UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA
Denkleiers • Leading Minds • Dikgopolo tša Dihlalefi

# Investigating Sales and Production Volumes of Metals using a Bayesian Change Point Detection Approach

BPJ 420 Final Report

Michael Ingham
13033132

Submitted in partial fulfilment of the requirements for the degree of
Bachelors of Industrial and Systems Engineering



September 28, 2017

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

**DEPARTEMENT BEDRYFS- EN SISTEEMINGENIEURSWESE**
**DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING**

| **FRONT PAGE FOR FINAL PROJECT DOCUMENT (BPJ 420) - 2017** | |
|---|---|
| **Information with regards to the mini-dissertation** | |
| **Title** | Investigating Sales and Production Volumes of Metals using Bayesian Change Point Detection |
| **Author** | Ingham, M.J. |
| **Student number** | 13033132 |
| **Supervisor/s** | Yadavalli, S; Das, S |
| **Date** | 2017/08/30 |
| **Keywords** | Bayesian change point detection, Mining, Metals, South africa |
| **Abstract** | This paper identified change points in the production volumes and sales of various metals in South Africa from the period 2003-2016. The socio-economic environment in which the mining sector operates is complicated, with countless factors influencing the production volumes and sales of metals. This complexity makes it difficult for mining stakeholders to accurately forecast the production and sales for specific metals. Possible causative events or factors were linked to identified change points in order to create a deeper understanding of the environment in which mining operates. This deeper understanding provides mining stakeholders with information on the events or factors that have the greatest impact on the performance of the various metals. This information allows mining stakeholders to focus forecasting efforts on the identified factors. Combining the focused forecasts with the impact that similar events had in the past helps the mining stakeholders to alter production levels or schedule investments before forecasted events take place, minimising the potential negative impact of said event. In this study, the monthly production volumes and sales of Gold, Platinum Group Metals (PGMs), Iron Ore and Manganese were analysed. The data spanned from 2003-2016 and was supplied by StatsSA. The data was analysed using the Bayesian Change Point Analysis (BCP) [Barry and Hartigan, 1993], the Dynamic Programming Algorithm (DP)[Bai and Perron, 2003] and the Non-Parametric Multiple Change-Point Analysis (MCP) [Matteson and James, 2014]. The results reveal that production drops were caused predominantly by mining strikes and increases in production costs, while the sales were |

| | |
|---|---|
| | influenced by changes in the exchange rates and rand value of the commodity. Future studies will use sales volumes instead of Actual Rand values in order to identify changes that can be attributed to shifts in the demand of each metal. |
| **Category** | Data Analysis |
| **Sensitive Parts** | N/A |
| **Declaration** | |
| 1. I understand what plagiarism is and I am aware of the University's policy in this regard.<br>2. I declare that this is my own original work<br>3. Where other people's work has been used (either from a printed source, internet or any other source) this has been carefully acknowledged and referenced in accordance with departmental requirements<br>4. I have not used another student's past work to hand in as my own<br>5. I have not allowed and will not allow, anyone to copy my work with the intention of handing it in as his/her own work | |
| **Signature** |  |

## Declaration of Originality

I, Michael Ingham, student number 13033132 hereby declare that this report is my own original work, and that the references listed provides a comprehensive list of all sources cited or quoted in this report.

# Executive Summary


This report investigates the total sales and employment statistics of several industrial metals in order to identify the most important metals in the South African context. The selected metals were then the subject of change point analysis that identified changes in the generative parameters of the production volumes and sales data of each metal.

Three univariate change point analysis methods have been reviewed to select the most appropriate method for the analysis, namely: Circular Binary Segmentation Algorithm (CBS) [Olshen, Venkatraman, Lucit and Wigler, 2004], Dynamic Programming Algorithm (DP) [Bai and Perron, 2003] and the Bayesian Change Point Analysis (BCP) [Barry and Hartigan, 1993]. A multivariate approach, namely the Non-Parametric Multiple Change-Point Analysis (MCP) [Matteson and James, 2014] was also investigated and applied in order to determine if there were any factors that influenced numerous metals.

The BCP and DP algorithms were selected to identify change points in each metal's production and sales data. The results from both methods were then compared and it was concluded that the BCP approach produced more informative results.

The change points identified were then linked to possible past events that could explain the changes. This was done in order to create a deeper understanding of the factors that influence the volumes of metals produced in South Africa as well as their respective sales. This information can be used to aid mining stakeholders in decision making. Mining stakeholders refers to management of mines as well as any potential investors. The information will allow stakeholders to make informed decisions based on outcomes of previous similar events. This information will allow mining stakeholders to react sooner to potential changes in metal exports rather than reacting to changes in the exports of metals. Formulating plans of action pre-emptively will help mines save money and make better strategic choices in terms of investment.

The Metals in South Africa literature review identified Platinum Group Metals (PGMs), Gold, Iron ore and Manganese as the four most important metals, in terms of Rand value of total sales, job creation and total salaries of employees. The literature review highlighted factors that influence the supply and demand of each metal, in order to gain a more in-depth understanding of the mining sector and its environment, as well as link the change points to possible causative events/factors.

The results reveal that production drops were caused predominantly by mining strikes and increases in production costs, while the sales were influenced by fluctuations in commodity prices and exchange rates. Future studies will use sales volumes instead of Actual Rand values in order to identify changes that can be attributed to shifts in the demand of each metal.

.

# Contents

# List of Figures



# List of Tables

# Abbreviations

AMCU: The Association of Mineworkers and Construction Union
BCP: Bayesian Change Point method
DP: Dynamic Programming Algorithm
BIC: Bayesian Information Criterion
CBS:Recursive Circular Binary Segmentation Algorithm
CRAN: Comprehensice R Archive Network
GDP: Gross Domestic Product
MCMC: Markov Chain Monte Carlo
MCP: Multiple Change Point Analysis of Multivariate Time Series
PGMs: Platinum Group Metals
RSS: Residual Sum of Squares

# 1 Introduction & Background

Since Gold was discovered in the Witwatersrand in 1886, the mining sector has formed the foundation of South Africa's economy. According to statistics released by the Chamber of Mines, mining provided one million jobs and contributed 7.7 % of the Gross Domestic Product (GDP) in 2015 [Chamber of Mines South Africa, 2015, pp 20]. As such, it is imperative for mining stakeholders to have an in-depth understanding of the behaviour of mining sector indicators such as sales and production volumes, in order to make informed decisions regarding their business plans.

The socio-economic environment within which the South African mining sector operates is complicated, with a vast number of factors influencing the production volumes and sales of metals. This complexity makes it challenging for mining stakeholders to react to any sudden changes, either in volume produced or price of the metal. It is important for the mining decision makers to identify sudden (unexpected) changes in production volumes and/or sales in order to take any necessary interventions. Once the ”change points” have been identified, possible causative events or factors can be linked to the identified change points. Hence there is value in a retrospective analysis, not only to determine the location (time/period) of the changes in the data series, but also whether the change was responsible for a significant change in the underlying data generating process. In this thesis the focus is thus to do a retrospective data driven Bayesian (univariate) and frequentist (univariate and multivariate non-parametric) change point analysis on a selected number of metals important to the South African economy.

# 2 Project Aim

The aim of this project is two-fold: first to identify significant locations of change in the production volumes and sales of metals in South Africa and second, to link possible causative events to the identified change points.

# 3 Project Approach, Scope & Deliverables

In order to achieve the project aim of identifying significant locations of change and thereafter linking possible causative events to the production volumes and sales of metals in South Africa, four steps needed to be implemented, as detailed below.

Phase 1: Literature review on metals mined in South Africa.
This phase investigated the metals mined in South Africa with the purpose of identifying the metals with the greatest contribution to the South African economy with regards to their respective total sales and job creation. The literature review also investigated factors that influence supply and demand of each metal, in order to better understand the dynamics of each metal's performance in terms of volumes produced and sales. This literature review is included in section 4.1.

Phase 2: Literature review on Change Point Analysis methods
This phase compared different data-driven statistical methods of identifying change points in order to determine which approach is the most suitable for the purpose of this project. Specifically, the *Bayesian Change Point Analysis* (BCP) [Barry and Hartigan, 1993], the *Dynamic Programming Algorithm* (DP) [Bai and Perron, 2003], the *Circular Binary Segmentation Algorithm* (CBS) [Olshen, Venkatraman, Lucit and Wigler, 2004] and the *Non-Parametric Multiple Change-Point Analysis* (MCP) [Matteson and James, 2014] were compared.

Phase 3: Change Point Analysis
In Phase 3, data obtained from [Statistics South Africa] was used. This data was in the form of monthly production volumes and sales (in Rands) for each metal. The algorithms selected in Phase 2 were used to identify change points in the production volumes and sales data series of the selected metals. In the univariate case, BCP provided a more appropriate tool for decision making for both production volumes and sales compared to the DP and CBS algorithms. In the multivariate case, the MCP algorithm was used on the production volumes data only, to identify whether change points in the combined series has different locations to the corresponding univariate series.

Phase 4: Discussion of Results.
In this phase the location of identified change points was linked to any possible events that occured around that time. Specifically the BCP algorithm results allow for the identification of the most probable change points and their possible potential causes. Validation of the algorithms was done in accordance with the first step in the approach formulated by Naylor and Finger [Naylor and Finger, 1967] which states that the model requires high face validity, which means that "the model appears to be a reasonable imitation of a real-world system to people who are knowledgeable to the real-world system".

# 4 Literature Review

## 4.1 Metals in South Africa

### 4.1.1 Abstract

This literature review focuses on metals produced in South Africa with the purpose of identifying the most important metals with regards to total sales and job creation based on 2016 data. Possible factors that influence the supply and demand of said metals were also investigated. The metals identified were then subjected to change point analysis, with regards their production volumes and sales. It was found that the Platinum Group Metals (PGMs) had the largest total sales among the metals mined in South Africa. PGMs comprise of Platinum, Palladium, Rhodium, Osmium, Iridium and Ruthenium. Gold had the second highest sales with Iron ore and Manganese having the third and fourth largest sales respectively. All four of these metals were also in the top five metals with regards to job creation in the mining sector. These four metals were therefore chosen to be the subject of the change point analysis presented here.

### 4.1.2 Importance of Mining in South Africa

South Africa's mining sector is one of the largest in the world, with total reserves worth an estimated R 20.3 trillion in 2012 [Brand South Africa, 2012] and is placed fifth largest in terms of GDP value [Chamber of Mines South Africa, 2017]. According to statistics released by the Chamber of Mines, mining directly employed 460 000 and accounted for 7.7% of GDP in 2015 [Chamber of Mines South Africa, 2015, pp 20]. South Africa is also the largest producer of Platinum, Chrome and Manganese in the world [U.S. Geological Survey, 2016, pp 202]. This combined with the fact that they are the seventh largest producer of Gold and coal makes South Africa a global powerhouse in the exportation of metals. Table 1 shows South Africa's total sales of selected metals in 2016. PGMs had the highest sales, with Gold, Iron ore and Manganese having the second, third and fourth highest sales respectively.

Table 1: Total Sales of various Commodities in 2016 [Statistics South Africa, 2017, pp9]

| Mineral Group | Sales (July-2016)(R million) |
|---|---|
| PGMs | 6909.8 |
| Gold | 6368.2 |
| Iron ore | 3683.2 |
| Manganese | 1274.8 |
| Chromium ore | 1049.1 |
| Copper | 223 |

The total number of employees that certain metal mines employ is also an important indicator of the importance of that metal to the economy. Table 2 shows, for selected metals, the total number employees for that metal, their percentage among total employees in the mining sector, as well as the total employee earnings in 2013.

Table 2: Number of Employees and Earnings per Commodity in 2013 [Chamber of Mines South Africa, 2014, pp 14]

| Commodity | Employees in SA Mining | % of Total Employees | Total Employee Earnings (R million) |
|---|---|---|---|
| PGMs | 191261 | 37.5 | 37709.1 |
| Gold | 131591 | 25.8 | 23904.9 |
| Iron ore | 21145 | 4.1 | 4845.1 |
| Chromium ore | 18359 | 3.6 | 3844.1 |
| Manganese | 9866 | 1.9 | 1948.5 |
| Copper | 3536 | 0.7 | 1245.2 |

Table 2 shows that PGMs, Gold, Iron ore and Chromium mines employ the most workers in South Africa's mining sector. PGMs, Gold and Iron ore are also the three largest in terms of total sales (in Rands) as shown in Table 1. Manganese was selected over Chrome as the fourth most important metal due to its larger total sales. To reiterate, the four specific metals selected for the change point analysis were PGMs, Gold, Iron ore and Manganese.

The remainder of this literature review investigates possible factors that influence the supply and demand of the selected metals.

#### 4.1.3 Factors that Influence Production Volumes of all Metals

This section briefly investigated the main factors that influence the supply side of all the metals mined in South Africa. A major factor that influences the production levels in all mines in South Africa is production costs in terms of fuel, electricity and labour costs, that has been increasing steadily. Figures 1 and 2 show the proportion of wages and electricity costs that make up the total production costs of the PGMs and Gold sector respectively. The figures shows that about 60% of the total production costs for both PGMs and Gold are made up by electricity and labour costs. Figure 3 shows the historic average selling price of electricity in South Africa, which has been steadily rising since the 1970s. Figure 4 shows the steady increase in South African labour costs.

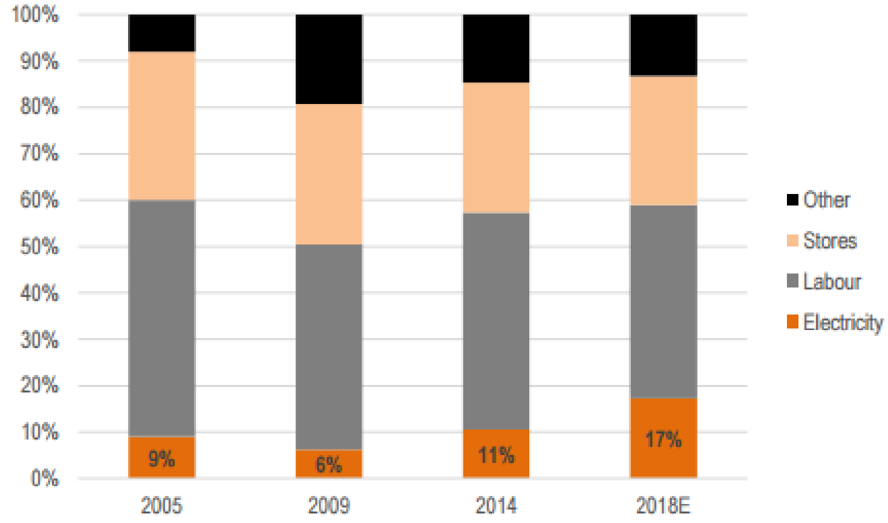



Figure 1: Cost Components for the PGMs Sector [Chamber of Mines South Africa, 2015, pp 24]

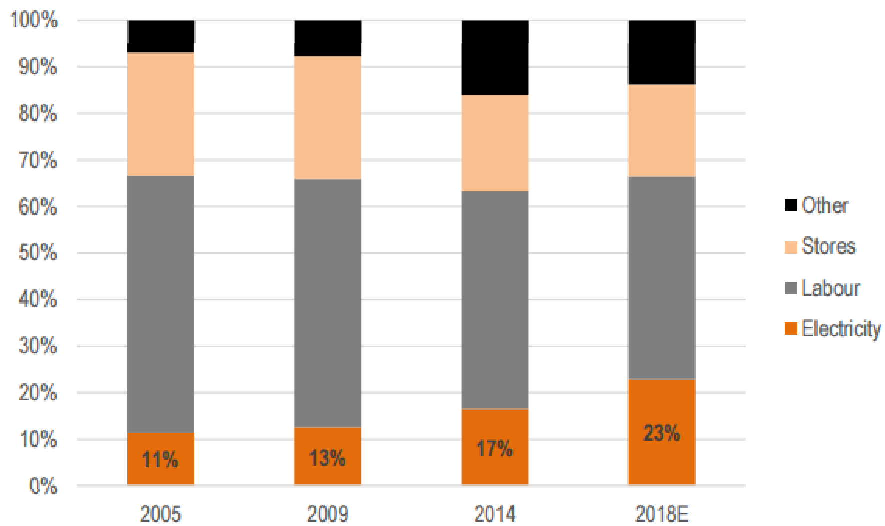



Figure 2: Cost Components for the Gold Sector [Chamber of Mines South Africa, 2015, pp 24]

