



**A RE-EVALUATION OF THE ESTIMATED OVERCHARGE BY THE SOUTH
AFRICAN CEMENT CARTEL**

A Research Report submitted in partial fulfilment of the Degree of
Master of Commerce (Economics/Economic Science)
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by

Alexander Brunette
Student No: 940720

Supervised by Professor Liberty Mncube

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Abstract

The topic of overcharge estimation regarding cartels is scarce in both the international and domestic regard. This paper aims to re-estimate the overcharge by the South African cement cartel after it was forced to disband following the end of the apartheid regime. In order to avoid the problem of spurious regression results, the time series data are thoroughly analysed for unit roots. To combat the presence of the confirmed nonstationarity, an error correction model is employed in order to yield more accurate estimates. When controlling for nonstationarity, it is found that the price overcharge is higher than that provided by static ordinary least squares regressions and is on par with more recent estimates.

Candidate's Declaration

Name of Candidate:	Alexander Brunette
Person Number:	940720
Degree:	Master of Commerce – Economics
Supervisor / Co-Supervisor:	Prof. Liberty Mncube
School:	Economics and Finance
Title of Thesis/Dissertation/ Research Report:	A Re-evaluation of the Estimated Overcharge by the South African Cement Cartel


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1. Introduction

The regulated South African cement cartel existed legally until 1994 at which time it could no longer operate as it did. The mandate to disband, however, was ignored by the cement producing firms and the firms chose collusive behaviour which continued for more than a decade until the cartel was uncovered. While research on the estimated cement cartel overcharges has been conducted, it has not taken the non-stationarity of time series variables into account, even though it is highly likely that these variables were nonstationary.

This characteristic of the time series data has important implications for the functional form of the empirical models. Further, the presence of trends in data can invalidate the usual asymptotic theory of ordinary least squares (“OLS”) estimators and test procedures. Any model of a price series has to take the (deterministic or stochastic) trend into account to produce accurate and robust estimates, otherwise the regression estimates will be spurious.

Choosing the proper set of variables to be included in econometric models and correctly taking account of the time series characteristics of the data does not complete the modelling exercise. This paper estimates two different approaches to calculating damages:(1) the dummy variable (DV) approach; and (2) an error correction model (ECM). We do this as a sensitivity analysis. This means that we report different specifications to see how much the results are changed by various changes in specification or procedure. Our assumption is that if we use many reasonable but different specifications and consistently find similar results, that greatly strengthens our confidence in those results. In assessing empirical work, one important characteristic to look for is consistency despite small changes to the specification and/or procedures, unless a specification is flawed.

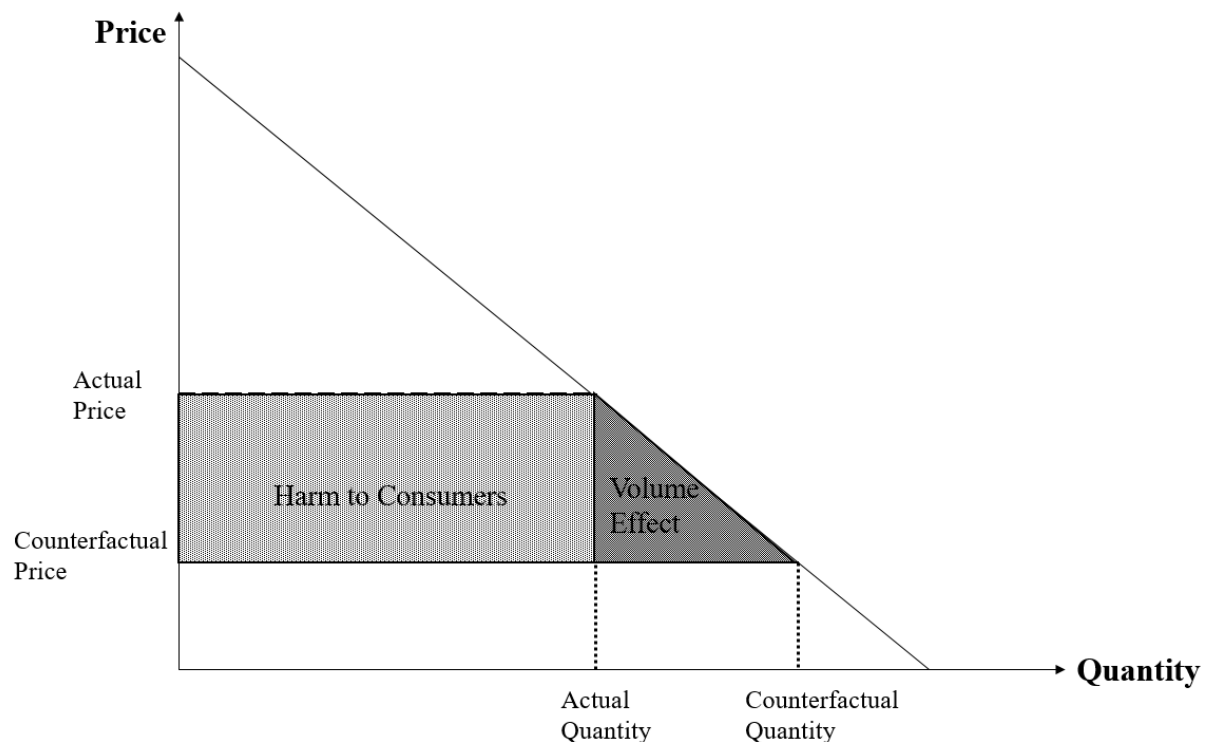
In section 2, the paper will provide a brief overview of the workings of a cartel in general and its implications to consumers while section 3 will provide a background on the South African cement cartel. This includes a description of the operational workings of the cartel and the investigation into the cartel. Section 4 provides background on overcharge estimation and elaborates on various techniques and when they are most applicable. In section 5, the paper introduces the methodology that will be employed as well as the econometric framework which will be followed by previous attempts at estimating the overcharge in section 6. Given the paper’s use of an ECM, cointegration, the corresponding tests for the concept, unit root tests and a description of the data will be described in sections 7 and 8. In the 9th section, we will report the results and provide a discussion thereof. This will include a comparison of the estimates found in my research with some of the existing research. The last sections conclude and provide references.

2. Cartels and Collusion

When firms collude, they generally reach an agreement on the terms of collusion and how to enforce the cartel, in order to gain an “advantage” over the competitive market. In most instances, this advantage takes the form of a higher price that the colluding firms are able to charge relative to the price that would have been charged in the presence of fair supply and demand. While collusion between firms often adopts the goal of unfair price setting, it can also adopt the goal of segmenting geographical markets so that territories “belong” to a specific firm (or small group of firms) or any other coordinated attempt to mutually benefit the colluding firms. In order to increase prices, and therefore increase profits (seeing that costs are generally unchanged), firms in a given market can machinate a cartel and sustain it if the market is characterised by favourable conditions. Doing so generally leads to a redistribution of welfare from consumers to producers, the members of the formed cartel (Motta, 1994).

Given the covert nature of collusion, when firms collude they utilise their created position of power to fix prices which results in the emergence of a deadweight loss to the economy and an overcharge to the consumer. Although the graph representing this is elementary, it is able to concisely convey the effect on prices and quantities from collusion and is therefore presented in Figure 1. The graph shows that two effects arise in the case of collusion: a decrease in the quantity sold and, perhaps more pertinent to this research, an increase in price. The counterfactual price is the price that would have prevailed in the

Figure 1



absence of the cartel and the actual price is the price that actually presented in the market. Thus, the difference between these prices would represent the price overcharge due to collusion and summarises what is to be investigated in this paper. The “Harm to Consumers” refers to the total damage to consumers by taking into consideration the quantity that was sold at the overcharged price. The darker, triangular shaded region shows the foregone welfare due to the reduction in quantity sold.

3. The South African Cement Cartel

The full history of the South African cement cartel is beyond the scope of this paper but in order to justify the research and provide context, relevant material on the cartel needs to be highlighted. This section, predominantly citing the *Consent Order - Lafarge* (2012), will discuss some of the key characteristics of the cement cartel, its history and important dates/events.

3.1. Background and Structure of the Cartel

Under the apartheid regime, the cement cartel was permitted to be in force legally. That is, the regulation in favour of competitive behaviour did not apply to the cartel. The main producers at the time included Lafarge, PPC, AfriSam and NPC. Freedom from antitrust law was permitted until 1995 when the competition authority ordered the dismantling of the cartel with the expectation that the colluding firms would initiate competitive pricing. Prior to the disbandment, the cartelists each benefited from an allocated market share that was based upon production capacity. The pricing of cement was set using the Twycross pricing model where a base price was determined by one of Lafarge’s factories and transport costs were added to set the consumer price.

It would seem rational that the cartelists simply maintained their market shares after 1996 when collusion was unlawful, which is precisely what they agreed upon. However, the allure of short-term gratification (or greed) ensured that one of the firms (PPC) deviated from the collusive agreement in order to gain higher market shares. At this point in the timeline, just before PPC’s deviation, the collusion could be described as a hybrid between tacit and explicit collusion since the agreement had not been formalised to the extent that it would prove to be in the future. Congruent with theory of cartel behaviour, the other firms responded to the deviation with punishment which resulted in a price war for the next two years, ending in 1998.

Realising the financial implications of the price war, firms reconvened in an attempt (which would prove to be successful) to re-establish the market structure that once favoured them so well. The assembly resulted in collusion in the form of allocation of market shares as mentioned above but also in the form of

agreement on how various types of cement would be priced (including the prohibiting of discounts on premium-grade cement) and a reduction in marketing and closure of offices in specific areas.

