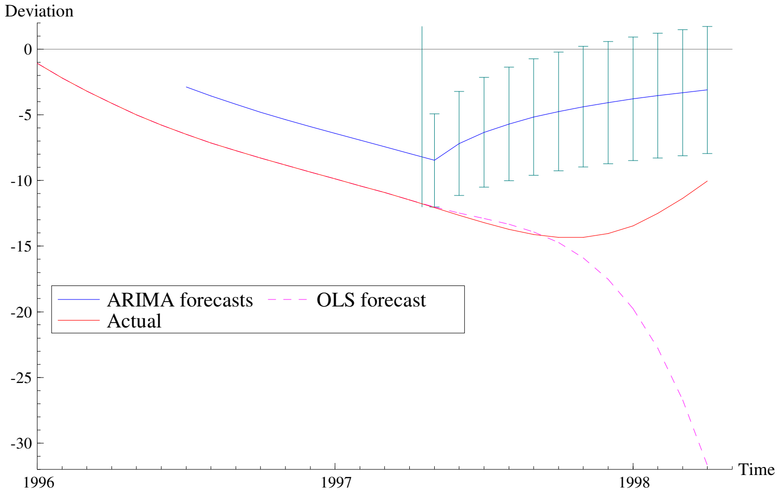


Figure A-12 Forecast of South Korean import of the turning point in September 1999

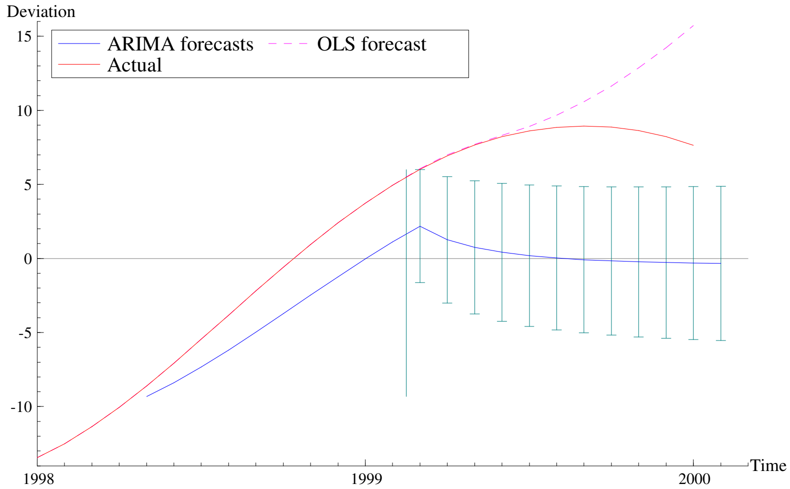


Figure A-13 Forecast of South Korean import of the turning point in April/ May 2001

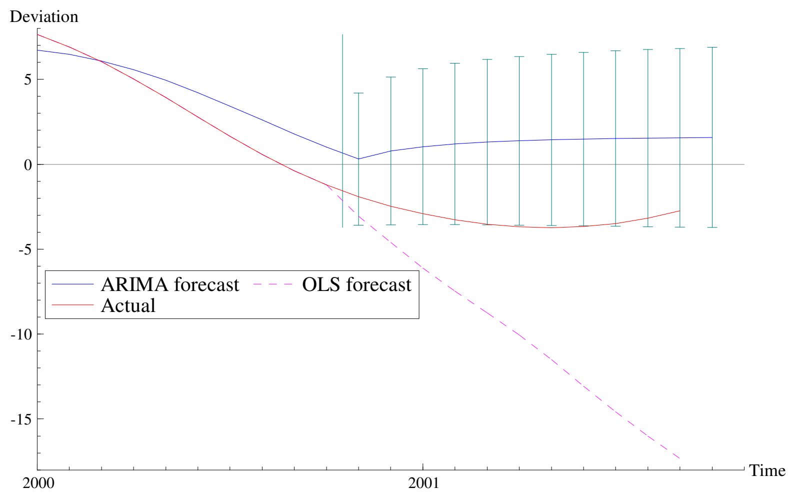
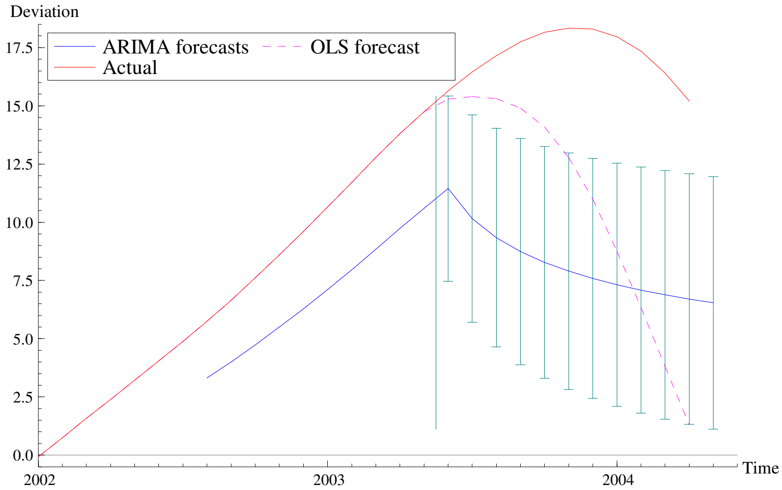