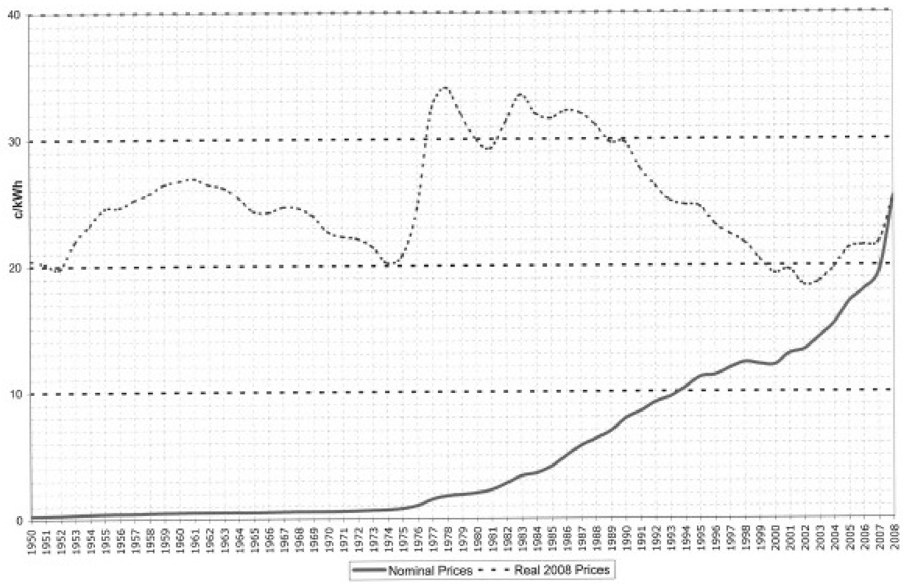



Figure 3: Average cost of Electricty in South Africa [Nersa.org.za, 2017]

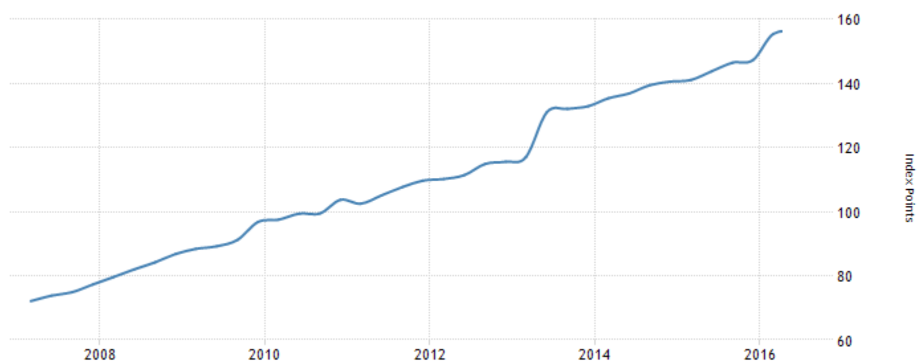



Figure 4: South Africa Labour Cost [Tradingeconomics.com, 2017]

Often events, natural or man-made, outside South African borders can have a significant impact on the economy. The following sections investigate some factors (supply side or demand side) that can influence the production volumes and sales of the specific metals that will be subject to change point analysis.

### 4.1.4 Gold

#### 4.1.4.1 Factors that Influence the Production Volume and Sales

The supply of metals are often negatively influenced by local factors such as strikes and production costs. The demand of metals is often influenced by the demand for users of the metal, as well the economic performance of the primary buyers/users of those metals. South Africa's Gold production has been decreasing since 1970 as shown in Figure 5 and has been attributed to the dwindling Gold reserves and increased production costs. The increased production costs are due to the Gold supply near the surface being depleted, causing mines to go deeper underground, which increases production costs. Other factors causing increased production costs are increased costs of labour, fuel and electricity as previously discussed. An additional cost factor that can negatively affect the production volumes of South African Gold mines is the decrease in the grade of Gold mined. The poor grade means that in order to obtain the same volume of gold, more ore must be mined. Table 3 shows the steady reduction in the grade of Gold mined in South Africa since 1970.

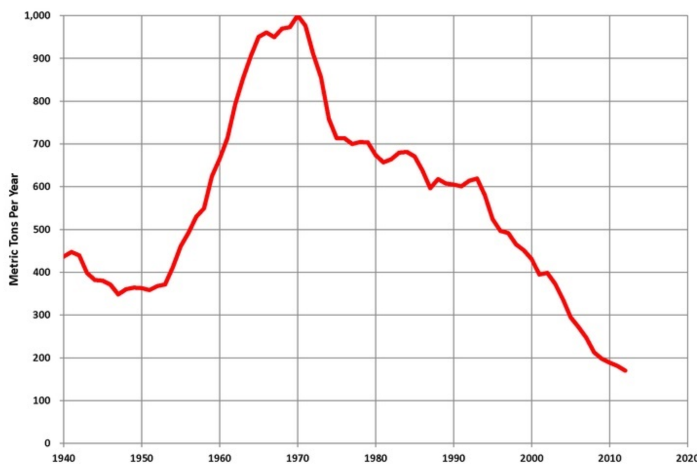



Figure 5: South Africa's Gold Production [Earle and Amey, 2017]

Table 3: Grade of Gold Mined in South Africa [Chamber of Mines South Africa, 2015, pp 29]

| Year | Ore Milled (metric tons) | Production (kg) | Grade (g/M ton) |
|---|---|---|---|
| 2004 | 59 702 | 282 031 | 4.72 |
| 2005 | 49 609 | 255 290 | 5.15 |
| 2006 | 50 349 | 235 043 | 4.67 |
| 2007 | 53 257 | 219 223 | 4.12 |
| 2008 | 50 999 | 182 490 | 3.58 |
| 2009 | 65 545 | 170 298 | 3.29 |
| 2010 | 73 803 | 160 646 | 3.04 |
| 2011 | 75 569 | 149 708 | 2.81 |
| 2012 | 66 119 | 124 252 | 2.91 |
| 2013 | 73 885 | 131 405 | 2.91 |

Table 4 shows the cost of production per Ounce (31.103 grams) of various Gold producing regions globally and shows that South Africa has the highest Gold production cost in the world. Figure 6 shows the Gold output of the top five Gold producing countries from 1960 until 2013.

Table 4: Cost of Production per Oz of Gold [GFMS Platinum Group Metals Survey, 2016, pp 29]

| US$/oz | 2015 | 2016 |
|---|---|---|
| South Africa | 1080 | 1035 |
| Other | 828 | 820 |
| World | 835 | 818 |
| North America | 812 | 784 |
| Australia | 765 | 782 |
| South America | 804 | 776 |

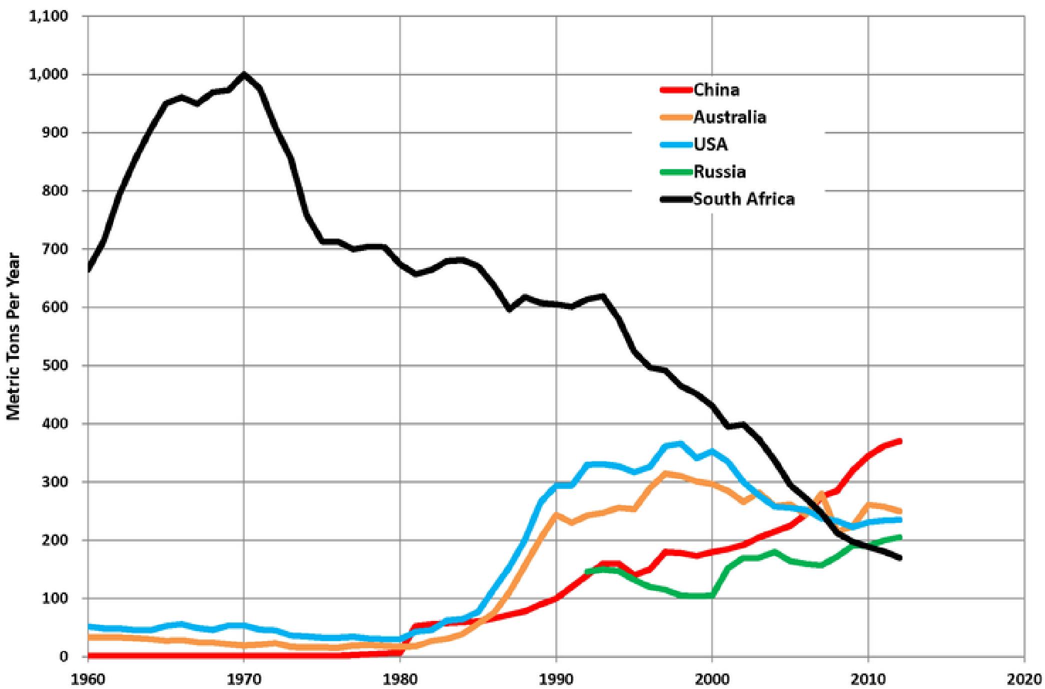



Figure 6: Trends in top 5 Gold producing Countries [Plazak, 2013]

Table 5: Gold Demand (tonnes) in 2016 [World Gold Council, 2016, pp 19]

| | 2014 | 2015 | Q2'14 | Q3'14 | Q4'14 | Q1'15 | Q2'15 | Q3'15 | Q4'15 | Q1'16 | Q1'16 vs Q1'15 % change |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Jewellery** | 2,482.0 | 2,397.5 | 589.5 | 591.5 | 686.0 | 596.9 | 513.7 | 623.7 | 663.2 | 481.9 | ↓ -19 |
| **Technology** | 348.5 | 333.8 | 86.6 | 89.5 | 89.4 | 83.3 | 83.5 | 82.9 | 84.1 | 80.9 | ↓ -3 |
| Electronics | 277.6 | 264.3 | 68.6 | 71.6 | 71.8 | 66.3 | 65.8 | 65.5 | 66.8 | 63.9 | ↓ -3 |
| Other industrial | 51.0 | 50.6 | 13.1 | 13.0 | 12.8 | 12.3 | 13.0 | 12.7 | 12.7 | 12.4 | ↑ 1 |
| Dentistry | 19.9 | 18.9 | 4.9 | 4.9 | 4.8 | 4.7 | 4.8 | 4.7 | 4.6 | 4.5 | ↓ -4 |
| **Investment** | 822.0 | 895.6 | 200.1 | 182.4 | 169.4 | 277.9 | 182.3 | 230.3 | 205.2 | 617.6 | ↑ 122 |
| Total bar and coin demand | 1,005.6 | 1,023.9 | 238.1 | 223.3 | 261.5 | 252.2 | 205.3 | 293.7 | 272.7 | 253.9 | ↑ 1 |
| Physical bar demand | 726.5 | 739.8 | 170.8 | 166.9 | 186.9 | 186.6 | 151.2 | 199.8 | 202.2 | 183.4 | ↓ -2 |
| Official coin | 202.9 | 212.4 | 48.8 | 35.7 | 54.5 | 50.2 | 40.1 | 72.6 | 49.5 | 58.7 | ↑ 17 |
| Medals/imitation coin | 76.2 | 71.7 | 18.6 | 20.8 | 20.1 | 15.4 | 14.0 | 21.3 | 21.0 | 11.8 | ↓ -24 |
| ETFs and similar products* | -183.6 | -128.3 | -38.0 | -40.9 | -92.1 | 25.6 | -23.0 | -63.4 | -67.6 | 363.7 | ↑ >300 |
| **Central banks and other inst.** | 583.9 | 566.3 | 157.2 | 174.9 | 133.9 | 112.3 | 127.2 | 167.9 | 158.8 | 109.4 | ↓ -3 |
| **Gold demand** | 4,236.4 | 4,193.1 | 1,033.5 | 1,038.3 | 1,078.7 | 1,070.4 | 906.7 | 1,104.7 | 1,111.3 | 1,289.8 | ↑ 21 |
| **LBMA Gold Price, US$/oz** | 1,266.4 | 1,160.1 | 1,288.4 | 1,281.9 | 1,201.4 | 1,218.5 | 1,192.4 | 1,124.3 | 1,106.5 | 1,182.6 | ↓ -3 |

*For a listing of the Exchange Traded Funds and similar products, please see the *Notes and definitions.*

Source: Metals Focus; GFMS, Thomson Reuters; ICE Benchmark Administration; World Gold Council

On the demand side, the decline in the South African Gold sector's output since 1970s (Figure 6) could have resulted in other countries having taken advantage of this drop in production and captured increased market space. Gold demand is largely impacted by the demand of products that use gold. Table 5 shows the demands for various products that are made from Gold in 2016 and shows that the majority of Gold is used in the manufacturing of jewellery, which was estimated to comprise of 57% of the total Gold demand in 2015. Official holdings and investments made up a combined 21% while industrial uses made up 8%.

#### 4.1.4.2 Gold Export Partners

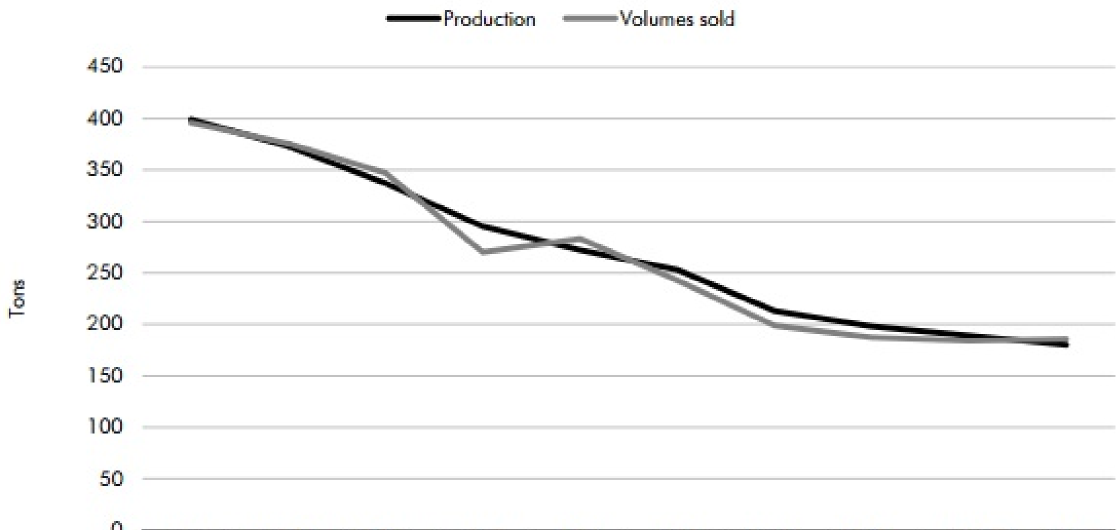
South Africa exports the majority of Gold produced, therefore it is important to know which are the main countries that import South African Gold, and their economic stability. Figure 7 shows the top-ten buyers and sellers of Gold in the world, and in the event of economic uncertainty, Gold investments generally increases as investors buy Gold as a form of hedging.


Figure 7: World's Largest Gold Buyers and Sellers [Perry, 2017]

Table 6: World's Largest Gold Buyers [World Gold Council, 2016, pp 23]

| Country | Demand (tonnes) |
|---|---|
| China | 956.7 |
| India | 864.3 |
| U.S.A. | 191.3 |
| Germany | 126.1 |
| Thailand | 90.2 |

It is evident from Figure 7 and Table 6 that China, India and the United States are the main buyers of South African Gold. As such constantly investigating the economic performance of these countries can provide better predictions of future demand of South Africa's Gold and inform the supply side decisions accordingly.




| | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|---|---|
| Production | 399 | 373 | 337 | 295 | 272 | 253 | 213 | 198 | 189 | 180 |
| Volumes sold | 396 | 376 | 347 | 270 | 283 | 243 | 199 | 187 | 184 | 186 |

Source: Statistics South Africa. Environmental Economic Accounts Tables.

