Evaluating Cartel Overcharge Models:

Model Stability and Reliability of Overcharge Estimates

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THESIS

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This thesis is dedicated to my Mom and Dad, who both didn't live to see this day, but whose love of learning and motivation to excel inspired me every day. My immediate family, John and Morgan, Den, Kat and Jerry and families provided me constant love, support, and encouragement. Without them it would never have been accomplished.

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SUMMARY

Free and fair competition provides benefits to consumers through lower prices and innovation and to society in general through more efficient resource allocation. When firms collude and raise prices, these benefits are reduced. In the U.S. and many jurisdictions around the world, antitrust laws (also called competition laws) protect consumers' interests by deeming certain types of business conduct illegal. Price fixing is one of these types of conduct.

The difference between the price paid as a result of cartel behavior and what would have been paid in the absence of the cartel (also known as the "but-for" world) is called the cartel overcharge. In the U.S. the Clayton Act allows for trebling of such damages. Thus, unreliably estimated cartel overcharges may have magnified effects.

Reliable estimation of counterfactual worlds that did not (and will never) exist creates many issues, both theoretical and empirical. I focus on forecasting methodologies often employed in cartel matters and address some of those issues. I suggest the use of recursive residuals and application of CUSUM and CUSUMSQ tests to use the forecasting framework often used in cartel overcharge estimation and to assess the reliability of predictions fundamentally driven by implied assumptions of model and parameter stability. The availability of standard, objective tests for model stability based on recursive residuals provide additional support to researchers attempting to reliably estimate cartel overcharges. Recursive residuals, to my knowledge, have not been used in the cartel overcharge estimation context.

I. INTRODUCTION

A. Background

Free and fair competition provides benefits to consumers through lower prices and innovation and to society in general through more efficient resource allocation. When firms collude and raise prices, these benefits are reduced. In the U.S. and many jurisdictions around the world, antitrust laws (also called competition laws) protect consumers' interests by deeming certain types of business conduct illegal.

Price fixing is one of these types of conduct. A price-fixing cartel may be defined as two or more firms that explicitly coordinate economic behavior related to price. For example, firms may agree to set price levels of products or services, the magnitude of price changes, production levels, or acceptable discount levels. A cartel overcharge is the difference between the higher prices that consumers pay as a result of the cartel's coordination, compared to the prices in the absence of the cartel behavior. The reliable estimation of cartel overcharges is the subject of this thesis.

With respect to laws against price fixing, in the U.S., Section 1 of the Sherman Act prohibits "[e]very contract, combination in the form of trust or otherwise, or conspiracy, in restraint of trade or commerce." U.S. courts have deemed coordinated practices whose sole purpose is to raise prices (or restrict output) to be *per se* illegal. (Carlton, 2005). Other types of coordinated activity may be judged under a "rule of reason" approach if their purpose is pro-competitive, but provision of the product or service may directly or indirectly set prices (e.g., ASCAP/ BMI music licensing fees). (Carlton, 2005).

Government enforcers of competition law have remedies for price-fixing violations that may include criminal prosecution and levying of fines. Violations of the Sherman Act are punishable with substantial fines and imprisonment for up to 10 years. (United States, 2011). In some jurisdictions, the victims of the price-fixing behavior – the customers who paid a higher amount than they would have in the absence of the cartel behavior – also have legal remedies, which including suing the cartel members for the amount of the overcharge plus reasonable attorney's fees. In the U.S., the Clayton Act allows for trebling of damages for violation of antitrust laws. (§ 4 Clayton Act, 15 U.S.C. § 15) Trebling of damages highlights the importance of reliable estimation of overcharges.

B. Statement of the Problem

At the heart of reliable estimation of cartel overcharges is making the best estimation of what the world without the cartel would have looked like. This is often termed the "but-for" world. Damages may then be estimated by comparing the world that did exist to the world that did not, due to the cartel.

Reliable estimation of counterfactual worlds that did not (and will never) exist creates many issues, both theoretical and empirical. In comparison to say, forecasting of macroeconomic variables, in which predictions can be compared to outcomes that actually do happen, the counterfactual or "but-for" world in a cartel scenario cannot be observed and evaluated in the same way. More closely related is policy analysis, in which researchers may consider several alternative policy proposals and model each of their potential outcomes. Comparison of outcomes and their likelihood are used to inform selection of the (*ex ante*) "best" policy. After a policy is chosen, researchers may compare the actual and predicted outcomes of the chosen policy to assess the reliability of their predictions, but cannot assess in the same way the reliability of predictions for policies never chosen.

While there are several types of approaches used by researchers and antitrust practitioners to estimate cartel overcharges, I focus on econometric forecasting/back casting methodologies in this paper, as it is often among the most rigorous of the current approaches. Reliable empirical modeling of cartel overcharges should be based on sound economic theory for the industry in question, include robustness tests of alternative specifications, and account for prediction error in the overcharge estimates. An important starting point in developing reliable cartel overcharge estimates, therefore, is developing a sound model for the world that did exist. This entails understanding the economic relationships among factors driving prices during the non-cartel period and how shocks or structural changes unrelated to a cartel may affect relationships and estimated outcomes. Then one may have a sound basis to start examining projections of counterfactual prices into the cartel period.

A frequent assumption (either explicitly stated or implied) is that base or "clean" period models are assumed to be stable into the cartel period. This allows researchers to simply apply the coefficient estimates from the base period to the cartel period and calculate overcharges as the difference between the predicted and actual prices. Figure 1 provides examples overcharge methodologies based on simple before/after averages and a cartel-period forecast. Thus, key to calculating reliable overcharge estimates is testing the stability of the model both in the base period and in the projected counterfactual world.

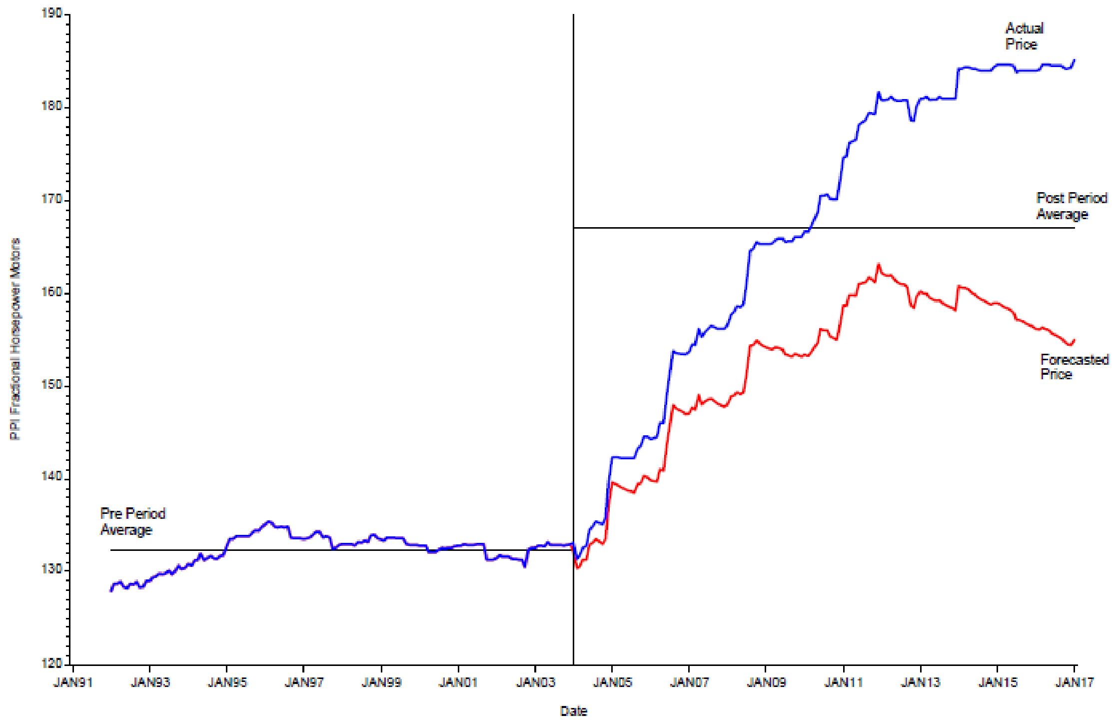

Figure 1. Examples of overcharge methodologies: average prices and forecast.

C. <u>Significance of the Problem</u>

In the literature published on cartel overcharges, stability tests are rarely employed. In practice, many times the simple difference between the point estimate (a prediction from a largely untested econometric model) and actual prices serve as the basis for damages. This simplistic methodology ignores many issues, but of particular interest here, it ignores prediction uncertainty and model stability issues. For example, a wide prediction interval may include the actual prices observed during the cartel and not provide a reliable basis for any overcharge damage estimates. Likewise, an unstable model, which may not even predict well within the base period (in-sample), would provide a questionable basis for cartel period (out-of-sample) predictions. In addition, simply applying the coefficient estimates from a stable base period to the cartel period implicitly assumes the model is stable across the two periods. However, if the model is unstable – that is, if the base period is different in substantial ways from the cartel period – in ways unrelated to the cartel – then applying the base period coefficients to the cartel period data may result in unreliable inferences about cartel overcharges.[1]

The significance of the problem with unreliably-estimated overcharges is that, as noted previously, in the U.S. the Clayton Act allows for trebling of antitrust damages. Thus, if base overcharge estimates are overestimated, trebled damages are likewise magnified.

D. Purpose of the Study

In this thesis, I discuss and implement empirical tests of model inputs and model stability to better assess the reliability of forecasted overcharge estimates from base or "clean" period models. Tests include standard time series tests not regularly employed in cartel overcharge estimation including recursive residuals tests of model stability. I also assess how such empirical tests may be used to provide useful information for

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[1] Some use econometric models include data from the whole time period, but with dummy variables that attempt to capture the cartel effect. The method of employing dummy variables, the timeframes specified and the inferences on the counterfactual prices based on this methodology of identifying cartel effects are not immune from conceptual and methodological criticisms. Model stability issues may arise here as well, but is not the specific focus of this thesis. Models with a cartel dummy variable may have issues for recursive residual analysis.

cartel dummy-variable models and compare overcharge estimate results from prediction and dummy-variable models.

Recursive residuals are standardized one-step-ahead prediction errors. Coefficient estimates and residuals are updated as additional observations are added to the estimation. (Stokes, 2011) As estimates are updated, deviations from standard Ordinary Least Squares ("OLS") assumptions, such as expected zero mean residual, may be detected. The magnitude of the deviations, assessed in the context of standard tests, such as cumulative sum of residuals ("CUSUM") or cumulative sum of squared residuals tests ("CUSUMSQ"), provide objective measures of model stability. As explained in more detail later, the CUSUM and CUSUMSQ tests provide a test statistic and confidence intervals based on deviations from the expected zero mean residual under the null hypothesis that the population parameters are stable.

E. Significance of the Study

Estimation of recursive residuals and application of CUSUM and CUSUMSQ tests provides a clear, easily understood way to use the forecasting framework often used in cartel overcharge estimation and assess the reliability of predictions fundamentally driven by implied assumptions of model and parameter stability. The availability of standard, objective tests for model stability based on recursive residuals provide additional support to researchers attempting to reliably estimate cartel overcharges. Recursive residuals, to my knowledge, have not been used in the cartel overcharge estimation context.

F. Organization of Paper

In Section II I review the relevant literature, discussing various cartel overcharge estimation methodologies employed by researchers and sources of cartel overcharge estimates reported in the literature. I also provide a background in the literature on the use of time series stationarity, structural break, and recursive residuals-based tests.

In Section III, I discuss data sources and the methodology. First, I examine the time series properties of the various data series related to the hypothetically cartelized product. The purpose of this is to better understand potential issues in specifying an econometric model over the proposed time frame. Often cartels exist over multiple years, or even decades. Pre- and post-cartel periods may have substantially different dynamics that may drive estimates that would differ from those that would have existed in the cartel period, even in the absence of the alleged cartel. Structural changes or exogenous shocks to key inputs may arise, for example, unrelated to the alleged cartel activity. Checks for stationarity of the data series (i.e. unit roots that may invalidate standard OLS test statistics) to be used in the analysis, Bai-Perron tests for structural breaks, and recursive residuals tests and will help inform the specifications for estimating cartel effects and developing reliable overcharge estimates.

I then develop and specify a model for the in-sample or base period. I use recursive residuals analysis to test model stability of the base period model. I also examine confidence intervals for the counterfactual price predictions, based on this model. I estimate recursive residuals and apply the CUSUM and CUSUMSQ tests on the full-period model, which incorporates the forecasted counterfactual price to check for stability of the modeling of the counterfactual world. This is an innovation in the use of recursive residuals in this context.

I then also estimate a dummy variable model, using information from the Bai-Perron structural break tests and CUSUM and CUSUMSQ tests to assess potential cartel-related break points. I use both the point estimate of the dummy variable and the confidence intervals to calculate a range of assumed damages.

In this way, I lay out several alternative robustness checks on cartel overcharge estimation. This methodology provides an improved conceptual and empirical framework for researchers to more reliably test and develop cartel overcharge estimates and consequently to also provide a more reliable basis for damages assessed on cartel participants. Section IV reports results and Section V concludes.

II. CONCEPTUAL FRAMEWORK AND RELATED LITERATURE

In this section, I review sources of overcharge estimates found in the literature, the methodologies used for generating these overcharge estimates, and an examination of a few publicly-available studies of individual cartel matters that use econometric techniques to estimate overcharges. I then review articles discussing overcharge estimation issues and challenges. I conclude the section with a review of some of the applications of the recursive residual technique discussed in the literature.

A. Description of methods to estimate overcharges

Overview of Sources of Cartel Overcharge Estimates

Cartel overcharges have been developed from numerous sources. Often, in the context of government investigations, rigorous empirical analyses to determine overcharge amounts are not needed, or not done. In the U.S. and many other jurisdictions, most price fixing is *per se* illegal. This means that the conduct is deemed sufficiently harmful, that the amount of specific harm to consumers need not be estimated to assess fines on cartel participants. While statutory requirements vary across jurisdictions, fines are often assessed on estimates of the affected volume, using guidelines for the specific percentages of sales to impose as fines, with lesser amounts imposed based on participation in leniency programs (e.g., first to come forward, those cooperating with the investigations). These fines therefore need not reflect the specific overcharge alleged to have occurred, or any other metric of harm experienced by consumers.