The reader should now understand that the success of a cartel depends drastically upon shared information. Perfect information flow should imply joint optimality of prices as well as sound accuracy in the detection of deviation from collusion.

It should come as no surprise then that the cartel devised a shrewd system in which to disseminate this information. An industry-specific organisation, known as the Cement and Concrete Institute (C&CI), was formed which could be considered somewhat of an information hub. The cartelists would submit data on sales relating to consumer types, packaging, transport types and geographic region. The auditors employed by the C&CI would compile the data from each firm and redistribute the collective data back to the firms so that they could assess it for deviations from collusion. As time progressed, this system of information exchange was optimised in the form of new templates of information being introduced and sales data that was shared on a more frequent basis. Information exchange through the organisation ceased in 2009, marking the likely end to explicit collusion. Providing the aggregated sales data with any utility was the high concentration of the market. Put loosely, the market concentration refers to how many firms make up the market and how much of the market they each own. A market with a high concentration of firms is, for obvious reasons, more likely to be characterised by collusion. A firm in the cement cartel could ascertain from the sales data how their market share had changed and due to the high concentration, determine the origin of the deviation. As mentioned above, punishment for any such deviation is inevitable but given the astute structure put into place by the cartel, said punishment can be effected without the destabilisation of the market.

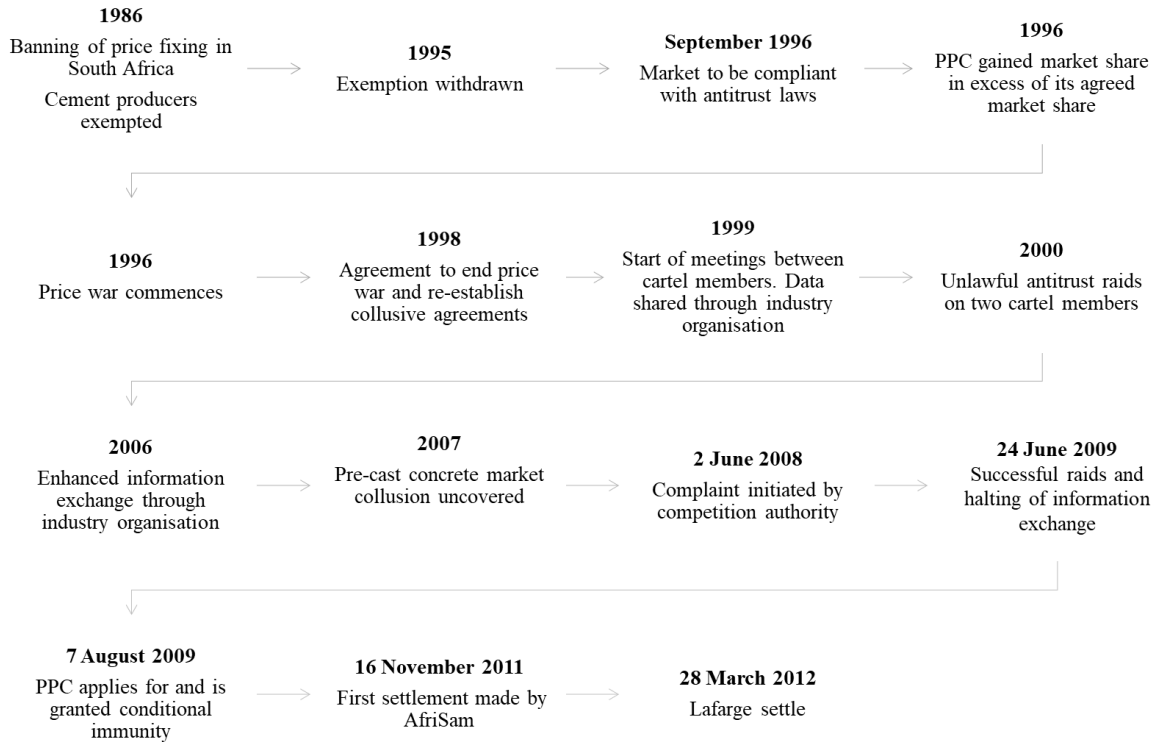
3.2. The Investigation

In the year 2000, an investigation was launched by the competition authority into the suspected cement cartel. Raids were performed on two of the producers and documents were seized. The raids, however, were in vain. The seized documents were to be returned as the raids were legally challenged. It was not until 2008, after the competition authority discovered a cartel in the precast concrete market in 2007, that another scoping study was launched into the cement market where the authority accused the firms of price fixing.

On the 24th of June 2009, the commission acted upon issued warrants for the seizure of documents at the premises of the cartelists. PPC, the largest producer, applied for leniency during August 2009 in exchange for its assistance in the investigation of the cartel. PPC had to terminate their data submissions to the industry organisation which would theoretically cripple the cartel through the starvation of information. On the 16 November 2011, the first settlement was made by AfriSam which was followed by the

settlement of Lafarge on 28 March 2012. Figure 2 provides a timeline of the key events that took place within the cement market and the investigation.

Figure 2



Source: Information used from (Consent Order - Lafarge, 2012)

3.3. The Structural Factors That Facilitated Collusion

As discussed, key to the success of the cartel was the submission and dissemination of data between cartelists. It has been established that the high degree of concentration in the market assisted in detecting the source of any deviation and allowed for swift, unobtrusive punishment.

Another structural factor that assisted in the maintenance of the cartel was the high barriers to entry. For decades, the market was dominated by the cartelists¹. Consider the opposite where there are no barriers to entry – other firms could enter the market and share profits with the existing cartelists until it is no longer profitable to do so. That is, the difficulty to enter the cement market supported the collusive outcome. The barriers to entry in a cement market take the form of high start-up costs. This includes the building of production facilities and ensuring that there are readily accessible production inputs. In addition, the cartelists were aware of the high barriers to entry which implies that there was less relative short-run

¹ It was only in 2014, a few years after the theorized end of the cartel, that Sephaku made its entrance as one of the significant firms in the market

profits by deviating from the collusive state when compared against the long-run profits. Put differently, if incumbents knew that another rival firm could enter at any time (due to low barriers to entry) and undercut the cartel, they would hardly value long-run profits associated with collusion and would thus deviate as described by Motta (2004).

There was also little product differentiation in the market. That is, cement as a product, regardless of which market it is sold in, is homogenous. From a theoretical perspective, a market characterised by a homogenous good can have opposing effects on the maintenance of a cartel. A homogenous good increases the potential gain from deviating from the collusive agreement. However, firms also place greater value on future losses from deviating, explains Harrington (2015). In practice, it could be argued that the ease of coordination and the feared potential foregone loss outweighs the short-run gain. The cartelists in the South African cement cartel had already seen that a competitive market does not suit their financial statements so deviation was unlikely after the industry organisation was formed.

Cement carries a high transportation cost in that, on a per-kilogram basis, it is not very valuable. This generally leads to a market that is segmented on a geographical basis which is certainly evident in the South African cement cartel market. That is, to keep costs low, a certain geographical area needs to be served by a producer in close proximity. Harrington (2015) shows that this is generally a feature that aids in the sustaining of a cartel.

The last factor that will be discussed in this paper is the typical demand for cement. The general result, as found by Rotemberg & Saloner (1986), is that increased demand leads to the hindrance of collusion. This specifically refers to the case where there is a positive shock to demand that is not permanent. In fact, one may intuitively deduce that a market with promised long-term, steady-increasing demand would be conducive to collusion – the discounted profit inflows are large relative to the temporary gains from deviation. However, when there is a positive fluctuation in demand, it is found to be tempting to retreat to a competitive state². Because the construction sector is the primary consumer of cement, there is a strong relationship between the demand for cement and the business cycle since the construction sector is very sensitive to the business cycle. Harrington (2015) argues that cyclical demand is likely to satisfy the participation requirement which implies the maintenance of the cartel.

Demand for cement is also generally price inelastic. As mentioned, the primary consumer of cement is the construction sector. In terms of overall construction costs on a given project, for example, the cost of cement is relatively small – Harrington (2015) quotes an estimate of approximately 2%, depending on the

² This is likely to have occurred in the cement market due to the 2010 FIFA World Cup where the cartel may have ceased its collusive operations, as argued by some authors.