Figure 8: South African Gold Volumes Produced vs. Sold [Statistics South Africa, 2014, pp 39]

Figure 8 indicates that the supply side of the South African Gold sector is the constraining factor, as the sector almost always sells as much Gold as they produce. As such, the focus of decision makers should be on the internal factors that impact the production volumes of South African Gold mines, rather than the external factors that influence demand.

### 4.1.5 Platinum Group Metals

#### 4.1.5.1 Factors that Influence the Production Volumes and Sales

One of the most significant factors that influences the production volumes of PGMs is the labour strikes, with the PGMs mining industry losing R 15.3 billion as a result of strikes in 2012 [GFMS Platinum Group Metals Survey, 2016, pp 7]. Another significant factor is the demand of products that use PGMs. Table 7 shows that auto catalysts are the main use of PGMs. These auto catalysts are used in car engines as emissions control devices. It can therefore be deduced that PGMs demand depends heavily on the car production levels of countries that buy South African PGMs. These countries will be identified in the next section.

Table 7: World Platinum Demand [GFMS Platinum Group Metals Survey, 2016, pp 7]

| **Demand** (000 ounces) | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | Change |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Autocatalysts | 3,896 | 4,047 | 3,514 | 2,502 | 2,918 | 2,990 | 2,856 | 2,843 | 2,957 | 3,011 | 2% |
| Jewellery | 2,210 | 2,061 | 1,847 | 2,678 | 2,201 | 2,388 | 2,585 | 2,646 | 2,548 | 2,456 | -4% |
| Chemical | 320 | 370 | 340 | 281 | 482 | 486 | 399 | 432 | 595 | 494 | -17% |
| Electronics | 404 | 397 | 292 | 254 | 252 | 225 | 195 | 169 | 162 | 151 | -7% |
| Glass | 449 | 431 | 507 | 91 | 505 | 338 | 323 | 84 | (50) | 163 | |
| Petroleum | 167 | 151 | 190 | 163 | 168 | 143 | 126 | 106 | 122 | 100 | -18% |
| Other Industrial | 463 | 472 | 456 | 431 | 494 | 559 | 621 | 649 | 700 | 721 | 3% |
| Retail Investment | (22) | 23 | 452 | 313 | 95 | 312 | 282 | 141 | 131 | 474 | 262% |
| **Total Demand** | **7,887** | **7,951** | **7,599** | **6,714** | **7,114** | **7,442** | **7,388** | **7,070** | **7,167** | **7,570** | **6%** |

### 4.1.5.2 Platinum Export Partners

This section serves to investigate the countries that buy South African PGMs. Figure 9 shows the demand of PGMs per Region. The graph shows that China is the largest user of PGMs with the Rest of the World's demand rising rapidly. Since South Africa produces the majority of the world's PGMs, it can be deduced that China is the main buyer of South Africa's PGMs and therefore the export volumes of South Africa's PGMs is most dependent on China's car production levels.

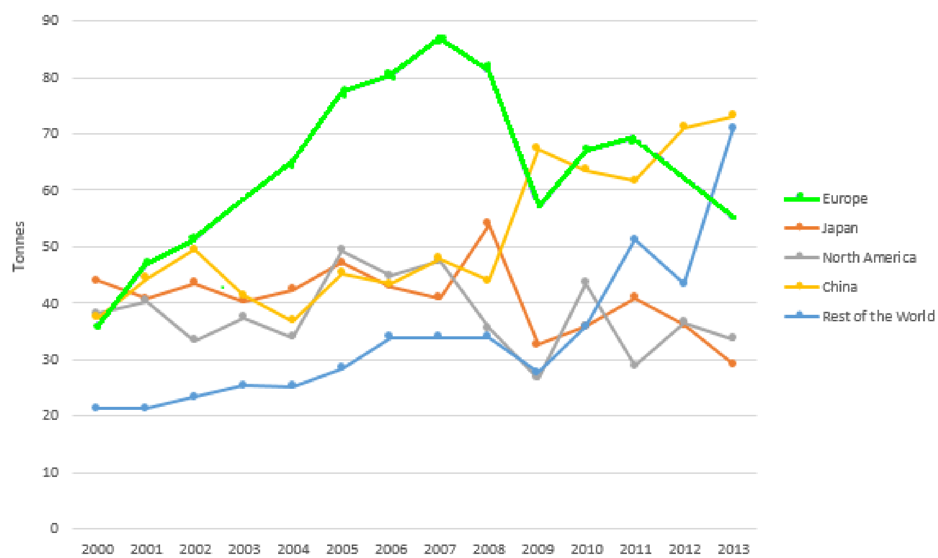



Figure 9: Platinum Demand per Region [Johnson, 2017]

#### 4.1.6 Iron Ore

##### 4.1.6.1 Factors that Influence Production Volumes and Sales

The main use of Iron ore is in the production of steel, with its main use in construction, where the support beams are made of steel. Another use is in the auto mobile industry. The performance of these industries will therefore have a strong impact on the demand for Iron ore. The following subsection identifies the countries that import the largest volumes of South Africa's Iron ore.

##### 4.1.6.2 Iron Ore Export Partners

The top 5 Iron ore importing countries in 2015 were:

1. China: US$1.78 billion (55% of total Manganese imports)
2. India: $233 million (7.2%)
3. South Korea: $188 million (5.8%)
4. Norway: $164 billion (5.1%)
5. Japan: $159 million (4.9%)

Source: [The World Factbook, 2017]

Since China is responsible for 63.5 % of the world's total Iron ore imports with South Africa being their third largest supplier [Booyens, 2013]. Thus the performance of the Chinese economy will have the greatest impact on the demand for South Africa's Iron ore. The performance of the Chinese construction and auto mobile sectors will be the most relevant as these sectors are the main users of Steel and therefore Iron ore. China has recently published plans to have halve the output of pellet and sintering plants in the steel-making hub of Tangstan city in an attempt to reduce pollution [Fin24, 2017]. Such an endeavour is an example of a factor that can significantly reduce the demand of Iron ore.

#### 4.1.7 Manganese

##### 4.1.7.1 Factors that Influence Production Volumes and Sales

The primary use of Manganese is in alloys such as steel, with up to 90 % of Manganese used for this purpose. The following subsection lists the top five Manganese importing countries in an effort to identify the main consumer of South African Manganese.

##### 4.1.7.2 Manganese Export Partners

The top 5 Manganese importing countries in 2015 are:

1. China: US$1.78 billion (55% of total Manganese imports)
2. India: $233 million (7.2%)
3. South Korea: $188 million (5.8%)
4. Norway: $164 billion (5.1%)
5. Japan: $159 million (4.9%)

Source: [Countries that import Manganese ore, 2015]

Since Manganese and Iron ore are mainly used in the production of Steel, the factors that influence both these metal's demand will be the same. Therefore the Chinese auto mobile and construction sectors will have the greatest impact on the demand for both metals.

#### 4.1.8 Conclusion

The aforementioned discussions informed the choice of PGMs, Gold, Iron ore, and Manganese as the four most important metals for the South African economy. As such, these four metals will be subject to change point analysis and discussion of results thereof.

### 4.2 The Analysis of Change Points

#### 4.2.1 Abstract

This literature review investigates certain change point analysis techniques – Bayesian as well as frequentist, with a view to identify the most suitable change point technique for the identification of time locations of change points. Both univariate and multivariate analysis approaches are explored. [Adams and MacKay, 2007] describe "change points" as locations where sudden variations in the underlying generative parameters of a sequence of data occur. Change point detection therefore involves ascertaining whether or not a statistically significant change (or several) in the parameters of the underlying data generating process has occurred, and consequently identifying the location of these change(s). Change point detection has application is of interest in a variety of areas including finance, biometrics and robotics.

In order to locate an "abrupt" change in the parameters of a sequence of measurements observed over time, statistical inference must be performed. [Upton and Cook, 2014] described statistical inference as "the process of deducing properties of an underlying distribution by analysis of data". Statistical inference has two main approaches, namely frequentist inference and Bayesian inference. Section 4.2.2 discusses Bayesian inference and the BCP algorithm developed by [Barry and Hartigan, 1993]. In section 4.2.3, frequentist inference is briefly discussed and two frequentist approaches , namely the DP [Bai and Perron, 2003] and the CBS [Olshen, Venkatraman, Lucit and Wigler, 2004] algorithms are introduced. [Erdman and Emerson, 2007] compared the BCP, DP and CBS methods and their findings were used to motivate the choice of BCP as most appropriate for our application. Note that BCP, DP and CBS are appropriate for univariate analysis. A multivariate approach is also introduced, namely the Non-Parametric Multiple Change-Point Analysis (MCP) [Matteson and James, 2014] in order to identify locations based on multiple series jointly under little distributional assumptions.

Based on the literature review for the univariate analysis BCP [Barry and Hartigan, 1993] was identified as the most informative method for the identification of change points, since the Bayesian approach offers a summary reflecting the probability associated with each of the change points identified. DP was chosen as the alternative frequentist method to compare with and MCP was the only implementation of multivariate analysis. The corresponding algorithms for BCP, DP and MCP were implemented in R using the open-source R package bcp, strucchange and ecp respectively. R was chosen as the platform as it is the most widely used statistical programming language in the data science field and as a result has numerous packages that implement statistical methodologies.

#### 4.2.2 Bayesian Inference

Bayes theorem is the basis for Bayesian inference in which the probability of a hypothesis is updated as more information becomes available. The standard form of Bayes theorem is

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

where $P(A)$ is the prior probability of event $A$, $P(B)$ is the prior probability of event $B$ $P(A|B)$ is the conditional probability of event A given event B and $P(B|A)$ is the conditional probability of event $B$ given event $A$ .
In Bayesian inference, Bayes theorem takes the following form

$$P(\theta|X) = \frac{P(X|\theta)P(\theta)}{P(X)}$$

From Bayes theorem, the following relationship is formed

$$P(\theta|X) \quad \propto \quad P(\theta).P(X|\theta)$$

where $\theta$ is the parameter of the data's distribution and $P(\theta)$ is the "mathematical belief" about the distribution of the parameter $\theta$, which can be based on prior information or assumptions. $X$ is observed data, $P(X)$ is the total probability of observing the data and is referred to as the marginal distribution and $P(X|\theta)$ is the corresponding likelihood function. Finally, $P(\theta|X)$ is the posterior distribution of $\theta$, which is the distribution of the parameters after factoring in the observed data. The result of a Bayesian approach is a probability distribution for the parameters that is updated based on observed evidence.

#### 4.2.2.1 Bayesian Change Point Analysis (BCP)

The Bayesian approach to change point detection states [Barry and Hartigan, 1993] that the sequence of data has an underlying sequence of generative parameters that are divided into contigious blocks. The blocks are divided so that all observations in a block have equal parameter values. Therefore each change point will be at the beginning of each new block. The notation set out by [Barry and Hartigan, 1993] is used for the remainder of this section. BCP assumes that the observations $X_i$, $i = 1, ..., n$, are independent and have a probability density that is dependent on $\theta_i, i = 1, ..., n$. The number of blocks is unknown with partitions $\rho = \{i_0, i_1, ..., i_b\}$ such that $0 = i_0 < i_1 < ... < i_n$ and $\theta_i = \theta_{i_b}$ when $i_{r-1} < i \leqslant i_r$ . $X_{ij}$ is the sequence of observations from $X_{i+1}$ to $X_j$, where $X_{i+1}$ is the observation at time point $i + 1$. The density of $x_{ij}$ given $\theta_j$ (when $\theta_{i+1} = \theta_{i+2} = ... = \theta_j$) is defined as $f_{ij}(x_{ij}|\theta_j)$.

The parameter values are approximated by Markov sampling techniques. Markov Chain Monte Carlo (MCMC) is a method that approximates complex integrals using stochastic sampling routines. The assumption is that the parameter sequence $\theta_i$ forms a Markov Chain. Given $\theta_i$, $\theta_{i+1}$ equals $\theta_i$ with probability $1 - p_i$ or has a density $f(\theta_{i+1}|\theta_i)$ with probability $p_i$.

The probability of a partition $\rho = (i_1, i_2, ..., i_b)$ is given by $f(p) = Kc_{i_0 i_1} c_{i_1 i_2} \cdots c_{i_{b-1} i_b}$, where $c_{ij}$ are "prior cohesions" for each possible block $ij$. Cohesions are of the form

$$c_{ij} = (j - i)^{-3} \text{ for } 0 < i < j < n \, ,$$

$$c_{ij} = (j - i)^{-2} \text{ for } i = 0 \text{ or } j = n,$$

and

$$c_{0n} = n^{-1}$$

Independent priors are specified for each parameter: $p, \mu_0, \sigma^2 \; and \; w = \sigma^2/(\sigma_0^2 + \sigma^2)$.

$$
\begin{aligned}
f(\mu_0) &= 1, & -\infty \leqslant \mu_o \leqslant \infty, \\
f(\sigma^2) &= 1/\sigma^2, & 0 \leqslant \sigma^2 \leqslant \infty, \\
f(p) &= 1/p_0, & 0 \leqslant p \leqslant p_0, \\
f(w) &= 1/w_0, & 0 \leqslant w \leqslant w_0,
\end{aligned}
$$

$p_0$ and $w_0$ are prespecified numbers between [0, 1], where $p$ is the probability of a location being identified as a change point and $w$ is the size of the changes. [Barry and Hartigan, 1993] recommend using initial values of $p_0 = 0.2$ and $w_0 = 0.2$. For demonstration only, Figure 10 shows the location of the change points according to BCP, DP and CBS. The vertical red lines are the change points identified by both DP and CBS. The black lines indicate the probability of a change point located at each position of the data set (according to BCP).

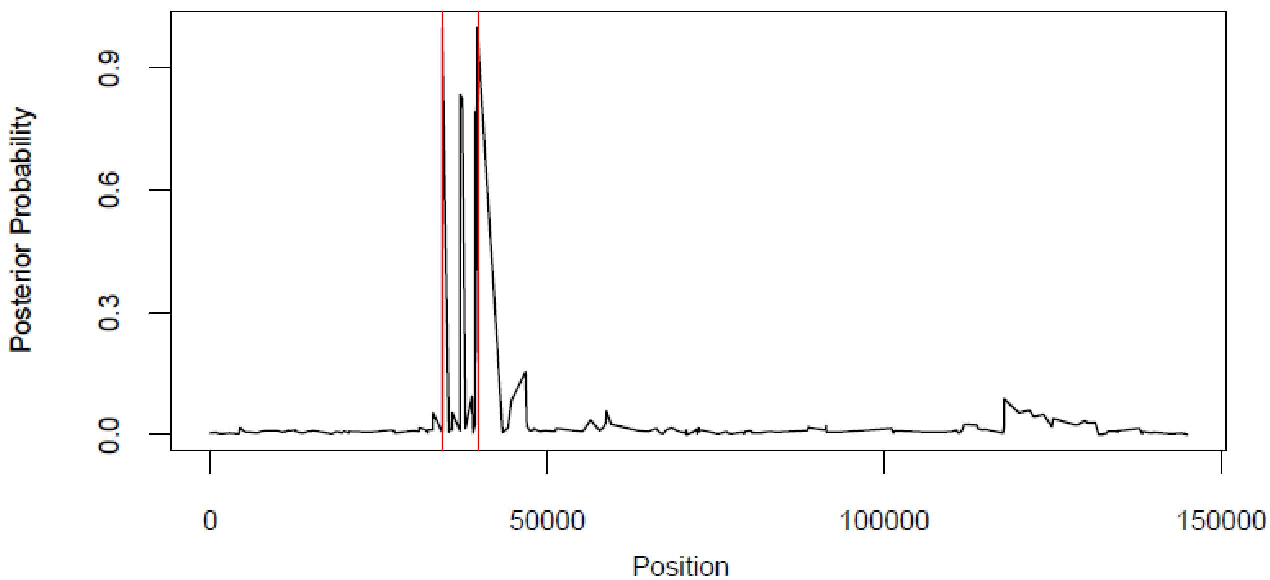



Figure 10: Change Point Estimates of the Three Change Point Approaches [Erdman and Emerson, 2007]

BCP thus not only identifies the location of the change point but also estimates the probability of a change at that location in the data set, which is a distinct advantage over DP and CBS, that merely identifies the locations of the change points. For detailed theoretical derivation of the BCP approach the reader may please refer to [Barry and Hartigan, 1993].

