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DEPARTMENT OF ECONOMICS

DETECTION OF UNCOMPETITIVE BEHAVIOR IN NATURAL RESOURCE AUCTIONS USING REGRESSION ANALYSIS

IN KYO JUNG
SPRING 2020

A thesis
submitted in partial fulfillment
of the requirements
for a baccalaureate degree
in Economics and Mathematics
with honors in Economics

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ABSTRACT

The following thesis will look at some solid quantitative methods to detecting collusive actions in an American Natural Resource action, specifically timber. Collusion has been outlawed in the United States since the late 1800s. However, enforcement has been a legal matter that has proved to be rather complicated.

While various statistical measures have been introduced to combat collusive behavior, they vary with respect to the specific action cartels are taking. This thesis will look at the linear regression approach comparing a “problematic”, or collusive, model and a competitive model.

Even though limitations are introduced due to the dataset being strictly of US origin, this analysis provides a solid framework as to how this method can be performed on a smaller scale auction performed in the state of New Hampshire.

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ACKNOWLEDGEMENTS

First, I'd like o thank Professor Sung Jae Jun for helping me with this thesis. None of this would have been possible without his assistance and that of Professor James Tybout. I also would like to thank my father and mother for giving me an opportunity to study at Penn State.

Chapter 1

1.1 Introduction

The procurement of natural resources has been an important part of infrastructure building for both governments and firms. The distribution of natural resources has been done most often in the form of auctions all around the world. Resources such as timber and natural gas are those most often auctioned off to government and private firms.

As these auction systems developed more and more noncompetitive behavior started to arise in the form of collusion and bid rigging. Thus, both legislation and different auction mechanisms have been introduced to curb this kind of behavior. In a bigger picture, both the Sherman Act of 1890 and Clayton of 1914 were introduced to curb collusive practices among bigger firms. Unfortunately, these legislations are often indecisive in more solidly quantifying collusion and detecting such behavior.

In response, on the suppliers' sides, more and more auctioneers introduced different forms of auctions to curb collusive behavior and incentivize honest bidding. One such auction mechanism introduced are the second price auctions: an auction system where the highest bidder wins the auction and pays the second highest bidder's bid value. In Game Theory, this auction system is Dominant Strategy Incentive Compatible for the bidders; when bidders bid their true value in an auction, their payoffs are guaranteed to be non-negative, adding further incentive to bid their true values. While this auction system, also known as the Vickrey auction, eliminates some incentive to bid untruthfully, it does not address the problem.

A more solid and quantitative method must be used to detect collusion. Due to the legal nature involved, without solid evidence, it is difficult to conclusively punish those who collude and promote competitive bidding. Many statistical methods have been proposed to tackle this issue and the following thesis will demonstrate the results of one such method on an American natural resource auction.

1.2 Historic Backgrounds on Timber Auctions and Anti-Collusion in the US

Looking at the historical background to natural resource auctions and measures to prevent collusive behavior in those auctions can further help one understand how the US reached its current state.

Auctions have been present in the US since the founding of the 13 colonies. While the auction methods have advanced with the passage of time and advancement of technology, the basic concepts and principles have remained relatively equal. While Americans auction off various items from Google advertisement slots to US treasury bills, this section will focus on the progression of natural resource auctions in the United States.

Laws regarding the exploitation of forests and lakes have been present prior to the establishment of the constitution and the Thirteen colonies. However, a more national effort to both implement and create new legislation lacked prior to the Union.

Concepts like auction format, first price auction, and a minimum bid were implemented during the early years of the nation. Both the minimum bid and minimum amount of land auctioned were set during this period of late 1700s and early 1800s. However, a big shift occurred in the 1870s.

In 1871, the first federal conservation agency was established: the United States Commission of Fish and Fisheries. This subsequently led to the creation of the American Forestry Association in 1875. The establishment of these agencies were the start of modern conservation efforts on the part of the federal government, and hence an increased role of the government in auctioning off resources and land.

At around this time, in 1890, the Sherman Anti-Trust Act was passed, and the government assumed a bigger role in introducing competition in the market and breaking up trusts. Furthermore, the Clayton Act of 1914 and the Federal Trade Commission Act of 1914 both took further steps to address the practices specifically: price fixing, colluding, and more. These have remained the go-to legislation for the government to convict potential collusion and anti-competitive behavior on the federal level.

