Characterizing Structural Changes In Prices Resulting From Competition Policy Intervention: Lessons From the Cement Cartel *

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Abstract

In recent times, the Competition Commission South Africa has intensified its enforcement activities. One of the most useful tools that the Commission has exploited is its dawn raid operations on suspected cartels. This paper introduces several neoteric approaches to characterizing cartel behaviour. In the first instance, I confront cement price data with the Bai and Perron (1998, 2003) structural break test to recover possible breaks due to competition policy (cartel bust). I find that the method is weakened by input costs susceptible to exogenous macroeconomic shocks. Other results from this exercise show that cartelized prices tend to react positively during economic downswings, suggesting possible evidence of pass-through at the product level. Secondly, I propose a new method for analyzing the influence of cartels on prices. Although it is couched on theory, it has potential usefulness for policy analysis. The results from that exercise show that cartels tend to be more proactive in periods characterized by low profits due to high input costs. These results buttress the findings in the Bai and Perron (1998, 2003) segment.

JEL-Classification: L4, C5, C32
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1 Introduction

2017 marks the 18^{th} year of the existence of the Competition Commission South Africa (henceforth the Commission). Throughout this period, there have been significant gains in the enforcement of the Competition Act No. 89 of 1998 (henceforth the Act). Landmark matters include the Massmart/ Walmart merger [1], the record R1.5 billion fine levied on Arcelor Mittal[2] for their role in the long steel and scrap metal cartels and the recent collusion referral of multiple large banks in the exchange rate market. Further, the World Bank (2016) noted that between 2005 and 2015, the Commission detected and sanctioned 76 cartels in South Africa outside the construction sector.

There is a widely accepted view that South African markets are still very much concentrated and require urgent structural reforms to boost competition (International Monetary Fund, 2017). The Commission has begun to utilize dawn raids as one of its most effective tools to secure evidence of collusion. These commitments by the Commission to dismantle cartels raises interest in the effectiveness of competition policy, more especially in the area of cartel busting.

These developments have emboldened researchers' interest in the empirical analysis of competition policy. Much of the has taken place in the context of cartels. However, South African studies in lore is sparse. A few studies have set the motion, with notable contributions in the bitumen (Boshoff, 2015), cement (Govinda et al., 2014), precast concrete products (Khumalo et al., 2014), as well the flour and wheat cartels (Mncube, 2014).

In doing so, local studies have focused on calculating the cartel overcharge price. This is the price obtained from estimating the difference between the actual price and the price that would have prevailed in the absence of the cartel. The central tenet of this measure is to compare market outcomes during the period of alleged collusion with those in a period without such collusion. Econometrically (in particular, Govinda et al. (2014) and Mncube (2014)), this is done by applying a time-dummy variable to separate the two hypothetical periods. In essence, the competition policy intervention, in casu, cartel busting, (or policy shock as I will use the phrases interchangeably throughout the paper) is treated as a structural break.

However, there are several caveats established in literature that might arise when competition policy intervention is treated as a structural break shock in econometric analysis. The most notable impasse arises from the perplexity in assigning the correct period for the structural break. There are views in literature that point to a non-smooth transition of competition after a cartel bust. The most insightful thesis is captured succinctly by Khumalo et al. (2014) in their "three period" tracing of the life of a cartel . The first period is when the cartel is actively in operation. The second period is the "transition period". This is the period that traces the price dynamics from the cartel market equilibrium to the competitive market equilibrium. This period is often characterized by a

[1] The merger faced opposition from government departments and labour unions on public interest grounds. The entities from government were, Economic Development, Trade & Industry and Agriculture, Forestry & Fisheries; And the unions were, South African Commercial, Catering & Allied Workers' Union (SACCAWU), the South African Clothing & Textile Workers' Union (SACTWU), and the Congress of South African Trade Unions (COSATU). Case No: 110/CAC/Jul11

[2] Case No: CR092Jan07/SA090Aug16

persistence of cartel equilibrium prices. And the last period is the competitive market phase, where market outcomes are assumed to be absent of any cartel influence.

There are several examples of this three period transition process. In the United States Lysine cartel uncovered in mid-1995, prices continued to rise in late 1995 and were sustained for nearly five months until 1996 post cartel intervention (Connor, 1997). Staying in the United State, in the vitamins cartel, (Kovacic et al., 2007) found that prices of two members of the cartel persisted well through the post-plea period.

Based on the observed data, literature challenges the conventional method of assigning structural breaks based on priori information. There is a high likelihood that the information sets of economic agents and the econometrician are misaligned. Econometric analyses that fail to align economic agents' and the econometrician's information sets can produce distorted inferences about the effects of policy intervention. The econometrician might assume the policy shock has a contemporaneous impact on competition parameters (*i.e.* prices). However, as literature points out, prices post the cartel bust might persist through "tacit collusion" because members of a cartel progressively develop an understanding of each others business (Khumalo et al., 2014). This is intensified if the cartel has fewer members and has lasted for a long period of time. In light of these drawbacks, it can be concluded that estimated coefficients of the cartel overcharge price in econometric models that identify structural breaks exogenously could potentially be bias and inconsistent.