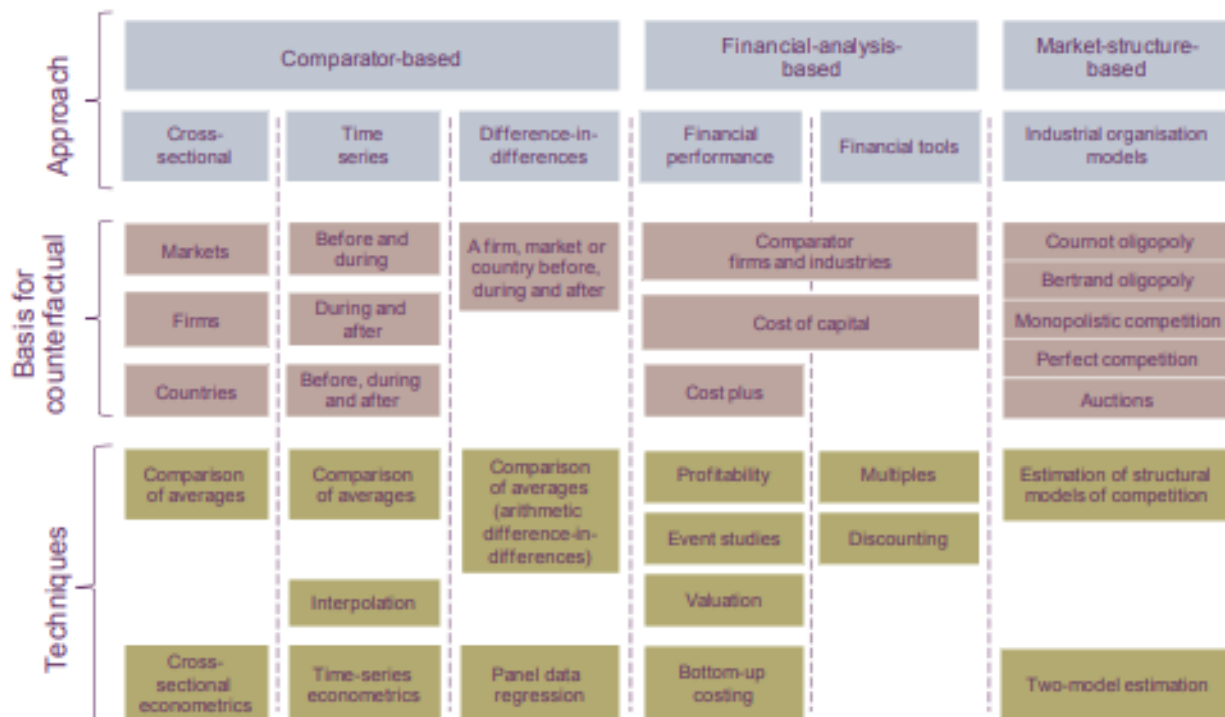
construction project. This inelastic demand is likely to support collusion because a collective increase in prices, from all producers, will significantly increase profits while leaving demand minimally reduced.

4. General Methods Employed in Overcharge Estimation

The methods of damage quantification are diverse. This is not necessarily due to any formal dispute or ongoing deliberation in the literature, where opposing schools of thought are present. Instead, each case of overcharge is unique and requires its own approach. Of course, this is not to say that existing approaches cannot be enhanced or analysed from another perspective. In fact, this very paper aims to do just that. To illustrate the multitude of already-used approaches, Figure 3 offers a summary of the common methods.

Without going into each of the techniques shown in the diagram, it is important to discuss the very general approach that can describe all of the techniques. Fundamentally, the researcher aims to find the difference between the actual data point(s) of interest that emerged (be it price, costs, valuations etc.) and the data point(s) that would have presented in the absence of anti-competitive behaviour.

Figure 3



Source: Oxera (2009)

Consider first the approach based upon market structure. It typically relies upon an amalgamation of empirical quantification, estimation and industrial organisation models and assumptions. These would be chosen and applied so that they aptly characterise the market under study so as to establish the but-for scenario which can be compared to the actual outcome that prevailed, as described in the Oxera (2009) piece. Similarly, the financial approach would use theory from finance to establish the but-for scenario so that a comparison could be done. This includes comparing the firm in question to a representatively comparable firm or industry, using information on costs with a bottom-up approach to estimate a fair retail price, as well as other methods.

The approach that concerns this paper, and the study of the South African cement cartel in general, is the comparator-based approach, particularly using time series data. When one has a comparable market or group of firms, the difference-in-differences technique can be used which uses richer panel data to draw estimates. The method effectively addresses the deficiencies of the time series and cross-sectional models by comparing a market absent of collusion to a market with collusion present over varying binary states of collusion. Seeing that there is no viable comparative market for the South African cement market, it would be most appropriate to use time series data that considers a time horizon from before the illegal collusion started, during the collusive period and after it.

In overcharge estimation studies that consider scenarios similar to that of the South African cement cartel, they typically make use of the ‘dummy variable’ (DV) approach and/or the ‘forecasting’ approach. The difference between the two is that the former uses data over the entire period which includes before, after and during the cartel period, whereas the latter uses data from a specific period of non-collusion, depending on the chosen benchmark.

That is, the dummy variable approach attempts to show the effect of collusion on price by controlling for all other significant variables. This is generally done by a straight-forward regression but some authors have adopted interesting specifications of their regression which includes, and is not limited to, two-stage least squares regressions, error correction models and, more recently, even specifications that include machine learning³. The dummy variable will take a value of 1 during times of collusion and a value of 0 otherwise. The coefficient of the dummy variable will provide insight into the overcharge due to the antitrust infringement while controlling for other variables.

The forecasting approach only considers data from the period before (or after, if backcasting) the competitive infringement and uses this data to forecast a price that would have presented. This forecasted price can then be compared to the actual price that was charged to estimate the amount of overcharge.

³ Very recent research by März (2021) provides encouraging results.

These approaches will only be valid when there is no change in the association between exogenous shocks and the price during the cartel period and otherwise. If this relationship were to change, for example – if the effect of the cost of inputs on price significantly changed, then the forecast approach should be cautiously interpreted because the forecasted (or backcasted) but-for prices would be inaccurate as described by Nieberding (2006).

Typically, the DV approach is better than the forecasting approach on an econometric basis where the estimates are less noisy, as discussed by Rubinfeld (2012). However, both approaches largely produce consistent estimates. The forecasting approach has a particular strength in that it allows one to estimate a fairly sound but-for price if the period, either before or after the antitrust infringement, is representative of a competitive market. Further, should the infringement period be tainted by complicating dynamics due to the anti-competitive conduct, the forecasting approach can provide a strong estimate of the overcharge in comparison to the DV approach. A significant weakness of the approach is that it forces the researcher to disregard knowledge of the market that would be beneficial to arriving at sound estimates. To illustrate, consider the case of a market that displays rapidly evolving technologies that are introduced at an increasing rate. The forecasting approach would probably underestimate the counterfactual evolving technology which could be properly accounted for in the DV approach.

5. Methodology

In terms of the econometric model, we use a simple ordinary least squares regression of a reduced-form equation. The regression can be used to navigate both mainstream approaches to overcharge estimation: the dummy variable (DV) and ECM approaches motivated by Nieberding (2006).

The reduced-form price equation that will be derived is based upon the structural model of conventional supply and demand. That is, the quantity of cement supplied is a function of price, demand factors and costs while quantity demanded is also a function of other exogenous variables and price. The quantity of cement demanded by consumers and supplied by producers can be described by the following two equations:

$$Q_t^d = \alpha_0 + \alpha_1 \text{cement}_t + \alpha_2 \text{buildings}_t + \alpha_3 \text{GFCF}_t + \alpha_4 \text{BCI}_t \quad (1)$$

$$Q_t^s = \beta_0 + \beta_1 cement_t + \beta_2 coal_t + \beta_3 gypsum_t + \beta_4 limestone_t + \beta_5 aggregate_t + \beta_6 ULC_t + \beta_7 electricity_t \quad (2)$$

Where Q_t^d and Q_t^s refer to the quantity of cement demanded and supplied, respectively. $cement_t$ refers to the price of cement at time t, $buildings_t$ refers to the number of building plans passed, $GFCF_t$ is the gross fixed capital formation and BCI_t is an index of building contractors' confidence. In terms of supply: $coal_t$, $gypsum_t$, $limestone_t$, $electricity_t$ and $aggregate_t$ refers to the unit price of the described resource, and ULC_t is unit labour cost in manufacturing. Further detail on the data is provided in the next section.

Usage of the equilibrium condition where quantity supplied equals quantity demanded results in a reduced form of the model. One has the option of choosing quantity or price as the regressand but data on cement quantities is scarce so it is more appropriate to model the equilibrium price in terms of the external supply and demand factors. Doing so gives the following reduced-form equation:

$$cement_t = \frac{\beta_0 - \alpha_0}{\alpha_1 - \beta_1} + \left(\frac{\beta_2}{\alpha_1 - \beta_1}\right) coal_t + \left(\frac{\beta_3}{\alpha_1 - \beta_1}\right) gypsum_t + \left(\frac{\beta_4}{\alpha_1 - \beta_1}\right) limestone_t + \left(\frac{\beta_5}{\alpha_1 - \beta_1}\right) aggregate_t + \left(\frac{\beta_6}{\alpha_1 - \beta_1}\right) ULC_t + \left(\frac{\beta_7}{\alpha_1 - \beta_1}\right) electricity_t - \left[\left(\frac{\alpha_2}{\alpha_1 - \beta_1}\right) buildings_t + \left(\frac{\alpha_3}{\alpha_1 - \beta_1}\right) GFCF_t + \left(\frac{\alpha_4}{\alpha_1 - \beta_1}\right) BCI_t\right] \quad (3)$$

Which can be written more concisely as:

$$Cement_t = \delta_0 + \delta_1 coal_t + \delta_2 gypsum_t + \delta_3 limestone_t + \delta_4 aggregate_t + \delta_5 ULC_t + \delta_6 buildings_t + \delta_7 electricity_t + \delta_8 GFCF_t + \delta_9 BCI_t \quad (4)$$

Where the δ_i coefficients are a function of the α_i and β_i coefficients by trivial substitution. It should be apparent that the δ_i coefficients for the demand variables are specified as being negative. Specifying the

model in a single equation framework, as in (4), is required given data constraints. However, in other cases of damage quantification that permit, it may be beneficial to specify the model as a system of equations. In this way, the researcher would recover the structural coefficients for insight.

Presenting the model as a log-log model has the advantage of reporting the results as elasticities (and therefore percentage overcharge instead of level proportions) and also reduces the variance of the series so all data (other than the dummy) will be in logarithmic form. However, we will omit the natural logarithm notation that generally prefixes the variable for ease of reading. It is also important to note that the estimated overcharge does not make any inference on the deadweight loss to the economy.

