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Recurrent collusion: Cartel episodes and overcharge in the South African cement market

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Abstract Collusion is often a recurrent phenomenon, with cartel periods interspersed by periods of greater competition. In developing countries in particular, industries with a history of legal collusion are often characterized by recurrent collusion. Canonical models implicitly treat collusion as recurrent by modelling collusion as a state-dependent outcome, often based on an unobserved demand state. Yet empirical studies have paid less attention to recurrent collusion. This paper proposes a Markov regime-switching (RS) model to detect recurrent periods of collusive damages and to estimate price overcharge in these cases. An empirical model of recurrent collusion must satisfy three properties. Firstly, it should account for different data-generating processes during collusive and non-collusive episodes. Secondly, it should be able to detect the dates and duration of collusive and non-collusive episodes. Thirdly, it should account for flexible transitions between collusive and non-collusive episodes. We argue that the RS model meets these requirements. We demonstrate these features in an application to the South African cement market, which, similar to cement markets in a number of other countries, have experienced recurrent collusion. Our results suggest that the exclusion of non-collusive periods – including price wars – yield higher overcharge estimates than conventional approaches. In competition policy, the RS model can act as a screening tool, to identify recurrent collusive behaviour. Courts may also find the RS model useful when estimating collusive damages, especially in private litigation, where the court must also determine the period of liability.

Keywords Collusion detection · Overcharge estimation · Markov-switching · Cement cartel · Recurrent collusion

JEL classification K21 · L41 · L43 · L61

1 Introduction

Collusion is often a recurrent phenomenon. In markets characterized by a history of legal collusion, illegal cartel conduct often reappears. In other markets subject to large demand shocks, successive periods of collusion are interspersed by price wars. Understanding and modelling recurrent collusion is therefore of importance to antitrust agencies, as it may have a significant impact on the size of price overcharge estimates. In private litigation cases, in particular, courts must often determine the exact period of harm and knowledge of interruptions in collusive effects is therefore important.

While canonical models of collusion implicitly treat cartel conduct as recurrent, there has been only limited attempts to model such behaviour empirically. This paper suggests a model that both identifies

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periods of harm – i.e. dates collusive periods – and estimates the size of the harm, by modelling the transition between collusive and non-collusive periods. In particular, the paper employs a Markov regime-switching (RS) methodology to model recurrent collusion in the South African cement market. As shown, the application holds insights for competition policy in both developed and developing countries, given the prevalence of collusion in the cement industry internationally.

The RS methodology explicitly allows for distinct data-generating processes during collusion and competition. This, in turn, allows for the detection of structural changes and, hence, the delineation of periods of collusive and non-collusive behaviour. By construction, the RS methodology allows for an estimation of an average price overcharge over a sample period that may include a number of collusive episodes. Furthermore, by using the information from the RS model the overcharge estimate can account for situations where transition took place over a period of time or the industry was in some intermediate state. In general, the Markov RS model is ideally designed to accommodate structural changes and transition between collusive and non-collusive periods.

Section 2 provides an overview of the literature on recurrent collusion, highlighting key requirements for an empirical model of recurrent collusion. Section 3 discusses the RS methodology, relating the method to recent work on structural breaks in collusion detection. Section 4 outlines the cement market case study and describes the data, Section 5 presents the results on recurrent collusion in this market. Section 6 concludes.

2 Recurrent collusion

Canonical models of collusion often treat collusion as a state-dependent outcome, usually related to demand. Green and Porter (1984) differentiate unobservable low- and high-demand states to study how alternative punishment strategies could ensure sustainable collusion. Rotemberg and Saloner (1986) differentiate between low- and high-demand states to show that the likelihood of collusion is lower in high-demand periods – originally seen as the counter-intuitive phenomenon of 'price wars' during business cycle booms. The Rotemberg and Saloner model relies on the assumption of serially-uncorrelated demand shocks. Haltiwanger and Harrington (1991) reach an opposite conclusion – of pro-cyclical collusion – by allowing for a dynamic specification in which the expected state of demand in future, rather than only the current demand state, affects the critical discount factor for collusion[1]. Bagwell and Staiger (1997) similarly model collusion – and the amplitude of collusive pricing – as dependent on the expected duration of business cycle expansions and recessions. Fabra (2006) models collusion as a function of business cycle phases, adding capacity constraints. Empirical studies of collusion also demonstrate its state-dependent nature: for a recent overview of empirical evidence on cartel formation and cartel breakup, and its relation to business cycle states, see Levenstein et al (2015) and Levenstein and Suslow (2016).

The state dependence of collusion implies a recurrent or episodic nature for collusion: continuous shifts in the underlying state of demand in these models generate alternating episodes of emergent and receding collusive behaviour. While recurrent collusion is therefore a standard feature of mainstream collusion models, there has been only limited attempts to empirically model this type of collusion, for example, when estimating collusive overcharge (see Boswijk et al (2017) for a recent attempt, to which we return in a subsequent section). An empirical understanding of recurrent collusion matters greatly to antitrust policy. In some antitrust regimes, collusion often returns in an illegal form in markets where cartels were historically legal or, at least, exempted from competition law (Connor, 2014, 163–175). More important, antitrust agencies often struggle with repeat offenses in collusion. In the EU, repeated offenses regularly feature as an aggravating condition in the determination of cartel damages: up to 2006, for example, at least 25% of cartel cases handled by the European Commission involved repeat offences as an aggravating factor. Recurrent collusion is a particular challenge for developing country regimes (Utton, 2011). For example, the World Bank highlights repeat offences over time and across multiple sectors as a fundamental challenge for South African anti-cartel policy (Purfield et al, 2016, 4). Consequently, the Bank has advised South African antitrust authorities to continue monitoring markets even after collusion has been prosecuted. Some industries such as the cement industry appear to be particularly prone to collusion as demonstrated in a later section. It is important, then, to develop empirical methods that would allow screening for recurrent collusion and estimating overcharges due to recurrent collusion.

[1] See also Kandori (1991), who finds similar results for alternative specifications of the correlation structure of demand shocks.

Recurrent collusion models suggest three key properties for an empirical model of collusive overcharge. Firstly, recurrent collusion requires an econometric approach that accounts for separate data-generating processes during collusion and competition. For example, Haltiwanger and Harrington show an asymmetric response in prices to demand shocks over recessions compared to booms. This implies that the intercept as well as parameters for demand or cost drivers in a price overcharge regression may all differ between collusive and non-collusive periods. Standard models of overcharge, which predominantly rely on a dummy variable approach, often focus on shifts in the intercept only. Secondly, and more important, an empirical model of recurrent collusion should be able to detect structural changes in the market to establish possible collusive episodes. In other words, the model should be able to detect the start and end of collusive and competitive episodes. Standard models of price overcharge rely on exogenously determined collusive periods, often provided by the court. In contrast, an empirical model of recurrent collusion must be able to simultaneously estimate the effect of a change from collusion to competition (and vice versa) on prices and the time period over which this effect persists. Thirdly, an empirical model of recurrent collusion should be able to account for various transitions between states of collusion and competition. The canonical models suggest that the realized price is the expected value of price over all possible states. This is consistent with the expectation – perhaps in markets with long-term contracts – that collusive effects may take time to show up in the price data or, conversely, to fade out. The empirical literature on collusion overcharge has grappled somewhat with this transition problem (Hüschelrath et al, 2016), given that conventional approaches tend to rely on sharp delineations of collusive and non-collusive periods. Nevertheless, current approaches require explicit assumptions regarding the duration and pace of transition. Ideally, a model of recurrent collusion should allow for transition in a flexible fashion. That is, the model should be able to accommodate both abrupt transitions and transition taking place over a period of time.

In the following section, we argue that the RS model satisfies the empirical requirements of a recurrent collusion model. Firstly, as the canonical models suggest, the model accounts for distinct data-generating processes during collusion and non-collusive episodes. Secondly, the model allows the determination of start and end dates of collusive and non-collusive episodes. Lastly, subsequent overcharge estimation should account for various transition phases.