Back to timber auctions, the Organic Act of 1897 established much of the rules to how the forest reserves in the US will be used. It also introduced measures to how timber auctions may be performed in the United States. Henceforth, these rules were pretty much in place and were not impacted much by the many environmentalist movements that swept the nation in the 1900s.

Finally, modern federal timber auction procedures are guided by the 1976 National Forest Management Act (NFMA) which provided the new authority for national forests.

As to the execution of individual timber auctions, the individual state governments adhere to federal guidance but are responsible for the specifics. Because of this much of the specifics differ from state to state. So, a timber auction from New Hampshire might be slightly different from a natural gas or timber auction from Alaska. This reflects the history of how the US timber auction system got here. Much of the specifics were set earlier in US history. However, the conservation movements and the corresponding legislation were mostly introduced in the federal level. This left most of the state legislation addressing timber auction unchanged. It only changed the guidelines as to the plots subject to auction and those reserved for conservation.

As to the anti-trust and anti-collusion legislation, their introduction allowed the government to effectively prosecute and curb collusive and anti-competitive behavior. This increase in prosecution extended to natural resource auctions. However, the question of concretely determining whether collusion has taken place remained a question. This is where statistics come in.

1.3 Literature Review

The literature review for this specific topic contains a lot of statistical elements. Throughout the evolution of collusive behavior, methods to detect such actions have also evolved as well. Various statistical methods have been developed to combat and detect collusive behavior. An example of spatial statistics can be seen in Heijnen's analysis of price collusion. Yet, using regression analysis to compare two different models have proved to be both effective and simple in execution.

On the other hand, the regression approach was mentioned by Porter and Zona in *Detection of Bid Rigging in Procurement Auctions* to analyze and detect collusion in highway contract auctions conducted in New York. First by analyzing a competitive model that implements the probability of victory of the bidders and constructing a profit function utilizing that probability, Porter and Zona was able to compare a competitive firm and a collusive firm. In fact, the data was actually *a priori* data with prosecution for the participants and ring leaders of the collusive scheme. Setting the null at no collusion, linear regression should show statistically similar coefficients for competitive firms and those suspected of collusion. This method was also proposed by Bajari and Ye (2003).

Bajari has also done analysis focusing on geographical location and combined it with the regression approach in Bajari and Summers (2002). Yet, a monumental paper in detecting collusion, with an emphasis on regression analysis, is Bajari and Ye (2003). By dividing the model into dynamic bidding and collusion, a similar procedure inspired from Porter and Zona was used to divide firms into competitive and cartel firms. Additionally, Bajari and Ye also looked into the economic efficiency that might be required for a cartel to run in the best interest of the cartel members. Even in a monumental paper like Bajari and Ye (2003), the data used for analysis was from isolated auction setups like. The paper also dove into the procedure behind the auctions in their analysis. Emphasizing the importance of thoroughly understanding the auction setting before running any analysis on the auction data.

However, with specific regard to timber auctions, many previous works have been conducted. Especially, the Saphores et al. (2006) *Detecting Collusion in Timber Auctions: An Application to Romania* provides detailed analysis on dataset and the two factors on the supply and demand side.

Additionally, though a little more difficult a study was also conducted by Li et.al (2003) to analyze timber auctions with random reserve prices. From these works one can realize that a relatively large literature has been amassed regarding analysis of collusive behavior in timber auctions. This may be partially explained by the afore mentioned relative pervasiveness of collusive behavior in timber auctions.

The study of prior literature establishes auction study and the study of collusion in auctions as a relative new field of study. However, one remains certain; it is of paramount importance to understand the auction setting and how it was run to analyze any presence of bid rigging and collusion. This is due to the fact that every collusive scheme is tailored to the specific auction setting and also set to the profit maximization goal set by the individual cartel members.