Now that the reduced-form price equation has been stated as (4), one simply has to add the dummy variable which takes a value of 1 during the period of collusion and 0 otherwise. Therefore, the equation to be estimated under the ordinary least squares DV approach can be stated as:

$$\begin{aligned}
 cement_t = & \delta_0 + \delta_1 coal_t + \delta_2 gypsum_t + \delta_3 limestone_t + \delta_4 aggregate_t + \delta_5 ULC_t + \delta_6 buildings_t \\
 & + \delta_7 electricity_t + \delta_8 GFCF_t + \delta_9 BCI_t + \delta_{10} dummy_t
 \end{aligned}
 \tag{5}$$

Once equation (5) has been estimated, the but-for prices can be obtained by setting the dummy variable to 0. Therefore, the researcher will have a set of actual prices that presented in the market, but-for prices and predicted prices based on (5) which can all be represented graphically to visually illustrate the overcharge during the cartel period. The coefficient on the dummy variable can be transformed, using $(e^{\delta_{10}} - 1) \times 100$, into an overcharge percentage.

Equation (5) does not account for the likelihood that the price at any time depends on its previous values, even after controlling for variables that describe demand and supply. Therefore, adding lagged dependent variables is required and the equation will be converted to an error correction model (ECM) where the regressand has been differenced. To calculate overcharge in the presence of time dynamics, consider the two general price equations for the predicted price and the but-for price:

$$\widehat{cement} = \lambda X + \theta dummy + \varphi \widehat{cement}_{-1}
 \tag{6}$$

$$cement^{BF} = \lambda X + \varphi cement_{-1}^{BF}$$

(7)

Where \widehat{cement} is the predicted price from (6), λ is a vector of parameters, X is a vector of exogenous variables with a constant, \widehat{cement}_{-1} is the lagged predicted price and $cement_{-1}^{BF}$ is the lagged price but for collusion. The dummy variable only appears in equation (6) because it takes a value of 1 during collusion, but is absent in equation (7) as it adopts a value of 0. If collusion commences at time $t = c$, the difference between the predicted cement price and the cement price but for the collusion in each period from then onward is given by subtracting equation (7) from (6):

$$(\widehat{cement} - cement^{BF})_c = \theta \quad (8)$$

$$(\widehat{cement} - cement^{BF})_{c+1} = \theta + \varphi(\widehat{cement}_{-1} - cement_{-1}^{BF}) = \theta(1 + \varphi) \quad (9)$$

$$(\widehat{cement} - cement^{BF})_{c+2} = \theta + \varphi(\widehat{cement}_{-1} - cement_{-1}^{BF}) = \theta(1 + \varphi + \varphi^2) \quad (10)$$

Recall that all of the data are in natural-logarithm form. As such, logarithmic properties can be exploited and the overcharge for each period can be written as:

$$\left(\frac{cement}{cement^{BF}} - 1\right) = e^\theta \left(\frac{\widehat{cement}_{-1}}{cement_{-1}^{BF}}\right)^\varphi - 1 \quad (11)$$

Therefore, if price dynamics are included, say equation (5) included a lagged cement price variable which is shown as equation (12) below, one could find the long-run equilibrium price by setting the price at a given period equal to the price at its previous (or future) price. That is, $cement_t = cement_{t-1} = cement_e$. Solving for equilibrium cement price:

$$cement_t = \delta_0 + \delta_1 coal_t + \delta_2 gypsum_t + \delta_3 limestone_t + \delta_4 aggregate_t + \delta_5 ULC_t + \delta_6 Buildings_t + \delta_7 electricity_t + \delta_8 GFCF_t + \delta_9 BCI_t + \theta dummy_t + \varphi cement_{t-1} \quad (12)$$

$$cement_e = \frac{\delta_1 K + \theta dummy_t}{(1 - \varphi)}$$

(13)

Where $\delta_i K = \delta_0 + \delta_1 coal_t + \delta_2 gypsum_t + \delta_3 limestone_t + \delta_4 aggregate_t + \delta_5 ULC_t + \delta_6 Buildings_t + \delta_7 electricity_t + \delta_8 GFCF_t + \delta_9 BCI_t$. The following expression provides the long-run impact of the collusion on the cement price that would have prevailed in fair competition:

$$\frac{\Delta cement_e}{\Delta dummy_t} = \frac{\theta}{1 - \varphi}$$
(14)

While this research will not be estimating a model that is represented in (12), the derivation of the method to calculate overcharge in a model that includes price dynamics is required for the error-correction model that will be estimated. Define the deviation from equilibrium to be the difference between the actual cement price, $cement_t$, and the equilibrium cement price, $cement_t^e$:

$$Deviation_t = (cement_t - cement_t^e)$$
(15)

An error-correction model can thus be specified so that the change in the price of cement at a given time, t , is a function of the change in the price of cement in the previous period, $(t - 1)$, and an error correction term being the deviation of equilibrium in the previous period:

$$\Delta cement_t = \Phi(\Delta cement_{t-1}) + \omega(cement_{t-1} - cement_{t-1}^e)$$
(16)

In order to ensure that $\omega(cement_{t-1} - cement_{t-1}^e)$ operates as a correcting term, the coefficient ω must be less than 0. If the price of cement in the previous period is less than the equilibrium price, i.e $Deviation_t < 0$, the change in current cement price (LHS of (16)) needs to be positive in order to correct the negative deviation from the previous period. This can only occur if $\omega < 0$. The same applies, but in an opposite direction, if the price of cement is greater than the equilibrium – the error correction term needs to be negative in order to correct prices back to their equilibrium level. Rewriting equation (4) lagged one period:

$$cement_{t-1}^e = \delta_0 + \delta_1 coal_{t-1} + \delta_2 gypsum_{t-1} + \delta_3 limestone_{t-1} + \delta_4 aggregate_{t-1} + \delta_5 ULC_{t-1} + \delta_6 buildings_{t-1} + \delta_7 electricity_{t-1} + \delta_8 GFCF_{t-1} + \delta_9 BCI_{t-1}$$
(17)

Substituting (17) into (16):

$$\begin{aligned}
\Delta cement_t &= \Phi(\Delta cement_{t-1}) \\
&+ \omega(cement_{t-1} \\
&- \{\delta_0 + \delta_1 coal_{t-1} + \delta_2 gypsum_{t-1} + \delta_3 limestone_{t-1} + \delta_4 aggregate_{t-1} \\
&+ \delta_5 ULC_{t-1} + \delta_6 buildings_{t-1} + \delta_7 electricity_{t-1} + \delta_8 GFCF_{t-1} + \delta_9 BCI_{t-1}\})
\end{aligned}
\tag{18}$$

Simplifying and adding the dummy variable gives the following ECM which will be estimated:

$$\begin{aligned}
\Delta cement_t &= \gamma_0 + \Phi(\Delta cement_{t-1}) + \gamma_1 cement_{t-1} + \gamma_2 coal_{t-1} + \gamma_3 gypsum_{t-1} + \gamma_4 limestone_{t-1} \\
&+ \gamma_5 aggregate_{t-1} + \gamma_6 ULC_{t-1} + \gamma_7 buildings_{t-1} + \gamma_8 electricity_{t-1} + \gamma_9 GFCF_{t-1} \\
&+ \gamma_{10} BCI_{t-1} + \theta dummy_t
\end{aligned}
\tag{19}$$

The above equation seeks to remove any presence of nonstationarity as well as control for any price movement that is related to prior prices. The γ_1 coefficient is interpreted as to what degree the current change in price, at time t, is determined by the change in price of the previous period. The other coefficients explain the relationship between the lagged supply and demand exogenous variables and the current change in price.

As shown above, the long-run effect of collusion on equilibrium of the cement market can be calculated by setting $\Delta cement_t = \Delta cement_{t-1}$ and $cement_{t-1} = cement^e$ and making $cement^e$ the subject of the equation:

$$\frac{\Delta cement^e}{\Delta dummy_t} = \frac{\theta}{\Phi}
\tag{20}$$

6. Prior Attempts to Estimate Overcharge in The South African Cement Cartel

There are papers (albeit few) that attempt to estimate the overcharge by the South African cement cartel. Some papers, such as that presented by Govinda, Khumalo & Mkhwanazi (2016) show (to their admission) conservative overcharge estimates of between 7.5% and 9.7%, depending on the model used. The authors, for similar reasons as ours, assumed a cartel end date of November 2009 and dismissed the

idea of a transition period which is discussed further below. The lower overcharge estimate of 7.5% resulted from a model that used the dummy variable approach using data similar to this paper. The authors noted that their analysis did not account for the financial crisis in the late 2000s which likely had a significant impact on input costs, particularly the price of oil. To remove this exogenous shock, the authors ran a two-stage least squares regression with a dummy variable for the crisis and instrumented this to the price of oil. In doing so, the estimate of the overcharge increased to 9.7%.

Even this larger estimated overcharge of 9.7% is relatively low if compared to the meta-analysis put forth by Connor (2007). Connor explains that in the presence of strong collusion, as in the case of the cement cartel, the overcharge can be as high as 30% for cartels, much higher than the 9.7% calculated by the authors.

In fact, another study by Boshoff and van Jaarsveld (2018) which also considers the South African cement cartel (although with a different approach) shows that the overcharge estimate is as high as 19.9%. This study is unique in that it adopts a Markov regime-switching (RS) model to determine the periods in which there was collusion and the periods where there was not. This is integrated into a general autoregressive distributed-lag (ARDL) model so that dynamics can be captured too. Most other research considers the dates of collusion as per court proceedings but it is obviously not the case that these dates are perfect. Therefore, a Markov RS model is used to predict the dates of collusion and apply the dummy variable more accurately. Put intuitively, it may be the case that there is a period during expected collusion (expected by the court) where no collusion was actually taking place. In this situation, prices of cement would actually be lower due to the temporary absence of collusion. If this is not accounted for, the overcharge estimate can be severely underestimated⁴.

