ASYMMETRIC PRICE TRANSMISSION: AN EMPIRICAL ANALYSIS OF THE RELATIONSHIP BETWEEN UG-2 CHROME ORE, CHARGE CHROME, NICKEL AND CHINESE DOMESTIC 304 STAINLESS STEEL COLD ROLLED COIL.

by

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DECLARATION OF ORIGINAL WORK

This page declares that the work produced is my own and was conducted whilst completing the degree of Masters of Commerce in Financial Markets whilst at Rhodes University. This thesis has not been submitted to other Universities, Technikons or Colleges for degree purposes.

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ABSTRACT

The goal of this study was to determine whether asymmetric price transmission (APT) exists between the prices of South African UG-2 Chrome ore, Charge Chrome, Nickel and Chinese Domestic 304 Stainless steel Cold Rolled Coil prices. Monthly time series data for the period January 2009 to July 2019 was analysed. The Non-Linear Autoregressive Distributive Lag (NARDL) model was applied to test for the presence of price asymmetry between the four variables. Firstly, it was observed that the four variables are cointegrated in the long-run. Secondly, no evidence of price asymmetry was found to be present within the Stainless steel supply chain. The reason for this is most likely due to the extremely close-knit and highly concentrated nature of this industry at each level within the supply chain. The industry can be very opaque to external observers even though the distribution of pricing information is very efficient for participants within the industry.

Keywords: Price transmission, Asymmetry, NARDL, Chrome ore, Ferrochrome, Stainless steel, Nickel, South Africa, China, Mining, Global trade

JEL Classification: L11, L72, N75, N77

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CHAPTER 1: INTRODUCTION

1.1. Context of the Research

Within the neo-classical framework, price flexibility is a critical ingredient which helps ensure the efficient allocation of resources and facilitates both vertical and horizontal market integration (Meyer and Cramon-Taubadel, 2004). As a consequence of prices being the primary mechanism interlinking various levels of the market, the speed and extent of their adjustments to shocks highlights not just the extent of market efficiency but also the actions and influence of key market participants in changing prices at the various levels in the market (Goodwin and Holt, 1999). According to economic theory, any exogenous supply- or demand-related price shock should cause symmetrical adjustments to the long-run market equilibrium, irrespective of whether the price shock was positive or negative (Simioni *et al*, 2013).

The two main explanations for asymmetric price transmission (APT) are the existence of adjustment costs and the presence of non-competitive markets (Ozertan *et al*, 2012). If APT exists, then, for example, either buyers (price decrease) or sellers (price increase) do not benefit from a given movement in prices to the same extent as they would under-price-symmetrical market conditions, where the price adjustment would be more rapid or of a greater magnitude (Capps and Sherwell, 2007). APT can broadly be classified according to three criteria. The first criterion aims to identify whether the magnitude or the speed of the price transmission is in fact asymmetric (Rajcaniova and Pokrivcak, 2013). The second criterion builds onto the economic theory by identifying whether the identified APT is positive or negative (Guerrero *et al*, 2016). Positive (negative) price asymmetry occurs in commodity markets when a downstream[1] price reacts more aggressively to upstream[2] price increases (decreases) than to price decreases (increases) (Guerrero *et al*, 2016). The third criterion used for classifying APT has to do with whether it impacts spatial or vertical price transmission. Price linkages along a given supply chain are referred to as vertical price transmission, whereas price linkages at the same level in the supply chain for a particular commodity, but in two different markets, are referred to as spatial price transmission.

[1] Downstream prices are paid at the retail level by consumers.
[2] Upstream prices are directly related to the cost of production and are paid by producers and not consumers.

Authors such as Abdulai (2002), Chen *et al* (2005), Saghaian *et al* (2018), Abdelradi and Serra (2015), McLaren (2015) and Qin *et al* (2016) have tested for APT in various global commodity markets. There is, however, an absence of studies regarding possible APT in the global Stainless steel industry. Determining whether or not APT is present in the global Stainless steel industry is of particular importance for South Africa, given China's dominant role in global Stainless steel and Ferrochrome production and South Africa's unique ability to meet China's resultant large demand for Chrome ore.

Chromium is an industrial metal that is primarily used to increase the corrosion resistance and strength of Stainless steel (International Stainless steel Forum, 2018). South Africa (72%) and Zimbabwe (12%) hold approximately 84% of the world's economically viable known Chrome ore reserves (KPMG, 2018). The South African reserves are found in the Bushveld igneous complex, which is the largest layered intrusion in the world, hosting more than half of the world's Platinum group metals (PGMs) as well as other associated minerals such as vanadium and, more importantly for this study, Chromium (Chamber of Mines, 2016). Currently South Africa is responsible for approximately half of global Chrome ore production (Tharisa Minerals, 2017). Chrome ore is extracted at both dedicated Chrome ore mines as well as being a by-product of Platinum group metal (PGM) mining (Dungwa, 2018).

South Africa produced approximately 15.1 million metric tons of Chrome ore in 2016. Approximately half of the mined ore was consumed locally in the production of Ferrochrome and the balance was exported, predominantly as unrefined ore to China (Tharisa Minerals, 2017).

UG-2 Chrome ore is extracted as a by-product during Platinum production and has become increasingly important in volume terms in recent years.

PGMs in South Africa are found in what are known as the Merensky reef and UG-2 reef. Increased focus on mining the UG-2 reef in recent times is the result of the depletion of the Merensky reef. The UG-2 reef contains low grade Chrome ore, which had historically been stockpiled as waste material by Platinum producers. Increased smelting capacity in China and ever increasing Platinum mining costs have seen UG-2 Chrome ore become an increasingly important commodity for UG-2 miners (Smith, 2015). In 2018 UG-2 Chrome ore made up 30% to 100% of free cash flow for PGM producers (Dungwa, 2018). However, the increased abundance of UG-2 Chrome ore has distorted the traditional global Chrome ore market, as UG-2 producers, for whom Chrome ore is a by-product of their PGM mining, have been able to gain a cost advantage over traditional Chrome producers (Smith, 2015).

Although total South African Chrome ore export statistics are readily available, the percentage contribution of UG-2 production to total exports is hard to determine as this information is closely held by key market players. Nonetheless, it is estimated that in 2017 UG-2 made up approximately 31% of South African production and 17% of global Chrome ore production (Constant, 2018). Due to its lower cost of production and the ability for it to be consumed by Chinese smelters, UG-2 Chrome ore has been adopted as the primary pricing benchmark for all grades of Chrome ore globally. The various other grades of Chrome ore trade at either a premium or discount to UG-2 Chrome ore.

China's Stainless steel production has grown from 13% of total global production in 2005 to 54% in 2016 (International Stainless steel Forum, 2017). As a result, China is the single largest Stainless steel producer in the world with a total production of 27 million tonnes at the end 2017. China's dominant position in global Stainless steel production makes it the number one consumer of Chrome ore and Ferrochrome annually. 304 grade Stainless steel[3], which has a standard chrome content of between 18-20%, was the most widely produced grade in 2016, and accounted for 47.2% of total Chinese Stainless steel production (International Stainless steel Forum, 2017).

China does not have its own Chrome ore resources, whilst South Africa sends approximately 90% of its Chrome ore exports to China. These exports made up 73% of Chinese Chrome ore imports at the end of 2017 (Creamer, 2017). Total global Chrome ore trade amounted to 15.9 million tons in 2017 with Chinese Chrome ore imports accounting for 13.9 million tons (Constant, 2018).

Ferrochrome (FeCr) is a type of ferroalloy made by alloying iron and chromium, with a general chromium content of 50%-70%. Ferrochrome is produced by reducing Chrome ore in an electric

[3] 304 grade Stainless steel is widely considered as the most common austenitic Stainless steel produced globally. It has a high nickel content of between 8% and 10.5% and a typical Chromium content of 18% to 20%. Other major alloying elements include carbon, manganese and silicon, with the remainder of the chemical composition primarily being made up of iron. The high percentage of Chromium and Nickel make 304 Stainless steel highly corrosion resistant.

arc furnace. Today most of the world’s Ferrochrome is produced by China and South Africa, with the balance coming from various sources such as India, Russia and Kazakhstan. South Africa’s Ferrochrome smelting industry is the second largest in the world and is responsible for 33% of global Ferrochrome production, with China being the largest at 43% (Creamer, 2017).

Stainless steel production is currently the largest consumer of Ferrochrome globally. Approximately 77% of global Ferrochrome production is used in the production of Stainless steel (Constant, 2018).

Charge Chrome is a type of Ferrochrome that has a typical specification of 50-60% chrome and 6-8% carbon (Westbrook Resources, 2018). High Carbon Ferrochrome has a typical specification of 60-70% chrome and 6-8.5% carbon (Westbrook Resources, 2018).

In 2017 Charge Chrome and High Carbon Ferrochrome accounted for 92.44% of global Ferrochrome production (Constant, 2018). At the end of 2016 South Africa accounted for 74.9% of Chinese Charge Chrome and High Carbon Ferrochrome imports (Creamer, 2017). Whilst at the end of 2017, China was the largest Ferrochrome producer globally with 5.47 million tons, followed by South Africa with 3.77 million tons (Constant, 2018).

Nickel is the crucial alloying element in the 300 series grades of Stainless steel. The use of Nickel results in the creation of an “austenitic” structure that provides these grades their strength, toughness, ductility and it also makes the Stainless steel non-magnetic (Stainless steel Information Center, 2019).

The London Metal Exchange (LME) is a futures exchange with the world's biggest market in futures and options contracts on base and other metals. The LME offers monthly contracts with expiry dates of up to 123 months from trade date, weekly contracts to six months and daily contracts up to three months. It offers worldwide reference pricing, hedging and the option to settle contracts through physical delivery. Nickel was added to the LME in 1979 (Fig, 2015).

Given the undeniable dependence of China on the South African Chrome industry, coupled with the reliance of South African exporters on imports by the Chinese Charge Chrome and Stainless steel industries, one would expect that potentially price symmetry (transmission efficiency) could be observed. Under these market conditions one could assume, for example, that an increase in

304 Stainless steel prices would cause an immediate increase in demand (and price) for Nickel, Charge Chrome and UG-2 Chrome ore. However, given China's dominant role as a buyer, this study will examine whether increases in the 304 Stainless steel prices are in fact transmitted to Charge Chrome, UG-2 Chrome ore and Nickel prices as rapidly as price decreases i.e. whether the market operates in a situation of APT.

1.2. Problem Statement

The abovementioned points indicate the need for further research to determine how responsive UG-2 Chrome ore, Charge Chrome and Nickel prices are to increases (decreases) in the 304 Stainless steel price, as well as *vice versa*. The establishment of whether or not price asymmetry is present in the 304 Stainless steel supply chain will provide South African Chrome industry participants and policy makers with a deeper understanding of the price transmission mechanisms operating within this industry. A better understanding of these mechanisms could potentially allow South African policy makers and producers to create a structure in which South Africa is able to fully benefit from its unique natural resource endowment and resultant dominance as a supplier of Chrome ore, without being at the mercy of China's dominant Charge Chrome and Stainless steel production capacity and consequent purchasing power.

1.3. Goals of the Thesis

The goal of this research is to investigate whether or not APT exists between the prices of South African UG-2 Chrome ore, Charge Chrome, Nickel, and Chinese Domestic 304 Stainless steel Cold Rolled Coil prices.

If it is found that the relationship between 304 Stainless steel, Nickel, Charge Chrome and UG-2 Chrome ore prices is symmetrical, this would emphasise the importance for South African UG-2 Chrome ore and Charge Chrome producers to leverage China's dependence on South African exports to help maximise the prices they are able to achieve in order to sustain a healthy South African Chrome industry. If it is found that increases in 304 Stainless steel prices are in fact not transmitted to UG-2 Chrome ore, Charge Chrome and Nickel prices as rapidly as price decreases i.e. the market operates in a situation of APT, South African UG-2 and Charge Chrome producers will need to find alternative ways to stop China from applying continued pressure on South African Chrome ore and Charge Chrome prices.

1.4. Methods, Procedures and Techniques

The principal method of research utilised is quantitative analysis and the paradigm employed is positivist. Time series analysis is employed to explore the historical relationship between UG-2 Chrome ore, Charge Chrome, Nickel and Chinese Domestic 304 Stainless steel Cold Rolled Coil prices. To determine if asymmetric price transmission is present, monthly pricing data for the period January 2009 to July 2019 was sourced from Metalbulletin[4]. Metalbulletin is considered one of the primary sources for global steel, non-ferrous and scrap metal pricing information. Pricing data for UG-2 Chrome ore is only available from January 2009, but the period chosen is still adequate in terms of the number of data points and includes periods of both rising and falling prices. Monthly frequency is selected because it closely matches the time required for market participants to carry out transactions. This ensures that the economic dynamics underlying the relationships between the variables are adequately captured, which is a critical requirement in testing for price asymmetry (Blank and Schmiesing, 1990). Furthermore, this study makes use of both descriptive and inferential statistics in its data analysis.

The Non-Linear Autoregressive Distributed Lag (NARDL) model is applied to test for both cointegration as well as long- and short-run price asymmetry within the 304 Stainless steel supply chain. The NARDL is preceded by unit root and Granger causality testing. A number of residual and stability diagnostic tests are also conducted.

1.5. Organisation of the Study

The study is organised as follows: Chapter 2 discusses the theory of asymmetric price transmission and provides an overview of the existing literature and empirical findings relating to asymmetric price transmission both globally and in South Africa. In Chapter 3, the data used in the empirical section of the study is explained in detail, along with the methods and procedures used. The empirical results and findings are presented in Chapter 4. Chapter 5 provides a conclusion to the study and puts forward possible recommendations for future research.

[4] www.metalbulletin.com

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This chapter firstly provides a brief discussion of the theory applicable to asymmetric price transmission, as an understanding of this theory is crucial when trying to determine how market structure affects price adjustments in the 304 Stainless steel supply chain. Secondly, this chapter provides a succinct review of the existing empirical findings on APT, both internationally and in South Africa. Section 2.2 discusses the theory of asymmetric price transmission. Section 2.3 provides detail on the Stainless steel supply chain. The existing empirical findings both globally and in South Africa are put forward in section 2.4. Section 2.5 concludes the chapter.

2.2. Theory of Asymmetric Price Transmission

This section will discuss the theory of asymmetric price transmission by firstly broadly focusing on the price transmission process. After which the types of asymmetry and the causes of asymmetric price transmission are put forward.

2.2.1 Price Transmission

Commodity market integration can be classified according to three avenues – globally, regionally and nationally. Integration happens vertically within these avenues, or horizontally across them. Vertical integration occurs between domestic, regional and international commodity markets, whilst horizontal integration occurs across domestic market segments (Jena, 2016).

Price transmission has been widely studied by various authors and can simplistically be explained as the impact of a change in one particular price on another price (Meyer and Cramon-Taubadel, 2004). Price transmission is typically quantified in terms of elasticity i.e. a percentage change in price in a particular market as a result of a one percent change of a price in another market. According to Meyer and Cramon-Taubadel (2004:1) "price theory plays a key role in neo-classical economics". Within the neo-classical framework, price flexibility is a critical ingredient which helps ensure the efficient allocation of resources and facilitates both vertical and horizontal market integration (Meyer and Cramon-Taubadel, 2004). As a consequence of pricing being the primary mechanism interlinking various levels of the market, the speed and extent of their adjustments to shocks highlights the actions and influence of key market participants at the various levels in the market (Goodwin and Holt, 1999).

Price transmission theory aims to explain how price changes at a given market level impact the prices at other market levels in the supply chain. The process of price transmission is extremely important to suppliers, intermediaries and consumers throughout a given supply chain. These three groups of participants stereotypically feel as though disproportionate fluctuations in prices between market levels are not fair and instead reflect "price gauging" (Schwartz and Willet, 1994). For example, a supplier might believe that it is not benefiting fairly from a given increase in retail prices, or alternatively consumers might feel that they are not befitting from a given decrease in manufacturing input costs.

It is important to note that various economic factors may have a significant impact on price transmission efficiency, including market concentration at each stage of the supply chain, as well as underlying supply and demand drivers. Price transmissions are typically classified as spatial, vertical and cross-commodity integration.

According to Fackler and Goodwin (2001), an economic market is the spatial area "within which the price of a good tends toward uniformity, allowance being made for transaction costs". Consequently, price transmission analysis is essential in order to determine how integrated are particular spatially separated markets.

Petzel and Monke (1979), who studied horizontal price transmission, argue that according to the law of one price the prices for different locations cannot shift independently given a fully integrated market system. Capps and Sherwell (2007) define vertical price transmission as the percentage change in the retail price of a given product due to a one percent change in the corresponding producer price. According to Vavra and Goodwin (2005) vertical price transmission can be defined by analysing the change generated at varying market levels given the speed, magnitude and direction of a particular change in price. Vertical price transmission therefore refers to the interaction between prices at various stages of a given supply chain and can be classified by type, speed and degree of price adjustment between those stages. Due to the intimate link between upstream and downstream prices, in a situation of perfect market efficiency there should be a state of price equilibrium between these two market levels.

Therefore, any external shocks to either upstream or downstream prices should cause both short and long-term adjustments back to a state of market equilibrium (Fackler and Goodwin, 2001). Lastly, cross-commodity price transmission refers to price transmission between two different commodities.

Typically, four key points are taken into consideration when studying price transmission, namely, lags, causality, market structure and asymmetry (Schwartz and Willet, 1994). A lag refers to the amount of time needed for a given price to change in response to a change in the price at another stage of the supply chain. Causality of price transmission refers to the direction of the price change i.e. are upstream prices affecting downstream prices or *vice versa*. Market structure explains how the type of product, market size and availability of information influence price transmission. Lastly, according to Meyer and Cramon-Taubadel (2004), asymmetry is when a price decrease (increase) at a given level in the supply chain has a greater impact on other prices in the supply chain than a price increase (decrease).

The foundation of causality is the idea of predictability. Therefore, causality is said to be present if past values of a particular market price improve the ability to forecast another given price (Granger, 1969). The direction of causality in a given supply chain may either flow upstream or downstream. The imperfect competition caused by certain market structures may adversely affect the price spread between different levels in a supply chain.

In a perfectly efficient market system consumers are able to buy a product at an affordable price and producers are able to get remunerative prices (Kanakaraj, 2010). The level of market efficiency is dependent on market conduct, market performance and the nature of the particular market's structure. Barriers to entry, firm size and buyer/seller concentration are the primary elements of market structure. These elements are what influence pricing and the nature of competition within a given market. Market conduct refers to the regulatory activities of governments, sales promotion strategies of producers, and the behaviour of all market agents when it comes to price determination. Consequently, this conduct shares a direct link with price formation. If prices are determined in a perfectly competitive manner then the market can be referred to as an efficient marketing system. Whereas, if market agents influence price determination through collusive behaviour, an inefficient marketing system will have been created as a result of imperfect price transmission (Antonova, 2013).

Market integration refers to the level of interconnectedness between primary, secondary and terminal markets. Markets are said to be integrated if the actions of agents in a particular market affect the actions of the agents in other markets. Petzel (1979) explains that integrated markets are markets in which the prices of differentiated products do not act independently of one another. According to Ravallion (1986), for any two regions the only difference between the price in the importing region and the price in the exporting region should be the transport cost between these two regions. Unintegrated markets may convey erroneous price information that may distort the marketing decision of producers and further facilitate inefficient product movement (Goodwin and Schroeder, 1991).

The economic results of market conduct and market structure ultimately represent market performance (Kanakaraj, 2010). Market performance reflects the level of investment, price level, profit margin and the reinvestment of profits. If a firm's sales price is exactly equal to its average cost (including "normal" profit) then the market is said to be efficient. As a result, it is possible to measure market efficiency by examining the level of prices and profit margins (Antonova, 2013).

Price transmission is classified as asymmetric when the adjustment of prices is not consistent with regards to characteristics that are internal or external to the system. Asymmetric price transmission has generated significant interest as; firstly, it does not align with the notion that downstream adjustments to upstream price shocks should be symmetric in terms of both timing and absolute size. Secondly, asymmetric price transmission has significant social and political consequences due to its impact on welfare distribution (Wlazlowski, 2001).

The possibility of an asymmetric reaction in price at a particular supply level to a change in price at another level in the supply chain is also important to consider. Price asymmetries are usually caused by structural rigidities or imperfect information but may also be influenced by the comparative market power of firms (Schwartz and Willet, 1994). Consequently, APT may result in some groups not benefitting as much from a given price change as would be the case if the market was operating in a state of price symmetry. APT may result in sellers not benefiting from an increase in prices at a particular supply level and buyers not benefiting from a decrease in prices.

According to economic theory, any exogenous supply or demand shock should cause symmetrical adjustments to the long-run market equilibrium, irrespective of whether the price shock was positive or negative (Simioni *et al*, 2013). Furthermore, microeconomic theory states that irrespective of the number of intermediaries between producers and consumers, an external demand/supply shock should not result in a different speed of adjustment to the long-run price equilibrium based on whether the price variation is positive or negative (Simioni *et al*, 2013).

However, in the case of APT either buyers (price decrease) or sellers (price increase) do not benefit from a given movement in prices to the same extent as they would under-price symmetrical market conditions, where the price adjustment was more rapid or of a greater magnitude (Capps and Sherwell, 2007).

The concept of price asymmetry does not have a unique meaning of describing the transmission mechanism between input and output prices, as that relationship can be examined in a variety of ways. For instance, it can refer to aspects of the relationship examined at a given point in time or over a long period of time. These are termed short-run (SR) and long-run (LR) classifications, respectively (Manera and Frey, 2005).

It is common for asymmetry and leads/lags to be analysed together. Lags and leads in price movements may occur because of structural rigidities in the supply chain, cumulative effects of prior price changes, and imperfect information. Studies such as Akaike (1970) and Darrat (1988), for example, focused on measuring lag length.

The two criteria used to measure market efficiency are price spread and market integration (Lele, 1971). Price spread can be described as the difference between the price paid by a consumer and the price received by a producer at a given point in time (Kanakaraj, 2010). Alternatively, the price spread can also be described as the difference between the production cost and the retail price of that product. This difference is typically comprised of the processing, assembling, storage, transportation, wholesale and retail charges. The narrower the price spread the more efficient the market is said to be. Furthermore, a narrow price spread allows both consumers and producers to benefit from reasonable profits and affordable prices, further contributing to market efficiency (Antonova, 2013). Frequently in literature, such as Schroeter and Azzam (1991) as well as Gardner (1975), the concept of "marketing margins" is discussed. The marketing margin is conceptually similar to the concept of price spreads and can be explained as the difference between the average price paid by consumers and payment received by producers for a given finished product or the equivalent quantity of raw materials (Beckman and Buzzell, 1995).

Unlike marketing margins, which are a static measurement of the relationship between different prices, price transmission tries to measure dynamic and/or static comparative price relationships. Price transmission can be defined as the statistical relationship between prices which can either be vertical or horizontal in nature (Antonova, 2013). In the context of the Stainless steel supply chain, vertical price transmission would be between the UG-2 chrome ore price, Ferrochrome, Nickel and the 304 Stainless steel prices. Whereas horizontal price transmission would be the relationship between South African produced Ferrochrome and Chinese produced Ferrochrome.

2.2.2 Types of Asymmetry

APT can broadly be classified according to three criteria. The first criterion aims to identify whether the magnitude or the speed of the price transmission is asymmetric (Rajcaniova and Pokrivcak, 2013). In order to better understand how the speed and magnitude of a change in price can be asymmetric it is easiest to use the relationship between input and output prices as reference. In the case of asymmetry, the direction in which a given input price changes will differently affect either the magnitude or the speed of a related change in output prices. For example, an increase in input prices may cause a greater increase in output prices when compared to the decreases in output prices that are the result of a decrease in input prices. The amount of time (speed) it takes for an output price to change can also vary depending on the direction of the input price change. This means that an increase in output prices might, for example, take only one period to adjust to an increase in input prices, but output prices may take more than one period to adjust to a decrease in input prices. Speed and magnitude are not mutually exclusive and so a combination of the two forms of asymmetry is possible (Peltzman, 2000).

A second criterion builds onto the economic theory by identifying whether the APT is positive or negative (Santiago *et al*, 2015). Positive price asymmetry occurs in commodity markets when downstream[5] prices react more aggressively to upstream[6] price increases than to upstream price

[5] Downstream prices are paid at the retail level by consumers.

decreases. Negative price asymmetry occurs in commodity markets when downstream prices react more aggressively to upstream price decreases than to price increases (Santiago *et al*, 2015).

The third criterion used for classifying APT has to do with whether it impacts vertical or spatial price transmission. Vertical APT deals with imperfect price transmission in a vertical supply chain (Vavra and Goodwin, 2005). An example of spatial APT is when a rise in one country's export price of a specific commodity causes a more significant reaction in another country's export price of that same commodity than an equivalent decrease. Therefore, the differences in price changes occur across geographical boundaries. It is important to note that both vertical and spatial APT can be classified by speed, magnitude and by whether it is positive or negative (Meyer and Cramon-Taubadel, 2004).

Under the short-run classification, measures of price asymmetry (symmetry) can be used to examine the simultaneous impact of input prices on output prices (contemporaneous effect asymmetry) as well as the impact of past values of a variable on its current value (distributed lag asymmetry). Specifically, contemporaneous price symmetry or asymmetry refers to whether a negative input price shock would have the same impact as a positive input price shock on the output price at a point in time (Manera and Frey, 2005).

Likewise, the long-run classification also looks at various aspects, such as: the reaction times of output prices following a shock to input prices (reaction time asymmetry); the cumulative impact of the negative or positive shocks to the input prices on output prices (cumulated impact asymmetry); and a number of other stylised equilibrium price adjustments centring on the level, momentum, path and regime styles. An analysis of the reaction time asymmetry measures how long a dependent variable takes to move back to the equilibrium level after a negative or positive shock has been experienced by the independent variable. Reaction time symmetry (asymmetry) means that the dependent variable would take the same (different) time period to readjust to equilibrium following either negative or positive shocks. If cumulated impact symmetry (asymmetry) is present, either the positive or negative shocks to input prices will produce the

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[6] Upstream prices are directly related to the cost of production and are paid by producers and not consumers. APT can largely explain the relationship between upstream and downstream prices.

same (different) impact on output prices when aggregated over a sufficient period of time (Manera and Frey, 2005).

Lastly, other specific types of price symmetry (asymmetry) classified under the long run category are still concerned about the convergence of the dependent variable to the equilibrium level but introduce additional aspects. These include the equilibrium adjustment path (symmetry or asymmetry), which refers to the proportion of the disturbance expected to be corrected within a given time period if the dependent variable is shifted away from the equilibrium level. The momentum price asymmetry (symmetry) looks at the speed of the adjustment, as well as whether the speed of the adjustment (momentum) depends on the direction (positive or negative) of the deviation. Finally, regime switching symmetry (asymmetry) studies all the above relationships within the specific constraints that different regimes place on one or more of the dependent variables. This implies that any specific aspect of the transmission mechanism between input and output prices will depend on the state of the world when the relationship is examined (Manera and Frey, 2005).

From the above, it is clear that the choice of time period (the short-run and long-run classification) can be an important cause of the different empirical findings of studies analysing the transmission mechanism between input and output prices. Even under each time period classification, the specific definition of price symmetry (asymmetry) as discussed above is another potential source of differences in results.

2.2.3 Causes of Asymmetric Price Transmission

The primary focus when explaining the causes of asymmetric price transmission below will be on vertical APT, which is the focus of this research. However, under section 2.2.3.4 explanations will also be provided for spatial APT. The two primary causes of APT that are studied most frequently are adjustment costs and non-competitive markets. However, it is important to note that other causes, such as inventory management, political intervention and asymmetric information are also very important possible causes that are important to consider.

2.2.3.1 Market Power

It is common for studies on APT to refer to non-competitive market structures as one of the main causes of APT. This is especially true in studies of agricultural supply chains (e.g. Miller and Hayenga, 2001), where consumers at the end of the supply chain and farmers at the beginning of the supply chain believe that imperfect competition in retailing and processing allows agents to exploit their market power. This exploitation is widely considered to cause positive APT. What this means is that margin-squeezing decreases in output prices (or increases in input prices) will be transmitted more completely and faster than the equivalent margin-stretching price increases (increases in output prices or decreases in input prices) (Karrenbrock, 1991). However, according to Bailey and Brorsen (1989) market power can also result in negative APT as a consequence of a firm believing that there is no competitor willing to match a price increase, but plenty who will be willing to match a price decrease. Authors such as Borenstein *et al* (1997) have indicated that market power can cause APT; with most predicting that market power will cause positive APT in a purely monopolised market context. But this assumption does not hold for the more commonly found oligopolistic market structures where both negative and positive APT is possible.

Attempts to study the link between market power and APT have to deal with two significant difficulties. Firstly, most studies of APT use time series data to analyse only one market or product (Meyer and Cramon-Taubadel, 2004). The problem with this is that unless significant changes in market power are known to have occurred during the sample period, this type of analysis does not provide a basis for comparing price transmission under conditions of less or more market power as there is no change in the "independent variable". The second significant difficulty that arises is that of finding a proxy for market power that considers more than just concentration and the number of firms. This proxy needs to be able to effectively capture firms actually exercising the market power that is seen as being the cause of APT (Meyer and Cramon-Taubadel, 2004).