Chapter 2

2.1 The Model

Porter's model relied on determining an optimal bid given the likely cost and using a probability distribution relative to other bidders. Some assumptions are at play here: the firms are aware of their costs with respect to the variables that needs to be analyzed and is not random. Each firm i is risk neutral and knows only the distribution of its competitors. The model is quite intuitive and encompassing; an equation like $Profit_i(b) = (b_i - c_i)\varphi_i(b)$ **(*)** can be drawn up. Here, b_i,c_i, and $\varphi_i(b)$ represents firm i's bid, its cost, and its probability of winning the auction. Applying the first order condition to the equation *: $\varphi_i(b) + (b_i - c_i) * \frac{d\varphi_i(b)}{db_i} = 0$. This is the basis of a competitive model of how firm i determines its bid b_i.

It is paramount to determine what variables play in the vector that determines firm i's probability of winning, $\varphi_i(b)$. Porter and Zona, due to the nature of the procurement auctions they were analyzing, analyzed based on the ranking of the bids. This was because Porter and Zona were concerned about the potential presence of phantom bidding: the appearance of a competitive auction.

2.2 The Supply and The Demand

As mentioned in the database section, New Hampshire provides the states and beyond with timber and is the 2nd biggest supplier of timber in the United States. Many of the timber auctioned are from state property, state forests, and a correctional facility. Therefore, these timber auctions were conducted under the appropriate forest conservation legislation.

The woods species range from all types of pine trees, oak trees, and maple trees. They also come in different product specifications: from Saw logs to Pallets. These can be used as variables in the regression analysis to include in the model.

Besides the saw logs and pallets there are 3 other products that are worth mentioning. These are: mat logs, roundwood, and pulp. Saw logs, Pallets, and mat logs are measured in millions board feet. Roundwood and pulp were measured in tons. Due to this disparity in units measured, for analysis dummy variables for saw logs, pallets, and mat logs will be used. From the data, round wood and pulps only consisted of under 10% of the entire data. Roundwood and pulp were excluded also because of the unit measured and the complexity in calculation round woods and pulps were excluded from analysis.

The demand side of the equation will depend on a lot of variables in a more complex model. However, this analysis will only look at specific variables that may be relevant for the specific bidders involved.

Per New Hampshire law RSA 227-I:9, all primary wood processing mills and wood concentration yards must register with the New Hampshire Division of Forests and Lands. Hence, information like location, mill type, operating capacity, and output of wood and timber products are available through the Division of Forests and Lands database. According to the

Directory of Sawmills & Lumber Wholesalers, most of those entering the auction are sawmills. Therefore, more primary products like logs would be demanded compared to more finished products like pallets.

Another big variable that may affect the demand is the distance between the bidders' production facilities and the source of the timber. Intuitively the further away a company must travel for the products the higher its costs will be. Therefore, the companies closer to the timber sites would have an incentive to bid higher than other people. This will be captured in the variable distance.

2.3 Database

The database that will be used for the assessment will focus on the timber auctions from New Hampshire. There are several reasons behind this arrangement. First, the nature of the resource is important. Timber is crucial in its economic impacts via both infrastructure investment impacts and its role on climate change and its impact on the economy at large. Due to this, timber and its appropriate distribution and use have been important for both developing and developed economies.

More minutely, there exists some pre-existing literature on bid rigging detection and auction theory using timber auctions as a model. An example of this is Baldwin et al. *Bidder Collusion at Forest Service Timber Sales* (1997) and Saphores et al. *Detecting Collusion in Timber Auctions: An Application to Romania*. Due to some pre-existing literature, modeling a competitive bidding environment using timber as a specific resource is easier than other resources like oil and gas, where relatively few works have been published on.

Finally, the comfort of the dataset in terms of simplicity and relevant variables made it an easy decision to use New Hampshire's timber auction bid results from the NH Division of Forests and Lands. Due to New Hampshire's reputation as one of the top timber suppliers in the US, the existence of active bidders also provided a bright outlook for unbiased analysis. Also, the number of auctions and exactness in results made choosing this specific dataset an easy choice.

New Hampshire is also well known in the US for providing the economy with quality timber from its woodlands. It is the second most forested state in the US after Maine, occupying around 81% of the state. Yet, the issues arising from the massive deforestation of areas, like the Amazon Rainforests and other vast forests, are not witnessed in the New Hampshire forests. Statistically, according to the New Hampshire Division of Forests and Lands, total land area has decreased from around 5.78 million acres to around 5.74 million acres between 1948 and 2012. One might wonder why the industrial development of the country and the use of timber and natural resources are so minutely correlated. The Division of Forests and Lands offer a plausible explanation.