To compare the overcharge estimate provided by the regime-switching model with estimates provided by dummy specifications as per court-determined dates and structural break tests, the authors provide the results as per Figure 4:

⁴ It is likely that a model that predicts collusion will be successfully challenged in court. From a theoretical standpoint, the model offers interesting insight.

Figure 4

RS model	Dummy variable without transition (Fig. 2)	Court determined dummy variable (Fig. 3)	Bai-Perron determined dummy variable
Static ARDL (Long-run)			
0.18	0.13	0.008	0.044
OLS contemporaneous variables			
0.12	0.112	0.021	0.022

Source: Boshoff & van Jaarsveld (2018)

The above estimates refer to data that is in logarithmic form so one would need to apply $[(e^{\text{estimate}} - 1) \times 100]$ to get the overcharge percentage. Each column refers to a different method of cartel dating, with the regime-switching model giving the highest overcharge and the court-determined dating model giving the lowest overcharge, one that is hardly significant. The authors argue that the Bai-Perron method of dating offers a low estimate of overcharge because the method fails to acknowledge the possible break in collusion between 2006 and 2008 that is recognised by the regime-switching model. This is possibly why the RS-model estimate is more than 10 percentage points higher than that proposed by Govinda, Khumalo & Mkhwanazi (2016).

The research by Govinda, Khumalo & Mkhwanazi (2016) postulated the existence of a transition period between the two states of collusion but found that their transition dummies were insignificant. As such, transition dummy variables were omitted and a single end date was elected. However, more recent research by Theron & van Niekerk (2017) argues for a transition period for two different specifications of the dummy. Firstly, two models are estimated: one where collusion ends in 2009 (after the raid) and another where it ends in 2011 after the first firm, AfriSam, settles. For each of these two models, the authors also allow a dummy specification that stipulates a linear transition phase, where collusion did not abruptly end. The specification that spanned the longest period of collusion is constructed to have ended at the end of 2013, before Sephaku Cement joined the market, which the authors assume to be the complete breakdown of collusion. The results from these four models are provided in Figure 5. Even though it is possible that collusion continued until AfriSam's settlement or that cement prices did not immediately decrease to their competitive levels, there is no real factual or economic basis for this assumption. That is, there may be various specifications of the indicator variable and interesting insight may be drawn from these specifications but it is difficult to justify cartel end-dates other than those that are factually supported.

Figure 5

	Model 1	Model 2	Model 3	Model 4
Cartel Period	January 1999 to June 2009	January 1999 to November 2011	January 1999 to November 2011	January 1999 to December 2013
Transition Period	None	None	July 2009 to November 2011	July 2009 to December 2013
Coefficient in logarithmic terms	0.0832	0.0977	0.0942	0.1215
Calculated percentage overcharge	8.68%	10.27%	9.88%	12.92%

Note: Overcharges percentages are calculated as $(\exp(\text{dummy coefficient}) - 1) \times 100$

Source: Theron & van Niekerk (2017)

7. Data

7.1 The Cartel Indicator Variable

There are a few candidates for the most accurate end to the cartel period. The most likely end of the cartel period seems to be either June 2008, when the Commission initiated its investigation, or June 2009, when the Commission conducted its search and seizure operation. We understand that the information exchange arrangement, which had provided the mechanism for collusion, ended in June 2009. It seems very likely that the cartel agreement started to break down around these events.

Note that section 4 of the settlement agreement between the Commission and AfriSam confirmed by the Tribunal in March 2011, records that “*AfriSam senior board members contacted the Commission soon after they became aware that the Commission had initiated an investigation against AfriSam, to understand the allegations. At the same time, AfriSam conducted a thorough internal investigation into the allegations.*” Similarly, section 4 of the settlement agreement between the Commission and Lafarge, confirmed by the Tribunal in March 2012, records that “*Lafarge contacted the Commission soon after it became aware that the Commission had initiated an investigation against Lafarge, to understand the allegations. At the same time Lafarge conducted a thorough investigation into the allegations.*” It does not seem likely that the cartel members would have continued with the collusive arrangements while well aware of the Commission’s investigation. The other potential end date is November 2009, when PPC was granted conditional immunity.

Correctly defining the period over which coordination took place is important when estimating overcharge. In particular, since the methodology used by Theron & van Niekerk (2017) and Boshoff & van Jaarsveld (2018) to calculate overcharges relies on data after the 2009 cartel end date, it is essential that the data specified by the model to be the result of competitive behaviour are in fact genuinely the outcome of such behaviour. It does not seem likely that the cartel continued post 2009. There is no factually sound basis to assume that the cartel ended in November 2011 or December 2013 just because there is a break in data at those points. As such, this research will assume June 2009 as marking the cessation of collusion.

7.2 The explanatory variables

The data used in this paper are similar to that of previous research but includes additional variables and also finds previously-used variables to be insignificant, probably due to the differing specifications. Quarterly data for the period starting 1994 and ending 2019 are considered. Given the underlying structural model that is used to specify the reduced-form price equation, it would be fitting to incorporate variables that drive supply and demand in the cement market⁵.

The supply drivers include coal, gypsum, limestone, aggregates, unit labour costs in manufacturing and electricity. The demand drivers include gross fixed capital accumulation, the building contractor's confidence index and the number of building plans passed. All series have been deflated by the Producer Price Index for Building and Construction.

The dummy variable is equal to one during the assumed cartel period of 1999Q1 to 2009Q2.

Figure 6

Variable Name	Description	Source
Cement	PPI of Selected Materials: Ordinary and Extended Cement	Statistics South Africa
Limestone	Total local sales – Unit value	Department of Mineral Resources
Gypsum	Local sales – Unit value	Department of Mineral Resources

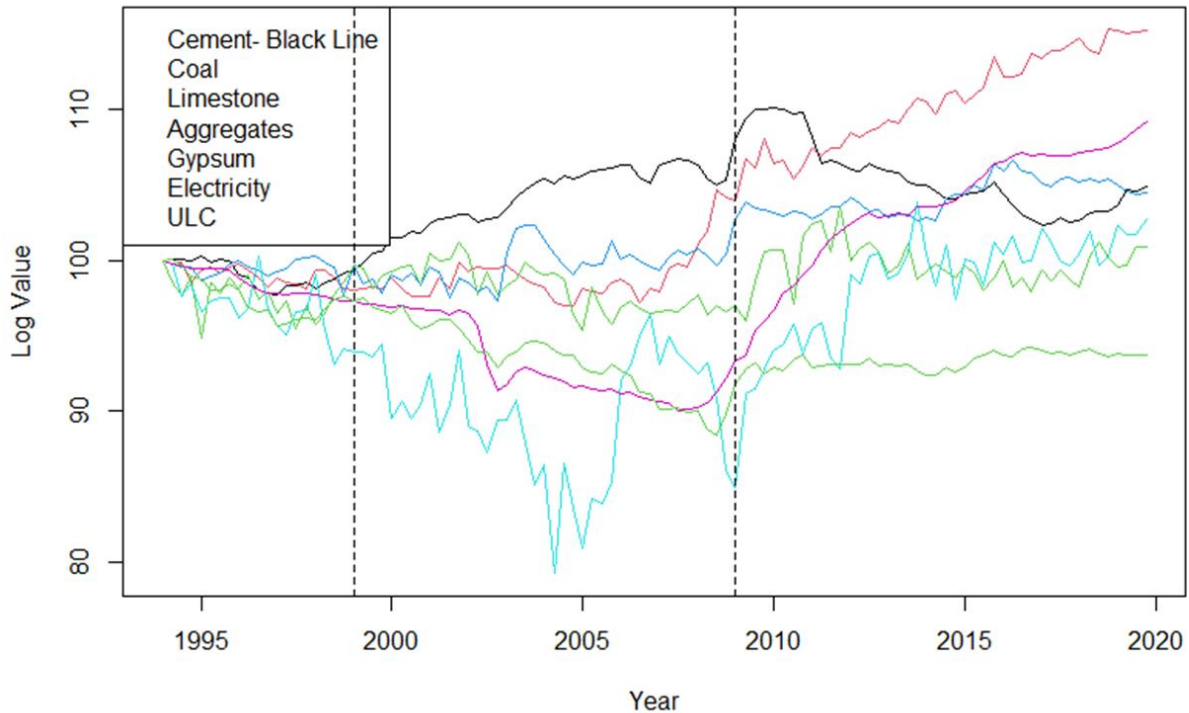
⁵ In the spirit of brevity, we have omitted detailed material on the cement production process since it is comprehensively provided by (Theron & van Niekerk, 2017). If the reader wishes to comprehensively understand the justification for some of the explanatory variables (particularly on the supply side), please refer to the mentioned paper.

Coal	Local sales – Unit value	Department of Mineral Resources
BCI	Building Confidence Index	Bureau for Economic Research
Buildings	Number of Building Plans Passed	Statistics South Africa
ULC	Manufacturing: Unit labour cost	South African Reserve Bank
GFCF	Gross Fixed Capital Formation: Construction	South African Reserve Bank
Electricity	PPI: Electricity	Statistics South Africa
Aggregate	Local sales – Unit value	Department of Mineral Resources

Of course, it is not possible to include all variables that have a relationship with the price of cement due to data availability, difficulty in measuring the variable or the variable not being significant. The error term in the regression will capture the total effect of the omitted regressors. Figure 7 below shows the cement price (in black) versus the values of the input costs (in various colours). It is not necessary to compare each of the supply drivers to each other or to the cement price but rather to compare the collective supply drivers to the cement price. At the commencement of collusion (marked by the leftward dotted line), it appears that the price of cement loses its correlation with the supply drivers where the cement price appears to be driven upwards. After collusion ends (marked by the vertical line at 2009), the cement price appears to track closer to supply drivers. This hints at the possibility that the cement price was not being driven so strongly by supply factors during the cartel period.