3 Methodology

The standard approach to determinining overcharge involves a reduced-form price equation of the following form[2], (Davis and Garcés, 2010, 357):

$$p_t = c_0 + \ d_t\omega \ + \sum_{l=1}^{m} a_l p_{t-l} + \sum_{l=0}^{n} \boldsymbol{\gamma}_l \boldsymbol{x}_{t-l} + \ \varepsilon_t \tag{1}$$

with $\varepsilon_t \ \sim \ N\left(0, \sigma^2\right)$, where p_t denotes price at time t, $\boldsymbol{x}_t$ denotes a vector of demand and cost drivers and d_t is a dummy variable for collusion, taking the values $d_t = 1$ for the collusion period and $d_t = 0$ for the non-collusion period. Equation 1 allows for two regimes, a collusive and a non-collusive regime. The two regimes are differentiated by unique intercepts: the intercept is equal to $c_0 + \ d_t\omega$ during collusive periods and c_0 during non-collusive periods. As discussed in the previous section, the standard model generally does not satisfy the requirements for an empirical model of recurrent collusion. Firstly, equation 1 is based on the assumption that coefficients are constant over the collusive and non-collusive periods, when the cost and/or demand pass-through to price can be structurally different (McCrary and Rubinfeld, 2014; White et al, 2006). Secondly (and perhaps most important), the timing of the collusive and non-collusive periods are determined outside of the model. As shown later, a model-based dating of the periods may yield higher overcharge estimates, as it will not necessarily include e.g. price wars in the collusive regime. Lastly, the transition between regimes is often ignored: standard models generally do not account for the duration and pace of transition from collusive to non-collusive periods and vice versa. Therefore, the standard model does not possess the three properties that are desirable when modelling recurrent collusion.

[2] The overcharge literature typically relies on static OLS models. OLS models provide asymptotically consistent estimators only in the presence of cointegration among the dependent variables, which are often unit root processes. Additionally, the autoregressive distributed lag (ARDL) form is preferable since it provides a better representation of the dynamic effects, see (Boshoff, 2015, 228) for discussion.

The Markov RS model was introduced by Goldfeld and Quandt (1973) and popularized by Hamilton (1989), who used the model to identify recurring business cycle states (expansions and recessions). Similar to recurrent collusive periods, business cycles are persistent and differ in length and severity. Consequently, RS models can be useful in dating recurrent collusive episodes and estimating overcharge.
We propose the following reduced-form RS model of price[3]:

$$p_t = \begin{cases} c_0 + \omega + \sum_{l=1}^{m} a_l p_{t-l} + \sum_{l=0}^{n} \boldsymbol{\gamma}_l \boldsymbol{x}_{t-l} + \varepsilon_t \ , & S_t = 1 \text{ (collusion)} \\ c_0 + \sum_{l=1}^{m} a_l p_{t-l} + \sum_{l=0}^{n} \boldsymbol{\gamma}_l \boldsymbol{x}_{t-l} + \varepsilon_t \ , & S_t = 2 \text{ (no collusion)} \end{cases} \tag{2}$$

with $\varepsilon_t \sim N\left(0, \sigma^2\right)$, where S_t is a discrete-value state variable that denotes the regime in operation at time t (collusion or no collusion). We denote the two regimes as collusive (for $S_t = 1$) and non-collusive (for $S_t = 2$). The difference between our approach in equation (2) and the standard approach is that we treat S_t as model-determined. We make no *a priori* assumption about whether a collusive ($S_t = 1$) or non-collusive ($S_t = 2$) regime is in operation at time t: equation (2) allows for separate data-generating processes for collusive and non-collusive regimes based on an assessment of the *probability* of being in a particular regime. In this sense, the RS methodology meets the first requirement of an empirical model of recurrent collusion. In this particular model, as shown in equation (2), the intercept is regime dependent, implying that we assume changes between the collusive and non-collusive regimes are reflected as shifts in the price level. Alternative RS specifications also allow for the a_l and $\boldsymbol{\gamma}_l$ parameters to be regime dependent. We first report results for the alternative specifications in section 5 and provide motivation for our specification choice.

The probability law governing the value of S_t is assumed to follow a two-regime first-order Markov chain with the following transition matrix[4]:

$$\boldsymbol{\xi} = \begin{bmatrix} \xi(S_t = 1|S_{t-1} = 1) & \xi(S_t = 2|S_{t-1} = 1) \\ \xi(S_t = 1|S_{t-1} = 2) & \xi(S_t = 2|S_{t-1} = 2) \end{bmatrix} = \begin{bmatrix} \xi_{11} & \xi_{12} \\ \xi_{21} & \xi_{22} \end{bmatrix} \tag{3}$$

where $\xi(S_t = j|S_{t-1} = i) = \xi_{ij}$denotes the probability of switching from regime i at time $t-1$ to regime j at time t. Equation (3) is referred to as the constant transition matrix. The methodology of Hamilton (1989) and Kim (1994) provide a recursive, likelihood-based approach to obtaining estimates of the filtered probability, $\xi(S_t = i|\Omega_T; \boldsymbol{\theta})$, that the model is in a particular regime at time t given all available information. See Appendix 1 for a brief explanation of the Hamilton (1989) and Kim (1994) procedures. We use the filtered probability estimates to date the collusive regimes and measure the speed of transition among collusive and non-collusive regimes. In this sense, the RS methodology meets both the second and third requirements for an empirical model of recurrent collusion.

Overcharge estimation is performed by replacing the intercept and dummy variable of Equation (1) with estimated regime probabilities, so that the β coefficient represents the overcharge percentage[5]:

$$p_t = \beta \alpha_{i,t} + \sum_{l=1}^{m} a_l p_{t-l} + \sum_{l=0}^{n} \boldsymbol{\gamma}_l \boldsymbol{x}_{t-l} + \varepsilon_t \tag{4}$$

where $\alpha_{i,t} = \xi(S_t = i|\Omega_T; \boldsymbol{\theta})$ is the smoothed regime probability obtained when estimating Equation (2). The smoothed probability is what accounts for two of the drawbacks of standard overcharge estimation. It provides an objective determination of the date at which collusion and competition occurred. Additionally, the smoothed probabilities account for variations in the speed and length of transition from competition to collusion and vice versa.

[3] We first verified that the optimal number of regimes, consistent with the data, is two. The results are reported in Appendix 2.

[4] Cement prices is a unit root process. Therefore, there is strong first order persistence and the Markov assumption is appropriate.

[5] Note that this is a single equation framework. A multiple equation framework was also estimated and the results indicated that there is no simultaneity. The results are available upon request.

3.1 **Links to existing methods for detecting structural breaks**

One could argue that models that allow testing for structural breaks may also satisfy the three requirements for an empirical model of recurrent collusion. Indeed, regime switching bears some resemblance to structural breaks. A structural break refers to an unexpected change in a time-series variable that can change the mean or parameters of the underlying statistical process generating the data. Structural break dates may signal the start or end of a collusive agreement. Therefore, structural break analysis have been proposed as a screening method for identifying whether collusion exists in a particular market (see Abrantes-Metz and Bajari, 2010, for an overview of collusion screens)

This literature has its origin in earlier work by Athey et al (2004) and Harrington (2004) who proposed an analysis of price variance. More recently, statistical tests for structural breaks have received attention. Hüschelrath and Veith (2014) compare average prices and average variation coefficients 12 months before, and 12 months after a suspected break period. Even so, the method still requires up-front specification of the suspected break periods. Crede (2015) provides an alternative structural break test on residual-based tests, derived from a standard OLS price model. For the case presented in this paper, following the methods provided by Crede, it is shown that determining the correct break dates is not possible(see Appendix 4). Furthermore, the effect and persistence of a structural change on price formation is not always clear.

A recent paper by Boswijk et al (2017) use a Bai-Perron multiple breakpoint test (for reference see Bai and Perron, 2003) and show that misdating the cartel effects leads to an underestimation of overcharge. Our results point to similar conclusions. Even so, the RS methodology differs in important ways. The first requirement for an empirical model of recurrent collusion is that it should allow for separate data-generating processes for collusive and non-collusive episodes. Put differently, all of the collusive episodes as drawn from the same population of possible episodes. This is because recurrent collusion implies a return to a similar collusive regime multiple times during the sample period. When the market shifts from non-collusive to collusive, multiple breakpoint tests may flag the shift, but it is not possible to infer from these tests whether the new collusive period is similar to previous collusive periods.

The second requirement for an empirical model of recurrent collusion is that it should determine the start and end dates of collusive and non-collusive episodes. It would appear that multiple breakpoint tests could meet this requirement. However, they require more *a priori* decisions. For example, the Bai-Perron test requires specification of a trimming parameter, which determines the minimum distance between breaks. As indicated in (Bai and Perron, 2003, :11), when the sample is not sufficiently large, a trimming parameter as small as 5% of the total sample size can lead to imprecise test results. Therefore, when two or more break dates are closer to one another than the trimming parameter the test will not detect both dates as breakpoints. In the results to follow, we show this to be the case for our data.

The third requirement for an empirical model of recurrent collusion is that it should deal flexibly with the transition between these collusive and non-collusive episodes. Multiple breakpoint tests treat shifts between collusive and non-collusive periods as sudden deterministic events and do not provide information about transition between the periods.

Consequently, we argue that the RS model is best suited to implement an empirical model of recurrent collusion.