#### 4.2.3 Frequentist Inference

[Renganathan, 2016] defines frequentist inference as follows: ”This paradigm calibrates the plausibility of propositions by considering (notional) repeated sampling of a population distribution to produce datasets similar to the one at hand. By considering the dataset’s characteristics under repeated sampling, the frequentist properties of a statistical proposition can be quantified”. The frequentist approach to inference regards the parameters $\theta$ as unknown and fixed. The frequentist approach is thus interested in calculating the best estimate of $\theta$ which is denoted as $\hat{\theta}$. The two frequentist methods investigated are DP and CBS.

#### 4.2.3.1 Dynamic Programming Algorithm (DP)

DP estimates the locations of changes using least squares regression. This approach finds change points that minimise residual sum of squares (RSS) of a linear model, afterwhich the Bayesian Information criterion (BIC) is used to find an optimal model. The BIC uses a compromise between RSS and the number of parameters.

DP assumes that the observations are independent $N(\mu_0, \sigma^2)$ and that the probability of a change point occurring at each point $i$ is given by $p$ and evaluates which segment achieves a global minimisation of the overall sum of square residuals. The formula for the optimal partition solves the following recursive equation:

$$SSR(\{T_{m,T}\}) = min[SSR(\{T_{m-1,j}\}) + SSR(j+1, T)]$$

where $T$ is the sample size, $m$ is the specified number of breaks for $j = 1, ..., m+1$ and $h$ is the specified minimum distance between breaks.

[Bai and Perron, 2003] details the procedure as follows: "The first step in the procedure is evaluating and storing the optimal one break partition for all sub-samples and their associated sum of squared residuals. The next step repeats the exercise, but searches for optimal partitions with two breaks. This is repeated until a set of $T - (m+1)h + 1$ optimal $(m-1)$ breaks partitions are obtained. The final step is determining which optimal $(M-1)$ breaks partitions yields an overall minimal sum of squared residuals when combined with an additional segment." For details of the DP algorithm the reader may please refer to [Bai and Perron, 2003].

[Erdman and Emerson, 2007] found that DP is not feasible for large sample sizes. This is due to the the least square calculations over all partitions being of order $O(n^2)$ in memory. This means that increased input uses quadratically more memory, making computation increasingly slow. The main drawback of DP according to [Erdman and Emerson, 2007] is that "it could not correctly adapt to the presence of isolated outliers or true, single-observation blocks as the algorithm does not allow for single-observation segments". This combined with the approach requiring a given number of change points, makes this approach less than optimal for the application in this project.

#### 4.2.3.2 Recursive Circular Binary Segmentation Algorithm (CBS)

[Erdman and Emerson, 2007] describe CBS as "a modification of binary segmentation [Sen and Srivastava, 1975]. It is an estimation algorithm which uses a likelihood ratio statistic to test the null hypothesis of no change points in a sequence. If the null hypothesis is rejected, the sequence is split and the test is recursively applied to the resulting sub-segments until no additional changes are detected." For details of the CBS algorithm please refer to [Olshen, Venkatraman, Lucit and Wigler, 2004]. A critism of CBS is that it does not guarantee that the optimal change points would be identified [Erdman and Emerson, 2007], and as such CBS will not be used to analyse the data for the remainder of the project.

### 4.2.4 Multivariate Analysis

#### 4.2.4.1 Non-parametric Multiple Change Point Analysis of Multivariate Data (MCP)

This approach uses a divisive estimation that "sequentially identifies change points via a bisection algorithm" [James and Matteson, 2014] under very mild assumptions. The MCP procedure is as follows:

"Multiple change points are estimated by applying a procedure for finding a single change point iteratively. Each iteration estimates a new change point location so that it divides an existing segment." MCP tests $H_0 : F_1 = F_2$ versus $H_A : F1 \neq F_2$, where $F_1$ and $F_2$ are unknown probability distributions. If $H_0$ is rejected, it is concluded that there is a change point at $\tau$. "For univariate observations with continuous distributions the familiar Kolmogorov-Smirnov test may be applied, and in the general case the approach in [Rizzo and Szèkely, 2010] may be applied [Matteson and James, 2014]". Although MCP is suitable for both univariate and multivariate series, in this project it is used for only multivariate change point detection.

#### 4.2.5 Conclusion

From the discussion of the change point methods discussed above, BCP was identified as the more informative choice for this project as it provides the probability of a change point at each observation of the data set. As such, BCP was chosen as the primary method for identifying the change points for univariate series, with DP being used as alternative method to compare with. Finally, MCP was used to locate change points for multiple series.

## 5 Development of Supplementary Mechanism

### 5.1 Bayesian Change Point Approach (BCP)

The Bayesian Change Point approach was performed in R. The package bcp was used to implement [Barry and Hartigan, 1993] product partition model using Markov Chain Monte Carlo (MCMC). The bcp() function performs the Bayesian analysis and takes five arguments,namely:

- x: numerical vector of data
- p0 and wo: values for hyperparameters
- burnin: number of "burn-in" iterations, these iterations are excluded from estimations and probabilities"
- mcmc: number of iterations used in the Markov Chain Monte Carlo algorithm
- return.mcmc: returns the posterior means and partitions if set to TRUE

### 5.2 Dynamic Programming Algorithm (DP)

DP uses least squares regression to estimate the locations of any changes. DP then evaluates the number of partition that achieves a global minimisation of the overall sum of square residuals.

DP was implemented using the strucchange package in R. The breakpoints() function performs the DP algorithm, with its inputs listed below.

- formula: a symbolic description for the model in which breakpoints will be estimated
- h: minimum segment size
- breaks: specified maximum number of breaks

### 5.3 Non-Parametric Multiple Change-Point Analysis (MCP)

MCP was implemented in R using the ecp package. This package performs the multiple change point analysis model created by [Matteson and James, 2014] while making as few assumptions as possible. The ecp package addresses many of the issues that other approaches have, as well as being suitable for both univariate and multivariate data. The function used was a divisive estimation that "sequentially identifies change points via a bisection algorithm" [Matteson and James, 2014].

The main inputs for the algorithm are listed below:

- X: T x d matrix with length of T and d-dimensional observations
- R: The maximum number of permutations to use in each iteration of the permutation test
- $\alpha$: The moment index used for determining the distance between and within segments

## 6 Model Validation

### 6.1 Bayesian Change Point Approach

The BCP approach was validated in accordance with the first step of the approach formulated by [Naylor and Finger, 1967] which states that if the approach has high face validity then "the model appears to be a reasonable imitation of a real-world system to people who are knowledgeable to the real-world system". For demonstration Figure 11 shows the total volume of South African Manufacturing from January 1998 (Month 0) to October 2016 (Month 226). A change point can easily be identified around the 130 month mark, where the trend of the linear regression model changes. BCP analysis of this data is presented in Figure 12 which identifies a change point around month 131 (November 2008), with a probability of 0.96. This was the time of the global economic crisis of 2008 which also affected the South African economy. BCP identified the correct change point and thus the approach is validated.

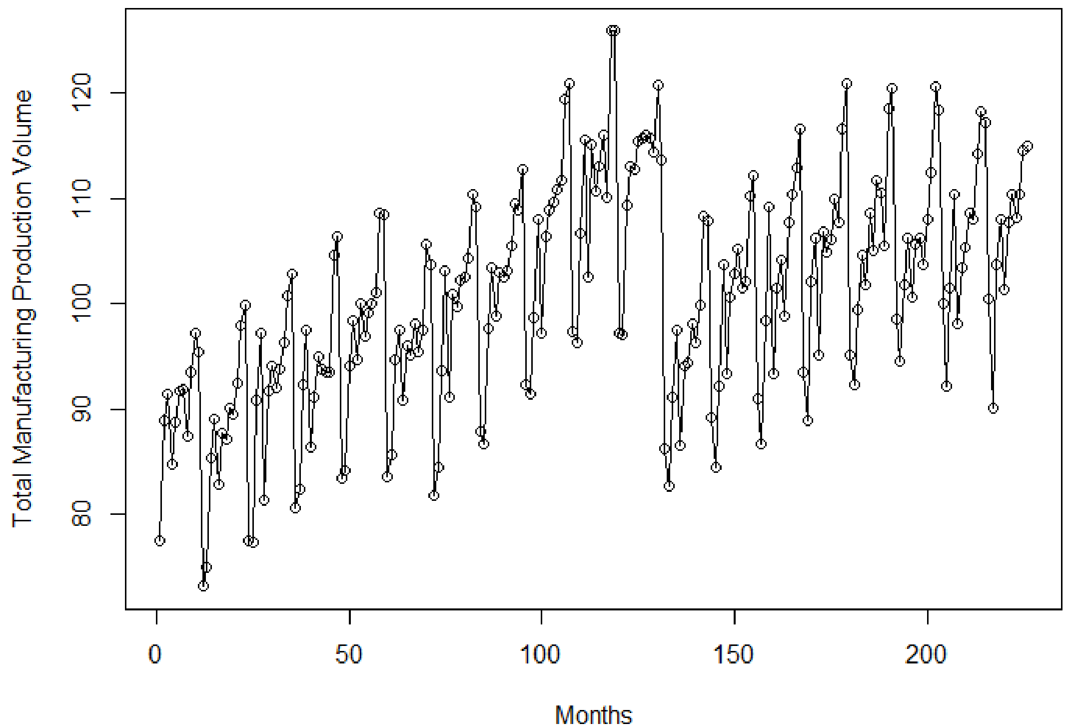



Figure 11: Physical Volume of South African Manufacturing Produced

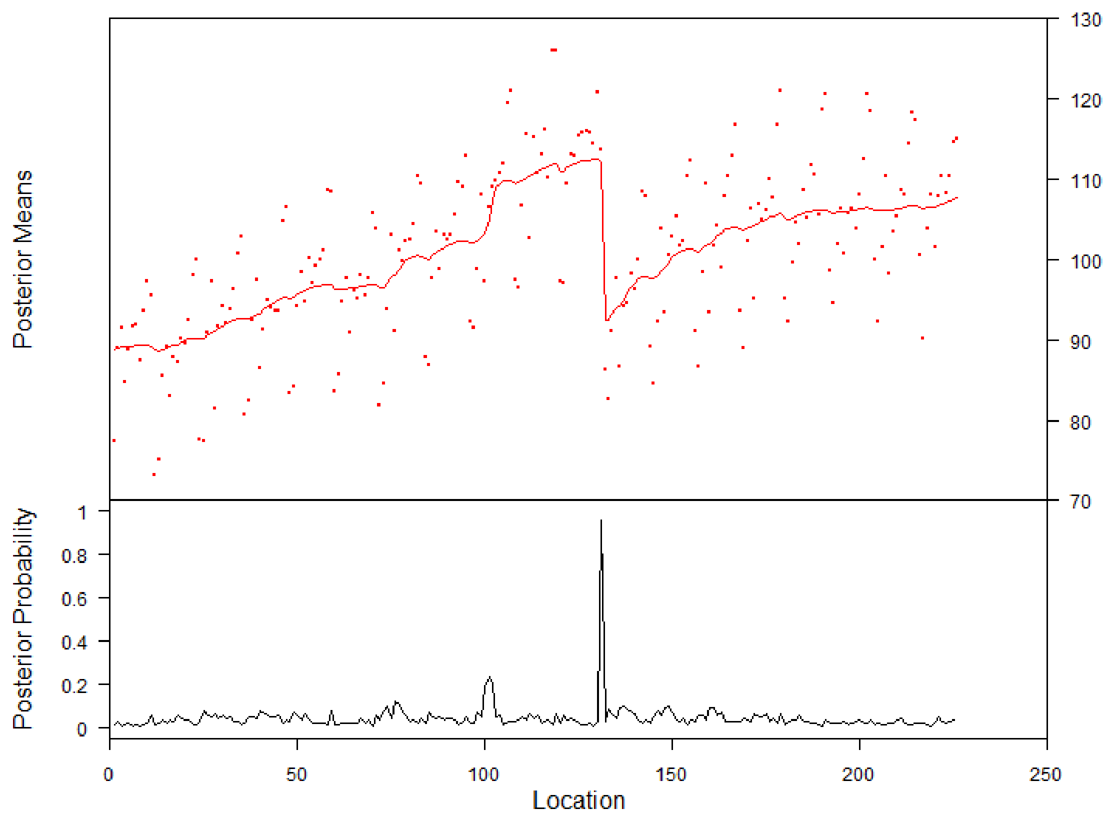



Figure 12: Change Point Identified by BCP in Physical Volume of South African Manufacturing Produced

## 6.2 Dynamic Programming Algorithm

A similar validation method was followed for the DP algorithm, using the same data. The change points identified by DP are shown in Table 8.

Table 8: Change Points Identified by the Dynamic Programming Algorithm

| Break Points Location | Date |
|---|---|
| 41 | 05/2001 |
| 98 | 02/2006 |
| 131 | 11/2008 |
| 164 | 08/2011 |

Table 8 shows that DP identified four change points compared to BCP which had only identified one. This indicates that DP identifies change points that BCP may have identified as having low probabilities of occurrence. It is to be noted that the correct change point at 11/2008 was identified by both DP and BCP.

When one change point is specified in the DP approach, the function identified location 76 as the change point instead of the correct change point, location 131. This can be the result of a number of factors that affect the accuracy of DP, such as "(i) a small sample size, (ii) small break size, (iii) a small segment size and break clustering" [Antoshin, Berg and Souto, 2008].

Model Validation combined with the Literature review of BCP and DP motivate the choice of BCP, as the more appropriate change point algorithm and therefore will be the preferred algorithm in this thesis for univariate analysis.

## 6.3 Non-Parametric Multiple Change-Point Analysis

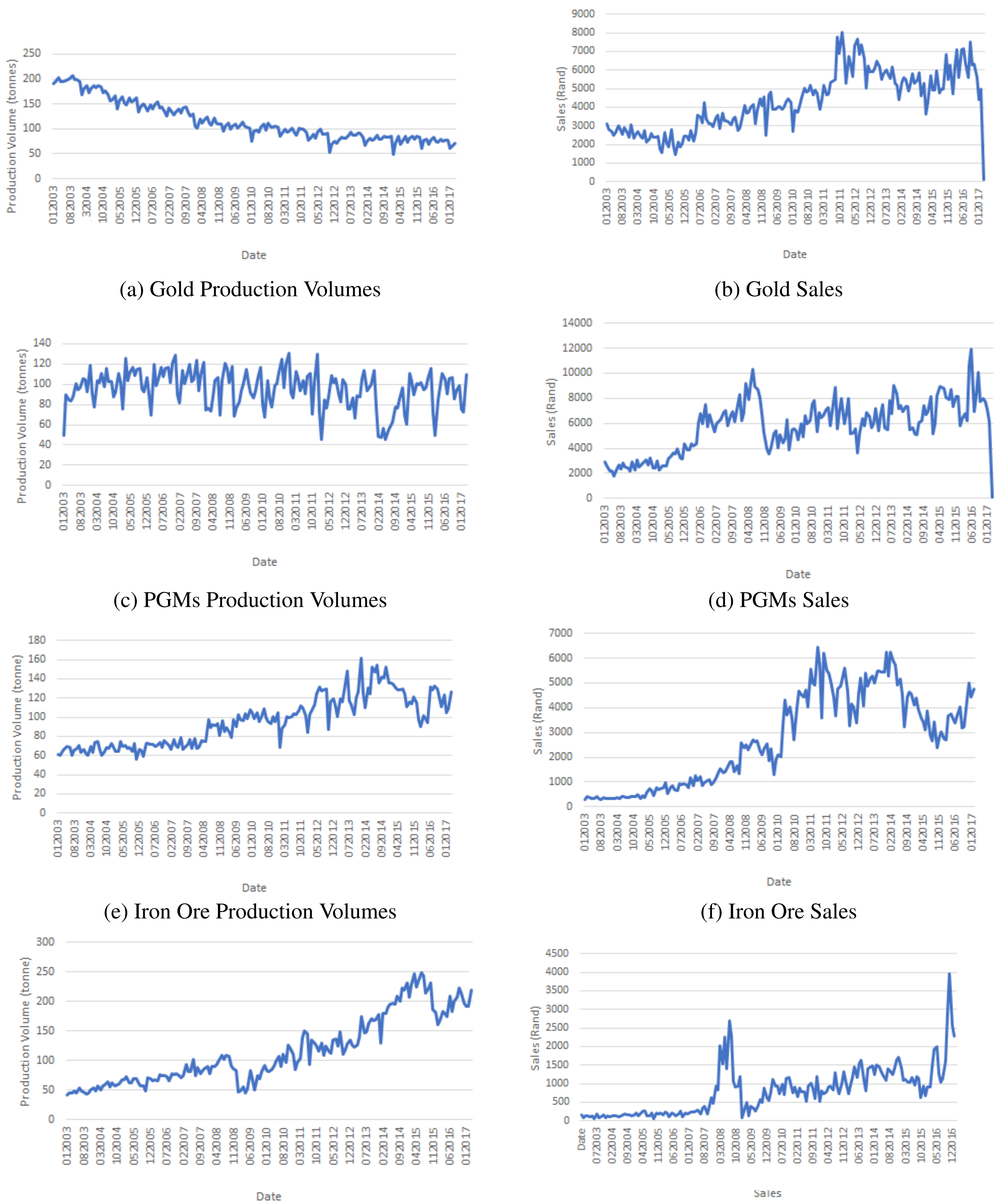
MCP, when applied to the series in Figure 11, identified five change points. These results are shown in Table 9. MCP identified the same change points as DP with the exception of 05/2004. The similarity of results serves as validation for the univariate capabilities of the MCP approach, but highlights the same apparent flaw as DP in identifying minor change points, with low probabilities of occurrence as observed from the BCP results.