This current paper is emboldened by these shortcomings. There are several contributions the paper aims to make in literature. Firstly, I propose a method that allows for testing and dating structural breaks without specifying the dates exogenously. My starting point is confronting the South African cement cartel data set[3] with the Bai & Perron (2003) structural break test (henceforth Bai and Perron). There are three notable benefits from this approach. Firstly, it does not require the econometricians to know the timing of the breaks beforehand. Secondly, it uses statistically founded techniques to detect the structural breaks, which reduces estimation errors associated with non-fundamental time dummy variables that might yield spurious policy recommendations. Thirdly, it provides an indication of the effectiveness of competition policy. In essence, the method yields results that test the veracity of structural breaks resulting from competition intervention. That is, if the break detected correlates with the timing of the cartel busting, it validates the predictions of cartel theories in competition treatise.

Further to this, I present a potentially new approach to understanding cartel behaviour through pricing data. This novel idea exploits the information that is generally discarded in the error term of a regression. My intuition begins with the assumption that firms in a competitive environment produce at the level where marginal costs are equal to the market price. Fundamentally, if prices are regressed on all possible exogenous costs, unobserved factors that influence prices are hoarded in the error term. On these grounds, error terms before the cartel is busted should be significantly larger than error terms post cartel bust. That is, the cartels' influence should transpire in the error term before

[3]In the interest of brevity, I only offer a brief overview of the cement cartel. For a more comprehensive background, see Govinda et al. (2014)

competition policy intervenes. To extract the "cartel's influence" on the prices, I take an average of the post-cartel error terms (guided by qualitative data) and subtract them from the pre-cartel errors to separate competitive factors from non-competitive factors. One shortcoming of this method is that it is derived purely on theoretical predictions. But with the necessary revisions, this technique should help with our understanding of how cartels influence prices in such empirical exercises.

The paper reaches three conclusions. First, in the presence of much larger exogenous shocks, pricing data only detect structural breaks associated with macroeconomic shocks. In this context, a plethora of the input regressors on cement prices are commodity-linked. In most instances, macroeconomic shocks tend to have a profound impact on commodities, especially those that are primarily used in industrial productions. This is reflected in the endogenous structural breaks detected in this exercise. A poignant outcome of the paper is that endogenously determined structural breaks do not coincide with the cartel period. Given that the transition process is unobservable, it evokes questions of whether the cartel persisted tacitly. Second, I find that accounting for macroeconomic shocks and other estimation issues increases the fit of the model and reduces the error variance. This bodes well for the 'cartel influence' parameter as results do show that the period after the cartel is busted exhibits less volatility in the unexplained parameter. Conversely, error term analysis of the period associated with the period pre-cartel exhibits a large variance, more especially during periods of persisting macroeconomic shocks on input cost shifters. While the assumptions of this approach are admittedly simplistic, the results show that the paper is taking the right step towards a more unified understanding of the influence of cartels on prices.

The remainder of the paper is organized as follows. In Section 2, I present a write-up on several studies which feature the application of the Bai and Perron methodology. This section is imbued by the literature review of Weideman et al. (2016). In Section 3, I provide a background of the South African cement cartel. In Section 4, I describe the Bai and Perron methodology and lay out a simple interpretation of the 'cartel influence' calibration. In Section 5, I provide a discussion of the data. In Section 6, I give the main findings of the paper. And finally, in Section 7, I conclude the study with a discussion of the results within the South African competition policy context and opine on future possible work.

2 The Use of Bai and Perron in literature

There are several instances of structural breaks in economic time series data. Economists have found evidence of occasional sudden breaks in many economic time series. For example, rate of growth of the economy alternates between periods of high growth (economic expansion) and periods of declining or negative growth (recession). The traditional Structural break approach assigns a date based on priori information and test whether a series has a break in the assigned date. Recently, a number of studies have developed different methodologies for determining dates endogenously, the seminal works being Bai and Perron who allow for multiple break point estimations.

The quintessential idea behind the Bai and Perron approach is to empirically evaluate whether there has been structural changes in the way two or more time series are related over time. Bai and Perron is a modelling approach with the goal of determining structural break dates endogenously. A recent study in South Africa by Weideman et al. (2016) uses the Bai and Perron approach to understand whether the renewable energy policies pursued by the South African government in the period 1990-2010 had any effect on the behaviour of consumers and producers of renewable energy. The estimated breaks coincide with policy changes that affected the demand of renewable energy.

Abroad, there is a multitude of literature in various economic topics on the application of the Bai and Perron methodology. For example, in Mensi et al. (2014), the authors study structural breaks in the time series of returns and volatility of crude oil prices. The results find that oil producing and exporting countries' (OPEC) decisions are anticipated by changes in the volatility of oil prices. The causes of the identified breaks are attributed to the sub-prime mortgage crisis of 2007 and the Asian financial crisis of 1997. In Papell et al. (2000), the authors look at structural breaks in the time series of unemployment for various developed countries. The estimated structural breaks correspond with post-World War II period. The conclusive narrative from that study suggested that unemployment tends to permanently increase during recessions, relative to other exogenous shocks.

With the comfort provided by these earlier works, Bai and Perron is a natural choice for the empirical policy analysis of cartels, as breaks due to cartel busting in time series are relatively unknown and unobservable. Below I provide a background of the cement cartel that forms the bedrock of this study.