In contrast, for private litigation, those by direct purchasers or indirect purchasers, specific claims of harm and compensation for damages are raised and estimated. In this realm, very detailed transaction and cost data may be available as part of legal discovery. Specific overcharge estimates may be reported, but the details of the experts' analyses are rarely made public and available for critical review and replication.

Similarly, third parties, such as academic researchers, consulting firms, governments and non-governmental organizations have attempted to estimate overcharges in the context of studying cartel behavior. Thus, in private litigation and in the economics literature generally, numerous approaches have been employed to estimate cartel overcharge damages.

The various techniques may usefully be organized into three primary groups: comparator, financial and market structure approaches. (Oxera, 2009). Comparator approaches may use benchmarks (or "yardsticks") from the same industry in a different geographic market or from a related market to compare to pricing during the cartel period in the affected industry or region. Comparator analyses may also examine prices before and after a cartel period to the pricing during the cartel period to estimate overcharges. This methodology assumes that the pre and/or post period reflects the competitive state of the industry and estimates drawn from these "clean" periods may be used to estimate the counterfactual competitive price during the alleged cartel period. Another comparator methodology is to perform a 'difference-in-differences' type of approach comparing changes in price for a cartelized market over time, against the change in price in a non-cartelized market over the same time period. (Oxera, 2009). The comparator approaches may be implemented in a very simple way, such as comparing average prices or margins, or in a more rigorous manner with econometric models run on time series, panel data, or time series/panel data. The data may be at a transactional level or at aggregated price index levels.

Financial approaches use benchmarks based on financial data such as rates of return, financial margins, or other cost information for the alleged cartel participants to compare before and after periods to measure harm. Another type of financial approach examines stock price reactions to news about cartel discovery and draws inferences from this to assess overcharges.

Finally, market structure approaches use the economic theory of the firm and the industrial organization literature on market structure and behavior to aid in developing models of pricing in counterfactual worlds. For example, a researcher may compare observed outcomes, such as price and output movements to those expected by economic theory for the applicable market structures such as duopolies, oligopolies, monopolistic competition, and perfect competition. Applicability of Bertrand, Cournot and Stackleberg regimes may also provide insight into the expected outcomes in oligopoly markets, which can be compared to the observed oligopolistic cartel outcomes.

B. Meta Analyses and Surveys of Cartel Overcharges

John Connor, former economics professor at Purdue University, has published extensively on cartel matters. He has collected extensive information on estimate cartel overcharges dating back to 1780, from numerous sources, including newspaper reports, published papers, and court documents. (Connor, 2004; Connor and Lande, 2005, 2008; Connor, 2007; Connor and Bolotova, 2006; Connor and Helmers, 2007; Connor, 2014a, 2014b).

Connor (2014), for example, surveys "more than 700 published economic studies and judicial decisions that contain 2,041 quantitative estimates of overcharges of hard-core cartels. The primary findings are: (1) that the *median* long-run overcharge for all types of cartels over all time periods is 23.0%; (2) the *mean* is at least 49%; (3) overcharges reached their zenith in 1891-1945 and have trended downward ever since; (4) 6% of the cartel episodes are zero; (5) median overcharges of international-membership cartels are 38% higher than those of domestic cartels; (6) convicted cartels are on average 19% more effective at raising prices than unpunished cartels; (7) bid-rigging conduct displays 25% lower mark-ups than price-fixing cartels; (8) when cartels operate at peak effectiveness, price changes are 60% to 80% higher than the whole episode; and (9) laboratory and natural market data find that the Cartel Monopoly Index (CMI) varies from 11% to 95%. Historical penalty guidelines aimed at optimally deterring cartels are likely to be too low."

Following in the footsteps of Connor, Bolotova (2009) collects and analyzes hundreds of overcharge estimates drawn from numerous sources. She finds the median overcharge is 20 percent of the selling price. She examines the correspondence between market structure and the level of overcharges, finding that more concentrated markets (that is, markets with market power concentrated in fewer firms' hands, thus easier to coordinate) result in higher overcharge estimates, consistent with Industrial Organization theory.

Connor’s estimates on average overcharges have been cited as evidence supporting various damage claims around the world. This has led to close review of many of the underlying studies and other sources for his overcharge averages. (Ehmer and Rosati, 2009; Boyer and Kotchoni 2015)

The Oxera (2009) report was developed for the European Commission to provide a framework for practitioners estimating antitrust damages. This study raises some of the typical concerns identified with the data underlying the Connor overcharge averages.

> This empirical data needs to be interpreted with caution. Not all studies would qualify as sufficiently robust. It may also be that the empirical studies tend to focus on cartels that have been operational and are most likely to have had an impact on the market; if this is the case then many cartels with no effect will not have been captured in these studies. (Oxera, 2009, p. ix).
>
> However, the amount of the overcharge in any particular damages case would ultimately need to be determined pursuant to the requirements of applicable national law. It is possible that a cartel, even if it were found to infringe Article 101, was ineffective and hence that the overcharge was negligible or zero. (Oxera, 2009, p. ix).

Boyer and Kotchoni (2015) examine Connor and Lande (2008), which reports mean overcharge estimates ranging between 31% and 49%, and Connor (2010) which used a larger set of data and found a 50.4% mean overcharge for “successful” cartels. Boyer and Kotchoni noted several issues that affect the reliability of these broadly-sourced estimates, including model error, estimation error, endogeneity bias and sample selection bias. Boyer and Kotchoni (2015) perform a meta-analysis, estimating a bias-corrected 15.47% mean overcharge.

Ehmer and Rosati (2009) point out a number of serious issues that affect average overcharge estimates reported in Connor (2009). One issue is the unreliability of the underlying estimates that, for the most part, rely on simple comparisons between periods without controlling for non-cartel-related factors that affect prices and may drive differences in prices over the time periods analyzed. They quote Connor (2009) "there may be substantial variation in the quality of the price data, the methods used, degrees of judicial scrutiny, and the professional orientation of the sources that could affect reliability." Emher and Rosati (2009) also discuss sample bias, biased estimation methodologies and calculation errors that further affect Connor's estimated average overcharges. They conclude:

> Importantly, virtually all flaws that we have identified bias his results upwards, that is, they tend to result in higher overcharge estimates. As a consequence of these flaws, not only does Connor's study fail to meet the standard for serious scientific work, but his results suffer from such a serious bias that they are all but irrelevant for policy purposes. (Ehmer and Rosati, 2009, p. 4).

These reviews of the underlying studies in Connor's database highlight the variability and potential unreliability of overcharge estimates that are not developed in a rigorous manner.

C. <u>Country-Based Survey data</u>

The Organization for Economic Cooperation and Development ("OECD") has published reports on cartel activity, fines and overcharge estimates for various cartels in member and some non-member countries, based on data from surveys it has implemented. The evidence is primarily individual cartel anecdotes, some incomplete survey responses, and summaries of averages of reported overcharges.

The OECD Report on the Nature and Impact of Hard Core Cartels, 2002 explains the substantial concerns arising from cartel activity which they “conservatively estimate exceeds many billions of U.S. dollars per year.” The report explains the various negative effects of cartels:

> Cartels harm consumers and have pernicious effects on economic efficiency. A successful cartel raises price above the competitive level and reduces output. Consumers choose either not to pay the higher price for some or all of the cartelised product that they desire, thus forgoing the product, or they pay the cartel price and thereby unknowingly transfer wealth to the cartel operators. Further, a cartel shelters its members from full exposure to market forces, reducing pressures on them to control costs and to innovate. All of these effects adversely affect efficiency in a market economy. (OECD, 2002, p. 2).

Of note, they address the difficulties in quantifying these effects:

> It is not easy to quantify these effects, however. It would require comparison of the actual market situation under the cartel to that which would exist in a hypothetical competitive market. Competition officials usually do not undertake to make such a calculation, both because it is difficult to do and because their laws usually do not require it. When an estimate of harm is necessary, however, most officials employ a proxy, which is the unlawful gain accruing to the cartel members from their activity. In its simplest form, this estimation is the product of the cartel “mark-up” above the competitive price and the commerce affected (in units) by the cartel agreement. Even this calculation can be difficult, as it requires an assessment both of the amount of ‘affected commerce’ and of what the ‘competitive’ price would have been absent the agreement. (OECD, 2002, p. 2).

The OECD’s Competition Committee conducted a survey of cartel cases from its members, collecting 199 cases over five years beginning in 1996. Unfortunately, the lack of detail in the survey responses prevented calculation of harm in many of the cases. The survey showed that the cartel markup can vary significantly across cases, and in some cases it was estimated to be over 50%. (OECD, 2002) However, a shortcoming of a simple survey of results is that the rigor of the analysis underlying the survey results is unknown. The OECD report agrees that estimating harm from cartels is difficult.

> That the harm from cartels is large is undisputed. Quantifying it precisely, however, is difficult. Data collected through a recent OECD survey provide some additional information on the magnitude of cartels' harm. The OECD's study permits the following general, non-scientific but important conclusion: The harm from cartels is even larger than has been previously thought, and conservatively exceeds the equivalent of billions of U.S. dollars per year. (OECD, 2002, p. 5).

This "non-scientific" conclusion again highlights the importance of providing reliable overcharge estimates so that reliable, scientifically-based conclusions may be made about the magnitude of harm caused by cartels.

D. Individual industry estimates

Many individual cartel events have been studied to more or less rigorous degrees. In this section, I describe some of the publicly-available overcharge estimates in the literature. Many economists have estimated overcharges in private litigation matters, the estimation details of which are not often available to the public. In this section I discuss the econometric approaches published with respect to the lysine, citric acid and cement cartels. None of these approaches employ tests of model stability.

Bolotova, Connor, Miller (2008) examine the lysine and citric acid cartel matters. They use monthly U.S. contract citric acid prices reported in Purchasing Magazine based on surveys of purchasers of chemical products. For lysine, they use data from a Plaintiff's report in the lysine litigation. They examine the effect of collusion on the mean and variance of prices. Using autoregressive conditional heteroskedasticy ("ARCH") models and generalized autoregressive conditional heteroskedasticy

(“GARCH”) models, they estimate positive and significant increases in prices during the alleged collusive periods for both citric acid and lysine. Specifically, they find the short-run mean price of citric acid was 9 cents per pound higher (an estimated 11.86% overcharge percentage) than in the non-collusive period and that the lysine price was 24.79 cents per pound higher than non-collusive periods, implying an estimated 24.42% overcharge. They find negative and significant conspiracy-period-related variance in the lysine matter and positive, but not significant variance during the cartel period in the citric acid cartel estimations. The authors put the higher lysine overcharge and lower price variability, and the lower price overcharge and higher variability in the citric acid case into context of geographic scope and competitor context to make sense of the findings and possible insight that price variance control may assist achieving higher price overcharges. The authors conclude that the price variability examination, in conjunction with the price overcharge estimation, provides additional useful information about cartel behavior and may be useful as a cartel screening methodology.

Hüschelrath *et al* (2013a) use publicly-available data on the cement market in Germany to analyze overcharges. The data include cement price indices collected and published by the German Federal Statistical Office, based on questionnaire responses by the major cement producers. They also include various indices for input costs and production, such as price indices for lime, electricity, lignite and cement production. They employ both dummy variable and difference-in-differences approaches to their estimation and find price overcharges ranging between 20.3% and 26.5% depending on the specific model and assumptions.

Of particular relevance to this thesis is that they acknowledge that there are many challenges to applying theoretical approaches for cartel overcharge estimation to real-world data, and thus advocate for taking multiple approaches to arrive at "robust and reliable" estimates of the counterfactual price. The authors state that "robust estimation of the so-called price overcharge is crucial for a coherent and welfare-improving private enforcement of the anti-cartel rules."

Hüschelrath *et al* (2013b) in contrast uses transaction-level data on cement, which include details such as gross prices, delivered quantities, location of delivery, rebates, cancellations, free deliveries, and types of customers. The data includes about 340,000 invoices both small and large customers of German cement producers. The authors use structural break analyses to help identify the likely end of the cartel period and compare the transaction data results to those based on publicly-available indices. They conclude that transaction data provides more detailed information on the timing of the breakdown in the cartel compared to the public data.

They also employ various econometric approaches to estimate the overcharge with disaggregated transaction data as well as aggregated transaction data. The two types of approaches are pooled reduced form regressions and static panel regressions employing either random or fixed effects in alternative specifications. In each case, they employ the "before-and-after" comparator approach. This allows the authors to focus on the differences created by the other variations. The results are fairly similar across the levels of aggregation; however they vary with the specific approach used with each level of data. For example, comparing results for regressions run on disaggregated and aggregated transaction data, the estimated overcharge percent in levels is 30.1% for the former and 31.4% for the latter. Likewise, for log-linear models, 38.4% and 36.8%; for random effects models, 25.0% and 27.1%; and for fixed effects models: 25.6% and 27.3%. These results highlight the importance of model choice in affecting overcharge estimates. In addition, the authors note that the estimated length of the cartel, the estimated start and end dates, and the methods used to identify break points may also affect substantially the estimates of overcharges and damages, especially in "before-and-after" approaches.

Frank and Schliffke (2013) discuss identifying the end of cartels and taking into account post-cartel behavior, which may affect the competitive benchmark used to evaluate the cartel overcharge. For example, if there is a slow decay in the cartel-induced prices due to "stickiness" factors, such as contract durations, information transmission and the like, that slow the return to competitive pricing, then a competitive benchmark including the higher prices would result in a lower overcharge estimate. Conversely, a post-cartel price war or punishment phase would result in prices lower than the competitive level, resulting in a higher overcharge estimate.

These authors, employing a "during-and-after" approach to cartel overcharge estimation add a post-cartel dummy to capture "off-equilibrium" prices. They systematically extend the post-cartel off-equilibrium by a month until the cartel effect coefficient does not vary significantly with additional extensions of the post-cartel off-equilibrium dummy time period. This method provides parallels to the application of recursive residuals analysis to test parameter stability as additional observations are added. Frank and Schliffke acknowledge that each cartel matter must be investigated individually so that events occurring in the post-cartel period should be evaluated as to whether they are related to the cartel, or the result of shocks that may occur even in the non-collusive world. In the latter case, there is an argument to include them in the competitive benchmark.