Table 9: Change Points Identified by Univariate MCP

| Break Points Location | Date |
|---|---|
| 42 | 06/2001 |
| 77 | 05/2004 |
| 132 | 12/2008 |
| 164 | 08/2011 |

# 7 Data

The data used is this thesis is in the form of monthly production volumes, as well as monthly sales (in Rands) for PGMs, Gold, Iron ore and Manganese. The data was obtained from StatsSA. The graphs in Figure 13 display the original data series.




(a) Gold Production Volumes

(b) Gold Sales

(c) PGMs Production Volumes

(d) PGMs Sales

(e) Iron Ore Production Volumes

(f) Iron Ore Sales

(g) Manganese Production Volumes

(h) Manganese Sales

Figure 13: Production Volumes and Sales (Rands) of Gold, PGMs, Manganese and Iron Ore

# 8 Results

## 8.1 Bayesian Change Point Approach Results

Date: Date of identified change point
Prob.: Posterior Probability of a Change Point at a specific location
X1: Posterior estimate of mean

Table 10: Bayesian Change Point Analysis for Gold Production

| | Date | Prob. | X1 |
|---|---|---|---|
| 12 | 12/2003 | 0.704 | 192.94 |
| 36 | 12/2005 | 0.742 | 154.83 |
| 60 | 12/2007 | 0.736 | 129.81 |
| 117 | 09/2012 | 0.814 | 88.70 |

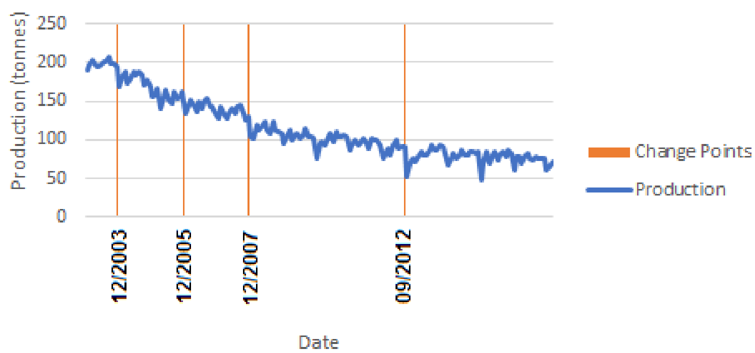



Figure 14: Change Points Identified for Gold Production

Table 11: Bayesian Change Point Analysis for Gold Sales

| | Date | Prob. | X1 |
|---|---|---|---|
| 41 | 05/2006 | 0.658 | 2617.50 |
| 104 | 08/2011 | 0.996 | 4953.19 |
| 153 | 09/2015 | 0.702 | 5183.62 |

Table 10 identified BCP change points at the end of the calendar year for 2003, 2005 and 2007. These changes were possibly due to the new production plans that are generally implemented at the beginning of each year in mines. Also it is to be noted that the quality of Gold ore decreases over time (as shown in Table 3), resulting in less Gold per metric ton mined. This combined with increased production costs (due to rises in labour, electricity and fuel) means that Gold production decreases over time. The probable cause of the 09/2012 change point could be attributed to the strikes in AngloGold Ashanti in September 2012.

In analysing the sales data for Gold (as also for other metals discussed below), it is to be noted that the sales figures are in actual Rands. Any change points identified in the sales series could be confounded with fluctuations in the strength of the Rand as well as the price of the commodity itself. As such, in the remainder of the discussion of results, the focus will be limited to the discussion of change points of production volumes of the metals only.

Table 12 and Figure 15 show the change points identified by BCP in PGMs production volumes. The probable cause of the change point identified in 12/2007 was a strike on 4 December 2007, where 240 000 workers protested unsafe working conditions [CNN, 2007]. The change point at 12/2011 was potentially caused by a strike at the Impala Platinum Mine in January 2012. A plausible cause for the change point at 01/2014, was a five month strike by The Association of Mineworkers and Construction Union (AMCU) workers. This strike was the longest wage strike in South African history and resulted in drastically reduced production for the first half of 2014. The change point at 02/2015 could have been the result of a rebound from the low production in 2014 as well as a 6% increase in demand (shown in Table 7). In December 2015 a change point occured as production dropped in January of 2016. This drop was due to a marginal surplus of PGMs created in 2015 [Topf, 2017]. This surplus was created by the inflated production that resulted from the rebound in 2015 and as a result production was lowered in order to reduce PGMs supply and as a result raise the price of the PGMs.

Table 12: Bayesian Change Point Analysis for PGMs Production

| | Date | Prob. | X1 |
|---|---|---|---|
| 60 | 12/2007 | 0.732 | 105.62 |
| 108 | 12/2011 | 0.738 | 107.11 |
| 133 | 01/2014 | 0.624 | 82.20 |
| 146 | 02/2015 | 0.708 | 79.68 |
| 156 | 12/2015 | 0.626 | 99.82 |

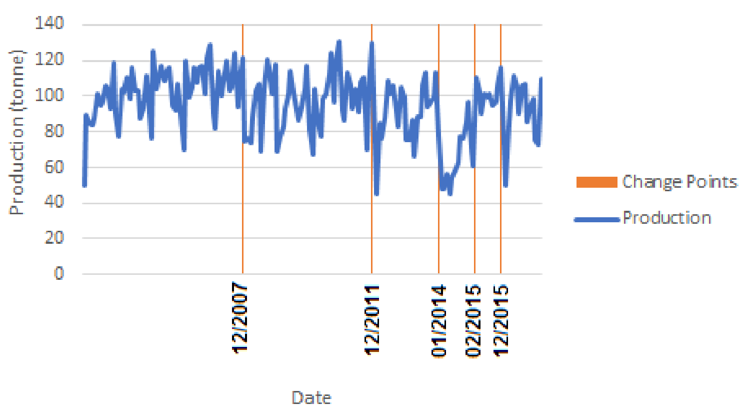



Figure 15: Change Points Identified for PGMs Production

The PGMs production volume change point identified by BCP show that all of the significant change points were influenced either directly or indirectly by labour strikes. The demand levels of PGMs also influenced production levels, with auto catalysts being the main contributor to the total demand of PGMs. Stakeholders in the PGMs sector therefore should keep an eye on the change in legislation regarding motor vehicles, as this is the main influence on changes in auto catalyst demand.

In Table 13 the change points identified by BCP up to 2014, were fluctuations in production, with the volumes subsequently increasing. The exception is 10/2012, which was probably caused by a miners strike at Kumba Iron Ore [Els, 2012]. In 2014 the Iron ore market became over saturated and the price of Iron ore plummeted. The main reason for the oversupply of Iron ore was that the Chinese steel industry cut back on their production. The plummeting Iron ore prices resulted in the mines cutting back on their production volumes.

Table 13: Bayesian Change Point Analysis for Iron Ore Production

| | Date | Prob. | X1 |
|---|---|---|---|
| 65 | 05/2008 | 0.960 | 72.74 |
| 96 | 12/2010 | 0.984 | 99.86 |
| 97 | 01/2011 | 0.742 | 71.87 |
| 112 | 04/2012 | 0.794 | 109.14 |
| 117 | 09/2012 | 1.000 | 127.60 |
| 118 | 10/2012 | 0.994 | 86.99 |
| 126 | 06/2013 | 0.992 | 143.75 |
| 131 | 11/2013 | 0.992 | 118.85 |
| 132 | 12/2013 | 0.992 | 160.54 |
| 136 | 04/2014 | 1.000 | 122.60 |
| 156 | 12/2015 | 0.988 | 116.10 |
| 161 | 05/2016 | 1.000 | 96.53 |

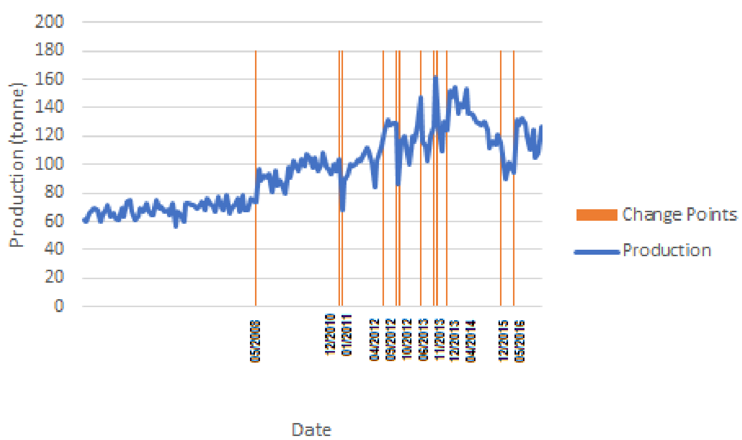



Figure 16: Change Points Identified for Iron Ore Production

Table 14: Bayesian Change Point Analysis for Manganese Production

| | Date | Prob. | X1 |
|---|---|---|---|
| 72 | 12/2008 | 0.906 | 91.27 |
| 99 | 03/2011 | 0.906 | 104.95 |
| 124 | 04/2013 | 0.704 | 136.22 |
| 141 | 09/2014 | 0.804 | 197.75 |
| 154 | 10/2015 | 1.000 | 229.19 |
| 161 | 05/2016 | 0.908 | 177.11 |

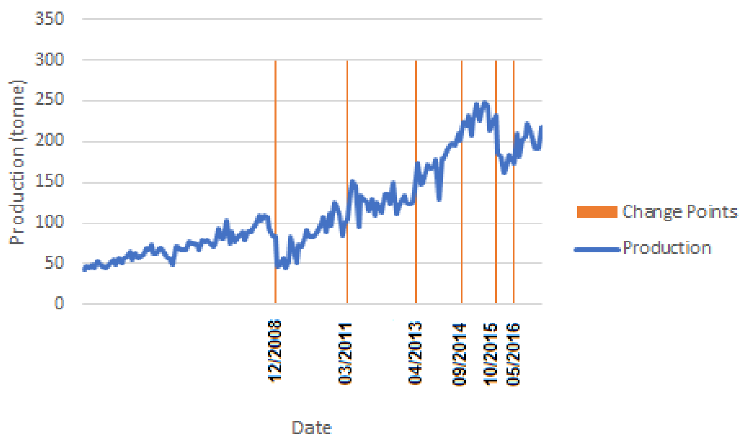



Figure 17: Change Points Identified for Manganese Production

Table 14 identifies change points by BCP for the Manganese production volumes, the most significant being the change points in 12/2008 and 10/2015. The former change point's potential cause was the economic crisis of 2008 and the latter potentially being attributed to the dropping Chinese Steel production levels. Since Chinese Steel production is the main user of steel products and 95% of Manganese is used in steel production, the Chinese Steel Industry should be studied in order to gain an understanding of the performance of Manganese in the South African context.

Given the shared usages of both Manganese and Iron ore, it is important to note that both metals identified share three change points, 04/2013, 01/2014, 05/2016 . These change points could possibly be linked to changes in the demand of steel and therefore Manganese and Iron ore. The remainder of the change points identified are possibly due to internal production issues and could be investigate further as appropriate.

## 8.2 Dynamic Programming Algorithm Results

Table 15 presents the DP change point results. Compared to the BCP results, DP picked up additional change points, which could be not significant. Two of the four change points identified by DP were also identified by BCP. These were 10/2007 and 09/2012.

Table 15: Dynamic Programming Algorithm for Gold Production

| Break Points Location | Date |
|---|---|
| 25 | 01/2005 |
| 58 | 10/2007 |
| 83 | 11/2009 |
| 117 | 09/2012 |

Table 16 shows that both change points identified by DP were also identified by BCP, namely 12/2011 and 02/2015. These two change points were two of the three most significant change points according to BCP.

Table 16: Dynamic Programming Algorithm for PGMs Production

| Break Points Location | Date |
|---|---|
| 108 | 12/2011 |
| 146 | 02/2015 |

Table 17 shows that two of the three change points identified by DP that were also identified by BCP, namely 05/2008 and 03/2012.

Table 17: Dynamic Programming Algorithm for Iron Ore Production

| Break Points Location | Date |
|---|---|
| 65 | 05/2008 |
| 111 | 03/2012 |
| 146 | 02/2015 |

Table 18 shows that DP identifies two of the same change points as BCP, namely 03/2011 and 01/2014.

Table 18: Dynamic Programming Algorithm for Manganese Production

| Break Points Location | Date |
|---|---|
| 39 | 03/2006 |
| 99 | 03/2011 |
| 133 | 01/2014 |

## 8.3 Non-Parametric Multiple Change-Point Analysis Results

The multivariate analysis investigated three scenarios, namely: (i) Gold and PGMs; (ii) Manganese and Iron ore; (iii) and all four metals. The logic in this grouping for the MCP analysis was that Gold and PGMs are both used as a means of hedging against negative economic performance, Manganese and Iron Ore are both used in steel production and all the metals are important to the South African economy. Table 19 and Figure 18 show the change points identified by MCP for the multivariate analysis of Gold and PGMs production volumes.

Table 19: Multiple Change Point Analysis for Gold and PGMs Production

| Break Points Location | Date |
|---|---|
| 58 | 10/2007 |
| 109 | 01/2012 |
| 142 | 10/2014 |

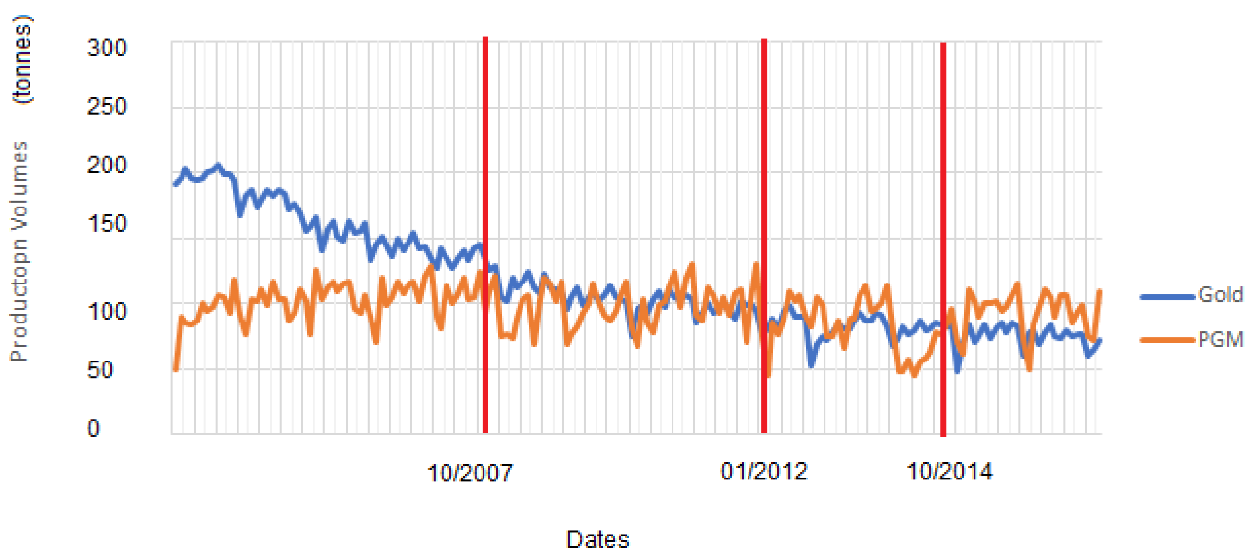



Figure 18: Change Points Identified in Multivariate Data of Gold and PGMs

Table 19 displays the three identified change points. The first change point (10/2007) was also identified in BCP's results for both Gold and PGMs as well as DP's results for Gold production. The second change point (01/2012) was identified in BCP and DP's results for PGMs production.