2.2.3.2 Adjustment and Menu Costs

The second significant cause of APT is that of adjustment or menu costs. Adjustment costs are often referred to as menu costs when discussing price changes. Adjustment costs are a result of firms changing the prices and/or quantities of their outputs and/or inputs. APT is said to be present when costs are observed to be asymmetric in relation to decreases or increases in prices and/or quantities (Meyer and Cramon-Taubadel, 2004).

According to Ward (1982), the fact that perishable goods retailers might be hesitant to increase prices, given the risk that reduced sales might cause food wastage, would result in negative APT. Speaking more generally, firms are expected to increase prices in periods of high demand and to decrease production and increase inventory in periods of low demand, instead of decreasing output prices, thus resulting in positive APT. The first difference between adjustment (menu) costs and market power is that, to the degree that adjustments costs are material, any APT caused by changes in these costs will not cause a significant enough welfare transfer to justify policy intervention by governments. The second difference is that although both are able to create asymmetries in the speed of price transmission, it is only market power that is able to cause long-term asymmetries in the magnitude of adjustment (Meyer and Cramon-Taubadel, 2004).

2.2.3.3 Other Causes of APT

Price support in the form of pricing floors is one of the causes of APT that cannot be incorporated under adjustments costs and market power. This type of government intervention would cause APT if market participants such as retailers and wholesalers believe that a decrease in raw material prices will only be short-lived, given that the government is expected to increase prices in order to protect raw material producers (Kinnucan and Forker, 1987). Pricing floors are expected to cause asymmetry in terms of the speed of adjustment, and not magnitude, which is similar to adjustment costs.

Von Cramon-Taubadel (1998) studied APT in the context of the marketing margin model proposed by Gardener (1975). In this proposed model, it was assumed that the farm-retail price spread is dependent on shifts in both supply at the farm-level and demand at the retail-level. Under the assumption of constant returns to scale and perfect competition, retail-level demand shifts are observed to have a greater impact on the farm-retail price spread then farm-level supply shifts, thus leading to the conclusion that APT exists. But Von Cramon-Taubadel (1998) argues that APT will occur only if the distribution of the supply and/or demand shifts is skewed.

2.2.3.4 Explanations for Spatial APT

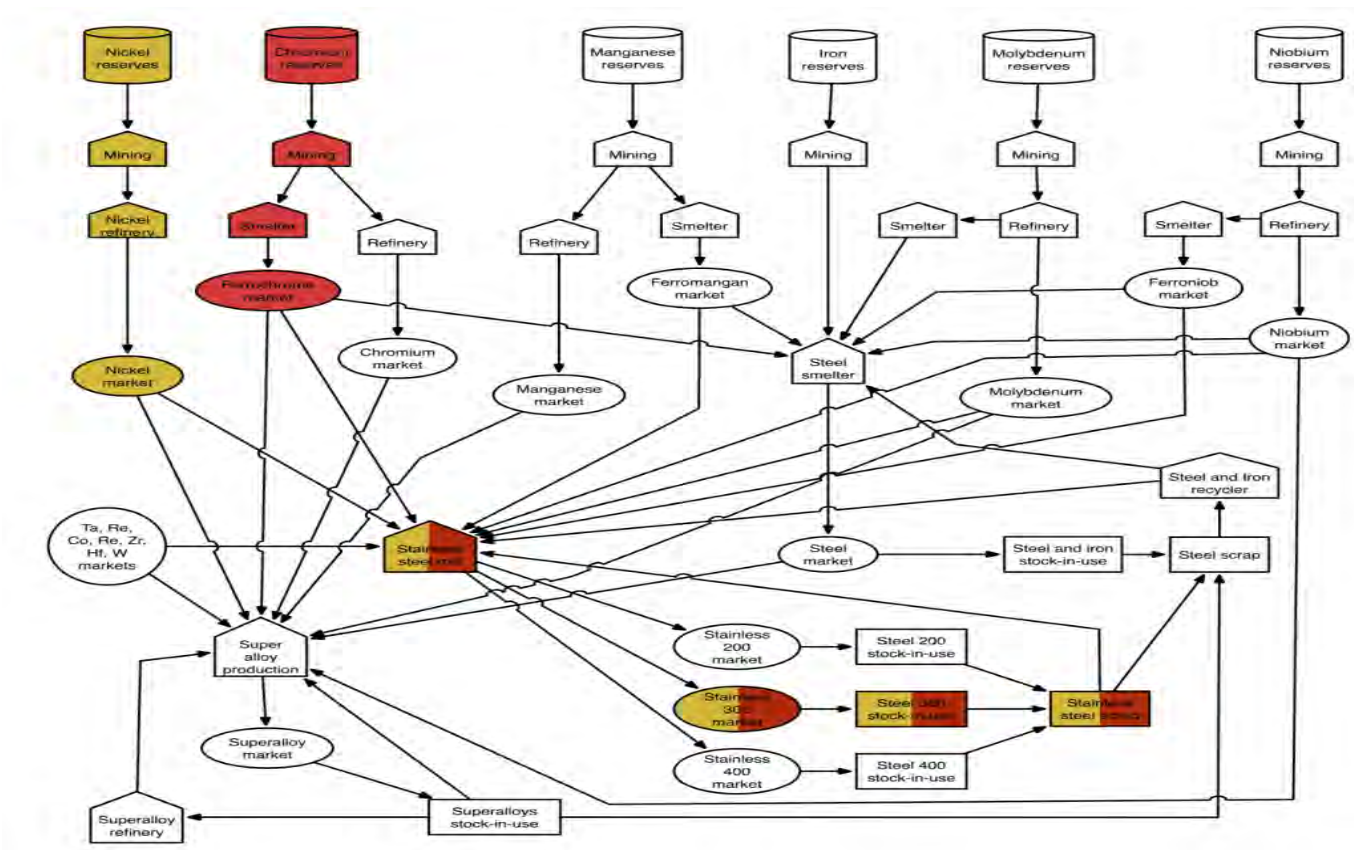
The previous sections focussed primarily on explaining the various nuances of vertical APT. Many of these nuances can be extended to the concept of spatial APT. Spatial APT is present when the input prices and the output prices of a given product do not refer to prices at different levels in the supply chain, but rather to prices for the same product at different geographical locations. Three possible reasons for spatial APT are asymmetric information, market power and asymmetric adjustment costs (Bailey and Brorsen, 1989). These reasons have been discussed earlier in the context of vertical APT. However, it is important to note that there are several nuances that are unique to spatial APT.

According to Abdulai (2000), because of a central market's size and its position as the central hub of network information, it might be less responsive to price changes in each of the individual peripheral markets than peripheral markets would be to changes in prices of the central market. An example of market power causing positive spatial APT would be when a firm which has local market power tries to prevent intrusion from regional players by quickly responding to a regional competitor dropping prices. However, if the local market player chose not to increase prices in response to an increase in prices by its regional competitor, this could be because the local player might try to expand sales by having a slower pricing reaction. As is the case with vertical APT, spatial APT can also be negative (Meyer and Cramon-Taubadel, 2004). Lastly, spatial APT may also occur if the cost of transportation of goods is different depending on the direction of trade. For example, if a given harbour has been built primarily to export, then it can be expected that the cost of importing through that same harbour would be higher (Goodwin and Piggott, 2001).

2.3 Stainless steel Supply chain

The focus of this section is to shed more light on the linkages between the key variables within the Stainless steel supply chain, namely: UG-2 chrome ore, Ferrochrome, Nickel and Chinese domestic 304 Stainless steel cold rolled coil. Figure 1 highlights the specific channels of the Stainless steel supply chain that are relevant for the purposes of this study, namely the Nickel and Chrome ore/Ferrochrome channels.

Figure 1: Flow chart for metals used in the production of Stainless steel using Iron, Manganese, Chromium and Nickel



Source: Sverdrup and Olafsdottir (2019)

2.3.1 UG-2 Chrome Ore

Chromite is a mineral found in the Earth's mantle. Chromite reserves that can be economically mined are referred to as Chrome ore. This Chrome ore is then typically crushed processed and turned into Chromite concentrate. 95% of global Chrome ore production is utilised to make Ferrochrome (KPMG, 2018).

In 2018 South Africa was the largest Chromite producer with 16 million tonnes and an estimated 200 million tonnes of remaining known saleable reserves of material (U.S. Department of the Interior, 2019). Currently the South African Chromium industry contributes approximately US$ 13.3 billion both directly and indirectly to the local economy per annum. The industry also creates 130 600 direct and indirect employment opportunities within South Africa (International Chromium Development Association, 2019)

The most common grade of saleable Chromite is Metallurgical grade Chrome ore concentrate, which makes up 93.8% of global production. Metallurgical grade Chrome ore concentrate has a Cr_2O_3 content of between 40 - 42% (Constant, 2019).

In 2018 76% of Chrome ore imported into China came from South Africa. At the end of 2018, China accounted for 86.5% of global Chrome ore imports, with the second largest importer being Russia with 4.8% (Afarak, 2018).

The source of Figures 2-7 is the International Chromium Development Association (2019).

Figure 2: Chrome Ore Importers, 2018

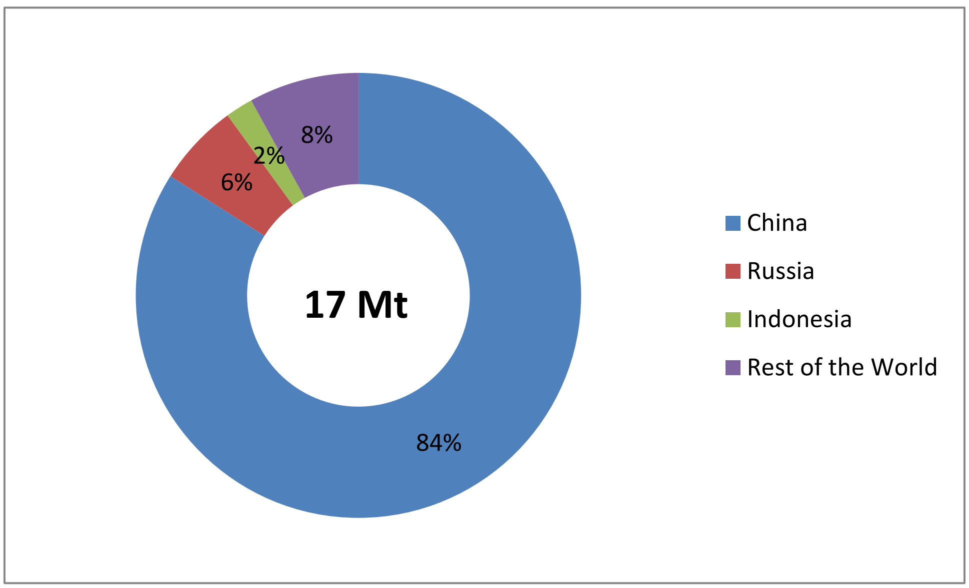
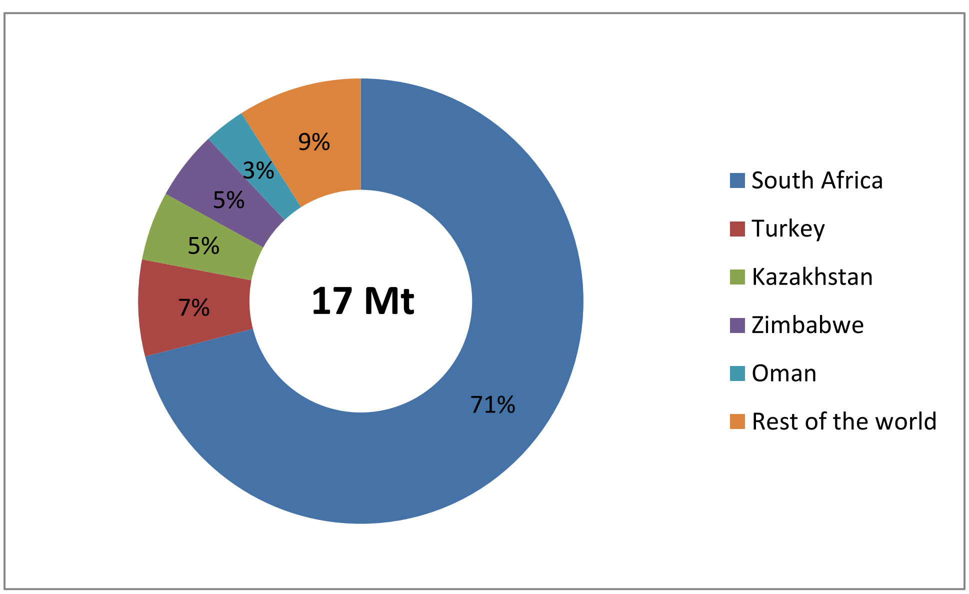


Figure 3: Chrome Ore Exporters, 2018



The total amount of Chrome ore exported and imported globally in 2018 was 17 million tonnes, of which South Africa was the largest exporter (71%) and China was the largest importer (84%). In South Africa, Chrome ore is extracted from the Bushveld Igneous Complex where it is either extracted at dedicated Chrome mines, or as a by-product at certain Platinum group metal mines.

Unlike the Merensky reef that has a high Platinum content, the UG-2 (Upper Group 2) reef has a higher Palladium and Chrome content. The UG-2 reef contains substantial quantities of Chromite, with a typical Chrome-to-Iron (Cr/Fe) ratio of 1.35. UG-2 ores contain between 10 and 25% Cr_2O_3 depending on the selected mining method and reef width. It is comparatively easy and cheap to extract the Chromite from a Platinum concentrator tailings stream at a consistent grade of 40-42% Cr_2O_3 (Cramer *et al*, 2004). As the traditional sources of high Cr/Fe ratio ores have been exhausted at the shallower economic depths, and therefore have become increasingly expensive sources of Chromite, technological developments have enhanced the ability to use fine Chromite viably to make satisfactory grades of Ferrochrome. Therefore, UG-2 fines have now become a cheap source of suitable feed to the Ferrochrome industry (Cramer *et al*, 2004).

Furthermore, due to the numerous challenges, including labour unrest, electricity shortages and weak metal prices, the profitability of PGM producers has been severely impacted in recent years, with over 50% of producers in 2018 being unprofitable (James, 2018). Consequently, PGM producers have invested heavily in UG-2 Chrome ore beneficiation as a means to help mitigate these losses. This is because UG-2 Chrome ore is a by-product of PGM mining and carries minimal beneficiation costs. Chrome ore now contributes approximately 5% to the revenue of PGM producers (James, 2018). UG-2 chrome ore also accounted for 28% of South African and 15% of global Chrome ore production at the end of 2018 (Constant, 2019).

Although Ferrochrome can be substituted for Chromium containing scrap, Chromium has no substitute in the primary end use, which is Stainless steel, and the secondary end use of Super alloys (U.S. Department of the Interior, 2019).

One of the reasons that have allowed China to ascend the Ferrochrome production ladder is the rapidly rising price of electricity supplied by Eskom in South Africa, the consequence of which is that South Africa is exporting increased quantities of non-beneficiated Chrome ore rather than

Ferrochrome. The stunting of South Africa's Ferrochrome production as a result of electricity constraints negatively affects socioeconomic conditions within the country. This is because the industry creates only 5.7 jobs per thousand tonnes of exported non-beneficiated ore, whereas, 17.3 jobs are created for every thousand tonnes of exported Ferrochrome (Creamer, 2019).

2.3.2 Ferrochrome

Ferrochrome is a Chromium and Iron alloy. Ferrochrome and Nickel are used as the base materials in the production of Stainless steel (KPMG, 2018).

Over 80% of global Ferrochrome is used in the production of Stainless steel (KPMG, 2018). From 2012 to 2016 China increased Ferrochrome imports, but the period after 2016 saw a decline in Chinese Ferrochrome imports due to increased domestic production capacity within China. Consequently, South African Ferrochrome exports to China have declined since 2015. Nonetheless South African produced Ferrochrome still accounts for half of Chinese imports (Afarak, 2018). High Carbon Ferrochrome and Charge chrome (93.7%) along with Low Carbon Ferrochrome (6.1%) account for 99.8% of global Ferrochrome production. Lastly, the Ferrochrome and Stainless steel markets are widely considered to be highly correlated because of the former's key role in the production of the latter (Constant, 2019).

Figure 4: Ferrochrome Importers, 2018

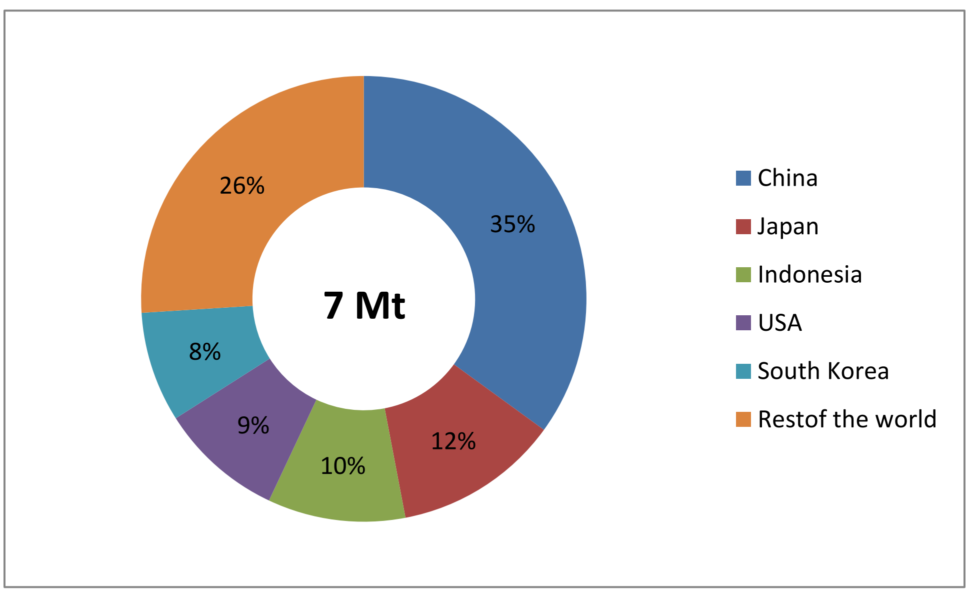
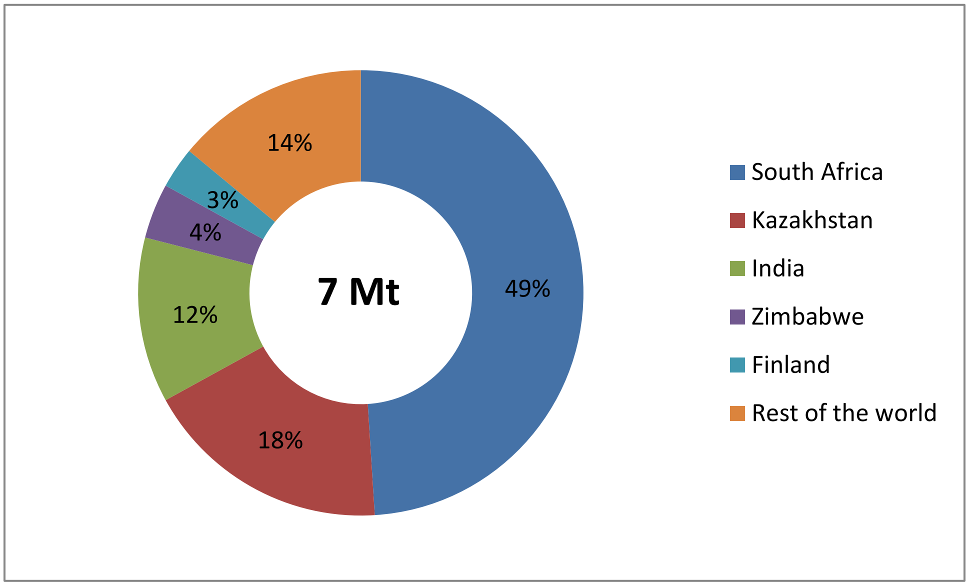


Figure 5: Ferrochrome Exporters, 2018



The total amount of Ferrochrome exported and imported globally in 2018 was 7 million tonnes, of which South Africa was the largest exporter (49% - see Figure 5) and China was the largest importer (35% - see Figure 4).

2.3.3 Nickel

In excess of two thirds of global Nickel production is used in the production of Stainless steel. As an alloying element, Nickel improves key properties of Stainless steel such as ductility, weldability and formability, whilst increasing corrosion resistance in particular applications. In addition to their intrinsic corrosion resistance, the types of Stainless steel which contain Nickel are easy to weld and form; furthermore, they can be used for high-temperature applications and yet remain ductile at very low temperatures (Nickel Institute, 2019). As mentioned above, unlike non-Nickel-containing Stainless steel and conventional steel, Nickel-containing Stainless steel is non-magnetic. This means that it can be made into a remarkably wide range of products, covering applications in the health sector, the chemical industry and domestic uses. In fact, Nickel is so essential that Nickel-containing grades account for 75% of global Stainless steel production. The most well-known of these are Type 304, which has a Nickel content of 8% and Type 316 which has a Nickel content of 11% (Nickel Institute, 2019).

2.3.4 Chinese Domestic 304 Stainless steel Cold Rolled Coil

In 2018 China was responsible for 52.6% of global Stainless steel production (Figure 6), which is a dramatic increase from 12.9% in 2005. In that same period the second largest producer, Europe, saw its share of global Stainless steel production decrease from 34.8% to 14.6%. China's total Stainless steel production in 2018 was 26.67 million tonnes (International Stainless steel Forum, 2019). China is also responsible for 45% of global steel consumption (Deloitte, 2019). What this means is that most (86%) of Chinese Stainless steel production is for its local market. This significant shift in global Stainless steel production to China has created a massive demand for imported Chrome ore and/or Ferrochrome, as China has no Chrome ore resources of its own. Currently the two largest uses of Stainless steel are metal products (37.6%) and mechanical engineering (28.8%), (International Stainless steel Forum, 2019).

Grade 304 cold rolled Stainless steel is widely regarded as the most common austenitic Stainless steel globally. In 2018 cold rolled flat (coil) accounted for 45% (Figure 7) of global Stainless steel production (International Stainless steel Forum, 2019). Grade 304 cold rolled Stainless steel contains a high Nickel content that is between 8% and 10.5% by weight, and a high Chromium content of 18% to 20% by weight. Other significant alloying elements include Carbon, Silicon and Manganese. The remainder of the chemical composition is primarily made up of Iron. The high amounts of Nickel and Chromium give 304 Stainless steel outstanding corrosion resistances. Common 304 Stainless steel applications include: appliances such as dishwashers and refrigerators, heat exchangers, piping, fasteners, food processing equipment and any other structures used in environments that would typically corrode standard carbon steel (Metal Supermarkets, 2018).

KPMG (2018) note that despite Stainless steel being the dependent variable it is widely considered that Stainless steel prices are the primary driver of Nickel, Ferrochrome and by extension Chrome ore prices.

Figure 6: Global Stainless steel Production, 2018

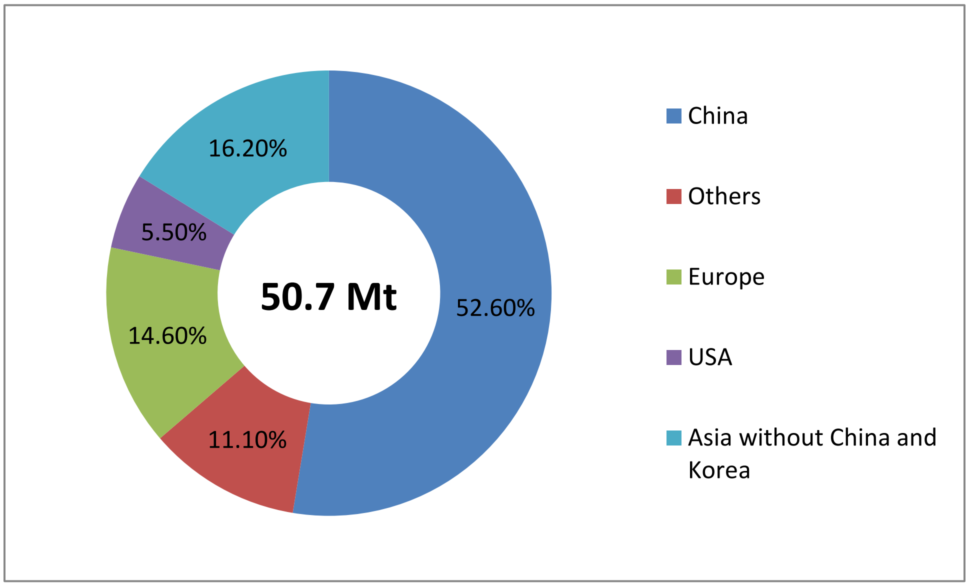
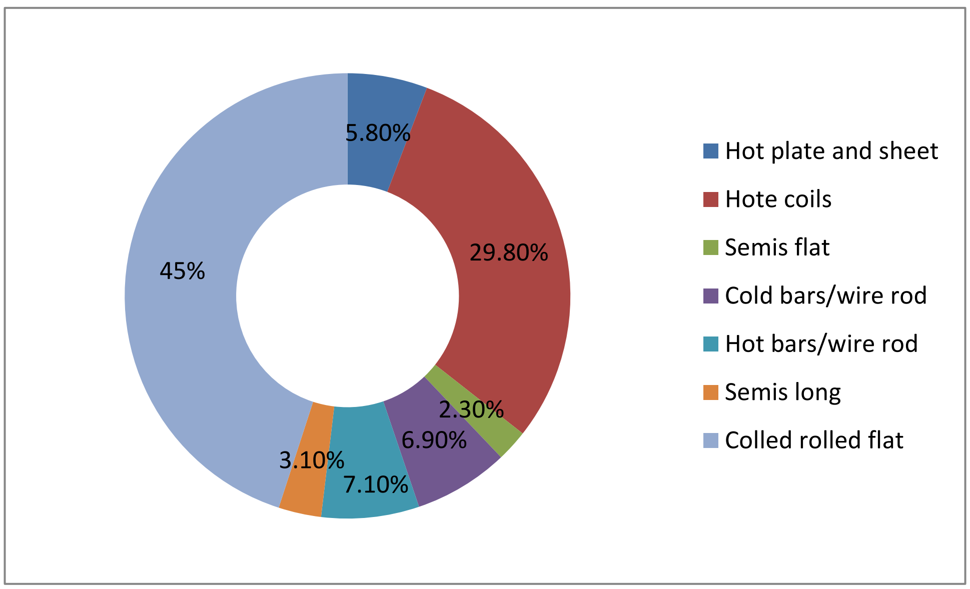


Figure 7: Stainless steel Production by Type, 2018



2.4 Existing Empirical Findings

As far as could be determined, no previous research has been done on asymmetric price transmission in the context of the 304 Stainless steel supply chain. The available literature on APT has focused mainly on agro-food and fuel supply chains. For example, Lopes and Burnquist (2018), studied APT in the Brazilian refined sugar market and Wlazlowski (2001), investigated possible APT between crude oil and petrol prices in the United Kingdom. The findings of previous studies have varied considerably and so there appear to be significant differences regarding the nature and strength of asymmetric price transmission in the various global agro-food and fuel supply chains studied.

2.4.1 International Findings

For the most part the existing research has had difficulty in consistently linking the relationship between APT theories to real world price movements, as well as identifying what type of APT is present in a given market. The international findings will be divided into three sub-sections, namely, causality, market structure and, lastly, asymmetry and lags.

2.4.1.1 Causality

The first important aspect of price transmission theory is causality. This aspect has been explored by various authors using different approaches in order to help understand the nature of causality in different supply chains.

Heien (1980) studied mark-up pricing in a dynamic model of the food industry. The dynamic model focused on retail and farm prices as well as quantities, under the assumption that increases in wholesale price are diffused to retail prices through mark-up pricing behaviour. The mark-up hypothesis was tested using the Granger-Sims causality test and the pricing relationships were estimated for twenty-two food commodities. It was shown that these mark-up relationships were primarily unidirectional from the wholesale to the retail level. Another interesting approach to studying marketing margins was employed by Wohlgenant (1989), who used both an empirical and conceptual framework for estimating the demand for farm outputs. These farm outputs are considered essential in creating the linkages between farm and retail prices. These linkages are then crucial when estimating the impact of farm product supplies, costs of marketing food and changes in retail demand on both farm and retail prices. It was concluded that the substitution elasticity between marketing inputs and farm outputs is a significant parameter distinguishing marketing behaviour and must be measured in order to more accurately estimate derived demand elasticities. Another very important paper on causality is that of Granger (1969) who put forth his theory of causality as the culmination of past related prices. Testable definitions of both feedback and causality were illustrated and proposed using basic two-variable models. He found that the issue of apparent instantaneous causality is caused by either not using a large enough class of causal variables or the slow pace of recording information.

Gi-Hwan and Chang-Soo (2018) set out to study the dynamic properties of causality and asymmetric price transmission within the distribution channel of the Korean tomato market. Through using the wholesale and retail price series for the analysis it was found that there is a casual relationship from the wholesale to retail prices. It was also observed through the application of a threshold partial adjustment model that retail prices respond more aggressively to increases in the wholesale prices than a decrease. Another interesting study on causality and price transmission is that of Sinha *et al* (2016), who set out to study the interdependence between different Indian onion markets with regards to wholesale prices. The goal of the study was to determine what the level of market integration was through the implementation of cointegration analysis. By using the Granger Causality test it was found that price transmission between the three markets (Mumbai, Nashik and Deli) was bi-directional. The study also found that the Nashik market was the dominant market in the price channel given that it is the main production hub.