E. Quantitative methods in antitrust

The academic literature also provides some insight into the technical and theoretical issues with modeling cartel overcharges. Connor (2008) supports the usefulness of simpler methods than econometrics to obtain reasonable estimates of cartel overcharge damages.

> "Yet, antitrust authorities are typically reluctant to calculate fines on the basis of damages because of perceived analytical challenges or because the fact-finders lack needed economic education. However, reasonable estimates of damages can often be quickly prepared using simpler methods than econometric modeling. More often than not, alternative estimates of cartel overcharges tend to be mutually supportive. The reluctance of antitrust authorities to base fines on damages seems to indicate an abundance of caution."

However, other researchers raise issues with both simple and more complex econometric approaches. The approaches that provide the most "reasonable" results under the circumstances may vary across many factors including the characteristics of the product or service at issue, data availability, geographic area, time period, and the degree of publicly-available information on the cartel participants and alleged misconduct.

Contrary to Dr. Connor's claim of reasonable estimates of damages based on simpler methods, one can clearly see the extent of variability in overcharge estimates based on various commonly-used approaches and assumptions. Assumptions inherent in the "simpler" approaches may yield consistent results with econometric approaches if the underlying assumptions hold constant, such as stability of the economic forces in the product/service market across time. If factors vary in non-trivial ways between cartel and non-cartel periods, so that the assumption of stability does not hold, then simple methods, such as comparisons of average prices, may give very different results from econometric approaches that control for more of the factors driving prices. The bottom line is that the technical details of the econometric methods do matter. And basing fines on measures of harm developed in unreliable ways raises questions of fairness.

The dummy variable approach and the forecasting approach both have potential challenges in reliable implementation. Rubinfeld (2008) discusses issues with both of these approaches to estimating cartel overcharges. He warns of the need for careful thought in utilizing any particular approach:

> There is, however, an important limiting assumption implicit in the dummy variable approach. That assumption is that the overall behavior of the regression model can be modeled in precisely the same way during both the conspiratorial and non-conspiratorial periods. This may be a reasonable assumption in some cases, but it should not be made without substantial thought. If prices are determined in rather complex ways, the use of a single dummy variable that will reflect mean differences between the benchmark and but-for periods may be too simplistic. In particular, if one or more of the explanatory variables in the model is correlated with the dummy variable, then the dummy variable and forecasting approaches are likely to generate different damage estimates. (Rubinfeld, 2008, p. 740)

With respect to forecasting models, he notes that a model that fits the benchmark period data well may not forecast well into the alleged cartel period. It may even be the case that the model does not fit the benchmark period extremely well. Therefore, not only does he suggest reporting goodness of fit measures for the benchmark period, but that researchers should also include some measure of the forecast reliability, such as standard errors, which may be calculated or simulated.

Nieberding (2006) compares dummy variable and forecasting approaches for estimating overcharges with reduced form models. He also notes that the literature (as of 2006) has largely ignored empirical issues associated with estimation of "unobserved but-for prices." He highlights the usefulness of employing error correction models to deal with typical time-series issues of nonstationary data, as well as short-term and long-term dynamics. Not controlling for these factors may result in spurious results and overstated goodness of fit for models as well as overstated significance levels of parameter estimates.

F. Time Series Tests

In this section, I briefly discuss stationarity, unit root tests and structural break tests. Time series analysis is a broad and extensively researched academic discipline. I only raise some of the considerations this literature has noted and some tests that a researcher examining cartel behavior may wish to consider in modeling approaches. While stationarity and structural break tests are standard in assessing time series models, they have not been used extensively in cartel modeling efforts, which often use data spanning long time periods. The importance of using such tests in such modeling applications is to understand if standard OLS assumptions are met, and thus that parameter estimates and significance tests are reliable, which may not be the case if data series used in the model are non-stationary or include un-modeled structural breaks.

A common test for stationarity employed by researchers is the Augmented Dickey-Fuller (“ADF”) test, which tests the null hypothesis of a unit root. If a unit root cannot be rejected, researchers often move to differencing the data series in the hopes of transforming the data to a stationary series. The differenced data are then checked for stationarity. If the null hypothesis of a unit root is now rejected, then researchers often proceed with their model estimation employing the differenced data. The idea is that with the stationary data series, standard OLS assumptions hold and reliable inferences may be made. However, differencing may remove important low-frequency information and induce other unintended statistical relationships. Thus, simply testing for unit roots and differencing data may create, not solve, reliable estimation considerations. For multiple variable regressions, testing the residual for stationarity may provide a way to proceed to retain such low-frequency information and induced estimation errors, even if individual variables are non-stationary. For example, if the residual is stationary, explanatory variables may be cointegrated even if individually they are non-stationary. Engle-Grainger and Phillips-Ouliaris cointegration tests may be used to test stationarity of the residual for regressions with multiple regressors.

Perron (2006) provides insight on the sometimes close relationship between structural breaks and unit roots. Understanding the nature of the issue of concern –

stationarity or structural breaks -- may be important in proper specification of models. Simply running a stationarity test may miss other factors driving movements in the data.

> A central message of the work by Perron (1989, 1990) is that, when the true process involves structural changes in the trend function, the power of such unit root tests can dramatically be reduced.
> It has also been documented that the presence of structural breaks in trend affects tests of the null hypothesis of stationarity (e.g., the Q or KPSS test) by inducing size distortions towards rejecting the null hypothesis too often (e.g., Lee et al.,1997). This is consistent with the effect on unit root tests in the sense that when trying to distinguish the two hypotheses, the presence of structural changes induces a bias in favor of the unit root representation. (Perron, 2006, pp. 51 -52)

Perron's work implies that adjusting a model's specification in response to unit root test results (e.g. first differencing) potentially may miss underlying structural break issues, and nevertheless does not address parameter or model stability issues. That is, identifying stationarity of data series and adjusting model specifications in response to this is not the end of the work needed to check that results are reliable.

Tests that can help identify structural breaks, such as Bai-Perron, Chow, Quandt Likelihood ratio or CUSUM/CUSUMSQ tests, may be helpful to provide potential information on the start or end of alleged cartel effects. For example, in the context of suspected cartel activity, a structural break in a product's price series, or breaks in previously stable relationships between prices of an alleged cartelized product and a related product, may result in further examination of the circumstances driving the observed pricing behavior or changes in behavior. A structural break is not, by itself, proof of conspiracy. For example, a structural break in final good prices may be due to a structural break in the price of an important input, not because of any shift in competitive behavior by the firms selling the final product.

Therefore, solely examining the price of a product in an alleged cartel is not sufficient for making a causal connection between the alleged cartel behavior and observed prices. A structural break in an underlying factor input may occur either in a clean period or the alleged cartel period. If such a structural break occurs during the alleged cartel period, then using estimates based on a pre-break period may results in biased estimates for the cartel period. A structural break in the base period may require revisions to the model specification to capture this effect and thus create a stable model and base for forecasting counterfactual cartel-period prices.

G. Recursive Residuals

In this section, I describe the background on the use of recursive residuals in the literature and some applications of this methodology.

The seminal paper on the use of recursive residuals in evaluating regression relationships is by Brown, Durbin and Evans (1975); although Kianifard and Swallow (1996) cite research claiming the origin of recursive residuals is found in Pizzetti (1891). Recursive residual analysis involves calculating standardized one-step-ahead prediction errors. Coefficient vectors and variances are updated as additional observations are added to the regression. (Stokes, 2011). The residuals from one-step-ahead prediction may provide indication of outliers, deviations from residual mean of zero or changing residual variance as observations are added. Thus, recursive residuals may be used in tests of parameter stability, outliers, heteroscedasticity, serial correlation, functional misspecification and model stability.

Kianifard and Swallow (1996) provide a useful formal exposition of recursive residuals. They write:

> The usual linear regression model can be written as $Y = X\beta + \varepsilon$, where Y = (y_i,…,y_n)' is an n x 1 vector of values of the response variable, β = (β_1,…, β_p)' is a *p* x 1 vector of unknown parameters, X = (x_1',… , x_n')' is an *n* x *p* matrix of explanatory variables with rank(X) = *p*, and $\varepsilon = (\varepsilon_1, \dots \varepsilon_n)'$ is a *n* x 1 vector of independent normal random variables with mean zero and (unknown) variance σ^2. $\beta =$ (X'X)$^{-1}$X'Y is the ordinary least squares (OLS) estimator of β.
>
> More formally, recursive residuals can be defined (and obtained) as follows for the regression model with iid normal disturbances ε: Let X_{j-1} denote the (j - 1) x p matrix consisting of the first j - 1 rows (observations) of X. Provided that (j - 1) ≥ p and assuming that ($X_{j-1}' X_{j-1}$) is nonsingular, β can be estimated by $\hat{\beta}$= $(X_{j-1}' X_{j-1})^{-1}$ X_{j-1}' Y_{j-1} where Y_{j-1} denotes the subvector consisting of the first j - 1 elements of Y. Using $\hat{\beta}_{j-1}$, one can "forecast" y_j to be $x_j' \hat{\beta}_{j-1}$.
>
> The forecast error is the difference (y_j - $x_j' \hat{\beta}_{j-1}$) and the variance of this forecast error is $\sigma^2[1 + x_j'(X_{j-1}' X_{j-1})^{-1} x_j]$.
>
> The recursive residuals are then defined as by Brown, Durbin, and Evans (1975):
>
> $$w_j = \frac{(y_j - x_j' \widehat{\beta}_{j-1})}{[1 + x_j'(X_{j-1}' X_{j-1}) - 1 x_j]^{.5}} \text{ for j = p+1,…,n.}$$

Thus, the recursive residual w_j is the scaled difference between the actual y_j and the predicted y_j based on the prior set of X and B. Recursive residuals analysis can test basic assumptions underlying OLS regressions, by testing both coefficient stability and behavior of the residuals as observations are added.

A useful feature of recursive residuals analysis of model stability is that it does not require any assumptions on the timing of shifts in underlying data to provide insight on stability. (Stokes, 2011; Greene, 2003). If the underlying factors/populations are stable, then the recursive residuals will not be systematically biased as additional observations are added to the regression. Recursive residuals are also homoscedastic because they are standardized and they are independent, as they are calculated from observations not including their own observation. Kennedy (2001).

Dufour (1982) delves into issues related to the instability of econometric relationships over time and that the importance of parameter stability in forecasting and policy simulations. He discusses the many ways that underlying instabilities may appear in modeling – generally as some sort of misspecification error, but also structural changes. He emphasizes the importance of “detecting and assessing parameter instability in linear regression models.” He states, “However, in the routine assessment of econometric models, there is a need for exploratory procedures aimed at being sensitive to a wide variety of instability patterns and capable of yielding information on the type and timing of structural change.” To this end, he suggests the use of recursive residuals analysis. He notes regarding recursive residuals “Under the conditions of the classical linear regression model and, in particular, if the regression coefficients are stable over time (or no specification error if present), these constitute a set of residuals with mean zero and scalar covariance matrix, similar in this respect to the BLUS residuals.” Recursive residuals also can provide graphical evidence of structural changes as well as provide significance tests.

Stokes (2011) provides examples of parameter and prediction stability tests with the cumulative sum ("CUSUM") and cumulative sum of squares ("CUSUMSQ") tests. Stokes discusses the Brown, Durbin and Evans (1975) proposal of the CUSUM test as a measure of parameter stability. The test consists of plotting the quantity

$$\Gamma_i = \sum_{j=K+1}^{i} w_j / \hat{\sigma}.$$

Stokes (2011) reports that the CUSUM test is particularly good at "detecting systematic departure of the β_i coefficients that results in a systematic sign on the first step ahead forecast error and that the CUSUMSQ test is useful when the departure of the β_i coefficients from constancy is haphazard rather than systematic but that there involves a systematic change in the accuracy of the estimated equation as observations are added." The CUSUMSQ test involves a plot of Γ_i^* defined as

$$\Gamma_i^* = \sum_{j=K+1}^{i} w_j^2 \quad / \quad \sum_{j=K+1}^{T} w_j^2.$$

Stokes (2011) further reports bounds estimates for Γ_i and Γ_i^* that are given in Brown, Durbin and Evans (1975). Stokes (2011) explains:

> Assuming a rectangular plot, the upper-right-hand value is 1.0 and the lower-left-hand value is 0.0. A regression with stable coefficients β_i will generate a Γ_i^* plot up the diagonal. If the plot lies above the diagonal, the implication is that the regression is tracking poorly in the early subsample in comparison with the total sample. A plot below the diagonal suggests the reverse, namely, that the regression is tracking better in the early subsample than in the complete sample.

With the plots of CUSUM and CUSUMSQ estimates and bounds generated by statistical models, such as SAS, situations in which the CUSUM or CUSUMSQ go beyond the 95% confidence bounds allow easy assessment of consistency with standard OLS regression assumptions along the various dimensions previously described. That is, in situation in which the CUSUM or CUSUMSQ estimates cross outside of the 95% confidence intervals, then the null hypothesis of stable parameters is rejected.

Several researchers have discussed the various useful applications of recursive residuals. Dufour (1982) reports applications including heteroscedasticity tests (Harvey and Phillips, 1974), serial correlation tests (Phillips and Harvey, 1974) and misspecification tests (Harvey and Collier, 1997). Belsley, Kuh and Welsch (1980) make the case for using recursive residuals to identify outliers. Godolphin (2009) reviews the use of recursive residuals as diagnostic tools for numerous econometric modeling issues. His extensive survey lists, for example, uses of recursive residuals for basic diagnostics in full rank datasets (Galpin and Hawkins, 1984) and for “studying influence and leverage” (Kianifard and Swallow, 1996). De Luna and Johanssen (2001) employ recursive residuals to aid in detecting endogeneity of variables, using sorting and graphs of the CUSUM of the recursive residuals. Perron (2006) discusses the local and global power of CUSUM and CUSUMSQ tests with the latter showing good global characteristics compared to other tests.