Table 20 and Figure 19 show the change points identified by MCP for the multivariate data of the Manganese and Iron ore production volumes.

Table 20: Multiple Change Point Analysis for Manganese and Iron Ore Production

| Break Points Location | Date |
|---|---|
| 51 | 03/2007 |
| 100 | 04/2011 |
| 136 | 04/2014 |

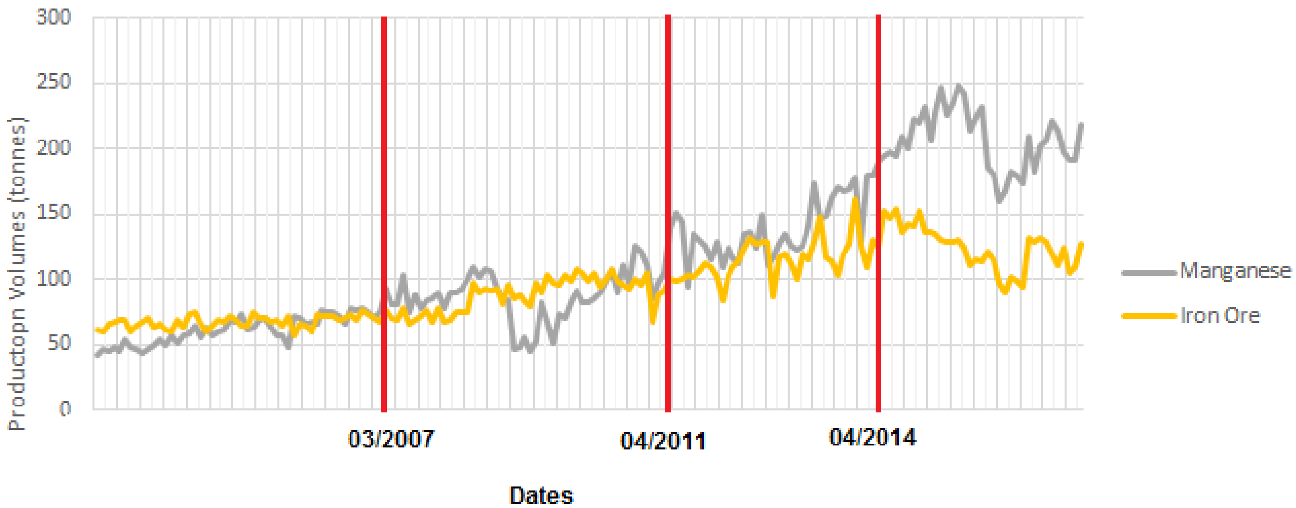



Figure 19: Change Points Identified in Multivariate Data of Manganese and Iron Ore

Table 20 shows that MCP identified two change points at similar points as the change points DP identified for Manganese production (04/2011; 04/2014) as well as a change point identified by BCP for Iron ore (04/2014) and Manganese (04/2011).

Table 21 and Figure 20 show the change points identified by MCP for the multivariate data of all four metal's production volumes.

Table 21: Multiple Change Point Analysis for Gold, PGMs, Manganese and Iron Ore Production

| Break Points Location | Date |
|---|---|
| 59 | 11/2007 |
| 100 | 04/2011 |
| 136 | 04/2014 |

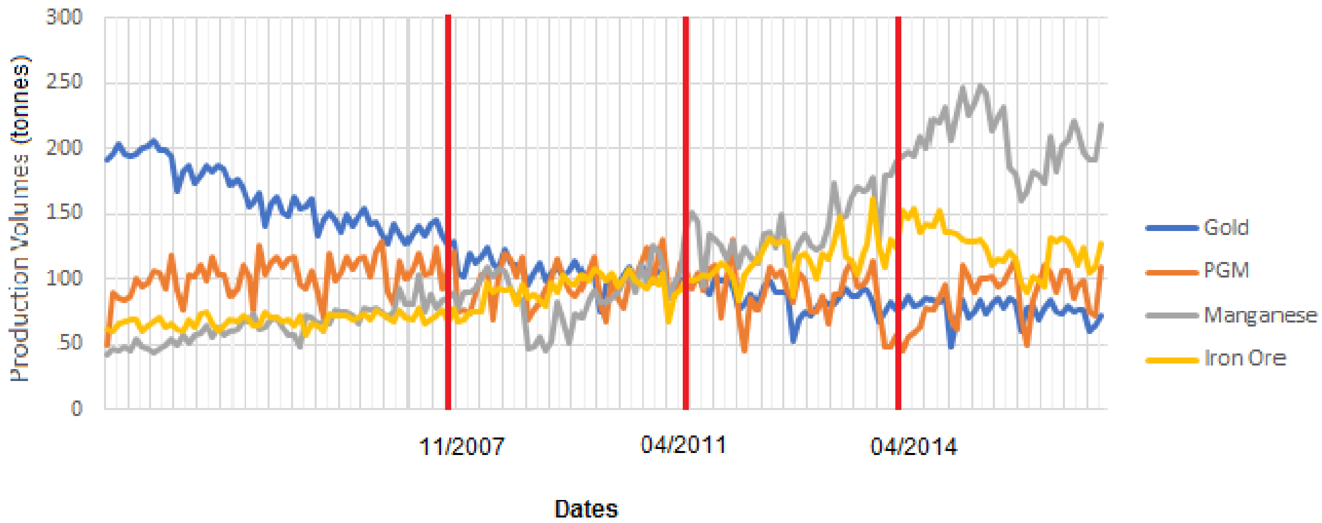



Figure 20: Change Points Identified in Multivariate Data of Gold, PGMs, Manganese and Iron Ore

Table 21 shows that MCP results when all the four production volume series were analysed together. MCP identified the same change point as BCP and DP for Gold production (11/2007). The second and third change points are shared with DP's change points from Manganese production volumes (04/2011, 04/2014).

# 9 Robustness Analysis

## 9.1 Bayesian Change Point Analysis

A Robustness Analysis was performed in order to determine the impact that a change in the initial parameter $p_0$ and $w_0$ would have on the ouput of the bcp package. [Bai and Perron, 2003] recommend using initial parameters of $p_0 = 0.2$ and $w_0 = 0.2$ These parameters must range from [0,1].

Shown below are graphs representing the change in the probability of a given change point occurring, as the initial change points change. Only the probabilities for $p_0 = w_0 = 0.2, 0.4, 0.6, 0.8, 1.0$ are shown due to ease of presentation, however all the combinations of $p_0$ and $w_0$ were investigated with similar results. The graphs show the varying probability of occurrence for each identified change point as $p_0$ and $w_0$ vary.

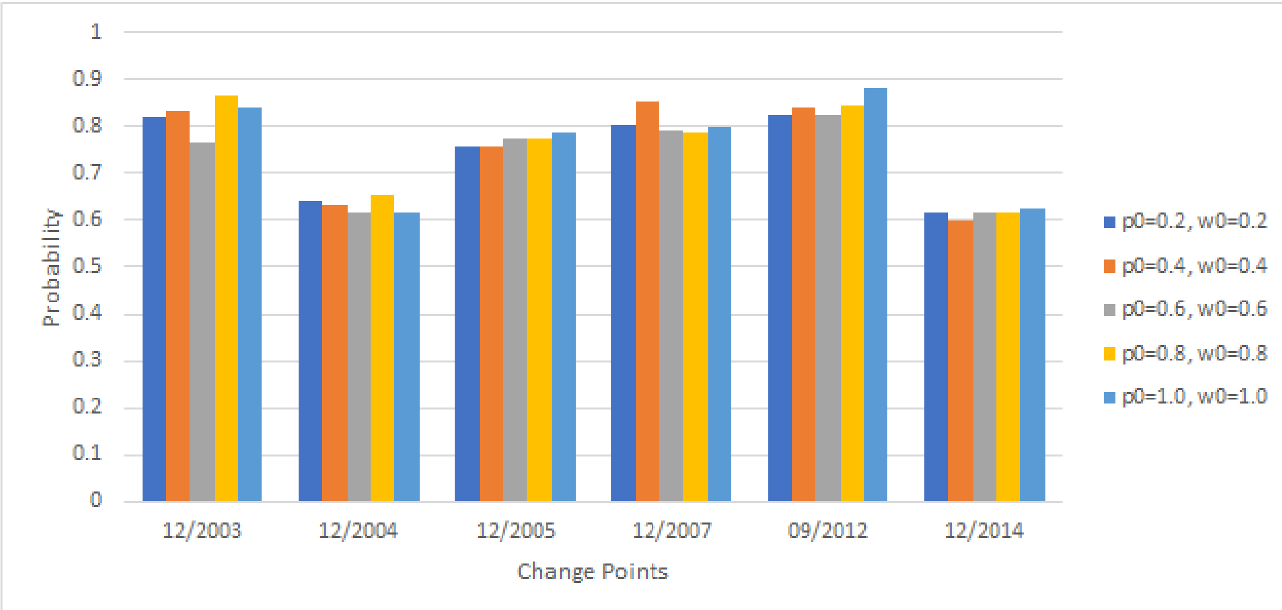



Figure 21: Probability of Identified Change Points with Varying Initial Parameters for Gold Production

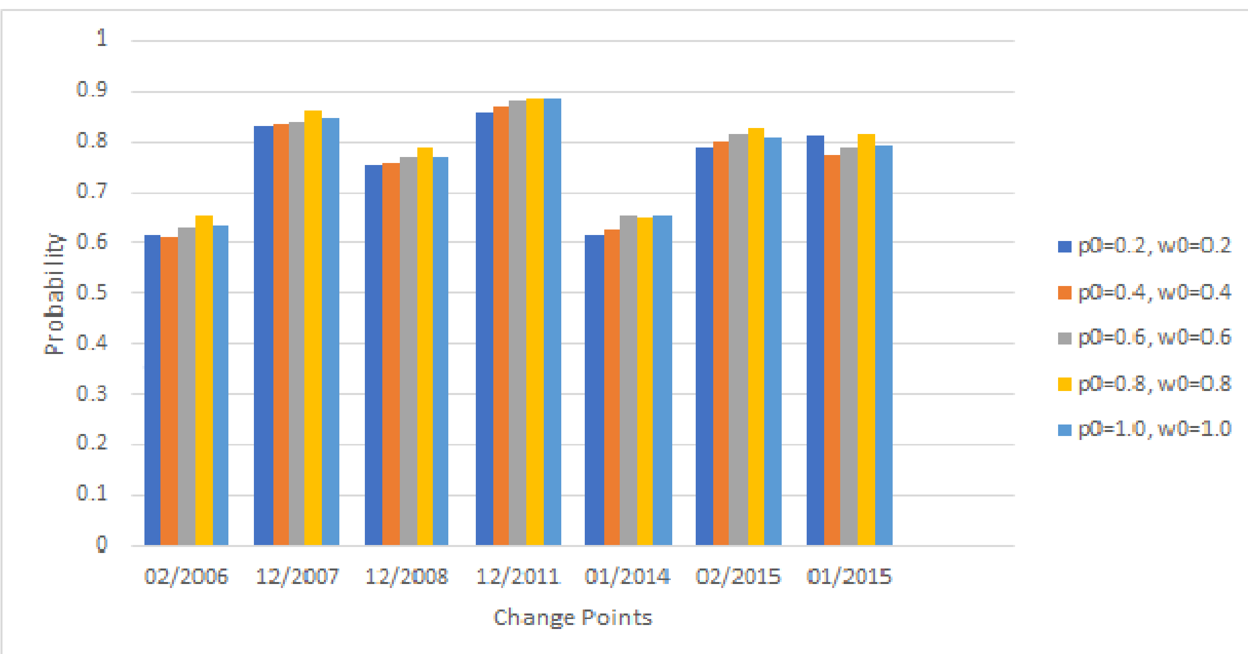



Figure 22: Probability of Identified Change Points with Varying Initial Parameters for PGMs Production

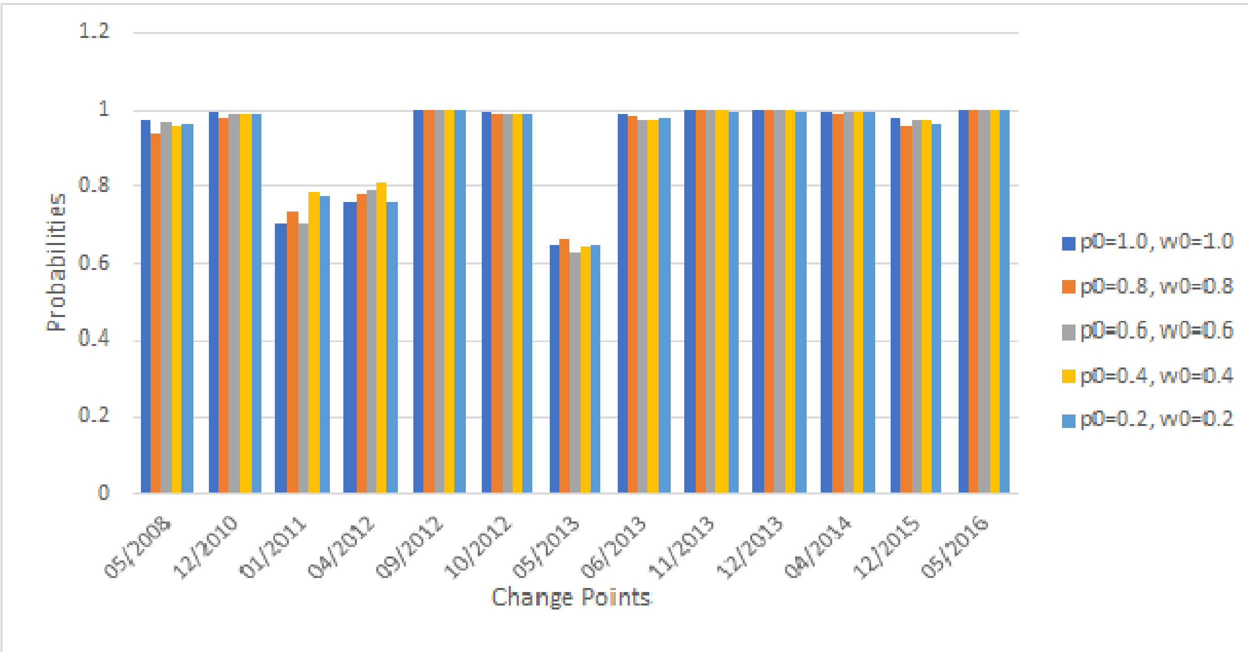



Figure 23: Probability of Identified Change Points with Varying Initial Parameters for Iron Ore Production