3 Background of the South African cement cartel

From the 1940s to its disbandment in 1996, the Competition Board, the predecessor to the Commission, sanctioned an official and legal cement cartel in South Africa. The cartel members comprised of three primary producers - Pretoria Portland Cement (PPC), Lafarge, Afrisam - and their jointly and equally owned subsidiary , Natal Portland Cement Cimpor (NPC). The cartel members, regulated by the South African Cement Producers Association (SACPA), agreed that each firm's market share would be proportional to their production capacities.

However, following the new dispensation, the exemption was withdrawn in 1995, upon which the members of the cartel were afforded a grace period until September 1996 to terminate all cartel agreements. However, agreements on market share allocation continued to operate post 1996. The cartel members allocated their supply in South Africa into two regions: (*i*) the Southern Region and (*ii*) the Northern Region. The Southern region was the territory of PPC as the only producer with plants in the Western Cape. The Northern Region (Limpopo, Gauteng, Mpumalanga, North West and Free State) was shared between all producers. Whilst the northern side of KwaZulu-Natal province was shared between all producers, NPC had exclusive supply in south KwaZulu-Natal. That meant, south KwaZulu-Natal volumes would effectively be shared equally between the three other producers through NPC. Allocated market shares of then were as follows (includes NPC shares):

- PPC $\Rightarrow$ 42% and 43%;
- Afrisam $\Rightarrow$ 35% and 36%;
- LaFarge $\Rightarrow$ 22% and 23%.

A company known as cement distributors South Africa (CDSA) was formed and took responsibility for all the cement sales and distribution in the Northern Region and the balancing of the cartel's interest. In the Southern region, where only PPC operated, a company called Cape Sales performed a similar role.

Following a short-lived price war that lasted until 1998 (presumable from 1996), the cement manufacturers came together in 1998 to agree on new terms of the cartel:

- Market shares in line with the Southern African Customs Union (SACU) legal cartel portions;
- Provincial market shares coinciding with the SACU legal cartel portions;
- Pricing parameters for various types of cement;
- Scaling back on marketing and distribution activities, with agreements to shutdown various depots in specific regions; and
- No discount on high quality cement.

In order to monitor and enforce the agreement and deal with the cartel problem of cheating, the cement producers devised an elaborate scheme of sharing detailed sales information through the industry association known as the Cement and Concrete Institute or C&CI. The information sharing saw individual firms submitting their monthly sales figures to the associationâs auditors.

Given the high concentration level of the cement industry, firms could use the aggregated data received from the association to monitor their own market share. If there were any deviations (above or below a particular target), a firm could discern from the data exactly where the deviations came from. Therefore targeted punishment or volume shedding could be undertaken without entering into a price war or in any way destabilizing the market.

Based on suspicion of ongoing cartel activity in the market, the Commission raided the premises of all cement producers around 1999. However, PPC successfully challenged this operation on legal grounds resulting in the Commission returning all seized documents. Consequently around early 2008, the Commission launched a scoping study into the markets for construction and infrastructure inputs. The initial analysis revealed worrying pricing trends in the cement industry. Based on these initial findings, the Commission launched a formal investigation into the cement industry around June 2008. Shortly thereafter, PPC applied for leniency around mid-2009 and fully agreed to cooperate with the Commission by providing information on the cement cartel and were granted immunity from prosecution. In addition, PPC also agreed to discontinue sharing detailed sales information through the industry association. Thus the Commissionâs finding was that the cartel arrangements that existed in the legalised period continued post their legally sanctioned period. In 2011 and 2012, consent orders were confirmed by the Competition Tribunal between the Commission, which resulted in Afrisam and Lafarge paying fines to the amount of R125 million and R149 million respectively. In February 2015, the Commission referred the case against the last member of the cartel, the jointly owned NPC.

4 Methodology

The implementation of the Bai and Perron methodology is perfectly summarized by Weideman et al. (2016). However, in this paper, I depart from their approach and follow a more simple path. The first step involves examining the unit root properties of the time series. Subsequent to this, I implement the necessary transformation to make the data stationary and estimate a simple OLS model. I then plot the errors to assess model assumptions, such as constant variance and linearity. Guided by this information, I apply the Bai and Perron methodology to estimate the structural breaks and reveal the appropriate break dates. Finally, I estimate the OLS model with the structural break dates as time dummy variables. For robustness, I account for possible endogeneity issues due to simultaneity of the dependent variable and one of the independent variables through a Generalized Method of Moments (henceforth GMM) estimation.

4.1 Bai and Perron methodology

The model starts with a time series $T = 1, 2, 3, 4...T$ with m structural breaks, allowing $m + 1$ multiple segments or partitions in the series. There are two set of coefficients, β and δ. The β matrix contains those coefficients that remain constant in the structural break partitions, and the δ matrix contains coefficients that vary in each structural break partition. The respective coefficients are estimated using OLS, such that they minimize the sum of the squared errors (henceforth SSR). The objective function is such that:

$$(Y - X\beta - \bar{Z}\delta)'(Y - X\beta - \bar{Z}\delta) = \sum_{i=1}^{m+1} \sum_{t=T\,i-1+1}^{T_i} [y_t - x_t'\beta - z_t'\delta_i]^2 \qquad (1)$$

SSR is calculated across all the time points in a given partition 1 to $m + 1$, and represented in a diagonal matrix $\bar{Z}$. These are then summed to obtain the global SSR, $S_T(T_1, T_2, ...T_m)$, which are specific to each partition or structural break date $(T_1, T_2, ...T_m)$.