Figure A-14 Forecast of South Korean import of the turning point in November 2003



V. China

The time series representing the eleven main categories for China are:

- Aggregate import of iron ore
- Construction activity

1. Government projects started
2. New construction started
3. Freight Transport

- Investments

4. Foreign direct investments (FDI)

- Production and manufacturing activity

5. Unemployment
6. Industrial production output
7. Heavy industry index
8. Industrial production of crude steel

- Export

9. Export of iron and steel products
10. Export to China
11. Export to Euro 15
12. Export to USA

- PMI

13. PMI

14. ISM

- CLI – OECD

15. CLI

- Commodity prices on steel

16. CRB – index

- Stock prices

17. Nippon Steel stock prices
18. BHP (iron ore mining) stock prices

- Interest rate

19. 5 year Government Treasury Bond

Results:

Correlation matrix:

	SANCons_sm	DIP_sm	DExStIr_sm	SADJapan_sm	SADEuro_sm
SANCons_sm	1.0000	0.91911	0.84208	0.77289	0.98380
DIP_sm	0.91911	1.0000	0.74006	0.92665	0.96736
DExStIr_sm	0.84208	0.74006	1.0000	0.75272	0.82189
SADJapan_sm	0.77289	0.92665	0.75272	1.0000	0.84592
SADEuro_sm	0.98380	0.96736	0.82189	0.84592	1.0000
DUSA_sm	0.91287	0.96149	0.64097	0.80544	0.95785
DIntrest_sm	0.43707	0.68673	0.24439	0.69472	0.51932

	DUSA_sm	DIntrest_sm
SANCons_sm	0.91287	0.43707
DIP_sm	0.96149	0.68673
DExStIr_sm	0.64097	0.24439
SADJapan_sm	0.80544	0.69472
SADEuro_sm	0.95785	0.51932
DUSA_sm	1.0000	0.61618
DIntrest_sm	0.61618	1.0000

Table A-3 Test for trend and seasonal deviations for Chinese data

Indicator	Trend	Seasonal
Import	X	0
Govern projects started	0	0
New construction started	X	X
Freight transport	X	0
Foreign direct investments	X	X
Unemployment rate	X	X
IP output	X	0
Heavy industry index	0	0
IP crude steel	X	0
Export of iron & steel products	X	0
Export Japan	X	X
Export Europe	X	X
Export USA	X	0
ISM	0	X
PMI	0	0
CLI	X	0
CRB	0	0
Nippon	0	0
BHP	X	0
Interest rate (5 year bond)	X	0

EQ(1) Modelling DImport by OLS-CS (using ForecastChina2.xls) - **not smoothed**

The estimation sample is: 1998 (1) to 2004 (12)

Dropped 12 observation(s) with missing values from the sample

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	-867.457	1028.	-0.844	0.402	0.0135
Gov_6	-0.00831654	0.02285	-0.364	0.717	0.0025
SADNewConstr_6	-0.0446966	0.06271	-0.713	0.479	0.0097
DTransport_6	0.0463838	0.2127	0.218	0.828	0.0009
SADFDI_6	1.29677	2.205	0.588	0.559	0.0066
SADUnempl_6	467.536	518.2	0.902	0.371	0.0154
DIP_6	-3.03766e-005	0.07702	-0.000394	1.000	0.0000
Ind Index_6	3.02489	7.680	0.394	0.695	0.0030
DIPSteel_6	0.113438	0.05067	2.24	0.029	0.0879
DExst&ir_6	-0.000455733	0.0006947	-0.656	0.515	0.0082
SADJapan_6	0.000311601	0.0001586	1.97	0.055	0.0691
SADEurope_6	-0.0795167	0.1207	-0.659	0.513	0.0083
DUSA_6	-1.89774e-005	6.557e-005	-0.289	0.773	0.0016
SAISM_6	5.36967	7.665	0.701	0.487	0.0093
PMI_6	11.1420	8.884	1.25	0.215	0.0294
DCLI_6	-86.4952	81.38	-1.06	0.293	0.0213
CRB_6	-0.656505	2.092	-0.314	0.755	0.0019
NIPPON_6	0.00986896	0.8741	0.0113	0.991	0.0000
DBHP_6	21.0515	43.38	0.485	0.629	0.0045
DIntrest_6	-49.7445	42.63	-1.17	0.249	0.0255