3.2 Limitations

The RS methodology outlined here meets the three requirements for an empirical model of recurrent collusion, as discussed earlier. Even so, the methodology also has limitations. The canonical models mentioned earlier feature an incentive constraint for cartel stability that is based on future profits: cartel members consider future cost and demand conditions when assessing the benefits of collusion relative to deviation and competition. This implies that, in empirical versions of these models, the propensity to shift between collusive and non-collusive regimes must be estimated from future demand and cost data. In contrast, our models constant transition probabilities are based on the entire history of prices, demand and cost factors. As explained above, these probabilities are merely the initial (or prior) probabilities and they are updated each time period, using a Bayesian approach, to obtain the filtered probabilities at that time-point. Therefore, the probabilities reported in this paper gradually assign greater weight to present than past data. Furthermore, these filtered probabilities are smoothed, using the Kim procedure, which involves weighting filtered probabilities at time $t-1$, t, and $t+1$ to obtain smoothed probabilities for time t. In this sense, the probabilities reflect local data. We acknowledge that this may underplay relevant data further into the future, under the assumption that firms could predict some of this data. Even so, this is not much different from alternative techniques, such as the structural break methods discussed in the next section. At its core, a structural break model relies on recursive fitting of the same model over two or more comparative sample periods, which, taken together, would represent the entire dataset. Therefore, the estimated parameters, and the accompanying test statistics for structural breaks, rely on the entire price history. Consequently, the RS methodology is best suited to model recurrent collusion. The following section describes the case used to demonstrate the technique.

4 Case study

Markets for inputs, such as cement, are often characterized by persistent collusion. In most markets, cement companies enjoyed some form of exemption from competition law until the 1980s, after which companies reverted to illegal collusion after a short period of competition. In at least some of these markets – Turkey, Pakistan, India and South Africa – collusion during the post-legal era took on a recurrent nature, as shown in table 1.

The recently concluded prosecution of collusion in the South African cement market offers an ideal case study for the RS methodology, providing rich information for evaluating the results from the RS model.

Table 1 Cement cartels

Country	Source	Sample	Overcharge	Multiple episodes	Multiple episode dates
South Africa	Fourie and Smith (1994) Govinda et al (2014)	1986 2008–2012	5%–10% 7.5%–9.7%	✓	1940–1996 1998–2009
Germany	Connor (2003) Lorenz (2008) Friederiszick and Röller (2010) Frank and Lademann (2010) Hüschelrath and Veith (2014) Hüschelrath et al (2013) Hüschelrath et al (2016)	1991–2001 1991–2001 1991–2001 1991–2001 1991–2001 1991–2001 1993–2003	11%–23% 16.9% 9.4% 10%–15% 16.1%–20.5% 20.3%–26.5% 25%–38.4%	✗	
Cement makers from France, Germany and Switzerland. Fined by Romania	UNCTAD (2005)	2000–2005	38%	✗	
Turkey	Dalkir (2006)	1993–2005	26%	✓	1993–1998 1999–2002 2002–2005
Egypt	Khimich (2014)	2003–2006	28.2%–39.3%	✗	
Brazil	Salvo (2010)	1988–2000	14.8%–21.8%	✗	
Pakistan	Pakistan Competition Commission decision (2009)	2008–2009	33.3%	✓	1998–1999 2000—2008
India	Competition Comission of India (2012)	2005–2006	45%-84%	✓	1996–1999 2000–2001 2006–2009
Poland	Polish antitrust authority report on cartels (2008)	1995–2006	28%	✓	1995–2000 2001–2006

4.1 South African case

In 1922, the first attempt was made to establish a cartel in the South African cement market. In 1986 price fixing was banned, although the South African antitrust authority allowed the cement cartel to persist based on public interest considerations at the time. Subsequently, cartel members formed the Cement Distributors (SA) (Pty) Ltd (CDSA) company, which was responsible for the distribution, sale, and balancing of members' interest.

The antitrust authority withdrew its exemption of the cement cartel in 1995, giving members until September 1996 to terminate the cartel. The authority envisioned that members would then set prices and distribute their products independently. Contrary to this aim, cartel members instead agreed in 1995 that each producer would retain the same market share as enjoyed under the legal cartel. Nevertheless, one of the cartel members violated the agreement in 1996, gaining a market share in excess of the agreed size and inviting retaliation by other producers. A price war ensued, lasting until 1998, during which producers again convened to discuss coordination. *Inter alia*, the meeting in 1998 culminated in agreements on market shares, pricing parameters, marketing, and distribution activities. The new agreement was similar to the agreement during the legal cartel period, again signalling recurrent collusion. To ensure compliance with the new agreement, an industry association was formed. Through this association, producers commenced sharing of detailed sales information, by geographic region, packaging type, transportation, and customer type. The association's auditors would aggregate the data and distribute it to the individual producers. The concentrated nature of the industry meant that producers could use this information to monitor market shares and devise strategies that are more profitable. Firms could, therefore, initiate target punishment or volume shedding without destabilising the market or causing a price war.

The new antitrust authority, established in South Africa in 1998, launched an investigation into the cement market in 2000. This led to raids on the premises of two cartel members. Both firms successfully challenged the raids on legal grounds, resulting in the return of the raided documents. In 2007, the South African antitrust authority uncovered a cartel in the precast concrete market. Consequently, it launched a scoping study into the construction and infrastructure inputs markets, and then into the cement market in June 2008.

In June 2008, the authority indicted all of the cartel members for price fixing and market allocation in the South African cement market. Warrants for search and seizure were issued in June 2009, and raids were conducted at the offices of one of the cartel members, after which the largest cartel member applied for, and was granted, conditional immunity in August 2009. In July 2010 and June 2011, two of the cartel members respectively met with the antitrust authority to present the findings from internal investigations into collusion. The first member reached a settlement agreement with the antitrust authority in September 2011 to the value of R128 million, to be paid in six annual instalments, with the first instalment payable in February of 2012. The second member reached a settlement agreement with the authority in March 2012 to the value of R148 million, to be paid within six months of the consent agreement. A third member has not yet reached a settlement with the antitrust authority (Commission refers a case of collusion against Natal Portland Cement Cimpor (Pty) Ltd Comission, 2015). Table 2 provides a detailed summary of the South African cement cartel.

4.2 **Data**

A reduced-form model of cement prices should account for the cost of inputs and for demand factors. The model of cement prices includes the price of lime and limestone[6] and electricity prices as cost drivers. Other cost drivers, such as coal, shale, silica sand, gypsum, and oil prices, were found to be statistically insignificant, with incorrect signs and diagnostic test problems. After production, cement is sold to either the domestic (retail) or construction market. Therefore, the demand side factors of the model include an index of cement sales in tonnes and a house price index. Table 3 reports the variables used and sources of the data. Specifications containing the variables from table 3 are deemed most appropriate. For the estimation, quarterly data is used from 1988Q1 to 2015Q4.

[6] The main inputs in South African cement production are limestone and lime, coal, shale, silica sand, and gypsum (Lafarge, n.d.; AfriSam, 2016). Limestone constitutes two-thirds of the raw materials used in South African cement manufacturing (Leach, 1994). Roughly one and a half tonnes of limestone is required to produce one tonne of cement (Ali, 2013).

Table 2 Timeline of South African cement cartel

1922	Start of price fixing by cartel.
1940	Market sharing agreement. Government regulation commences.
1956	Cartel adopts a new differentiated pricing model.
1984 – 1985	Price cuts of 24% in selected areas drives out Spanish importer.
1986	Banning of price fixing in South Africa, cement producers exempted.
1995	Exemption from antitrust laws withdrawn.
1995 – September 1996	Transition period to terminate legal cartel.
1996 – 1998	Price war.
1998	Meeting to end price war and agree on new (illegal) cartel.
1999	Start of regular meetings between cartel members, with data shared through industry organisation.
2000	Unsuccessful antitrust raids on two cartel members.
2006	Enhanced information exchange through industry organization.
2007	Antitrust agency uncovers cartel in related pre-cast concrete markets.
2 June 2008	Antitrust complaint initiated against cartel members.
24 June 2009	Antitrust raids on cartel members; information exchange stops.
7 Augustus 2009	Leading cartel member applies for and is granted immunity.
20 September 2011	One cartel member settles.
5 March 2012	Another cartel member settles.