4.2 Testing the number of structural break dates

To test the hypothesis of 0 versus some m number of breaks, Bai and Perron propose a sup-F type test. This is done by constructing an F-test where the break dates $(T_1, T_2, ...T_k)$ are evaluated indirectly using the fraction of the time series in which the dates appears. Basically, $\frac{T_i}{T} = \lambda_i$ for $i = 1, 2, 3..., k$, such that:

$$F_T(\lambda_1, \lambda_2, ..., \lambda_k; q) = (\frac{T - (k+1)q - p}{kq})\frac{\hat{\delta}'R'(R(\bar{Z}M_x\bar{Z}))^{-1})R\hat{\delta}}{SSR_k} \qquad (2)$$

Where the R matrix allows $(\hat{\delta}R) = \delta_1' - \delta_2', \delta_2' - \delta_3', ..., \delta_k' - \delta_k + 1'$. The matrix $M_x = X - (X(X'X)^1 X')$. The SSR_k is the SSR under the alternative hypothesis. The value of the SSR_k depends on the structural break dates under the alternative, $(T_1, T_2, ..., T_k)$ of k breaks. Before the sup-F test can be applied, possible break points are limited such that they form the following set:

$$\Lambda_\epsilon = \{(\lambda_1, \lambda_2, ..., \lambda_k); |\lambda_i + 1 - \lambda_i| \geq \epsilon; \lambda_1 \geq \epsilon, \lambda_k \leq 1 - \epsilon\} \tag{3}$$

The ϵ is an arbitrary small number called a trimming parameter. The purpose of this trimming parameter is to specify the shortest possible length a partition or structural break may be as a fraction of the total length of the time series. The trimming parameter for the current study is set at default 0.15. Given this, the sup-F statistic can be defined as follows:

$$F(k; q) = sup_{(\lambda_1, \lambda_2, ..., \lambda_k)\epsilon\Lambda_\epsilon} F_T(\lambda_1, \lambda_2, ..., \lambda_k; q) \tag{4}$$

This procedure aims to maximize the F statistics. In this regard, the break dates are arranged such that they yield the largest F statistics. The best model with k breaks is selected and compared with the base of no break. The hypothesis test set-up is as follows:

$$\begin{aligned} H_o &: m = 0 \\ H_a &: m = k \end{aligned} \tag{5}$$

This hypothesis requires a specific number of breaks be known a priori. Bai and Perron suggest the use of a double-maximum test (henceforth Dmax test.) In the Dmax test approach, some upper bound M breaks is specified. Applying this assumption to the F-test, the expression now becomes:

$$\begin{aligned} &DmaxF_T(M, q, a_1, a_2, ..., a_m) \\ &\quad = max_{1 \leq m \leq M} a_m sup_{(\lambda_1, \lambda_2, ..., \lambda_k)\epsilon\Lambda_\epsilon} F_T(\lambda_1, \lambda_2, ..., \lambda_k; q) \end{aligned} \tag{6}$$

In equation (6), $(a_1, a_2, ...a_m)$ are fixed weights associated with breaks 1 to M. In this case, the null hypothesis can be re-written as follows:

$$\begin{aligned} H_o &: m = 0 \\ H_a &: m \; is \; between \; 1 \; and \; M \end{aligned} \tag{7}$$

It is noted in Bai and Perron that the selection of these arbitrary breaks may introduce further information as to the likelihood of various numbers of breaks being selected. However, this remains a theoretical quandary since no precise guideline on the selection of weights exists.

With this in mind, Bai and Perron introduce two versions of the Dmax test, UDmax and WDmax. The UDMax test sets the weight $(a_1, a_2, ..., a_M)$ equal to unity. A problem with the UDMax test is that if the outcomes are equally weighted, the power of the test decreases as the number of m breaks increases. This is caused by the drop in the critical values for large values of m. Bai and

Perron propose the WDMax test to overcome this problem. The two versions of the test can be expressed as follows:

$$\begin{aligned} &UDmaxF_T(M, q, a_1, a_2, ..., a_m) = max_{1 \leq m \leq M} a_m sup_{(\lambda_1, \lambda_2, ..., \lambda_k) \epsilon \Lambda_\epsilon} F_T(\lambda_1, \lambda_2, ..., \lambda_k; q) \\ &WDmaxF_T(M, q, a_1, a_2, ..., a_m) \\ &= max_{1 \leq m \leq M} \frac{c(q, \alpha, 1)}{c(q, \alpha, m} sup_{(\lambda_1, \lambda_2, ..., \lambda_k) \epsilon \Lambda_\epsilon} F_T(\lambda_1, \lambda_2, ..., \lambda_k; q) \end{aligned} \tag{8}$$

$c(q, \alpha, m)$ represents the asymptotic critical for the test sup $sup_{(\lambda_1, \lambda_2, ..., \lambda_k) \epsilon \Lambda_\epsilon} F_T(\lambda_1, \lambda_2, ..., \lambda_k; q)$ for an arbitrary level of significance α and the number of breaks, m. q represents the number of time varying parameters in the model. As the critical values drop for the higher levels of m, the weight assigned to that 'maximum' F statistic rises.