Sigma	194.98	RSS	1976888.34
R^2	0.177387	F(19,52) =	0.5902 [0.896]
log-likelihood	-470.097	DW	2.41
no. of observations	72	no. of parameters	20
mean(DImport)	16.6389	var(DImport)	33377.5

EQ(2) Modelling DImport_sm by OLS-CS (using ForecastChina2.xls) - **smoothed**

The estimation sample is: 1998 (1) to 2004 (12)

Dropped 12 observation(s) with missing values from the sample

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	233.675	65.52	3.57	0.001	0.1965
Gov_sm_6	0.0386047	0.003571	10.8	0.000	0.6921
SANCons_sm_6	-0.0170497	0.005868	-2.91	0.005	0.1397
DTrans_sm_6	-0.241859	0.02088	-11.6	0.000	0.7207
SADFDI_sm_6	0.555395	0.3252	1.71	0.094	0.0531
SADUnempl_sm_6	108.035	35.83	3.02	0.004	0.1488
DIP_sm_6	0.144255	0.03696	3.90	0.000	0.2265
IndIndex_sm_6	-1.28892	0.6464	-1.99	0.051	0.0710
DIPSteel_sm_6	-0.225038	0.03441	-6.54	0.000	0.4512
DExStIr_sm_6	-3.06332e-005	4.578e-005	-0.669	0.506	0.0085
SADJapan_sm_6	-0.000282686	6.610e-005	-4.28	0.000	0.2602
SADEuro_sm_6	0.178289	0.05039	3.54	0.001	0.1940
DUSA_sm_6	0.000191934	1.205e-005	15.9	0.000	0.8300
SAISM_sm_6	4.46238	0.8572	5.21	0.000	0.3426
PMI_sm_6	-7.46028	1.245	-5.99	0.000	0.4083
DCLI_sm_6	122.249	20.13	6.07	0.000	0.4149
CRB_sm_6	0.696186	0.08842	7.87	0.000	0.5438
NIPPON_sm_6	-0.241342	0.02974	-8.11	0.000	0.5587
DBHP_sm_6	130.104	7.573	17.2	0.000	0.8502
DIntrest_sm_6	-31.6260	17.43	-1.81	0.075	0.0596

Sigma	0.0292613	RSS	0.0445236958
R^2	0.999996	F(19,52) =	6.776e+005 [0.000]**
log-likelihood	163.819	DW	1.85
no. of observations	72	no. of parameters	20
mean(DImport_sm)	17.3032	var(DImport_sm)	153.103

Figure A-15 ACF plot of Chinese iron ore import

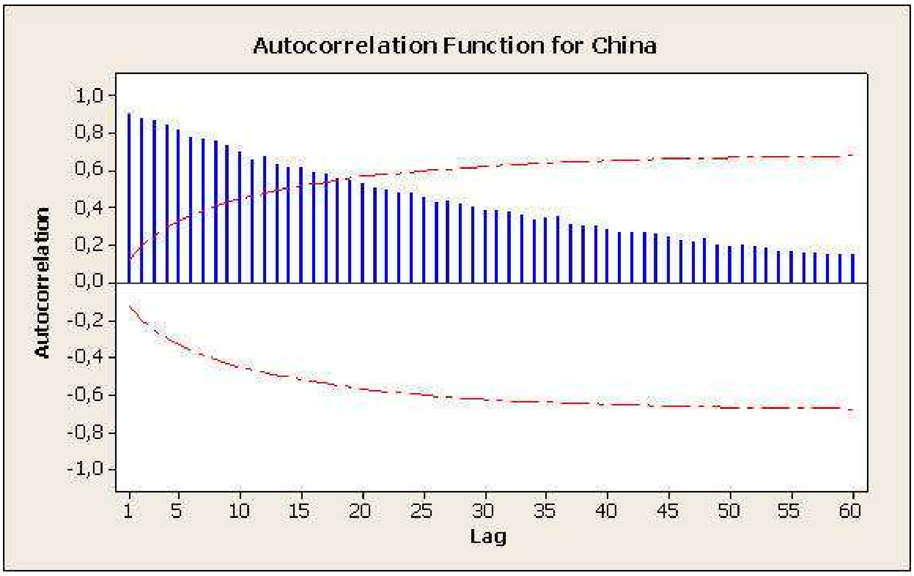


Figure A-12 ACF plot for differentiated Chinese import iron ore