Table 3 Variables

Variable	Description	Source
Cement Price Index $(\boldsymbol{P})$	PPI of Selected materials -Building materials: Ordinary and extended cement	Statistics SA
Limestone and Lime $(\boldsymbol{LL})$	Industrial minerals: Limestone and lime: Total – Local sales [South Africa] (Unit value (Rand/t))	Department of Mineral Resources
Cement sales $(\boldsymbol{S})$	Industrial minerals: Cement: Total – Local sales [South Africa] (unit sales in ton)	Department of Mineral Resources
House Price Index $(\boldsymbol{HP})$	Middle class houses: All sizes between 80-400 square meters, up to R 3,6 million in 2012 prices.	ABSA Bank
Industrial electricity prices* $(\boldsymbol{PME})$	Real industrial cement prices, cents per kilowatt hour (c/kWh)	Department of Energy
PPI for building and construction materials**	Producer Price Index (PPI): Building and Construction Materials	Statistics SA

**Not available in quarterly format. Yearly data was converted to quarterly data by using standard linear interpolation.*
***This variable is used to deflate nominal values.*

5 Results

The results provide evidence in favour of recurrent collusion in the South African cement market. As discussed below, the statistical evidence supports a two-regime model of cement prices over a standard (or 'one regime') model. The two-regime Markov RS model is used to date the recurring periods of collusive damage. As noted earlier, we rely on the regime probabilities of the model to determine collusive episodes. For a comparison of the periods suggested by the RS model to those of structural break methods, refer to Appendix 4. After determining the collusive regime periods, we proceed to estimate cartel overcharge. To illustrate the potential pitfalls of incorrectly classifying the timing of damages, we compare our overcharge results to results obtained when using court-determined dates and structural-break-determined dates. Throughout, we present selected econometric output, with additional output reported in Appendix 2 and 4. Lower-case variable names indicate logarithms of the real index value. Our estimated models pass all diagnostic tests (see Appendix 3).

5.1 Choice of RS model

The first step in estimating the Markov RS model is to decide which parameters should be regime-dependent and to identify the optimal number of regimes. As explained in the methodology section, the standard approach is to allow the intercept to vary by regime (this is effectively the dummy variable technique). The Markov RS methodology is more flexible, in that it allows the slope parameters and the covariance matrix to be regime dependent. The information criteria in table 4 (AIC, SBC and HQC) are used to determine whether this is necessary. For the South African cement market, the results support only a regime-changing intercept. Intuitively, this implies that, during periods of collusion, the cartel adds a constant mark-up, but that the impact of demand and cost drivers on price is unchanged. This behaviour is consistent with empirical evidence for other South African markets with a history of collusion (see Boshoff (2015) on overcharge in the South African bitumen cartel). The information criteria support a two-regime model over a three-regime[7] model. As explained in the next subsection, we rely on qualitative evidence to identify the two regimes as, respectively, a collusive regime (i.e. one of collusive effect) and a non-collusive regime (i.e. one of no collusive effect).

Table 4 Information criteria for Markov-switching model specifications

Regimes	Model	AIC	SBC	HQC
2	MSI	**-4.13**	**-3.83**	**-3.85**
2	MSIH	-1.52	-0.82	-1.24
2	MSIAH	-2.62	-1.36	-2.11
3	MSI	-2.58	-1.79	-2.26
3	MSIH	-1.38	-0.54	-1.04
3	MSIAH	-3.1	-1.15	-2.31

The abbreviations indicate which parameters are specified to be regime dependent, where (I) indicates the intercept term, (H) the variance, and (A) all the autoregressive coefficients

5.2 Detecting periods of collusive damages

Intuitively, the regime probability for a specific time period refers to the probability of a particular regime driving cement prices in that time period, given all available information. In this model, regime one ($S_t = 1$)

[7] One interesting three-regime model, for the purposes of studying recurrent collusion in the cement market, would be one whose three regimes can be identified respectively as a legal collusion regime, an illegal collusion regime, and a non-collusive regime. Alternatively, another interesting model would be one whose three regimes can be identified respectively as a collusion regime, a competitive regime (before episodes before 2011) and another competitive regime (post-2011, to signal greater competition). The data clearly support only a two-regime model, which indicate that all collusive episodes are generated by the same regime. Similarly, all non-collusive episodes are generated by the same regime.

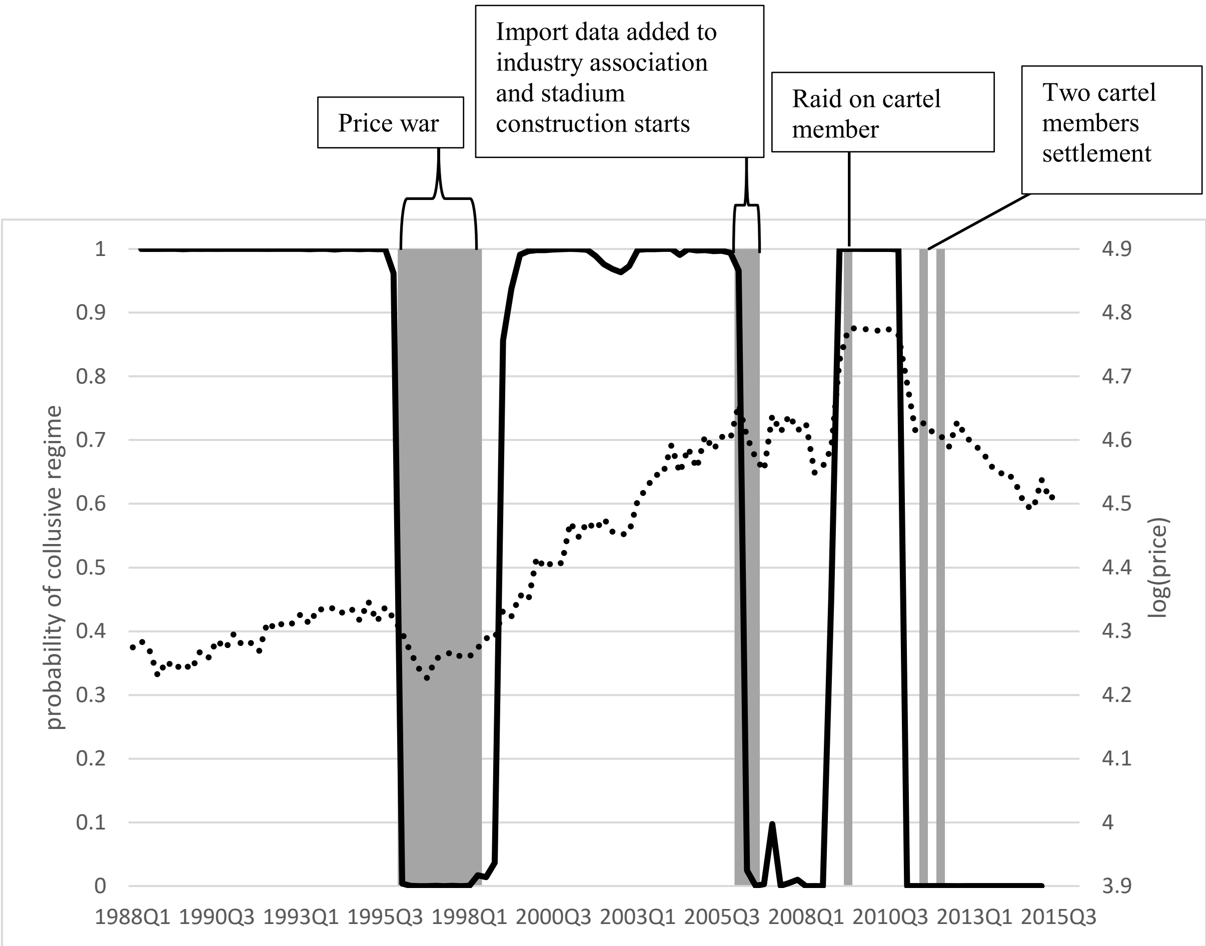

Fig. 1 Cartel regime probabilities

is identified as the collusive regime and the smoothed probability structure of this regime is used to identify the periods during which this regime dominates. The probability structure of regime one (and cement price, in log form) is reported in figure 1, with the grey areas indicating significant events.

Our identification of regime one as a collusive regime is confirmed by qualitative evidence from the case. As noted earlier, figure 1 regime one probabilities are high for the period 1986 to 1995, which is exactly the period during which the legal cartel was in operation. The termination of the legal cartel in 1996 – and the subsequent price war – shows up in lower price levels and low regime one probabilities. As noted, from 1998 to 2006 the cartel was re-established in illegal form and operated in full force, despite some antitrust efforts to investigate collusion: during this period, regime one probabilities are again very high. Interestingly, these probabilities decline significantly in 2006. There are at least two explanations that point to the temporary collapse of the cartel during this period. Firstly, the cartel became increasingly concerned with import information. In retrospect, we know that imports played an increasingly important role and it appears that the cartel had to lower its prices in order to compete with imports. It is also reasonable that the cartel lowered its prices below a competitive level in order to drive the importers out, similar to what was done in 1984 to 1985. Another explanation is related to demand. In May 2004, FIFA announced that South Africa was to host the 2010 Football World Cup. This event required the construction of a number of large football stadia for which the ground work and demolition began in 2006, and for which official construction began in February 2007 (Club, 2007). This positive demand shock, consistent with the prediction of Rotemberg and Saloner (1986) and other models, would have undermined collusion. Alternatively, the later part of the 2006-2008 period also coincides with the global financial crisis and the subsequent Great Recession, which, although comparatively mild in South Africa, depressed economic conditions in the construction industry. As noted, some other canonical models predict that such a large negative demand shock could undermine collusion. Whichever is the appropriate explanation, there is now significant evidence that collusive behaviour broke down, as reflected in the regime one probabilities. As noted earlier, in June 2009, the antitrust authority raided the offices of one cartel member and settlement agreements with this and another cartel member followed in September 2011 and March 2012, respectively. The regime probabilities are consistent in identifying shifts, with the model leaving the collusive regime approximately four quarters prior to conclusion of the settlement agreements.