4.3 Testing the number break dates

Bai and Perron have two approaches for obtaining the number of breaks. Antoshin et al. (2008) summarize the two approaches as follows. The first is a global approach, which has the advantage of assuring that only the biggest breaks (*i.e.* those that cause the biggest reduction in the SSR) will be selected (as opposed to the sequential breaks selection), at least asymptotically. Another way to determine the breaks in this setup is by way of a sequential approach. The approach starts with the single break that minimizes the SSR. Then, for each resulting partition, the single break that minimizes the SSR is determined. The process is repeated sequentially, hence the name. In this paper, I assume a null of 'Zero versus an unknown number of breaks', and proceed to apply a global test.

4.4 A simple layout of the "cartel influence" calibration

The idea behind this calibration starts off with the assumption that in a competitive environment, profits are maximized at $p = mc$. From this assumption, the regression specification arises. Expressly, cement price is regressed on its cost shifters as the competitive market equilibrium outcome predicts. This is log-linearized, thus the coefficient elasticities are marginal elasticities. Completing the regression, is the error term, ϵ, where all the omitted explanatory power is captured. This will include the other influences over and above input-cost factors on price.

Now, assume an arbitrary $\epsilon_{pre-bust}$, which captures the errors from dates before the cartel is busted. Secondly, assume $\epsilon_{post-bust}$ that captures the errors in the regression after the cartel bust date, which is known in the records. If $\epsilon_{post-bust} = (\epsilon_1^*, \epsilon_2^*, ..., \epsilon_k^*)$, then by applying Khumalo et al. (2014)'s logic on the life of a cartel, there should be a convergence such that $\lim_{k \to \infty} \epsilon_k = 0$. That is, the influence of the cartel, assuming no other shocks, disappears over time, in accordance with Khumalo et al. (2014)'s course of thought.

So the cartels' influence during the period of its operation can be extracted dynamically, if we assume, post competition policy intervention, the market returns to the competitive state (gradually of course). This is captured as follows:

$$CI_t = |E[(\epsilon_{post-bust}) - \epsilon_{pre-bust_t}]| \,\forall\, t_{pre-bust} \quad (9)$$

In equation (9), the 'cartel influence', denoted by CI, is calculated as the absolute value between the average of the post-bust error values and the individual error values corresponding to each year before the Commission intervened.

5 Data

The cement price index[4] is modelled as a function of the inputs that go into the production process of cement in South Africa and other factors that might influence local prices, like imports. The exogenous variables are: (log) coal, (log)limestone, (log) iron ore, (log) oil, (log) cement imports and the demand variable, (log) construction Gross Value Added (GVA). Using construction as an independent variable raises questions of endogeneity. I circumvent this issue by estimating a GMM using (log) building plans passed and Gross Fixed Capital Formation: Residential as instruments. The sample period for the data is monthly from January 2000 - December 2016. The data departs from the erstwhile study of Govinda et al. (2014) on two aspects, the exclusion of electricity and inclusion of imports. Electricity is excluded as there is no reliable time-series for the required length of the sample. Imports are included on their theoretical underpinnings on market definition. The data is summarized in table 1 in the appendix.

6 Results

6.1 Results of the stationarity testing

The results of the Augmented Dickey-Fuller unit root test show that at levels, all the series are not stationary. When integrated once, I(1), the test reports evidence in favour of stationary at the 1% level of statistical significance for all the series.

6.2 OLS model results

Table 2 in the appendix summarizes the estimates for all the regressions. The output for the OLS regression are presented in column 1, marked LS. As expected, growth in the construction sector results in a significant increase in the price of cement. A 1 percent increase in construction activity, results in a 15 percent increase in the average price of cement. More interestingly is the sign and magnitude of imports. The regression output indicates a negative relationship as predicted in theory, however, the elasticity is very small, at around 0.4. An increase in the price of iron ore yields a corresponding increase in the price of cement as predicted. On the other hand, an increase in the price of oil produces a negative response from cement prices. And lastly, a 1 percent increase in the price of lime stone causes cement prices to increase by as much as 10 percent. Lime stone is the key ingredient in the manufacturing of cement.

[4] Granted excess and permission to use on a private request from Statistics South Africa.

Worth discussing is the sign of energy predictors, coal and oil. Conventional wisdom would preclude that the resulting estimates are indicative of firm behaviour in the manufacturing sector. When the price of coal increases, manufacturers will seek cheaper alternatives, thus that increase may not be passed-through the final price. A similar narrative can be prefixed on the surprising direction of oil prices. Manufacturers constantly seek to minimize their energy costs because most of the shocks on commodities used for energy are difficult to pass-through unless they persist. Oil price shocks tend to be non-transitory. This means should manufacturers seek to pass-through these costs, they could face a "menu-cost". An inspection of the residuals suggests a structural break in 2004 and 2009.