III. METHODS

The proposed time series and stability tests are intended to apply to any cartel model in which overcharges are being estimated. The industry examined in this thesis, fractional horsepower motors, is chosen solely for demonstrating the proposed methodology and has not, to my knowledge, been the object of cartel investigations. The shifts and trends in the data, however, with a stable period and then abrupt price increases, may be consistent with pricing patters found in alleged cartels. Such patterns may also be consistent with competitive outcomes and increases in underlying cost drivers. In either case, it provides a useful case study for testing cartel overcharge methodologies and assessing potential findings of harm, even when no evidence of actual cartel activity has been alleged in this specific industry.

A. Design

I create a hypothetical cartel scenario using data on the fractional horsepower motors industry. These motors are typically small, less than one horsepower (i.e. "fractional") and, according to a website dedicated to such motors, www.fractionalhorsepowermotors.com, they are used in many automotive applications and small appliances. An allegation of cartel activity may be based on observed common price increases, for example. However, common price increases may also be the result of common cost shocks. For products such as motors with substantial copper and steel inputs, common price increases may be the result of input cost shocks. Steel and copper are inputs that are used in numerous industries, and hence these input costs are not affected significantly by demand changes in the industry of interest here, fractional horsepower motors. That is, the input cost may be modeled as exogenous to the dynamics of any particular market, even one which experiences price fixing. [2] From visual inspection of the fractional horsepower motor PPI, a potential cartel period to examine is 2004 and continue through the end of the data in 2016. (See the Appendix for variable descriptions, source and plots).

For such a hypothesized cartel, a key issue in estimating the overcharge would be whether the proposed model can reliably estimate the effect of the cartel separately from other factors that may also drive price changes during the cartel period. If the underlying relationships are stable, then a well-specified model may more reliably capture the cartel effect. If the underlying relationships are not stable, then reliable predictions of the cartel effect may be more difficult to estimate.

Based on understanding of the industry dynamics and observed data trends, I hypothesize that “clean period” or “base” samples from the relatively stable price period will result in estimates that understate the prediction error in the cartel period. I also hypothesize that an unadjusted model based on this base period will fail stability tests based on recursive residual CUSUM and CUSUMSQ tests.

The basic model specification is as follows. The dependent variable is the Producer Price Index for fractional horsepower motors. This is expressed as a function

[2] As has been publicly reported, several U.S. steel manufacturers are alleged to have agreed to reduce output and thus to raise the price of various types of steel sold as inputs to manufacturers in the U.S. This would be viewed as an exogenous shock or structural change to an important input to some domestic products, such as household electronic appliances, automobiles, small motors.

of input costs (the LME copper closing cash price, and iron and steel PPI), and a demand factor, personal consumption expenditures on consumer durables.[3]

I then run an autoregressive model, using recursive residuals as a potential screen for cartel beginnings or ends, over the period January 1992 to the end of 2016. In the context of a cartel investigation, potential dates of cartel activity may be known, or suspected. Recursive residuals may provide some valuable insight into these dates. Bai-Perron structural break tests are also run.

The cartel period is assumed to begin January 2004. I test the model's predictions and stability in the base period sample and examine the confidence intervals around the estimates. SAS output shows the requested 95% confidence intervals around the dependent variable estimates for both the base period and the cartel period. This provides information on how well the model fit the base period and some measure of uncertainty about the predicted prices. I also examine the CUSUM and CUSUMSQ plots based on the recursive residuals for the base period regressions to assess model stability within the base period. If the model is unstable within the sample, it is hard to support reliability of the model outside the sample period.

For the next step, I replace the actual prices with the predicted prices for the full model and test model stability. This is, I believe, is an innovative approach to directly testing the point estimates that researchers may develop as the best estimate of the counterfactual world. Often, the testing stops with the base period model and the estimated cartel period prices are assumed as a reliable basis for overcharge damages.

[3] A general manufacturing PPI was also included by was highly correlated with steel and copper input costs and thus excluded from the reported specifications.

This dataset now reflects the model's "best" estimates for base period and counterfactual world prices, all else constant.

I re-estimate the model, assuming this is the world as it had happened and assess goodness of fit and model stability with the recursive residuals. Again, the CUSUM and CUSUMSQ tests are run using the recursive residuals to assess model stability.

Finally, I run the full-period model on the original data, including a cartel period dummy variable. This specification would include the volatile period of steel and copper costs as well as the recessionary period. I compare the damage estimates based on the prediction model and the cartel dummy variable model.

B. Data and Specification

To illustrate the methodology, I use publicly-available price, cost and production indices. Following Hüschelrath *et al* (2013a)'s use of publicly-available indices, I use a producer price index ("PPI") for electric motors as the dependent variable, and estimate a model based on indices for input costs and demand factors. These indices include the LME spot price for copper, a PPI for iron and steel, and a consumer durables spending metric. Plots of the data series used are included in the Appendix. Copper and steel account for an estimated 50% or more of the material costs of an electric motor. (See, for example, Sahni *et al*, 2009)

IV. RESULTS

A. Full Model Regression

I use SAS PROC AUTOREG as it has the functionality to run recursive residuals and output CUSUM and CUSUMSQ tests, among other useful test statistics. I run an autoregressive model with 3 lags, with SAS choosing which to include in the model estimation. Parameter estimates are listed below.

TABLE I

FULL REGRESSION MODEL PARAMETER ESTIMATES

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	5.0169	0.4177	12.01	<.0001
log_lme_cu	1	0.000124	0.004460	0.03	0.9778
log_iron_steel	1	0.0297	0.0134	2.21	0.0278
log_cdur_spend	1	-0.0205	0.0122	-1.68	0.0948
AR1	1	-1.1676	0.0370	-31.59	<.0001
AR3	1	0.1681	0.0374	4.49	<.0001

The signs are in the expected directions, with spending on consumer durables, representing derived demand for products containing small motors, decreasing with increases in the cost of motors. The cost of fractional horsepower motors increase as input costs of copper and iron and steel increase.

B. Stationarity and Structural Breaks

When checking for stationarity with more than one regressor, SAS uses the Engle-Granger Cointegration test with the ADF stationarity option to evaluate the null hypothesis of no cointegration (i.e. a unit root). The results reported in Table II indicate the null hypothesis cannot be rejected.

TABLE II

FULL REGRESSION MODEL ENGLE-GRANGER COINTEGRATION TEST

Engle-Granger Cointegration Test			
Type	Lags	Tau	Pr < Tau
Single Mean	0	-0.4125	0.9750
Trend	0	-3.6628	0.2769

Instead of simply differencing the data, I check for the existence of structural breaks in the data. Table III below reports the results of the Bai-Perron test for multiple structural breaks, which indicates rejection of no structural breaks and indeed finds evidence for five structural breaks, with trimming of 15% at both the beginning and end of the sample.

TABLE III

FULL MODEL BAI AND PERRON MULTIPLE STRUCTURAL BREAK TESTS

Bai and Perron's Multiple Structural Change Tests			
WDmaxF Tests			
Number of Breaks	Alpha	WDmaxF	Pr > WDmaxF
5	0.1000	22623.148	<.0001
	0.0500	23951.683	<.0001
	0.0250	25124.0013	<.0001
	0.0100	26591.8954	<.0001

Bai and Perron's Multiple Structural Change Tests			
supF(l+1|l) Tests			
l	New Break	supF(l+1|l)	Pr > supF(l+1|l)
0	201	3999.86953	<.0001
1	145	11888.0319	<.0001
2	228	1434.41616	<.0001
3	228	1434.41616	<.0001
4	228	1172.80017	<.0001
5	130	1134.91994	<.0001

C. Full Model Stability

As a screen for the following cartel estimation, I run the recursive residuals test on the full time period. Figure 2 shows a scatter plot of the recursive residuals. Figure 3 and Figure 4 show the CUSUM and CUSUMSQ results respectively, indicating a failure to have a stable model over the entire period.

I use the observed pricing changes and the results of the CUSUM and CUSUMSQ tests to identify two hypothetical cartel regimes, as shift in underlying model parameter estimates may indicate a change in economic behavior. First, I examine a hypothetical cartel period based on the 2010 point when the CUSUM statistic exceeds the 95% confidence interval. Here I assume the cartel existed until that point and then fell apart, perhaps due to the impact of the Great Recession. In the second hypothetical, I use the upward shift in both pricing and the recursive residuals in 2004 as a hypothetical start of cartel activity.

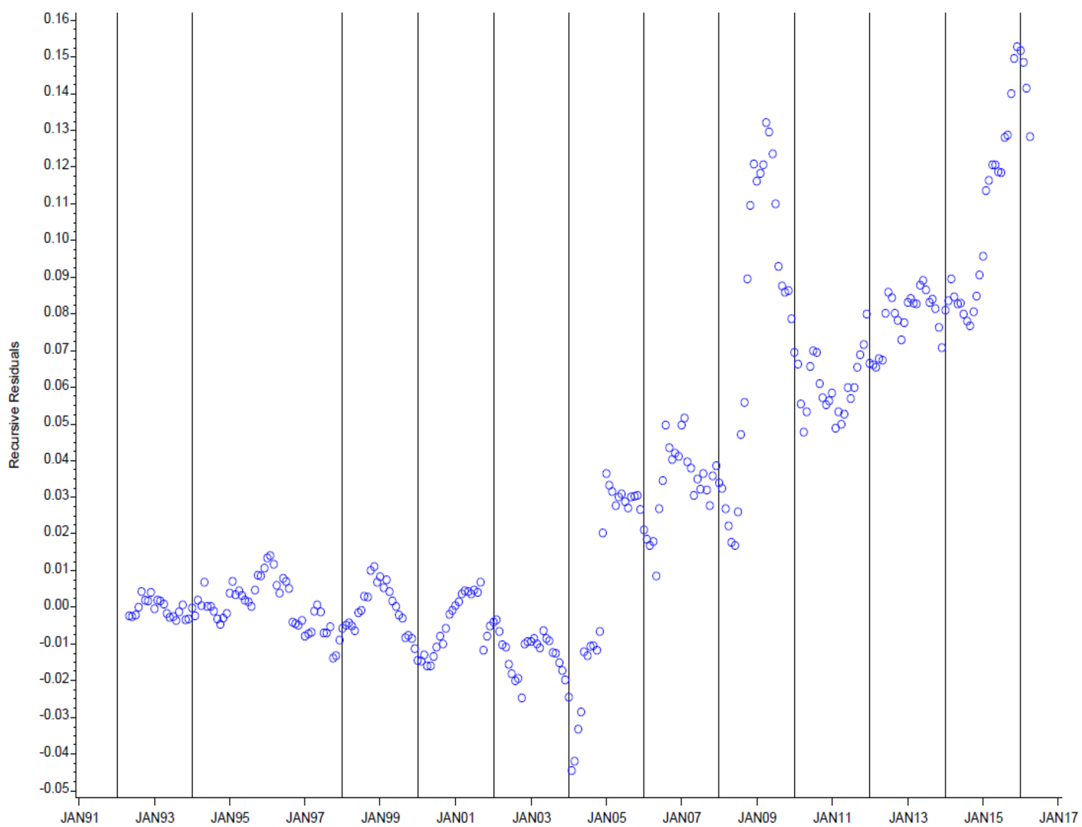

Figure 2. Scatter plot of recursive residuals for 1992 – 2016.

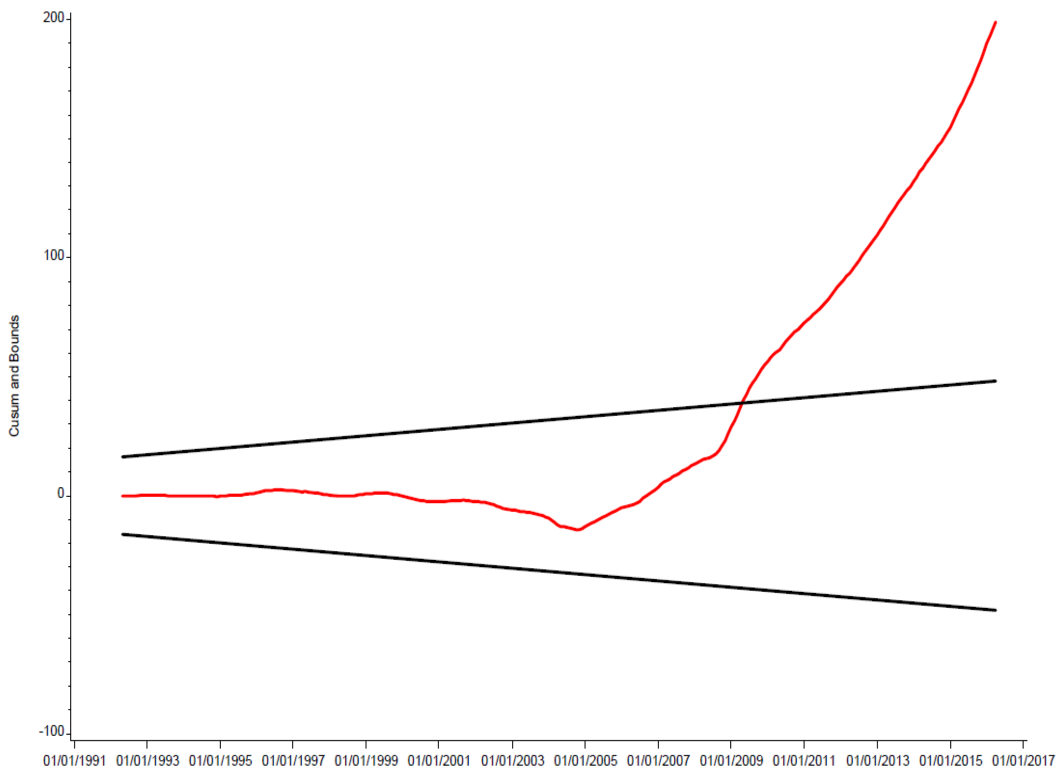

Figure 3. CUSUM and Bounds from Recursive Residuals for Full Model 1992 – 2016.