2.4.1.2 Market Structure

The second important aspect of price transmission theory is market structure. Hall *et al* (1979) investigated the relationship between wholesale-retail marketing margins and market concentration in the context of the United States retail beef industry. This study built on previous studies which explored the relationship between price-cost margins and the market structural variables of capital intensity and concentration across various industries. This study employed an error components model in order to test the hypothesis that dominant retailers are inclined to raise prices without any justification, such as increased costs, and, furthermore, do not pass on to consumers the benefit of lower input costs achieved through improved procurement arrangements. It was found that the level of market concentration in a given region does affect the price-cost marketing margin. Schroeter and Azzam (1991) likewise set out to study market power, marketing margins and price uncertainty in the pork industry. Their study provided both an empirical and conceptual framework for analysing marketing margins in a non-competitive food-processing industry experiencing uncertainty regarding output pricing. The primary finding was that farm/wholesale margins were more consistent than they were fifteen years prior. However, the output price risk component continued to persist throughout the sample period.

Adams *et al* (1987), studied price determination in the United States shrimp market by examining the quarterly and monthly price determination process for both small and medium shrimp in order to study price leadership between the various market levels. Using Sims, Haugh-Pierce and Granger methods, potential causal relationships were assessed. Price models at the ex-vessel, wholesale and retail levels market levels were estimated after including marketing costs, total retail supply, beginning stocks, imports of raw headless shrimp, landings, prices of competing products and income. It was found that monthly prices typically showed unidirectional causality from the ex-vessel to the retail price level. It was also found that quarterly prices were interdependently determined between market levels. Lastly it was observed that price responses between the market levels were symmetric with landings, imports of own-size shrimp and beginning stocks being the most important price determinants.

Lopez (1984) set out to measure oligopoly power and production responses in the food processing industry of Canada. The study focused on the measurement of factor demand responses and various other characteristics of the Canadian food processing industry. An essential characteristic of the study was that it allowed for non-competitive behaviour of the industry and therefore allowed for the estimation of the severity of oligopoly power. The primary results of the study were that the price-taking (output) behaviour was rejected and consequently it was found that the degree of oligopoly power was significant. Another important result was that the industry appears to be relatively responsive to movements in the factor price structure. Capital and raw food materials showed lower sensitivity, whereas energy and labour showed greater sensitivity to variations in price.

Arnade *et al* (2017) studied the transmission of international prices to local domestic Chinese agricultural markets. The study period covered the period when China was both opening up to international trade and also adjusting its agricultural policies in response to changing global market conditions. An ECM model which can differentiate between short and long run transmission was used and allowed the authors to test if China is able to influence international commodity prices. The results for the various commodities showed large differences in transmission. An important finding was that long-run price transmission was much higher than the short-run transmission of international commodity prices to Chinese domestic prices, which suggest the government's stabilization policies did in fact delay, but not eliminate price shock transmissions.

Bakucs *et al* (2014), set out to determine whether or not market structure influences price transmission in the agro-food sector. The reason for the focus on market structure is because most literature on price transmission within various agro-food sectors is related to the existence of price asymmetry, but does not look at the reasons behind either the presence or absence of asymmetry within a given agro-food sector, despite the large amount of theoretical literature which provides numerous explanations for the existence of price asymmetry. Meta-analysis was implemented with a focus on the institutional and organisational characteristics of the agro-food supply chain. It was observed that price asymmetry was more likely to be present within the farm-retail chain for countries or sectors with higher levels of governmental support, fragmented farm structure and more stringent price control regulation in the retail sector.

2.4.1.3 Asymmetry and Lags

Although causality and market structure play an essential part in the theory of price transmission, the primary focus of this study is the influence of asymmetry and lags on price movements in the 304 Stainless steel supply chain.

Marsh and Brester (1989) studied intertemporal price adjustments within the United States beef market using weekly data. A reduced form intertemporal model was estimated for slaughter, carcass and boxed beef prices. It was found that prices respond conjointly to variations in economic information in week t as well as $t-1$. However, it was found that the existence of this relationship also resulted in substantial intertemporal lags. This was evident as prices were found to only stabilise between nine and fourteen weeks after a given market shock. Other important elements affecting price transmission between the various levels of the beef market included: the red-meat market structure was found not to be perfectly competitive, thus implying uncertainty and risk in both the production and price decision making processes; traders could potentially rely on seasonal price trends and consequently react to product and weekly price variations cautiously; and delays were caused by the transaction costs related to different types of price discovery, such as forward contracting, formula pricing and cash negotiation (Marsh and Brester 1989).

Ward (1982) studied price asymmetry between the shipping point and the wholesale and retail level of certain fresh vegetables using Wolffram's (1971) asymmetry model. Granger's causality test was used to indicate the direction of the price linkage and the procedures for handling discontinuous time series were shown. It was found that wholesale prices lead both shipping point and retail prices. This asymmetric behaviour in the retail-wholesale relationship showed that decreases in wholesale prices were reflected more completely than increases in wholesale prices. Wholesale price decreases were also shown to be more fully transmitted to shipping point prices when compared to increases in wholesale prices. Ward's (1982) findings further strengthen the assumption that no single mark-up pricing rule is able to accurately depict the relationship between retail and farm prices (Gardner, 1975). Furthermore, two primary reasons for price asymmetry are put forward: the comparative perishability of vegetables and the advantage wholesalers have when it comes to information assimilation at the different market levels as well as comparative differences in concentration (Ward, 1982).

Jaffry (2004) set out to determine if asymmetry was present between the auction and retail prices within the French fresh hake supply chain. The study tested for cointegration between the retail and auction prices by employing the Engle and Granger two-step method, along with the Momentum Autoregression (M-TAR) and Threshold Autoregression (TAR) Enders and Granger methodologies. It was found that pricing behaviour of retailers is asymmetric in nature, as retailers would respond rapidly to increases in auction prices but would adjust more slowly to decreases in auction prices. This finding is important because, by ignoring the price transmission asymmetries at the different supply chain levels, margin calculations will be inherently biased.

Chen *et al* (2017) examined possible asymmetric effects between international crude oil prices and China's refined oil prices using an asymmetric error correction model (AECM). Using monthly data, the authors attempted to determine whether China's diesel and petrol prices adjust to changes in international crude oil prices. It was found that China's diesel and petrol price increase rapidly when international crude oil prices increase but decrease much more slowly when international crude oil prices decrease, meaning that asymmetry is present.

Lopes and Burnquist (2018) made use of an error correction model to study asymmetric price transmission in the context of Brazil's refined sugar industry. The study looked at the transmission patterns and price relations between retailers and producers. It was found that the transmission of price shocks is bidirectional and that price transmission symmetry from retailers to producers cannot be rejected in both the short and the long run. However, negative price transmission asymmetry was present in the transmission of prices from producers to retailers. What this means is that a decrease in the prices of producers will have a stronger effect on reducing retail prices, compared to the effect of an increase in producer prices on retail prices.

Atil *et al* (2014) set out to study the asymmetric and nonlinear pass-through of crude oil prices to gasoline and natural gas prices through the implementation of the non-linear autoregressive distributed lags (NARDL) model. This approach allowed for the simultaneous testing of both long- and short-run nonlinearities. It also allowed for the quantification of the respective response of natural gas and gasoline prices to both negative and positive shocks to the oil price through the asymmetric dynamic multipliers. It was observed that although the price transmission mechanism is not the same oil prices do asymmetrically affect natural gas and gasoline prices.

Luqman and Kouser (2018) applied both the linear and non-linear autoregressive distributed lag (ARDL) models to study the asymmetrical linkages between foreign exchange and stock markets in the G8+5 countries as well as Pakistan. It was found that there are asymmetrical linkages between the observed currency and equity markets.

2.4.2 South Africa

This section discusses some of the limited existing empirical findings regarding the impact of APT on price movements within the context of South Africa.

Cutts and Kirsten (2002) investigated the concepts of market concentration and asymmetric price transmission in four South African agro-food supply chains. This study was motivated by the rapid increases in South African food retail prices between 2002 and 2003. An asymmetric error correction model was applied to determine how market concentration increases the level of asymmetry, by analysing the degree of asymmetry between retail and commodity prices in South Africa for cooking oil, maize meal, bread and fluid milk. It was found that South African industries that are viewed as being concentrated to some degree showed a high level of asymmetric price transmission, but that the level of asymmetry is relatively lower for perishable retail products.

Louw *et al* (2017) studied the inflationary consequences of vertical price transmission on South African food supply chains. Due to their importance as staples of low(er) income consumers the maize-to-maize meal and wheat-to-bread supply chains were studied. It was found that full price transmission occurs in the latter supply chain, but incomplete price transmission is present in the former. Maize prices were found to be determined at the retail level and then transmitted to the commodity level, whereas prices in the bread supply chain are determined at both the consumer and producer levels.

Alemu and Ogundeji (2010) used producer and retail price indices obtained from Statistics South Africa for the purpose of studying price transmission within the South African food market. The authors applied both the Engle-Granger and Enders and Siklos Dickey-Fuller procedures in order to test for both cointegration and asymmetric price transmission. The following four models were fitted: threshold autoregressive, momentum consistent threshold autoregressive, momentum threshold autoregressive and the Engle-Granger model. It was found that price asymmetry is present between retail and producer prices and that the causal relationship flows from producers to retailers. What this means is that retailers adjust more slowly to price shocks that squeeze their market margin than to shocks that stretch their market margin i.e. positive asymmetric price transmission.

Karoro *et al* (2009) set out to examine exchange rate pass-through (ERP) to import prices in South Africa in order to determine the speed and magnitude of the pass-through as well whether it is asymmetric or not. It was observed that ERP is higher in periods of rand depreciation in comparison to periods of rand appreciation. It was also found that the pass-through is higher in periods of small changes in the exchange rate.

Asumadu Sarkodie and Adams (2020) set out to study electricity access and income inequality in South Africa by applying Bayesian and NARDL analyses. The study examined the impact of inequality in the distribution of income, income level and the influence of corruption on access to electricity in South Africa between 1990 and 2017. It was observed that the long-run asymmetric effects of income level are related to a positive impact on electricity access. However, it was also found that corruption hinders the progress towards electricity access for all.

2.5 Conclusion

This chapter firstly provided a brief overview of the theory of APT, including its potential causes. Based on the literature it can be assumed that consumers are concerned when retailers increase the prices of their products in response to an increase in wholesale prices but do not decrease their prices when wholesale prices decrease. This attention to variations in changes in product prices is particularly important for goods that form part of consumers' daily expenditure. Chrome ore producers are also expected to show a strong interest in any variations between Ferrochrome, Nickel and 304 Stainless steel prices. Secondly, it is evident from the existing international and South African empirical findings that both the degree of asymmetric price transmission and the methodologies employed to test for asymmetry vary widely across both commodities and authors. As far as could be determined, there are no existing studies on asymmetric price transmission within the 304 Stainless steel supply chain. Chapter 3, which follows, will discuss the data and methodology employed to examine APT in this study.

CHAPTER 3: DATA AND METHODOLOGY

3.1. Introduction

This chapter firstly provides a description of the data used in the analysis, the data period, their source, as well as rationalisations for why the specific variables were chosen. This is followed by an overview of the inferential statistics and econometric models applied in Chapter 4. The econometric model employed to test for both cointegration as well as long- and short-run asymmetry within the 304 Stainless steel supply chain is the Non-Linear Autoregressive Distributed Lag (NARDL) model. The NARDL is preceded by unit root and Granger causality testing. A number of residual and stability diagnostic tests will also be conducted. The chapter is organised as follows: the sample period, data source and descriptive statistics will be discussed in sections 3.2 to 3.4. Section 3.5 puts forward the Augmented Dickey-Fuller and Phillips-Perron Unit root tests whilst section 3.6 sets out the Granger Causality test. Sections 3.7 and 3.8 describe the non-linear ARDL (NARDL) model specification as well as the relevant residual and stability diagnostic tests. Section 3.9 concludes the chapter.

3.2. Sample Period

Monthly average pricing data for the period January 2009 to July 2019 was sourced from Metalbulletin[7]. Monthly frequency was selected because it closely matches the time required for market participants to carry out transactions i.e. Chinese Ferrochrome and Stainless steel producers purchase Chrome ore, Ferrochrome and Nickel on a monthly basis. This ensures that the economic dynamics underlying the relationship between the variables are adequately captured, which is a critical requirement in testing for price asymmetry (Blank and Schmiesing, 1990). The sample period was chosen due to limitations in data availability as the UG-2 chrome ore price series was only available from January 2009. However, this includes periods of both rising and falling prices, which makes it possible to achieve the objectives of this study (see Figures 8-10 in Chapter 4).

[7] www.metalbulletin.com

3.3. Data Source

All four price series listed in Table 1 are drawn from Fastmarkets Metalbulletin (Metalbulletin), which has more than 130 years of expertise in the field of providing public information and prices for the global steel, non-ferrous and scrap metal markets (Metalbulletin, 2019). Metalbulletin's reporters talk to various market participants who are intricately involved in the buying and selling of the raw material or product of interest, with strong representation of both sides of the market, including consumers, producers and traders. It is important to note that Metalbulletin can be considered a secondary data source.

Table 1: Data Series used in the Analysis

UG-2 Chrome Ore USD/tonne CIF China Monthly Average	Chrome Ore
Charge Chrome USD/tonne CIF China Monthly Average	Ferrochrome
304 Stainless Steel USD/tonne CIF China Monthly Average	Stainless steel
Nickel 3 months LME Official USD/tonne Monthly Average	Nickel

3.4. Descriptive Statistics

The analysis computes the average prices in the estimation time, January 2009 – July 2019 for the four variables of interest; Stainless steel, Nickel, Ferrochrome, and Chrome ore. The skewness is used to detect if the data is perfectly symmetrical around the mean, as a normal distribution has a skewness of zero. Negative values for the skewness indicate that the data is skewed to the left and positive values for the skewness indicate that the data is skewed to the right (Özdemir, 2016 and Ball, 2018). The Jarque and Bera statistic is used to confirm if the data conforms to normality (Premaratne and Bera, 2017); when this p-value value is less than 5% (significant) the null hypothesis that the data is normally distributed is rejected. This is followed by stochastic time series analysis that graphs the price variables over the estimation period - January 2009 to July 2019.

The kurtosis of Y_t is defined as:

$$K_y = E\left[\frac{(Y_t - \mu)^4}{\sigma^4}\right] \quad [1]$$

The skewness of Y_t is defined as:

$$SK_y = E\left[\frac{(Y_t - \mu)^3}{\sigma^3}\right] \quad [2]$$

The Jarque-Bera test of Y_t is defined as:

$$JB = \frac{n}{6}\left[S^2 + \frac{(k-3)^2}{24}\right] \quad [3]$$

Where n is the number of observations (or degrees of freedom in general); S is the sample skewness, K is the sample kurtosis (Mestre Barao, 2008).

3.5 Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit Root Tests

The Stainless steel, Nickel, Ferrochrome and Chrome ore price series must be tested for stationarity prior to running the NARDL model. This is because two non-stationary series may have the property that a particular linear combination of them is stationary (Johansen, 1995). Furthermore, two cointegrated series will not drift too far apart over the long run (Becketti, 2013). This is done to verify that the mean, variance and covariance remain both constant and independent of the point in time at which they were measured (Gujarati, 1995).

A key assumption of the Dickey Fuller test is that the error terms μ_t are both identically and independently distributed. The ADF test was developed from the DF test in order to deal with any potential serial correlation in the error terms by including the lagged difference terms of the regression. Phillips and Perron employ nonparametric statistical methods to deal with the serial correlation in the error terms without needing to include lagged difference terms (Gujarati, 2004).

The ADF test generally involves the estimation of the following regression equation (Enders, 2010).

$$\Delta Y_t = \beta_0 + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{n} \Delta Y_{t-1} + \varepsilon_t \quad [4]$$

Where ε_t is a pure white noise error term. The ADF tests for the presence of a unit root in the time series ($\delta = 1$) against the alternative that the series is stationary ($\delta < 1$).

The PP test involves fitting the regression [5], where we are allowed to include a trend term or exclude the constant and the results are used to calculate the test statistics.

$$Y_t = \alpha + \rho Y_{t-1} + \varepsilon_t \qquad [5]$$

Unlike the ADF, the PP is more overtly nonparametric meaning that there is no assumption that the error term ε_t in [5] is white noise (Leybourne and Newbold, 1999). For a series to be stationary, the null hypothesis should be rejected in both the ADF test and PP test.

According to Sek (2019), the first requirement in order to determine whether or not the Non-Linear Autoregressive Distributed Lag Model (NARDL) can be applied is to determine the order of integration of the four variables. This is because in order to apply the NARDL the variables have to be I (0) and/or I (1), but none of the variables should be I (2). If found to be I (2), the data needs to be differenced and then tested again. This iterative process is performed until the order of integration is determined for each of the four variables in order to ensure that none of the variables are I (2) for purposes of applying the NARDL. The null hypothesis to be tested is that the time series data is non-stationary against the alternative hypothesis that the data is stationary (no unit roots).

3.6. Granger Causality Test

According to the Granger causality test developed in 1969 by Clive Granger, previous values of a particular time series can be employed to measure the ability to predict the future value of another given time series and thus allow for the testing of causality of these two variables. For example, Stainless steel prices would therefore Granger cause Chrome ore prices if it can be shown that Stainless steel prices provide statistically significant information about the future Chrome ore price values (Granger, 1969). In this example it means that Stainless steel prices are useful in forecasting changes in the Chrome ore price. It is important to note that the Granger causality test is based on the following two key principles namely: the cause happens before its effect and the cause has unique information relating to the future values of the effect (Granger, 1969).

X_t has a causal effect on $\mathrm{Y_t}$ if:

$$P\left(Y\ (t+1)\ \epsilon\ A \mid \Omega\ (t)\right) = P\left(Y\ (t+1)\ \epsilon\ A \mid \Omega_{-x}\ (t)\right) \qquad [6]$$

Where A is an arbitrary non empty set, $\Omega\ (t)$ is the information available in the entire universe as of time t, and Ω_{-x} is the information available in the entire universe as of time X_t (Granger, 1969).

Jacomini and Burnquist (2018) suggest that it is useful to predict the direction of the relationship between the given variables, which is performed using the Granger causality test. In case of a bi-directional relationship, two equations can be estimated, with input and output prices specified as endogenous variables in one of the equations. Odhiambo (2009) notes that the Granger-Causality test method is preferred over other alternative techniques due to its favourable response to both large and small samples.

3.7. NARDL Model Specification

Linear Autoregressive Distributed Lag Model (ARDL)

The most commonly used econometric models among studies looking at the price transmission mechanism include the single equation auto-regressive distributed lag model (ARDL) (Cameron and Trivedi, 2010).

The ARDL model put forward by Pesaran and Shin (1999) was developed to examine long-run cointegrating relationships when the underlying variables are I (1).The advantages of using the ARDL cointegration approach over other cointegration approaches is because it does not impose the restrictive assumption that all the underlying regressors be integrated of the same order. Thus, the ARDL approach can be applied even if the underlying regressors are integrated of I (0), I (1) or fractionally (Odhiambo, 2009).

The general form ARDL model specification:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \ldots\ldots + \beta_p Y_{t-p} + \alpha_0 X_t + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots\ldots + \alpha_q X_{t-q} + \varepsilon_t \qquad [7]$$

Whereby ε_t is a random "disturbance" term. The model is "autoregressive", in the sense that Y_t is determined (in part) by the lagged values of itself. It also has a “distributed lag” component, in the form of consecutive lags of the explanatory variable “X” (Mostafavi *et al*, 2016).

Non-Linear Autoregressive Distributed Lag Model (NARDL)

It is widely understood that economic and financial time series data are cointegrated and therefore follow a long-term equilibrium trend, but linear cointegration tests such as the linear ARDL and Johansen cointegration test fail to adequately detect these cointegrating relationships (Nadia Mohd and Mansur, 2017).

The non-linear ARDL (NARDL) model recently developed by Shin *et al* (2014) employs both positive and negative partial sum decompositions, which allows for the detection of asymmetric effects in both the short and long-term.

When likened to the classical cointegration models such as the Johansen procedure the NARDL model holds some distinct advantages. Firstly, it performs better when determining cointegrating relationships within small samples. Secondly, the NARDL can be applied irrespective of whether the regressors are I (0) and/or I (1), but not I (2) (Romilly *et al*, 2001). Therefore, the asymmetric NARDL framework is highly suitable for the purpose of answering our research question as it not only allows for the ability to gauge both long and short-run asymmetries, but also for the detection of "hidden cointegration" (Shin *et al*, 2014). It was Granger and Yoon (2002) who further developed the idea that the cointegrating relationship can be defined between the negative and positive components of the underlying variables they referred to as "hidden cointegration". For example, a positive shock to the Stainless steel price may have a larger total impact on the Chrome ore price in the short-run , while a negative shock has a larger total impact in the long-run, or *vice versa*.

The general form NARDL model specification is:

$$Y_t = \beta_0 + \beta_1^+ X_t^+ + \beta_1^- X_t^- + U_t \quad [8]$$

$$X_t^+ = \sum_{j=1}^{t} \Delta X_t^+ = \sum_{j=1}^{t} max\left(\Delta X_j, 0\right); \qquad X_t^- = \sum_{j=1}^{t} \Delta X_t^- = \sum_{j=1}^{t} max\left(\Delta X_j, 0\right) \quad [9]$$

$$\Delta Y_t = \alpha_0 + \rho Y_{t-1} + \theta^+ X_{t-1}^+ + \theta^- X_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta Y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta X_{t-j}^+ + \pi_j^- \Delta X_{t-j}^-) + e_t \quad [10]$$

Source: Shin *et al* (2014)

In equation [8], Y is the dependent variable and X is the independent variable and the term "t" refers to time. β_0, β_1^+ and β_1^- are long-run parameters. X_t^+ and X_t^- are partial sums of both positive and negative changes in X_t that are defined in [9] (Zhao-Hua, 2018).

Following Shin *et al* (2014), we re-construct model [8] as the error correction model detailed by equation [10]. Where α, ρ, θ^+ and θ^- are the long-run parameters whilst γ, $\pi^+$and π^- are the short-run parameters. The joint null hypothesis that no long-run relationship exists $H_0: \rho = \theta+ = \theta- = 0)$ will be tested using the F-test put forward by Pesaran *et al* (2001) and Narayan (2005). If H_0 is rejected at the 5% significance level, then it can be concluded that a long-run relationship exists between the targeted variables.

Furthermore, the long-run coefficient of X^+ and X^- are respectively calculated as $\beta_1^+ = -\theta^+/\rho$ and $\beta_1^- = -\theta^-/\rho$. Both long-run $(H_0: \beta_1^+ = \beta_1^-)$ and short-run $(H_0: \sum_{j=0}^{q} \pi_j^+ = \sum_{j=0}^{q} \pi_j^-)$ price asymmetries will be tested for using the Wald test (Pesaran *et al*, 2001).

The general form NARDL in equation [10], set out by Shin *et al* (2014), will be adapted to create the following four regression models in order to examine both the non-linear long-run cointegrating relationships as well as any short- and long-run price asymmetries within the Stainless steel supply chain.

$$\begin{aligned}\Delta Dependent\ Variable_t &= \alpha_0 + \rho Dependent\ Variable_{t-1} + \theta^+ Independent\ Variable_{t-1}^+ \\ &+ \theta^- Independent\ Variable_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta Dependent\ Variable_{t-j} \\ &+ \sum_{j=0}^{q-1} (\pi_j^+ \Delta Independent\ Variable_{t-j}^+ + \pi_j^- \Delta Independent\ Variable_{t-j}^-) + e_t\end{aligned} \qquad [11]$$

<u>*NARDL Model 1: Chrome ore (Dependent) & Stainless steel (Independent)*</u>

$$\begin{aligned}\Delta Chrome\ ore_t = \alpha_0 &+ \rho Chrome\ ore_{t-1} + \theta^+ Stainless\ steel_{t-1}^+ + \theta^- Stainless\ steel_{t-1}^- \\ &+ \sum_{j=1}^{p-1} \gamma_j \Delta Chrome\ ore_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta Stainless\ steel_{t-j}^+ + \pi_j^- \Delta Stainless\ steel_{t-j}^-) \\ &+ e_t\end{aligned}$$

NARDL Model 2: Ferrochrome (Dependent) & Stainless steel (Independent)

$$\Delta Ferrochrome_t = \alpha_0 + \rho Ferrochrome_{t-1} + \theta^+ Stainless\ steel_{t-1}^+ + \theta^- Stainless\ steel_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta Ferrochrome_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta Stainless\ steel_{t-j}^+ + \pi_j^- \Delta Stainless\ steel_{t-j}^-) + e_t$$

NARDL Model 3: Nickel (Dependent) & Stainless steel (Independent)

$$\Delta Nickel_t = \alpha_0 + \rho Nickel_{t-1} + \theta^+ Stainless\ steel_{t-1}^+ + \theta^- Stainless\ steel_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta Nickel_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta Stainless\ steel_{t-j}^+ + \pi_j^- \Delta Stainless\ steel_{t-j}^-) + e_t$$

NARDL Model 4: Stainless steel (Dependent) & Chrome ore, Ferrochrome, Nickel (Independent)

$$\begin{aligned}\Delta Stainless\ steel_t &= \alpha_0 + \rho Stainless\ steel_{t-1} + \theta^+ Chrome\ ore_{t-1}^+ + \theta^- Chrome\ ore_{t-1}^- \\ &+ \theta^+ Ferrochrome_{t-1}^+ + \theta^- Ferrochrome_{t-1}^- + \theta^+ Nickel_{t-1}^+ + \theta^- Nickel_{t-1}^- \\ &+ \sum_{j=1}^{p-1} \gamma_j \Delta Stainless\ steel_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta Chrome\ ore_{t-j}^+ + \pi_j^- \Delta Chrome\ ore_{t-j}^-) \\ &+ \sum_{j=0}^{q-1} (\pi_j^+ \Delta Ferrochrome_{t-j}^+ + \pi_j^- \Delta Ferrochrome_{t-j}^-) + \sum_{j=0}^{q-1} (\pi_j^+ \Delta Nickel_{t-j}^+ + \pi_j^- \Delta Nickel_{t-j}^-) \\ &+ e_t\end{aligned}$$

NARDL Long-Run Form and Bounds Test

Based on Pesaran and Shin (1998) as well Pesaran *et al* (2001), we will apply a practical bounds-testing procedure for the existence of a stable long-run relationship which holds true irrespective of whether the underlying regressors are I(0) or I(1).

The ARDL bounds testing approach is a cointegration method formulated by Pesaran *et al* (2001) and adapted by Shin *et al* (2014) to test for the presence of a long run non-linear relationship between the given variables. This relatively new method holds numerous advantages over other more classical cointegration tests. Firstly, the approach can be used even if the series are I (0) and/or I (1). Secondly, the unrestricted ECM can be derived from the NARDL bounds test through the implementation of a transformation. The bounds test is in fact a test for co-integration between given series integrated of order I (0) and/or I (1) but not I (2) (Simbachawene, 2018).

Wald test for Asymmetry

The Wald test is used to test for the significance of certain explanatory variables in a given statistical model. The Wald test, as explained by Agresti (1990) and Polit (1996) is one way of testing if the parameters related to a group of explanatory variables are equal to zero. If the Wald test is significant for a given explanatory variable or group of explanatory variables then we can conclude that the parameters associated with these variables are not equal to zero. According to Altman (1991), a t-test can be used to determine whether the parameter is significant when considering a single explanatory variable.

As previously mentioned the Wald test will be implemented in order to test for the presence of both short and long-run price asymmetries within the Stainless steel supply chain. The null hypothesis of the Wald test is therefore a state of price symmetry against the alternative hypothesis of price asymmetry (Zmami and Ben-Salha, 2019).

The short- and long-run asymmetries will also be tested for using the standard Wald test. In particular, we will investigate the null hypotheses of no asymmetry in both the long-run ($\beta_X^+ = \beta_X^-$) as well as in the short-run ($\pi_j^+ = \pi_j^-$). According to Olowofeso *et al* (2017) a rejection of one, both or neither will result in one of the following model specifications:

Long-run and short-run symmetry model

$$\Delta Y_t = \rho Y_{t-1} + \theta X_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta Y_{t-j} + \sum_{j=0}^{q-1} \pi_j \Delta X_{t-j} + \epsilon_t \quad [12]$$

Long-run symmetry, short-run asymmetry model

$$\Delta Y_t = \rho Y_{t-1} + \theta X_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta Y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ X_{t-j}^+ + \pi_j^- X_{t-j}^-) + \epsilon_t \quad [13]$$

Long-run asymmetry, short-run symmetry model

$$\Delta Y_t = \rho Y_{t-1} + \theta^+ X_{t-1}^+ + \theta^- X_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta Y_{t-j} + \sum_{j=0}^{q-1} \pi_j X_{t-j} + \epsilon_t \qquad [14]$$

Long-run and short-run asymmetry model

$$\Delta Y_t = \rho Y_{t-1} + \theta^+ X_{t-1}^+ + \theta^- X_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta Y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ X_{t-j}^+ + \pi_j^- X_{t-j}^-) + \epsilon_t \qquad [15]$$

NARDL Dynamic Multiplier Graphs

The cumulative dynamic multiplier graphs allow us to graphically plot the asymmetric adjustment patterns following both positive and negative shocks to the given explanatory variables. It is important to note that this has significant theoretical appeal as it allows one to visually depict in a clear manner the adjustment to a new equilibrium following a shock to the system (Shin *et al*, 2014).