6.3 Bai and Perron results

The results of the Bai and Perron methodology are presented in table 2 in the appendix. As previously stated, both the UDmax and WDmax statistics allowed for up to five breaks in the null hypothesis. More than five breaks is not possible, since the minimum segment size specified by the trimming parameter would be violated. The results show that there exist up to five structural breaks in this model. UDmax determined one break, whereas WDmax determined all five. The estimated break dates are: 2003M01, 2005M08, 2008M02, 2009M01 and 2014M05. All breaks are confirmed at the 5% level of significance.

The results above identify five break dates. The 2003 -2005 breaks can be attributed to oil shocks in that period. In 2003, the price of oil rose above \$30 reaching \$60 in late 2005. The rise is largely attributed to a bevy of factors, including Middle East tensions at the time and soaring demand from China. 2008 and 2009 breaks can be ascribed to the global financial crisis which is considered by many economists to have been the worst financial crisis since the Great Depression of the 1930s. The break in 2014 aligns with the 2014 oil glut. From the determined dates, it is clear that the estimated breaks do not correlate with the cartel referral period. (Govinda et al., 2014) assign a break in 2008m06. However, this coincides with great financial crisis. Owing to the huge economic shock from the financial crisis, it is likely that their 'cartel overcharge' parameter is over-or-underestimated. But there are other estimations issues in (Govinda et al., 2014), most notably non-stationarity in their data. One major consequence of non-stationarity data is that the test-statistics tend to be misleading. Non-stationary OLS coefficients explode with time. This is often refelcted in the magnitude of the coefficients and the R-square. Evidently, both indicators are significantly large in the erstwhile study of (Govinda et al., 2014). The wheat and flour study by Mncube (2014) suffers from the same issues, with $R - square$ estimates of up to 0.95.

6.4 Results of regressions with breaks

Based on the break dates provided by the Bai and Perron diagnostic testing above, The OLS regression is re-estimated, accounting for the determined breaks. A time-dummy variable associated with the year and month of the break is assigned, taking the value 1 in the break period and 0 otherwise. A break will easily be interpreted as a rise or drop in the price of cement at that time. The results of the estimation are reported in column 2 (LS with breaks) and column 3 (GMM with breaks) of Table 1.

OLS estimates of the model with the inclusion of the estimated time dummy variables is fairly robust. The adjusted R-square, which is a fairly better measure of fit increases to 25%. However, there is a broad-based decline in the elasticities of input costs shifters. The impact of construction demand on cement prices declines to 12%. A 1% shock to import supply decreases cement prices by 0.2% at the 10% level of significance. The costs of energy from coal has no significant impact on cement prices. All other elasticities are slightly lower but still significant. The time dummy variables regressed on cement prices are 2003m1 and 2009m1. The former corresponds with a persistent oil shock of the early 2000s. The latter is the financial crisis. The coefficient corresponding to the 2003m1 oil price shock is positive. The financial crisis also results in a positive impact on cement prices. These results validate the earlier hypothesis that when shocks are persistent, firms will pass-through the costs, hence the higher prices.

The GMM estimation results are presented in column 3 of Table 1, marked GMM with breaks. Most profoundly is the increased explanatory power of the endogenous variable, construction. The elasticity has increased to 15% on a 1% level of statistical significance. Imports still have a negative impact on cement prices. Interestingly, in this model, both energy cost are insignificant in explaining variations in the price of cement. However, limestone, which is the key ingredient in the making of cement undergoes a significant adjustment, bearing a very significant elasticity coefficient. Moreover, these results confirm the premise laid out in the initial OLS results discussion that negative input price shocks, more especially in energy-linked commodities like oil are passed-on through higher prices. Both time dummy variables are positive and significant.

In conclusion, the estimated structural breaks are significant in explaining movements in the price of cement. However, for the goal of our exercise, the estimated breaks do not confirm the presence of a cartel, or a structural break resulting from competition policy intervention. That is, endogenous structural break estimations do not detect breaks outside macroeconomic shocks. But this is expected. Some of the cost-shifters in the specification are highly volatile and reactionary to exogenous shocks. Commodity prices display pro cyclical behaviour, falling in recessions and rising in booms. Nonetheless, some positives can be drawn from this exercise. Firstly, I can ascertain that persistent negative commodity shocks are transmitted to prices.In periods of economic activity, cement producers were able to buffer their losses through increased prices. This remains a hypothesis that worth testing over a large panel of cartel activities. However, there is an important lesson for competition authorities. Monitoring of concentrated markets should be increased in this period as it has potential to reveal cartels and deter cartel abuse on consumers through higher prices.

6.5 Calculating the cartel influence parameter

Earlier I introduced a concept which I termed, "cartel influence" on prices. The mechanics of calculating this parameter are fairly simple but novel on the most part. The crux of the approach is to treat the cartel behaviour or influence as part of all the unexplained factors that determine prices.

Figure 1 in the appendix traces the residuals from the GMM estimation.