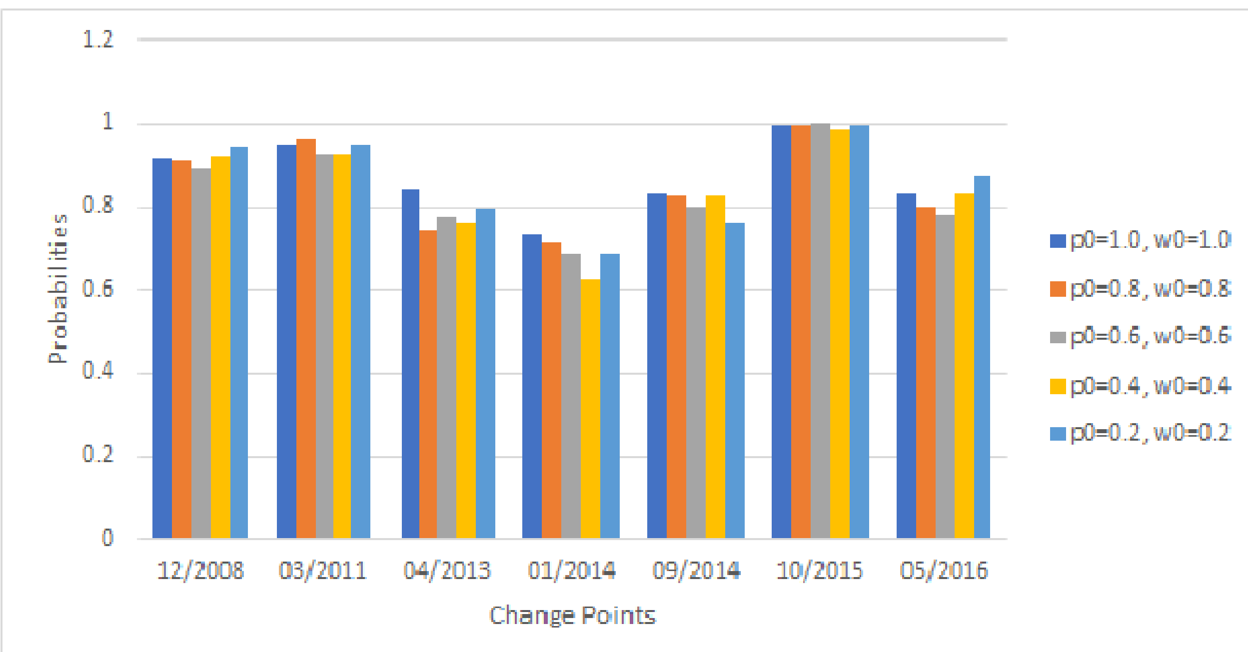



Figure 24: Probability of Identified Change Points with Varying Initial Parameters for Manganese Production

Figures 21 and 22 shows the probabilities of the identified change points for the Gold and PGMs production data. These graphs show minimal fluctuation as the initial parameters are manipulated. Figures 24 and 23 show the probabilities of the identified change points for the Manganese and Iron Ore production respectively. Both these graphs also show minimal fluctuation in probabilities as the initial parameters vary. The varying values of $p_0$ and $w_0$ did not result in the identification of new change points.

It can be concluded from the Robustness Analysis of the BCP results that the output of the model is not influenced greatly by the changing of the initial parameters $p_0$ and $w_0$.

## 9.2 The Dynamic Programming Algorithm

The robustness analysis of DP was performed in order to determine the impact that varying values of the parameter $h$ had on the results of DP. [Bai and Perron, 2003] describe $h$ as "the minimal segment size, given as a fraction of the sample size or as an integer of the minimum observations in a segment". [Bai and Perron, 2003] recommend using $h = 15$. The South African manufacturing production was used for this robustness analysis.

Table 22: Robustness of Change Points Identified by the Dynamic Programming Algorithm

| $h$ | Break Point Location | | | |
|---|---|---|---|---|
| 5 | 41 | 100 | 131 | 148 |
| 10 | 41 | 100 | 131 | 148 |
| 15 | 41 | 100 | 131 | 148 |
| 20 | 41 | 100 | 131 | 163 |
| 30 | 41 | 100 | 131 | 163 |
| 40 | 41 | 91 | 131 | 172 |
| 50 | 76 | | | |

Table24 shows that as h increases, the accuracy of the identified change points deteriorates. This makes sense, as $h$ increasing causes the model to ignore change points with segments with less observations than the value of $h$. The DP Algorithm is therefore not robust to variation in the initial parameter $h$.

## 9.3 Non-Parametric Multiple Change-Point Analysis

The main parameter in the package $ecp$ is the value of $\alpha$. [James and Matteson, 2014] describe $\alpha$ as "the moment index used for determining the distance between and within segments". [James and Matteson, 2014] recommend using values of $\alpha$ between (0,2]. In order to show the impact of varying values of $\alpha$, a univariate data series with changes in mean and variance was used. The change points are at points 100, 200 and 300. The effects of varying $\alpha$ values are shown below.

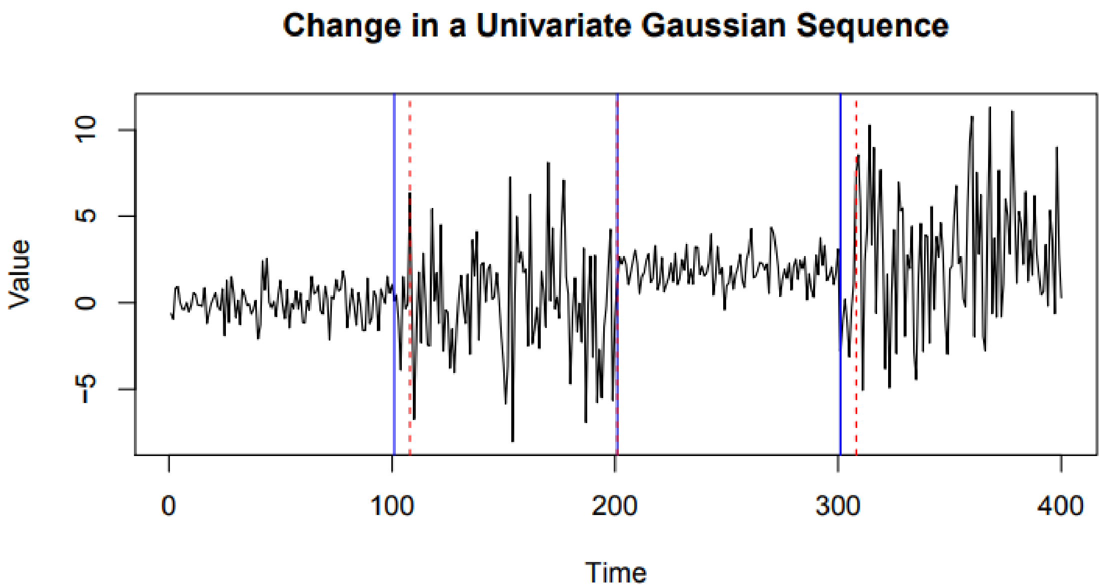



Figure 25: Change Points Identified with $\alpha = 1$ [James and Matteson, 2014]

In Figure 25 the solid blue vertical lines represent the true change points and the dotted red line represents the change points identified by the model. Figure 25 shows the results obtained with $\alpha = 1$. It is evident that the model identified all of the correct change points.

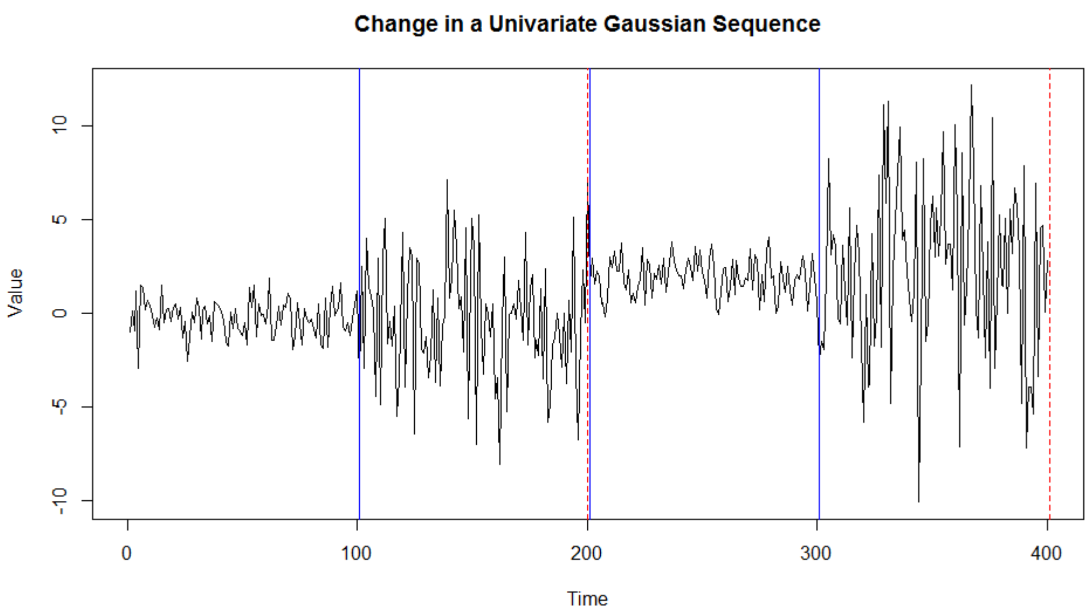



Figure 26: Change Points Identified with $\alpha = 2$ [James and Matteson, 2014]

In Figure 26 the results are shown for when $\alpha = 2$. It is evident from Figure 26 that when $\alpha = 2$, the model is only able to pick up changes in mean and not both mean and variance [James and Matteson, 2014].

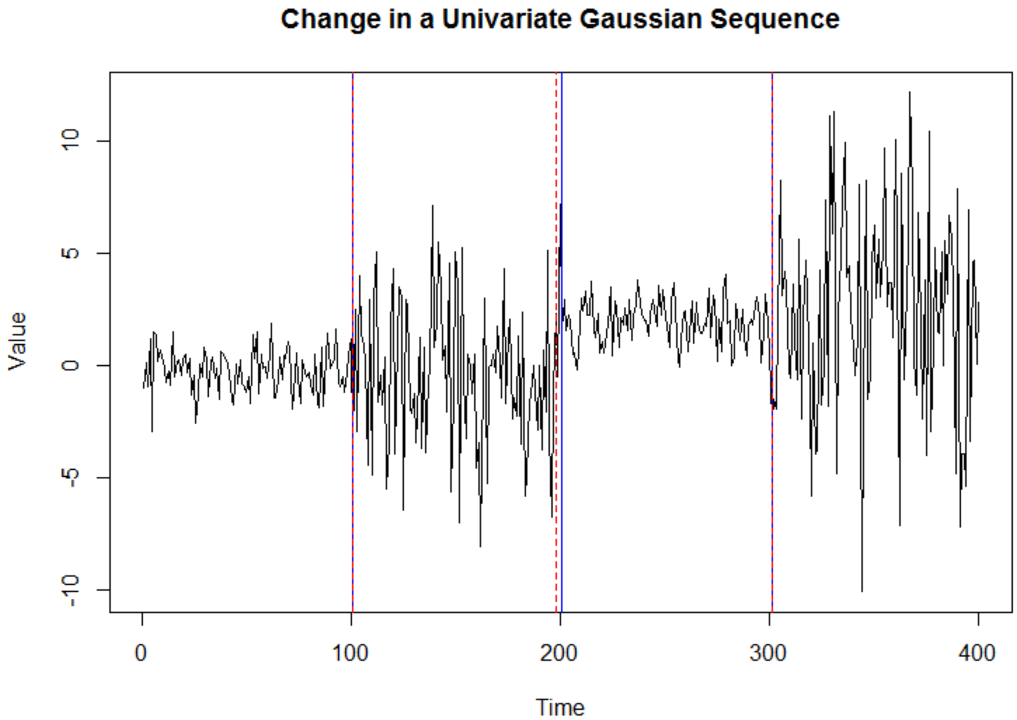



Figure 27: Change Points Identified with $\alpha = 0.5$ [James and Matteson, 2014]

Figure 27 shows the results for $\alpha = 0.5$. This value of $\mathtt{alpha}$ identifies all of the change points with greater precision than when $\alpha = 1$. Varying values of $\alpha$ between (0,2] were used, with the change points shown below.

Table 23: Robustness of Change Points Identified by MCP for Univariate Data

| $\alpha$ | Break Point Location | | | | |
|---|---|---|---|---|---|
| 0.2 | 1 | 100 | 198 | 301 | 401 |
| 0.4 | 1 | 101 | 198 | 301 | 401 |
| 0.6 | 1 | 101 | 198 | 301 | 401 |
| 0.8 | 1 | 101 | 200 | 301 | 401 |
| 1.0 | 1 | 101 | 200 | 301 | 401 |
| 1.2 | 1 | 101 | 200 | 301 | 401 |
| 1.4 | 1 | | 200 | 327 | 401 |
| 1.6 | 1 | | 200 | 327 | 401 |
| 1.8 | 1 | | 200 | 327 | 401 |
| 2.0 | 1 | | 200 | | 401 |

Table 23 shows that the model is most accurate with $\alpha = 0.8, 1.0, 1.2$ with values of $\alpha$ tending to 2.0 resulting in an inability for the model to detect changes in variation. Values of $\alpha$ tending to 0.0 did not lose much accuracy.

When using the production volumes of Manganese and Iron ore for the multivariate analysis, the approach showed no variation due to changing $\alpha$ values. This is due to the approach identifying changes due to variation in the mean and not variation. These results are shown below.

Table 24: Robustness of Change Points Identified by MCP for Multivariate Data

| $\alpha$ | Break Point Location | | |
|---|---|---|---|
| 0.2 | 51 | 100 | 136 |
| 0.4 | 51 | 100 | 136 |
| 0.6 | 51 | 100 | 136 |
| 0.8 | 51 | 100 | 136 |
| 1.0 | 51 | 100 | 136 |
| 1.2 | 51 | 100 | 136 |
| 1.4 | 51 | 100 | 136 |
| 1.6 | 51 | 100 | 136 |
| 1.8 | 51 | 100 | 136 |
| 2.0 | 51 | 100 | 136 |

# 10 Proposed Implementation

The information gained in this project can be of use to stakeholders in the mining sector as it provides an additional empirical tool to get more insight into the nuances of the production series. This, combined with the knowledge of events and factors that may have the greatest impact on the production volumes of the identified metals will allow stakeholders to focus on intervention efforts in future to mitigate undesirable outcomes. The information provided by the model will also help with activity planning and future investments. An example would be the decision to open a new shaft or managing labour related issues in the sector. The stakeholders would have an idea of the future performance of the metal in question as well as the long-term trends, which would allow the stakeholders to make an informed decision on whether to open a new mine shaft.

# 11 Conclusion

Platinum, Gold, Iron ore and Manganese were identified as the four metals with the largest sales and employee numbers in South Africa and were thus selected as the subject of the project. The factors that influence the supply and demand of the identified metals were also briefly investigated. This was done in order to improve the understanding of the mechanisms that affect the performance of each metal.

BCP [Barry and Hartigan, 1993] and DP [Bai and Perron, 2003] algorithms were selected to identify the change points in the production volumes and sales data of the metals. The results of each method were then compared and it was found that BCP provided the more informative results because it is enabled to provide the probability of occurrence associated with each identified change point.

The results from the BCP analysis were then investigated in order to link possible causative events to the identified change points. These events were discussed in detail in the results section of this report.

# 12 Recommendations

Based on the learnings from this thesis, for future projects the main recommendation would be:
obtaining sales data in tonnes , instead of the Rand value of sales, for the metals chosen. This would allow for meaningful change points to be identified in the sales data as the change point would not be influenced by fluctuations in the exchange rate and commodity prices. The analysis could also be expanded to include other metals and/or commodities.

# References


[Adams and MacKay, 2007] Adams, R. P. and MacKay, D. J. (2007). Bayesian online changepoint detection. *arXiv preprint arXiv:0710.3742*.

[Antoshin, Berg and Souto, 2008] Antoshin, S., Berg, A., Souto, M. (2008). Testing for Structural Breaks in Small Samples. *IMF Working Paper*, 18(1):1–22.

[Bai and Perron, 2003] Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1):1–22.