Choosing the proper set of variables to be included in the regression model does not complete the modelling exercise. The main issue, however, is the functional form of the models. It is crucial to take the characteristics of time series data into account. We discuss these characteristics in the following section. We also test several functional forms in our modelling exercise.

Figure 7



8. Characteristics of Time Series Variables

The issue that often arises with time series data is that of nonstationarity. In order for the reader to appreciate the use of an error correction model, we will provide a description of the concepts of stationarity and cointegration. The papers that have studied the South African cement cartel have not necessarily delved into these subjects, possibly because it was not required in their chosen approaches but this paper certainly demands it. The tests used for these concepts will then be explained and results will be provided and discussed.

8.1. Stationarity

One can weakly define a stationary time series as one that has a variance and average that does not change over time. Further, the covariance between any two data points in the process does not depend on time itself but rather only the distance between them. This is what is generally termed as ‘weak’ stationarity but in most cases, a process that exhibits weak stationarity is generally strictly stationary too (where all joint distributions are invariant with respect to time). To formalise the concepts of stationarity

and the unit root testing that follows, let x_t denote a time series where $t = 1, 2, \dots, T$. A weakly stationary series has:

1. $E[x_t] = \mu$ for all $t = 1, 2, \dots, T$.
2. $Var(x_t) = \sigma_t^2$.
3. $Cov(x_t, x_{t+j}) = \gamma_j$ where γ_j refers to autocovariance.

Although it is not completely relevant to this study since it is difficult to differentiate between the two in finite samples, I will briefly elaborate on the difference between ‘trend’ and ‘difference’ stationarity. A trend stationary series is characterised by having a trend and a disturbance term that is stationary. That is, a trend stationary series can be written as

$$x_t = \beta_0 + \beta_1 t + \epsilon_t \tag{21}$$

Where t represents the time trend and ϵ_t is an independent and identically distributed process. In this case, the varying mean can be explained by the trend term and if the series were to be detrended, the series would be stationary. Algebraically, (22) is stationary:

$$x_t - \beta_0 - \beta_1 t = \epsilon_t \tag{22}$$

A more in depth explanation of trend stationary processes is beyond the scope of this research but information on the concept is abundant and widely available⁶.

A difference stationary process is one that can be made to be stationary by taking first differences of a series that is covariance nonstationary. In opposition to the temporary effects of shocks in trend stationary processes, shocks in difference stationary processes are permanent. Consider the pure random walk:

$$x_t = x_{t-1} + \epsilon_t \tag{23}$$

Expressing this for each time period starting at time $t = 0$ to time $t = k$:

⁶ See (Pesaran, 2015) for a theoretical and graphical explanation. It should be noted that the variance of a trend stationary process is finite, the expected time it takes for crossings of the trend is finite and shocks have temporary effects on the process.

$$t = 0: x_t = x_0 \tag{24}$$

$$t = 1: x_1 = x_0 + \epsilon_1 \tag{25}$$

$$t = 2: x_2 = x_1 + \epsilon_2 = x_0 + \epsilon_1 + \epsilon_2 \tag{26}$$

Therefore, at time $t = k$:

$$t = k: x_k = x_0 + \sum_{i=0}^k \epsilon_i \tag{27}$$

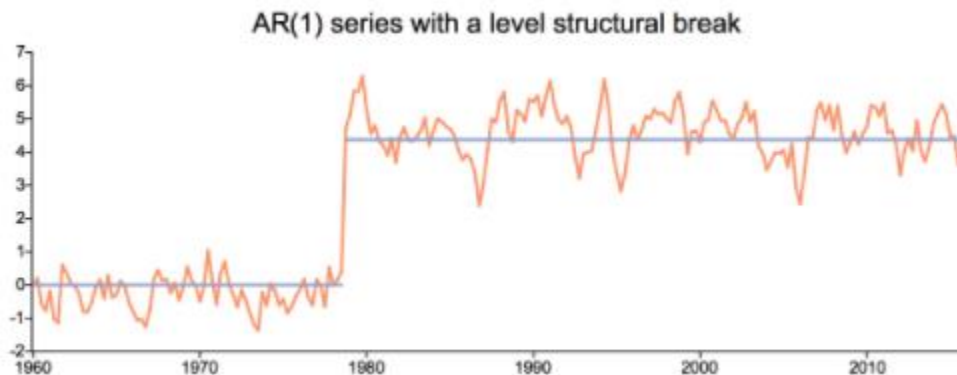
It can be seen that shocks in a given period are inherited by future periods and thus, the process is said to be ‘integrated’.

Testing for a unit root in a series can be done by various tests. Some of the more popular tests are discussed and performed below⁷. An issue that cannot be ignored is how a structural break can impact a conclusion of the presence of a unit root. That is, performing one of the unit root tests may yield a result in favour of nonstationarity if there is a structural break in the data where the series actually displays stationarity absent of the structural break. This bias of a rejection of stationarity in favour of nonstationarity is investigated and confirmed by Perron (1989) and can be graphically explained by Figure 8.

Overcharge estimation in the form that this research inherently adopts has this issue of a structural break, in this case being the structural change of collusion and then non-collusion. Therefore, the price of cement may actually be stationary in the periods prior to collusion, during collusion and after collusion but the changes in price due only to the structural change will yield false confirmation of nonstationarity when performing the required tests.

⁷ If the model is estimated using a structural approach, stationarity can be checked in a multivariate setting as described by (Juselius, 2007). For the purposes of this paper, where a reduced-form price equation is used, testing for stationarity in the univariate case is appropriate.

Figure 8



Source: (adisuryap, 2019)

There are ways in which one could test for unit roots when structural breaks are present which range from rather simplistic to more advanced. If there is an *a priori* knowledge on the dates of the structural breaks, unit root tests could be conducted for the periods that do not include a structural break. So if a series is shown to have a unit root when the entire period is tested and the series still shows to have a unit root prior to the known structural change and after the structural change, it is likely that the series does contain a unit root. One such test that allows for two structural breaks, as well as unknown dates for the breaks, is that offered by Lee & Strazicich (2003) which remedies issues of the null hypothesis that the test offered by Lumsdaine & Papell (1997) presented. The focus of this paper is not the testing for stationarity so it will be assumed that the time series do not have a structural break. That is, we only wish to show that nonstationarity exists in some of the variables, thus justifying the ECM approach.

Another difficulty in unit root testing arises in the form of low power and size distortion of these tests. Loosely put, the power of a test refers to its ability to differentiate between a true and false null hypothesis while the size refers to the chosen significance level of the test. Work by Haldrup & Jansson (2005) elaborates on what motivates the size and power issues and describes other tests that address each of them. In addition, the concern of specification of the test equation is of relevance to the size and power problems. That is, should the test equation cater for a constant or a trend (or both)? Whether or not a trend is included is generally left to the discretion of the researcher but it is generally accepted to include a constant. Analysis on the generalised least squares approach to the Augmented Dickey-Fuller test (which will be discussed below) by Harvey et al. (2009) suggests that one should generally use the demeaned and detrended case to remove the risk of not accounting for the trend to ensure robust inference. This does,

however, come with a loss in power. Therefore, in my unit root testing I will predominantly rely on a model that accounts for both a constant and a trend.

a. Testing for Unit Roots

When dealing with time series data, the problem of persistence in the data becomes one to consider. The seminal work of Granger and Newbold (1974) showed that by regressing one nonstationary time series on another nonstationary series, one can find a relationship between the two series even though a relationship does not exist. Put formally, consider the two random walks x_t and y_t that are constructed to be uncorrelated:

$$x_t = x_{t-1} + \vartheta_t \tag{28}$$

$$y_t = y_{t-1} + \pi_t \tag{29}$$

Where $E(\vartheta_t, \pi_s) = 0$ for any t, s and $E(\vartheta_t, \vartheta_{t-h}) = 0 = E(\pi_t, \pi_{t-h}) \forall h \neq 0$. Also, the error terms of both series are independent and identically distributed. It is obvious that both series are integrated of order one, $I(1)$. The authors conducted a Monte Carlo analysis and ran a regression, $y_t = \delta_0 + \delta_1 x_t$, on a sample of 50 observations and simulated 100 samples. Their results showed that their tests rejected the null hypothesis that δ_1 was equal to zero more than 75% of the time. That is, their regression results concluded that there was a significant relationship between the two series even though they were not correlated⁸.

Relying on intuition rather than a textbook explanation, if two series each have a trend, and both of these series trend together by chance, a conclusion can be made that there is some relationship between these two series. This can occur even if the two series are intentionally constructed to have no real relationship between them. Therefore, nonstationary processes carry a difficulty in inference so it is important that series are checked for nonstationarity.

In order to navigate the process supporting each test, I will briefly provide theory on each test and how they differ. The Dickey-Fuller (DF) test will not be used directly in my unit root testing but there are other tests that will be used that are derived from the Dickey-Fuller test⁹. The first of these popular tests is the

⁸ Other regression results included a Durbin-Watson statistic near zero, a high R^2 and low standard errors associated with the estimated coefficient. Further, increasing the size of the sample does not change the outcome of a spurious regression.