Before proceeding with any calculations, it worth studying the residuals. The shaded area has much smaller residual volatility compared to the preceding periods. According to the records, market shares among the members of the cartel started reflecting some return to competitive equilibrium circa 2012 (Govinda et al., 2014). This will form the foundation for the "competitive residual average" parameter that indicates the impact of competition on prices.

Following Khumalo et al. (2014), I assume that residuals in this period do not exhibit signs of any cartel presence and represent the competition. The assumption is colossal but in the absence of statistical techniques to identify the competitive period, the next best alternative is to draw conclusions from market share trends and the qualitative data collected from phone calls and meetings with industry players.

Figure 2 in the appendix presents the absolute value of the "cartel influence" on cement prices. I calculate the absolute value because I am merely interested in the magnitude of influence, rather than the direction. The cartel influence plot appear to be buttress the paper's earlier hypothesis on pricing behaviour around periods of persisting macroeconomic shocks. The 2000s oil glut is captured by large spikes (first shaded area) and a similar pattern occurs in the recovery years of the global financial crisis. Other than that, the influence is relatively mute, albeit positive. However, there is enough evidence from this calibration to extract some understanding of cartelized products during periods of booms and busts.

7 Conclusion and way forward

The study has presented potential drawbacks associated with erstwhile studies that assume a cartel referral contemporaneously affects prices. Econometric estimates of cartel overcharge parameters in those settings tend to be biased. This may result in misleading policy analysis. Nonetheless, the current study builds from those works in order to furnish a potential solution to circumvent this problem. However, statistically founded techniques used in this paper do not identify structural breaks resulting from competition policy intervention. But lessons were drawn about the behaviour of cartels in periods of persisting macroeconomic shocks. This opens an entirely new research area that espouse competition reforms in concentrated markets. The most positive take away from this paper is the introduction of a potential new tool that can be used to understand cartels. The cartel influence parameter provided supports several hypothesis made throughout the paper. I believe with a richer dataset, it is possible to extract a precise measure of a cartel influence using this simple measure.

Ultimately, the objective of this paper was to produce alternative empirical methods in understanding the impact of cartels on prices, more especially in the context of South Africa. This is a prefatory condition necessary for ex-post evaluations and reviews. More importantly, it provides data-driven support for reinforcing policy with more powers to ensure further success and effectiveness. Already, the paper has find evidence encouraging competition authorities to be more proactive in periods of low economic activity.

Future work in this area of empirical competition policy analysis should seek to exploit the non-linearity in cartel data. Several techniques have been developed to allow for endogenous switching, à la Markov or simple regime switching models. This allows for better data-driven policy research and more importantly, the sound recommendations that will be realized.

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A brief overview of GMM

OLS estimates parameters of the conditional expectation of $y_i = x_i\beta + \epsilon$ under the assumption that $E[\epsilon|x] = 0$. Standard probability theory implies that

$$E[\epsilon|x] = 0 \Rightarrow E[x\epsilon] = 0 \tag{10}$$

So that the population moment conditions for OLS are

$$E[x(y - x\beta)] = 0 \tag{11}$$

and the corresponding sample moment conditions are

$$\frac{1}{N}\sum_{i=1}^{n} x_i(y_i - x_i\beta) = 0 \tag{12}$$

Solving for β

$$\hat{\beta}_{OLS} = \left(\sum_{i=1}^{n} x_i' x_i\right)^2 \sum_{i=1}^{n} x_i' y_i \tag{13}$$

GMM estimators (Hansen, 1982) choose the estimates that minimize a quadratic form of the moment conditions. These estimates gets as close to solving the over-identified system as possible. GMM reduces to the standard Method of Moments when the number of parameters equals the number of moment conditions.

For q population moment conditions

$$E[m(w_i, \theta] = 0 \tag{14}$$

Where m is a $q \times 1$ vector of functions whose expected values are zero in the population. w_i is the data and θ is a $k \times 1$ vector of parameters, where $k \leqslant q$.

The sample moments that corresponds to the population moments are denoted as

$$\bar{m}(\theta) = \frac{1}{N}\sum_{i=1}^{N} m(w_i, \theta) \tag{15}$$

When k, the GMM choses the parameters that are as close as possible to solving the over-identified system of moment conditions

$$\hat{\theta}_{GMM} = argmin_{\theta}\ \bar{m}(\theta)' W \bar{m}(\theta) \tag{16}$$

Appendix

Table 1: Data Sources

Series name	Source	Description
Cement Price Index	StatsSA	Price Adjustment Provisions: Work Group and Selected Materials Indices
Coal price	Department of Minerals	Local sales: Unit value (Rand/t)
Limestone and shale	StatsSA	PPI for selected materials: Aggregated crushed stone.
Iron ore	International Monetary Fund	China (CFR Tianjin Port) (United States dollars/MT)
Oil	International Monetary Fund	United States dollars per barrel
Portland cement imports	South African Revenue Service	Rand value of Portland cement, aluminous cement and associated products
Construction GVA	StatsSa	Gross Value Added at basic prices

*All data base=2012

OLS specification:

$$P_t^{Cement} = \beta_0 + \beta_2 P_{t-1}^{Construction} + \beta_3 P_{t-2}^{Imports}$$
$$+\beta_1 P_t^{Coal} + \beta_4 P_t^{Ironore} + \beta_5 P_{t-3}^{Oil} + \beta_6 P_{t-2}^{Limestone} + \beta_7 timedummy + \epsilon_t$$

Where *timedummy* is the estimated breaks from the Bai-Perron test.