[Barry and Hartigan, 1993] Barry, D. and Hartigan, J. A. (1993). A bayesian analysis for change point problems. *Journal of the American Statistical Association*, 88(421):309–319.

[Booyens, 2013] . SA seventh-largest iron-ore producer. [online] Mining Weekly. Retrieved from: http://www.miningweekly.com/article/sa-seventh-largest-iron-ore-producer-2013-07-26 [Accessed 23 Sep. 2017].

[Brand South Africa, 2012] . Mining and minerals in South Africa. [online] Retrieved from: https://www.brandsouthafrica.com/investments-immigration/business/economy/mining-and-minerals-in-south-africa [Accessed 23 Sep. 2017].

[Chamber of Mines South Africa, 2010] Chamber of Mines South Africa. *Facts & Figures 2010* (pp 22). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 01 Mar. 2017].

[Chamber of Mines South Africa, 2010] Chamber of Mines South Africa. *Facts & Figures 2010* (pp 32). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 01 Mar. 2017].

[Chamber of Mines South Africa, 2014, pp 5] Chamber of Mines South Africa. Table 1: Commodity Summary. In *Facts & Figures 2013/2014* (pp 5). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 10 Feb. 2017].

[Chamber of Mines South Africa, 2014, pp 8] Chamber of Mines South Africa. *Facts & Figures 2013/2014* (pp 8). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 10 Feb. 2017].

[Chamber of Mines South Africa, 2014, pp 12] Chamber of Mines South Africa. *The Future of the South African Mining Industry* (pp 12). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/presentations/send/7-2015/165-future-sa-mining-industry-oct2015 [Accessed 29 Apr. 2017].

[Chamber of Mines South Africa, 2014, pp 14] Chamber of Mines South Africa. Table 7: Number of Employees & Earnings, 2013. In *Facts & Figures 2013/2014* (pp 14). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 10 Feb. 2017].

[Chamber of Mines South Africa, 2014, pp 18] Chamber of Mines South Africa. Table 11: SA iron ore production & sales. In *Facts & Figures 2013/2014* (pp 18). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 10 Feb. 2017].

[Chamber of Mines South Africa, 2014, pp 19] Chamber of Mines South Africa. Figure 13: Employee & earnings in SA iron ore mines. In *Facts & Figures 2013/2014* (pp 19). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 10 Feb. 2017].

[Chamber of Mines South Africa, 2014, pp 19] Chamber of Mines South Africa. Table 12: SA Manganese production & sales. In *Facts & Figures 2013/2014* (pp 19). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 10 Feb. 2017].

[Chamber of Mines South Africa, 2014, pp 20] Chamber of Mines South Africa. Figure 14: Employment & earnings - SA manganese mines. In *Facts & Figures 2013/2014* (pp 20). Retrieved from http://www.chamberofmines.org.za/industry-news/publications/facts-and-figures [Accessed 10 Feb. 2017].

[Chamber of Mines South Africa, 2015, pp 20] Chamber of Mines South Africa. *Mining in South Africa: The Challenges and the Opportunities* (pp 20). Retrieved from http://http://www.chamberofmines.org.za/industry-news/publications/presentations/send/7-2015/269-mining-in-south-africa-the-challenges-and-opportunities [Accessed 29 Apr. 2017].

[Chamber of Mines South Africa, 2015, pp 24] Chamberofmines.org.za. (2017). *The Future of the South African Mining Industry* (pp 24) [online] Retrieved from http://www.chamberofmines.org.za/industry-news/publications/presentations/send/7-2015/165-future-sa-mining-industry-oct2015 [Accessed 20 Apr. 2017].

[Chamber of Mines South Africa, 2015, pp 29] Chamberofmines.org.za. (2017) Table 20: SA gold, ore milled & grade/ton. In. *The Future of the South African Mining Industry* (pp 29) [online] Retrieved from http://www.chamberofmines.org.za/industry-news/publications/presentations/send/7-2015/165-future-sa-mining-industry-oct2015 [Accessed 20 Apr. 2017].

[Chamber of Mines South Africa, 2016] Chamberofmines.org.za. (2017) . *Mine SA 2016 Facts and Figures Pocketbook*

[Chamber of Mines South Africa, 2017] Chamberofmines.org.za. (2017). *Gold-Chamber of Mines South Africa* [online] Retrieved from http://www.chamberofmines.org.za/sa-mining/gold [Accessed 14 Apr. 2017].

[CNN, 2007] *Miners on strike over death toll* [online] Retrieved from: http://edition.cnn.com/2007/WORLD/africa/12/04/africa.mining/ [Accessed 16 Sep. 2017].

[Council for Geoscience, 2017] Geoscience.org.za (2017). *Council for Geoscience.* [online]. Retrieved from http://www.geoscience.org.za/images/Maps/selectedactivemines.gif [Accessed 14 Apr. 2017].

[Countries that import Manganese ore, 2015] The Observatory of Economic Complexity. (2017). *Countries that import Manganese ore (2015)* [online] Retrieved from: http://atlas.media.mit.edu/en/visualize/tree_map/hs92/import/show/all/2602/2015/ [Accessed 22 Apr. 2017].

[Earle and Amey, 2017] Earle B. Amey, H. (2017). *USGS Minerals Information: Gold.* [online] Minerals.usgs.gov. Retrieved from https://minerals.usgs.gov/minerals/pubs/commodity/gold/ [Accessed 14 Apr. 2017].

[Els, 2012] Els, F (2012) *South African strikes spread to iron ore — MINING.com.* [online] Retrieved from: http://www.mining.com/south-africa-strike-spreads-to-iron-ore-mine-top-news-reuters-28818/ [Accessed 17 Sep. 2017].

[Erdman and Emerson, 2007] Erdman, C. and Emerson, J. W. (2007). bcp: An r package for performing a bayesian analysis of change point problems. *Journal of Statistical Software*, 23(3).

[Fin24, 2017] *Iron ore succumbs to bear market and may extend slump*[online] Retrieved from: http://www.fin24.com/Markets/Commodities/iron-ore-succumbs-to-bear-market-and-may-extend-slump-20170925 [Accessed 26 Sep. 2017].

[GFMS Platinum Group Metals Survey, 2016, pp 7] Thomson Reueters (2016). *GFMS Platinum Group Metals Survey 2016.* (pp 7) [online] Retrieved from https://pinnacleresources.files.wordpress.com/2016/02/gfms-platinum-group-metals-survey-2016.pdf [Accessed 14 Apr. 2017].

[GFMS Platinum Group Metals Survey, 2016, pp 9] Thomson Reueters (2016). *GFMS Platinum Group Metals Survey 2016.* (pp 9) [online] Retrieved from https://pinnacleresources.files.wordpress.com/2016/02/gfms-platinum-group-metals-survey-2016.pdf [Accessed 14 Apr. 2017].

[GFMS Platinum Group Metals Survey, 2016, pp 29] Thomson Reueters (2016). *GFMS Platinum Group Metals Survey 2016.* (pp 29) [online] Retrieved from https://pinnacleresources.files.wordpress.com/2016/02/gfms-platinum-group-metals-survey-2016.pdf [Accessed 14 Apr. 2017].

[GFMS Platinum Group Metals Survey, 2016, pp 35] Thomson Reueters (2016). *GFMS Platinum Group Metals Survey 2016.* (pp 35) [online] Retrieved from https://pinnacleresources.files.wordpress.com/2016/02/gfms-platinum-group-metals-survey-2016.pdf [Accessed 14 Apr. 2017].

[Golden Dragon Capital, 2017] Golden Dragon Capital. (2017). *World Gold Reserves- Golden Dragon Capital.* [online]. Retrieved from http://www.goldendragoncapital.com/gold/world-gold-reserves/ [Accessed 14 Apr. 2017].

[James and Matteson, 2014] James, N.A. and Matteson, D.S. (2014). bcp: An r Package for Nonparametric Multiple Change Point Analysis of Multivariate Data *Journal of Statistical Software*, 62(7).

[Johnson, 2017] Johnson Matthey . (2017). *Precious Metals Management.* [online]. Retrieved from http://www.platinum.matthey.com/services/market-research/market-data-tables [Accessed 16 Apr. 2017].

[Lee, 1989, pp 36] Lee P.M. (1989) *Bayesian Statistics: An Introduction*, 1: 36

[Leonghuat.com, 2017] *Effects of Mn, P, S, Si & V on the Mechanical Properties of Steel.* [online] Retrieved from: https://www.leonghuat.com/articles/elements.htm [Accessed 26 Apr. 2017].

[Matteson and James, 2014] Matteson, DS. and James, NA., (2014) A Nonparametric Approach for Multiple Change Point Analysis of Multivariate Data. *Journal of the American Statistical Association*, 109(505), 334345.

[Naylor and Finger, 1967] Naylor, T.and Finger,J.M.,(1967). Verification of Computer Simulation Models. *Management Science*, 2:B92–B101.

[Nersa.org.za, 2017] *Historic Eskom Selling Price.* [online] Retrieved from: http://www.nersa.org.za# [Accessed 26 Apr. 2017].

[Olshen, Venkatraman, Lucit and Wigler, 2004] Olshen, A. B., Venkatraman, E. S., Lucito, R., and Wigler, M. (2004). Circular binary segmentation for the analysis of array-based dna copy number data. *Biostatistics*, 5(4):557–572.

[Perry, 2017] Gold Buyers and Producers. (2017). *CARPE DIEM: World's Largest Gold Buyers and Producers.* [online]. Retrieved from http://mjperry.blogspot.co.za/2008/09/map-worlds-largest-gold-buyers-and.html [Accessed 14 Apr. 2017].

[Plazak, 2013] Commons.wikimedia.org. (2013).*Top 5 Gold Producers.png-Wikimedia Commons.* Retrieved from http://en.wikipedia.org/wiki/List_of_countries_by_gold_production [Accessed 15 Apr. 2017].

[Renganathan, 2016] Renganathan, V. (2016). Overview of frequentist and bayesian approach to survival analysis. *Applied Medical Informatics* , 38(1):25.

[Rizzo and Szèkely, 2010] Rizzo, M. L., and Szèkely, G. J. (2010), Disco Analysis: A Nonparametric Extension of Analysis of Variance *The Annals of Applied Statistics*, 4(2), 10341055.

[Sen and Srivastava, 1975] Sen, A. and Srivastava, M. S. (1975). On tests for detecting change in mean. *The Annals of Statistics*, 3(1):98–108.

[Statistics South Africa] [Statistics South Africa *EEA Compendium Tables 2017*. Retrieved from: http://www.statssa.gov.za/?page_id=1854&PPN=Report-04-05-20

[Statistics South Africa, 2014, pp 39] Statistics South Africa. Figure 3.3.1: Gold production and volumes sold, 2002-2011. In *Environmental Accounts Compendium 2014* (pp 39). Retrieved from http://www.statssa.gov.za/publications/Report-04-05-20/Report-04-05-202014.pdf [Accessed 14 Apr. 2017].

[Statistics South Africa, 2014, pp 44] Statistics South Africa. Figure 3.4.1: PGMs production and volumes sold, 2002-2011 In *Environmental Accounts Compendium 2014* (pp 44). Retrieved from http://www.statssa.gov.za/publications/Report-04-05-20/Report-04-05-202014.pdf [Accessed 14 Apr. 2017].

[Statistics South Africa, 2014, pp 62] Statistics South Africa. Figure 4.1.5a: Production/extraction of gold and employment in the gold mining industry, 1994-2011. In *Environmental Accounts Compendium 2014* (pp 62). Retrieved from http://www.statssa.gov.za/publications/Report-04-05-20/Report-04-05-202014.pdf [Accessed 14 Apr. 2017].

[Statistics South Africa, 2014, pp 65] Statistics South Africa. Figure 4.1.6a: Production/extraction of PGMs and employment in the PGMs mining industry, 1994-2011 In *Environmental Accounts Compendium 2014* (pp 65). Retrieved from http://www.statssa.gov.za/publications/Report-04-05-20/Report-04-05-202014.pdf [Accessed 14 Apr. 2017].

[Statistics South Africa, 2017, pp9] Statistics South Africa. Table 11: Mineral sales at current prices by mineral group. In *Mining: Production and sales (Preliminary)*. (pp 9) Retrieved from: http://www.statssa.gov.za/?page_id=1854&PPN=P2041&SCH=6745

[The World Factbook, 2017] The World Factbook *Field Listing: Imports- Commodities* Central Intelligence Agency. Retrieved from: https://www.cia.gov/library/publications/the-world-factbook/fields/2058.html [Accessed 22 Apr. 2017].

References

[Topf, 2017] MINING.com. *Platinum and palladium markets to go into deficit in 2016: GFMS — MINING.com.* [online] Retrieved from: http://www.mining.com/platinum-palladium-markets-go-deficit-2016-gfms/ [Accessed 16 Sep. 2017].

[Tradingeconomics.com, 2017] *South Africa Labour Costs — 1970-2017 — Data — Chart — Calendar — Forecast.* [online] Retrieved from: http://www.tradingeconomics.com/south-africa/labour-costs [Accessed 26 Apr. 2017].

[Tradingeconomics.com, 2017] *South Africa Labour Costs — 1970-2017 — Data — Chart — Calendar — Forecast.* [online] Retrieved from: http://www.tradingeconomics.com/south-africa/exports [Accessed 29 Apr. 2017].

[Upton and Cook, 2014] Upton, G. and Cook, I., (2014). *A dictionary of statistics 3e.* Oxford university press.

[U.S. Geological Survey, 2016, pp 202] U.S. Geological Survey. (2016). *Mineral commodity summaries 2016: U.S. Geological Survey* (pp 202).Retrieved from: http://dx.doi.org/10.3133/70140094 [Accessed 22 Apr. 2017].

[World Gold Council, 2016, pp 19] World Gold Council. Table 2: Gold demand (tonnes). In *Gold Demand Trends First quarter 2016* (pp 19). Retrieved from http://www.gold.org/supply-and-demand/gold-demand-trends/back-issues/gold-demand-trends-full-year-2016 [Accessed 15 Apr. 2017].

[World Gold Council, 2016, pp 23] World Gold Council. Table 8: Consumer demand in selected countries (tonnes) . In *Gold Demand Trends First quarter 2016* (pp 23). Retrieved from http://www.gold.org/supply-and-demand/gold-demand-trends/back-issues/gold-demand-trends-full-year-2016 [Accessed 15 Apr. 2017].

# Appendix A: Industry Sponsorship Form

**Department of Industrial & Systems Engineering**
**Final Year Projects**
**Identification and Responsibility of Project Sponsors**

All Final Year Projects are published by the University of Pretoria on *UPSpace* and thus freely available on the Internet. These publications portray the quality of education at the University and have the potential of exposing sensitive company information. It is important that both students and company representatives or sponsors are aware of such implications.

**Key responsibilities of Project Sponsors:**

A project sponsor is the key contact person within the company. This person should thus be able to provide the best guidance to the student on the project. The sponsor is also very likely to gain from the success of the project. The project sponsor has the following important responsibilities:

1. Confirm his/her role as project sponsor, duly authorised by the company. Multiple sponsors can be appointed, but this is not advised. The duly completed form will considered as acceptance of sponsor role.
2. Review and approve the Project Proposal, ensuring that it clearly defines the problem to be investigated by the student and that the project aim, scope, deliverables and approach is acceptable from the company's perspective.
3. Review the Final Project Report (delivered during the second semester), ensuring that information is accurate and that the solution addresses the problems and/or design requirements of the defined project.
4. Acknowledges the intended publication of the Project Report on UP Space.
5. Ensures that any sensitive, confidential information or intellectual property of the company is not disclosed in the Final Project Report.

**Project Sponsor Details:**

| | |
|---|---|
| Company: | CSIR |
| Project Description: | Modelling behaviour of exports of industrial metals from South Africa |
| Student Name: | Michael Ingham |
| Student number: | 13033132 |
| Student Signature: | |
| Sponsor Name: | Prof. Sonali Das |
| Designation: | Principal Researcher (Statistics) |
| E-mail: | sdas@csir.co.za |
| Tel No: | 012 841 3713 |
| Cell No: | |
| Fax No: | |
| Sponsor Signature: | |
| Dated: | 21/February/2017 |