We note that our model may appear to identify periods with merely rising prices as collusive. Of course, price increases *per se* do not imply collusion. It is, however, important to note that our regimes are determined in a model that already controls for cost and demand drivers.

This application to delineate collusive episodes in the cement market also highlights some limitations of our RS methodology. It is clear from the case study that the last breakdown (in 2011) was prompted by investigations and legal proceedings initiated by the competition authorities, while earlier breakdowns may have been driven by demand factors. The model presented in (2) and (3), consistent with other approaches such as structural break testing (discussed later), does not distinguish between regime shifts triggered by demand or cost factors and those triggered by risk of competition policy prosecution. There are at least three challenges in attempting to incorporate prosecution risk in this model. Firstly, it would require quantifying prosecution risk in a particular market or sector of the economy. We know that the South African competition authority increasingly focused on collusive behaviour from the mid-2000s and also identified intermediate input markets (such as cement) as focus industries. The challenge would lie in quantifying this change in focus and, hence, increase in prosecution risk using a single variable. This is beyond the scope of this paper. Secondly, such a variable would be correlated with demand and cost factors. For example, one driver of the focus of the South African authority on collusion in the mid-2000s and beyond was the impact of sharp commodity price increases and the strong economic expansion in the run-up to the global financial crisis and the impact on pricing behaviour in South Africa. This identification problem must be overcome if we are to isolate the effect of enforcement risk on regime switching. Lastly, the current generation of RS models do not allow a distinction between regimes determined by demand/cost factors in combination with regimes determined by prosecution risk. While some RS models allow consideration of more than one variable for a particular regime, they do not allow us to identify which variable in that set is determining the switch to any particular regime. Our RS model relies on an unobserved switching variable determined by the data. We argue that this is sufficient and even preferable in the context of damage estimation (which is the focus of this paper), although the above limitations are certainly relevant when the aim is to better understand the drivers of collusive behaviour and recurrent collusion, in particular.

5.3 **Overcharge estimation**

The overcharge estimation follows from the model used to determine the timing of damages caused by collusive episodes, as set out in equation (4). As explained, the coefficient of the regime probability for collusion is used in the overcharge estimation, allowing a dynamic overcharge percentage that accounts for multiple episodes and reflects transitions between collusive and non-collusive regimes.

The results for the price overcharge model are reported in table 5. As shown, the cost and demand coefficients have the expected signs (positive) and sizes. The model suggests a statistically significant, average cartel overcharge of 18%. That is, on average, during the various periods of collusion, prices were 18% higher than during the other (non-collusive) periods.

As noted, the overcharge estimate from the two-regime Markov RS model accounts for smooth transitions between collusive and non-collusive periods. One may compare this to the overcharge estimates of models relying on a standard dummy variable. In figure 2 we compare a dummy variable based on the collusive periods identified by our RS model, but not allowing for any transition, with our regime probabilities, to highlight the discrepancies between the RS and standard approach.

In figure 3 we compare our regime probabilities with a dummy variable based on court-established dates. This can be termed the conventional approach to overcharge estimation, where the dummy variable dates are provided to the econometrician, instead of inferred from data. The discrepancy, especially during the 2006-2008 period, is clear.

Table 6 compares the overcharge estimates of the RS model with those obtained by using the dummies from figure 2 and 3. In addition, table 6 also includes the overcharge estimate based on a dummy variable

Table 5 Static estimates for overcharge calculation

Variable	Coefficient	Std. Error	t-Statistic	p-value
lime and limestone	0.22	0.09	2.33	0.02
house price	0.18	0.02	9.59	0.00
sales	0.54	0.09	5.74	0.00
*electricity prices**	0.05	0.02	0.63	0.53
overcharge	0.18	0.09	1.94	0.05

**The coefficient of electricity is regime dependent. For a discussion refer to Appendix 2.*

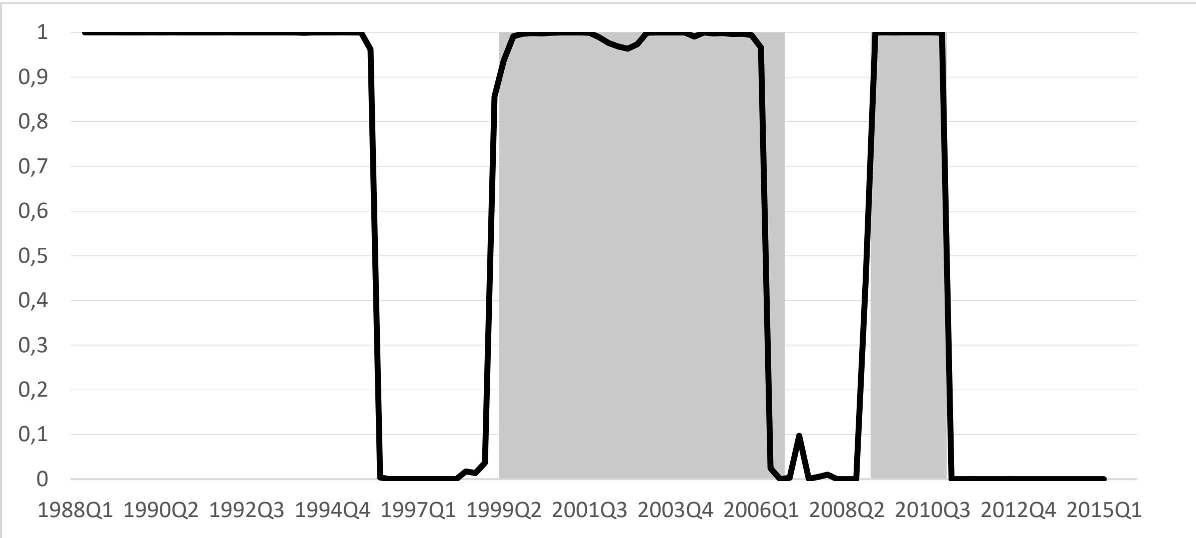

Fig. 2 Sharp transition dummy (grey) versus smoothed probabilities (black line)

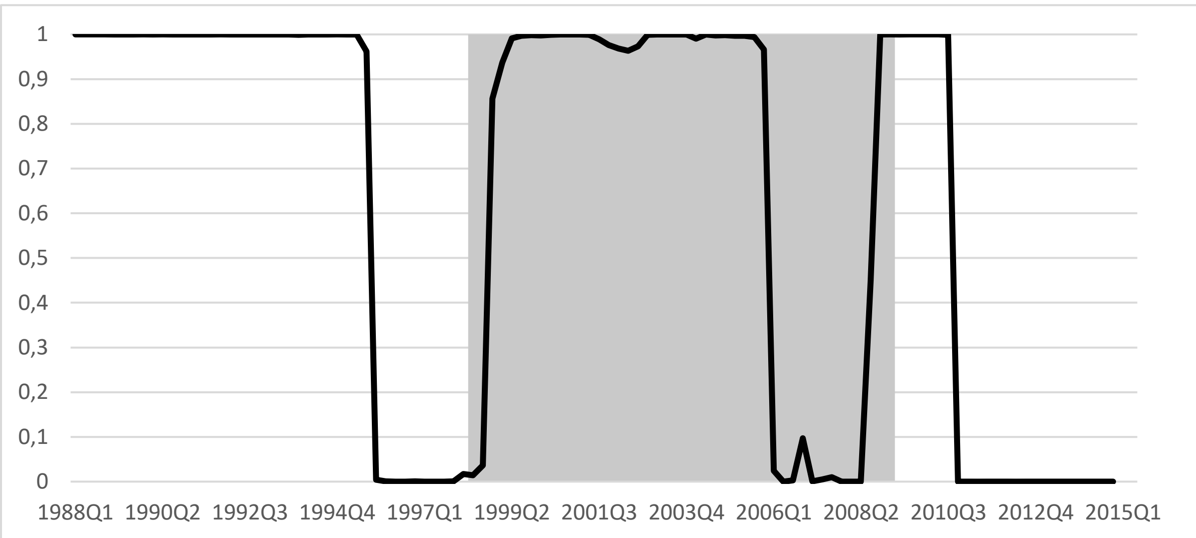

Fig. 3 Court-determined dummy (grey) versus smoothed probabilities (black line)

constructed using the break dates indicated by the Bai-Perron test. Table 6 also includes a second set of results based on static OLS models – which are often employed in practice – rather than the ARDL method used in this paper. The results highlight the implication of incorrectly identifying the timing of collusion damages. It is also clear that failing to control for smooth transition results in an underestimation of the overcharge.