The cumulative asymmetric dynamic multiplier effects of a given unit change in X_t on Y_t can be evaluated as follows:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial X_t^+}, \qquad m_h^- = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial X_t^-}; \; h = 0, 1, 2, \ldots \qquad [16]$$

Source: Olowofeso *et al* (2017)

Where $h \to \infty$, $m_h^+ \to \theta^+$ and $m_h^- \to \theta^-$ are the dynamic adjustment patterns, where $\beta^+ = -\theta^+/\rho$ and $\beta^- = -\theta^-/\rho$ are the long-run coefficients (Shin *et al*, 2014).

The cumulative dynamic multiplier graphs set out by Shin *et al* (2014) and Olowofeso *et al* (2017) will be adapted in order to graphically plot out the asymmetric adjustment patterns following both positive and negative shocks to the different explanatory variables within the Stainless steel supply chain.

3.8. Residual Diagnostic Tests & Stability Diagnostics

The other key assumptions of the NARDL model aside from the order of integration is that there should be no heteroscedasticity, the errors should be serially independent, and the model must be stable (Meo, 2018). In order to check this, we apply the Breusch-Godfrey Serial Correlation LM Test, Breusch-Pagan-Godfrey test for Heteroskedasticity and the Ramsey RESET Test.

3.8.1 Residual Diagnostics

3.8.1.1 Breusch-Godfrey Serial Correlation LM Test

The Breusch–Godfrey Serial Correlation LM test tests for the occurrence of serial correlation that has not been considered in a given proposed model structure and which, if found to be present, would mean that incorrect conclusions would be deduced from other tests, or that sub-standard estimates of model parameters are attained if it is not considered (Breusch and Godfrey, 1978). The regression models for which the test can be used include cases where lagged values of the dependent variables are used as independent variables in the model's depiction for later observations. As the test is founded on the concept of Lagrange multiplier testing, it is occasionally referred to as the LM test for serial correlation (Asteriou and Hall, 2011).

3.8.1.2 Heteroskedasticity Test: Breusch-Pagan-Godfrey

The Breusch–Pagan-Godfrey test is widely employed to test for heteroskedasticity. It tests if the variance of the errors from a regression is dependent on the independent variable values, i.e. heteroskedasticity is found to be present. The basis of the Breusch–Pagan-Godfrey test is a chi-squared test. If the test statistic has a p-value below the threshold (e.g. $p < 0.05$) then the null hypothesis (homoscedasticity) is rejected (Breusch and Pagan, 1979).

3.8.2 Stability Diagnostics: Ramsey RESET Test

The Ramsey Regression Equation Specification Error (RESET) test is a general specification test used to help judge the appropriateness of a given model. The RESET test aims to determine whether non-linear combinations of the fitted values do help describe the response variable (Ramsey, 1969). The insight behind the test is that if non-linear combinations of the explanatory variables do have any power in explaining the response variable, then the non-linear model is correctly specified as the data generating process is found to be better approximated by a non-linear instead of an alternative linear functional form (Ramsey, 1974).

3.9. Conclusion

This chapter discussed the data and variables used in the analysis and detailed the different methods that were employed in order to obtain the results presented in Chapter 4. The sample period, data source and descriptive statistics were discussed in sections 3.2 to 3.4. Section 3.5 put forward the Augmented Dickey-Fuller and Phillips-Perron Unit root tests whilst section 3.6 set out the Granger causality test. Sections 3.7 and 3.8 described the NARDL model specification as well as the relevant residual and stability diagnostic tests. After reviewing the relevant literature set out in Chapter 3, the methods put forth in this chapter were believed to be the most suitable for the study's objectives. Chapter 4 presents the empirical findings obtained using the methods and procedures laid out in Chapter 3.

CHAPTER 4: EMPIRICAL RESULTS

4.1. Introduction

This chapter puts forward and discusses the empirical results obtained using the methods and tests discussed in the previous chapter. Sections 4.2, 4.3 and 4.4 set out the descriptive statistics, time series analysis as well as the ADF and PP unit root tests. Section 4.5 shows the Granger causality test results. The four NARDL models and their related residual and stability diagnostic tests are put forward in sections 4.6 and 4.7. Then sections 4.8 to 4.9 set out the results of the NARDL long run form and bounds test as well as NARDL error correction regression. The results of the Wald tests for asymmetry and the NARDL dynamic multiplier graphs are given in sections 4.10 and 4.11. Section 4.12 concludes the chapter.

4.2. Descriptive Statistics

Table 2: Summary of Descriptive Statistics

	Chrome ore	**Ferrochrome**	**Nickel**	**Stainless steel**
Mean (USD per tonne)	189.5674	1 124.4490	15 268.6900	2 633.4810
Std. Dev.	58.7042	161.0858	4 655.0960	550.5288
Skewness	1.5066	0.0903	0.6501	0.4909
Kurtosis	6.0857	2.7056	2.7841	2.5411
Jarque-Bera	98.4272	0.6313	9.1911	6.2147
Probability	0.0000***	0.7293	0.0101***	0.0447**

Source: Author's own estimates using EViews 11

Note: ***, **, & * indicate rejection of the null hypothesis at the 1%, 5% and 10% significant levels, respectively. Rejecting the null hypothesis at a given level of significance, say 10% leads to rejection at all higher levels of significance.

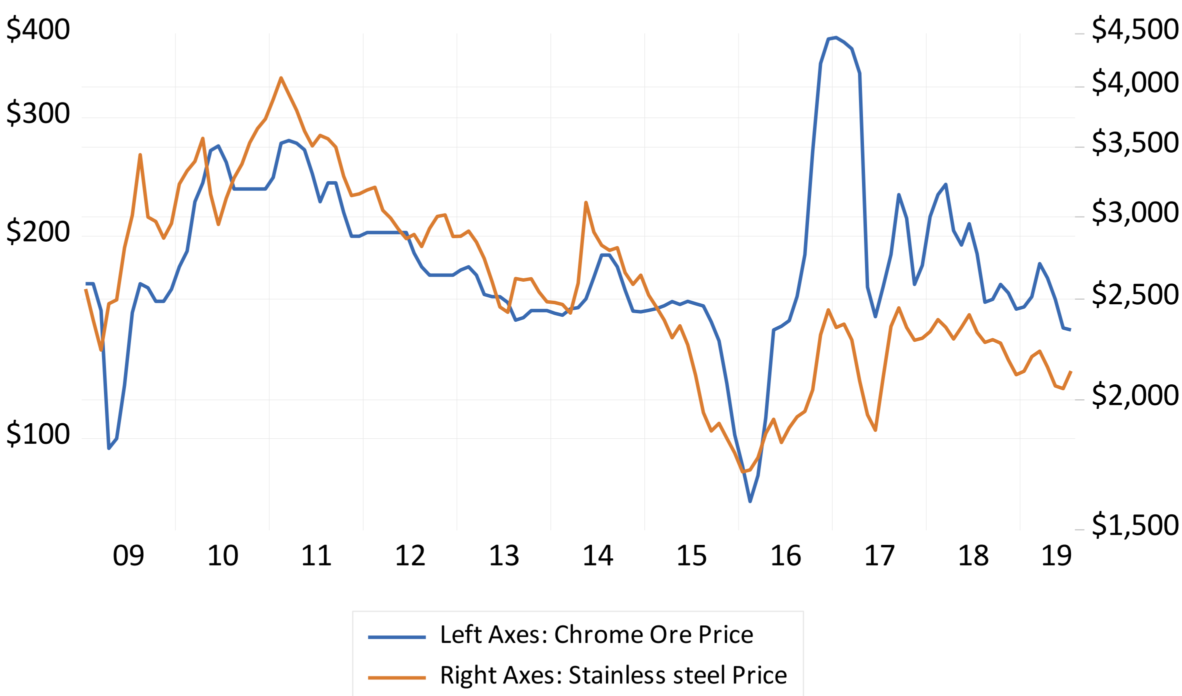
The Histograms and full descriptive statistics for the Chrome ore, Ferrochrome, Nickel and Stainless steel price series are presented in Figures A2-A5.

Table 2 provides a summary of the key descriptive statistics. The individual data distribution of Chrome ore (1.5066), Ferrochrome (0.0903), Nickel (0.6501) and Stainless steel (0.4909) are all positively skewed to the right with Chrome ore being the most severely skewed. The Jarque-Bera (JB) statistic is used to test the normality of the four price series. Considering the JB statistic probability values of Chrome ore, Ferrochrome, Nickel and Stainless steel, it can be concluded that only the Ferrochrome price series is normally distributed. This is because the JB statistics of the Chrome ore, Nickel and Stainless steel price series are all statistically significant at the 5% level, whilst the Ferrochrome JB statistic is not significant at the 10% level.

4.3. Time Series Analysis of the Stainless Steel Supply Chain Variables

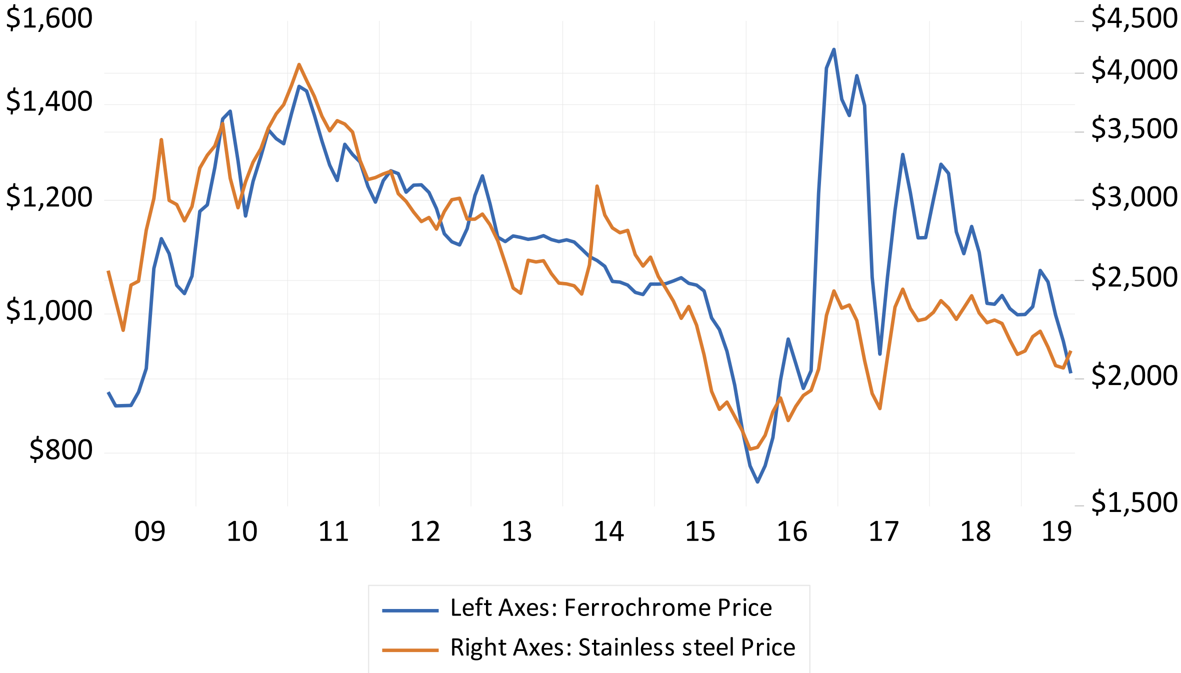
Figures 8-10 visually depict the relationships between the main variables within the Stainless steel supply chain, discussed previously.

Figure 8: Chrome ore and Stainless steel price per tonne, January 2009 - July 2019



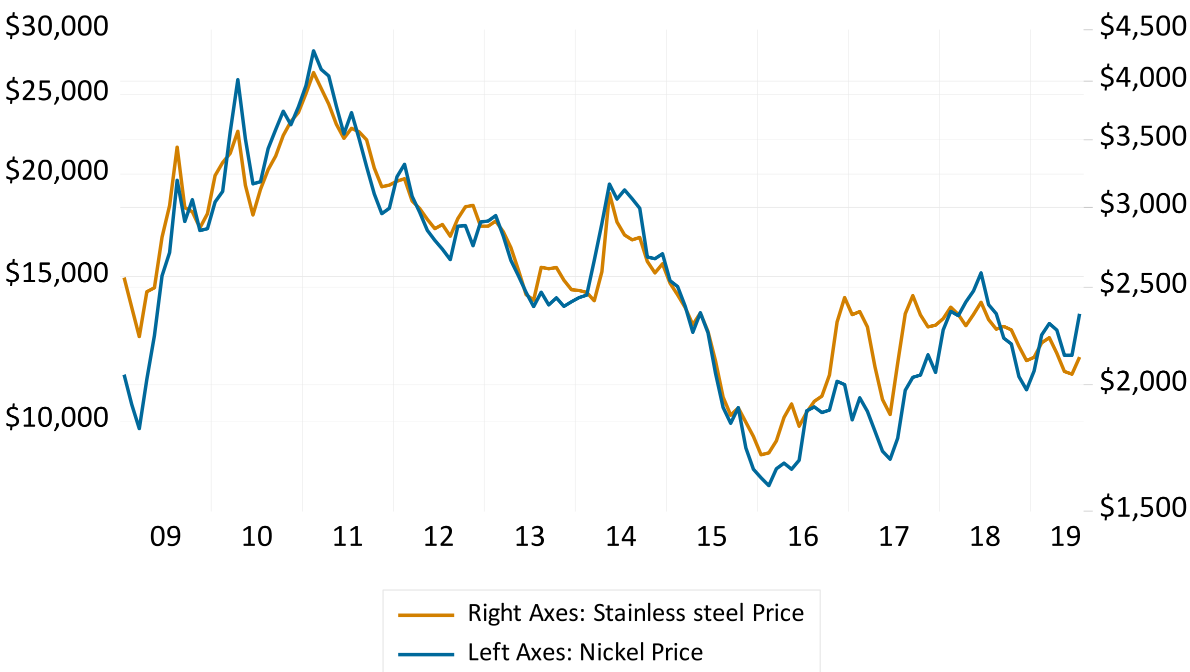
Source: Author's own estimates using EViews 11

Figure 9: Ferrochrome and Stainless steel price per tonne, January 2009 - July 2019



Source: Author's own estimates using EViews 11

Figure 10: Stainless steel and Nickel price per tonne, January 2009 - July 2019



Source: Author's own estimates using EViews 11

All four price series do not exhibit constant averages over time. There is greater variation in all the price series from mid-2016 to the end of the sample period. However, visually the Stainless steel price exhibits less volatility than the other three prices, suggesting that price increases and decreases are more intense at the input than output levels. By contrast, all the price series were relatively less volatile with a broadly declining trend over the period from around 2010 to around the end of 2015. The 2015/2016 period was characterised by very large, but short-lived, positive shocks to the price series, in particular the prices of Chrome ore and Ferrochrome.

Nickel started at a low note in 2009 ($ 10,500), steeply climbed to a peak in the mid-year before slightly dropping at the end of 2009. The prices picked up and climbed to around $ 26,000 in 2010 before dropping mid-year and climbing steeply again to a record high of $28,000 at the end of 2010. From the beginning of 2011 a drastic decline in Nickel prices is observed until 2013, with short term upward spikes in between. At the beginning of 2014 a steep increase in the Nickel prices is observed, reaching around $ 18,000, before dropping again mid-year and continued to do so at an increased rate (negative growth) until mid-year 2015 where it reached a record low ($ 8,000). The Nickel price picked up in 2016 and dropped again in 2017 before increasing steeply in 2018 and decreasing once more in 2019.

Stainless steel, like Nickel prices, started at a low point in 2009 ($ 2,500) as a consequence of the Global Financial Crisis, and steeply climbed to a record peak in 2011, with two spikes in mid-2009. From the beginning of 2011 a drastic decline in Stainless steel prices is observed until late 2013, with short term upward spikes in between. At the beginning of 2014 there is a short-lived steep increase in Stainless steel prices, before dropping steeply towards mid-2015 to a record low for the estimation period. There was a short term reversal of the negative trends at the end of 2015, where an increase in Stainless steel prices is observed until mid-2016, before falling steeply in 2017, rising again and the steadily decreasing in 2018 and in 2019. The (obvious) question that arises is, what factors could have caused such high variations between 2009 and 2011, and a decline in the prices from 2012 to 2019. The sharp increase between 2009 and 2011 was most likely brought about by China's high growth rates and infrastructure development projects that occurred over this period to offset the negative impact of the Global Financial Crisis. China rapidly expanded its Stainless steel production during this period in order to support these infrastructure development plans. The slow decline in prices between 2012 and

2019 is due to a slowdown in China's growth compared to the period between 2009 and 2011. China's GDP growth rate increased from 6.4% in 2009 to 9.5% in 2011 but then decreased to 7.9% in 2012 and 6.1% in 2019 (Trading Economics, 2020).

Over the same period Ferrochrome and Chrome ore prices followed a similar pattern to that of Nickel and Stainless steel between 2009 and 2011, where there was a general increase in the price of Ferrochrome and Chrome ore. There were three noticeable peaks; mid-2009, 2010 and in mid-2011 a record high was reached for the 2009- 2015 period. There was a decline in both the Ferrochrome and Chrome ore prices from mid-2011, through 2012 and 2013 where there was a modest pickup followed by a decline in 2013. Ferrochrome and Chrome ore prices steadily declined between 2013 and 2015 before a drastic fall in mid-2015 - to a record low for the whole estimation period - prior to picking up again. Between 2016 and 2017, a sudden steep rise/increase is observed until the highest price in the estimation period is achieved.

What practically occurred within the market during the 2015-2017 periods is as follows: During 2015, there was a collapse in the Chrome ore price because of a sharp decline in growth of the Chinese economy, which reduced demand for Stainless steel. This forced many South African Chrome ore producers to reduce production. The resultant decrease in Chrome ore supply was significant and subsequently caused a shortage in Q4 of 2016 when Stainless steel demand was at the same time being revived in China (KPMG, 2018). This shortage of Chrome ore supply and revived Stainless steel demand started a recovery in prices during the second half of 2016. The increase in prices between 2016 and 2017 resulted in a large supply surge from Chrome ore producers in South Africa as well as other countries such as India. This pricing surge ultimately peaked in Q1 of 2017. As Chinese Ferrochrome producers restocked their Chrome ore inventories in Q2 of 2017, there was a strong correction in Chinese demand and subsequently Chrome ore prices. The demand collapse in Q2 of 2017 was followed by a strong recovery in Q3 and another subsequent rush to buy, which drove prices back up again (KPMG, 2018). This is followed by a drastic drop at the beginning of 2017, followed by up and down spikes of declining trends in 2018 and 2019.

4.4. Augmented Dickey-Fuller Unit Root Test (ADF) & Phillips-Perron Unit Root Test (PP)

Table 3: ADF and PP Unit Root Test Results

Variables	Test for Unit Root in	ADF Unit Root Test			PP Unit Root Test		
		ADF test statistic	P-Value	Order of Integration	PP test statistic	P-Value	Order of Integration
Chrome ore	Level	-3.838504	0.0033 ***	I (0)	-2.803023	0.0607*	I (1)
	1st Difference	-7.260347	0.0000 ***		-6.617992	0.0000 ***	
Ferrochrome	Level	-2.408593	0.1415	I (1)	-2.721317	0.0732*	I (1)
	1st Difference	-10.90017	0.0000 ***		-6.496026	0.0000 ***	
Nickel	Level	-1.954444	0.3067	I (1)	-1.731916	0.4128	I (1)
	1st Difference	-9.051228	0.0000 ***		-8.957786	0.0000 ***	
Stainless steel	Level	-1.673461	0.4422	I (1)	-1.310968	0.6231	I (1)
	1st Difference	-7.693358	0.0000 ***		-8.824623	0.0000 ***	

Source: Author's own estimates using EViews 11

Note: ***, **, & * indicate rejection of the null hypothesis at the 1%, 5% and 10% significant levels, respectively. Rejecting the null hypothesis at a given level of significance, say 10% leads to rejection at all higher levels of significance.

The EViews ADF and PP unit root test outputs are presented in Tables A1-A8.

Given the requirement of the NARDL model that none of the variables should be I (2); The ADF and PP unit root tests were used to determine the order of integration of the four data series. The null hypothesis for both the ADF and PP was that each of the series contains a unit root.

Hypothesis: Chrome ore, Ferrochrome, Nickel and Stainless steel data series each has a unit root.

Null hypothesis H0: $\delta = 0$ (unit root)

Alternative hypothesis H1: $\delta = 1$ (no unit root)

As summarised in Table 3, the four price series were tested for stationarity using only an intercept as based on Figures 8-10 there does not appear to be any evidence of a deterministic trend in any of the variables. Both the ADF and PP tests were implemented at level and first difference terms.

The ADF and PP unit root tests both rejected the null hypothesis at the 1% significance level and concluded that the Ferrochrome, Nickel and Stainless steel price series are I (1). Whereas, for the Chrome ore price series the ADF concluded at the 1% significance levels that it is I (0) in contrast to the PP which concluded that the Chrome ore price series is I(1).

Having confirmed that the four data series are I (0) and/or I (1) but not I (2), we proceed with the Granger Causality testing.

4.5. Granger Causality

Table 4: Granger Causality Test Results

Pairwise Granger Causality Tests			
Null Hypothesis:	**F-Statistic**	**Prob.**	**Direction of Causality**
Stainless steel prices do not Granger Cause Chrome ore prices	3.84181	0.0115 ***	Bi-directional
Chrome ore prices do not Granger Cause Stainless steel prices	3.43345	0.0193 ***	Bi-directional
Stainless steel prices do not Granger Cause Ferrochrome prices	5.10444	0.0024 ***	Bi-directional
Ferrochrome prices do not Granger Cause Stainless steel prices	4.19089	0.0074 ***	Bi-directional
Stainless steel prices do not Granger Cause Nickel prices	3.55858	0.0165 ***	Uni-directional

Source: Author's own estimates using EViews 11

Note: ***, **, & * indicate rejection of the null hypothesis at the 1%, 5% and 10% significant levels, respectively. Rejecting the null hypothesis at a given level of significance, say 10% leads to rejection at all higher levels of significance.

The EViews Pairwise Granger Causality test output is presented in Table A9.

As summarised in Table 4, bi-directional Granger causality was found to be present at the 1% level of significance between Stainless steel and Chrome ore prices as well as between Ferrochrome and Stainless steel prices. Meaning that in a Granger sense past prices of Stainless steel should be able to help predict future prices of both Chrome ore and Ferrochrome. Similarly, the past prices of both Chrome ore and Ferrochrome should be able to help predict future prices of Stainless steel. Furthermore, uni-directional Granger causality was found to be present between Stainless steel and Nickel prices at the 1% significance level. Meaning that in a Granger sense there is strong evidence that past Stainless steel prices should be able to help predict future prices of Nickel but not *vice versa*. Next we estimate the four NARDL models.

4.6. Non-Linear Autoregressive Distributed lags (NARDL) model

The results of the four NARDL models are reported in Table 5 below. Following a general to specific procedure, the final four models were considered with a maximum of four lags.

Table 5: Output Summary of the Four NARDL Models

Model 1: Chrome Ore (Dependent) - Stainless steel		
Variable	**Coefficient**	**Prob.***
DCHROME_ORE(-1)	0.30403	0.00030***
DSTAINLESS_STEEL_POS	0.02347	0.35410
DSTAINLESS_STEEL_POS(-1)	0.06090	0.02330**
DSTAINLESS_STEEL_NEG	0.04839	0.01700***
DSTAINLESS_STEEL_NEG(-1)	0.03607	0.06480*
C	-12.19612	0.08670*
R-squared	0.28052	
F-statistic	9.20162	
Prob(F-statistic)	0.00000***	

Model 2: Ferrochrome (Dependent) - Stainless steel		
DFERROCHROME(-1)	0.58243	0.00000***
DFERROCHROME(-2)	-0.60568	0.00000***
DFERROCHROME(-3)	0.15416	0.07540*
DSTAINLESS_STEEL_POS	0.06075	0.33290
DSTAINLESS_STEEL_POS(-1)	0.16426	0.05330**
DSTAINLESS_STEEL_POS(-2)	-0.06919	0.38190
DSTAINLESS_STEEL_POS(-3)	0.19329	0.00770***
DSTAINLESS_STEEL_POS(-4)	-0.11385	0.03170**
DSTAINLESS_STEEL_NEG	0.14502	0.00260***
DSTAINLESS_STEEL_NEG(-1)	0.09262	0.09820*

C	-25.33674	0.15350
R-squared	0.57384	
F-statistic	14.81181	
Prob(F-statistic)	0.00000***	
Model 3: Nickel (Dependent) - Stainless steel		
DNICKEL(-1)	0.17922	0.04330**
DNICKEL(-2)	-0.22513	0.01140***
DSTAINLESS_STEEL_POS	5.55712	0.00000***
DSTAINLESS_STEEL_POS(-1)	0.60338	0.66600
DSTAINLESS_STEEL_POS(-2)	2.41242	0.02300**
DSTAINLESS_STEEL_NEG	7.58763	0.00000***
DSTAINLESS_STEEL_NEG(-1)	-2.70463	0.01870***
DSTAINLESS_STEEL_NEG(-2)	3.70722	0.00010***
C	-1 285.09000	0.00000
R-squared	0.65512	
F-statistic	27.06893	
Prob(F-statistic)	0.00000***	
Model 4: Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel		
DSTAINLESS_STEEL(-1)	0.10075	0.29950
DSTAINLESS_STEEL(-2)	-0.25052	0.00750***
DSTAINLESS_STEEL(-3)	-0.22363	0.01260***
DFERROCHROME_POS	0.38593	0.17230
DFERROCHROME_NEG	-0.10469	0.72930
DFERROCHROME_NEG(-1)	0.44567	0.22370

DFERROCHROME_NEG(-2)	0.21539	0.57320
DFERROCHROME_NEG(-3)	0.64517	0.09150*
DFERROCHROME_NEG(-4)	-0.84959	0.00340***
DNICKEL_POS	0.05365	0.00000***
DNICKEL_POS(-1)	0.02114	0.19860
DNICKEL_POS(-2)	0.02246	0.15740
DNICKEL_POS(-3)	-0.01164	0.42600
DNICKEL_POS(-4)	0.02401	0.05140**
DNICKEL_NEG	0.10269	0.00000***
DNICKEL_NEG(-1)	-0.02243	0.13680
DNICKEL_NEG(-2)	-0.00410	0.77710
DNICKEL_NEG(-3)	0.03482	0.00950***
DCHROME_ORE_POS	0.43563	0.59520
DCHROME_ORE_NEG	0.79930	0.32060
DCHROME_ORE_NEG(-1)	-0.25923	0.80280
DCHROME_ORE_NEG(-2)	-1.78733	0.04100**
DCHROME_ORE_NEG(-3)	0.13689	0.87220
DCHROME_ORE_NEG(-4)	1.63417	0.01430***
C	-48.49291	0.31560
R-squared	0.76240	
F-statistic	12.83485	
Prob(F-statistic)	0.00000***	

Source: Author's own estimates using EViews 11

Note: ***, **, & * indicate rejection of the null hypothesis at the 1%, 5% and 10% significant levels, respectively. Rejecting the null hypothesis at a given level of significance, say 10% leads to rejection at all higher levels of significance.

The EViews NARDL model estimation outputs are presented in Tables A10-A14.

The p-value for the F-test is significant at the 1% level of significance in all four models providing sufficient evidence to conclude that the four regression models fit the data well. The F-test of overall significance evaluates all of the coefficients jointly whilst the t-test for each coefficient studies them individually (Nau, 2020). R-squared measures the strength of the relationship between the four models and their relevant dependent variable. However, it is not considered a formal test for any relationship. The hypothesis test for this relationship is the F-test of overall significance. If the overall F-test is significant, it can be concluded that R-squared is statistically not equal to zero, and the correlation between the four models and their relevant dependent variable is statistically significant (Nau, 2020).

The results shown above in table 5 indicate that the estimated four NARDL models are good because the coefficient of determination in each of the four models ranges from 0.28 up to 0.76. It was observed that those lagged values of the dependent variable along with Stainless steel prices only account for 28% of the changes in the Chrome ore price but have a much greater influence on the Ferrochrome (57%) and Nickel (65%) prices in models 1-3. However, the Stainless steel price is heavily influenced by lagged value of itself alongside Chrome ore, Ferrochrome and Nickel prices as these four variables account for 76% of the changes in the Stainless steel price as shown in model 4.

Furthermore, the results of each of the four models also indicate that the relationship between the dependent and explanatory variables are not false, because each of the F-statistics have a highly statistically significant value of 9.20***, 14.81***, 27.06*** and 12.83*** respectively. Therefore, the four regression models fit the data better than if the models did not contain independent variables, meaning that the independent variables in each of the four models improve the fit (Frost, 2020).