First, the clearance of forests for residential areas is quoted as the majority of the decline of forested areas. Additionally, the changing definition of what exactly the term "forestlands" and "timberlands" refer to has sometimes increased the amount of forest areas measured for official accounts.

The ownership of the forest lands of New Hampshire is also useful when analyzing the auctions surrounding these lands. According to the Division of Forests and Lands, most, around 73% of the land is owned by individuals. The federal government owns around 17% and the public owns around 10%. Because most of the acres are owned by individuals for house sites, the management of timber property by these small-scale owners has raised concerns for timber auction designers and the state. Yet, this issue will not be addressed when analyzing bid rigging and bid results of these datasets.

Now one must dive deeper into the specifics of how the timber auction and sale happens. For over 100 years, timber has been auctioned and sold off in New Hampshire under the auspices of the Forest Management Bureau. Under the authority of RSA227-H:1, to perform sound forestry practices and principles the Forest Management Bureau has been performing sales and auctions of timber.

According to the New Hampshire Division of Forests and Lands:

> All timber sales on state lands go through an extensive planning process and site analysis … Timber harvests are sold through a public bid process in accordance with procedures adopted by Governor and council. All interested parties capable of being determined to be a "Responsible Bidder" as defined in RSA 28:8-e will be provided the opportunity to bid on any offered timber sale. … A showing date is scheduled and notices are sent to prospective bidders. Bidders are provided a prospectus at a showing and have two weeks to submit their bids from the date of the showing.

Aside the legal elements of the sale, the auction takes the form of a first price sealed bid auction: the standard for many natural resource auctions. Through observations of practices in other natural resource auctions like oil and gas, first price sealed bid auction.

Specifically, the analysis will involve auction data from the auctions from May 9, 2019 until November 21, 2019. This is the most recent auction dataset obtainable from the NH Division of Forests and Lands.

Generally, the participants are from both the states of Vermont and New Hampshire. The smaller scale of the auctions and participants was another reason why the data set was so appropriate for an assignment like this. Additionally, this enables one to add another variable to the analysis: distance. On a bigger international scale, analysis using distance may be more difficult due to the potential difference in nationality complicating analysis. As a hypothesis, there may be some correlation between bid prices or bid rigging tendencies and the distance between the forested area and companies' storages.

Chapter 3

3.1 Methodology

Early on, analyzing the specifics of bid rigging seemed not to be a priority for many researchers. Obviously, Porter and Zona's 1994 work, *Detection of Bid Rigging in Procurement Auctions,* demonstrated how econometric methods could be used to detect bid rigging. They used a priori data with court records and actual verdicts. Thus, the conclusions drawn from the study were concrete and incriminating implications brought up by the writers were not problematic.

However, inherently, using econometric methods to detect collusion is not only incredibly difficult, but a uniform method may not even exist. Due to the illegal nature and the implications that follow the act of collusion, detecting collusion and drawing up a conclusive case is very difficult. Due to this the variables and specific econometric methods used are important in what results one may draw.

The methodology that will be used for the analysis will be more simplistic than other conventional research papers. Much of statistics have been used to determine both collusion and bid rigging. Especially for collusion in price setting, spatial statistics has been used. Examples of studies are Heijnen et al. *Screening for Collusion: A Spatial Statistics Approach* where screening for local cartels in the Dutch gasoline market was conducted.

For this analysis, regression analysis and hypothesis testing will be used. This is due to their relative simplicity in operation. Regression analysis is relatively simple compared to other statistical tools, especially involving spatial statistics. Regression analysis was used by many prior studies and has proven to lead to meaningful conclusions.

Hypothesis testing will come into play when comparing a "collusive" model and a competitive model. How a "collusive" model will be developed will be explained in the theory section. The testing will be done by comparing the regression coefficients setting the null hypothesis as $H_0: B_{i,actual} = B_{i,competitive}$ and the alternative hypothesis as $H_1: B_{i,actual} \neq B_{i,competitive}$. When sufficient data evidence to reject the null hypothesis through conventional hypothesis testing procedure is established, one can more confidently establish potential collusive intentions among the bidders.