Table 6 Overcharge coefficient comparison

Collusive regime probability	Dummy without transition (figure 2)	Court determined dummy (figure 3)	Bai-Perron determined dummy
	Static ARDL (Long-run)		
0.18	0.13	0.008	0.044
	OLS contemporaneous variables		
0.12	0.112	0.021	0.022

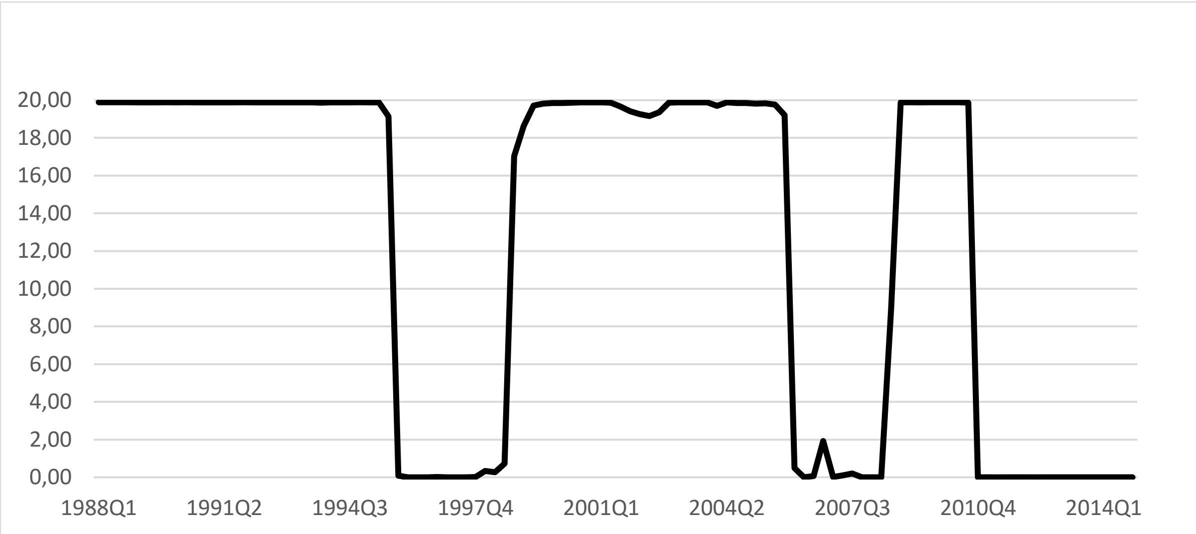

Fig. 4 Dynamic overcharge estimates (% relative to average non-collusive price)

Given smooth transitions between collusion and non-collusive periods, one can also obtain a dynamic overcharge estimate for every period. Such an estimate is obtained by using the collusive regime probability overcharge coefficient in conjunction with the actual regime probability. This is reported in figure 4. The overcharge is calculated as $100 \times \left(e^{\beta} - 1\right) \times \alpha_{1,t}$ where β is the overcharge coefficient and $\alpha_{1,t}$ is the probability of being in the collusive regime ($S_t = 1$). During the collusive regime the overcharge ranges approximately between 19.16% and 19.89% with transition phases lasting two to four quarters.

6 Conclusion

While recurrent collusion is a feature of a number of canonical models as well as an important policy issue, empirical studies of recurrent collusion is lacking. We employ a two-regime Markov RS model to study recurrent collusion in the South African cement market. The South African cement cartel case is taken as a suitable case for studying the properties of recurrent collusion, given the prevalence of recurrent collusion in cement industries internationally and the extent of information available from the court proceedings. We show that the Markov RS model offers a better fit than standard models and can be used to detect both the timing of damages and to determine price overcharge. The estimated overcharge ranges between 19.2%

and 19.9% and we find that these estimates are significantly higher than estimates suggested by alternative methods.

The paper demonstrates a specific version of the Markov RS model, with two regimes and a regime-shifting intercept, tailored to the market features of the South African cement market. In other settings, where the data dictates more complex regime dependence, the RS methodology allows for *inter alia* regime-dependent cost and demand drivers. In general, the RS model is a flexible tool, which can provide antitrust agencies and litigants with information about the underlying data-generating process driving prices in the market of interest: the RS model can signal the presence of multiple regimes and date the respective regimes, which, combined with other evidence, can confirm the presence of recurrent collusion. The RS model can also provide insights to courts and litigants seeking to estimate the price overcharge due to collusion. Again, its flexibility in modelling transition between collusive and non-collusive periods will be determined by the data, making it attractive for application in a variety of settings.

Beyond its technical contribution, this paper has implications for how collusive behaviour is understood. Collusion is complex in nature and it is prejudicial for empirical models to assume that cartels operate uninterrupted over long periods. Future work should extend the application to a larger dataset of markets, to test the performance of the methodology across a variety of markets and antitrust regimes, including markets where other evidence suggests that collusion does not recur.

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Appendix 1: Methodology - Filter and smoothing

We start with the conditional log likelihood function of Equation (5) given by:

$$L(\boldsymbol{\theta}) = \sum_{i=1}^{T} log f(p_t \mid \Omega_{t-1};\ \boldsymbol{\theta}) \tag{5}$$

where $\Omega_t = \{p_t,\ p_{t-1},\ \ldots,\ p_1, p_0, \boldsymbol{x}_t, \boldsymbol{x}_{t-1}, \ldots, \boldsymbol{x}_0\}$ denote the collection of all the observed variables up to time t, and $\boldsymbol{\theta} = (\sigma,\ a_1,\ \ldots\ , a_4,\ \gamma_1,\ \ldots\ , \gamma_4,\ c_0,\ \omega,\ p_{11}, p_{22})^{'}$ is a vector of population parameters. Maximum likelihood estimation (MLE) of equation 5 requires construction of the conditional density function $f\left(p_t \mid \Omega_{t-1};\ \boldsymbol{\theta}\right)$. Following Hamilton (1989), the conditional densities are constructed recursively as follow. Suppose that $P(S_{t-1} = j\Omega_{t-1};\ \boldsymbol{\theta})$ is known. Given the state variable $S_t = j$ and the previous observations the conditional probability density function is given as:

$$f(p_t|S_t = i, \Omega_{t-1}; \boldsymbol{\theta}) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(p_t - c_i + \sum_{l=1}^{m} a_l p_{t-l} + \sum_{l=0}^{n} \gamma_l \boldsymbol{x}_{t-l})^2}{2\sigma}\right) \tag{6}$$

To construct $f\left(p_t \mid \Omega_{t-1};\ \boldsymbol{\theta}\right)$ Hamilton use the following equations

$$\begin{aligned} \xi_{i,t-1} = P(S_t = i|\Omega_{t-1}; \boldsymbol{\theta}) &= \sum_{j=1}^{2} P(S_t = i|S_{t-1} = j, \Omega_{t-1}; \boldsymbol{\theta}) P(S_{t-1} = j, \Omega_{t-1}; \boldsymbol{\theta}) \\ &= \sum_{j=1}^{2} p_{ij} P(S_{t-1} = j, \Omega_{t-1}; \boldsymbol{\theta}) \end{aligned} \tag{7}$$

Since p_{ij} is known and $P\left(S_{t-1} = j \mid \Omega_{t-1}; \boldsymbol{\theta}\right)$ is assumed as given we have $\xi_{i,t-1}$. Now to derive $f\left(p_t \mid \Omega_{t-1};\ \boldsymbol{\theta}\right)$ we use

$$f(p_t|\Omega_{t-1}; \boldsymbol{\theta}) = \sum_{i=1}^{2} f(p_t|S_t = i, \Omega_{t-1}; \boldsymbol{\theta}) P(S_t = i|\Omega_{t-1}; \boldsymbol{\theta}) \tag{8}$$

Substituting 7 into 8 and re-arranging we have

$$f(p_t|\Omega_{t-1};\boldsymbol{\theta}) = \sum_{i=1}^{2}\sum_{j=1}^{2} f(p_t|S_t = i, \Omega_{t-1};\boldsymbol{\theta})\xi_{i,t-1} \tag{9}$$

Now that we have $f(p_t \mid \Omega_{t-1};\boldsymbol{\theta})$ the next step is to update 7 so that we can calculate $f(p_{t+1} \mid \Omega_t;\boldsymbol{\theta})$ where

$$f(p_{t+1}|\Omega_t;\boldsymbol{\theta}) = \sum_{i=1}^{2} f(p_{t+1}|S_t = i, \Omega_t;\boldsymbol{\theta})\xi_{i,t} \tag{10}$$