⁹ Information regarding each of the DF tests, whether the process contains a trend and/or constant or neither, and critical values can be found in (Dickey & Fuller, 1979) and (Dickey & Fuller, 1981).

Augmented Dickey-Fuller (ADF) test. Considering the limiting assumption of an AR(1) specification that the DF tests uses, the ADF test extends the specification to include p lags so that it caters for a process generated by, say:

$$x_t = \mu + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_p x_{t-p} \quad (30)$$

If it were assumed that x_t was generated by an AR(1) process, the error term would be autocorrelated. Therefore, by adding lagged differenced variables, the test controls for potential serial correlation. The number of lags can be determined in a number of ways but I have elected to use the information criteria approach, specifically using the Akaike Information Criterion (AIC)¹⁰. The generalised regression would take the form (and could include a trend term):

$$\Delta x_t = \mu + \alpha x_{t-1} + \sum_{k=1}^{p-1} \psi_k \Delta x_{t-k} + \epsilon_t \quad (31)$$

The results of the ADF- τ_τ (which includes trend and non-zero mean terms) and ADF- τ_μ (includes only a constant) tests are provided in Figure 9 where the critical values are provided by Hamilton (1994) and Dickey & Fuller (1981), depending on which specification of the test was selected. The ADF test proposes the null hypothesis that a unit root is present and adopts the alternative hypothesis of stationarity. That is, if the test statistic is “more negative” than the critical value, one can reject the null in favour of stationarity.

The second unit root test that I have elected to use is the test put forth by Elliott et al. (1996) which is a modified version of the standard DF test. The test essentially estimates a time series by generalised least squares (GLS) and then applies the DF test to check for a unit root. The authors argue that this process attempts to remedy the issue of low power and when a deterministic component is present, power is significantly improved over the DF test. This is done by applying a different method in estimating the coefficients on these deterministic components. The equation to be estimated adopts the same form as that of the ADF’s except the test is applied to a series¹¹, \bar{x}_t , that has been demeaned and/or detrended by using

¹⁰ Another common approach that can be used is the general-to-specific approach where one would initially consider a high lag order and run the regression. Significance analysis could be performed on the highest-order lag. The process would then iteratively remove a lag as the estimate is found to be insignificant.

¹¹ To obtain the demeaned series of x_t , let $\bar{x}_t = x_t - y_t \omega$ where ω is estimated by generalised least squares.

GLS estimates:

$$\Delta \bar{x}_t = \alpha \bar{x}_{t-1} + \sum_{k=1}^{p-1} \psi_k \Delta \bar{x}_{t-k} + \epsilon_t \quad (32)$$

The unit root test results in Figure 9 include results for both the DF-GLS^r test, where \bar{x}_t is the local GLS demeaned and detrended series for x_t , and the DF-GLS^u test where \bar{x}_t is the demeaned series for x_t . Like the ADF tests, the DF-GLS tests propose a null hypothesis that there exists a unit root against the alternative hypothesis of stationarity. The critical values for the DF-GLS tests are taken from Table 1 of Elliott et al. (1996) and Mackinnon (1991).

The last unit root test that I have used is the KPSS test by Kwiatkowski et al. (1992) which is different to the abovementioned tests from a hypothesis testing perspective. Instead of having a null hypothesis of a unit root, the KPSS test tests the null that the series is stationary. Therefore, if the ADF or DF-GLS tests cannot reject their respective null hypotheses, you would expect the opposite from the KPSS test. To show this algebraically, the series can be written:

$$x_t = f(t) + r_t + v_t \quad (33)$$

Where $f(t)$ is a constant (or also a trend in the case of the KPSS^r test), r_t is a stochastic trend that is a function of its lagged value and an independent and identically distributed series with a mean of 0 and variance σ^2 (i.e. $r_t = r_{t-1} + u_t$) where v_t is stationary residual. When $\sigma^2 = 0$, r_t does not exist and since v_t is stationary, testing the null that $\sigma^2 = 0$ is testing that x_t is stationary. If $f(t)$ is stated as a function of a constant and a trend, testing that $\sigma^2 = 0$ is the same as testing for trend stationarity. The critical values for the KPSS test are taken from the paper by Kwiatkowski et al. (1992) and I have tested for both the KPSS^r and KPSS^u tests.

Figure 9 provides the test statistics for the various tests employed and compares them to the relevant critical values which are provided in the notes to the table.

Figure 9: Unit Root Tests

Variable	ADF- τ_{τ}	ADF- τ_{μ}	DF-GLS $^{\tau}$	DF-GLS $^{\mu}$	KPSS $^{\mu}$	KPSS $^{\tau}$
Cement	-1.9949	-2.3128	-1.2799	-0.7117	1.1035 (***)	0.439 (***)
Coal	-2.0291	0.2231	-1.1555	0.3632	1.8869 (***)	0.4603 (***)
Limestone	-2.4954	-2.3735	-2.0219	-1.8771 (*)	0.4938 (**)	0.0967
Buildings	-3.0676	-2.4123	-2.8216 (*)	-1.5521	1.1951 (***)	0.1686 (**)
Gypsum	-2.8251	-1.3204	-1.2688	-1.1598	0.7898 (***)	0.4239 (***)
Electricity	-1.7096	0.1492	-1.198	-0.7912	1.0819 (***)	0.4994 (***)
BCI	-2.3802	-1.012	-2.4109	-0.3233	1.1974 (***)	0.1378 (*)
ULC	-1.7797	-1.9595	-1.1287	-0.3459	1.1915 (***)	0.4321 (***)
GFCF	-1.827	-1.4488	-1.5263	-1.4813	1.0569 (***)	0.248 (***)
Aggregate	-4.1974 (***)	-1.2211	-2.5775	-0.9595	1.859 (***)	0.2487 (***)

The critical values (1% | 5% | 10%) of the various tests are: ADF- τ_{τ} (-3.99 | -3.43 | -3.13); ADF- τ_{μ} (-3.46 | -2.88 | -2.57); DF-GLS $^{\tau}$ (-3.46 | -2.93 | -2.64); DF-GLS $^{\mu}$ (-2.59 | -1.94 | -1.62); KPSS (0.347 | 0.463 | 0.739). The notation ‘*’, ‘**’ and ‘***’ refer to the rejection at the 10%, 5% and 1% levels, respectively.

It should be clear to see that in terms of the ADF tests, nearly all of the series could not reject the null of a unit root. The dependent variable in this study shows to have a unit root in all tests and rejects the null of stationarity in the KPSS tests at the 1% level. Similar results are also found for Coal, Gypsum, Electricity, the building contractor’s confidence index (BCI), unit labour costs (ULC) and gross fixed capital formation (GFCF). The test results for these series leave little doubt to the conclusion that they display characteristics associated with nonstationary time series. The test statistics for Limestone offer opposing conclusions where the DF-GLS $^{\mu}$ test rejects the null of a unit root (although only at the 10% level) and the KPSS $^{\tau}$ test fails to reject the null of stationarity. The DF-GLS $^{\tau}$ test also provides a test statistic for the Buildings series that concludes stationarity at the 10% level but the remaining tests conclude nonstationarity. The ADF- τ_{τ} test that provides a conclusion of stationarity for the Aggregate series is also the only test that makes this conclusion. Given the conflicting test results, and given the general absence of certainty in such tests, any researcher should be hesitant to conclude stationarity or nonstationarity with

conviction. However, the results show that the series do, at the very least, display characteristics of nonstationarity.

8.2. Cointegration

A common remedy for the presence of a unit root in the data is first differencing the series so that it becomes stationary. The resulting series would then be said to be integrated of order zero. Another way in which the complications of nonstationarity may be eluded is if the time series are cointegrated. As a brief explanation, cointegration refers to the case where two or more variables have an associating relationship that spans the long term. That is, over time, one variable may pull another variable in its direction of movement which is to imply that these variables are cointegrated and form a long-term equilibrium. For an overview of cointegration and how the concept can be used in the presence of nonstationarity, see work by Hendry & Pretis (2016) which provides a more comprehensive, although not necessarily complex, explanation.

In the event that the data were available, a methodology that incorporated a structural system of equations could have been used instead of the reduced form. In this case, one could approach the analysis of potential cointegration with the Johansen approach. This paper, due to the unavailability of data, adopts a single-equation methodology that aims to only estimate how various variables have an effect on price. When set in this framework, the common approaches to cointegration analysis are generally the Engle-Granger two-step approach (Engle & Granger, 1987), the Engle-Granger-Yoo three-step approach and the (Stock & Watson, 1993) dynamic ordinary least squares approach. The full derivation of these cointegration tests and how they are applied is beyond the scope of this research.

9. Results

The results from previous studies on the South African cement cartel already show the variation in the overcharge estimate given differing approaches to the problem. The results put forth by this paper are not intended to support or undermine previous attempts, but rather demonstrate the range of the overcharge that can be estimated depending on the approach that is adopted.

In order to establish somewhat of a benchmark, Figure 10 provides estimation results for a static model. As already mentioned, the data are in natural log form so estimates must be interpreted as such. The column of estimates refers to a specification where it is assumed that collusion ceased in June 2009, when the cement producers were raided after search and seizure warrants were issued.

All variables but the intercept, Buildings and BCI are significant. Estimating a more parsimonious version where these variables are excluded does not significantly impact the estimates. Interestingly, the coefficients on unit labour costs and coal are negative and significant at the 1% level in both models.