4.7. Residual and Stability Diagnostic Tests

Table 6: NARDL Residual and Stability Diagnostic Output Summary

NARDL Residual & Stability Diagnostic Output Summary						
	Serial Correlation LM Test		Heteroskedasticity Test		Ramsey Reset Test	
	Obs*R-squared	Prob. Chi-Square(4)	Obs*R-squared	Prob. Chi-Square(24)	t-statistic	Prob.
1. Chrome Ore (Dependent) - Stainless steel	3.996923	0.4064	4.040775	0.5436	1.671627	0.0973*
2. Ferrochrome (Dependent) - Stainless steel	8.341827	0.0798*	9.056132	0.5268	0.165532	0.8688
3. Nickel (Dependent) - Stainless steel	4.8787	0.3	12.97194	0.1128	0.746345	0.457
4. Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel	3.299429	0.509	29.60481	0.1982	0.489919	0.6253

Source: Author's own estimates using EViews 11

Note: ***, **, & * indicate rejection of the null hypothesis at the 1%, 5% and 10% significant levels, respectively. Rejecting the null hypothesis at a given level of significance, say 10% leads to rejection at all higher levels of significance.

The EViews NARDL residual and stability diagnostics test outputs are presented in Tables A15-A29.

Before analysing the long term and short term impacts that positive and negative changes to the independent variable have on the dependent variable in each of the four models, we first have to judge the adequacy of the dynamic specification of each model based on the LM serial correlation, RESET and Heteroscedasticity tests. The results for these tests are presented in Table 6. As the probability values of all three tests are not statistically significant at the 5% level for the four NARDL Models, we fail to reject the null hypothesis in each case and conclude that these four models have no serial correlation, are homoscedastic and are well specified. Given that the series of diagnostic tests reported in Table 6 show that the overall performance of the four estimated NARDL models is satisfactory, we can proceed with the cointegration testing.

4.8. NARDL Long Run Form and Bounds Test

Table 7: NARDL Long Run Form and Bounds Test Output Summary

NARDL Long Run Form and Bounds Test Output Summary			
	F-statistic	**1% Upper Bound Limit I(0)**	**1% Upper Bound Limit I(1)**
1. Chrome Ore (Dependent) - Stainless steel	19.4022		
2. Ferrochrome (Dependent) - Stainless steel	15.48966	4.13	5
3. Nickel (Dependent) - Stainless steel	22.00104		
4. Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel	10.24455	2.88	3.99

Source: Author's own estimates using EViews 11

The EViews NARDL long run form and bounds test outputs are presented in Tables A30-A34.

If the calculated $F_{statistic}$ is greater than the critical value for the upper bound limit, then we can conclude that there is a long-run co-integrating relationship present between the variables.

The $F_{statistics}$ of the four NARDL long-run form bounds tests in each case all exceed the upper bound critical values at the 1% level of significance as highlighted in Table 7. Firstly, the $F_{statistics}$ indicate that when Chrome ore, Ferrochrome or Nickel are the dependent variable they all co-move with Stainless steel in the long term. Secondly, when Stainless steel is the dependent variable it co-moves simultaneously with Chrome ore, Ferrochrome and Nickel in the long term.

4.9. NARDL Error Correction Regression

Table 8: NARDL Error Correction Regression Output Summary

NARDL Error Correction Regression Output Summary		
	CointEq(-1)* Coefficient	**Prob Value**
1. Chrome Ore (Dependent) - Stainless steel	-0.695971	0.00***
2. Ferrochrome (Dependent) - Stainless steel	-0.869103	0.00***
3. Nickel (Dependent) - Stainless steel	-1.045907	0.00***
4. Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel	-1.373387	0.00***

Source: Author's own estimates using EViews 11

Note: ***, **, & * indicate rejection of the null hypothesis at the 1%, 5% and 10% significant levels, respectively. Rejecting the null hypothesis at a given level of significance, say 10% leads to rejection at all higher levels of significance.

The EViews error correction regression outputs are presented in Tables A35-A39.

The error correction terms of each of the four models in Table 8 are significant at the 1% level, meaning that there is a strong/effective convergent process towards long run equilibrium in the face of short run adjustments or shocks in each of these cases.

According to Nkoro and Uko (2016), the error correction term depicts what portion of the disequilibrium is being corrected, i.e. the degree to which any disequilibrium in the previous period is being adjusted in Y_t. A negative error correction term is evidence of convergence and a positive coefficient indicates a divergence. If the coefficient equals 1, then 100% of the adjustment takes place within the period (month) or if the coefficient equals 0.5, then 50% of the adjustment takes place each period (month). Lastly if the coefficient equals 0 then there is no adjustment within the period. Furthermore, the error correction term should be within the unit circle and therefore not lower than -2 (Loayza and Ranciere, 2005).

Model 1: Chrome Ore (Dependent) - Stainless steel

Approximately 69% of departures from the long-run equilibrium are corrected each period (month). The response to the shock can be described as a negative speed of adjustment. The error correction term is -0.69. This means that there is approximately a 69% adjustment of the Chrome ore price in response to every one-unit shock to the Stainless steel price. In other words, 69% of the deviation from the long run equilibrium is corrected for each period (month) and so the Chrome ore price decreases back to the long run equilibrium. This appears to indicate that there is an under correction by the Chrome ore price in response to a shock caused by the Stainless steel price.

Model 2: Ferrochrome (Dependent) - Stainless steel

Approximately 86% of the deviation from the long run equilibrium is corrected for each period (month) and so the Ferrochrome price decreases back to the long run equilibrium. This appears to indicate that there is an under correction by the Ferrochrome price variable in response to a shock caused by the Stainless steel price.

Model 3: Nickel (Dependent) - Stainless steel

Approximately 104% of the deviation from the long run equilibrium is corrected for each period (month) and so the Nickel price decreases back to the long run equilibrium. This appears to indicate that there is an overcorrection by the Nickel price variable in response to a shock caused by the stainless steel price.

Model 4: Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

Approximately 137% of the deviation from the long run equilibrium is corrected for each period (month) and so the Stainless steel price decreases back to the long run equilibrium. This appears to indicate that there is an overcorrection by the Stainless steel price variable in response to a shock caused by the Nickel, Ferrochrome and Chrome ore prices.

4.10. Wald Test: Price Asymmetry

As mentioned in section 3.7, the short- and long-run asymmetries are estimated using the standard Wald test.

4.10.1 Long-Run Asymmetry

Table 9: NARDL Wald Test: Long-Run Asymmetry

NARDL Wald Test: Long-Run Asymmetry			
	F-statistic	**Prob(F-statistic)**	**Result**
1. Chrome Ore (Dependent) - Stainless steel	0.007573	0.93	Fail to reject H0
2. Ferrochrome (Dependent) - Stainless steel	0.733255	0.39	
3. Nickel (Dependent) - Stainless steel	0.190944	0.66	
4. Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel	0.412247	0.52	

Source: Author's own estimates using EViews 11

Note: ***, **, & * indicate rejection of the null hypothesis at the 1%, 5% and 10% significant levels, respectively. Rejecting the null hypothesis at a given level of significance, say 10% leads to rejection at all higher levels of significance.

The EViews Wald test outputs for long-run asymmetry are presented in Tables A40-A44.

Long-run Asymmetries: The Wald test was performed setting the null hypothesis as H_0: $\beta_X^+ = \beta_X^-$ in order to examine the asymmetries between β_X^+ and β_X^-. The results of each long-run price asymmetry Wald test are summarised in Table 9. The calculated F-statistics for the four NARDL models are all statistically insignificant at the 10% level. Hence, we fail to reject H_0 at the 10% level, implying the presence of symmetries and that the influence of β_X^+ and β_X^- in each of the four models is the same i.e. there is no long-run price asymmetry present within the Stainless steel supply chain.

4.10.2 Short-Run Asymmetry

Table 10: NARDL Wald Test: Short-Run Asymmetry

NARDL Wald Test: Short-Run Asymmetry			
	F-statistic	**Prob(F-statistic)**	**Result**
1. Chrome Ore (Dependent) - Stainless steel	0.529221	0.47	Fail to reject H0
2. Ferrochrome (Dependent) - Stainless steel	0.205905	0.65	
3. Nickel (Dependent) - Stainless steel	0.243073	0.62	
4. Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel	2.560498	0.11	

Source: Author's own estimates using EViews 11

Note: ***, **, & * indicate rejection of the null hypothesis at the 1%, 5% and 10% significant levels, respectively. Rejecting the null hypothesis at a given level of significance, say 10% leads to rejection at all higher levels of significance.

The EViews Wald test outputs for short-run asymmetry are presented in Tables A45-A48.

Short-run Asymmetries: Wald test was performed setting the null hypothesis as H_0: $\pi_j^+ = \pi_j^-$ in order to examine the asymmetries between π_j^+ and π_j^-. The results of each short-run price asymmetry Wald test are summarised in Table 10. The calculated F-statistics for the four NARDL models are all statistically insignificant at the 10% level. Hence, we fail to reject H_0 at the 10% level, implying the presence of symmetries and that the influence of π_j^+ and π_j^- in each of the four models is the same i.e. there is no short-run price asymmetry present within the Stainless steel supply chain.

4.11. NARDL Dynamic Multiplier Graphs

The analysis of the dynamic effects between the four pricing variables can be further enhanced by studying the dynamic multiplier graphs.

The EViews NARDL dynamic multiplier graphs for the four models are presented in Figures A6-A10.

For purposes of interpreting the NARDL dynamic multiplier graphs the solid black line depicts the positive impact of the independent variable on the dependent variable whilst the black dotted line depicts the negative impact. The dashed red line depicts the asymmetry in the short run and lastly, the dotted red lines depict the upper and lower confidence bands showing the confidence values in order to measure the statistical significance of the asymmetry. If the zero line is found to be between the lower and upper bands, then the asymmetric effects are not significant (Rocher, 2017).

Figure A6 and Figure A7: NARDL Dynamic Multiplier Stainless steel (Dependent) and Ferrochrome

Figure A6 and A7 respectively plot the dynamic effects of positive and negative changes in the Chrome ore and Ferrochrome prices. We observe that the Stainless steel price responds rapidly both positively and negatively to increases and decreases in the Chrome ore price. It can be observed that the response to positive changes in the Chrome ore price is more gradual than to negative changes. The impact became relatively smooth after about 9–10 months corresponding to its equilibrium state. We also observed that the Stainless steel price also responds rapidly and negatively to both increases and decreases in the Ferrochrome price. The response to positive changes in the Ferrochrome price is also more gradual than to negative changes. The impact similarly became relatively smooth after about 9–10 months. It is important to note that visually it appears that the asymmetry was significant in the impact of both Chrome ore and Ferrochrome prices on Stainless steel prices as the confidence intervals fell outside of zero.

Figures A8, A9 and A10: NARDL Dynamic Multiplier Chrome Ore, Ferrochrome and Nickel (Dependent) - Stainless steel

Figures A8, A9 and A10 respectively plot the dynamic effects of positive and negative changes in the Stainless steel price. As regards the positive and negative changes in the Chrome ore price, we see a symmetric and speedy response of the Chrome ore price whilst achieving an equilibrium state after about 3-4 months. Similarly, we observe a symmetric and speedy response of the Ferrochrome price whilst also achieving an equilibrium state after about 3-4 months. Comparatively in relation to positive and negative changes in the Nickel price, we show a symmetric and speedy response of the Nickel price whilst achieving an equilibrium state after about 5-6 months.

4.12. Conclusion

This chapter presented and discussed the empirical results obtained using the methods and tests discussed in the previous chapter. Sections 4.2, 4.3 and 4.4 set out the descriptive statistics, time series analysis as well as the ADF and PP unit root tests. The Granger causality test results were put forward in section 4.5. The four NARDL models and their related residual and stability diagnostic tests were put forward in sections 4.6 and 4.7. Then sections 4.8 to 4.9 set out the results of the NARDL long run form and bounds test as well as NARDL error correction regression. The results of the Wald tests for asymmetry and the NARDL dynamic multiplier graphs were given in sections 4.10 and 4.11. Chapter 5, which follows, concludes the study by providing a summary of the main results and findings as well as recommendations for future research.

CHAPTER 5: CONCLUSION

5.1. Introduction

According to Rapsomanikis *et al* (2003) price transmission from global to domestic markets is central to understanding the extent of the integration of economic agents in the market process. However, there is still a significant amount of uncertainty regarding the nature of price transmission in the 304 Stainless steel supply chain due to a lack of research. The goal of this study was therefore to determine the nature of price transmission between South African UG-2 Chrome Ore, Charge Chrome, Nickel and Chinese Domestic 304 Stainless steel Cold Rolled Coil prices in order to establish whether APT exists. Chapter 2 provided an overview of the existing literature and empirical findings which have been reported both locally and internationally across various commodity supply chains. Chapter 3 provided a description of the data used in the analysis as well as the methods and procedures employed to achieve the empirical results. Finally, the empirical results were presented in Chapter 4.

5.2. Summary of Findings

The goal of this research was to investigate whether or not APT exists between the prices of South African UG-2 Chrome ore, Charge Chrome, Nickel and Chinese Domestic 304 Stainless steel Cold Rolled Coil prices.

The main conclusions which can be drawn from this study are:

- Chrome ore prices had the largest coefficient of variation at 30.97% followed by Nickel prices with 30.49%. Stainless steel prices had a coefficient of variation of 20.90% and Ferrochrome prices 14.33%. Thus, prices were more stable in the highly concentrated downstream Ferrochrome and Stainless steel markets and more volatile in the upstream Chrome ore and Nickel markets.
- The results of the Bounds test showed that the dependent and independent variables in each of the four models all co-move (bound together) in the long run, that is there is strong evidence of cointegration at the 1% level of significance within the various stages of the Stainless steel supply chain.

- There is no statistically significant evidence of either short- or long-run price asymmetry between the various stages of the Stainless steel supply chain.

As discussed in chapter 2 the subject of asymmetric price transmission has received significant attention in economic literature over the years for two main reasons.

Firstly, the existence of asymmetric price transmission is not in line with the expectations of the economic theories of perfect competition and monopolies, which presume that under certain regularity assumptions downstream responses to upstream shocks, ought to be symmetric in terms of timing and absolute size.

Secondly, asymmetric price transmission has been found to occur in markets such as the oil market), which has important welfare implications, because of the oil market's size, global dependence on oil and its important share of average household income and expenditure. It is important to note that asymmetric price transmission implies welfare redistribution from consumers to large companies and so it has severe socio-political consequences.

Given the extremely concentrated nature of the Stainless steel, Ferrochrome and Chrome ore industries it is on the one hand very surprising to find no evidence of price asymmetry within the supply chain because dominant players might be expected to exploit their dominance to their own advantage at the expense of other players in the supply chain. But on the other hand, it is also not all that surprising given that, although the market is highly concentrated, the individual industry players i.e. UG-2 Chrome ore miners, Ferrochrome smelters and Stainless steel smelters are heavily dependent on one another. This is because there are not any significant substitutes available at any stage in the supply chain, as South Africa is the only country that can provide Chrome ore in the volumes required by China and the Chinese Ferrochrome and Stainless steel smelters are the only buyer large enough to consume South Africa's Chrome ore and Ferrochrome export volumes. Furthermore, South African Chrome ore and Ferrochrome producers all have sales teams based in China who gather market intelligence and negotiate prices with Chinese Ferrochrome and Stainless steel producers on a daily basis, thus leading to the efficient distribution of pricing information.

The results of this study cannot be directly compared to another study of the Stainless steel supply chain, given that such a previous study has not been done before. One can, however, still compare the findings with the price asymmetry studies done on other global supply chains such oil and agriculture products as highlighted in Chapter 2. Atil *et al* (2014) and Chen *et al* (2017) set out to study the potential asymmetric and non-linear pass through of crude oil prices to petrol, diesel and natural gas prices. Both authors observed that in their respective studies crude oil prices do asymmetrically affect downstream refined products such as petrol, diesel and natural gas. They argued that these asymmetric affects are generally to be expected given the highly concentrated nature of the global crude oil and petroleum industries. This is interesting in the context of the current study as one would have expected price transmission to follow a similar asymmetric path within the Stainless steel supply chain due to the industry also being highly concentrated and ultimately controlled by a few key industry participants.

On the other hand, authors such as Lopes and Burnquist (2018) as well as Louw *et al* (2017) provide interesting insight into price asymmetry within the Brazilian refined sugar market and South African staple food supply chains respectively. Burnquist (2018) found that within Brazil's refined sugar market price transmission from retailers to producers was symmetrical but that transmission from producers to retailers was asymmetrical. This is in contrast to the Stainless steel supply chain where it is seen that the Stainless steel producers ("retailers") are the commanding force whereas in the Brazilian sugar industry it is the producers who hold the power and are able to put pricing pressure on the retailers. Louw *et al* (2017) found that full price transmission occurs within the wheat-to-bread supply chain, but that price transmission was incomplete within the maize-to-maize meal supply chain. More interestingly the maize price was determined at the retail level whereas prices in the bread supply chain were determined at both the consumer and producer levels. The price determination within the bread supply chain is very interesting in the context of the current study as both consumers (Stainless steel mills) and producers (Chrome ore mines and Ferrochrome Smelters) strongly participate in the price discovery process, which possibly is one of the reasons for the lack of price asymmetry within the Stainless steel supply chain.

Despite no price asymmetry being detected within the stainless steel supply chain, it is still very important that the welfare redistribution effects be taken seriously by the South African authorities and key stakeholders in the context of the South African Chrome ore and Ferrochrome industry. This is because South Africa's dominance with regards to economically viable Chrome ore reserves is not on its own enough to ensure that the full benefit of the South African Chrome and Ferrochrome industry is transmitted to the industry's key corporate stakeholders, employees and local communities.

A deeper analysis of the policy issues related to this sector such as unreliable electricity supply, rising electricity costs and illegal mining activity would seem appropriate because of the fact that no price asymmetry was found. Which means that the sustainability issues faced by the South African Chrome ore and Ferrochrome industry are far more complex than simply correcting for price asymmetry, which was thought might exist as a consequence of China's dominance in Stainless steel and Ferrochrome production along with its reliance on South African produced UG-2 Chrome ore.

Unreliable power supply coupled with a sharp increase in electricity prices is the primary reason for a decrease in the viability of the South African PGM-Chrome ore and upstream Ferrochrome industries. Furthermore, in 2019 there were steep increases in input costs from electricity, labour and suppliers of approximately 8.66% for the PGM-Chrome ore industry. This increase was almost double the national producer inflation rate of 4.76% in the same year. Disruptions to both PGM-Chrome ore and Ferrochrome operations as a consequence of community protests have also negatively impacted the financial viability and global competitiveness of these operations (Minerals Council, 2019). A proposed Chrome ore export tax as well as the continued prevalence of illegal mining will also continue to help undermine production and investment in new PGM-Chrome ore mines (Minerals Council, 2019).

5.3. Future Research Areas

As far as could be determined there has to date not been any previous study on price asymmetry in the global Stainless steel supply chain. Therefore, there is still a lot of opportunity for further research areas within this important industry and its supply chain that were not covered in this study.

The first area which should be considered for future research is the impact that physical stock/inventory levels of Chrome ore, Ferrochrome, Stainless steel and Nickel have on price adjustments at the different levels in the Stainless steel supply chain. This is because at any given point in time Ferrochrome and Chrome ore producers will all be carrying Chrome ore inventory. At the same time Ferrochrome producers will also be carrying Ferrochrome stocks and Stainless steel producers will be carrying stocks of Ferrochrome, Nickel and Stainless steel. It is probable that changes in these stocks and their respective impacts on under and/or over supply heavily influence price movements. The challenge faced here is that the Stainless steel supply chain is not very transparent and so it will be difficult to accurately determine how much stocks individual Chrome ore, Ferrochrome and Stainless steel producers are carrying at any point in time.

A second important factor to be considered for future research is the large influence that the Chinese government has on the Chinese Stainless steel and Ferrochrome industries, through its strong centralised control, as well as its ability and willingness to provide significant financial support to what are perceived to be strategically important industries. This is important because the prices of the four variables in the Stainless steel supply chain are not just driven by free market supply and demand principles, but also heavily influenced by Chinese national policy decisions.

Thirdly, the impact of the US$ / ZAR and US$ / Renminbi ¥ exchange rates on pricing of these four variables is also an important consideration, given the large impact currency volatility can have on international trade and a global supply chain such as that of Stainless steel and its inputs which are all priced in US$. The industry is also unique because of its geographic concentration in South Africa (Chrome ore and Ferrochrome) and China (Ferrochrome and Stainless steel).

Given that COVID-19 has wreaked havoc not only on the Chinese economy but also the South African economy, another potentially interesting area of research would be to test possible changes in price transmission before and after the COVID-19 pandemic.

Finally, research should be conducted into identifying the factors which must be addressed in order to increase capital investment in the South African Chrome ore and Ferrochrome industries and secondly, how South African Chrome ore and Ferrochrome producers should approach the price transmission mechanisms that are inherently present in the Stainless steel supply chain, in order to ensure that they are able to extract the maximum benefit for the local industry and for South Africa as a whole. Currently, three constraints on such capital investment are believed to be high electricity costs, unstable electricity supply as well as trade unions (Minerals Council, 2019). Besides addressing South Africa's electricity issues and trade unions, the recent proposal by the South African government to implement a Chrome ore export tax could also potentially provide the South African Chrome ore and Ferrochrome industry a lifeline. Therefore, although not covered in this study an additional future area of research that could also be considered is the likely impact and appropriateness of a tax on Chrome ore exports. More specifically an analysis of the likely impact of this tax on price dynamics, and potential price asymmetries, within the global Stainless steel supply chain would likely offer important new insights. However, as evidenced by China's superior strength within the BRICS bloc and the ongoing trade war between Australia and China. a likely scenario is that China would try and push any sort of export tax back onto South African Chrome ore producers instead of absorbing the cost themselves.

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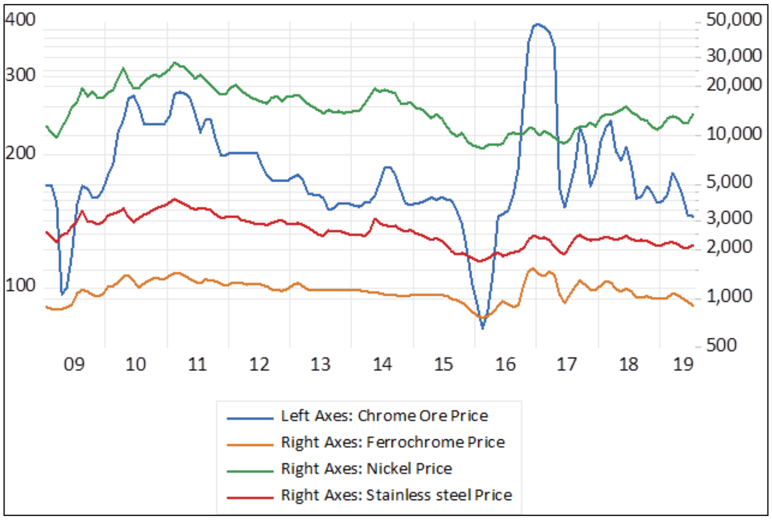
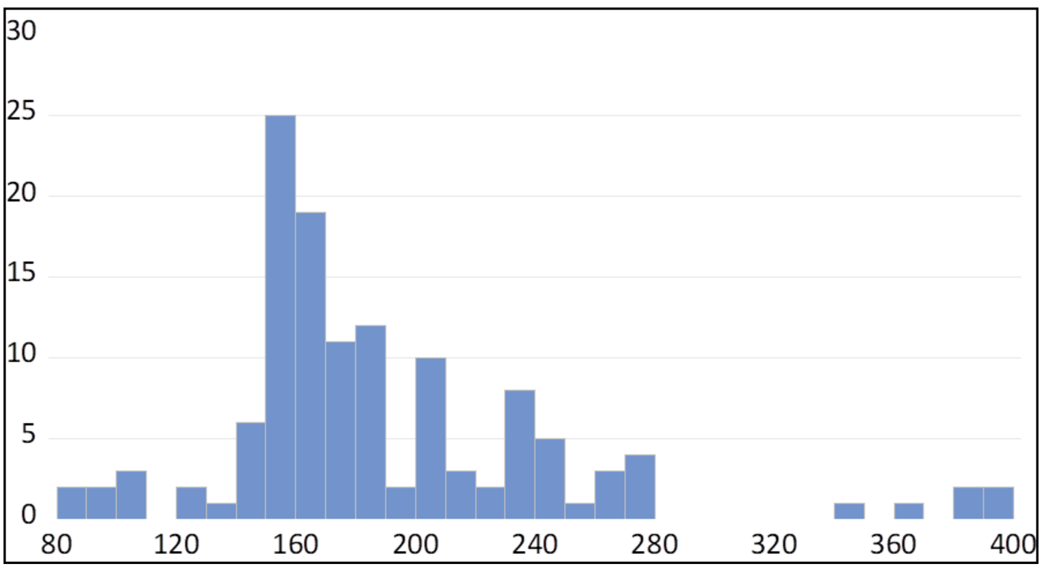
APPENDIX

Figure A1: Chrome ore, Ferrochrome, Nickel and Stainless steel monthly pricing data, January 2009 - July 2019



Source: Author's own estimates using EViews 11

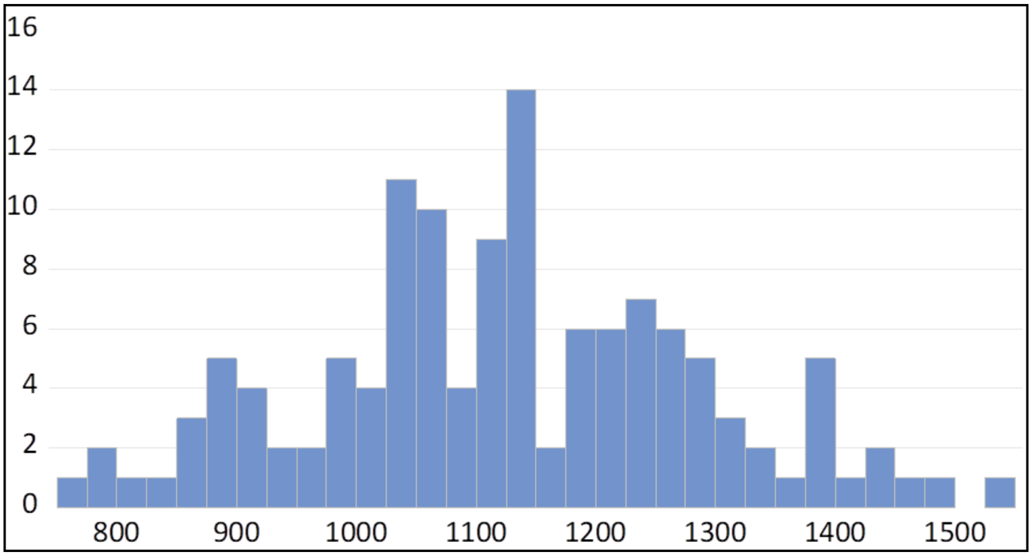
Figure A2: Chrome ore, Descriptive Statistics



Series: Chrome Ore	
Sample 2009M01 2019M07	
Observations 127	
Mean	189.5674
Median	173.2500
Maximum	395.0000
Minimum	80.6300
Std. Dev.	58.7042
Skewness	1.5066
Kurtosis	6.0857
Jarque-Bera	98.4272
Probability	0.0000

Source: Author's own estimates using EViews 11

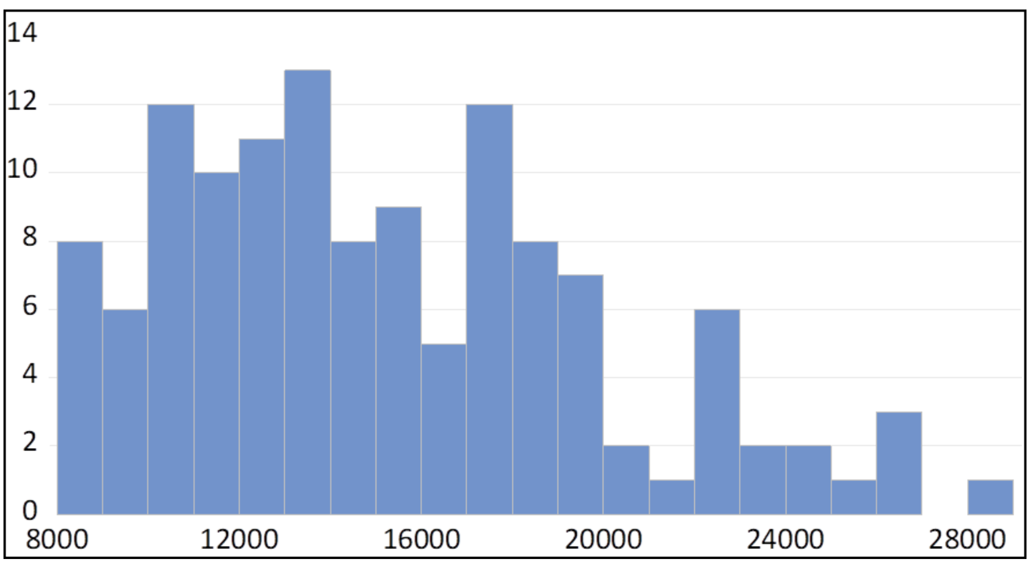
Figure A3: Ferrochrome, Descriptive Statistics



Series: Ferrochrome	
Sample 2009M01 2019M07	
Observations 127	
Mean	1 124.4490
Median	1 123.7650
Maximum	1 529.7110
Minimum	763.6101
Std. Dev.	161.0858
Skewness	0.0903
Kurtosis	2.7056
Jarque-Bera	0.6313
Probability	0.7293