First, one of the limitations to this methodology is related to coming up with a theoretical competitive model. Obviously, coming up with the coefficients through regression analysis for the actual data is not difficult. However, there may be many different factors and variables involved in setting up a model for a competitive bidding model. This will be further explained in the ***The Supply and The Demand*** section.

The essence of the analysis will mainly hinge on regression analysis and hypothesis testing. It is true that there are more intrinsic and sophisticated methods to determine bid rigging and collusion; yet, for the purpose of this research, it's sufficient to draw the desirable results using the two methods mentioned.

3.2 Regression Matrix and Chow Test

The Regression equation is best represented in Matrix Form. We will statistically determine if $B_i - a_i = 0$ for all $i = 0, 1, 2, 3$, this will be the null hypothesis: that the previous equation is true. The alternative hypothesis will be if $B_i - a_i \neq 0$ for any one of $i = 0, 1, 2, 3$. In matrix form, we will be testing: $\begin{bmatrix} 1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & -1 \end{bmatrix} * \begin{bmatrix} B_0 \\ B_1 \\ B_2 \\ B_3 \\ a_0 \\ a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$. For further reference, the matrix $\begin{bmatrix} 1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & -1 \end{bmatrix}$ will be referred to as the $\boldsymbol{A\ Matrix}$. The Chow Test will make testing this relatively simple.

The Chow Test was introduced in the 1960s and does the following: it tests whether the true coefficients in two linear regression models on different data sets are equal. For this specific analysis we will assume the distribution is a standard Chi Squared Distribution with degrees freedom $k = 3$.

First, we let $[Cov - Var]$ be the covariance variance matrix for the coefficients and let $[\hat{\gamma}]$ be the vector of the estimates of the coefficients. Then the Chow Test statistic, *W*, with the matrix environment is as follows: $([\boldsymbol{A\ Matrix}] * [\hat{\gamma}])^T * ([\boldsymbol{A\ Matrix}] * [Cov - Var] * [\boldsymbol{A\ Matrix}]^T)^{-1} * ([\boldsymbol{A\ Matrix}] * [\hat{\gamma}])$.

Once we calculate *W*, we observe the p-value and either reject or fail to reject the null hypothesis.

Chapter 4

4.1 Analysis

The approach for analysis will be very similar to that of Porter (1993). Dividing the collection of data into three groups: the data in its entirety, the collection of only suspicious firms, and the collection that excludes those suspicious firms.

The suspicious firms will be henceforth called firm 1, 2, 3 respectively. These firms were marked suspicious mainly due to their heavy participation in the auctions. Surprisingly these three firms accounted for 36% of the 690 total bids collected. It was quite eye opening that approximately 11% of the bidder accounted for almost 36% of the total bids submitted. One of the most common methods of bid rigging is sending signals through repeated bidding.

Even if it isn't outright illegal activities like collusion, it is still worth analyzing the difference between a regular bidder and one that is not. This analysis can definitely help explain some of the subtle differences in behavior a regular bidder might demonstrate compared to one who is not a regular bidder.

The main variables for the analysis are as follows: the distance, volume of the wood, saw logs, pallets, mat logs. First, the distance measures the distance between the bidder's base of operation (or HQ) and the site where the timber products were harvested. Due to the cost of transportation, this variable is expected to be negatively related to the bid submitted. The further away a timber site is, the less appealing it is for a company looking to purchase the products.

Next, the volume of wood variable measures the volume of the timber offered in a particular auction. This is expected to be positively related to the bid submitted. This is due to the fact that costs exist for submitting a bid. Conventionally, a baseline bid amount is set for every bidder; every bidder must bid at a minimum of the baseline bid to qualify as a proper bidder. However, for this specific collection of auctions, that baseline bid concept does not exist; yet the nature of the paperwork and administrative cost the state imposes on the various participants. Therefore, it is in the best interest for the bidder to procure the most amount of timber products with the least number of bids submitted.

Finally, the variables saw logs, pallets, and mat logs are dummy variables based on the products offered. These dummy variables consider how different each bidders' demand functions are. Pallets are a more manufactured product than saw logs and mat logs. Since many of the bidders are sawmills conducting their own manufacturing operations, the positive coefficients for saw logs and mat logs are expected to be significantly higher than that of pallets. Many of these sawmills have no need for pallets.