The conditional density function $f(p_{t+1} \mid S_t = i,\ \Omega_t;\ \boldsymbol{\theta})$ will have the same form as in (A2). Therefore, the only requirement to calculate (A6) is $\xi_{i,t} = P(S_t = i \mid \Omega_t;\boldsymbol{\theta})$. This is calculated by simply updating $\xi_{i,t-1}$ to reflect the information contained in p_t. The update is performed using a Bayes' rule:

$$\xi_{i,t} = P(S_t = i|\Omega_t;\boldsymbol{\theta}) = \frac{f(p_t|S_t = i, \Omega_{t-1};\boldsymbol{\theta})\xi_{i,t-1}}{f(p_t|\Omega_{t-1};\boldsymbol{\theta})} \tag{11}$$

Therefore, $f(y_t \mid \Omega_{t-1};\boldsymbol{\theta})$ is obtained for $t = 1,\ 2,\ \ldots\ ,T$ by assigning a starting value $P(S_{t-1} = j\Omega_{t-1};\ \boldsymbol{\theta})$ to initialize the filter and then to iterate equations 7 to 11. The question that remains is how to set $P(S_{t-1} = j \mid \Omega_{t-1};\ \boldsymbol{\theta})$ to initialize the iterations for the filter? When S_t is an ergodic Markov chain, the standard procedure is to simply set $P(S_{t-1} = j \mid \Omega_{t-1};\ \boldsymbol{\theta})$ equal to the unconditional probability $P(S_0 = i)$. The unconditional probabilities is given by

$$P(S_0 = 1) = \frac{1 - p_{22}}{2 - p_{11} - p_{22}} \tag{12}$$

$$P(S_0 = 2) = 1 - P(S_0 = 1) = \frac{1 - p_{11}}{2 - p_{11} - p_{22}} \tag{13}$$

An advantage of the Hamilton filter is that it directly evaluates $P(S_t = i \mid \Omega_t;\boldsymbol{\theta})$, which is referred to as the "filtered" probability. The estimates of $P(S_t = i \mid \Omega_t;\boldsymbol{\theta})$ can further be improved by "smoothing". This is done by using the information set in the final period Ω_T, in contrast to the filtered estimates that only use the contemporaneous information set Ω_t. The likelihood of the observed data appearing in different periods is linked together by the transition probabilities. Therefore, the likelihood of being, for example, in regime i in period t is improved by using information about the future realisations of p_d, where $d > t$. A suitable smoothing technique is provided by Kim (1994). The smoothing method requires only a single backward recursion through the data. Kim (1994) shows that the joint probability under the Markov assumption is given by

$$\begin{aligned} P(S_t = i, S_{t+1} = j|\Omega_T;\boldsymbol{\theta}) &= P(S_t = i|S_{t+1} = j, \Omega_T;\boldsymbol{\theta})P(S_{t+1} = j|\Omega_T;\boldsymbol{\theta}) && (14)\\ &= \frac{P(S_t = i|S_{t+1} = j, \Omega_t;\boldsymbol{\theta})}{P(S_{t+1} = j|\Omega_t;\boldsymbol{\theta})}P(S_{t+1} = j|\Omega_T;\boldsymbol{\theta}) && (15)\end{aligned}$$

To move from 14 to 15, it is important to note that under the correct assumptions, if S_{t+1} is known, the future data in $(\Omega_{t+1},\ \ldots\ ,\Omega_T)$ will contain no additional information about S_t. Therefore, by marginalizing the joint probability with respect to S_{t+1}, the smoothed probability in period t is obtained by

$$\begin{aligned} P(S_t = i|\Omega_T;\boldsymbol{\theta}) &= \sum_{j=1}^{2} P(S_t = i, S_{t+1} = j|\Omega_T;\boldsymbol{\theta})\\ &= \sum_{j=1}^{2} \frac{P(S_t = i|S_t = iS_{t+1} = j, \Omega_t;\boldsymbol{\theta})}{P(S_{t+1} = j|\Omega_t;\boldsymbol{\theta})}P(S_{t+1} = j|\Omega_T;\boldsymbol{\theta}) && (16)\end{aligned}$$

Appendix 2: Motivation and choice of Markov RS model

Consider a standard ARDL model of price with the following form:

$$p_t = c_0 + \sum_{l=1}^{m} a_l p_{t-l} + \sum_{l=0}^{n} \gamma_l \boldsymbol{x}_{t-l} + \varepsilon_t \tag{17}$$

with $\varepsilon_t \sim N\left(0, \sigma^2\right)$, where p_t denotes price at time t, $\boldsymbol{x}_t$ denotes a vector of demand and costs drivers as shown in table 3 The residual diagnostics is reported in table 7.

Table 7 ARDL residual diagnostic tests

Test	H_0	Test statistic	**p-value**
Jarque-Berra	Residuals are normally distributed	$\chi^2(2) = 15.38$	0.26
Breusch-Godfrey Serial correlation LM	No 2^{nd} order serial correlation in residuals	$(n-2) \times R^2 = 8.66$	0.01
Breusch-Pagan-Godfrey Heteroskedasticity	No heteroskedasticity	$n \times R^2 = 42.03$	0.01
ARCH-LM	No autoregressive Conditional Heteroskedasticity	$n \times R^2 = 1.18$	0.28
Ramsey RESET	No misspecification	$F(1, 99) = 0.81$	0.37

The residuals of the ARDL model (equation 17) exhibit heteroskedasticity and serial correlation. Such a result is to be expected in the presence of regime changes, since the residuals will no longer be Gaussian. From the diagnostic tests it is evident that the linear functional form of equation 17 is unsuitable. This result could be anticipated, given the prior knowledge of the cement cartel and cement price regime shifts. Therefore, standard least square estimation of 17, including a dummy variable to capture overcharges, will not give an accurate measure of the true overcharge.

In various specifications the coefficient of the electricity variable had the incorrect sign. Specifically it was found that there is a negative relationship between electricity prices and the price of cement, which is not a sensible conclusion. A graphical investigation of figure 5 provides some insight as to why this was the case.

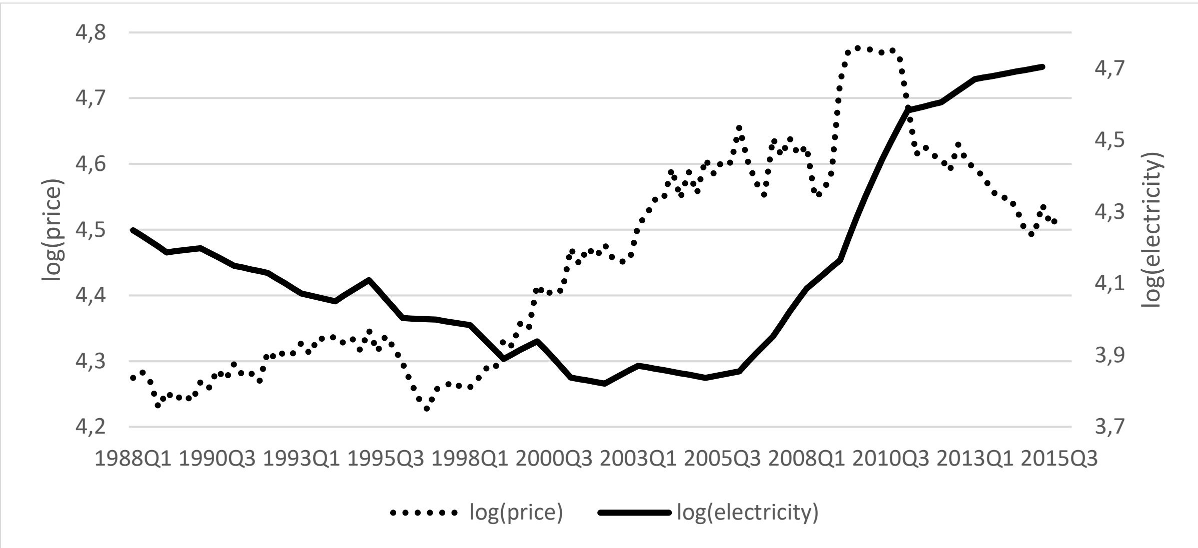

Fig. 5 Cement price and industrial electricity prices

There appears to be time periods for which there is positive correlation and time periods for which there is negative correlation. It is therefore sensible to make the coefficient of electricity regime dependent. The results confirms this sentiment, where the coefficient for electricity is negative in the non-collusive regime ($S_t = 2$) and positive in the collusive regime ($S_t = 1$).

Appendix 3: Diagnostic tests

This section reports the diagnostic tests for both the Markov RS model, (that generated the transition probabilities for the two regimes) and the final ARDL model that was used to calculate the overcharge. Diagnostic tests for the ARDL model is reported in table 8. As shown, the ARDL model passess the standard diagnostic tests.