Source: Author's own estimates using EViews 11

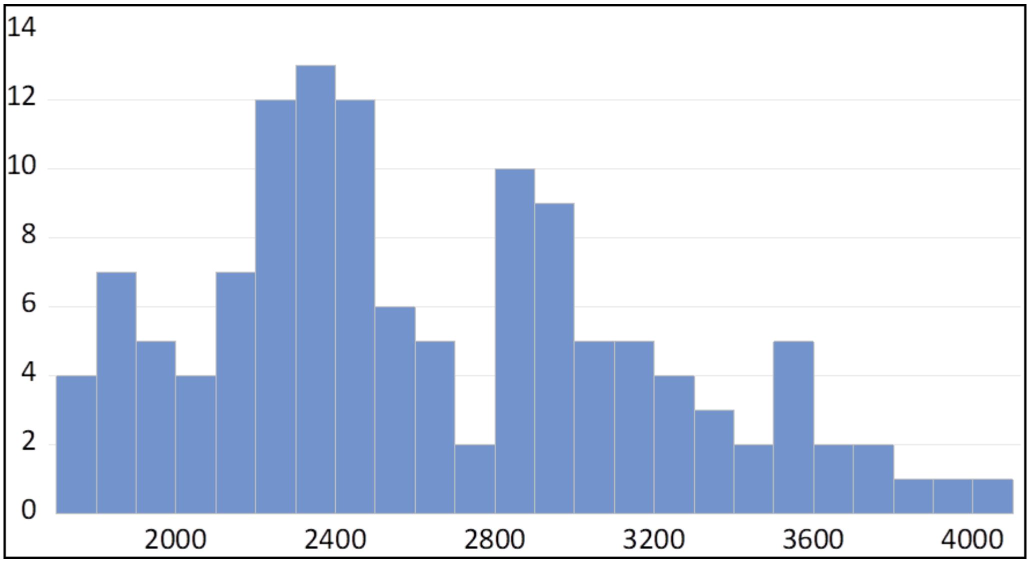
Figure A4: Nickel, Descriptive Statistics



Series: Nickel	
Sample 2009M01 2019M07	
Observations 127	
Mean	15 268.6900
Median	14 346.0000
Maximum	28 265.5000
Minimum	8 341.7860
Std. Dev.	4 655.0960
Skewness	0.6501
Kurtosis	2.7841
Jarque-Bera	9.1911
Probability	0.0101

Source: Author's own estimates using EViews 11

Figure A5: Stainless steel, Descriptive Statistics



Series: Stainless steel	
Sample 2009M01 2019M07	
Observations 127	
Mean	2 633.4810
Median	2 495.7270
Maximum	4 080.6780
Minimum	1 705.1290
Std. Dev.	550.5288
Skewness	0.4909
Kurtosis	2.5411
Jarque-Bera	6.2147
Probability	0.0447

Source: Author's own estimates using EViews 11

Table A1: Chrome ore Unit Root Test (ADF)

Null Hypothesis: CHROME_ORE has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.838504	0.0033
Test critical values:	1% level	-3.483312	
	5% level	-2.884665	
	10% level	-2.57918	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(CHROME_ORE)

Method: Least Squares

Sample (adjusted): 2009M03 2019M07

Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CHROME_ORE(-1)	-0.130518	0.034002	-3.838504	0.0002
D(CHROME_ORE(-1))	0.466569	0.080274	5.812173	0
C	24.69854	6.754529	3.65659	0.0004

R-squared	0.250522	Mean dependent var	-0.2
Adjusted R-squared	0.238235	S.D. dependent var	24.9961
S.E. of regression	21.81638	Akaike info criterion	9.026906
Sum squared resid	58066.44	Schwarz criterion	9.094786
Log likelihood	-561.1817	Hannan-Quinn criter.	9.054482
F-statistic	20.38994	Durbin-Watson stat	1.925571
Prob(F-statistic)	0		

Null Hypothesis: D(CHROME_ORE) has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.260347	0
Test critical values:	1% level	-3.483312	
	5% level	-2.884665	
	10% level	-2.57918	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(CHROME_ORE,2)

Method: Least Squares

Sample (adjusted): 2009M03 2019M07

Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CHROME_ORE(-1))	-0.599991	0.082639	-7.260347	0
C	-0.123198	2.057437	-0.059879	0.9523

R-squared	0.299993	Mean dependent var	-0.008
Adjusted R-squared	0.294302	S.D. dependent var	27.38163
S.E. of regression	23.00216	Akaike info criterion	9.124924
Sum squared resid	65079.21	Schwarz criterion	9.170177
Log likelihood	-568.3077	Hannan-Quinn criter.	9.143308
F-statistic	52.71265	Durbin-Watson stat	1.855397
Prob(F-statistic)	0		

Source: Author's own estimates using EViews 11

Table A2: Ferrochrome Unit Root Test (ADF)

Null Hypothesis: FERROCHROME has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.408593	0.1415
Test critical values:	1% level	-3.483751	

	5% level		-2.884856	
	10% level		-2.579282	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(FERROCHROME)

Method: Least Squares

Sample (adjusted): 2009M04 2019M07

Included observations: 124 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FERROCHROME(-1)	-0.078128	0.032437	-2.408593	0.0175
D(FERROCHROME(-1))	0.661303	0.074827	8.837763	0
D(FERROCHROME(-2))	-0.482347	0.079572	-6.06175	0
C	88.62562	36.93592	2.399443	0.018

R-squared	0.450044	Mean dependent var	0.371098
Adjusted R-squared	0.436295	S.D. dependent var	69.9183
S.E. of regression	52.49486	Akaike info criterion	10.79103
Sum squared resid	330685.2	Schwarz criterion	10.88201
Log likelihood	-665.0441	Hannan-Quinn criter.	10.82799
F-statistic	32.73309	Durbin-Watson stat	1.82417
Prob(F-statistic)	0		

Null Hypothesis: D(FERROCHROME) has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=12)

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-10.90017	0
Test critical values:	1% level		-3.483751	
	5% level		-2.884856	
	10% level		-2.579282	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(FERROCHROME,2)

Method: Least Squares

Sample (adjusted): 2009M04 2019M07

Included observations: 124 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FERROCHROME(-1))	-0.895293	0.082136	-10.90017	0
D(FERROCHROME(-1),2)	0.547587	0.07629	7.177692	0
C	0.389764	4.807318	0.081077	0.9355

R-squared	0.500394	Mean dependent var	-0.388889
Adjusted R-squared	0.492136	S.D. dependent var	75.10916
S.E. of regression	53.52623	Akaike info criterion	10.82212
Sum squared resid	346672	Schwarz criterion	10.89035
Log likelihood	-667.9712	Hannan-Quinn criter.	10.84983
F-statistic	60.59539	Durbin-Watson stat	1.854834
Prob(F-statistic)	0		

Source: Author's own estimates using EViews 11

Table A3: Nickel Unit Root Test (ADF)

Null Hypothesis: NICKEL has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=12)

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-1.954444	0.3067
Test critical values:	1% level		-3.483312	
	5% level		-2.884665	
	10% level		-2.57918	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(NICKEL)

Method: Least Squares

Sample (adjusted): 2009M03 2019M07

Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NICKEL(-1)	-0.044883	0.022965	-1.954444	0.0529
D(NICKEL(-1))	0.218812	0.088436	2.474232	0.0147
C	710.5515	367.2804	1.93463	0.0554

R-squared	0.067701	Mean dependent var	24.33352
Adjusted R-squared	0.052418	S.D. dependent var	1218.694
S.E. of regression	1186.324	Akaike info criterion	17.01881

Sum squared resid	1.72E+08	Schwarz criterion		17.08669
Log likelihood	-1060.676	Hannan-Quinn criter.		17.04639
F-statistic	4.429668	Durbin-Watson stat		1.990527
Prob(F-statistic)	0.013895			

Null Hypothesis: D(NICKEL) has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.051228	0
Test critical values:	1% level	-3.483312	
	5% level	-2.884665	
	10% level	-2.57918	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(NICKEL,2)

Method: Least Squares

Sample (adjusted): 2009M03 2019M07

Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(NICKEL(-1))	-0.803068	0.088725	-9.051228	0
C	23.33244	107.3184	0.217413	0.8282

R-squared	0.39978	Mean dependent var	19.25014
Adjusted R-squared	0.3949	S.D. dependent var	1542.452
S.E. of regression	1199.846	Akaike info criterion	17.03364
Sum squared resid	1.77E+08	Schwarz criterion	17.0789
Log likelihood	-1062.603	Hannan-Quinn criter.	17.05203
F-statistic	81.92473	Durbin-Watson stat	1.976178
Prob(F-statistic)	0		

Source: Author's own estimates using EViews 11

Table A4: Stainless steel Unit Root Test (ADF)

Null Hypothesis: STAINLESS_STEEL has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.673461	0.4422
Test critical values:	1% level	-3.483312	
	5% level	-2.884665	
	10% level	-2.57918	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(STAINLESS_STEEL)

Method: Least Squares

Sample (adjusted): 2009M03 2019M07

Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STAINLESS_STEEL(-1)	-0.03696	0.022086	-1.673461	0.0968
D(STAINLESS_STEEL(-1))	0.231045	0.088043	2.624225	0.0098
C	96.39101	59.54766	1.618721	0.1081

R-squared	0.065884	Mean dependent var	-2.049091
Adjusted R-squared	0.050571	S.D. dependent var	138.1523
S.E. of regression	134.6138	Akaike info criterion	12.6664
Sum squared resid	2210745	Schwarz criterion	12.73428
Log likelihood	-788.6502	Hannan-Quinn criter.	12.69398
F-statistic	4.302407	Durbin-Watson stat	1.977649
Prob(F-statistic)	0.015647		

Null Hypothesis: D(STAINLESS_STEEL) has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.693358	0
Test critical values:	1% level	-3.483751	
	5% level	-2.884856	
	10% level	-2.579282	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(STAINLESS_STEEL,2)

Method: Least Squares

Sample (adjusted): 2009M04 2019M07				
Included observations: 124 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(STAINLESS_STEEL(-1))	-0.870751	0.113182	-7.693358	0
D(STAINLESS_STEEL(-1),2)	0.091943	0.089866	1.023117	0.3083
C	-0.582148	12.19195	-0.047749	0.962
R-squared	0.406064	Mean dependent var		1.905421
Adjusted R-squared	0.396247	S.D. dependent var		174.6357
S.E. of regression	135.6946	Akaike info criterion		12.68259
Sum squared resid	2227977	Schwarz criterion		12.75082
Log likelihood	-783.3204	Hannan-Quinn criter.		12.7103
F-statistic	41.36286	Durbin-Watson stat		1.966043
Prob(F-statistic)	0			

Source: Author's own estimates using EViews 11

Table A5: Chrome ore Unit Root Test (PP)

Null Hypothesis: CHROME_ORE has a unit root			
Exogenous: Constant			
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.803023	0.0607
Test critical values:	1% level	-3.482879	
	5% level	-2.884477	
	10% level	-2.57908	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	588.4702
HAC corrected variance (Bartlett kernel)	837.9261

Phillips-Perron Test Equation

Dependent Variable: D(CHROME_ORE)

Method: Least Squares

Sample (adjusted): 2009M02 2019M07

Included observations: 126 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CHROME_ORE(-1)	-0.087757	0.037195	-2.359358	0.0199
C	16.46841	7.392411	2.227746	0.0277

R-squared	0.042963	Mean dependent var	-0.198413
Adjusted R-squared	0.035245	S.D. dependent var	24.89592
S.E. of regression	24.45326	Akaike info criterion	9.247149
Sum squared resid	74147.25	Schwarz criterion	9.29217
Log likelihood	-580.5704	Hannan-Quinn criter.	9.26544
F-statistic	5.56657	Durbin-Watson stat	1.151864
Prob(F-statistic)	0.019869		

Null Hypothesis: D(CHROME_ORE) has a unit root

Exogenous: Constant

Bandwidth: 13 (Newey-West automatic) using Bartlett kernel

			Adj. t-Stat	Prob.*
Phillips-Perron test statistic			-6.617992	0
Test critical values:	1% level		-3.483312	
	5% level		-2.884665	
	10% level		-2.57918	
*MacKinnon (1996) one-sided p-values.				
Residual variance (no correction)				520.6336
HAC corrected variance (Bartlett kernel)				221.8262
Phillips-Perron Test Equation				
Dependent Variable: D(CHROME_ORE,2)				
Method: Least Squares				
Sample (adjusted): 2009M03 2019M07				
Included observations: 125 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CHROME_ORE(-1))	-0.599991	0.082639	-7.260347	0
C	-0.123198	2.057437	-0.059879	0.9523
R-squared	0.299993	Mean dependent var		-0.008
Adjusted R-squared	0.294302	S.D. dependent var		27.38163
S.E. of regression	23.00216	Akaike info criterion		9.124924
Sum squared resid	65079.21	Schwarz criterion		9.170177

Log likelihood	-568.3077	Hannan-Quinn criter.	9.143308
F-statistic	52.71265	Durbin-Watson stat	1.855397
Prob(F-statistic)	0		

Source: Author's own estimates using EViews 11

Table A6: Ferrochrome Unit Root Test (PP)

Null Hypothesis: FERROCHROME has a unit root			
Exogenous: Constant			
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.721317	0.0732
Test critical values:	1% level	-3.482879	
	5% level	-2.884477	
	10% level	-2.57908	
*MacKinnon (1996) one-sided p-values.			
Residual variance (no correction)			4542.975
HAC corrected variance (Bartlett kernel)			5412.538
Phillips-Perron Test Equation			
Dependent Variable: D(FERROCHROME)			
Method: Least Squares			
Sample (adjusted): 2009M02 2019M07			
Included observations: 126 after adjustments			

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FERROCHROME(-1)	-0.095282	0.037846	-2.517622	0.0131
C	107.518	43.04841	2.497608	0.0138

R-squared	0.04863	Mean dependent var	0.215096
Adjusted R-squared	0.040958	S.D. dependent var	69.37865
S.E. of regression	67.94298	Akaike info criterion	11.29096
Sum squared resid	572414.8	Schwarz criterion	11.33598
Log likelihood	-709.3305	Hannan-Quinn criter.	11.30925
F-statistic	6.338421	Durbin-Watson stat	1.107172
Prob(F-statistic)	0.01309		

Null Hypothesis: D(FERROCHROME) has a unit root

Exogenous: Constant

Bandwidth: 42 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.496026	0
Test critical values:	1% level	-3.483312	
	5% level	-2.884665	
	10% level	-2.57918	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	3954.777
HAC corrected variance (Bartlett kernel)	981.5021

Phillips-Perron Test Equation

Dependent Variable: D(FERROCHROME,2)

Method: Least Squares

Sample (adjusted): 2009M03 2019M07

Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FERROCHROME(-1))	-0.577577	0.081889	-7.05314	0
C	0.117003	5.670545	0.020633	0.9836

R-squared	0.287975	Mean dependent var	-0.229651
Adjusted R-squared	0.282186	S.D. dependent var	74.82687
S.E. of regression	63.39623	Akaike info criterion	11.15256
Sum squared resid	494347.1	Schwarz criterion	11.19781
Log likelihood	-695.0348	Hannan-Quinn criter.	11.17094
F-statistic	49.74678	Durbin-Watson stat	1.536756
Prob(F-statistic)	0		

Source: Author's own estimates using EViews 11

Table A7: Nickel Unit Root Test (PP)

Null Hypothesis: NICKEL has a unit root

Exogenous: Constant

Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.731916	0.4128
Test critical values:	1% level	-3.482879	

	5% level		-2.884477	
	10% level		-2.57908	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	1440412
HAC corrected variance (Bartlett kernel)	1831746

Phillips-Perron Test Equation

Dependent Variable: D(NICKEL)

Method: Least Squares

Sample (adjusted): 2009M02 2019M07

Included observations: 126 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NICKEL(-1)	-0.036132	0.023166	-1.559714	0.1214
C	569.0302	370.0787	1.537592	0.1267

R-squared	0.019241	Mean dependent var	16.83423
Adjusted R-squared	0.011332	S.D. dependent var	1216.725
S.E. of regression	1209.812	Akaike info criterion	17.05006
Sum squared resid	1.81E+08	Schwarz criterion	17.09508
Log likelihood	-1072.154	Hannan-Quinn criter.	17.06835
F-statistic	2.432707	Durbin-Watson stat	1.568602
Prob(F-statistic)	0.121376		

Null Hypothesis: D(NICKEL) has a unit root

Exogenous: Constant

Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.957786	0
Test critical values:	1% level	-3.483312	
	5% level	-2.884665	
	10% level	-2.57918	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	1416595
HAC corrected variance (Bartlett kernel)	1269355

Phillips-Perron Test Equation

Dependent Variable: D(NICKEL,2)

Method: Least Squares

Sample (adjusted): 2009M03 2019M07

Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(NICKEL(-1))	-0.803068	0.088725	-9.051228	0
C	23.33244	107.3184	0.217413	0.8282

R-squared	0.39978	Mean dependent var	19.25014
Adjusted R-squared	0.3949	S.D. dependent var	1542.452
S.E. of regression	1199.846	Akaike info criterion	17.03364
Sum squared resid	1.77E+08	Schwarz criterion	17.0789
Log likelihood	-1062.603	Hannan-Quinn criter.	17.05203
F-statistic	81.92473	Durbin-Watson stat	1.976178
Prob(F-statistic)	0		

Source: Author's own estimates using EViews 11

Table A8: Stainless steel Unit Root Test (PP)

Null Hypothesis: STAINLESS_STEEL has a unit root			
Exogenous: Constant			
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.310968	0.6231
Test critical values:	1% level	-3.482879	
	5% level	-2.884477	
	10% level	-2.57908	
*MacKinnon (1996) one-sided p-values.			
Residual variance (no correction)			18759.19
HAC corrected variance (Bartlett kernel)			19973.64
Phillips-Perron Test Equation			
Dependent Variable: D(STAINLESS_STEEL)			

Method: Least Squares

Sample (adjusted): 2009M02 2019M07

Included observations: 126 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STAINLESS_STEEL(-1)	-0.02829	0.022416	-1.26204	0.2093
C	71.24773	60.38798	1.179833	0.2403

R-squared	0.012682	Mean dependent var	-3.366767
Adjusted R-squared	0.00472	S.D. dependent var	138.3913
S.E. of regression	138.0643	Akaike info criterion	12.70906
Sum squared resid	2363658	Schwarz criterion	12.75408
Log likelihood	-798.6709	Hannan-Quinn criter.	12.72735
F-statistic	1.592746	Durbin-Watson stat	1.542948
Prob(F-statistic)	0.209303		

Null Hypothesis: D(STAINLESS_STEEL) has a unit root

Exogenous: Constant

Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.824623	0
Test critical values:	1% level	-3.483312	
	5% level	-2.884665	
	10% level	-2.57918	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	18091.94
HAC corrected variance (Bartlett kernel)	13620.25

Phillips-Perron Test Equation

Dependent Variable: D(STAINLESS_STEEL,2)

Method: Least Squares

Sample (adjusted): 2009M03 2019M07

Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(STAINLESS_STEEL(-1))	-0.790075	0.087769	-9.00173	0
C	-1.199613	12.13322	-0.09887	0.9214

R-squared	0.397151	Mean dependent var	1.997493
Adjusted R-squared	0.39225	S.D. dependent var	173.9332
S.E. of regression	135.5954	Akaike info criterion	12.6731
Sum squared resid	2261492	Schwarz criterion	12.71835
Log likelihood	-790.0687	Hannan-Quinn criter.	12.69148
F-statistic	81.03115	Durbin-Watson stat	1.968271
Prob(F-statistic)	0		

Source: Author's own estimates using EViews 11

Table A9: Pairwise Granger Causality Tests

Pairwise Granger Causality Tests

Sample: 2009M01 2019M07

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
FERROCHROME does not Granger Cause CHROME_ORE	124	3.61807	0.0153
CHROME_ORE does not Granger Cause FERROCHROME		1.59384	0.1946
NICKEL does not Granger Cause CHROME_ORE	124	2.32296	0.0786
CHROME_ORE does not Granger Cause NICKEL		0.94584	0.4209
STAINLESS_STEEL does not Granger Cause CHROME_ORE	124	3.84181	0.0115
CHROME_ORE does not Granger Cause STAINLESS_STEEL		3.43345	0.0193
NICKEL does not Granger Cause FERROCHROME	124	3.60569	0.0155
FERROCHROME does not Granger Cause NICKEL		1.18661	0.318
STAINLESS_STEEL does not Granger Cause FERROCHROME	124	5.10444	0.0024
FERROCHROME does not Granger Cause STAINLESS_STEEL		4.19089	0.0074
STAINLESS_STEEL does not Granger Cause NICKEL	124	3.55858	0.0165
NICKEL does not Granger Cause STAINLESS_STEEL		0.25449	0.858

Source: Author's own estimates using EViews 11

Table A10: NARDL Model Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

Dependent Variable: DSTAINLESS_STEEL

Method: ARDL

Sample (adjusted): 2009M07 2019M07

Included observations: 121 after adjustments

Maximum dependent lags: 4 (Automatic selection)

Model selection method: Akaike info criterion (AIC)

Dynamic regressors (4 lags, automatic): DFERROCHROME_POS

DFERROCHROME_NEG DNICKEL_POS DNICKEL_NEG

DCHROME_ORE_POS DCHROME_ORE_NEG

Fixed regressors: C

Number of models evalulated: 62500

Selected Model: ARDL(3, 0, 4, 4, 3, 0, 4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
DSTAINLESS_STEEL(-1)	0.100754	0.096587	1.043133	0.2995
DSTAINLESS_STEEL(-2)	-0.250516	0.09173	-2.731013	0.0075
DSTAINLESS_STEEL(-3)	-0.223625	0.087905	-2.543937	0.0126
DFERROCHROME_POS	0.385931	0.28066	1.375084	0.1723
DFERROCHROME_NEG	-0.104686	0.30162	-0.34708	0.7293
DFERROCHROME_NEG(-1)	0.44567	0.363903	1.224696	0.2237
DFERROCHROME_NEG(-2)	0.215386	0.381015	0.565294	0.5732
DFERROCHROME_NEG(-3)	0.645172	0.37849	1.704596	0.0915
DFERROCHROME_NEG(-4)	-0.849593	0.283265	-2.99929	0.0034
DNICKEL_POS	0.053649	0.012375	4.335256	0

DNICKEL_POS(-1)	0.02114	0.016331	1.29447	0.1986
DNICKEL_POS(-2)	0.02246	0.015761	1.424987	0.1574
DNICKEL_POS(-3)	-0.01164	0.01456	-0.799445	0.426
DNICKEL_POS(-4)	0.024013	0.01217	1.973139	0.0514
DNICKEL_NEG	0.102692	0.00959	10.70772	0
DNICKEL_NEG(-1)	-0.022427	0.014949	-1.500204	0.1368
DNICKEL_NEG(-2)	-0.004096	0.01443	-0.283875	0.7771
DNICKEL_NEG(-3)	0.034815	0.01315	2.647503	0.0095
DCHROME_ORE_POS	0.435628	0.817137	0.533115	0.5952
DCHROME_ORE_NEG	0.799304	0.800554	0.998438	0.3206
DCHROME_ORE_NEG(-1)	-0.259231	1.035237	-0.250407	0.8028
DCHROME_ORE_NEG(-2)	-1.787333	0.862772	-2.071617	0.041
DCHROME_ORE_NEG(-3)	0.13689	0.848793	0.161276	0.8722
DCHROME_ORE_NEG(-4)	1.634167	0.654756	2.495842	0.0143
C	-48.49291	48.06959	-1.008806	0.3156
R-squared	0.762398	Mean dependent var		-5.539346
Adjusted R-squared	0.702997	S.D. dependent var		135.0123
S.E. of regression	73.57894	Akaike info criterion		11.61638
Sum squared resid	519730.7	Schwarz criterion		12.1940

			2
Log likelihood	-677.7907	Hannan-Quinn criter.	11.85098
F-statistic	12.83485	Durbin-Watson stat	1.966985
Prob(F-statistic)	0		
*Note: p-values and any subsequent tests do not account for model selection.			

Source: Author's own estimates using EViews 11

Table A11: NARDL Model Chrome ore (Dependent) – Stainless steel

Dependent Variable: DCHROME_ORE				
Method: ARDL				
Sample (adjusted): 2009M04 2019M07				
Included observations: 124 after adjustments				
Maximum dependent lags: 4 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (4 lags, automatic): DSTAINLESS_STEEL_POS				
DSTAINLESS_STEEL_NEG				
Fixed regressors: C				
Number of models evalulated: 100				
Selected Model: ARDL(1, 1, 1)				
Note: final equation sample is larger than selection sample				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
DCHROME_ORE(-1)	0.304029	0.081969	3.709067	0.0003
DSTAINLESS_STEEL_POS	0.023466	0.025225	0.930248	0.3541
DSTAINLESS_STEEL_POS(-1)	0.0609	0.026494	2.298655	0.0233
DSTAINLESS_STEEL_NEG	0.048394	0.019998	2.419939	0.017
DSTAINLESS_STEEL_NEG(-1)	0.036069	0.01935	1.864028	0.0648
C	-	7.059077	-	0.0867

	12.19612		1.72772
R-squared	0.280523	Mean dependent var	-0.080651
Adjusted R-squared	0.250037	S.D. dependent var	25.06171
S.E. of regression	21.70355	Akaike info criterion	9.040006
Sum squared resid	55583.18	Schwarz criterion	9.176471
Log likelihood	-554.4803	Hannan-Quinn criter.	9.095441
F-statistic	9.201615	Durbin-Watson stat	1.903876
Prob(F-statistic)	0		
*Note: p-values and any subsequent tests do not account for model selection.			

Source: Author's own estimates using EViews 11

Table A12: NARDL Model Ferrochrome (Dependent) – Stainless steel

Dependent Variable: DFERROCHROME

Method: ARDL

Sample (adjusted): 2009M07 2019M07

Included observations: 121 after adjustments

Maximum dependent lags: 4 (Automatic selection)

Model selection method: Akaike info criterion (AIC)

Dynamic regressors (4 lags, automatic): DSTAINLESS_STEEL_POS

DSTAINLESS_STEEL_NEG

Fixed regressors: C

Number of models evalulated: 100

Selected Model: ARDL(3, 4, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
DFERROCHROME(-1)	0.582426	0.094145	6.186511	0
DFERROCHROME(-2)	-0.605684	0.094987	-6.37651	0

DFERROCHROME(-3)	0.154155	0.08589	1.794797	0.0754
DSTAINLESS_STEEL_POS	0.060753	0.062469	0.972523	0.3329
DSTAINLESS_STEEL_POS(-1)	0.164259	0.084096	1.953242	0.0533
DSTAINLESS_STEEL_POS(-2)	-0.06919	0.078817	-0.87785	0.3819
DSTAINLESS_STEEL_POS(-3)	0.193289	0.071249	2.712847	0.0077
DSTAINLESS_STEEL_POS(-4)	-0.113848	0.052323	-2.17586	0.0317
DSTAINLESS_STEEL_NEG	0.145015	0.046981	3.086679	0.0026
DSTAINLESS_STEEL_NEG(-1)	0.092623	0.055528	1.668048	0.0982
C	-25.33674	17.63069	-1.43708	0.1535
R-squared	0.573838	Mean dependent var		-0.057894
Adjusted R-squared	0.535096	S.D. dependent var		70.699
S.E. of regression	48.20529	Akaike info criterion		10.67532
Sum squared resid	255612.5	Schwarz criterion		10.92949
Log likelihood	-634.857	Hannan-Quinn criter.		10.77855
F-statistic	14.81181	Durbin-Watson stat		2.043447
Prob(F-statistic)	0			
*Note: p-values and any subsequent tests do not account for model selection.				

Source: Author's own estimates using EViews 11

Table A13: NARDL Model Nickel (Dependent) – Stainless steel

Dependent Variable: DNICKEL

Method: ARDL

Sample (adjusted): 2009M05 2019M07

Included observations: 123 after adjustments

Maximum dependent lags: 4 (Automatic selection)

Model selection method: Akaike info criterion (AIC)

Dynamic regressors (4 lags, automatic): DSTAINLESS_STEEL_POS

DSTAINLESS_STEEL_NEG

Fixed regressors: C

Number of models evalulated: 100

Selected Model: ARDL(2, 2, 2)

Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
DNICKEL(-1)	0.179222	0.087689	2.043834	0.0433
DNICKEL(-2)	-0.225129	0.087492	-2.573148	0.0114
DSTAINLESS_STEEL_POS	5.557115	0.92829	5.986399	0
DSTAINLESS_STEEL_POS(-1)	0.603376	1.39406	0.432819	0.666
DSTAINLESS_STEEL_POS(-2)	2.412416	1.046488	2.305249	0.023
DSTAINLESS_STEEL_NEG	7.587632	0.707209	10.72899	0
DSTAINLESS_STEEL_NEG(-1)	-2.704631	1.133625	-2.385825	0.0187
DSTAINLESS_STEEL_NEG(-2)	3.707217	0.910491	4.071667	0.0001
C	-1285.09	289.8407	-4.433781	0
R-squared	0.655122	Mean dependent var		18.4487
Adjusted R-squared	0.63092	S.D. dependent var		1220.018
S.E. of regression	741.185	Akaike info criterion		16.12473

Sum squared resid	62626491	Schwarz criterion	16.3305
Log likelihood	- 982.6711	Hannan-Quinn criter.	16.2083 2
F-statistic	27.06893	Durbin-Watson stat	1.98363 3
Prob(F-statistic)	0		
*Note: p-values and any subsequent tests do not account for model selection.			