4.2 Results

After running an OLS regression on the variables mentioned above, 2 problems were observed. In fact, the distance variable and the final bid submitted were not statistically correlated. This can be explained by the fact that many of the sawmills were from either New Hampshire or Vermont and were considerably close to the State Forests. So, the impact of distance is consistent across all the bidders. All the bidders were within a 300 – 400 km radius of the foresting site. The difference in distance were not significant enough to warrant the inclusion of the distance variable in the final analysis. A more global dataset is required if an analysis like this is to be conducted. The appropriate solution for this issue is to simply remove the distance variable from the OLS regression model. Since it has no role in explaining the final bids, it cannot be considered an explanatory variable anymore.

Another issue that rose was with the dummy variable for pallets. The t-value for pallets were extraordinarily high. A plausible explanation for this may be because of the fundamental difference between pallets and a product like saw logs. Saw logs and mat logs are more primary in their uses; they are far more adequate for sawmills than pallets and thus more representative of the demand functions for the bidders involved in this auction. Since most of the auction participants required more raw resources like logs, a somewhat manufactured product like pallets may misrepresent the demand of the auction participants. This raised cause for concern. The appropriate solution was to remove the said variable alongside the distance variable removed earlier.

Now, we divide the sample into three: one consisting of the entire database, one consisting of only the "problematic" bidders, and one consisting only of the "competitive" bidders. The OLS analysis is as follows:

Table 1. Table of Regression results of 3 Models

	Entire Database (1)	Problematic Database (2)	Only Competitive Database (3)
Volume.in. MBF.TONS	0.317***		
	(0.054)		
Sawlogs	76.331***		
	(8.689)		
Matlogs	90.451***		
	(14.648)		
Volume.in. MBF.TONS		0.397***	
		(0.089)	
Sawlogs		65.181***	
		(14.400)	
Matlogs		85.104***	
		(24.816)	
Volume.in. MBF.TONS			0.284***
			(0.066)
Sawlogs			80.346***
			(10.730)
Matlogs			92.210***
			(17.909)
Constant	51.339***	39.779***	56.784***
	(7.438)	(12.180)	(9.232)
Observations	690	209	481
R2	0.169	0.201	0.161
Note:		*p<0.1; **p<0.05; ***p<0.01	

As seen from the above table the coefficients are visibly different among the different Databases demonstrating a difference in bidding behavior. However, to more specifically quantitate the existence or lack thereof a difference in bidding behavior, we turn to the Chow test.

The Chow test is a useful statistical test to test the null hypothesis of statistical equivalence of coefficients between two linear regression models. More specifically, we test the null hypothesis of: $\begin{bmatrix} B_0 - a_0 \\ B_1 - a_1 \\ B_2 - a_2 \\ B_3 - a_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$. The testing condition would be that if either one of the values in the vector on the right hand side of the equation is not equal to 0, the Chow test would fail as there is evidence to show that a difference in bidding behavior exists.

We run the Chow test twice: between the entire database and problematic database, and between the problematic Database and the solely competitive database. First, the chow test between the entire database and problematic database yields the following results. At a 10% confidence level, we ***reject*** the null hypothesis presented above. However, at a 5% confidence level, we ***fail to reject*** the null hypothesis (p value = 0.079). So, in this case the results are on the fence and may lead to some inconclusive conclusions.

However, the results are drastically different when we compare the problematic database with the competitive database. The results of the Chow test are as follows: we ***reject*** the null hypothesis at any confidence level (p value = 0.007). Therefore, the results comparing the competitive model and the problematic model is far more convincing than when we compare just the problematic model to the entirety of the dataset.

An interesting part of this Chow test with the database is when we exclude the intercept from the test; we run the Chow test without the intercept variable B_0. The Chow test yields some surprising results: we ***fail to reject*** the null hypothesis at any level. The analysis behind this will be addressed in the **Limitations** section.

4.3 Limitations

As with any study, there are some limitations present in the study. First, as mentioned earlier the variables of distance had to be removed due to the lack of correlation. The impact of distance was negligent in this study because both the source of the timbers sold and the companies buying were in negligible distances. In most cases, the distance between the source of the timber and companies' operation facilities were no further than 500 kms. Also, the distances between companies were also negligible. Such limitations could be addressed when conducting more of an international study. Comparing countries in an auction setting would demonstrate the role a variable such as distance can play in bidding behavior.