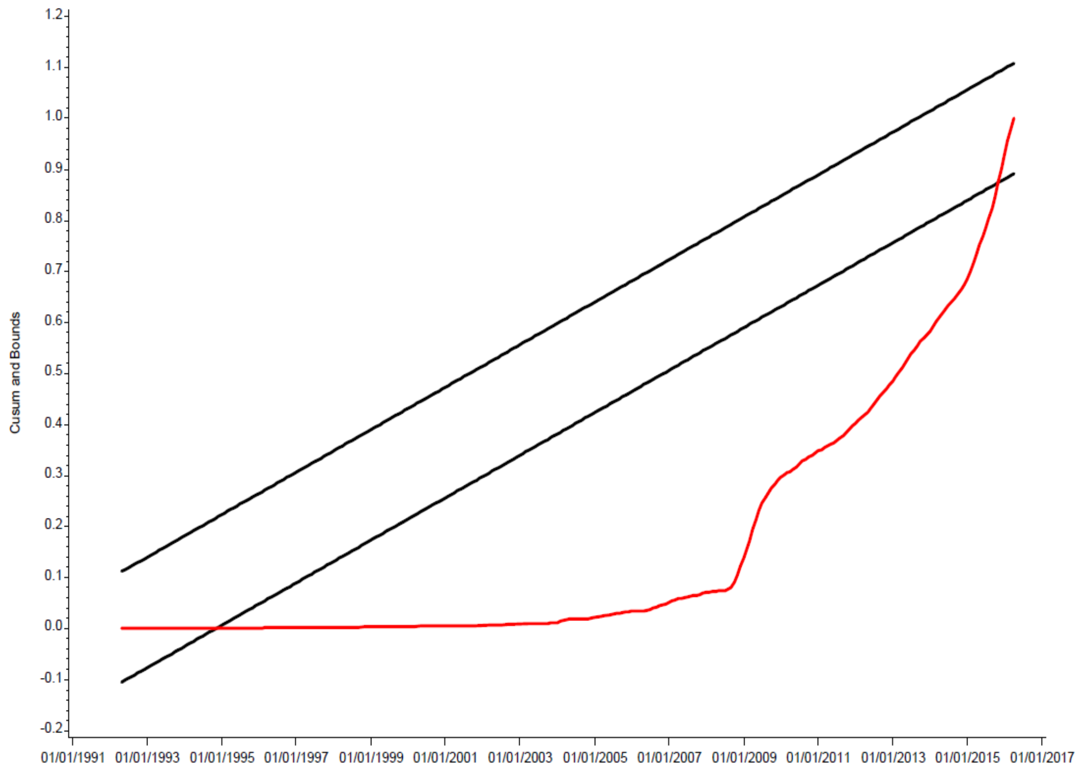

Figure 4. CUSUMSQ and Bounds from Recursive Residuals for Full Model 1992 – 2016.

D. <u>Base Period Estimations:</u>

<u>D1. Assuming Cartel Period 1992 – 2010, Base Period 2011 - 2016</u>

For this base period model, I assume the cartel ended with the 2010 point where the full-period CUSUM exceeded the 95% confidence interval, indicating unstable parameters. Table IV reports the Engle-Granger cointegration test results which reject the null hypothesis of no cointegration. Table V reports the parameter estimates for the base model. I find that the model does not fail either of the CUSUM and CUSUMSQ tests for model stability. Figure 5 and Figure 6 present the CUSUM and CUSUMSQ plots and confidence bounds. Figure 7 shows the model fit for the base period estimation and Figure 8 shows the SAS-generated prediction of the cartel period (1992 – 2010) based on this base period estimation. These tables and figures provide some evidence to support a reasonable base period estimation from which to predict cartel period overcharges, in that at least the base period parameters are stable and cointegration tests reject non-stationarity.

TABLE IV

BASE PERIOD 2011-2016 ENGLE-GRANGER COINTEGRATION TEST

Engle-Granger Cointegration Test			
Type	Lags	Tau	Pr < Tau
Single Mean	0	-5.0007	<.0010
Trend	0	-4.4567	0.0473

TABLE V

BASE PERIOD 2011-2016 REGRESSION PARAMETER ESTIMATES

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	3.8237	0.3778	10.12	<.0001
log_lme_cu	1	-0.0233	0.0121	-1.93	0.0588
log_iron_steel	1	0.0515	0.0225	2.29	0.0257
log_cdur_spend	1	0.1832	0.0392	4.68	<.0001
AR1	1	-0.7101	0.1062	-6.69	<.0001

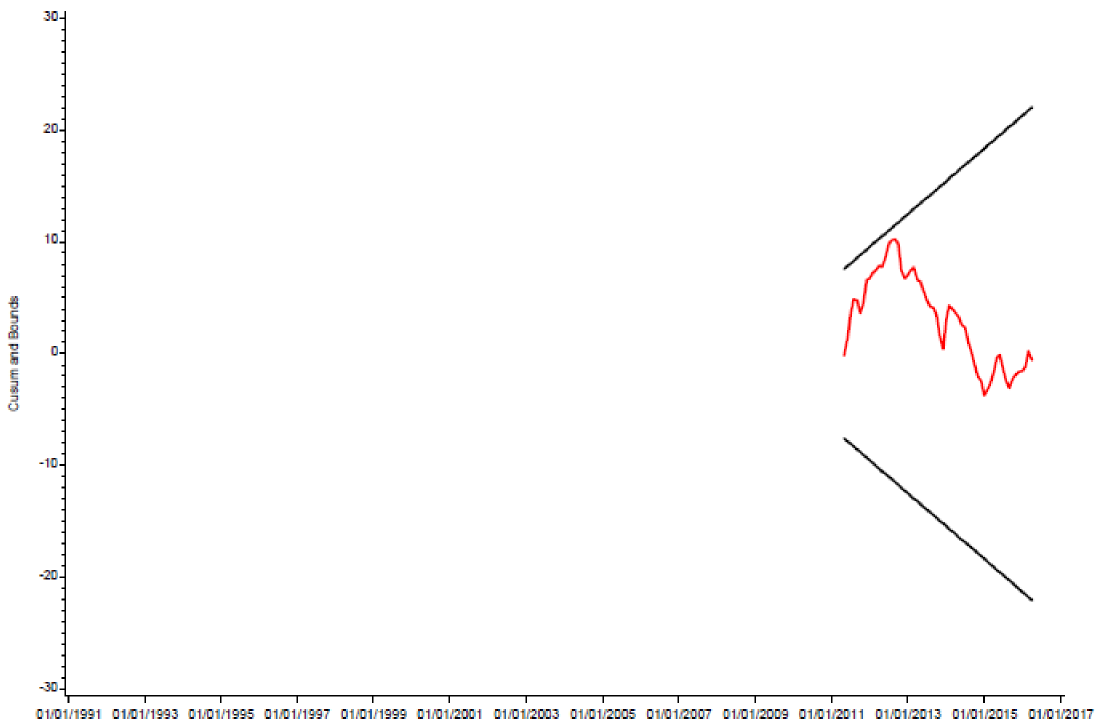

Figure 5. CUSUM and Bounds for Base Period Model 2011 – 2016.

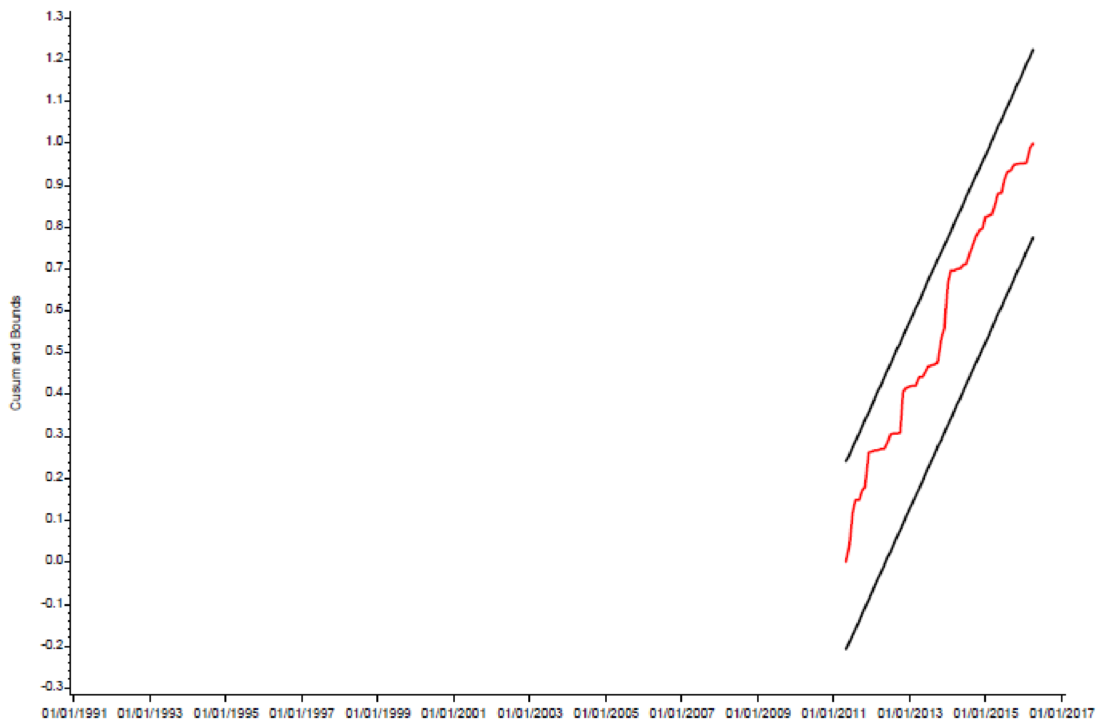

Figure 6. CUSUMSQ and Bounds for Base Period Model 2011 – 2016.

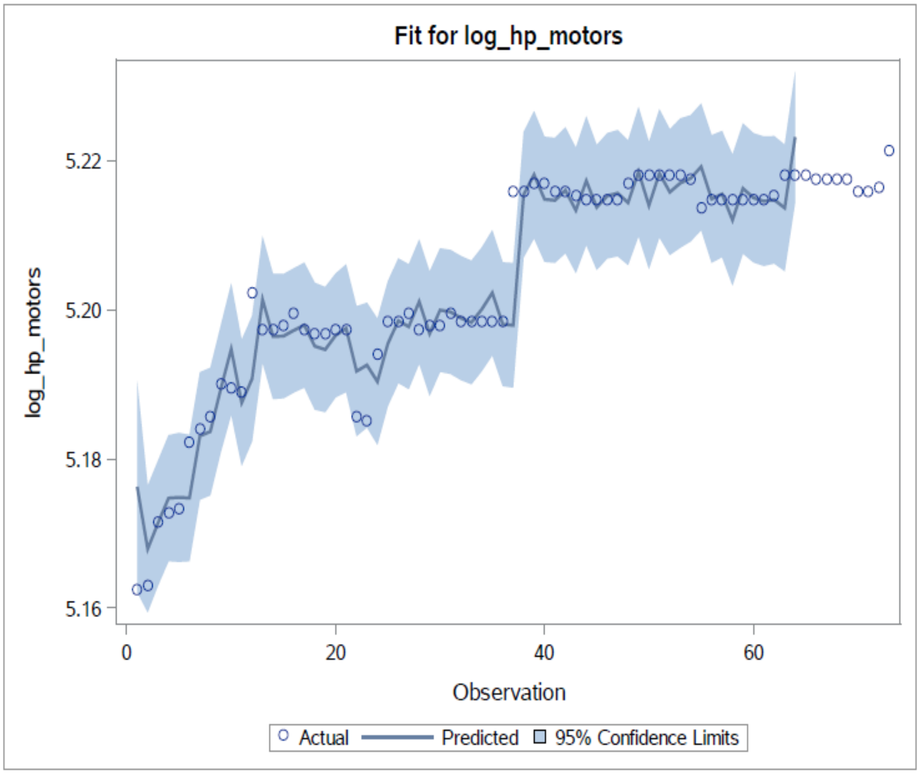

Figure 7. Model fit for base period model estimation 2011 – 2016.

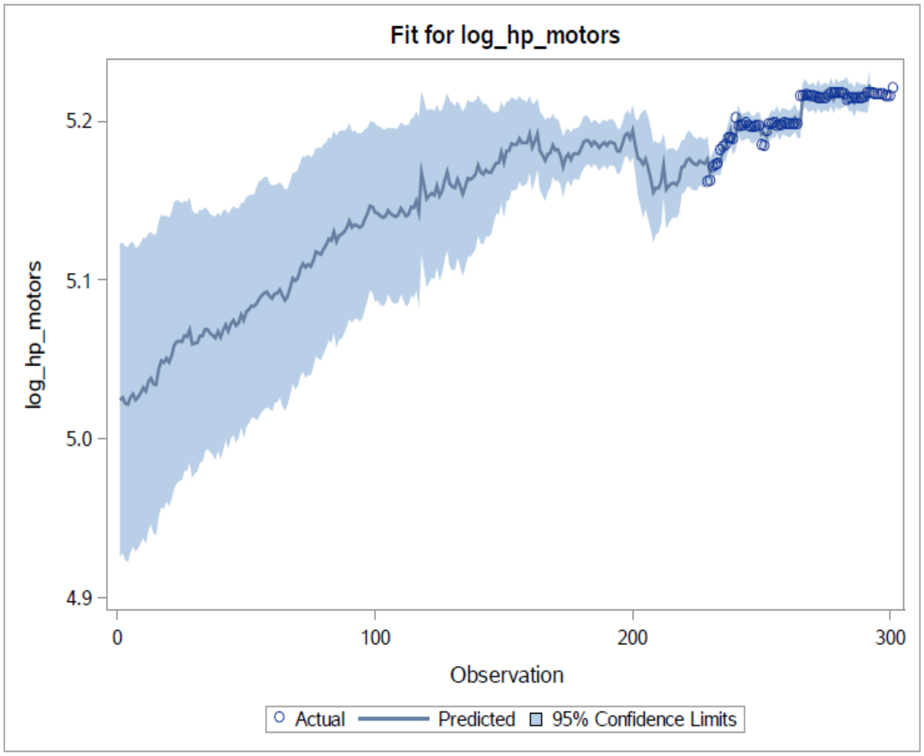

Figure 8. Prediction of 1992-2010 from base period estimation 2011 – 2016.