Source: Author's own estimates using EViews 11

Table A14: Breusch-Godfrey Serial Correlation LM Test Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

Breusch-Godfrey Serial Correlation LM Test:				
Null hypothesis: No serial correlation at up to 4 lags				
F-statistic	0.644745	Prob. F(4,92)		0.632
Obs*R-squared	3.299429	Prob. Chi-Square(4)		0.509
Test Equation:				
Dependent Variable: RESID				
Method: ARDL				
Sample: 2009M07 2019M07				
Included observations: 121				
Presample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSTAINLESS_STEEL(-1)	-0.208648	0.241376	-0.864412	0.3896
DSTAINLESS_STEEL(-2)	0.179584	0.167467	1.072353	0.2864
DSTAINLESS_STEEL(-3)	-0.113802	0.149027	-0.763632	0.447
DFERROCHROME_POS	0.010426	0.284297	0.036673	0.9708
DFERROCHROME_NEG	0.01621	0.308823	0.05249	0.9583
DFERROCHROME_NEG(-1)	-0.009304	0.368518	-0.025248	0.9799
DFERROCHROME_NEG(-2)	0.038328	0.396035	0.096781	0.9231
DFERROCHROME_NEG(-3)	0.014623	0.388651	0.037624	0.9701
DFERROCHROME_NEG(-4)	-0.018371	0.286956	-0.064022	0.9491
DNICKEL_POS	0.000419	0.012527	0.03346	0.9734
DNICKEL_POS(-1)	0.007881	0.019744	0.399145	0.6907
DNICKEL_POS(-2)	0.000566	0.018328	0.030878	0.9754
DNICKEL_POS(-3)	0.000422	0.016385	0.025756	0.9795
DNICKEL_POS(-4)	0.002444	0.012549	0.194732	0.846
DNICKEL_NEG	6.35E-05	0.009776	0.006499	0.9948
DNICKEL_NEG(-1)	0.022305	0.028052	0.795133	0.4286
DNICKEL_NEG(-2)	-0.020795	0.021376	-0.972793	0.3332
DNICKEL_NEG(-3)	0.01008	0.016683	0.60422	0.5472
DCHROME_ORE_POS	0.101657	0.843007	0.120588	0.9043

DCHROME_ORE_NEG	-0.13023	0.826269	-0.157612	0.8751
DCHROME_ORE_NEG(-1)	0.348323	1.095423	0.31798	0.7512
DCHROME_ORE_NEG(-2)	-0.307634	0.903997	-0.340304	0.7344
DCHROME_ORE_NEG(-3)	-0.151018	0.900274	-0.167747	0.8672
DCHROME_ORE_NEG(-4)	0.259633	0.702219	0.369732	0.7124
C	-3.313766	50.03009	-0.066235	0.9473
RESID(-1)	0.238728	0.263087	0.907409	0.3666
RESID(-2)	-0.234668	0.188073	-1.247748	0.2153
RESID(-3)	0.087596	0.171539	0.510646	0.6108
RESID(-4)	-0.078963	0.126847	-0.622507	0.5351
R-squared	0.027268	Mean dependent var		-6.74E-13
Adjusted R-squared	-0.268781	S.D. dependent var		65.81101
S.E. of regression	74.12963	Akaike info criterion		11.65484
Sum squared resid	505558.6	Schwarz criterion		12.32491
Log likelihood	-676.1181	Hannan-Quinn criter.		11.92698
F-statistic	0.092106	Durbin-Watson stat		1.999064
Prob(F-statistic)	1			

Source: Author's own estimates using EViews 11

Table A15: Breusch-Godfrey Serial Correlation LM Test Chrome Ore (Dependent) - Stainless steel

Breusch-Godfrey Serial Correlation LM Test:				
Null hypothesis: No serial correlation at up to 4 lags				
F-statistic	0.949245	Prob. F(4,114)		0.4384
Obs*R-squared	3.996923	Prob. Chi-Square(4)		0.4064
Test Equation:				
Dependent Variable: RESID				
Method: ARDL				
Sample: 2009M04 2019M07				
Included observations: 124				
Presample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DCHROME_ORE(-1)	0.113293	0.236665	0.478705	0.6331

DSTAINLESS_STEEL_POS	-0.008997	0.025883	-0.347601	0.7288
DSTAINLESS_STEEL_POS(-1)	0.002973	0.029272	0.101549	0.9193
DSTAINLESS_STEEL_NEG	-0.001835	0.020811	-0.088153	0.9299
DSTAINLESS_STEEL_NEG(-1)	-0.004132	0.022871	-0.180664	0.857
C	1.70882	7.234936	0.23619	0.8137
RESID(-1)	-0.081028	0.261073	-0.310366	0.7568
RESID(-2)	-0.200704	0.116937	-1.716335	0.0888
RESID(-3)	-0.013438	0.102878	-0.130625	0.8963
RESID(-4)	-0.084024	0.094639	-0.887842	0.3765
R-squared	0.032233	Mean dependent var		-2.57E-14
Adjusted R-squared	-0.044169	S.D. dependent var		21.25784
S.E. of regression	21.72224	Akaike info criterion		9.071757
Sum squared resid	53791.55	Schwarz criterion		9.2992
Log likelihood	-552.449	Hannan-Quinn criter.		9.16415
F-statistic	0.421887	Durbin-Watson stat		1.939835
Prob(F-statistic)	0.921093			

Source: Author's own estimates using EViews 11

Table A16: Breusch-Godfrey Serial Correlation LM Test Ferrochrome (Dependent) - Stainless steel

Breusch-Godfrey Serial Correlation LM Test:				
Null hypothesis: No serial correlation at up to 4 lags				
F-statistic	1.962205	Prob. F(4,106)		0.1056
Obs*R-squared	8.341827	Prob. Chi-Square(4)		0.0798
Test Equation:				
Dependent Variable: RESID				
Method: ARDL				
Sample: 2009M07 2019M07				
Included observations: 121				
Presample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DFERROCHROME(-1)	0.504817	0.340451	1.482789	0.1411
DFERROCHROME(-2)	-0.540577	0.240172	-2.250797	0.0265

DFERROCHROME(-3)	0.373703	0.18506	2.019364	0.046
DSTAINLESS_STEEL_POS	0.01446	0.06312	0.229089	0.8192
DSTAINLESS_STEEL_POS(-1)	-0.048916	0.090255	-0.541977	0.589
DSTAINLESS_STEEL_POS(-2)	-0.101183	0.118661	-0.852713	0.3957
DSTAINLESS_STEEL_POS(-3)	0.16088	0.093371	1.723024	0.0878
DSTAINLESS_STEEL_POS(-4)	-0.099003	0.063561	-1.557611	0.1223
DSTAINLESS_STEEL_NEG	-0.008423	0.04716	-0.178596	0.8586
DSTAINLESS_STEEL_NEG(-1)	-0.067476	0.087723	-0.769194	0.4435
C	-2.875586	17.88167	-0.160812	0.8725
RESID(-1)	-0.518109	0.355126	-1.458945	0.1475
RESID(-2)	0.285065	0.188294	1.513941	0.133
RESID(-3)	0.11023	0.16033	0.687522	0.4933
RESID(-4)	-0.329442	0.147575	-2.232372	0.0277
R-squared	0.068941	Mean dependent var		-6.78E-14
Adjusted R-squared	-0.054029	S.D. dependent var		46.15305
S.E. of regression	47.38346	Akaike info criterion		10.67001
Sum squared resid	237990.4	Schwarz criterion		11.01659
Log likelihood	-630.5354	Hannan-Quinn criter.		10.81077
F-statistic	0.56063	Durbin-Watson stat		1.962857
Prob(F-statistic)	0.889703			

Source: Author's own estimates using EViews 11

Table A17: Breusch-Godfrey Serial Correlation LM Test Nickel (Dependent) - Stainless steel

Breusch-Godfrey Serial Correlation LM Test:			
Null hypothesis: No serial correlation at up to 4 lags			
F-statistic	1.135817	Prob. F(4,110)	0.3435
Obs*R-squared	4.8787	Prob. Chi-Square(4)	0.3
Test Equation:			
Dependent Variable: RESID			
Method: ARDL			
Sample: 2009M05 2019M07			
Included observations: 123			

Presample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DNICKEL(-1)	0.009758	0.266336	0.036639	0.9708
DNICKEL(-2)	0.349506	0.256389	1.363187	0.1756
DSTAINLESS_STEEL_POS	0.29961	0.969065	0.309174	0.7578
DSTAINLESS_STEEL_POS(-1)	0.160322	2.14225	0.074838	0.9405
DSTAINLESS_STEEL_POS(-2)	-2.669428	2.005016	-1.331375	0.1858
DSTAINLESS_STEEL_NEG	0.047232	0.722342	0.065388	0.948
DSTAINLESS_STEEL_NEG(-1)	-0.116021	2.113542	-0.054894	0.9563
DSTAINLESS_STEEL_NEG(-2)	-2.156179	1.810506	-1.190926	0.2362
C	244.9211	413.477	0.592345	0.5548
RESID(-1)	-0.051926	0.281907	-0.184195	0.8542
RESID(-2)	-0.422794	0.27324	-1.547334	0.1247
RESID(-3)	-0.138453	0.117921	-1.174114	0.2429
RESID(-4)	-0.053622	0.11006	-0.487205	0.6271
R-squared	0.039664	Mean dependent var		-3.96E-12
Adjusted R-squared	-0.0651	S.D. dependent var		716.4718
S.E. of regression	739.4252	Akaike info criterion		16.1493
Sum squared resid	60142460	Schwarz criterion		16.44652
Log likelihood	-980.182	Hannan-Quinn criter.		16.27003
F-statistic	0.378606	Durbin-Watson stat		1.921679
Prob(F-statistic)	0.968616			

Source: Author's own estimates using EViews 11

Table A18: Breusch-Pagan-Godfrey Heteroskedasticity Test Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
Null hypothesis: Homoskedasticity				
F-statistic	1.295683	Prob. F(24,96)		0.1885
Obs*R-squared	29.60481	Prob. Chi-Square(24)		0.1982
Scaled explained SS	46.01359	Prob. Chi-Square(24)		0.0044
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample: 2009M07 2019M07				
Included observations: 121				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1365.525	6084.528	0.224426	0.8229
DSTAINLESS_STEEL(-1)	21.92691	12.22579	1.793497	0.076
DSTAINLESS_STEEL(-2)	-19.4488	11.61094	-1.675041	0.0972
DSTAINLESS_STEEL(-3)	-8.045217	11.12683	-0.723047	0.4714
DFERROCHROME_POS	4.228041	35.52527	0.119015	0.9055
DFERROCHROME_NEG	-24.71259	38.17832	-0.647294	0.519
DFERROCHROME_NEG(-1)	-9.17442	46.06191	-0.199176	0.8425
DFERROCHROME_NEG(-2)	-3.88768	48.22797	-0.08061	0.9359
DFERROCHROME_NEG(-3)	21.70135	47.90831	0.452977	0.6516
DFERROCHROME_NEG(-4)	-16.31541	35.85496	-0.455039	0.6501
DNICKEL_POS	3.405834	1.566399	2.174308	0.0321
DNICKEL_POS(-1)	-1.476634	2.067162	-0.714329	0.4768
DNICKEL_POS(-2)	2.188526	1.99505	1.096978	0.2754
DNICKEL_POS(-3)	2.189266	1.843028	1.187864	0.2378
DNICKEL_POS(-4)	-0.36861	1.540447	-0.239288	0.8114
DNICKEL_NEG	1.257798	1.213933	1.036135	0.3027
DNICKEL_NEG(-1)	1.235721	1.892267	0.653037	0.5153
DNICKEL_NEG(-2)	2.063311	1.826488	1.12966	0.2614
DNICKEL_NEG(-3)	1.628213	1.664525	0.978184	0.3304

DCHROME_ORE_POS	-92.37058	103.4312	-0.893063	0.3741
DCHROME_ORE_NEG	75.99195	101.3321	0.74993	0.4551
DCHROME_ORE_NEG(-1)	-29.23684	131.0377	-0.223118	0.8239
DCHROME_ORE_NEG(-2)	6.985967	109.2075	0.06397	0.9491
DCHROME_ORE_NEG(-3)	-10.07181	107.4381	-0.093745	0.9255
DCHROME_ORE_NEG(-4)	-30.98302	82.87736	-0.373842	0.7093
R-squared	0.244668	Mean dependent var		4295.295
Adjusted R-squared	0.055835	S.D. dependent var		9584.867
S.E. of regression	9313.439	Akaike info criterion		21.29809
Sum squared resid	8.33E+09	Schwarz criterion		21.87573
Log likelihood	-1263.534	Hannan-Quinn criter.		21.53269
F-statistic	1.295683	Durbin-Watson stat		2.271518
Prob(F-statistic)	0.188453			

Source: Author's own estimates using EViews 11

Table A19: Breusch-Pagan-Godfrey Heteroskedasticity Test Chrome Ore (Dependent) - Stainless steel

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
Null hypothesis: Homoskedasticity				
F-statistic	0.794956	Prob. F(5,118)		0.5554
Obs*R-squared	4.040775	Prob. Chi-Square(5)		0.5436
Scaled explained SS	47.81262	Prob. Chi-Square(5)		0
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample: 2009M04 2019M07				
Included observations: 124				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	75.79772	751.4643	0.100867	0.9198
DCHROME_ORE(-1)	-7.298737	8.725914	-0.836444	0.4046
DSTAINLESS_STEEL_POS	1.072605	2.685303	0.399435	0.6903
DSTAINLESS_STEEL_POS(-1)	-2.905241	2.820352	-1.030098	0.3051
DSTAINLESS_STEEL_NEG	-1.24431	2.128841	-0.584501	0.56
DSTAINLESS_STEEL_NEG(-1)	-0.717639	2.059879	-0.348389	0.7282
R-squared	0.032587	Mean dependent var		448.2514
Adjusted R-squared	-0.008405	S.D. dependent var		2300.772
S.E. of regression	2310.421	Akaike info criterion		18.37542
Sum squared resid	6.30E+08	Schwarz criterion		18.51189
Log likelihood	-1133.276	Hannan-Quinn criter.		18.43086
F-statistic	0.794956	Durbin-Watson stat		1.920312
Prob(F-statistic)	0.55539			

Source: Author's own estimates using EViews 11

Table A20: Breusch-Pagan-Godfrey Heteroskedasticity Test Ferrochrome (Dependent) - Stainless steel

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
Null hypothesis: Homoskedasticity				
F-statistic	0.889887	Prob. F(10,110)		0.5451
Obs*R-squared	9.056132	Prob. Chi-Square(10)		0.5268
Scaled explained SS	37.39338	Prob. Chi-Square(10)		0
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample: 2009M07 2019M07				
Included observations: 121				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1638.603	2463.819	-0.665066	0.5074
DFERROCHROME(-1)	-2.342516	13.15633	-0.178052	0.859
DFERROCHROME(-2)	14.01114	13.27401	1.055531	0.2935
DFERROCHROME(-3)	-14.57351	12.00274	-1.214182	0.2273
DSTAINLESS_STEEL_POS	9.286725	8.729865	1.063788	0.2898
DSTAINLESS_STEEL_POS(-1)	-12.68851	11.75203	-1.079687	0.2826
DSTAINLESS_STEEL_POS(-2)	10.33313	11.01441	0.938147	0.3502
DSTAINLESS_STEEL_POS(-3)	8.661857	9.956811	0.869943	0.3862
DSTAINLESS_STEEL_POS(-4)	-11.4187	7.31192	-1.561656	0.1212
DSTAINLESS_STEEL_NEG	2.255393	6.565388	0.343528	0.7319
DSTAINLESS_STEEL_NEG(-1)	1.382899	7.759797	0.178213	0.8589
R-squared	0.074844	Mean dependent var		2112.5
Adjusted R-squared	-0.009261	S.D. dependent var		6705.521
S.E. of regression	6736.499	Akaike info criterion		20.55498
Sum squared resid	4.99E+09	Schwarz criterion		20.80914
Log likelihood	-1232.576	Hannan-Quinn criter.		20.6582
F-statistic	0.889887	Durbin-Watson stat		1.832336
Prob(F-statistic)	0.545091			

Source: Author's own estimates using EViews 11

Table A21: Breusch-Pagan-Godfrey Heteroskedasticity Test Nickel (Dependent) - Stainless steel

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
Null hypothesis: Homoskedasticity				
F-statistic	1.680028	Prob. F(8,114)		0.1107
Obs*R-squared	12.97194	Prob. Chi-Square(8)		0.1128
Scaled explained SS	15.31747	Prob. Chi-Square(8)		0.0533
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample: 2009M05 2019M07				
Included observations: 123				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	773043.9	324333.1	2.383487	0.0188
DNICKEL(-1)	6.210515	98.12454	0.063292	0.9496
DNICKEL(-2)	-39.76931	97.90363	-0.406209	0.6854
DSTAINLESS_STEEL_POS	-1419.242	1038.761	-1.366283	0.1745
DSTAINLESS_STEEL_POS(-1)	2551.266	1559.96	1.635468	0.1047
DSTAINLESS_STEEL_POS(-2)	579.9329	1171.025	0.495235	0.6214
DSTAINLESS_STEEL_NEG	736.1774	791.37	0.930257	0.3542
DSTAINLESS_STEEL_NEG(-1)	199.9777	1268.532	0.157645	0.875
DSTAINLESS_STEEL_NEG(-2)	881.1077	1018.844	0.864811	0.389
R-squared	0.105463	Mean dependent var		509158.5
Adjusted R-squared	0.042688	S.D. dependent var		847680
S.E. of regression	829389.6	Akaike info criterion		30.16512
Sum squared resid	7.84E+13	Schwarz criterion		30.37089
Log likelihood	-1846.155	Hannan-Quinn criter.		30.24871
F-statistic	1.680028	Durbin-Watson stat		1.778337
Prob(F-statistic)	0.110684			

Source: Author's own estimates using EViews 11

Table A22: Ramsey RESET Test Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

Ramsey RESET Test

Equation: DSTAINLESS_NICKEL_FECR_CR_NARDL

Omitted Variables: Squares of fitted values

Specification: DSTAINLESS_STEEL
DSTAINLESS_STEEL(-1)

DSTAINLESS_STEEL(-2) DSTAINLESS_STEEL(-3)

DFERROCHROME_POS DFERROCHROME_NEG

DFERROCHROME_NEG(-1)
DFERROCHROME_NEG(-2)

DFERROCHROME_NEG(-3)
DFERROCHROME_NEG(-4)

DNICKEL_POS DNICKEL_POS(-1) DNICKEL_POS(-
2)

DNICKEL_POS(-3) DNICKEL_POS(-4)
DNICKEL_NEG

DNICKEL_NEG(-1) DNICKEL_NEG(-2)
DNICKEL_NEG(-3)

DCHROME_ORE_POS DCHROME_ORE_NEG

DCHROME_ORE_NEG(-1) DCHROME_ORE_NEG(-2)

DCHROME_ORE_NEG(-3) DCHROME_ORE_NEG(-4)
C

	Value	df		Probability
t-statistic	0.489919		95	0.6253
F-statistic	0.240021	(1, 95)		0.6253
Likelihood ratio	0.305325		1	0.5806
F-test summary:				
	Sum of Sq.	df		Mean Squares
Test SSR	1309.808		1	1309.808
Restricted SSR	519730.7		96	5413.861
Unrestricted SSR	518420.8		95	5457.062
LR test summary:				
	Value			
Restricted LogL	-677.7907			

Unrestricted LogL	-677.6381			
Unrestricted Test Equation:				
Dependent Variable: DSTAINLESS_STEEL				
Method: Least Squares				
Sample: 2009M07 2019M07				
Included observations: 121				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSTAINLESS_STEEL(-1)	0.110111	0.098835	1.114089	0.2681
DSTAINLESS_STEEL(-2)	-0.24668	0.092427	-2.668914	0.0089
DSTAINLESS_STEEL(-3)	-0.216437	0.089467	-2.419198	0.0175
DFERROCHROME_POS	0.360577	0.286491	1.258599	0.2113
DFERROCHROME_NEG	-0.118707	0.30417	-0.390264	0.6972
DFERROCHROME_NEG(-1)	0.432298	0.36637	1.179948	0.241
DFERROCHROME_NEG(-2)	0.209579	0.382716	0.547609	0.5852
DFERROCHROME_NEG(-3)	0.652247	0.380271	1.715215	0.0896
DFERROCHROME_NEG(-4)	-0.861371	0.285407	-3.018044	0.0033
DNICKEL_POS	0.052511	0.012639	4.154575	0.0001
DNICKEL_POS(-1)	0.02234	0.016578	1.347571	0.181
DNICKEL_POS(-2)	0.020604	0.016272	1.266228	0.2085
DNICKEL_POS(-3)	-0.012103	0.014649	-0.826201	0.4108
DNICKEL_POS(-4)	0.022856	0.012445	1.836554	0.0694
DNICKEL_NEG	0.104391	0.010234	10.20005	0
DNICKEL_NEG(-1)	-0.026167	0.016839	-1.553985	0.1235
DNICKEL_NEG(-2)	-0.00465	0.014531	-0.320014	0.7497
DNICKEL_NEG(-3)	0.03396	0.013318	2.549973	0.0124
DCHROME_ORE_POS	0.453086	0.821164	0.551761	0.5824
DCHROME_ORE_NEG	0.881847	0.821211	1.073838	0.2856
DCHROME_ORE_NEG(-1)	-0.287359	1.040943	-0.276056	0.7831
DCHROME_ORE_NEG(-2)	-1.777988	0.866417	-2.052115	0.0429
DCHROME_ORE_NEG(-3)	0.14345	0.852278	0.168313	0.8667
DCHROME_ORE_NEG(-4)	1.617063	0.658289	2.456462	0.0158

C	-51.04479	48.54127	-1.051575	0.2957
FITTED^2	0.000217	0.000443	0.489919	0.6253
R-squared	0.762996	Mean dependent var		-5.539346
Adjusted R-squared	0.700627	S.D. dependent var		135.0123
S.E. of regression	73.87193	Akaike info criterion		11.63038
Sum squared resid	518420.8	Schwarz criterion		12.23113
Log likelihood	-677.6381	Hannan-Quinn criter.		11.87437
F-statistic	12.23352	Durbin-Watson stat		1.949998
Prob(F-statistic)	0			

Source: Author's own estimates using EViews 11

Table A23: Ramsey RESET Test Chrome Ore (Dependent) - Stainless steel

Ramsey RESET Test				
Equation: DCHROME_DSTAINLESS_NARDL				
Omitted Variables: Squares of fitted values				
Specification: DCHROME_ORE DCHROME_ORE(-1)				
DSTAINLESS_STEEL_POS DSTAINLESS_STEEL_POS(-1)				
DSTAINLESS_STEEL_NEG DSTAINLESS_STEEL_NEG(-1) C				
	Value	df	Probability	
t-statistic	1.671627	117	0.0973	
F-statistic	2.794337	(1, 117)	0.0973	
Likelihood ratio	2.926707	1	0.0871	
F-test summary:				
	Sum of Sq.	df	Mean Squares	
Test SSR	1296.54	1	1296.54	
Restricted SSR	55583.18	118	471.0439	
Unrestricted SSR	54286.64	117	463.9884	
LR test summary:				
	Value			
Restricted LogL	-554.4803			
Unrestricted LogL	-553.017			
Unrestricted Test Equation:				
Dependent Variable: DCHROME_ORE				
Method: Least Squares				
Sample: 2009M04 2019M07				
Included observations: 124				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DCHROME_ORE(-1)	0.348118	0.085522	4.07053	0.0001
DSTAINLESS_STEEL_POS	0.014928	0.025551	0.584224	0.5602
DSTAINLESS_STEEL_POS(-1)	0.061392	0.026296	2.334622	0.0213

DSTAINLESS_STEEL_NEG	0.045446	0.019926	2.280779	0.0244
DSTAINLESS_STEEL_NEG(-1)	0.031121	0.019431	1.601573	0.1119
C	-11.22859	7.029878	-1.597267	0.1129
FITTED^2	0.007633	0.004566	1.671627	0.0973
R-squared	0.297306	Mean dependent var		-0.080645
Adjusted R-squared	0.26127	S.D. dependent var		25.06171
S.E. of regression	21.54039	Akaike info criterion		9.032532
Sum squared resid	54286.64	Schwarz criterion		9.191742
Log likelihood	-553.017	Hannan-Quinn criter.		9.097207
F-statistic	8.250337	Durbin-Watson stat		1.857186
Prob(F-statistic)	0			

Source: Author's own estimates using EViews 11

Table A24: Ramsey RESET Test Ferrochrome (Dependent) - Stainless steel

Ramsey RESET Test				
Equation: DFERROCHROME_DSTAINLESS_NARDL				
Omitted Variables: Squares of fitted values				
Specification: DFERROCHROME DFERROCHROME(-1)				
DFERROCHROME(-2) DFERROCHROME(-3) DSTAINLESS_STE				
EL_POS DSTAINLESS_STEEL_POS(-1) DSTAINLESS_STEEL_P				
OS(-2) DSTAINLESS_STEEL_POS(-3) DSTAINLESS_STEEL_PO				
S(-4) DSTAINLESS_STEEL_NEG DSTAINLESS_STEEL_NEG(-1)				
C				
	Value	df		Probability
t-statistic	0.165532		109	0.8688
F-statistic	0.027401	(1, 109)		0.8688
Likelihood ratio	0.030414		1	0.8616
F-test summary:				
	Sum of Sq.	df		Mean Squares
Test SSR	64.24059		1	64.24059
Restricted SSR	255612.5		110	2323.75
Unrestricted SSR	255548.3		109	2344.48
LR test summary:				
	Value			
Restricted LogL	-634.857			
Unrestricted LogL	-634.8418			
Unrestricted Test Equation:				
Dependent Variable: DFERROCHROME				
Method: Least Squares				
Sample: 2009M07 2019M07				
Included observations: 121				

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DFERROCHROME(-1)	0.583939	0.095004	6.146473	0
DFERROCHROME(-2)	-0.606123	0.095446	-6.350407	0
DFERROCHROME(-3)	0.154882	0.086384	1.792954	0.0758
DSTAINLESS_STEEL_POS	0.063818	0.065422	0.975479	0.3315
DSTAINLESS_STEEL_POS(-1)	0.162757	0.084956	1.915786	0.058
DSTAINLESS_STEEL_POS(-2)	-0.069452	0.079184	-0.877098	0.3824
DSTAINLESS_STEEL_POS(-3)	0.194037	0.071709	2.70589	0.0079
DSTAINLESS_STEEL_POS(-4)	-0.115147	0.053139	-2.166912	0.0324
DSTAINLESS_STEEL_NEG	0.146016	0.047576	3.069117	0.0027
DSTAINLESS_STEEL_NEG(-1)	0.092339	0.055801	1.654789	0.1008
C	-25.46956	17.72732	-1.43674	0.1537
FITTED^2	-0.000137	0.00083	-0.165532	0.8688
R-squared	0.573946	Mean dependent var		-0.057894
Adjusted R-squared	0.530949	S.D. dependent var		70.699
S.E. of regression	48.41983	Akaike info criterion		10.6916
Sum squared resid	255548.3	Schwarz criterion		10.96887
Log likelihood	-634.8418	Hannan-Quinn criter.		10.80421
F-statistic	13.34871	Durbin-Watson stat		2.041833
Prob(F-statistic)	0			

Source: Author's own estimates using EViews 11

Table A25: Ramsey RESET Test Nickel (Dependent) - Stainless steel

Ramsey RESET Test					
Equation: DNICKEL_DSTAINLESS_NARDL					
Omitted Variables: Squares of fitted values					
Specification: DNICKEL DNICKEL(-1) DNICKEL(-2) DSTAINLESS_STE					
EL_POS DSTAINLESS_STEEL_POS(-1) DSTAINLESS_STEEL_P					
OS(-2) DSTAINLESS_STEEL_NEG DSTAINLESS_STEEL_NEG(					
-1) DSTAINLESS_STEEL_NEG(-2) C					
	Value	df		Probability	
t-statistic	0.746345		113	0.457	
F-statistic	0.557031	(1, 113)		0.457	
Likelihood ratio	0.604837		1	0.4367	
F-test summary:					
	Sum of Sq.	df		Mean Squares	
Test SSR	307201.8		1	307201.8	
Restricted SSR	62626491		114	549355.2	
Unrestricted SSR	62319289		113	551498.1	
LR test summary:					
	Value				
Restricted LogL	-982.6711				
Unrestricted LogL	-982.3687				
Unrestricted Test Equation:					
Dependent Variable: DNICKEL					
Method: Least Squares					
Sample: 2009M05 2019M07					
Included observations: 123					
Variable	Coefficie	Std. Error		t-Statistic	Prob.

	nt			
DNICKEL(-1)	0.19297	0.08977	2.1496	0.0337
DNICKEL(-2)	-0.210567	0.089807	-2.34465	0.0208
DSTAINLESS_STEEL_POS	5.937821	1.060792	5.597534	0
DSTAINLESS_STEEL_POS(-1)	0.20445	1.495554	0.136705	0.8915
DSTAINLESS_STEEL_POS(-2)	2.491265	1.053836	2.363997	0.0198
DSTAINLESS_STEEL_NEG	7.416606	0.744718	9.958939	0
DSTAINLESS_STEEL_NEG(-1)	-2.391339	1.210919	-1.974814	0.0507
DSTAINLESS_STEEL_NEG(-2)	3.635036	0.917377	3.962422	0.0001
C	-1238.83	296.9463	-4.1719	0.0001
FITTED^2	-4.06E-05	5.44E-05	-0.746345	0.457
R-squared	0.656814	Mean dependent var		18.4487
Adjusted R-squared	0.62948	S.D. dependent var		1220.018
S.E. of regression	742.6292	Akaike info criterion		16.13608
Sum squared resid	62319289	Schwarz criterion		16.36471
Log likelihood	-982.3687	Hannan-Quinn criter.		16.22895
F-statistic	24.02967	Durbin-Watson stat		1.984975
Prob(F-statistic)	0			

Source: Author's own estimates using EViews 11

Table A26: NARDL Long Run Form and Bounds Test Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

ARDL Long Run Form and Bounds Test
Dependent Variable: D(DSTAINLESS_STEEL)
Selected Model: ARDL(3, 0, 4, 4, 3, 0, 4)
Case 2: Restricted Constant and No Trend
Sample: 2009M01 2019M07
Included observations: 121

Conditional Error Correction Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-48.49291	48.06959	-1.008806	0.3156
DSTAINLESS_STEEL(-1)*	-1.373387	0.155775	-8.816464	0
DFERROCHROME_POS**	0.385931	0.28066	1.375084	0.1723
DFERROCHROME_NEG(-1)	0.351949	0.318001	1.106753	0.2712
DNICKEL_POS(-1)	0.109622	0.018818	5.825515	0
DNICKEL_NEG(-1)	0.110983	0.018433	6.02103	0
DCHROME_ORE_POS**	0.435628	0.817137	0.533115	0.5952
DCHROME_ORE_NEG(-1)	0.523797	0.972669	0.538515	0.5915
D(DSTAINLESS_STEEL(-1))	0.474141	0.11518	4.116534	0.0001
D(DSTAINLESS_STEEL(-2))	0.223625	0.087905	2.543937	0.0126
D(DFERROCHROME_NEG)	-0.104686	0.30162	-0.34708	0.7293
D(DFERROCHROME_NEG(-1))	-0.010965	0.328498	-0.033378	0.9734
D(DFERROCHROME_NEG(-2))	0.204421	0.289021	0.707288	0.4811
D(DFERROCHROME_NEG(-3))	0.849593	0.283265	2.99929	0.0034
D(DNICKEL_POS)	0.053649	0.012375	4.335256	0
D(DNICKEL_POS(-1))	-0.034833	0.017082	-2.039144	0.0442
D(DNICKEL_POS(-2))	-0.012373	0.014435	-0.857127	0.3935

D(DNICKEL_POS(-3))	-0.024013	0.01217	-1.973139	0.0514
D(DNICKEL_NEG)	0.102692	0.00959	10.70772	0
D(DNICKEL_NEG(-1))	-0.030719	0.015463	-1.986588	0.0498
D(DNICKEL_NEG(-2))	-0.034815	0.01315	-2.647503	0.0095
D(DCHROME_ORE_NEG)	0.799304	0.800554	0.998438	0.3206
D(DCHROME_ORE_NEG(-1))	0.016276	0.81938	0.019863	0.9842
D(DCHROME_ORE_NEG(-2))	-1.771057	0.771776	-2.294782	0.0239
D(DCHROME_ORE_NEG(-3))	-1.634167	0.654756	-2.495842	0.0143

* p-value incompatible with t-Bounds distribution.

** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DFERROCHROME_POS	0.281007	0.200138	1.404064	0.1635
DFERROCHROME_NEG	0.256263	0.22977	1.115305	0.2675
DNICKEL_POS	0.079819	0.010405	7.670943	0
DNICKEL_NEG	0.08081	0.00991	8.154788	0
DCHROME_ORE_POS	0.317193	0.596654	0.531619	0.5962
DCHROME_ORE_NEG	0.381391	0.707919	0.538749	0.5913
C	-35.30898	34.19568	-1.032557	0.3044

EC = DSTAINLESS_STEEL - (0.2810*DFERROCHROME_POS + 0.2563

*DFERROCHROME_NEG + 0.0798*DNICKEL_POS + 0.0808

*DNICKEL_NEG + 0.3172*DCHROME_ORE_POS + 0.3814

*DCHROME_ORE_NEG - 35.3090)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	10.24455	10%	1.99	2.94
K	6	5%	2.27	3.28
		2.50%	2.55	3.61
		1%	2.88	3.99
Actual Sample Size	121		Finite Sample: n=80	
		10%	2.088	3.103
		5%	2.431	3.518
		1%	3.173	4.485

Source: Author's own estimates using EViews 11

Table A27: NARDL Long Run Form and Bounds Test Chrome Ore (Dependent) - Stainless steel

ARDL Long Run Form and Bounds Test

Dependent Variable: D(DCHROME_ORE)

Selected Model: ARDL(1, 1, 1)

Case 2: Restricted Constant and No Trend

Sample: 2009M01 2019M07

Included observations: 124

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-12.19612	7.059077	-1.72772	0.0867
DCHROME_ORE(-1)*	-0.695971	0.081969	-8.49064	0
DSTAINLESS_STEEL_POS(-1)	0.084366	0.019298	4.371787	0
DSTAINLESS_STEEL_NEG(-1)	0.084462	0.019172	4.405557	0
D(DSTAINLESS_STEEL_POS)	0.023466	0.025225	0.930248	0.3541
D(DSTAINLESS_STEEL_NEG)	0.048394	0.019998	2.419939	0.017

* p-value incompatible with t-Bounds distribution.

Levels Equation

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSTAINLESS_STEEL_POS	0.12122	0.02763	4.387187	0
DSTAINLESS_STEEL_NEG	0.121359	0.027467	4.41832	0
C	-17.5239	10.05103	-1.74349	0.0839

EC = DCHROME_ORE - (0.1212*DSTAINLESS_STEEL_POS + 0.1214

*DSTAINLESS_STEEL_NEG - 17.5239)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	19.4022	10%	2.63	3.35
K	2	5%	3.1	3.87
		2.50%	3.55	4.38
		1%	4.13	5
Actual Sample Size	124		Finite Sample: n=80	
		10%	2.713	3.453
		5%	3.235	4.053
		1%	4.358	5.393

Source: Author's own estimates using EViews 11

Table A28: NARDL Long Run Form and Bounds Test Ferrochrome (Dependent) - Stainless steel

ARDL Long Run Form and Bounds Test

Dependent Variable: D(DFERROCHROME)

Selected Model: ARDL(3, 4, 1)

Case 2: Restricted Constant and No Trend

Sample: 2009M01 2019M07

Included observations: 121

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-25.33674	17.63069	-1.43708	0.1535
DFERROCHROME(-1)*	-0.869103	0.115975	-7.4939	0
DSTAINLESS_STEEL_POS(-1)	0.235264	0.055281	4.255755	0
DSTAINLESS_STEEL_NEG(-1)	0.237638	0.055573	4.276136	0
D(DFERROCHROME(-1))	0.451529	0.081178	5.562219	0
D(DFERROCHROME(-2))	-0.154155	0.08589	-1.7948	0.0754
D(DSTAINLESS_STEEL_POS)	0.060753	0.062469	0.972523	0.3329
D(DSTAINLESS_STEEL_POS(-1))	-0.010251	0.068227	-0.15026	0.8808
D(DSTAINLESS_STEEL_POS(-2))	-0.079441	0.055414	-1.4336	0.1545
D(DSTAINLESS_STEEL_POS(-3))	0.113848	0.052323	2.175864	0.0317
D(DSTAINLESS_STEEL_NEG)	0.145015	0.046981	3.086679	0.0026

* p-value incompatible with t-Bounds distribution.

Levels Equation

Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSTAINLESS_STEEL_POS	0.270697	0.063482	4.264182	0
DSTAINLESS_STEEL_NEG	0.273429	0.063647	4.295994	0
C	-29.15275	20.63007	-1.41312	0.1604
EC = DFERROCHROME - (0.2707*DSTAINLESS_STEEL_POS + 0.2734 *DSTAINLESS_STEEL_NEG - 29.1528)				
F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	15.48966	10%	2.63	3.35
K	2	5%	3.1	3.87
		2.50%	3.55	4.38
		1%	4.13	5
Actual Sample Size	121		Finite Sample: n=80	
		10%	2.713	3.453
		5%	3.235	4.053
		1%	4.358	5.393

Source: Author's own estimates using EViews 11

Table A29: NARDL Long Run Form and Bounds Test Nickel (Dependent) - Stainless steel

ARDL Long Run Form and Bounds Test

Dependent Variable: D(DNICKEL)

Selected Model: ARDL(2, 2, 2)

Case 2: Restricted Constant and No Trend

Sample: 2009M01 2019M07

Included observations: 123

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1285.09	289.8407	-4.433781	0
DNICKEL(-1)*	-1.045907	0.115164	-9.081872	0
DSTAINLESS_STEEL_POS(-1)	8.572906	1.081878	7.924094	0
DSTAINLESS_STEEL_NEG(-1)	8.590218	1.080507	7.95017	0
D(DNICKEL(-1))	0.225129	0.087492	2.573148	0.0114
D(DSTAINLESS_STEEL_POS)	5.557115	0.92829	5.986399	0
D(DSTAINLESS_STEEL_POS(-1))	-2.412416	1.046488	-2.305249	0.023
D(DSTAINLESS_STEEL_NEG)	7.587632	0.707209	10.72899	0
D(DSTAINLESS_STEEL_NEG(-1))	-3.707217	0.910491	-4.071667	0.0001

* p-value incompatible with t-Bounds distribution.

Levels Equation

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSTAINLESS_STEEL_POS	8.196622	0.765923	10.70162	0

DSTAINLESS_STEEL_NEG	8.213175	0.762245	10.77497	0
C	-1228.685	252.9662	-4.85711	0
EC = DNICKEL - (8.1966*DSTAINLESS_STEEL_POS + 8.2132 *DSTAINLESS_STEEL_NEG - 1228.6847)				
F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	22.00104	10%	2.63	3.35
K	2	5%	3.1	3.87
		2.50%	3.55	4.38
		1%	4.13	5
Actual Sample Size	123		Finite Sample: n=80	
		10%	2.713	3.453
		5%	3.235	4.053
		1%	4.358	5.393

Source: Author's own estimates using EViews 11

Table A30: NARDL Error Correction Regression Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

ARDL Error Correction Regression

Dependent Variable: D(DSTAINLESS_STEEL)

Selected Model: ARDL(3, 0, 4, 4, 3, 0, 4)

Case 2: Restricted Constant and No Trend

Sample: 2009M01 2019M07

Included observations: 121

ECM Regression

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DSTAINLESS_STEEL(-1))	0.474141	0.106162	4.466202	0
D(DSTAINLESS_STEEL(-2))	0.223625	0.082724	2.703273	0.0081
D(DFERROCHROME_NEG)	-0.104686	0.247597	-0.42281	0.6734
D(DFERROCHROME_NEG(-1))	-0.010965	0.286431	-0.038281	0.9695
D(DFERROCHROME_NEG(-2))	0.204421	0.266562	0.76688	0.445
D(DFERROCHROME_NEG(-3))	0.849593	0.244843	3.469958	0.0008
D(DNICKEL_POS)	0.053649	0.009566	5.608128	0
D(DNICKEL_POS(-1))	-0.034833	0.012781	-2.725307	0.0076
D(DNICKEL_POS(-2))	-0.012373	0.011342	-1.090924	0.278
D(DNICKEL_POS(-3))	-0.024013	0.009339	-2.571396	0.0117
D(DNICKEL_NEG)	0.102692	0.00733	14.0097	0
D(DNICKEL_NEG(-1))	-0.030719	0.011279	-2.723633	0.0077
D(DNICKEL_NEG(-2))	-0.034815	0.010479	-3.322298	0.0013
D(DCHROME_ORE_NEG)	0.799304	0.691186	1.156423	0.2504
D(DCHROME_ORE_NEG(-1))	0.016276	0.725395	0.022437	0.9821
D(DCHROME_ORE_NEG(-2))	-1.771057	0.706195	-2.507885	0.0138
D(DCHROME_ORE_NEG(-3))	-1.634167	0.603176	-	0.008

				2.709273	
CointEq(-1)*	-1.373387		0.14646	- 9.377228	0
R-squared	0.850066	Mean dependent var			- 1.856969
Adjusted R-squared	0.825319	S.D. dependent var			169.9606
S.E. of regression	71.0347	Akaike info criterion			11.50067
Sum squared resid	519730.7	Schwarz criterion			11.91658
Log likelihood	-677.7907	Hannan-Quinn criter.			11.66959
Durbin-Watson stat	1.966985				
* p-value incompatible with t-Bounds distribution.					
F-Bounds Test		Null Hypothesis: No levels relationship			
Test Statistic	Value	Signif.		I(0)	I(1)
F-statistic	10.24455		10%	1.99	2.94
K	6		5%	2.27	3.28
			2.50%	2.55	3.61
			1%	2.88	3.99

Source: Author's own estimates using EViews 11

Table A31: NARDL Error Correction Regression Chrome Ore (Dependent) - Stainless steel

ARDL Error Correction Regression

Dependent Variable: D(DCHROME_ORE)

Selected Model: ARDL(1, 1, 1)

Case 2: Restricted Constant and No Trend

Sample: 2009M01 2019M07

Included observations: 124

ECM Regression

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error		t-Statistic	Prob.
D(DSTAINLESS_STEEL_POS)	0.023466		0.018049	1.300111	0.1961
D(DSTAINLESS_STEEL_NEG)	0.048394		0.014537	3.328891	0.0012
CointEq(-1)*	-0.695971		0.078016	-8.92087	0
R-squared	0.400674	Mean dependent var			0.112903
Adjusted R-squared	0.390768	S.D. dependent var			27.45919
S.E. of regression	21.4328	Akaike info criterion			8.991618
Sum squared resid	55583.18	Schwarz criterion			9.059851
Log likelihood	-554.4803	Hannan-Quinn criter.			9.019336
Durbin-Watson stat	1.903876				
* p-value incompatible with t-Bounds distribution.					
F-Bounds Test		Null Hypothesis: No levels relationship			
Test Statistic	Value	Signif.		I(0)	I(1)
F-statistic	19.4022		10%	2.63	3.35
K	2		5%	3.1	3.87
			2.50%	3.55	4.38
			1%	4.13	5

Source: Author's own estimates using EViews 11

Table A32: NARDL Error Correction Regression Ferrochrome (Dependent) - Stainless steel

ARDL Error Correction Regression				
Dependent Variable: D(DFERROCHROME)				
Selected Model: ARDL(3, 4, 1)				
Case 2: Restricted Constant and No Trend				
Sample: 2009M01 2019M07				
Included observations: 121				
ECM Regression				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DFERROCHROME(-1))	0.451529	0.071875	6.282153	0
D(DFERROCHROME(-2))	-0.154155	0.079444	-1.94042	0.0549
D(DSTAINLESS_STEEL_POS)	0.060753	0.053419	1.137286	0.2579
D(DSTAINLESS_STEEL_POS(-1))	-0.010251	0.059262	-0.17299	0.863
D(DSTAINLESS_STEEL_POS(-2))	-0.079441	0.048308	-1.64446	0.1029
D(DSTAINLESS_STEEL_POS(-3))	0.113848	0.045809	2.485262	0.0145
D(DSTAINLESS_STEEL_NEG)	0.145015	0.039512	3.670134	0.0004
CointEq(-1)*	-0.869103	0.108937	-7.978	0
R-squared	0.631299	Mean dependent var		-0.677836
Adjusted R-squared	0.60846	S.D. dependent var		76.00874
S.E. of regression	47.5611	Akaike info criterion		10.62574
Sum squared resid	255612.5	Schwarz criterion		10.81058
Log likelihood	-634.857	Hannan-Quinn criter.		10.70081
Durbin-Watson stat	2.043447			
* p-value incompatible with t-Bounds distribution.				
F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)

F-statistic	15.48966	10%	2.63	3.35
K	2	5%	3.1	3.87
		2.50%	3.55	4.38
		1%	4.13	5

Source: Author's own estimates using EViews 11

Table A33: NARDL Error Correction Regression Nickel (Dependent) - Stainless steel

Dependent Variable: D(DNICKEL)					
Selected Model: ARDL(2, 2, 2)					
Case 2: Restricted Constant and No Trend					
Sample: 2009M01 2019M07					
Included observations: 123					
ECM Regression					
Case 2: Restricted Constant and No Trend					
Variable	Coefficient	Std. Error		t-Statistic	Prob.
D(DNICKEL(-1))	0.225129		0.084468	2.665264	0.0088
D(DSTAINLESS_STEEL_POS)	5.557115		0.813169	6.833895	0
D(DSTAINLESS_STEEL_POS(-1))	-2.412416		0.962466	-2.506493	0.0136
D(DSTAINLESS_STEEL_NEG)	7.587632		0.567865	13.36169	0
D(DSTAINLESS_STEEL_NEG(-1))	-3.707217		0.849234	-4.365368	0
CointEq(-1)*	-1.045907		0.110053	-9.503687	0
R-squared	0.784335	Mean dependent var			0.200272
Adjusted R-squared	0.775118	S.D. dependent var			1542.797
S.E. of regression	731.6209	Akaike info criterion			16.07595
Sum squared resid	62626491	Schwarz criterion			16.21313
Log likelihood	-982.6711	Hannan-Quinn criter.			16.13167
Durbin-Watson stat	1.983633				

* p-value incompatible with t-Bounds distribution.					
F-Bounds Test		Null Hypothesis: No levels relationship			
Test Statistic	Value	Signif.		I(0)	I(1)
F-statistic	22.00104		10%	2.63	3.35
K	2		5%	3.1	3.87
			2.50%	3.55	4.38
			1%	4.13	5

Source: Author's own estimates using EViews 11

Table A34: NARDL Wald Test Long-Run Asymmetry Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

Wald Test:				
Equation: DSTAINLESS_LRFORM				
Test Statistic	Value	df		Probability
t-statistic	-0.642065		96	0.5224
F-statistic	0.412247	(1, 96)		0.5224
Chi-square	0.412247		1	0.5208
Null Hypothesis: C(7)=C(8)				
Null Hypothesis Summary:				
Normalized Restriction (= 0)		Value		Std. Err.
C(7) - C(8)			-0.001362	0.002121
Restrictions are linear in coefficients.				

Source: Author's own estimates using EViews 11

Table A35: NARDL Wald Test Long-Run Asymmetry Chrome Ore (Dependent) - Stainless steel

Wald Test:			
Equation: DCHROME_DSTAINLESS_LRFORM			
Test Statistic	Value	df	Probability
t-statistic	-0.087026	118	0.9308
F-statistic	0.007573	(1, 118)	0.9308
Chi-square	0.007573	1	0.9307
Null Hypothesis: C(3)=C(4)			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(3) - C(4)		-9.70E-05	0.001114
Restrictions are linear in coefficients.			

Source: Author's own estimates using EViews 11

Table A36: NARDL Wald Test Long-Run Asymmetry Ferrochrome (Dependent) - Stainless steel

Wald Test:			
Equation: DFERROCHROME_DSTAINLESS_LRFORM			
Test Statistic	Value	df	Probability
t-statistic	-0.8563	110	0.3937
F-statistic	0.733255	(1, 110)	0.3937
Chi-square	0.733255	1	0.3918
Null Hypothesis: C(3)=C(4)			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(3) - C(4)		-0.002374	0.002773
Restrictions are linear in coefficients.			

Source: Author's own estimates using EViews 11

Table A37: NARDL Wald Test Long-Run Asymmetry Nickel (Dependent) - Stainless steel

Wald Test:			
Equation: DNICKEL_DSTAINLESS_LRFORM			
Test Statistic	Value	df	Probability
t-statistic	-0.436971	114	0.663
F-statistic	0.190944	(1, 114)	0.663
Chi-square	0.190944	1	0.6621
Null Hypothesis: C(3)=C(4)			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(3) - C(4)		-0.017313	0.039619
Restrictions are linear in coefficients.			

Source: Author's own estimates using EViews 11

Table A38: NARDL Wald Test Short-Run Asymmetry Stainless steel (Dependent) - Chrome ore, Ferrochrome, Nickel

Wald Test:			
Equation: DSTAINLESS_LRFORM			
Test Statistic	Value	df	Probability
t-statistic	-1.600155	96	0.1129
F-statistic	2.560498	(1, 96)	0.1129
Chi-square	2.560498	1	0.1096
Null Hypothesis: C(19) + C(20) + C(21) + C(22) = C(23) + C(24) + C(25)			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(19) + C(20) + C(21) + C(22) - C(23) - C(24) - C(25)		-0.054727	0.034201
Restrictions are linear in coefficients.			

Source: Author's own estimates using EViews 11

Table A39: NARDL Wald Test Short-Run Asymmetry Chrome Ore (Dependent) - Stainless steel

Wald Test:				
Equation: DCHROME_DSTAINLESS_LRFORM				
Test Statistic	Value	df		Probability
t-statistic	-0.727476		118	0.4684
F-statistic	0.529221	(1, 118)		0.4684
Chi-square	0.529221		1	0.4669
Null Hypothesis: C(5) = C(6)				
Null Hypothesis Summary:				
Normalized Restriction (= 0)		Value		Std. Err.
C(5) - C(6)			-0.024928	0.034266
Restrictions are linear in coefficients.				

Source: Author's own estimates using EViews 11

Table A40: NARDL Wald Test Short-Run Asymmetry Ferrochrome (Dependent) - Stainless steel

Wald Test:				
Equation: DFERROCHROME_DSTAINLESS_LRFORM				
Test Statistic	Value	df	Probability	
t-statistic	-0.453768	110		0.6509
F-statistic	0.205905	(1, 110)		0.6509
Chi-square	0.205905	1		0.65
Null Hypothesis: C(7)+C(8)+C(9)+C(10)=C(11)				
Null Hypothesis Summary:				
Normalized Restriction (= 0)		Value	Std. Err.	
C(7) + C(8) + C(9) + C(10) - C(11)		-0.06011		0.132461
Restrictions are linear in coefficients.				

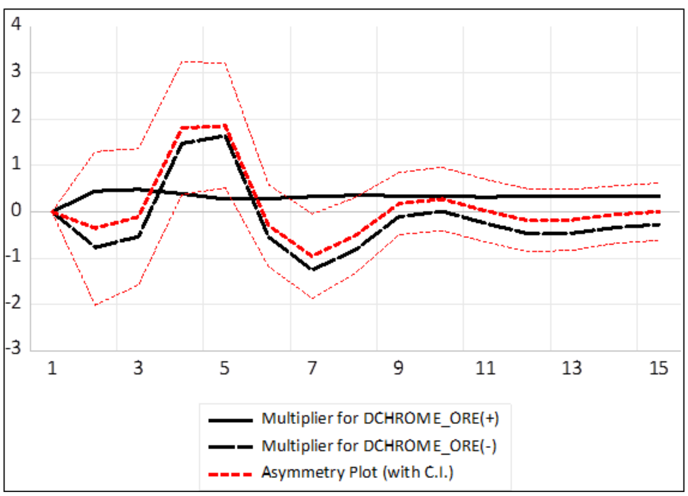
Source: Author's own estimates using EViews 11

Table A41: NARDL Wald Test Short-Run Asymmetry Nickel (Dependent) - Stainless steel

Wald Test:			
Equation: DNICKEL_DSTAINLESS_LRFORM			
Test Statistic	Value	df	Probability
t-statistic	-0.493024	114	0.6229
F-statistic	0.243073	(1, 114)	0.6229
Chi-square	0.243073	1	0.622
Null Hypothesis: C(6) + C(7) = C(8)+C(9)			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(6) + C(7) - C(8) - C(9)		-0.73572	1.492253
Restrictions are linear in coefficients.			

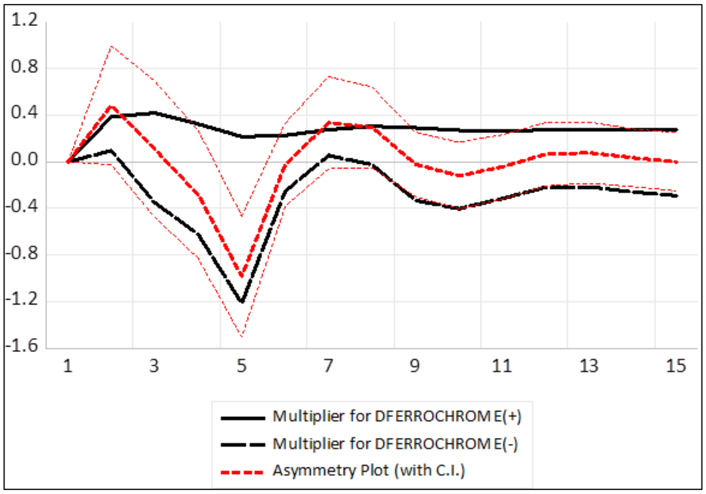
Source: Author's own estimates using EViews 11

Figure A6: NARDL Dynamic Multiplier Stainless steel (Dependent) - Chrome ore



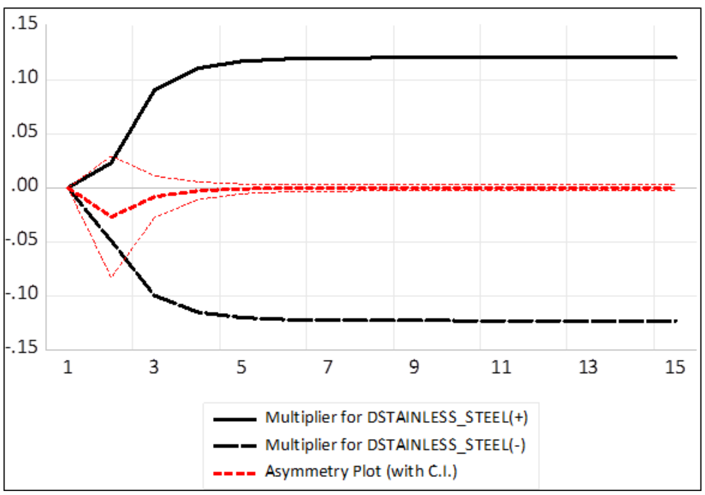
Source: Author's own estimates using EViews 11

Figure A7: NARDL Dynamic Multiplier Stainless steel (Dependent) - Ferrochrome



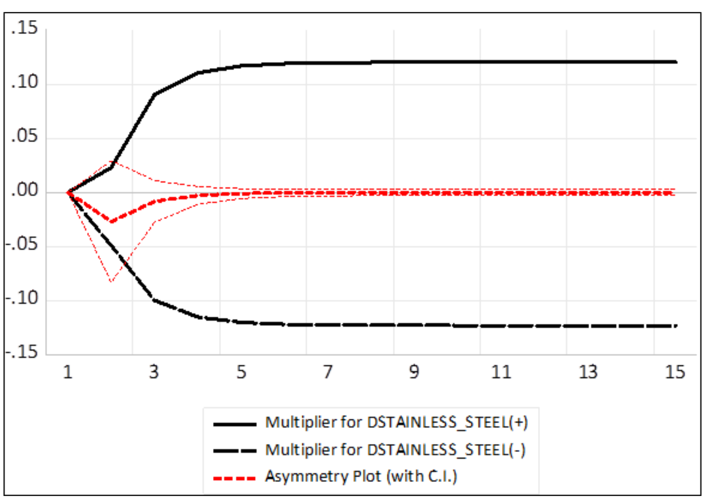
Source: Author's own estimates using EViews 11

Figure A8: NARDL Dynamic Multiplier Chrome Ore (Dependent) - Stainless steel



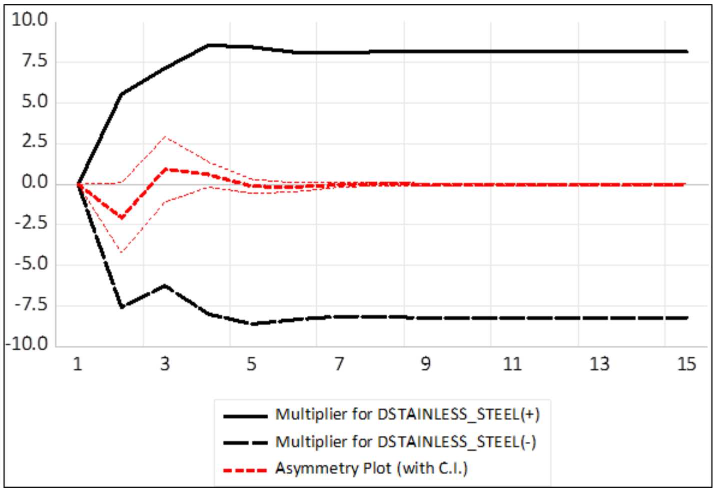
Source: Author's own estimates using EViews 11

Figure A9: NARDL Dynamic Multiplier Ferrochrome (Dependent) - Stainless steel



Source: Author's own estimates using EViews 11

Figure A10: NARDL Dynamic Multiplier Nickel (Dependent) - Stainless steel



Source: Author's own estimates using EViews 11