Another limitation that must be addressed is mentioned earlier: the drastic difference in analysis once the intercept coefficient is excluded. Then we ask: what role those the intercept coefficient play in these two models? One aspect of bidding behavior the intercept coefficient may capture is how repeated bidders adjust their behaviors as the perform more bids. Since the basis of division between the competitive and problematic bidders was the fact that the problematic bidders bid far more often than the competitive bidders. So, one must leave room for a change to take place in bidding behavior as the problematic bidders participate in more bids.

One way this issue could be tackled could be by performing a time series analysis. This study took out the impact time may have in bidding behavior. A potential learning curve may exist for newer bidders and this learning curve will get eliminated as the bidder participates in more bids. A bidder among the problematic bidders may have the following thought process: “from previous auctions I know a certain bid x is guaranteed to outbid a certain number of bidders”. In our model, the intercept in the problematic model may represent this predetermined x. Whereas, the intercept in the purely competitive model may be factor in the predisposed price the bidders are willing to pay in response to their demand function.

In more legal senses, room for collusive behavior is left most open when auctions are repeated, and the same bidders participate. Their collusive intentions are signaled behind the change in bidding behavior as the participate in more auctions. This leaves behind no contextual or solid evidence for collusive behavior.

These are the two main limitations that are present in this study. Both are ones that can be easily addressed with minor changes in database and analytical methods.

Chapter 5

5.1 Conclusion

Unfortunately, non-competitive behavior has been ever present in all facets of human history. Collusion in bidding and bid-rigging are just small parts of that non-competitive behavior manifesting in an auction setting. Much effort and progress has been made to accurately detect these behaviors from spatial statistics analysis to regression analysis. With regards to regression analysis, one must acknowledge that models are only as good as the assumptions use. As to our analysis, I believe dividing our dataset using the assumption that 3 out of 27 firms accounting for 36% of the total bids is unusual is a solid assumption to base our model on.

We clearly see that a difference in bidding behavior does exist between the “problematic” 3 bidders and the rest of the participants. Now whether that constitutes as collusion and illegal behavior is for a court of law to decide. However, this basic model has been able to demonstrate how a difference in bidding behavior can be quantitatively demonstrated used regression models.

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In Kyo Jung (Academic Vita)

Education 2016- 2020

The Pennsylvania State University, University Park, PA
Bachelor of Science in Economics; Theory and Quantitative Methods Module
Bachelor of Science in Mathematics with System Analysis Option
Minor: Statistics
Schreyer Honors College

Skills

Language	***Computer***	***Interests***
fluent English	Microsoft Office	International Business
fluent Korean	Python	Communication/Presentation
conversational Spanish	Matlab	Data Collection/ review/ analysis
		International Cultural business

Work Experience

Business Translator, Seoul, South Korea *summers 2016 to 2019*

- Worked one on one with a Korean cosmetics company, the LS life science company, to help finalize a contract with a Mexican buyer. Communicated primarily in Spanish.
- Finalized the contract successfully to allow many Korean cosmetic products like moisturizing masks and lotions to appear on Mexican store shelves.
- Liaised with store owners from Mexico and helped them conduct market research for the Korean cosmetics market.

COEX Business Mixer Coordinator, Seoul, South Korea *summer 2019*

- Managed an international business mixer event for different licensing companies from around the world and Korea.
- Learned many new business terms and concepts used in the licensing, caricature, and animation industry.
- Cooperated with co-workers who were students from different backgrounds. Some of my co-workers were graduate students from China and Germany. Others were from the Korean labor force.
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Relevant Research Experience

REU Program Intern, the Pennsylvania State University *fall 2018*

- Worked under Professor Jingting Fan in the Economics Department.
- Used and familiarized the Panda statistical package on Python.
- Used Python to edit the 160 years of industrial census data for easier analysis.

Schreyer Honors Thesis, the Pennsylvania State University *fall 2019-spring 2020*

- Writing a 30 to 40 page Thesis paper. Currently finished.
- Focusing on using previous auction data to detect collusion in auctions involving natural resources; also, on what auction planners can do to deter collusion.
- My thesis supervisor is Professor Sung Jae Jun in the Economics Department.