D2: Assuming Cartel Period 2004 – 2016, Base Period 1992 – 2003

For this base period model, I assume the cartel began in 2004, following observed pricing increases and recursive residual increases, indicating a possible shift underlying economic behavior. Table VI reports the Engle-Granger Cointegration test fails to reject no cointegration for this base period. Table VII reports the parameter estimates for the base model. Figure 9 shows the prediction and 95% confidence intervals for the time period estimated (1992 - 2003), while Figure 10 shows the SAS-generated prediction of the cartel period (2004 - 2016) based on this base period estimation. I find that the model fails both the CUSUM and CUSUMQ tests for model stability. Figures 11 and 12 present the CUSUM and CUSUMSQ plots and confidence bounds. This would not present a reliable base from which to estimate cartel overcharges, given the model is unstable even in the base period.

TABLE VI

BASE PERIOD 1992-2003 ENGLE-GRANGER COINTEGRATION TEST

Engle-Granger Cointegration Test			
Type	Lags	Tau	Pr < Tau
Single Mean	0	-2.1222	0.6884
Trend	0	-3.5171	0.3298

TABLE VII

BASE PERIOD 1992-2003 REGRESSION PARAMETER ESTIMATES

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	4.9140	0.1704	28.84	<.0001
log_lme_cu	1	0.004673	0.004787	0.98	0.3307
log_iron_steel	1	0.0193	0.0297	0.65	0.5167
log_cdur_spend	1	-0.0253	0.0113	-2.24	0.0264
AR1	1	-0.9929	0.009114	-108.94	<.0001

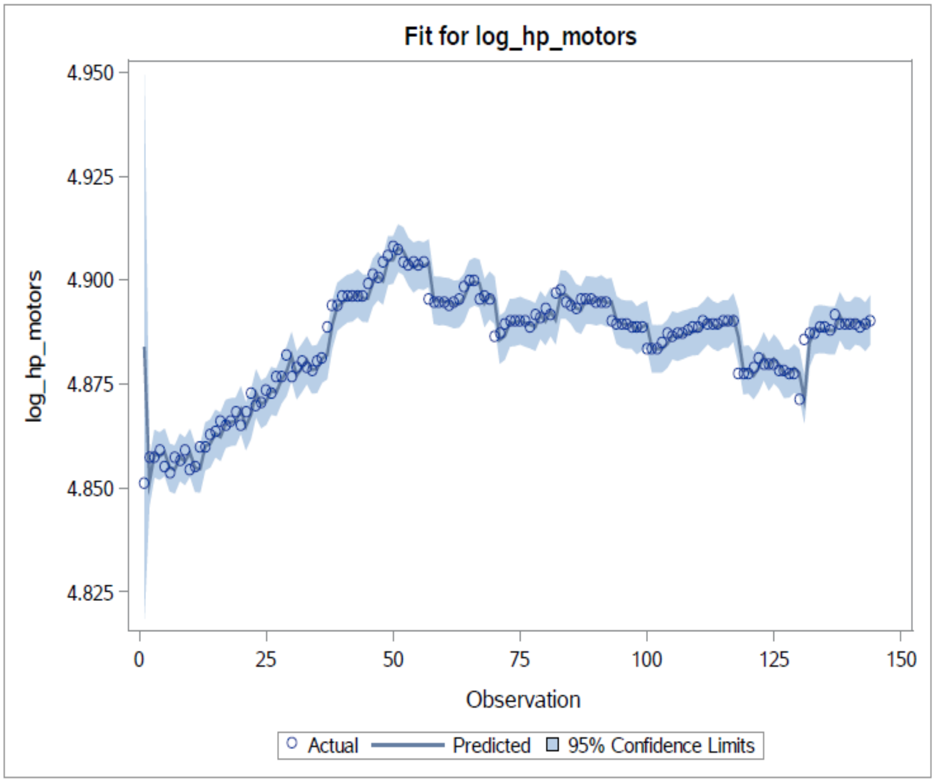

Figure 9. Model fit for base period model estimation 1992-2003.

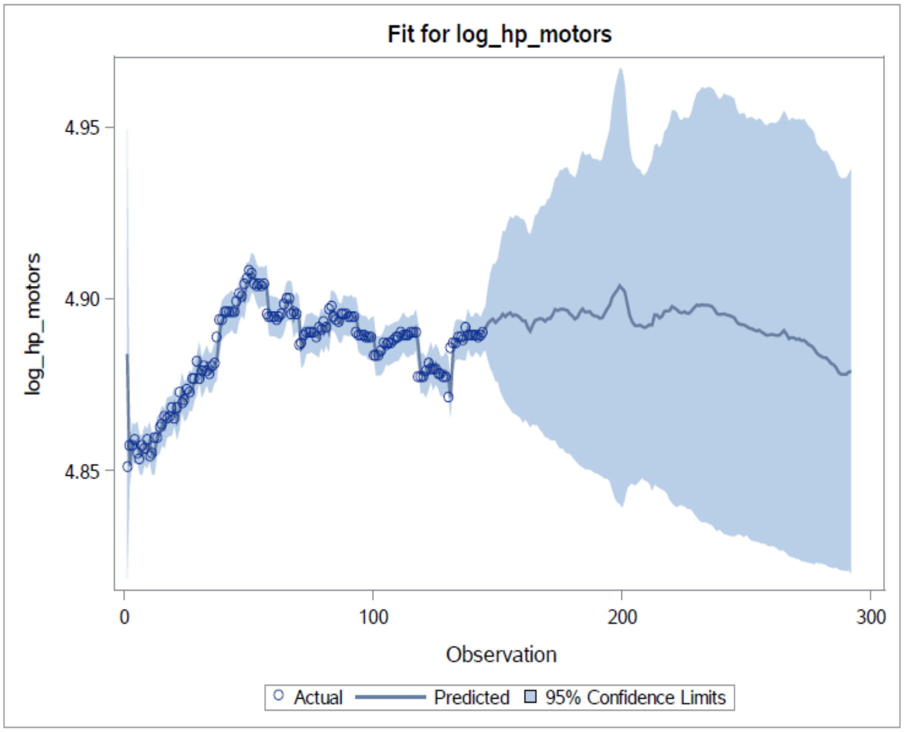

Figure 10. Prediction of 2004-2016 from base period estimation 1992-2003.

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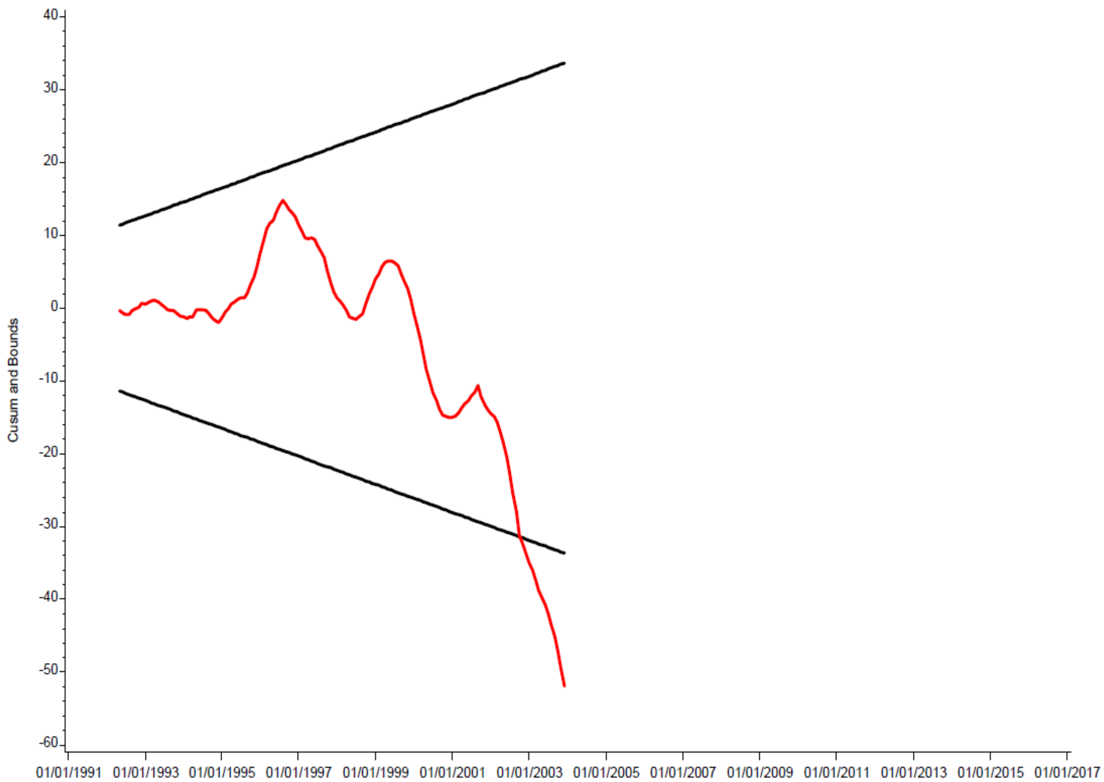

Figure 11. CUSUM and Bounds for Base Period Model 1992-2003.

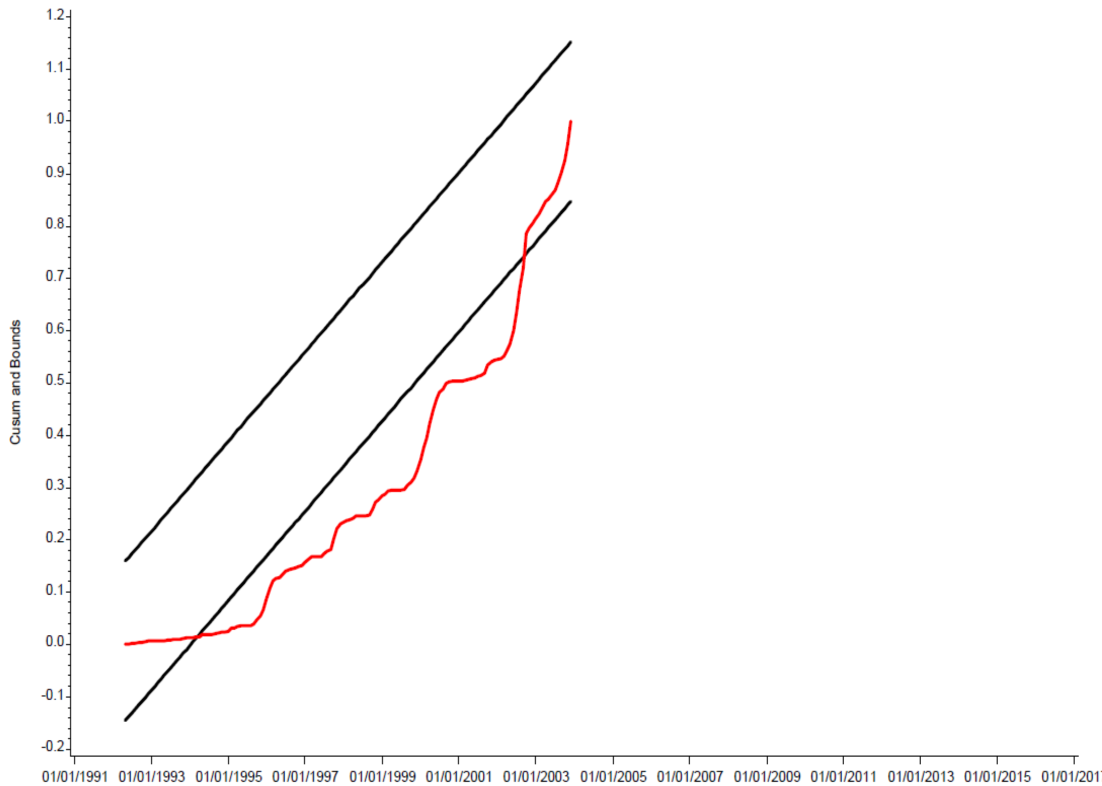

Figure 12. CUSUMSQ and Bounds for Base Period Model 1992-2003.

E. Full Period "Counterfactual World" Model

For this step, I replace the actual prices with the predicted "counterfactual world" prices, for both the base and hypothetical cartel period, based on coefficients estimated from the base period. This dataset now reflects the model's "best" estimates of the base period and hypothetical counterfactual world pricing, holding all else constant. A critical question is whether this alternative, constructed world is consistent, meets basic econometric assumptions for stability, and serves as a reliable benchmark from which to measure overcharges. Applying recursive residuals tests to this newly constructed dataset provides a means of directly testing these propositions.

All fail the CUSUM and CUSUMSQ tests. Figure 13 and Figure 14 present the CUSUM and CUSUMSQ plots and bounds for the hypothetical cartel period running 1992 – 2010 and Figure 15 and Figure 16 present the same plots, for the hypothetical cartel period running 2004 – 2016.

The charts show instability in the relationships between price and the explanatory variables. Therefore, in any rigorous estimation of cartel overcharges, this exercise highlights the importance of testing for and dealing with uncertainty in the predictions based on in-sample data, testing the implied 'best' estimates for consistency and stability, and testing alternative specifications for robustness.