Table 1: Regression results of the determinants of cement prices

	LS	LS with breaks	GMM with breaks
Construction GVA	0.150407**	0.129195**	0.158497*
	(2.524163)	(2.315236)	(3.224601)
Cement imports	-0.003552**	-0.002877***	-0.002539***
	(-2.082095)	(-1.794953)	(-1.738873)
Coal	-0.044264***	-0.012183	-0.017694
	(-1.800981)	(-0.514046)	(-0.607166)
Iron ore	0.052950 *	0.048454*	0.045766*
	(3.738212)	(3.653483)	(3.295920)
Oil	-0.044229*	-0.025801**	-0.012546
	(-3.316323)	(-1.995729)	(-1.454235)
Lime stone	0.102156***	0.092775***	0.118242**
	(1.878324)	(1.782252)	(2.029503)
Dummy-2003m01	-	0.013502***	0.014969*
	-	(1.899400)	(5.602736)
Dummy-2009m01	-	0.038490*	0.043935*
	-	(5.179144)	(6.9009437)
Constant	0.001530**	0.001247*	0.000934*
	(2.535507)	(2.201628)	(1.975031)
R-squared	0.170688	0.283929	0.278438
Adjusted R-squared	0.144906	0.253937	0.248214

Standard errors are in parenthesis. Significance levels: * 1%, ** 5%, *** 10%

Table 2: Summary of Bai and Perron Results

Breaks	F-Statistics	Critical Values
1*	3.517222	21.87
2*	3.134654	18.98
3*	2.917096	17.23
4*	2.765398	15.55
5*	2.623119	13.40
UDMax statistic	24.62055*	UDmax critical value (22.04)**
WDMax Statistic	29.96816*	WDMax critical values (23.81)**

*Significant at the 0.05 level
** Bai-Perron (Econometric Journal, 2003) critical values

Estimated Break dates					
1	2010M02				
2	2005M08	2009M01			
3	2005M08	2009M01	2014M06		
4	2003M02	2005M08	2009M01	2014M06	
5	2003M02	2005M08	2008M02	2009M01	20114M05

Figure 1: GMM residuals

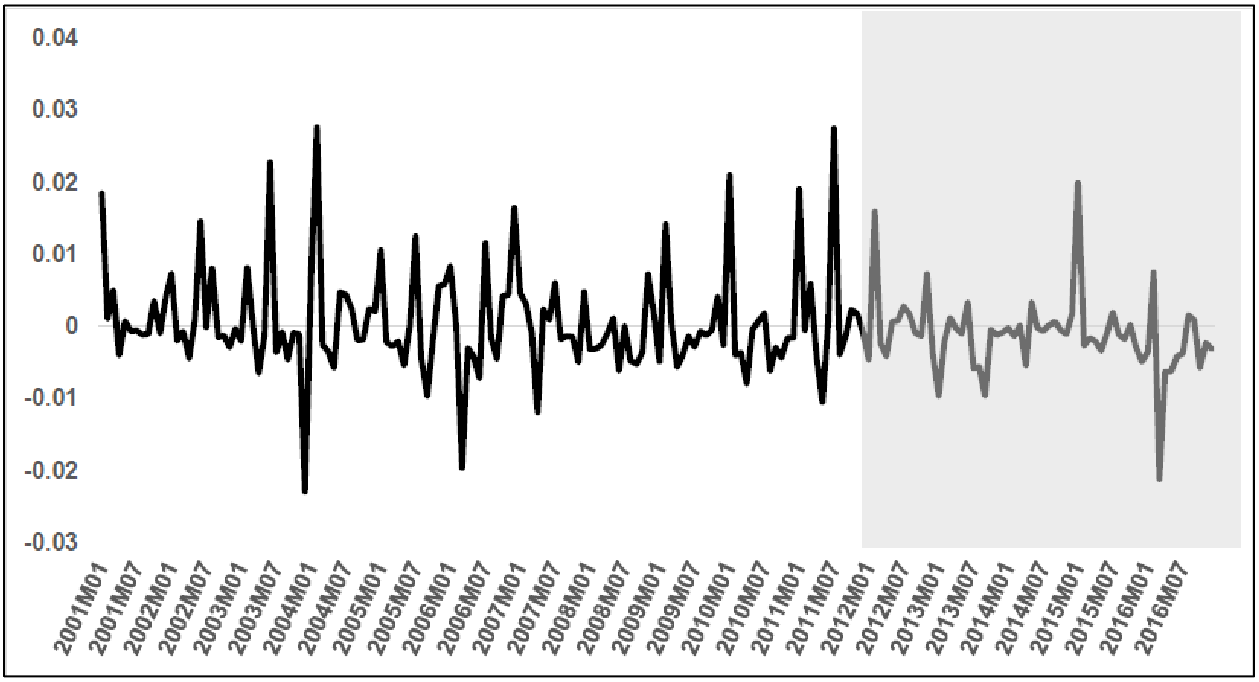

Figure 2: Cartel influence