Figure 10

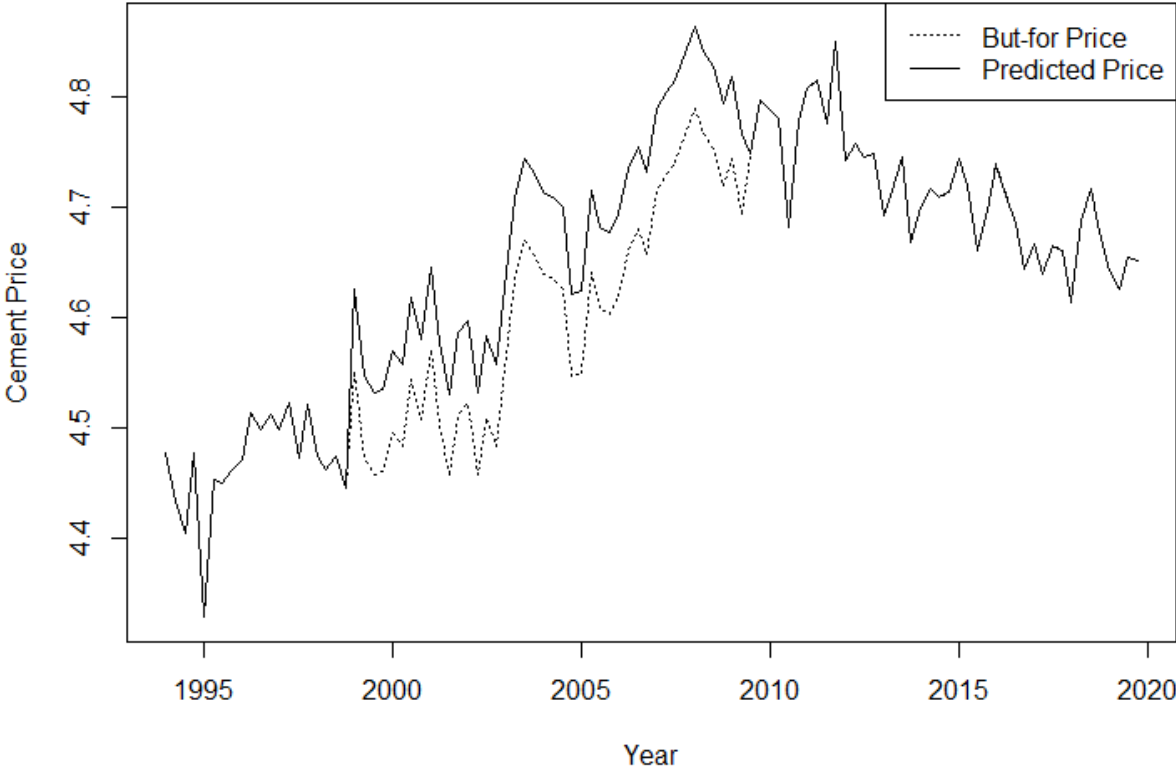
Variable	Dummy = 1 (1999Q1 – 2009Q2)
Intercept	0.65085 (1.70534)
Buildings	0.04355 (0.05255)
BCI	-0.00196 (0.02510)
Aggregate	0.60664 (0.18544) ***
ULC	-0.62409 (0.13003) ***
Coal	-0.22979 (0.07578) ***
GFCF	0.16316 (0.05918) ***
Limestone	0.54853 (0.11934) ***
Dummy	0.07445 (0.03311) **
F(8, 95)	31.46 ***
Adjusted R-squared	0.7029

*Standard errors are shown in parentheses. Significance at the 1%, 5% and 10% levels are indicated respectively by '***', '**' and '*'.*

If unit labour costs were to increase by 1%, the price of cement would decrease by 0.62%. Given the significance of limestone in the production process¹², the coefficient of the Limestone variable is significant and positive – a 1% increase causes an approximate increase of 0.5% in the cement price. We have elected to omit the Electricity and Gypsum variables from the above specifications as their inclusion resulted in the complete insignificance of the dummy variable which is not theoretically justified.

As already indicated, the overcharge due to collusion is calculated using the coefficient on the dummy variable¹³. If collusion were assumed to end in 2009, the overcharge amounts to 7.73%. Figure 11 offers a graphical perspective of the overcharge due to collusion, where predicted prices are compared to but-for prices. The but-for prices are determined by letting the dummy variable equal zero for the entire period.

Figure 11



Before considering the results of the ECM, it should be noted that we have acknowledged the issue with regards to the dating of the South African cement cartel, specifically the end-date, and how previous

¹² Again, see Theron & van Niekerk (2017) for a more detailed description of the production and value chain.

¹³ See formula provided in notes under Figure 5

studies have addressed this problem. While there may be theoretical reason for extending the cartel end-date, that is justified by actual events such as settlement agreements or econometric insight, we assume that explicit collusion ended no later than June 2009. In the context of real-world application of overcharge estimation on this particular case, there is little that concretely justifies the lengthening of the cartel period after the raids. However, given the years of shared information between the firms, the lack of differentiation of products, the growth of the cement market, the multi-market contact and the fact that there were no entrants until 2014 suggests that there was possibly some dwindling form of tacit collusion after 2009. Not all of the regression results have been included but if the dummy variable is constructed so that explicit collusion ceases in 2009, and linearly decreases for the following two years, the overcharge estimate increases significantly to 17.24% if the same regressors are used as in Figure 10. Interestingly, Coal loses its significance in this regression.

The estimation results for the ECM are provided in Figure 12. Again, the results refer to a cartel period that ended in June 2009. Given the dynamic nature of the model, the coefficients cannot be interpreted in the same manner as the static case. Equation (20)¹⁴ is described as the ratio of the coefficient of the dummy variable to the lagged price. The equation provides the long-run effect of the collusive behaviour on equilibrium price. Recall that by construction of the ECM, Φ is less than zero. Therefore, the negative coefficients on the $cement_{t-1}$ variable are actually positive. From the below, the ratio is $(0.01866/0.09823) = 0.18996 \approx 19\%$.

Figure 12

Variable	Dummy = 1 (1999Q1 – 2009Q2)
<i>Intercept</i>	0.39412 (0.39229)
<i>cement</i> _{t-1}	-0.09823 (0.03515) ***
<i>aggregate</i> _{t-1}	-0.05841 (0.05397)

¹⁴ For ease of reference: $\frac{\Delta cement^e}{\Delta dummy_t} = \frac{\theta}{\Phi}$

$electricity_{t-1}$	0.08858 (0.03591)
$coal_{t-1}$	-0.62409 (0.03731) **
$\Delta cement_{t-1}$	0.22580 (0.09995) **
$limestone_{t-1}$	-0.03781 (0.03647)
$gypsum_{t-1}$	-0.03127 (0.01567) **
$GFCF_{t-1}$	0.02439 (0.01685)
ULC_{t-1}	0.02640 (0.05026)
$dummy_t$	0.01866 (0.01061) *

*Standard errors are shown in parentheses. Significance at the 1%, 5% and 10% levels are indicated respectively by '***', '**' and '*'.*

Therefore, the results provided by the approach that aims to control for nonstationarity appears to provide an overcharge that is significantly higher than that of the static model. In fact, the overcharge of 19% is similar to that provided by Boshoff & van Jaarsveld (2019) but not due to the same reasons. Their paper controlled for the possible recurrent nature of the collusion while our estimate controls for nonstationarity. The takeaway should not be that the estimates are similar but rather that once model complications/biases are accounted for, the actual overcharge can be higher than previously predicted. Broadening the comparison to foreign cement markets, the overcharge percentage of 19% is consistent with the average overcharge that prevailed in cartels in domestic markets, as shown by Connor (2007).

10. Conclusion

This research aims to provide a broad understanding of cartels and how they operate. That is, the workings of a cartel and their impact on the economy and consumers was discussed in order to provide justification for estimating overcharge. In order to establish perspective on the employed approach, other approaches were discussed which included approaches that are market-structure based, financial-analysis based and comparator-based models. The most suitable for the case of the South African cement cartel was the approach that is based on time series data which compared periods of collusion against the absence of collusion. Importantly, it should be established that there is no one correct way to approach the task of overcharge estimation.

Settling on any one overcharge estimate should obviously be avoided, as illustrated in the above discussion. With reference to only the South African cement cartel, research discussed in the literature review section has shown that the estimate can be tainted by incorrect dating, external events such as the 2008 financial crisis, varying specifications of the dummy variable and the assumption of recurrent, and therefore interrupted, collusion. These can all be controlled for to yield a 'more accurate' estimate, as each paper claims. While dating remains a contentious issue, this paper resorts to the factually sound assumption of a cartel end-date of June 2009, differing from the wide array of dummy variable specifications offered by others.

It should be clear that various tests can be employed in the search for a unit root, each having their own advantages and disadvantages. If one is found, the results of the chosen model could be spurious and lead to conclusions that may not represent reality. As such, nonstationarity needs to be controlled for, which can be done through simple techniques such as first-differencing, or through more complex models such as the error correction model which preserves insight on long-term relationships. This research attempted to deal with time series complications, specifically controlling for the presence of unit roots, by using an error correction model which was justified by the results of the unit root tests.

The use of the ECM yielded an overcharge estimate that is approximately 11 percentage points greater than the estimate given by a basic ordinary least squares regression on static variables. This higher estimate is consistent with research that has attempted to control for complications. What is unique, however, is that an ECM can be used in any paper that attempts to calculate overcharge where nonstationarity is present. This refinement of prior research differs in that it can be broadly applied while other attempts refine the approach by controlling for aspects (such as recurrent collusion and the 2008 financial crisis) that are specific to the South African cement cartel.

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