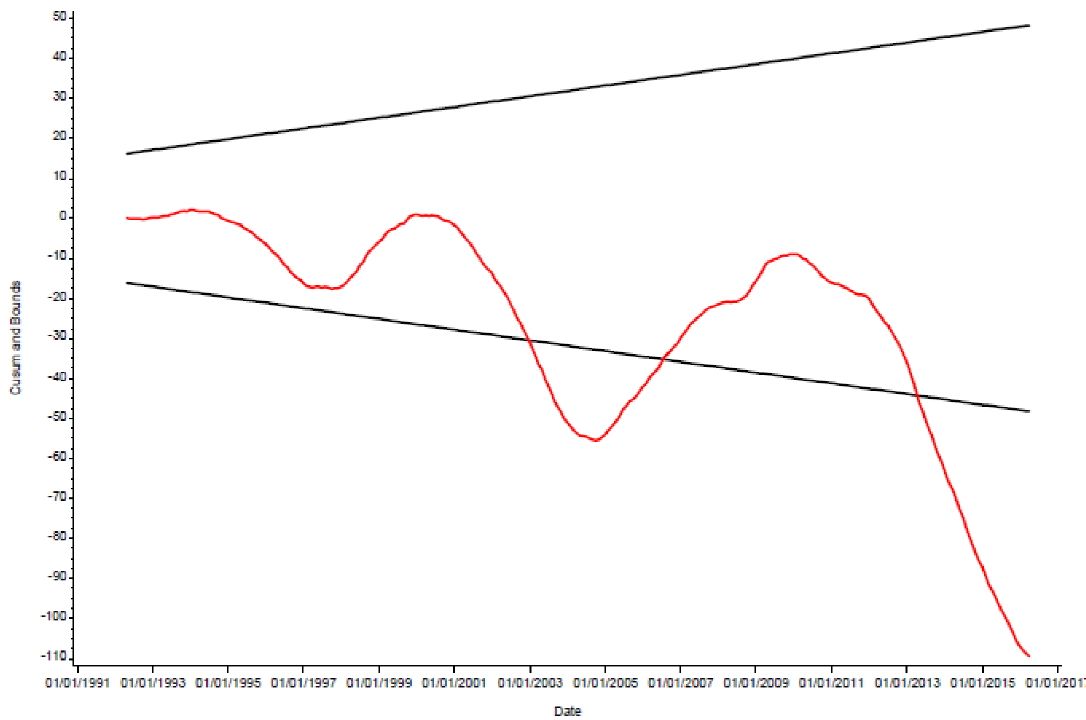

Figure 13. CUSUM and bounds for full model based on 2011–2016 base period.

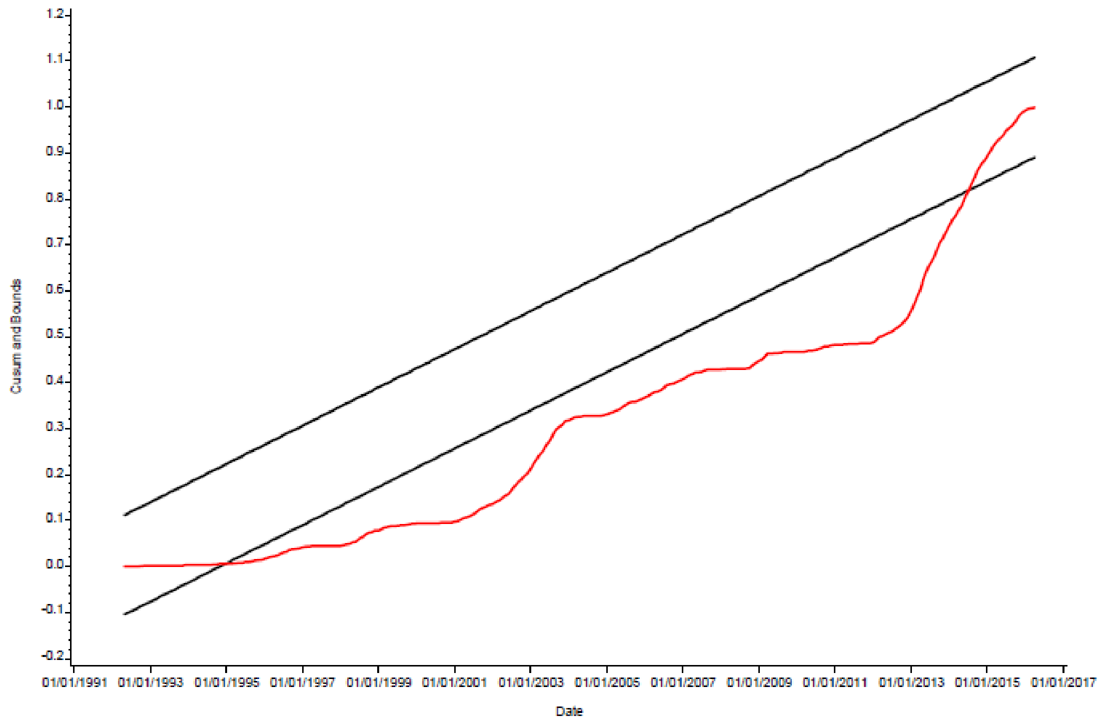

Figure 14. CUSUMSQ and bounds for full model based on 2011–2016 base period.

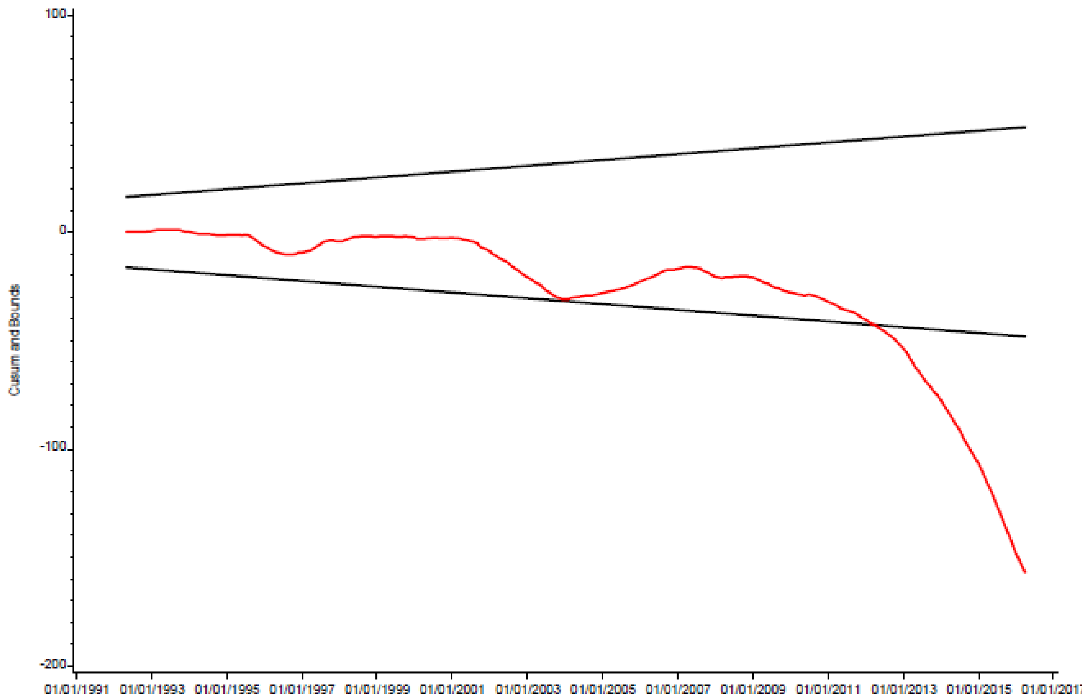

Figure 15. CUSUM and bounds for full model based on 1992-2003 base period.

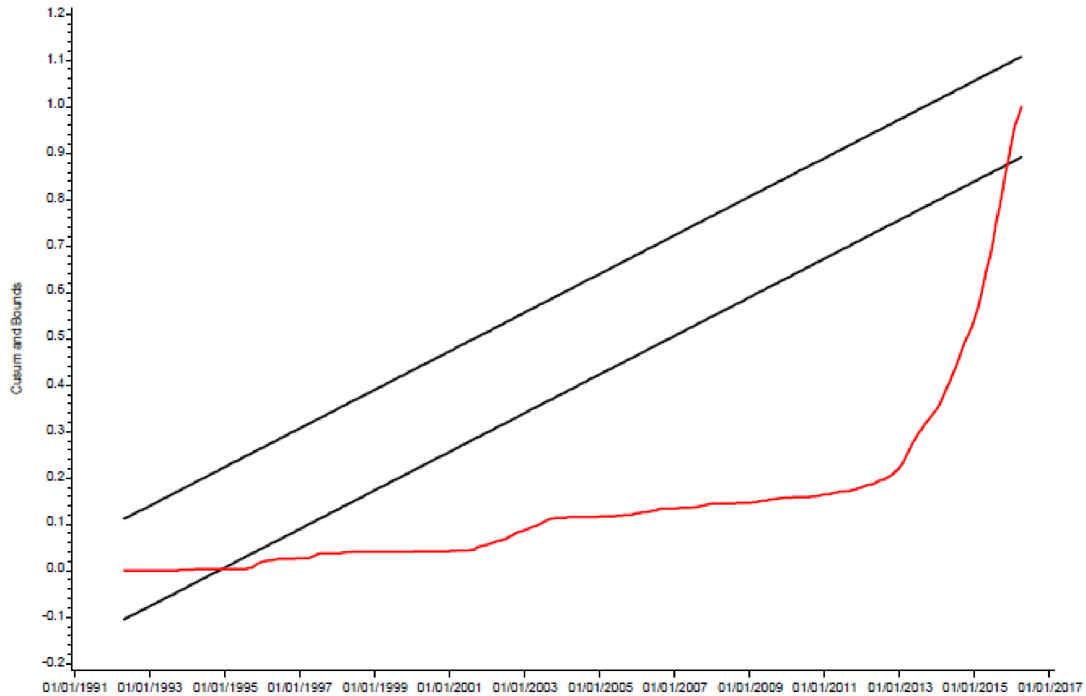

Figure 16. CUSUMSQ and bounds for full model based on 1992-2003 base period.

F. Dummy Variable Approach

Another approach oven employed by researchers in calculating cartel overcharges is known as the dummy variable approach. In this section, I report results from running the same full period specifications with the addition of a cartel dummy variable that is 0 except for the cartel period, in which it is set to 1. I compare the OLS regression results with the cartel dummy, to the results of the autoregressive model with the cartel dummy to show the importance of controlling for serial correlation.

First, I examine the results for the hypothetical cartel running from 1992 – 2010. Table VIII report the results of the OLS regression. It shows a high R-square, of .92 and shows a negative and significant cartel effect of -13.4 percentage points (after exponentiating the coefficient estimate). That is, I find that the cartel period was about 13 percentage points *lower* on average during the assumed cartel period than the non-cartel period, all else constant. Table IX reports the results for the autoregressive model with the cartel dummy variable. Here, the dummy variable is again negative and significant; however it shows a lower cartel period price differential of 1.2 percentage points on average compared to the non-cartel period, all else constant.

TABLE VIII
OLS DUMMY VARIABLE REGRESSION: HYPOTHETICAL CARTEL 1992-2010

Number of Observations Read	301
Number of Observations Used	292
Number of Observations with Missing Values	9

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	4.79795	1.19949	921.51	<.0001
Error	287	0.37357	0.00130		
Corrected Total	291	5.17152			

Root MSE	0.03608	R-Square	0.9278
Dependent Mean	4.99758	Adj R-Sq	0.9268
Coeff Var	0.72192		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	3.50807	0.06657	52.70	<.0001
log_lme_cu	1	0.05439	0.01132	4.81	<.0001
log_iron_steel	1	0.13786	0.02705	5.10	<.0001
log_cdur_spend	1	0.06538	0.01161	5.63	<.0001
conspire_1992_2010	1	-0.12573	0.00665	-18.90	<.0001

TABLE IX
AUTOREGRESSIVE DUMMY VARIABLE MODEL: HYPOTHETICAL CARTEL 1992 – 2010

Maximum Likelihood Estimates			
SSE	0.00559523	DFE	284
MSE	0.0000197	Root MSE	0.00444
SBC	-2290.3053	AIC	-2319.7193
MAE	0.00256152	AICC	-2319.2105
MAPE	0.05124346	HQC	-2307.9372
Log Likelihood	1167.85966	Transformed Regression R-Square	0.0572
Durbin-Watson	1.6898	Total R-Square	0.9989
		Observations	292

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	5.0823	0.4863	10.45	<.0001
log_lme_cu	1	-0.000232	0.004718	-0.05	0.9608
log_iron_steel	1	0.0291	0.0141	2.06	0.0400
log_totmanuf	1	-0.005974	0.0380	-0.16	0.8751
log_cdur_spend	1	-0.0236	0.0119	-1.98	0.0489
conspire_1992_2010	1	-0.0121	0.004357	-2.79	0.0057
AR1	1	-1.2610	0.0589	-21.40	<.0001
AR2	1	0.2614	0.0593	4.41	<.0001

Next I examine the results for the hypothetical cartel running from 2004 - 2016. Table X reports the results of the OLS regression. It shows a high R-square, of .84 and shows a negative and significant cartel effect of -6.8 percentage points (after exponentiating the coefficient estimate). That is, I find that the cartel period was about 7 percentage points *lower* on average during the assumed cartel period than the non-cartel period, all else constant. Table XI reports the results for the autoregressive model with the cartel dummy variable. Here, the dummy variable is weakly positive, and not significant. That is, it cannot be distinguished statistically from a zero difference between the cartel and non-cartel periods, all else constant.

The next section will put the various approaches and estimates in direct comparison to better draw conclusions on the cartel modeling exercises shown here.

TABLE X
OLS DUMMY VARIABLE REGRESSION: HYPOTHETICAL CARTEL 2004-2012

Number of Observations Read	301
Number of Observations Used	292
Number of Observations with Missing Values	9

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	4.36861	1.09215	390.39	<.0001
Error	287	0.80291	0.00280		
Corrected Total	291	5.17152			

Root MSE	0.05289	**R-Square**	0.8447
Dependent Mean	4.99758	**Adj R-Sq**	0.8426
Coeff Var	1.05836		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	2.18554	0.17623	12.40	<.0001
log_lme_cu	1	0.07516	0.01712	4.39	<.0001
log_iron_steel	1	0.25807	0.04140	6.23	<.0001
log_cdur_spend	1	0.13561	0.01938	7.00	<.0001
conspire_2004_2016	1	-0.06574	0.01844	-3.57	0.0004

TABLE XI

AUTOREGRESSIVE DUMMY VARIABLE MODEL: HYPOTHETICAL CARTEL 2004 – 2012

Maximum Likelihood Estimates			
SSE	0.00575731	**DFE**	285
MSE	0.0000202	**Root MSE**	0.00449
SBC	-2287.6408	**AIC**	-2313.3781
MAE	0.00258163	**AICC**	-2312.9837
MAPE	0.05162495	**HQC**	-2303.0688
Log Likelihood	1163.68904	**Transformed Regression R-Square**	0.0270
Durbin-Watson	1.4489	**Total R-Square**	0.9989
		Observations	292

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	5.0176	0.4164	12.05	<.0001
log_lme_cu	1	0.0000933	0.004470	0.02	0.9834
log_iron_steel	1	0.0295	0.0135	2.19	0.0294
log_cdur_spend	1	-0.0204	0.0123	-1.67	0.0967
conspire_2004_2016	1	0.001075	0.004388	0.25	0.8066
AR1	1	-1.1681	0.0370	-31.56	<.0001
AR3	1	0.1685	0.0375	4.50	<.0001

V. DISCUSSION

The various modeling approaches described in this thesis may be summarized in the following tables. I report three basic approaches to modeling cartel overcharges: the simple before/after means, dummy variable approach and forecasting. Table XII shows that the simple mean difference in the PPI values from the non-cartel period to the cartel period is almost 30%. That is, the mean of the early 1992 – 2010 hypothetical cartel period PPI is about 30% lower than the mean of the presumed non-cartel period 2011- 2016. However, if actual cartel behavior were alleged for these time periods, and econometric modeling of the time periods were required, it is useful to note that the differences in the approaches are dramatic and create different results. The forecasting model, while it predicted well within the non-cartel period (2011- 2016), as the CUSUM and CUSUMSQ tests showed, it failed both stability tests for the counterfactual world estimation. Here, the mean predicted values and confidence intervals show an approximately 21 percentage point overcharge compared to the actual observed values in the hypothetical cartel period. And this in a period for which there was no actual allegation of cartel behavior!