Table 8 ARDL diagnostic tests

Test	H_0	Test statistic	p-value
Jarque-Berra	Residuals are normally distributed	$\chi^2(2) = 0.64$	0.73
Ljung-Box	Data is independently distributed (i.e. no serial correlation)	$\chi^2(10) = 10.64$	0.39
Breusch-Pagan-Godfrey Heteroskedasticity	No heteroskedasticity	$n \times R^2 = 29.96$	0.62
ARCH-LM	No autoregressive Conditional Heteroskedasticity	$n \times R^2 = 13.17$	0.11

The ARDL model relies on regime probabilities calculated from the RS model. Performing diagnostic tests for an RS model is more complex than in standard linear models and, until recently, the applied literature has often relied on only a few (if any) of these tests (Breunig et al, 2003; Smith, 2008). A challenge faced when performing diagnostic tests for an RS model is that the true residuals are unobserved, as they are dependent on the unobserved state variable. To overcome this issue, we follow the methodology proposed in Maheu and McCurdy (2000), according to which expected residual are calculated, conditioned on past information. Smoothed values obtained from the Kim filter cannot be used to construct the residuals, as the filter includes future information and, as a result, the current residual will contain future information. Table 9 reports selected diagnostic tests for the RS model, which we are capable of generating. These appear satisfactory. Normality tests on residuals in an RS model are more complicated and the RS model performs less well on our version of these tests. While deviation from normality may be problematic for inference, this is not the main focus of our paper. Therefore, in sum, we are confident of the stability of the model.

Table 9 RS diagnostic tests

Test	H_0	Test statistic	p-value
Ljung-Box	Data is independently distributed (i.e. no serial correlation)	$\chi^2(8) = 9.48$	0.3
ARCH-LM	No Auto Regressive Conditional Heteroskedasticity	$\chi^2(12) = 8.24$	0.77

Appendix 4: Comparison to structural breaks

The recursive residuals (figure 6) crosses the significance band at various time points and do not give a clear indication for how long these possible breaks affected the price series. While the CUSUM test (figure 7) provides a better picture, the result is not as convincing as the probabilities of figure 1. The test indicates a break in the model from 2001 to around 2007. These dates do not accurately depict our prior knowledge of the cement case since it would suggest that damages was only observed three years after the cartel was formed and ceased two years before the information exchange was terminated.

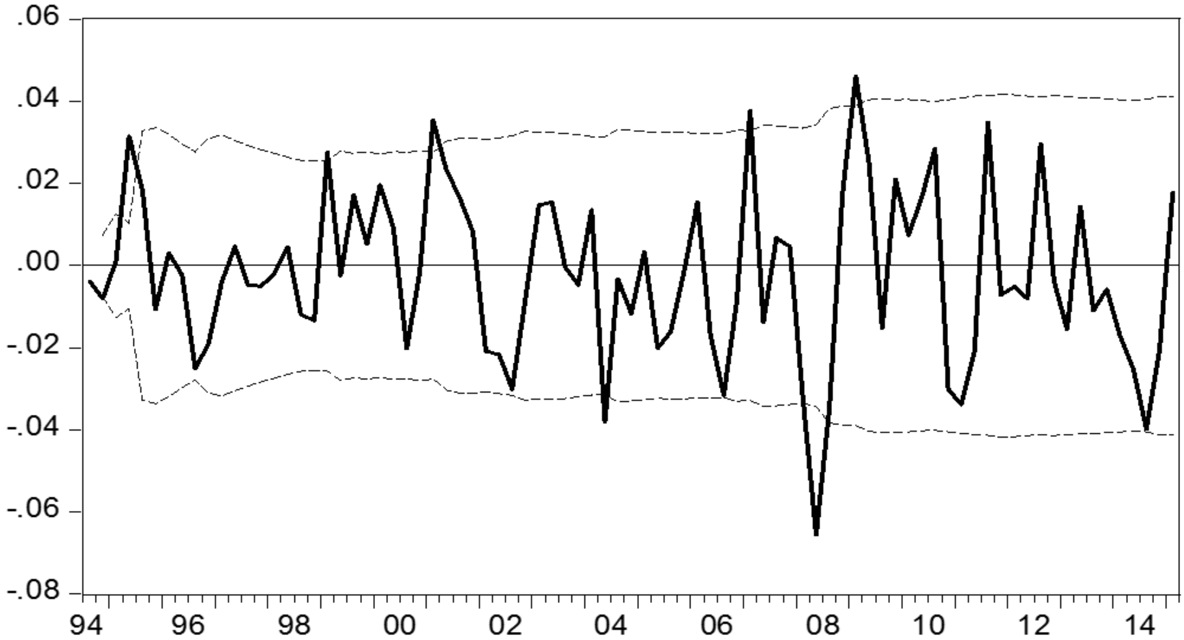

Fig. 6 Recursive residuals

The Bai-Perron test (10) treats the break dates as unknown and estimate them along with the regression coefficients using least squares estimation. The break points are estimated as 1996Q2, 2005Q2 and 2009Q2. This certainly a more accurate depiction of the changes in the d.g.p. compared to the recursive residuals and squared CUSUM. However as expected the test takes 1996Q2 as the first brake date. Therefore, construction of a dummy variable based on this test will include the price war during this time as part of the collusive regime and lead to a lower overcharge estimation.

Table 10 Bai-Perron break test

Break Test	F-statistic	Scaled F-statistic	Critical Value
0 vs. 1 *	22.95	114.77	18.23
1 vs. 2 *	18.09	90.45	19.91
2 vs. 3 *	5.41	27.06	20.99
3 vs. 4	1.34	6.68	21.71

The Bai-Perron test treats the break dates as unknown and estimate them along with the regression coefficients using least squares estimation. The break points are estimated as 1996Q2, 2005Q2 and 2009Q2. This certainly a more accurate depiction of the changes in the d.g.p. compared to the recursive residuals and squared CUSUM. However as expected the test takes 1996Q2 as the first brake date. Therefore, construction of a dummy variable based on this test will include the price war during this time as part of the collusive regime and lead to a lower overcharge estimation.

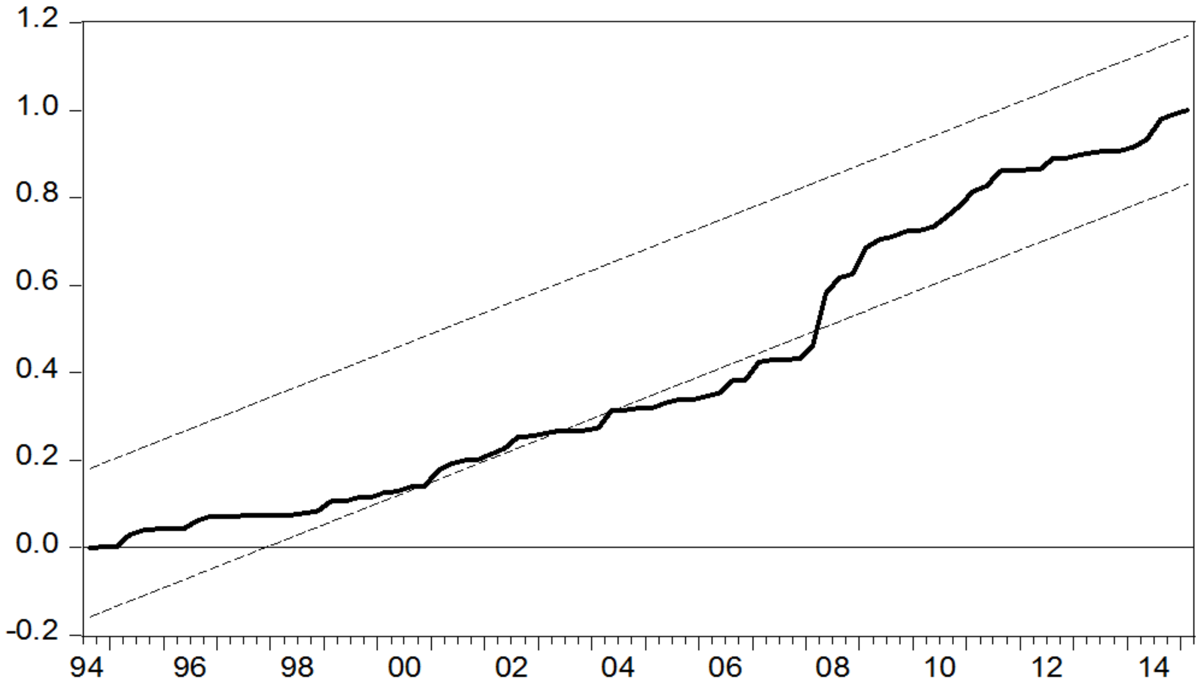

Fig. 7 CUSUM of squares

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