Table XII
COMPARISON OF OVERCHARGES: HYPOTHETICAL CARTEL 1992-2010

	Cartel 1992 - 2010	Non-Cartel 2011- 2016	Overcharge Pct.
Simple Average	140.33	182.05	-29.73
Dummy Variable OLS			-6.8
Dummy Variable AR Model			0
Forecast AR Model mean lower confidence limit	161.36		15.37
Forecast AR Model mean upper confidence limit	178.24		27.87
Forecast AR Model mean predicted value	169.53		21.42

Table XIII shows that the simple mean difference in the PPI values from the non-cartel period (1992 – 2003) to the hypothetical cartel period (2004 – 2016) is about 26%. A simplistic interpretation is that this is a large cartel overcharge. The forecasting model for these time periods failed the CUSUM and CUSUMSQ tests for the base period, indicating a poor base from which to forecast. Indeed, it failed both stability tests for the counterfactual world estimation. Here, the mean predicted values and confidence intervals show an approximately 19 percentage point *lower* price compared to the actual observed values in the cartel period. The forecasting and dummy variable approaches show no positive overcharge for this hypothetical cartel, while the simple comparison of means before and after does. This underlines the importance of multiple approaches and more than simplistic approaches to estimating overcharges.

Table XIII
COMPARISON OF OVERCHARGES: HYPOTHETICAL CARTEL 2004-2016

	Non-cartel	Cartel	
	1992 - 2003	2004 - 2016	Overcharge Pct.
Simple Average	132.39	167.08	26.20
Dummy Variable OLS			-13.4
Dummy Variable AR Model			-1.2
Forecast AR Model mean lower confidence limit		126.77	-22.83
Forecast AR Model mean upper confidence limit		140.27	-14.84
Forecast AR Model mean predicted value		133.34	-18.94

This thesis adds to the literature by examining well known approaches to modeling cartel overcharges and shows the sensitivity to various estimation approaches and modeling considerations. Applying recursive residuals and CUSUM, CUSUMSQ tests to normal modelling will add another check on the reliability of overcharge estimates. This can be seen by models that forecast well in sample, but fail outside of the sample – e.g. in the alleged cartel period. The fact that overcharges may be trebled in private litigation raises the importance of properly estimating such overcharges.

APPENDIX

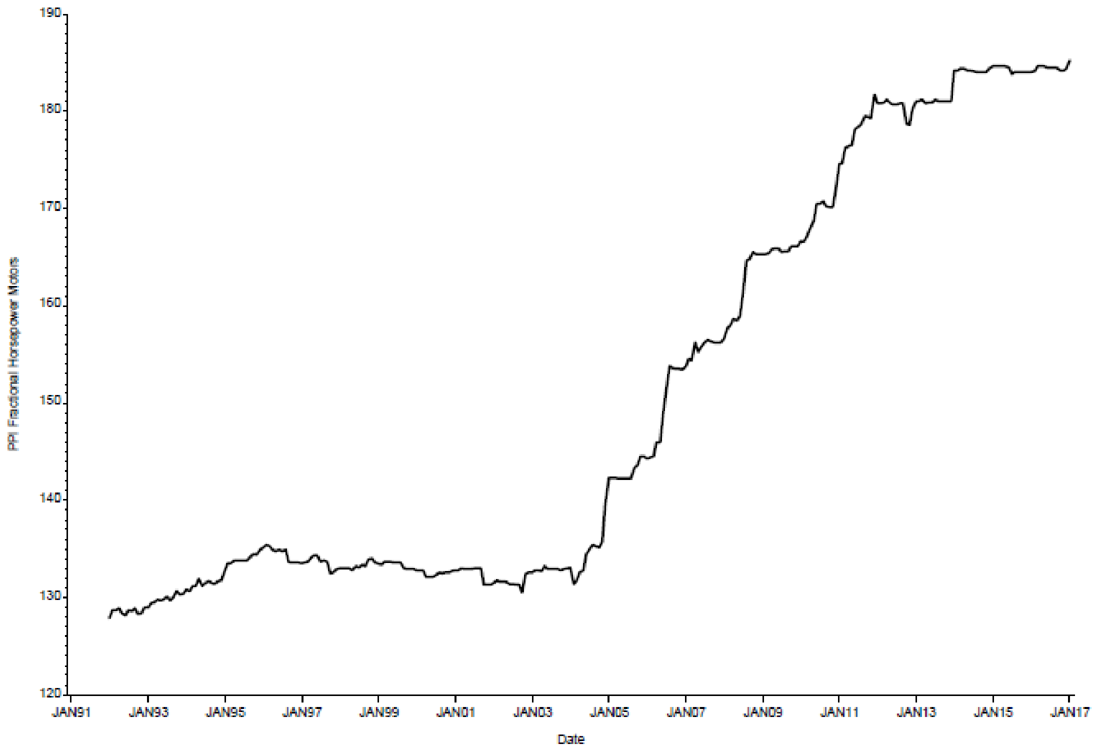

Figure 17. Plot of U.S. fractional motors PPI.

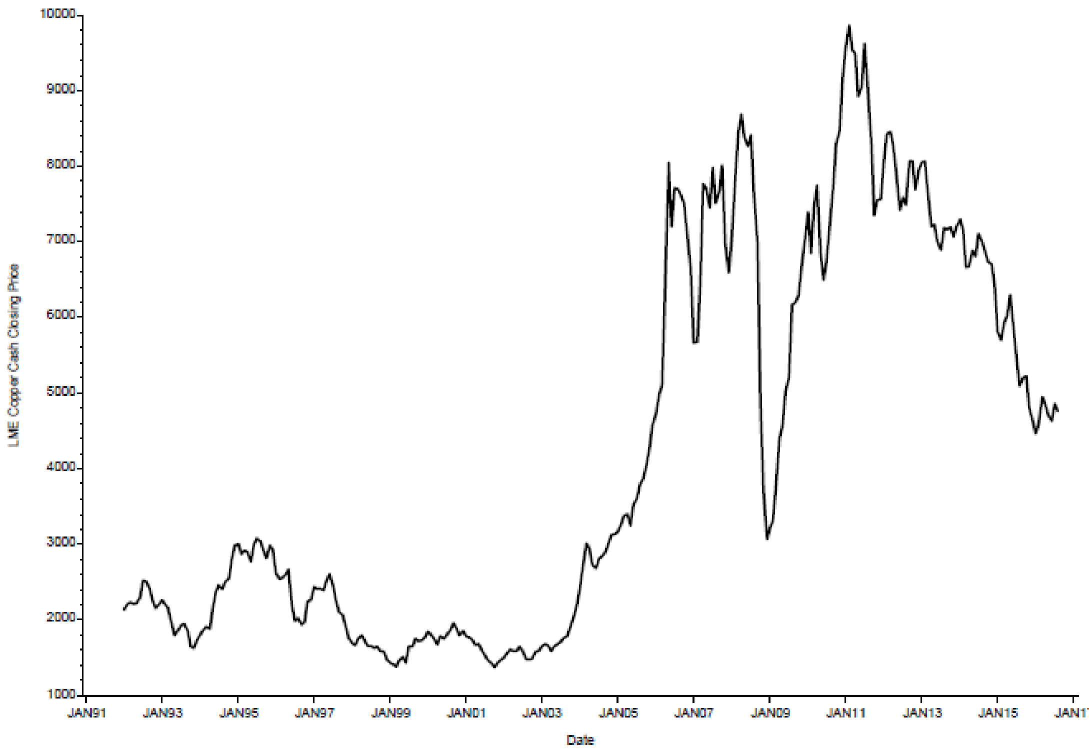

Figure 18. Plot of LME copper cash closing price.

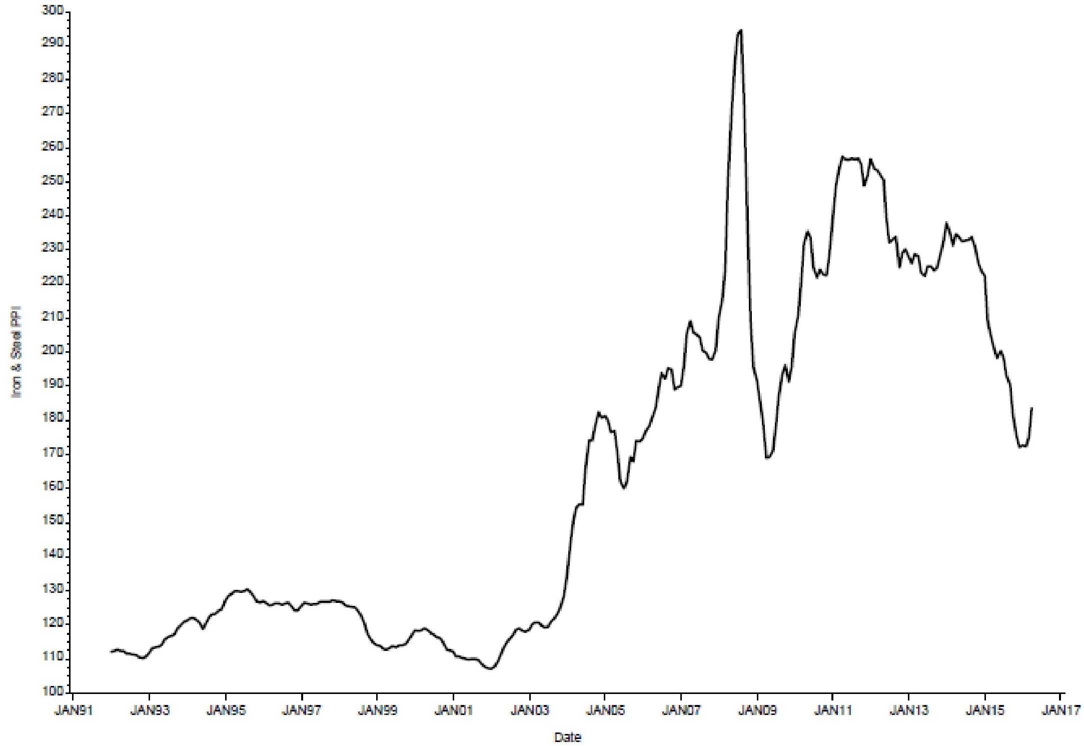

Figure 19. Plot of iron & steel PPI.

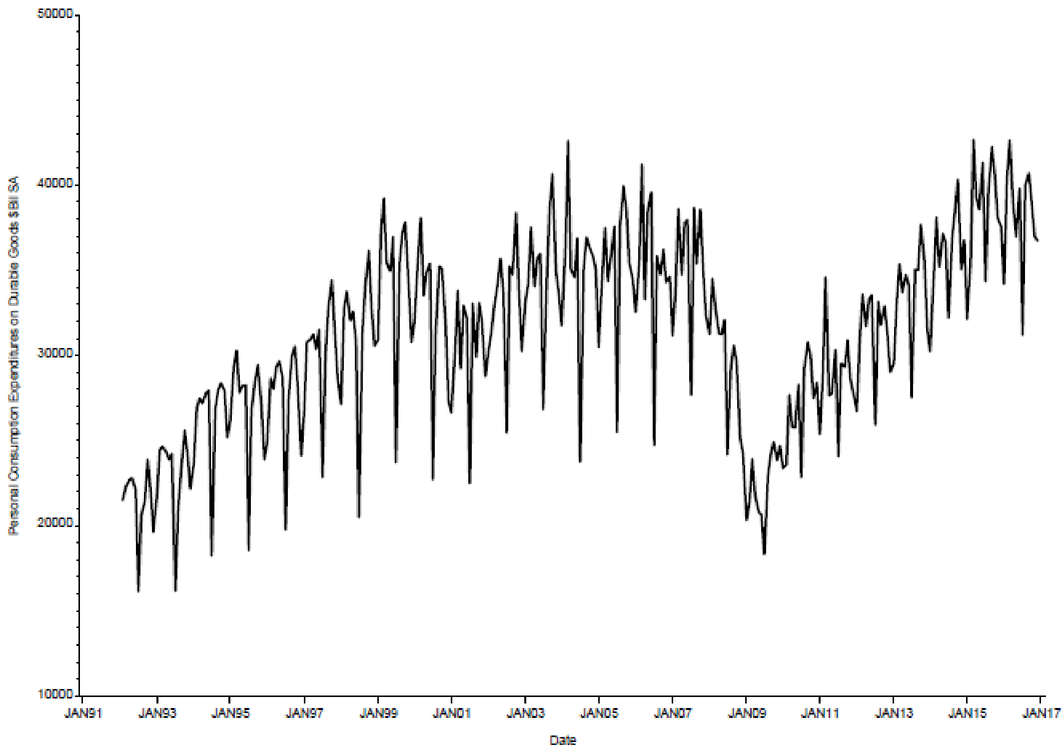

Figure 20. Plot of personal consumption expenditures on durable goods, $bill SA.

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